BGSG

Volume 59

Research Paper

Correspondence to:
Constantinos Nefros
kostasnefros@central.ntua.gr

DOI number:
http://dx.doi.org/10.12681/bgsg.29038

Keywords:
Landslides, GIS, Geodatabase, MCDA, LSA

Citation:
Nefros, C. and Loupsakis, C. (2022), Introducing A Global Geospatial Database and GIS Techniques as A Decision-Making Tool for Multicriteria Decision Analysis Methods in Landslides Susceptibility Assessment. Bulletin Geological Society of Greece, 59, 68-103.

Publication History:
Received: 24/12/2021
Accepted: 04/05/2022
Accepted article online: 18/05/2022

The Editor wishes to thank three anonymous reviewers for their work with the scientific reviewing of the manuscript and Ms Emmanouela Konstantakopoulou for editorial assistance.

Introducing a Global Geospatial Database and GIS Techniques as a Decision-Making Tool for Multicriteria Decision Analysis Methods in Landslides Susceptibility Assessment

Constantinos Nefros [1, *] and Constantinos Loupasakis [2]

Laboratory of Engineering Geology and Hydrogeology, School of Mining and Metallurgical Engineering, National Technical University of Athens, 9 Heroon Polytechniou St., 15780, Zografou, Athens, Greece

[1]kostasnefros@central.ntua.gr, https://orcid.org/0000-0002-2075-4112 (corresponding author),

[2] cloupasakis@metal.ntua.gr, https://orcid.org/0000-0003-1822-6510

Abstract

Every year landslides cause many fatalities and destroy numerous infrastructures around the world. Due to their catastrophic results, scientific research studies are conducted, on a continuous basis, trying to determine the controlling and triggering factors, and to evaluate their contribution-weight to that phenomenon. In this direction, many of these studies use multicriteria decision analysis methods as they are quite effective and can be applied rather quickly. However, a large percentage of the new studies that use these methods, is usually devoted to the analysis of many previous research studies and the validation of their results, which usually leads to serious delays and requires significant resources. In this research, 82 relevant past studies are evaluated, and their results are integrated into a worldwide geospatial database, to present its potential as a decision-making tool, during the landslide susceptibility assessment. As it is revealed the results of its statistical and spatial correlation with the examined region's prevailing parameters in a geographical information system environment, can provide critical indications- suggestions to a researcher and along with the applicability of the multicriteria decision analysis methods, that contain the use of other experts' knowledge and experience, to lead to the rapid identification of the most critical landslide causal factors and the initial evaluation of their contribution-weight. These indications accelerate significant the whole process and reduce the risk for possible biased conclusions, which can render the whole method ineffective.

Moreover, this study highlights the geodatabase's potential to incorporate open-access data, from external spatial databases and to use them, during the process of the landslide susceptibility assessment.

Keywords: *Landslides, GIS, Geodatabase, MCDA, LSA.*

Περίληψη

Κάθε χρόνο οι κατολισθήσεις προκαλούν πολλούς θανάτους και καταστρέφουν μεγάλο αριθμό έργων υποδομής σε όλο τον κόσμο. Εξαιτίας των καταστρεπτικών τους αποτελεσμάτων, επιστημονικές ερευνητικές μελέτες πραγματοποιούνται συνεχώς, προσπαθώντας να προσδιορίσουν τους παράγοντες που προκαλούν και ενεργοποιούν μία κατολίσθηση και να προσδιορίσουν τη συνεισφορά – βάρος τους σε αυτό το φαινόμενο. Σε αυτή την κατεύθυνση, πολλές από αυτές τις μελέτες χρησιμοποιούν μεθόδους πολυκριτηριακής ανάλυσης, καθώς είναι αρκετά αποτελεσματικές και μπορούν να εφαρμοστούν αρκετά γρήγορα. Παρόλα αυτά ένα μεγάλο ποσοστό των νέων μελετών που χρησιμοποιούν τέτοιες μεθόδους, συνήθως αφιερώνεται στην ανάλυση πολλών προηγούμενων μελετών και στην επιβεβαίωση των αποτελεσμάτων τους, γεγονός που συνήθως οδηγεί σε σημαντικές καθυστερήσεις και απαιτεί αυξημένους πόρους. Σε αυτή την έρευνα, 82 σχετικές προηγούμενες μελέτες αξιολογούνται και τα αποτελέσματά τους ενσωματώνονται σε μία παγκόσμια γεωχωρική βάση δεδομένων, για να παρουσιαστούν οι δυνατότητες χρήσης της βάσης ως εργαλείο λήψης αποφάσεων κατά την εκτίμηση κατολισθητικής επιδεκτικότητας. Όπως αποκαλύπτεται η στατιστική και χωρική της συσχέτιση με παράγοντες που επικρατούν στην εξεταζόμενη περιοχή σε ένα περιβάλλον γεωγραφικού συστήματος πληροφοριών (ΓΣΠ), μπορεί να χρησιμοποιηθεί για να παρέχει κρίσιμες ενδείξεις – προτάσεις σε έναν ερευνητή και μαζί με την εφαρμογή πολυκριτηριακών μεθόδων ανάλυσης, που περιλαμβάνουν τη χρήση της γνώσης και της εμπειρίας και άλλων ειδικών, να τον οδηγήσει στην ταχεία αναγνώριση των πιο κρίσιμων παραγόντων εκδήλωσης μίας κατολίσθησης και την αρχική εκτίμηση της συνεισφοράς-βάρους τους. Αυτές οι ενδείξεις- προτάσεις επιταχύνουν συνολικά τη διαδικασία και να μειώνουν το ρίσκο για πιθανά μεροληπτικά συμπεράσματα, τα οποία μπορούν να καταστήσουν τη μέθοδο αναποτελεσματική. Επιπρόσθετα αυτή η μελέτη αναδεικνύει τις δυνατότητες της γεωβάσης να ενσωματώνει ανοιχτής πρόσβασης δεδομένα, από εξωτερικές χωρικές γεωβάσεις και να τα χρησιμοποιεί κατά τη διαδικασία της εκτίμησης κατολισθητικής επιδεκτικότητας.

Λέξεις Κλειδιά: *Κατολισθήσεις, ΓΣΠ, Γεωβάση, Πολυκριτηριακές Μέθοδοι Ανάλυσης, Εκτίμηση κατολισθητικής επιδεκτικότητας.*

1. INTRODUCTION

Due to climate change, natural phenomena tend to have an increasing influence in peoples' everyday life (Hesmati, 2020; Papanikolaou and Diakakis, 2011). Their intensity, sometimes combined with man-made factors, leads to enormous natural disasters which in turn cause the loss of many human lives and the destruction of a great number of critical infrastructures (Papanikolaou and Diakakis, 2011; Sauerborn and Ebi, 2012). Among these natural disasters, landslides have a significant worldwide impact (IGOS, 2004; Kirschbaum et al., 2015) and are of scientific interest due to their catastrophic results. As it is proved by previous (Dilley et al., 2005) and more recent studies (Kirschbaum et al., 2015), the landslides are happening all over the world, in nearly every country, sometimes caused by completely different reasons.

The causal factors that influence the stability of a slope are generally divided into two main categories, the preparatory factors, which degrade the stability of the slope preparing the failure and the triggering factors, which activate the landslide (Cruden and Vandine, 2013). Most common causal factors are the unfavorable slope angle, the slope aspect, the geology and the land use/ land cover, while the most common triggering factors are the intense or prolonged rainfall, the earthquakes and the various erosion processes and human activities (Westen et al., 2006; Ladas et al., 2007a; Ladas et al., 2007b; Rozos et al., 2010; Kouli et al., 2014). The assessment of the propensity of soil or rock in a region to create a landslide, according to the local characteristics, is expressed with the landslide susceptibility assessment (LSA) (Chalkias et al. 2014). A serious problem during the LSA, is that there are no universal guidelines about the selection of the appropriate causal factors (Shahabi and Hashim (2015)). Thus, the researchers sometimes spend a significant part of their research on analysing relevant previous research studies and validating their results, which can lead to serious delays, especially in case that they concern a great number of research studies. As Guzzetti (2005) points out about the LSA, the difficulty mostly lays in the availability of the relevant information, and on the complexity and the amount of it, especially when the research concerns large areas. Moreover, the results' validation can be also a quite difficult task, especially in cases where the researcher does not provide or pose restricted access to the initial data (Lin et al. (2017).

In general, the methods that the researchers use to perform an LSA, can be distinguished to quantitative and qualitative ones. The quantitative methods are usually based on numerical expressions between the prevailing factors and the probability of the occurrence of a landslide (Guzzetti, 2005; Reichenbach et al., 2018). More specifically, the researcher through a mathematical model, tries to simulate the landslide's mechanism and to calculate the Landslide Susceptibility of the area. However, the applicability of this method often requires significant processing resources and an extended historical landslide record (inventory), which in many areas is not available. Moreover, these methods have been proved to be ineffective for places where large environmental changes took place in the recent past or are expected to happen in the near future (Westen et al., 2006).

On the other hand, the qualitative methods use qualitative criteria and terms to evaluate the landslide susceptibility of a region (Westen et al., 2006; Chalkias et al., 2014; Anbalagan et al., 2015). They are based on the opinion of a scientific team, called the "experts", to identify the critical characteristics of an area that can render it prone to a landslide (Chalkias et al., 2014; Tavoularis et al., 2015). The experts are usually people with strong academic background who are rather familiar with the specific features of the examined region. An example of qualitative methods are the multicriteria decision analysis (MCDA) methods, such as the Analytical Hierarchy Process (AHP). In AHP, the selected experts, by following a specific process determine the weight- contribution of each factor and conduct the relevant LSA (a hypothetical example, which has been developed for the needs of this study, analyses the steps followed during the APH and is presented in Supplementary Material Tables 1,2 and 3 (SM- Tables 1, 2 and 3)). MCDA methods can risk of being ineffective if the experts are not selected properly by the researcher (e.g., in Kil et al. (2016), it is presented how the profession of each expert, can lead to completely different judgements of the most critical causal factors' selection and on the relevant weights' attribution) or if the selected experts, proceed to biased judgements (Nicu 2018, Xiong et al.,2018 and Moradi and Rezaei, 2014). However, MCDA methods can produce susceptibility maps with high reliability, provided that the use of experts will not lead to biased conclusions (Gorsevski et al., 2006), in contradiction to the nowadays increasing trend in LSA, to replace the opinion of experts with computer algorithms (Westen et al., 2006).

The main objective of this research is to analyze and organize spatially, the knowledge gained by the MCDA methods, used in previous studies, and to provide their results directly to a researcher, reducing that way, the time and sources needed for a new study and improving this new study's efficacy. This is achieved by creating a geospatial database (geodatabase), which integrates spatially the results of 82 scientific studies that use MCDA methods, and by using their statistical analysis, to the standardization of the whole process. By using this geodatabase, a researcher can decide to use a smaller number of experts, to propose to the experts a variety of potential landslide causal factors, to compare and validate the results of the conducted study with the relative ones of the geodatabase's and to identify and therefore to exclude possible outlier values. The experts also, by using the proposed geodatabase, have direct and immediate information- suggestions on the potential landslide causal factors that they can use, along with their relative importance-weight which can be applied during the MCDA method of the conducted new study.

The proposed procedure does not introduce a new method, and, a researcher cannot conduct an LSA, based exclusively on the geodatabase's results. Therefore, it does not eliminate the need for experts, and their contribution to the conduction of the LSA remains indispensable. The experts due to their personal knowledge and experience, are the only capable ones, that can evaluate if they should accept all, some or none of the results of the geodatabase, according to the particular characteristics of the examined area. Nonetheless, this judgement should be justified. Thus, through the geodatabase's use, the risk for possible biased conclusions and the necessary time for selecting the most critical causal factors and determining their relative importance, can be significantly reduced. However, it is significant to note that the use of the geodatabase, limits but does not eliminate the possibility for biased conclusions. As it happens with every tool used in LSA (Guzzetti, 2005), this geodatabase is going to be efficient only if it is used by experienced researchers- professionals.

The potentiality of the geodatabase also emerges by its statistical and spatial analysis in a broader level, with GIS techniques, and its interconnection with spatial data derived from external open access sources. Hence, correlations of the causal factors' weights included into the geodatabase with local characteristics, such as the climate of a region, are revealed, which can be subsequently used in areas not spatially covered by the geodatabase.

2. METHODOLOGY

As it is shown in Figure 1, the proposed geodatabase integrates the results of 82 scientific research studies, that use MCDA methods for the LSA, spatially covering a large part of the world, which mainly includes Europe and Asia but also contains Africa (Ethiopia, Morocco, Rwanda), Australia (New Papua Guinea) and America (Canada, Chile, USA) (SM-Figure 1).

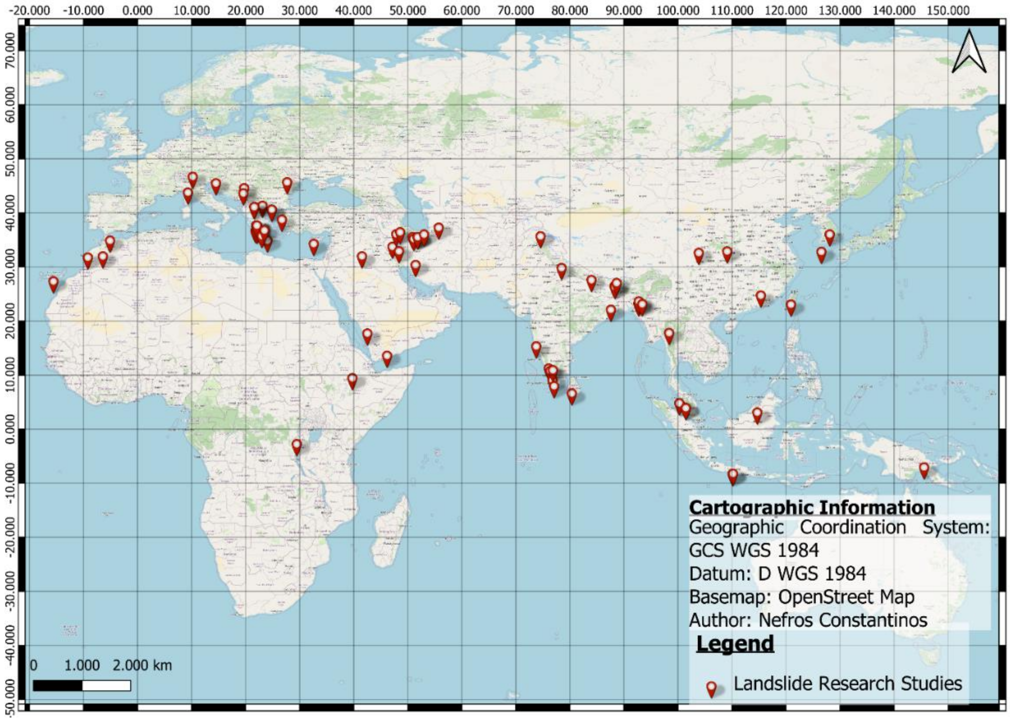


Fig. 1: Geodatabase's Landslide Research Studies, focused on Europe, Asia, and Africa.

The geodatabase's inputs, contain the spatial characteristics of each research study (such as the region, the country and the coordinates of the examined landslide events included in each research study), the landslide causal factors, their relevant weights, and other characteristics, such as the author's name, the year of the research, the method used and the use or not of validation methods. It is significant to note that some scientific research studies (such as Rozos et al. 2010), apply two or more MCDA methods in the same area or apply a MCDA method in two different areas (such as Tavoularis and Kirkos, 2019), and therefore, these results are included in the geodatabase as distinct records. Table 1 summarises the research studies used as sources in the geodatabase, grouped per country and region (a more detailed version of this table is provided in SM-Table 4). The location of each researcher (e.g., the institution that the first author belongs to), is not recorded in the geodatabase.

Table 1. Research Studies used in the Geodatabase

ID	Country	Region	Reference	Method
1	Austria	Vorarlberg - Eastern Alps	Ruff and Czurda (2008)	Heuristic
2	Bulgaria	Simitli	Ivanova (2014)	AHP
3	Canada	British Columbia’s Coast Mountains	Blais-Stevens et al. (2012)	Fuzzy Logic
4	Chile	Socoroma, Arica Parinacota	Rodriguez et al. (2013)	AHP
5	China	Anyuan County	Chen et al. (2019)	SWARA
6		Zhen'an County, Shan’xi Province	Zhao et al. (2017)	Fuzzy-AHP
7		Zhangzha town Jiuzhaigou	Yi et al. (2019)	AHP - FR
8	Cyprus	Western Cyprus	Myronidis et al. (2015)	AHP
9	Ethiopia	Tarmaber District	Abay et al. (2019)	AHP -WLC
10	Greece	North Messinia	Ladas et al. (2007a)	AHP
11		East Messinia	Ladas et al. (2007b)	AHP
12		Peloponnese	Chalkias et al. (2014)	Fuzzy Weighting
13		Perfection of Xanthi	Tsangaratos and Rozos (2013)	AHP
14		Perfection of Xanthi	Tsangaratos and Rozos (2013)	RES
15		North-eastern part of Achaia prefecture	Rozos et al. (2010)	AHP
16		North-eastern part of Achaia prefecture	Rozos et al. (2011)	RES
17		Tsakona area, Arcadia	Tavoularis et al. (2015)	RES
18		East Achaia prefecture	Rozos et al. (2010)	AHP
19		East Achaia prefecture	Rozos et al. (2011)	RES
20		North Peloponnese	Kavoura and Sabatakakis (2020)	Modified LSI
21		West Crete Island	Kouli et al. (2014)	WLC
22		Kithira island	Tavoularis and Kirkos (2019)	RES
23		Ydra island	Tavoularis and Kirkos (2019)	RES
24	India	West Bengal	Roy and Saha (2019)	Fuzzy-AHP
25		Maharashtra	Patil and Panhalkar (2019)	AHP
26		Coonoor and Ooty	Rahaman et al. (2014)	AHP
27		Tehri	Kumar and Anbalagan (2016)	AHP
28		southern Western Ghats, Kerala	Achu and Reghunath (2017)	AHP
29		Eastern Darjeeling Himalaya	Mandal and Mandal (2018)	AHP
30		Kottayam District, Kerala	Ajin et al. (2016)	Heuristic
31		Lachung Basin, Sikkim	Anbalagan et al. (2015)	Field Knowledge
32		Saitual Town, Mizoram	Lallianthanga and Lalbiakmawia (2013)	Field Knowledge
33		Kolasib	Lallianthanga and Lalbiakmawia (2014)	Field Knowledge
34		Aizawl city and Aibawk town	Laldintluanga et al. (2016)	Field Knowledge
35		Wayanad	Jishnu et al. (2017)	WOA
36		Aizawl City and Lengpui Airport	Laltlankima and Lalbiakmawia (2016)	AHP

37		Nadugani, Gudalur Taluk,	Saranathan and Mani (2016)	Multi-criterion analysis
38		Shiv-Khola watershed, West Benghal	Mandal and Maiti (2011)	AHP
39	Indonesia	Yogyakarta	Xiong et al. (2018)	AHP
40		Kaligesing	Bachri and Shresta (2010)	AHP
41	Iran	Khorramabad	Mokarram and Zarei (2018)	Fuzzy-AHP
42		Sari	Mijani and Neysani Samani (2017)	Fuzzy-AHP
43		Lorestan province	Abedini and Tulabi, 2018	AHP
44		Golestan province north	Tazik et al. (2014)	Fuzzy-AHP
45		Mazandran Province	Arabameri et al. (2019)	AHP
46		Mazandran Province	Arabameri et al. (2019)	LDA
47		Mazandran Province	Arabameri et al. (2019)	AHP - SI
48		Dena	Moradi et al. (2012)	AHP
49		Zanjan Province	Boroumandi et al. (2015)	AHP
50		Alborz	Moradi and Rezaei (2014)	AHP
51		Tehran metropolitan	Pourghasemi et al. (2013)	AHP
52		Kermanshah	Maleki et al. (2014)	AHP
53	Italy	Rupinaro catchment Liguria	Cignetti et al. (2019)	AHP
54	Malaysia	Cameron Highlands	Shahabi and Hashim (2015)	AHP
55		Cameron Highlands	Shahabi and Hashim (2015)	SMCE
56		Sarawak, Borneo	Vijith and Dodge-Wan (2019)	AHP
57		Penang Island	Khodadad and Jang (2015)	AHP
58	Morocco	Oum Er Rbia high basin,	El Jazouli et al. (2019)	AHP -WLC
59		Oued Laou basin	Semlali et al. (2019)	AHP
60		Safi	El Bchari et al. (2019)	AHP
61	Nepal	Kaski district	Bhatt et al. (2013)	AHP
62	North Macedonia	North Macedonia	Milevski et al. (2019)	AHP
63		North Macedonia	Milevski et al. (2019)	FR
64	Pakistan	Karakoram Highway	Ali et al. (2019)	AHP-WLC
65	Papua New Guinea	Eastern highlands province	Jana et al. (2015)	Undefined
66	Romania	Bârlad Plateau, East Romania	Grozavu et al. (2017)	AHP
67	Rwanda	Karongi	Nahayo et al. (2019)	AHP
68	S. Korea	Jeju Island	Quan and Lee (2012)	AHP
69		South Korea (national scale)	Kil et al. (2016)	AHP
70	Saudi Arabia	Abha Watershed	Mallick et al. (2018)	Fuzzy-AHP
71	Serbia	Fruška gora mountain	Marjanović et al. (2013)	AHP
72		Ljubovija Municipality western Serbia	Krušić et al. (2017)	AHP
73	Slovenia	Sava and Sora River	Komac (2006)	Fuzzy-AHP
74		Slovenia (national scale)	Komac and Zorn (2009)	WOE
75	Spain	Tirajana, Gran Canaria	Hervas de Diego et al. (2001)	AHP
76	Sri Lanka	Kegalle District	Perera et al. (2018)	SMCE

77	Taiwan	Chen-Yu-Lan Watershed	Nguyen and Liu (2019)	AHP
78	Thailand	Mae Chem , Northern Thailand	Intarawichian and Dasananda (2010)	AHP-WLC
79	Turkey	Western Black Sea region, Abdipaşa, Abdipaşa/Ulus/Bartın	Ercanoglu et al. (2008)	AHP
80		Ayvalik	Akgun et al. (2011)	AHP
81	USA	Idaho, Salmon - Challis	Sprague- Wheeler (2003)	Undefined
82		Rocky Mountains in north central Idaho	Gorsevski et al. (2006)	Fuzzy-AHP

where AHP: Analytic Hierarchy Process, LDA: linear discriminant analysis, LSI: landslide susceptibility index, SI: statistical index, SMCE: spatial multicriteria evaluation, SWARA: stepwise weight assessment ratio analysis, WOA: weighted overlay analysis, and WLC: weight linear combination.

Figure 2 illustrates the structure of the database, constructed in MySQL, using the phpMyAdmin tool, with two tables, named as “studies” and “factors_weight”. The value “ID” is the primary key for the table “studies” and the foreign key for the table “factors_weight”, and the “Factors_ID” is the primary key for the table factors_weight.

Figure 3 displays the environment of the database. For the development of the database, the MySQL workbench software is used. The two tables are inserted in a GIS environment, and the “studies” are represented as a distinct GIS layer. For that purpose, QGIS software, is used.

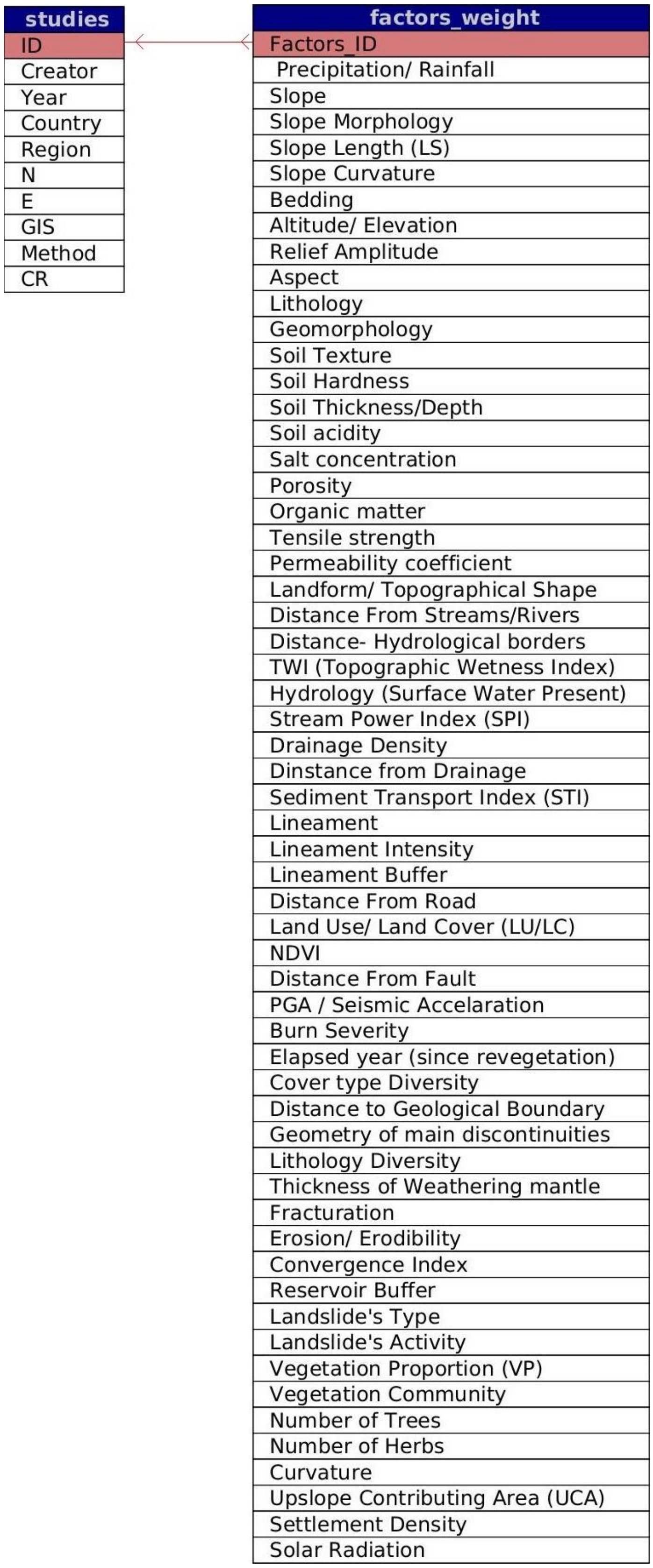
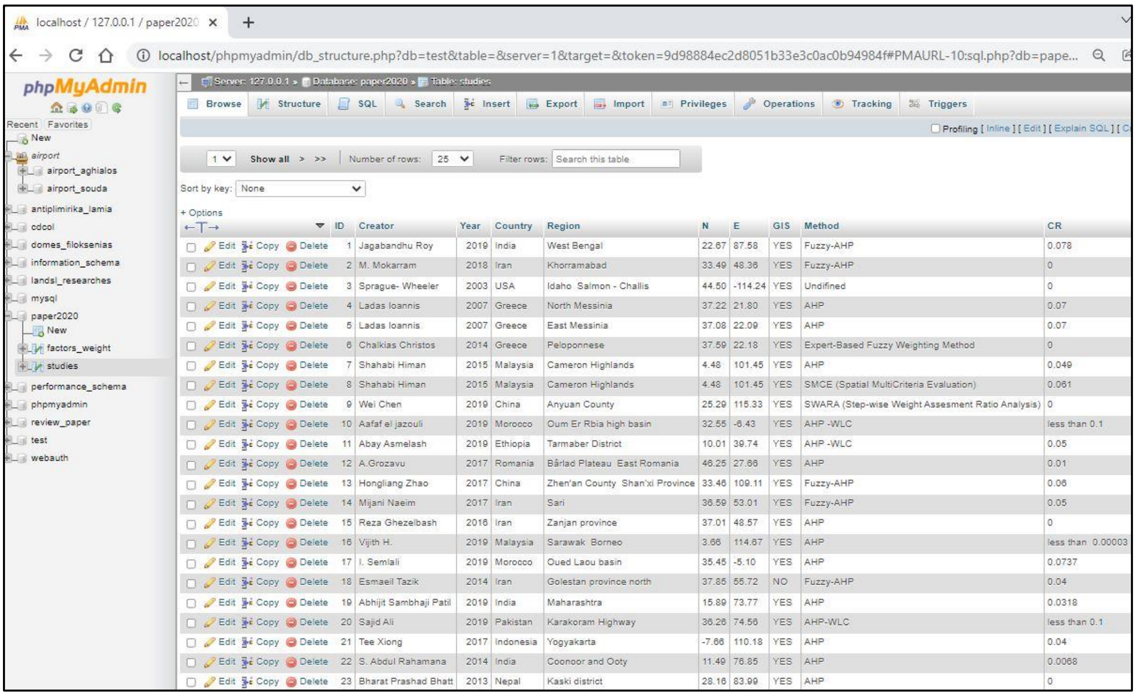


Fig. 2: Database Diagram presenting the tables of the database and the different fields of each table.



ID	Creator	Year	Country	Region	N	E	GIS	Method	CR
1	Jagabandhu Roy	2019	India	West Bengal	22.67	87.58	YES	Fuzzy-AHP	0.078
2	M. Mokarram	2018	Iran	Khorramabad	33.49	48.36	YES	Fuzzy-AHP	0
3	Sprague- Wheeler	2003	USA	Idaho Salmon - Challis	44.50	-114.24	YES	Undifined	0
4	Ladas Ioannis	2007	Greece	North Messinia	37.22	21.80	YES	AHP	0.07
5	Ladas Ioannis	2007	Greece	East Messinia	37.08	22.09	YES	AHP	0.07
6	Chalkias Christos	2014	Greece	Peloponnese	37.59	22.18	YES	Expert-Based Fuzzy Weighting Method	0
7	Shahabi Himan	2015	Malaysia	Cameron Highlands	4.48	101.45	YES	AHP	0.049
8	Shahabi Himan	2015	Malaysia	Cameron Highlands	4.48	101.45	YES	SMCE (Spatial MultiCriteria Evaluation)	0.061
9	Wei Chen	2019	China	Anyuan County	25.29	115.33	YES	SWARA (Step-wise Weight Assesment Ratio Analysis)	0
10	Aafaf el jazouli	2019	Morocco	Oum Er Rbia high basin	32.55	-6.43	YES	AHP -WLC	less than 0.1
11	Abay Asmelash	2019	Ethiopia	Tarmaber District	10.01	39.74	YES	AHP -WLC	0.05
12	A.Grozavu	2017	Romania	Bârlad Plateau East Romania	46.25	27.66	YES	AHP	0.01
13	Hongliang Zhao	2017	China	Zhen'an County Shan'xi Province	33.46	109.11	YES	Fuzzy-AHP	0.06
14	Mijani Naeim	2017	Iran	Sari	36.59	53.01	YES	Fuzzy-AHP	0.05
15	Reza Ghezelbash	2016	Iran	Zanjan province	37.01	48.57	YES	AHP	0
16	Vijith H.	2019	Malaysia	Sarawak Borneo	3.66	114.67	YES	AHP	less than 0.00003
17	I. Semlali	2019	Morocco	Oued Laou basin	35.45	-5.10	YES	AHP	0.0737
18	Esmaeil Tazik	2014	Iran	Golestan province north	37.85	55.72	NO	Fuzzy-AHP	0.04
19	Abhijit Sambhaji Patil	2019	India	Maharashtra	15.89	73.77	YES	AHP	0.0318
20	Sajid Ali	2019	Pakistan	Karakoram Highway	36.26	74.56	YES	AHP-WLC	less than 0.1
21	Tee Xiong	2017	Indonesia	Yogyakarta	-7.66	110.18	YES	AHP	0.04
22	S. Abdul Rahamana	2014	India	Coonoor and Ooty	11.49	76.85	YES	AHP	0.0068
23	Bharat Prashad Bhatt	2013	Nepal	Kaski district	28.16	83.99	YES	AHP	0

Fig. 3: Research Table in phpMyAdmin.

3. RESULTS AND DISCUSSION

3.1. GIS Techniques and the geodatabase as a decision-making tool

The following results that emerge from the statistical processing of the geodatabase, reveal good practices and common weaknesses that most researchers do during the MCDA, and can be used as part of the process standardization. Figure 4 shows the most common factors used worldwide, in the LSA research studies, according to the geodatabase's records. As it can be noted the most frequent ones are the slope angle (or slope in brief), the lithology, the land use/ land cover, the slope aspect (or aspect in brief) and the precipitation.

Another interesting statistical result that arises from the geodatabase, is about the number of the causal factors that is used in the research studies. It is significant to note that in many of these studies, the selection of that number, which is decided by the experts, is not further analytically explained. Thus, in these cases, the selection of the number of the causal factors, seems to be arbitrary or empirical which leads to the conclusion that the whole process needs to be standardized about this procedure.

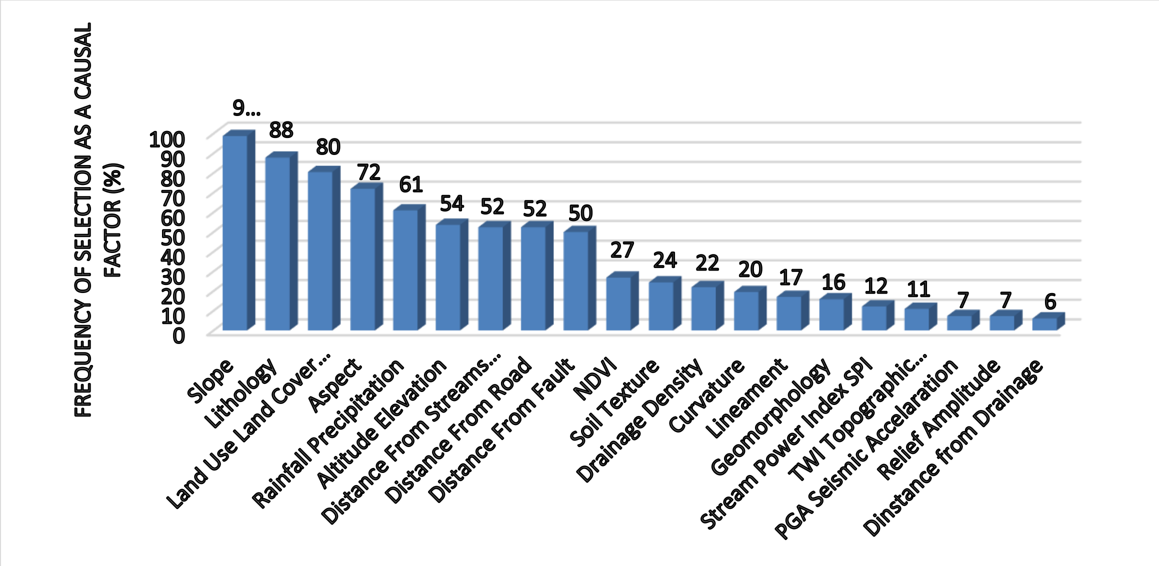


Fig. 4: Most Frequent causal factors for LSA in the geodatabase.

Figure 5 illustrates the number of the geodatabase's research studies, according to the number of the causal factors that they choose to use during the AHP. As it can be observed, the number of the causal factors varies from 4 (e.g., Cignetti et al., 2019) to 25 (e.g., Kil et al., 2016), while most of the research studies use from 5 to 10 causal factors, during the LSA, which seems to be a good practice in general. Relevant Charts can be produced for a local or a national level, according to the requirements of the research (SM- Figures 2, 3, 4 and 5).

In the following paragraphs the potential capabilities of the proposed geodatabase (created for this research study), when used along with GIS techniques as a decision-making tool during the LSA, are briefly presented.

The database can be used to illustrate how often a landslide causal factor is being selected. For example, for the precipitation factor, the database shows that in a worldwide basis, the 60.98% of the research studies select it as causal factor, whereas over a particular country, such as Greece, the results are significantly differentiated and the relative percentage rise to 85.71%. This is achieved, through the ability of the GIS, to combine two or more criteria (SM- Figure 6 and SM– Figure 7). The relatively big weight of the precipitation, that is usually attributed to areas in Greece, creates the indication for a potential correlation of this causal factor with the climate of the area. Similar indications, also arise for the "distance from faults" causal factor (the relative percentage worldwide is 50% and for Greece is 85,71%). Therefore, these indications are going to be further explored in the following paragraphs of this study, in a bigger spatial level.

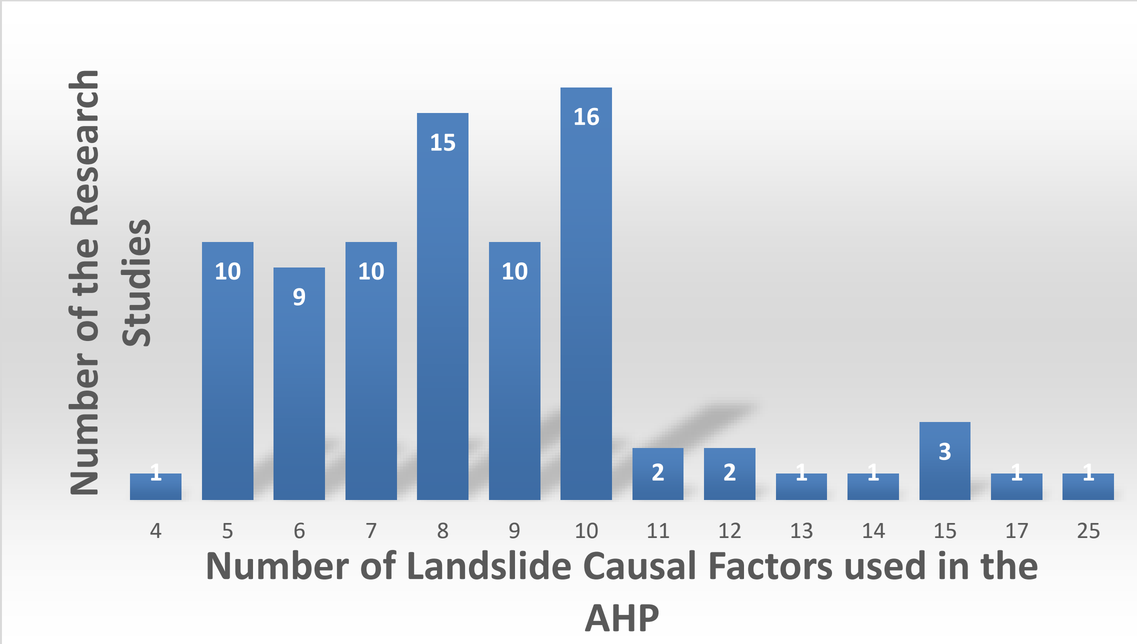


Fig. 5: Number of the Geodatabase's Research Studies according to the Causal Factors, in a worldwide level.

Additionally, the geodatabase can be used to determine the causal factors that are frequently selected as the most critical ones, over a particular region. As it was mentioned before, the experts in order to apply an MCDA method, primarily have to identify the landslide causal factors and to determine their relative contribution to the landslide mechanism, based on their personal judgement. By using the geodatabase, the experts have directly some initial suggestions-indications concerning the causal factors that they can use, along with a relative range of their weights. The justification of the acceptance, editing or rejection of these suggestions, according to the experts' personal judgement, can lead to the reduction of the risk for possible biased conclusions. Additionally, because of the direct supply of the geodatabase's results and its ability to be easily modified to include one or a combination of new search criteria-filters (e.g., to include a bigger area, to provide the results only of the research studies that use the RES method and/or of the research studies that were conducted after 2015), the process can be significantly accelerated and at the same time the resources that are required, to be reduced. It is the experts, however, who based on these results-suggestions, other spatial characteristics that are provided by GIS techniques (e.g., variance of the weight along with the distance from the examined area) and their personal judgement (e.g., about the examined area's special characteristics), have the necessary knowledge to decide if they should keep, alter, or reject these suggestions. Thus, in a hypothetical example, where the investigated area was affected recently by wildfires that did not affect the neighboured areas (where the geodatabase's records derive from), the experts can decide to use the causal factor "NDVI" or "burned severity" instead of the others proposed by the geodatabase.

Moreover, in case that a dispute arises between the experts (e.g., about which causal factors should be selected) the geodatabase can be used supportively to an expert's choices. Thus, the use of the geodatabase can reduce the possibility of biased conclusions resulted by the experts' subjectivity and at the same time to act supportively to their decisions. In the following paragraphs relative examples are analyzed, focusing on the use of the geodatabase in the Peloponnese peninsula of Greece, which is randomly selected for that purpose (SM- Figure 8 and SM- Figure 9).

In this example, the user can use QGIS tools (e.g., box plot, polar chart, scatter plot or ternary plot) to find out the distribution and the extreme values of a weight of a causal factor, such as the precipitation, limiting the results only to the research studies of the geodatabase, which have been conducted in the area of interest. These tools, used in a GIS environment, can provide a clear illustration to the user, about the statistical variance of the values of a magnitude. As an example, figure 6 displays the weight attributed to the causal factor precipitation, limiting the results only to the research studies that are included in the area of interest. The spots represent the different research studies, the y axis the precipitation's weight, and the x axis the ID of each study. As it can be observed the weight of the precipitation has one extreme maximum value, which is over 0.2 (20%), two extreme minimum values that are lower than 0.04 (4%), while most of the values range from 0.0868 to 0.18. For that purpose, the scatter plot tool, of plotly plugin of QGIS is used.

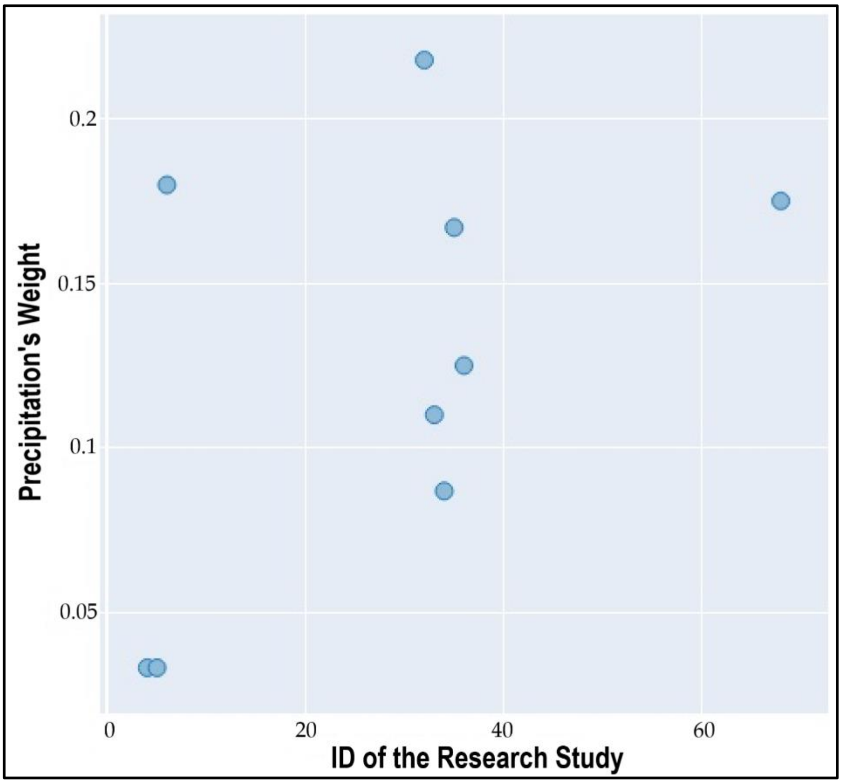


Fig. 6: Precipitation's Weight as a causal factor in LSA over Peloponnese peninsula, Greece.

Furthermore, the QGIS tools, mentioned in the previous paragraph, can be used to illustrate the variance of the weights of the causal factors used in a research study, compared with the rest of the studies, conducted in the area of interest. Figure 7 illustrates a characteristic example where for a certain region (Peloponnese peninsula), nine (9) research studies are included in the geodatabase, and each one of them is presented separately in vertical layout. The most common (between these 9 studies) landslide causal factors (slope, rainfall/precipitation, altitude/elevation, aspect and lithology) are illustrated with different colors (e.g., the slope is illustrated with the blue color). The x axis contains the fid of each research study and the y axis the relevant causal factor's weight. For the first research study (fid 1 in the x axis), the weights of the most common causal factors are: W_{slope} = 0.209, $W_{Rainfall}$ = 0.033, W_{aspect} = 0.021, $W_{Lithology}$ = 0.269 while the altitude is not contained as a causal factor. This Figure (7) provides to the users, a clear illustration of the variance of the weights of the most common causal factors in the area of interest. By using that, the users can easily compare the causal factors' weights attributed by the research studies and afterwards to examine, if it is required, to exclude some of them, according to the region's special characteristics and their personal judgement. For example, the density of the spots in the y axis for the research study with id 4, compared with the relevant density of the spots of the research study with id 5, is rather small, which leads to the conclusion that in the research study with id 4 some of the causal factors are favored, while at the same time in the research study with id 5, the causal factors have similar contribution to the LSA. It is significant to note that for the examined area of interest, the “slope”, the “rainfall”, the “aspect”, the “lithology” and the “altitude” are the most common causal factors, used in the 9 different research studies, revealing a relative homogeneity, concerning the LSA, in the area of interest. The rest of the causal factors differ between the research studies and are not included in the graph as they would not provide any critical information and they would increase the complexity of the graph (Graphs have been made by using the Scatter plot tool of plotly plugin of QGIS).

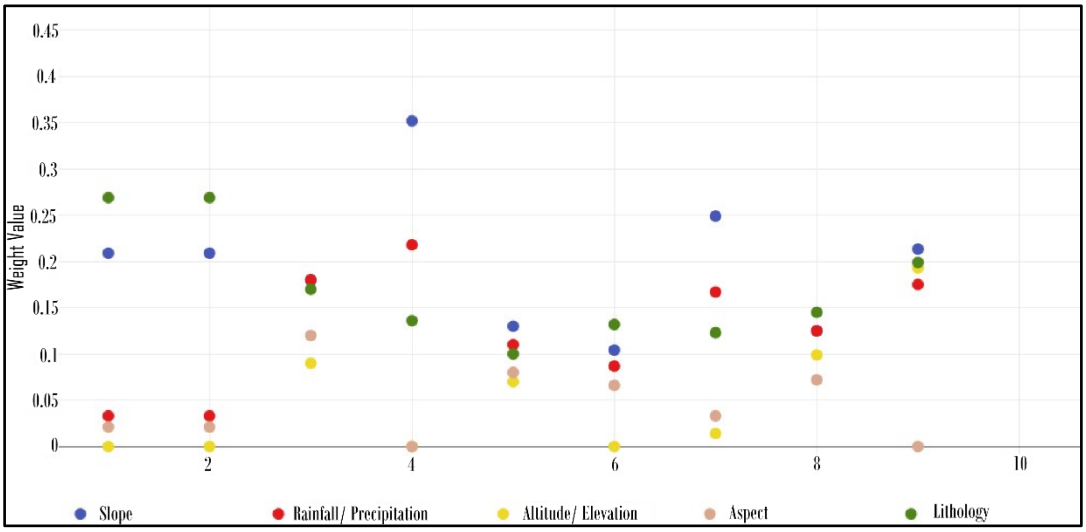


Fig. 7: Graph with 5 most common causal factors and their weights’ variance.

Also, many times the researcher needs to examine if the weight of a causal factor (e.g., the precipitation, the slope), change in relation with the distance from the examined area. In that case, the researcher needs to evaluate if the local parameters differentiate the terrain or the hydrological conditions over a certain distance (e.g., Starkel and Sarkar 2002, where the rainfall was correlated with the distance from the mountain front) and therefore the geodatabase’s records that are over that distance (buffer) need to be further excluded from the processing. GIS contributes significantly to that purpose because of its ability to spatially combine different characteristics of the geodatabase and of the prevailing parameters to the area of interest (a relevant hypothetical example, is presented in SM- Figure 10 and in SM- Figure 11, where the results of the geodatabase are limited by applying a distance- buffer of 60km of the examined area).

The main purpose of this analysis is to present the potentiality of the geodatabase when it is used with GIS and not to include every possible GIS technique. It is evident that other, similar techniques may also be used, for the same or similar purposes (e.g., using boxplots to identify possible outlier values, using the inverse distance weighted (IDW) tool to evaluate the potential weight of a causal factor according to the relative distances of the geodatabase's research studies (geodatabase's records), using multiple buffer rings tool to create distance zones from the examined area).

As it was shown in the previous paragraphs, the proposed geodatabase significantly reduces the risk of potential biased conclusions, as it combines the results of different research studies, which were conducted by different researchers in the broader area, with the experts' knowledge and experience. Thus, an expert that want to perform an initial LSA, can use the provided geodatabase as a decision-making tool, to determine the causal factors, that are usually selected in the broader area of interest, along with the relative range of their weights. However, it is significant to note that the experts still need to use a MCDA method and their personal judgements, to adjust these data, according to the area's special characteristics. Moreover, the experts can also use the geodatabase to identify possible extreme values used during previous research studies, which if they do not arise from the areas' special characteristics should be excluded from the conducted LSA. Additionally, in some cases, the geodatabase can be used for an initial rapid LSA, especially in areas where the landscape has changed recently or where a landslides' inventory does not exist, or it is incomplete. However, it is significant to note that even in these cases (that an initial rapid LSA is required), MCDA methods still need to be used and the experts should take the final decisions about the use, modification, or rejection of the geodatabase's results-indications.

3.2 Statistical and Spatial Processing of the Geodatabase in a broader level

Many interesting results also emerge from the statistical and spatial processing of the Geodatabase by expanding its results, so as not to be limited in a local region, such as Peloponnese peninsula (which was presented in the previous paragraphs), but to include a broader spatial level, such as a country. Thus, the geodatabase can be used to determine the most common causal landslide factors in a national level, using a similar procedure, to the one followed in a regional level. These findings, as happens with all the geodatabase's results, are aiming to aid the researcher-experts, and their use or not is a decision that should be based exclusively on their judgement. Also, the geodatabase can be used to enrich a national inventory of a country, by extracting the location of the landslides examined in the research studies of the geodatabase. This can be achieved because most of the research studies of the geodatabase, study and analyze the most significant landslides occurred in a country, in the recent past. It is significant to note though, that a complete national inventory, requires a great number of landslides and therefore the geodatabase can be used only complementary to a national inventory. As an example, Figure 8 illustrates the research studies of the geodatabase that analyze areas where landslide occurred in Iran, from 2008 to 2019.

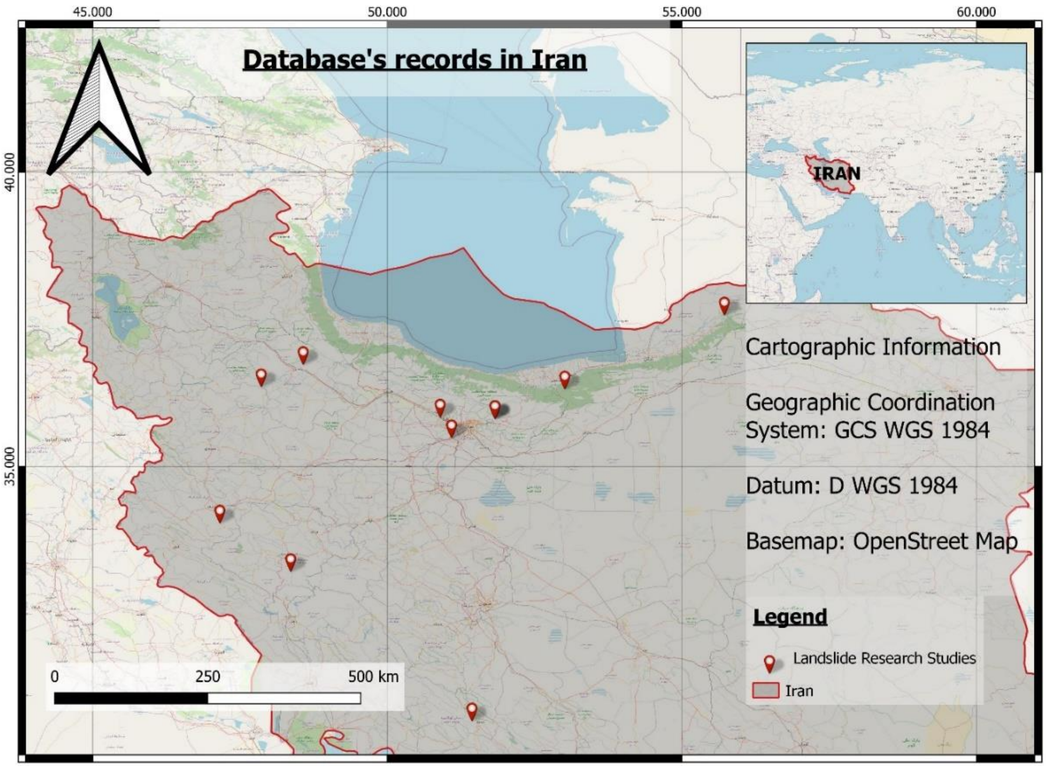


Fig. 8: Database's use in national level (Iran).

By running a relative query or by counting directly the number of the research studies that correspond to each country of the geodatabase, it becomes apparent that India is the country with the most records in the geodatabase (15 out of 82 that corresponds to 18,29% of the total geodatabase's records). This location refers only to the landslide event examined in each research study and not to the location of the researchers or their institutes (which is not recorded in the geodatabase). This result (of India recording the majority of research studies) highlights the high interest of the scientific community for the landslides occurred in that country, which is mainly because India is the second country in the worldwide ranking on the landslide reports, and the first one on the landslide fatalities (Kirschbaum et al., 2015).

Furthermore, GIS offers to the researcher the ability to simultaneous display the statistical and spatial characteristics of a landslide causal factor in a local and in a broader level. For example, the researcher can illustrate the spatial variance of the values of the weight of a causal factor, such as the “Land Use/Land Cover”, in a worldwide level, and at the same time to check this value in a specific location and to access its overall statistics (e.g., min, max, mean value) (SM- Figure 12). By using similar GIS techniques, the researcher can also limit the results over a specific location (e.g., a peninsula).

In addition, the GIS offers the opportunity to interconnect the geodatabase with global spatial data gathered from external open access sources- geodatabases. Thus, the researcher can identify possible patterns about the LSA and to apply them, in areas that are not spatially covered by the geodatabase or to modify the geodatabase’s results, based on the observed correlations. Figure 9 presents an example where the values of the landslide causal factor "distance from faults” of the geodatabase, are illustrated simultaneously with the worldwide "active faults" lines (the spatial data for “active faults” lines derived by Styron and Pagani, 2020 and are not part of this study). The research studies that do not consider this factor to be a critical causal factor during their LSA, are only symbolized with the “research study” symbol (there is not a symbol for the “Distance from Faults” weight, next to it). As it can be observed, according to the geodatabase’s results, in countries, such as Greece, the factor “Distance from Faults” is common in many LSA research studies while at the same time the “active faults” lines, according to Styron and Pagani (2020) spatial data, are also dense for that area. On the other hand, in areas, such as the South of India, where the relative active faults lines are sparse, the “Distance from Faults”, is also rarely used as a causal factor in the geodatabase. Thus, in this hypothetical example, that a researcher wants to perform a LSA in the country of “Georgia”, (where, as it shown in Figure 9, it is not spatially covered from the geodatabase but where the active faults lines, according to Styron and Pagani (2020) geodatabase, are dense), by using the proposed geodatabase, the researcher has the indirect indication- suggestion that the “Distance from Faults” can be a potential landslide causal factor. Subsequently, the expert can also use the geodatabase to receive potential initial suggestions (derived from areas covered from the geodatabase) that can help him with the relevant weight attribution of that causal factor (“distance from faults"). As it happens with all the outputs of the geodatabase, these correlations with the spatial data gathered from external open access sources, can be used only as indications-suggestions and the final decisions about their use should be made exclusively by the experts, who are going to evaluate them along with the other characteristics of the area. Furthermore, the expert can investigate possible further correlations in a more detailed level (e.g., about the attributed weight of a causal factor and the density of the "active faults" lines), by examining the geodatabase along with national or local open access external geodatabases, such as the Ganas et al. (2013) "active faults" geodatabase, which is more precise and detailed, but it is spatially limited in a national level (Greece) – (SM-Figure 13).

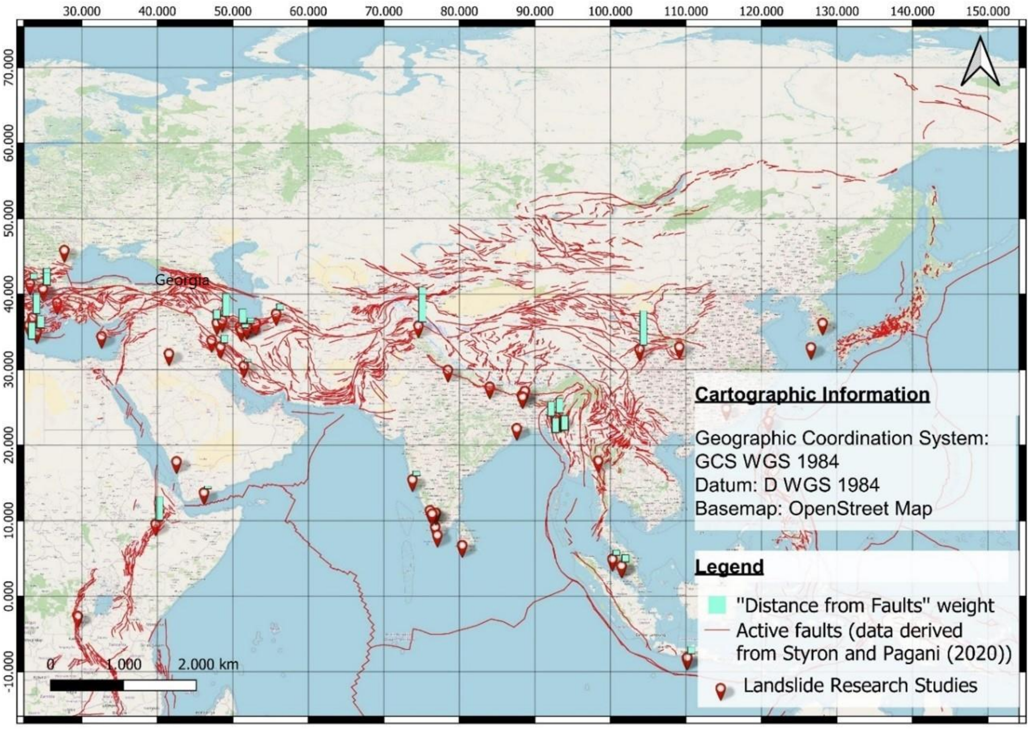


Fig. 9: Projecting the weight of the Geodatabase's causal factor "Distance from faults" along with the open access external worldwide geodatabase of Styron and Pagani (2013) about active faults lines.

Also, the geodatabase can be dynamically correlated with spatial data gathered from other external open access sources which are regularly updated. Figure 10, presents an example, where the weight of the causal factor "precipitation", is illustrated along with Köppen – Geiger Climate Classification data. Köppen – Geiger Climate Classification is a method that divides the climate of the world in 5 main classes, using a capital letter, and 30 subclasses, using a small letter. Due to the climate crisis the final map is regularly updated by scientists (Kottek et al., 2006; Beck et al., 2018). As it can be observed in Figure 10, the attributed precipitation's weight is rather big in places characterized by the letters "s" or "w", which relatively corresponds to dry summer (s) or dry winter (w). The identification of such patterns is rather significant as it can lead the researcher to spatially correlate the geodatabase with data derived from external sources, and afterwards to use their updates to relatively adjust the geodatabases' results. Hence, the future modifications of the Köppen – Geiger Climate Classification, such as the change of some areas' characterization from the letter "s", or "d", to another letter or vice versa, can be used by the researcher to relatively adjust the weight of the precipitation in these areas, incorporating to the LSA, the upcoming changes, due to climate change. Thus, in a hypothetical example, due to a modification of a Köppen – Geiger Climate Classification, the climate of a region that nowadays is characterized with the letter "s" (dry summer), changes, because of the climate crisis, with the letter a (hot summer). In this example, a researcher who wants to perform a LSA in that region, by using the above conclusion, about the correlation of the precipitation's weight with the areas characterized by the letter "s" or "d", and the information that the climate of the examined region is going to change from "s" to "a" (derived by the external open access geodatabase), has the initial indication- suggestion to consider reducing the weight of the precipitation as a causal factor for that region, during the LSA.

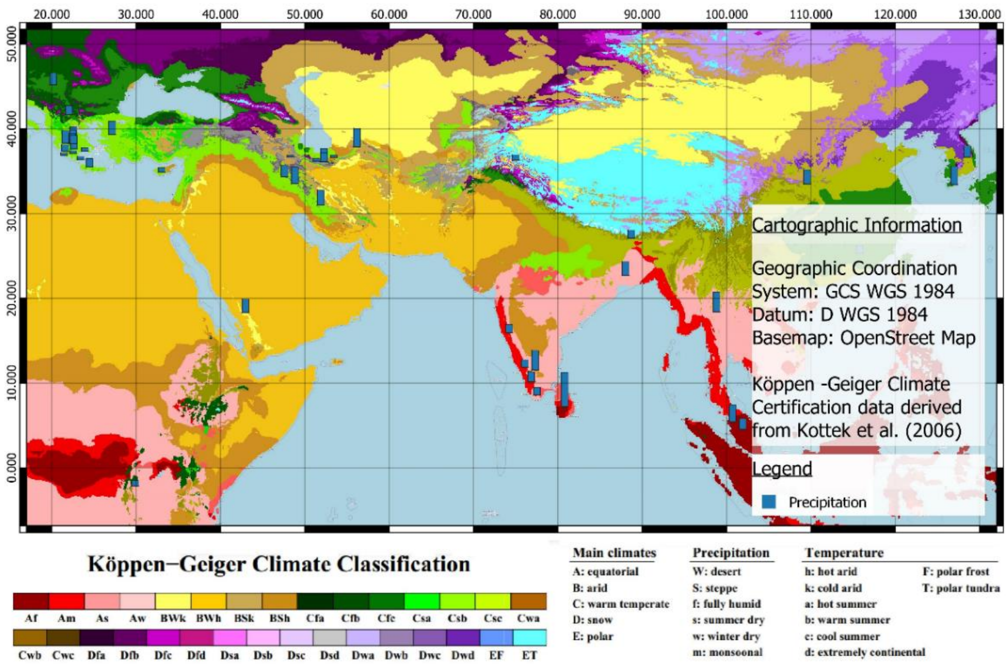


Fig. 10: Using Geodatabase and Köppen -Geiger Climate Certification Map (classification data derived from Kottek et al., (2006)).

Likewise, the geodatabase can be easily connected with other geodatabases or other landslide studies' results in order to study in general the landslide mechanism and the methods used worldwide for the LSA. Hence, Figure 11 displays the geodatabase focused on Europe, Africa, Asia and Australia along with the global landslide catalog (GLC) provided by the USA - National Aeronautics and Space Administration's (NASA's) Open Data Portal, as has been compiled since 2007 and have been afterwards regularly updated, at NASA Goddard Space Flight Center (Kirschbaum et al., 2015) (SM- Figure 14 presents the relative geodatabase's results focused in America). As it can be observed, a great part of the distribution of the research studies of the geodatabase is following the relevant distribution of the recorded landslides of the GLC. This means that the interest of the scientific community, as it is illustrated by the published scientific studies of the geodatabase, is mainly focused in areas where landslides are frequently happening, as it is also illustrated in the GLC.

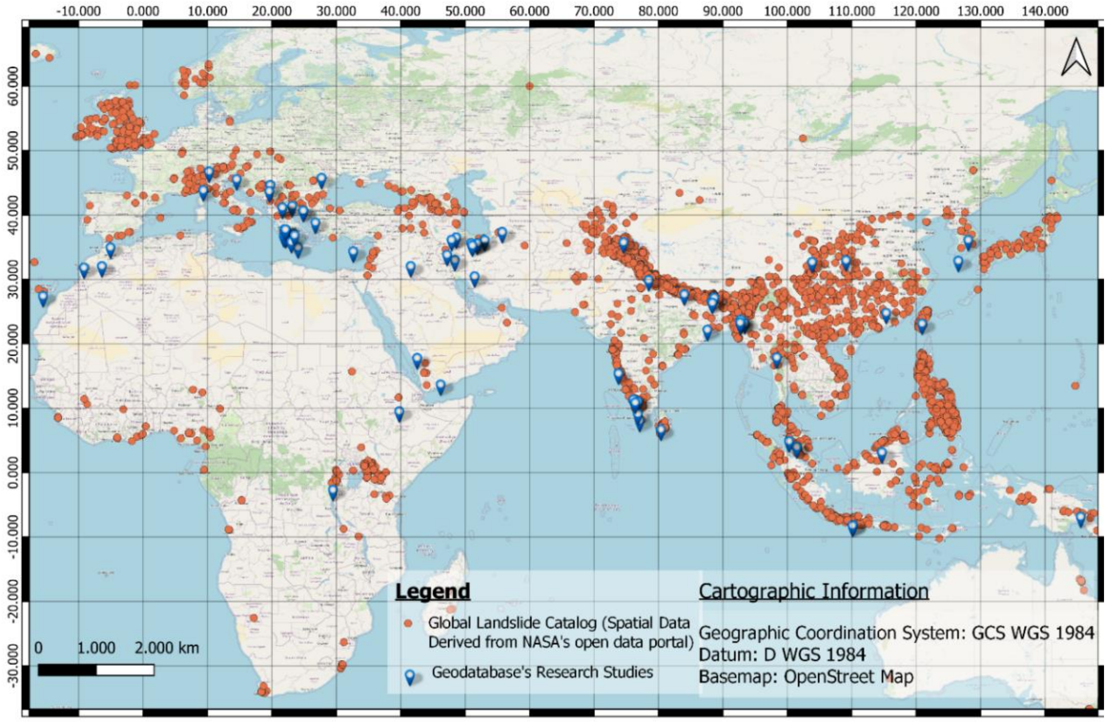


Fig. 11: Spatial distribution of the research studies contained in the geodatabase along with the global landslide catalog (GLC) provided by USA-NASA open data portal, focused on Europe, Africa, Asia and Australia.

Nevertheless, there are some regions, where the recorded landslides, according to the GLC, are frequent but are not included in the geodatabase. This is happening because some countries, such as the US, UK, Canada, France, and Italy have developed, over the years, relative national landslide inventories (Malamud et al., 2004; Westen et al., 2006; Lin et al., 2017) and these large volumes of these landslide inventories, which in some cases can been easily accessible through internet (Westen et al. 2006), has led to a more frequently use of the statistical methods in that areas (Lin et al..2017) compared with other methods, such as of the MCDA methods. Thus, the MCDA methods are usually rare in some of these countries, such as the UK, while in some others, such as Italy, are used more often, as they can provide direct and efficient results, especially in areas with special geomorphological characteristics (such as hilly-mountainous and highly human-influenced areas - Cignetti et al. (2019)). On the contrary, in countries, where a national landslide inventory does not exist at all or it is not considered to be as a complete one, the MCDA methods are more frequently used, and therefore the geodatabase's research studies are illustrated more frequently there, as it shown in Figure 11.

4. CONCLUSIONS

Landslides are over time in high scientific interest due to their devastating results and their complex nature. Nowadays, the scientific community has available, advanced technological tools, such as the Geographic Information Systems (GIS) and the geodatabases, which, when combined, can significantly assist its efforts to understand and analyze the landslide mechanism.

Multi-Criteria Decision Analysis (MCDA) methods are widely used in landslide susceptibility assessment (LSA), as they can be applied rapidly and with a very good accuracy, even in areas where a landslides inventory does not exist, or the landscape has changed recently. Their main disadvantage is that their efficacy depends significantly on the experts' personal judgements, about the determination of the most critical landslide causal factors and the evaluation of their relative weights and is not guaranteed. These personal judgements can render the MCDA method to be either efficient, (when the expert combines successfully the knowledge in LSA gained through his personal experience with the knowledge of the area's special characteristics) or inefficient (when the judgements are not justified and are based exclusively on biased conclusions).

During this research a geodatabase is created by integrating the results of 82 research studies that use MCDA methods to perform a LSA. These results contain spatial characteristics of the examined landslide, the causal factors, their weights, and the verification methods used in each research study. By that way, the previously knowledge in LSA generated by the previous studies, which also integrate the broader area's special characteristic, is gathered and spatially provided to the future researcher, as a decision-making tool, reducing the risk of possible biased conclusions and the time required for the method’s applicability. Besides the advantages that the geodatabase is offering, the use of experts, remains indispensable. Moreover, the statistical analysis of the geodatabase offers interesting results, which can be part of the standardization of the process while at the same time its spatial analysis and correlation with other spatial data reveals patterns concerning the correlation of the LSA causal factors with local and worldwide parameters. Finally, the geodatabase, can be used along with external databases that are regularly updated, such as the future climate projections of the Köppen – Geiger Climate Classification data, to provide updated indications-suggestions concerning the LSA, such as the use of precipitation as a causal factor or not. Finally, it is significant to note that according to the authors’ knowledge, a similar geodatabase, that integrates spatially the results of previous LSA research studies, does not exist in the scientific literature.

5. DATA AVAILABILITY

All data used have been derived from open access sources. The basic functions of the geodatabase are presented in the following geoportal: http://geoland.metal.ntua.gr (SM-Figures 15 and 16). However, a GIS environment is required, to apply all the functions of the geodatabase which are described in this study, and therefore the geodatabase can be also provided via email, upon request.

6. CONFLICTS OF INTEREST

The authors declare that they have no conflict of interest regarding this publication.

7. FUNDING STATEMENT

The authors received no financial support for the research, authorship and/or publication of this article.

8. SUPPLEMENTARY MATERIAL

This article contains as supportive material, 16 Figures (SM- Figure 1-16) and 4 Tables (SM- Table 1-4).

9. REFERENCES

Abay, A., Barbieri, G. and Woldearegay, K. 2019. GIS-based landslide susceptibility evaluation using Analytical Hierarchy Process (AHP) approach: The case of Tarmaber District, Ethiopia. *Momona Ethiopian Journal of Science*, 11(1), 14-36. https://doi.org/10.4314/mejs.v11i1.2 .

Abedini, M., and Tulabi, S. 2018. Assessing LNRF, FR, and AHP models in landslide susceptibility mapping index: a comparative study of Nojian watershed in Lorestan province, Iran. *Environmental Earth Sciences*, 77, 405. https://doi.org/10.1007/s12665-018-7524-1.

Achu, A.L., and Reghunath, R. 2017. Application of analytical hierarchy process (AHP) for Landslide Susceptibility Mapping: A study from southern Western Ghats, Kerala, *India. Proceedings of the Disaster, Risk and Vulnerability Conference (DRVC2017), Thiruvananthapuram, India, 29–31 March 2017*.

Ajin, R.S., Loghin, A.M,. Vinod, P.G., Jacob, M.K,. Krishnamurthy, R.R. 2016. Landslide susceptible zone mapping using ARS and GIS techniques in selected taluks of Kottayam district, Kerala, India, *International Journal of Applied Remote Sensing and GIS*, 3(1), 16-25.

Akgun, A., Kıncal, C., and Pradhan, B. 2011. Application of remote sensing data and GIS for landslide risk assessment as an environmental threat to Izmir city (west Turkey). *Environmental monitoring and assessment*, 184, 5453-70. https://doi.org/10.1007/s10661-011-2352-8.

Ali, S., Biermanns, P., Haider, R., and Reicherter, K. 2019. Landslide susceptibility mapping by using a geographic information system (GIS) along the China–Pakistan Economic Corridor (Karakoram Highway), Pakistan. *Natural Hazards and Earth System Science*, 19, 999–1022. https://doi.org/10.5194/nhess-19-999-2019.

Anbalagan, R., Kumar, R., Lakshmanan, K., Parida, S., and Neethu, S. 2015. Landslide hazard zonation mapping using frequency ratio and fuzzy logic approach, a case study of Lachung Valley, Sikkim. *Geoenviron. Disasters*, 2, (1). https://doi.org/10.1186/s40677-014-0009-y.

Arabameri, A., Pradhan, B., Rezaei, K., Lee, S., and Sohrabi, M. 2019. An Ensemble Model for Landslide Susceptibility Mapping in a Forested Area. *Geocarto International*, 1-25. https://doi.org/10.1080/10106049.2019.1585484.

Bachri, S., and Shresta, R.P. 2010. Landslide Hazard Assessment Using Analytic Hierarchy Processing (AHP) and Geographic Information System in Kaligesing Mountain Area of Central Java Province Indonesia. *5th Annual International Workshop & Expo on Sumatra Tsunami Disaster & Recovery 2010*, 9, 108–112.

Beck, H. E., Zimmermann, N. E., McVicar, T. R., Vergopolan, N., Berg, A., & Wood, E. F. 2018. Present and future Köppen–Geiger climate classification maps at 1-km resolution. *Scientific Data*, 5, 180214. https://doi.org/10.1038/sdata.2018.214.

Bhatt, B.P., Awasthi, K.D., Heyojoo, B.P., Silwal, T., and Kafle, G. 2013. Using Geographic Information System and Analytical Hierarchy Process in Landslide Hazard Zonation. *Applied Ecology and Environmental Sciences*, 1(2), 14-22. https://doi.org/10.12691/aees-1-2-1.

Blais-Stevens, A., Behnia, P., Kremer, M., Page A., Kung R., and Bonha-Carter G. 2012. Landslide susceptibility mapping of the Sea to Sky transportation corridor, British Columbia, Canada: comparison of two methods. *Bulletin of Engineering Geology and the Environment*, 71. 447–466. https://doi.org/10.1007/s10064-012-0421-z.

Boroumandi, M., Khamehchiyan, M., and Nikudel, M.R. 2015. Using of Analytic Hierarchy Process for Landslide Hazard Zonation in Zanjan Province, Iran. In: Lollino G. et al. (Eds) *Engineering Geology for Society and Territory*. Springer, Cham, 951-955. https://doi.org/10.1007/978-3-319-09057-3_165.

Chalkias, C., Ferentinou, M., and Polykretis, C. 2014. GIS Supported Landslide Susceptibility Modeling at Regional Scale: An Expert-Based Fuzzy Weighting Method. *ISPRS International Journal of Geoinformation*, 3, 523-539. https://doi.org/10.3390/ijgi3020523.

Chen, W., Hong, H., Panahi, M., Shahabi, H., Wang, Y., Shirzadi, A., Pirasteh, S., Alesheikh, A.A., Khosravi, K., Panahi, S., Rezaie, F., Li S., Jaafari, A., Bui, D.T. and Bin Ahmad, B. 2019. Spatial Prediction of Landslide Susceptibility Using GIS-Based

Data Mining Techniques of ANFIS with Whale Optimization Algorithm (WOA) and Grey Wolf Optimizer (GWO). *Applied Sciences*, 9, 3755. https://doi.org/10.3390/app9183755.

Cignetti, M., Godone, D., and Giordan, D. 2019. Shallow landslide susceptibility, Rupinaro catchment, Liguria (northwestern Italy). *Journal of Maps*, 15:2, 333-345, https://doi.org/10.1080/17445647.2019.1593252.

Cruden, D., and Vandine, D. 2013. Classification, Description, Causes and Indirect Effects: Canadian Technical Guidelines and Best Practices related to Landslides. Geological Survey of Canada. Open File 7359, 22p.

Dilley, M., Chen, R.S., Deichmann, U., Lerner-Lam, A.L. and Arnold, M. 2005. Natural Disaster Hotspots: A Global Risk Analysis. Washington, DC: World Bank. © World Bank. https://openknowledge.worldbank.org/handle/10986/7376.

El Bchari, F., Theilen-Willige, B., and Ait Malek, H. 2019. Landslide hazard zonation assessment using GIS analysis at the coastal area of Safi (Morocco). *Proceeding of the International Cartographic Association (ICA)*, 2, 24. https://doi.org/10.5194/ica-proc-2-24-2019.

El Jazouli, A., Barakat, A., and Khellouk, R. 2019. GIS-multicriteria evaluation using AHP for landslide susceptibility mapping in Oum Er Rbia high basin (Morocco). *Geoenvironmental Disasters*, 6, 3 2019. https://doi.org/10.1186/s40677-019-0119-7.

Ercanoglu, M., Kasmer, O, and Temiz, N. 2008. Adaptation and comparison of expert opinion to analytical hierarchy process for landslide susceptibility mapping. *Bulletin of Engineering Geology and the Environment*, 67, 565-578. https://doi.org/10.1007/s10064-008-0170-1.

Ganas, A., Oikonomou, I. A., & Tsimi, C. (2013). NOAfaults: a digital database for active faults in Greece. *Bulletin of the Geological Society of Greece*, 47(2), 518-530. https://doi.org/10.12681/bgsg.11079.

Gorsevski, P., Jankowski, P., and Gessler, P. 2006. Heuristic approach for mapping landslide hazard integrating fuzzy logic with analytic hierarchy process. *Control and Cybernetics*, 35, 121–146.

Grozavu, A., Patriche, C., and Mihai, F. 2017. Application of AHP method for mapping slope geomorphic phenomena. *Proceedings of the 17th International Multidisciplinary Scientific GeoConference SGEM 2017, 29 June - 5 July 2017, Albena, Bulgaria*. https://doi.org/10.5593/sgem2017/23/S11.046.

Guzzetti, F. 2005. Landslide Hazard and Risk Assessment– Concepts, Methods and Tools for the Detection and Mapping of Landslides, for Landslides Susceptibility Zonation and Hazard Assessment, and for Landslide Risk Evaluation. PhD Thesis. Mathematics-Scientific Faculty, University of Bonn, Bonn, Germany. 389 p. https://nbn-resolving.org/urn:nbn:de:hbz:5N-08175.

Hervas de Diego, J., and Barredo Cano, J. I. 2001. Evaluacion de la Susceptibilidad de Deslizamientos mediante el uso conjunto de SIG, teledeteccion y metodos de evaluacion multicriterio. Aplicacion al barranco de Tirajana (Gran Canaria). *V Simposio Nacional sobre Taludes y Laderas Inestables, Madrid, Spain, 27–30 November 2001*, 305-316.

IGOS, 2004. Geohazards Theme Report: For the Monitoring of our Environment from Space and from Earth. European Space Agency Publication, Rome (Italy), p.55.

Intarawichian, N., and Dasananda, S. 2010. Analytical Hierarchy Process for landslide susceptibility mapping in lower Mae Chem watershed, Northern Thailand. *Suranaree Journal of Science and Technology*, 17(3), 277–92.

Ivanova, E. 2014. Landslide Susceptibility Mapping using Frequency Ratio and Analytic Hierarchy Process (AHP): Comparative study of two areas in Bulgaria. *Analysis and Management of Changing Risk for Natural Hazards: International Conference, Padua, Italy, 18-19 Nov, p. AP23-1–AP23-9.*

Jana, Sujoy & Sekac, Tingneyuc & Pal, Dilip. 2015. Landslide Hazard Investigation in Papua New Guinea-A Remote Sensing & GIS Approach. *International Journal of Scientific Engineering and Research*, 3, 79-83.

Jishnu E S, Ajith Joseph K, Sreenal Sreedhar, George Basil. 2017. Hazard mapping of landslide vulnerable zones in a Rainfed region of southern peninsular India – A Geospatial Perspective. *International Research Journal of Engineering and Technology*, 4, 7, pp.1350-1357.

Kavoura, K., and Sabatakakis, N. 2020. Investigating landslide susceptibility procedures in Greece. *Landslides*, 17, 127–145. https://doi.org/10.1007/s10346-019-01271-y.

Khodadad, S., and Jang, D.H. 2015. A comparative study of Analytical Hierarchy Process and Ordinary Least Square methods for landslide susceptibility mapping using GIS technology. *Tojsat - Journal of science and technology*, 2015, 5 (2), 7–16. https://www.tojsat.net/journals/tojsat/volumes/tojsat-volume05-i02.pdf.

Kil, S.H., Lee, D.K., Kim, J.H., Li, M.H., and Newman, G. 2016. Utilizing the Analytic Hierarchy Process to Establish Weighted Values for Evaluating the Stability of Slope Revegetation based on Hydroseeding Applications in South Korea. *Sustainability*, 8(1), 58. https://doi.org/10.3390/su8010058.

Kirschbaum, D., Stanley, T., and Zhou, Y. 2015. Spatial and temporal analysis of a global landslide catalog. *Geomorphology*, 249, p.4-15. https://doi.org/10.1016/j.geomorph.2015.03.016.

Komac, B., and Zorn, M. 2009. Statistical landslide susceptibility modeling on a national scale: The example of Slovenia. *Revue roumaine de géographie*, 53(2), 179-195.

Komac, M. 2006. A landslide susceptibility model using the Analytical Hierarchy Process method and multivariate statistics in perialpine Slovenia. *Geomorphology*, 74, 17-28. https://doi.org/10.1016/j.geomorph.2005.07.005.

Kottek, M., J. Grieser, C. Beck, B. Rudolf, and Rubel, F. 2006. World Map of the Köppen-Geiger climate classification updated. *Meteorologische Zeitschrift*, 15, 3, 259 - 263. https://doi.org/10.1127/0941-2948/2006/0130.

Kouli, M., Loupasakis, C., Soupios, P., Rozos, D., and Vallianatos, F. 2014. Landslide Susceptibility Mapping by comparing the WLC and WofE Multi-Criteria Methods in the West Crete Island, Greece. *Environmental Earth Sciences*, 72. https://doi.org/10.1007/s12665-014-3389-0.

Krušić, J., Marjanović, M., Samardzic-Petrovic, M., Abolmasov, B., Andrejev, K., and Miladinović, A. 2017. Comparison of expert, deterministic and Machine Learning approach for landslide susceptibility assessment in Ljubovija Municipality, Serbia. *Geofizika*, 34. 251-273. https://doi.org/10.15233/gfz.2017.34.15.

Kumar, R., and Anbalagan, R. 2016. Landslide Susceptibility Mapping Using Analytical Hierarchy Process (AHP) in Tehri Reservoir Rim Region, Uttarakhand. *Journal of the Geological Society of India*, 87. https://doi.org/10.1007/s12594-016-0395-8.

Ladas I., Fountoulis I., and Mariolakos I. 2007a. Using GIS and Multicriteria decision analysis in landslide susceptibility mapping - A case study in Messinia Prefecture area (SW Peloponnesus, Greece*). Bulletin of the Geological Society of Greece*, 40 (4): 1973-1985 https://doi.org/10.12681/bgsg.17240.

Ladas I., Fountoulis I., and Mariolakos I. 2007b. Large scale landslide susceptibility mapping using gis-based weighted linear combination and multicriteria decision analysis – a case study in northern Messinia (SW Peloponnesus, Greece). *Proceedings of the 8th Panhellenic Congress of the Geographical Society of Greece*, 1, 99-108.

Laldintluanga H., Lalbiakmawia, F. and Lalbiaknungi, Er. 2016. Landslide Hazard Zonation Along State Highway Between Aizawl City and Aibawk Town, Mizoram, India. *Using Geospatial Techniques*, 5, 342-355.

Lallianthanga R.K., and Lalbiakmawia, F. 2013. Micro-Level Landslide Hazard Zonation of Saitual Town, Mizoram, India Using Remote Sensing and GIS Techniques. *International Journal of Engineering Sciences & Research Technology*, 2(9), 2531-2546.

Lallianthanga R.K., and Lalbiakmawia, F. 2014. Landslide Susceptibility Zonation of Kolasib District, Mizoram, India Using Remote Sensing and GIS Techniques. *International Journal of Engineering Sciences & Research Technology*, 3 (3), 1402-1410.

Laltlankima, F. and Lalbiakmawia, F. 2016. Landslide Hazard Zonation Along National Highway Between Aizawl City and Lengpui Airport, Mizoram, India Using Geospatial Techniques. *International Journal of Engineering Sciences & Research Technology*, 5(7), 1024–1033. https://doi.org/10.5281/zenodo.57980.

Lin, L., Lin, Q., and Wang, Y. 2017. Landslide susceptibility mapping on a global scale using the method of logistic regression. *Natural Hazards and Earth System Sciences*, 17, 1411-1424. https://doi.org/10.5194/nhess-17-1411-2017.

Malamud, B.D., Turcotte, D.L., Guzzetti, F. and Reichenbach, P. 2004. Landslide inventories and their statistical properties. *Earth Surf. Process. Landforms*, 29, 687-711. https://doi.org/10.1002/esp.1064.

Maleki, Mohammad & Rahmati, Mahdis & Sadidi, Javad & Babaee, Ehsan. 2014. Landslide risk zonation using AHP method and GIS in Malaverd catchment, Kermanshah, Iran. *Conference Paper at the International Conference on Geospatial Information Research (GI Research 2014), 15-17 November 2014, Iran*.

Mallick, J., Singh, R.K., AlAwadh, M.A., Islam S., Khan R. A. and Qureshi N. M. 2018. GIS-based landslide susceptibility evaluation using fuzzy-AHP multi-criteria decision-making techniques in the Abha Watershed, Saudi Arabia. *Environmental Earth Sciences*, 77, 276. https://doi.org/10.1007/s12665-018-7451-1.

Mandal, S., and Maiti, R. 2011. Landslide Susceptibility Analysis of Shiv-Khola Watershed, Darjiling: A Remote Sensing & GIS Based Analytical Hierarchy Process (AHP). *Journal of the Indian Society of Remote Sensing*, 40. https://doi.org/10.1007/s12524-011-0160-9.

Mandal, B., and Mandal, S. 2018. Analytical hierarchy process (AHP) based landslide susceptibility mapping of Lish river basin of Eastern Darjeeling Himalaya, India. Advances in Space Research. 62. https://doi.org/10.1016/j.asr.2018.08.008.

Marjanović, M., Abolmasov, B., Djuric, U., and Bogdanovic, S. 2013. Impact of geo-environmental factors on landslide susceptibility using an AHP method: A case study of Fruska Gora Mt., Serbia. *Geoloski anali Balkanskoga poluostrva*, 74, 91-100. https://doi.org/10.2298/gabp1374091m.

Mijani, N. and Neysani Samani, N. 2017. Comparison Of Fuzzy-Based Models in Landslide Hazard Mapping. International Archives of the Photogrammetry. *Remote Sensing and Spatial Information Science*, XLII-4/W4, 407–416. https://doi.org/10.5194/isprs-archives-XLII-4-W4-407-2017.

Milevski, I., Dragicevic, S., and Zorn, M. 2019. Statistical and expert-based landslide susceptibility modeling on a national scale applied to North Macedonia. *Open Geosciences*, 11, 750-764. https://doi.org/10.1515/geo-2019-0059.

Mokarram, M., and Zarei, A.R. 2018. Landslide Susceptibility Mapping Using Fuzzy-AHP. *Geotechnical and Geological Engineering*, 36, 3931–3943. https://doi.org/10.1007/s10706-018-0583-y.

Moradi, M., Bazyar, M.H., and Mohammadi, Z. 2012. GIS-based landslide susceptibility mapping by AHP method, a case study, Dena City, Iran. *Journal of Basic and Applied Scientific Research*, 2(7), 6715-6723.

Moradi, S., and Rezaei, M. 2014. A GIS-based comparative study of the analytic hierarchy process, bivariate statistics and frequency ratio methods for landslide susceptibility mapping in part of the Tehran metropolis, Iran. *Geopersia*, 4, 45-61. https://doi.org/10.22059/jgeope.2014.51191.

Myronidis, D., Papageorgiou, C., and Theophanous, S. 2015. Landslide susceptibility mapping based on landslide history and analytic hierarchy process (AHP). *Natural Hazards*, 81. https://doi.org/10.1007/s11069-015-2075-1.

Nahayo, L., Kalisa, E., Maniragaba, A., and Nshimiyimana, F. 2019. Comparison of analytical hierarchy process and certain factor models in landslide susceptibility mapping in Rwanda. *Modeling Earth Systems and Environment*, 5, 885–895. https://doi.org/10.1007/s40808-019-00575-1.

Nguyen T.T.N., and Liu, C.C. 2019. A New Approach Using AHP to Generate Landslide Susceptibility Maps in the Chen-Yu-Lan Watershed, Taiwan. *Sensors*, 19, 505. https://doi.org/10.3390/s19030505.

Nicu, I. C. 2018. Application of analytic hierarchy process, frequency ratio, and statistical index to landslide susceptibility: an approach to endangered cultural heritage. *Environmental Earth Sciences*, 77, 79. https://doi.org/10.1007/s12665-018-7261-5.

Papanikolaou D., and Diakakis M. 2011. Changes in the intensity and distribution of natural disasters. Report for the Climate Change Impacts Study Committee. Bank of Greece.

Patil, A.S., and Panhalkar, S.S. 2019. Analytical hierarchy process for landslide hazard zonation of South-Western ghats of Maharashtra, India. *Disaster Advances*, 12(1), 26-33.

Perera, E., Ranagalage, M., Jayawardana, D., and Jayasingha, P. 2018. Spatial Multi Criteria Evaluation (SMCE) Model for Landslide Hazard Zonation in Tropical Hilly Environment: A Case Study from Kegalle. *Geoinformatics and Geostatistics: An Overview*, S3, 1-9. https://doi.org/10.4172/2327-4581.S3-004 .

Pourghasemi, H. R., Moradi, H. and Aghda, S. 2013. Landslide susceptibility mapping by binary logistic regression, analytical hierarchy process, and statistical index models and assessment of their performances. *Natural Hazard*, 69, 749–779. https://doi.org/10.1007/s11069-013-0728-5 .

Quan, H.C., and Lee, B.G. 2012. GIS-based landslide susceptibility mapping using analytic hierarchy process and artificial neural network in Jeju (Korea). *KSCE Journal of Civil Engineering*, 16, 1258-1266. https://doi.org/10.1007/s12205-012-1242-0.

Rahaman, S. A., Aruchamy S., and Jegankumar R. 2014. Geospatial Approach on Landslide Hazard Zonation Mapping Using Multicriteria Decision Analysis: A Study on Coonoor and Ooty, Part of Kallar Watershed, The Nilgiris, Tamil Nadu. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, XL, 1417-1422. https://doi.org/10.5194/isprsarchives-XL-8-1417-2014.

Reichenbach, P., Rossi, M., Malamud, B., Mihir, M., and Guzzetti, F. 2018. A review of statistically- based landslide susceptibility models. *Earth-Science Reviews*, 180, 60-91. https://doi.org/10.1016/j.earscirev.2018.03.001.

Rodriguez, A., Tapia, A., and Albornoz C. 2013. Mass Movement Susceptibility in the Socoroma Valley Andean Precordillera of Arica and Parinacota. *Diálogo Andino*, 44, 25–39. https://doi.org/10.4067/S0719-26812014000200004.

Roy, J., and Saha, S. 2019. Landslide susceptibility mapping using knowledge driven statistical models in Darjeeling District, West Bengal, India. *Geoenvironmental Disasters*, 6, 11. https://doi.org/10.1186/s40677-019-0126-8.

Rozos, D., Bathrellos, G., and Skilodimou, H. 2010. Landslide susceptibility mapping of the northeastern part of Achaia Prefecture using Analytical Hierarchical Process and GIS techniques. *Bulletin of Geological Society of Greece*, 43, 1637–1646. https://doi.org/10.12681/bgsg.11338.

Rozos, D., Bathrellos, G., and Skillodimou, H. 2011. Comparison of the implementation of rock engineering system and analytic hierarchy process methods, upon landslide susceptibility mapping, using GIS: A case study from the Eastern Achaia County of Peloponnesus, GREECE. *Environmental earth sciences*, 63, 49-63. https://doi.org/10.1007/s12665-010-0687-z.

Ruff, M. and Czurda, K. 2008. Landslide susceptibility analysis with a heuristic approach in the Eastern Alps (Vorarlberg, Austria). *Geomorphology*, 94(3–4), 314-324. https://doi.org/10.1016/j.geomorph.2006.10.032.

Saranathan, S.E., and Mani, S. 2016. Landslide Susceptibility Zonation mapping using Multi-criterion Analysis–CNG 37 Ghat section, Nadugani, Gudalur Taluk, The Nilgiris–Using Geological Factors. *International Journal of Earth Sciences and Engineering*, 09(04), 1441 - 1446.

Sauerborn, R., and Ebi, K. 2012. Climate change and natural disasters – integrating science and practice to protect health. *Global Health Action*, 5, 1-7. https://doi.org/10.3402/gha.v5i0.19295.

Semlali, I., Ouadif, L., and Bahi, L. 2019. Landslide susceptibility mapping using the analytical hierarchy process and GIS. *Current Science*, 116(5), 773-779. https://doi.org/10.18520/cs/v116/i5/773-779.

Shahabi, H., and Hashim, M. 2015. Landslide susceptibility mapping using GIS-based statistical models and Remote sensing data in tropical environment. *Scientific Reports*, 5, 9899. https://doi.org/10.1038/srep09899.

Sprague- Wheeler, D.K. 2003. The use of remote sensing imagery for evaluation of post-wildfire susceptibility to landslide and erosion hazards in the Salmon Challis National Forest, Lemhi County, Idaho. MSc Thesis, Idaho State University, Idaho, Pocatello ID 83209-8130.

Starkel, L. and Sarkar, S. 2002. Different frequency of threshold rainfalls transforming the margin of Sikkimese and Bhutanese Himalayas. *Studia Geomorphologica Carpatho–Balcanica*, 36, 51-67.

Styron, R., and Pagani, M. 2020. The GEM Global Active Faults Database. *Earthquake Spectra*, 36, 160-180. https://doi.org/10.1177/8755293020944182.

Tavoularis, N., Koumantakis, I., Rozos, D., Koukis, G. 2015. An implementation of rock engineering system (RES) for ranking the instability potential of slopes in Greek territory. An application in Tsakona area (Peloponnese -prefecture of Arcadia). *Bulletin of the Geological Society of Greece*, 49, 38-58. https://doi.org/10.12681/bgsg.11049.

Tavoularis, N., and Kirkos M. 2019. Estimation of landslide susceptibility in some islands of the Attica Region, through the use of Rock Engineering System (RES). *Conference: 8th Hellenic Congress of Geotechnical Engineering, 6-8 November 2019, Athens, Greece*.

Tazik, E., Jahantab, Z., Bakhtiari, M., Rezaei, A., and Kazem Alavipanah, S. 2014. Landslide susceptibility mapping by combining the three methods Fuzzy Logic, Frequency Ratio and Analytical Hierarchy Process in Dozain basin. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, XL-2/W3, 267–272. https://doi.org/10.5194/isprsarchives-XL-2-W3-267-2014,.

Tsangaratos, P., and Rozos, D. 2013. Producing landslide susceptibility maps by applying expert knowledge in a GIS – based environment. *Bulletin of the Geological Society of Greece*, 47(3), 1539-1549. https://doi.org/10.12681/bgsg.10993.

Vijith H., and Dodge-Wan, D. 2019. Modelling terrain erosion susceptibility of logged and regenerated forested region in northern Borneo through the Analytical Hierarchy Process (AHP) and GIS techniques. *Geoenvironmental Disasters*, 6, 8. https://doi.org/10.1186/s40677-019-0124-x.

Westen, C.J., Asch, T.W.J., and Soeters, R. 2006. Landslide hazard and risk zonation-why is it so difficult? Bull Eng Geol Environ. *Bulletin of Engineering Geology and Environment*, 65, 167-184. https://doi.org/10.1007/s10064-005-0023-0 .

Xiong, T., Indrawan, I., and Putra, D. 2018. Landslide Susceptibility Mapping Using Analytical Hierarchy Process, Statistical Index, Index of Enthropy, and Logistic Regression Approaches in the Tinalah Watershed, Yogyakarta. *Journal of Applied Geology*, 2(1), 78-93. https://doi.org/10.22146/jag.39983.

Yi, Y., Zhang, Z., Zhang, W., Xu, Q., Deng, C., and Li, Q. 2019. GIS-based earthquake-triggered-landslide susceptibility mapping with an integrated weighted index model in Jiuzhaigou region of Sichuan Province, China. *Natural Hazards and Earth System Sciences*, 19, 1973–1988. https://doi.org/10.5194/nhess-19-1973-2019.

Zhao H, Yao L, Mei G, Liu T, Ning Y. A. 2017. Fuzzy Comprehensive Evaluation Method Based on AHP and Entropy for a Landslide Susceptibility Map. *Entropy*, 19(8), 396. https://doi.org/10.3390/e19080396.