

Available online at http://www.journalcra.com

International Journal of Current Research Vol. 10, Issue, 03, pp.66992-66999, March, 2018 INTERNATIONAL JOURNAL OF CURRENT RESEARCH

# **RESEARCH ARTICLE**

## GIS-BASED LANDSLIDE SUSCEPTIBILITY MAPPING BY ANALYTICAL HIERARCHY PROCESS: A CASE STUDY, BURDUR PROVINCE

## <sup>1</sup>Kerem Hepdeniz and <sup>\*2</sup>İbrahim İskender Soyaslan

<sup>1</sup>Mehmet Akif Ersoy University Bucak EG Technical Sciences and Vocational School of Higher Education, Department of Architecture and Urban Planning, Burdur, Turkey

<sup>2</sup>Mehmet Akif Ersoy University, Faculty of Engineering and Architecture, Civil Engineering Department, Burdur,

Turkey

ARTICLE INFO	ABSTRACT				
<i>Article History:</i> Received 22 <sup>nd</sup> December, 2017 Received in revised form 09 <sup>th</sup> January, 2018 Accepted 24 <sup>th</sup> February, 2018 Published online 30 <sup>th</sup> March, 2018	The creation of landslide susceptibility maps is a critical step in helping organizers, local authorities, and policy makers with disaster planning. As such, the reliability of these landslide susceptibility maps is essential for decreasing loss of life and property. Increasing populations and settlements in sloped areas have generally enhanced the effect of landslides. In this study, a geographic information system and analytical hierarchy process were used to determine landslide susceptibility zones in Burdur province. For this purpose, ten parameters; distance to fault, wetness index, slope aspect, distance to fault, maps and distance to study users.				
Key words:	selected as conditioning factors associated with active landslides. The results of this study indicate				
AHP, Burdur, GIS, landslide, susceptibility.	that 11.63% of the investigation area has a high susceptibility and 1.57% has a very high susceptibility. The findings of this study are important for long-term land use planning, emergency decisions, minimization of potential landslide hazards, and saving lives.				

*Copyright* © 2018, *Kerem Hepdeniz and İbrahim İskender Soyaslan*. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

**Citation: Kerem Hepdeniz and İbrahim İskender Soyaslan, 2018.** "Gis-based landslide susceptibility mapping by analytical hierarchy process: a case study, burdur province", *International Journal of Current Research*, 10, (03), 66992-66999.

## **INTRODUCTION**

A landslide, defined as the movement of a mass of rock, debris, or earth down a slope (Cruden, 1991), is a destructive natural disaster that affects a large number of people and has a negative effect on settlements, stream drainage, transportation, agriculture, forest land, and water resources. In the last 50 years, 13.494 landslides occurred in Turkey, where they are the second most frequent natural disaster, after earthquakes, and result in significant loss of life and property (Ercanoglu et al., 2008; AFAD, 2015). In order to mitigate and control the problems caused by landslides, inventory mapping. susceptibility mapping, hazard mapping, and risk assessment have to be undertaken (Upreti and Dhital, 1996). These studies are also very important for future projects such as urban development and regional land-use planning projects (Ercanoglu et al., 2008). However, there are no standard procedures in place for evaluating landslide susceptibility or landslide hazard and risk (Kayastha et al., 2013). Many researchers have used different techniques, such as pair wise comparison (Westen, 1993; Süzen and Doyuran, 2004;

## \*Corresponding author: İbrahim İskender Soyaslan,

Mehmet Akif Ersoy University, Faculty of Engineering and Architecture, Civil Engineering Department, Burdur, Turkey.

Chaudhary), frequency ratio (Lee and Talip, 2005; Yalcin et al., 2011; Choi et al., 2012; Mohammady et al., 2012; Ozdemir and Altural, 2013; Hong et al., 2015), logistic regression (Ohlmacher and Davis, 2003; Lee et al., 2007; Bai et al., 2010; Mancini et al., 2010; Pradhan, 2010; Wang et al., 2013; Shahabi et al., 2014; Trigila et al., 2015; Patriche et al., 2016; Chen et al., 2017 ), and fuzzy logic-artificial neural network (Ercanoglu and Gokceoglu, 2002; Pistocchi et al., 2002; Oh and Pradhan, 2011; Ilanloo, 2011; Barrile et al., 2016) to assess landslide susceptibility. In this study, geographic information system (GIS) techniques were combined with analytical hierarchy process (AHP), developed by Saaty (1980) (Saaty, 1980), to obtain a landslide susceptibility map for a landslide-prone area in Burdur province, Turkey, using distance to fault, wetness index, aspect, distance to stream, rainfall, distance to road, curvature, land cover, slope, and litho logy criteria.

### **MATERIALS AND METHODS**

The study area is located between  $36.53^{\circ}$  and  $37.50^{\circ}$  north latitude and  $29.24^{\circ}$  and  $30.53^{\circ}$  east longitude (Figure 1). The average topographic elevation is about 1000 m; Koçaş Mountain, at an altitude of 2598 m, is the highest point in

Burdur province. The area of Burdur province is  $6887 \text{ km}^2$ , and it has many lakes. The topography of the province is very rough and mountainous. Approximately 5% of the study area has a slope angle greater than 40°. The soils are generally clayey and calcareous.

AHP was used to obtain standardised weights for the different layers, and the landslide susceptibility maps were generated by GIS techniques such as interpolation, buffer zone, and raster calculator. A summary flowchart of the methodological approach is provided in Figure 2.



Figure 1. Location map of the study area



Figure 2. Generalized flow chart of the methodology employed in the study

A continental climate is dominant, and winters are generally harsh, while summers are arid and warm. Average monthly temperatures vary from 2.5°C to 24.3°C; July is the warmest month and January is the coldest. Annual rainfall varies from 398 mm to 804 mm; August is the driest month, with 8 mm of rainfall, and December is the rainiest, with 63 mm between 1926 and 2016 years (MGM, 2015). In this study, Digital Elevation Model (DEM), acquired from Aster–GDEM and with a resolution of 30 m, was used. Slope, aspect, and curvature maps were generated from DEM. Roads and streams were digitised from scanned 1/25.000scale topographical maps. Lithology, active fault, and land use maps were obtained from the Mineral Research and Exploration General Directorate (MTA) (1997). All digitised vector maps were converted to a raster format using Arc GIS 10 software. AHP is one of the most simple methods of multi-criteria decision analysis (Saaty, 1980), such as site selection, regional planning, suitability analysis and landslide susceptibility analysis (Shahabi *et al.*, 2014). Decomposition, comparative judgement, and synthesis of priorities are the three principles of the method (Malczewski and Rinner, 2015). The pair wise comparison is the basic measurement made in the context of the AHP procedure, using a scale from 1/9 to 9, where 9 is the most important and 1/9 is the least important (Saaty, 1977). By this techniques, each parameter which is important for landslide susceptibility maps were organized into a matrix (Table 1). One of the strengths of the pair wise comparison method is that it allows the determination of rating inconsistencies by the consistency index (CI), which is related to the eigenvalue method:

$$CI = \frac{\lambda max - n}{n - 1} \tag{1}$$

Where  $\lambda_{max}$  is the maximal eigenvalue and n is the order of the comparison matrix. The consistency ratio (CR), which is the ratio of CI and RI, is given by

$$CR = \frac{CI}{RI} \tag{2}$$

Where RI is the average random consistency index, calculated

by Saaty (1977) (34), shown in Table 2.

In this research, RI10= 1.49 because of using 10 criteria. A CR<0.10 indicates a reasonable level of consistency in the pairwise comparisons. However, if CR >0.10, the ratio is indicative of inconsistent judgements.[33]. (Table 3). The eigenvectors of each matrix (Table 4) landslide susceptibility index (LSI) were calculated by a procedure based on the weighted linear sum:

$$LSI = \sum_{p=1}^{n} W_j W_{ij}$$
(3)

where Wj = weight value of causative factor, Wij = weight value of class i of causative factor j, and n = the number of causative factors.

### Table 1. Pairwise comparison matrix and significance weight of the landslide causative factors (continues)

		1/0	1/4			3	3	0.0	0,007
(8) Talus	3	1/6	1/4	6	3	3	3	1	0.067
				1/	1/				
[7] Volcanic sediment	1	1/9	1/7	6	3	1	1		0.037
[6] Travertine	1	1/9	1/7	1/	1/	1			0,037
• •	10	1000	825039	3	335 11 11 11 11 11 11 11 11 11 11 11 11 11				
[5] Peridotite	3	1/6	1/4	1/	1				0.067
[4] Melange	6	1/5	1/3	1					0,109
[3] Limestone	7	1/4	1						0,175
[2] Pebble Stone-	8	1							0,468
[1] Alluvial deposits	1								0,040
Geology									
[6] >50	9	7	4	3	2	1			0,428
[5] 40-50	8	6	з	2	1				0,244
[4] 30-40	6	4	2	1					0,146
[3] 20-30	4	3	1						0,097
[2] 10-20	2	1							0,049
[1] 0-10	1			12	10				0,036
Slope			12	6	3				
[6] Irrigation area	1/4	1/4	3	4	1/	1			0,059
[5] Sparse vegetation	1	1	6	1/	1				0,135
[4] Meadow	3	3	8	1					0,454
[3] Settled	1/7	1/7	1						0,038
[2] Cultivated area	1	1							0,157
[1] Forest	1								0,157
Land cover									
[3] Convex	1/3	6	1						0,243
[2] Flat	1/9	1							0,067
[1] Concave	1								0,690
Curvature				2	22				0,002
[5] >4000	1/7	1/5	1/3	1/	1				0.062
[4] 3000-4000	1/6	1/4	1/2	1					0.080
[3] 2000-3000	1/5	1/3	1						0.108
[2] 1000-2000	1/4	1							0.186
[1] 0-1000	1								0.564

#### Table 2. Random consistency index

n	1	2	3	4	5	6	7	8	9	10	11	12	13	14	
RI	0	0	0,58	0,90	1,12	1,24	1,32	1,41	1,45	1,49	1,51	1,53	1,56	1,57	

Causative factors		Ν	Λ <sub>max</sub>	CI	CR	RI
All		10	11.2110	0.13455	0.08911	1.49
Distance to fault	t	7	7.47673	0.07945	0.06019	1.32
Wetness index		4	4.26315	0.08771	0.09746	0.90
Aspect		9	9.63846	0.07980	0.05504	1.45
Distance	to	5	5.12289	0.03072	0.02743	1.12
streams						
Distance to roads		5	5.33475	0.08368	0.07472	1.12
Curvature		3	3.08243	0.04121	0.07106	0.58
Land cover		6	6.24347	0.04869	0.03927	1.24
Slope		6	6.16087	0.03217	0.02594	1.24
Geology		8	8.71887	0.10269	0.07283	1.41

Table 3. Causative factors

#### Table 4. Total weights of the subcriteria

Criteria (C)	Subcriteria (Sc)	Weight (Cwi)	Sunweight (SCwi)	Total weight (Twi)
Distance	0-1000	0.026	0.211	0,005486
to fault	1000-2000	2.54.675552	0.135	0.003510
0.000.000000	2000-3000		0.073	0.001898
	3000-4000		0.059	0.001534
	4000-5000		0.057	0.001482
	5000-6000		0.036	0,000936
	>6000		0,000	0,000330
Wotnoss	0.5	0.024	0,425	0,011134
Index	E 10	0,034	0,07	0,002364
index	10 15		0,090	0,003204
	10-15		0,23	0,007820
A	15-20	0.004	0,604	0,020536
Aspect	Flat	0,031	0,036	0,001116
	North		0,062	0,001922
	Northeast		0,031	0,000961
	East		0,057	0,001767
	Southeast		0,03	0,000930
	South		0,041	0,001271
	Southwest		0,293	0,009083
	West		0,292	0,009052
	Northwest		0,158	0,004898
Distance	0-1000	0,024	0,518	0,012432
to stream	1000-2000	1.5	0,203	0,004872
	2000-3000		0,129	0,003096
	3000-4000		0,09	0,002160
	>4000		0,060	0,001440
Rainfall	0-500	0.05	0.078	0.003900
	500-550	1028/0020	0.133	0.006650
	550-600		0.267	0.013350
	600-650		0.522	0.026100
Distance	0-1000	0.055	0.564	0.031020
to road	1000-2000	0,000	0 186	0.010230
101000	2000-3000		0 108	0.005940
	3000-4000		0.08	0,004400
	>4000		0.062	0.003410
Cupieture	Convex	0.095	0,002	0,059650
Curvature	Flat	0,085	0,09	0,038650
	Casasus		0,007	0,005695
Land power	Concave	0.197	0,243	0,020655
Land Cover	Cultivated area	0,107	0,157	0,029359
	Cultivated area		0,157	0,029359
	Settled		0,030	0,007106
	Meadow		0,454	0,084898
	Barren land		0,135	0,025245
-	Irrigated area		0,059	0,011033
Slope	0-10	0,187	0,036	0,006732
	10-20		0,049	0,009163
	20-30		0,097	0,018139
	30-40		0,146	0,027302
	40-50		0,244	0,045628
	>50	_	0,428	0,080036
Lithology	Alluvion	0,321	0,04	0,012840
	Pebble-Sandstone-Mudstone		0,468	0,150228
	Limestone		0,175	0,056175
	Melange		0,109	0,034989
	Peridotite		0,067	0,021507
	Travertine		0.037	0.011877
	Volcanite		0.037	0.011877
	Slope wash		0,067	0,021507

### Landslide conditioning factors

There are no general rules regarding the selection of factors in landslide susceptibility mapping (Ayalew and Yamagishi, 2005). The nature of the location area determines the selection of landslide-causing parameters, and these parameters are incorporated to enhance the accuracy and reliability of the susceptibility mapping method (Shahabi *et al.*, 2014; Dragicevic *et al.*, 2015). Ten possible landslide causing layers; distance to fault, wetness index, aspect, distance to streams, rainfall, distance to roads, curvature, land cover, slope, and lithologywere analyzed for landslide susceptibility mapping. *Distance to Fault;* Faults are the weakness zones of the earth's surface, and they are important factors in landslide susceptibility mapping (Esmaeil *et al.*, 2014).

During an earthquake, lateral and vertical forces unbalance the stability of slopes and cause landslides; as a result, landslide probability increases closer to a lineament (Lee and Evangelista, 2006; Owen *et al.*, 2008; Moore *et al.*, 1988). Burdur is located on the first degree earthquake zone and active fault maps were obtained from the Mineral Research and Exploration General Directorate (MTA) (1997). In this study, faults were buffered in seven different zones, and each zone was weighted by AHP (Figure 3a). *Topographic Wetness Index;* Topographic wetness index, also known as compound topographic index (Moore *et al.*, 1998), is one of the most important factors in landslide susceptibility mapping. It combines local upslope contribution area and slope and it is calculated using the expression

W=ln (As/tan b)

where W is the wetness index, As is the specific catchment area, and b is slope angle (Ercanoglu *et al.*, 2008). Topographic wetness index is generally used as a part of shallow landslide susceptibility mapping; areas with high index values indicate greater potential susceptibility of landslide (Figure 3b). *Aspect;* Aspect has a forced effect in a landslide event and determines parameters such as exposure to solar radiation, drying winds, and rainfall. Thus, it has an indirect effect on vegetation to grow, which in turn affects soil stability. In this study, DEM was used to generate aspect values and then reclassify them into nine categories: flat (-1), north (0°–22.5°, 337.5°–360°), northeast (22.5°-67.5°), east (67.5°-112.5°), southeast (112.5°-157.5°), south (157.5°-202.5°), southwest (202.5°-247.5°), west (247.5°-292.5°), and northwest (292.5°-337.5°) (Figure 3c).



Figure 3. Parameter maps used in the study: a) distance to fault, b) topographic wetness index, c) aspect, d) distance to streams, e) rainfall, f) distance to road, g) curvature, h) land cover, i) slope, j) lithology

Kerem Hepdeniz and İbrahim İskender Soyaslan. Gis-based landslide susceptibility mapping by analytical hierarchy process: A case study, burdur province



Figure 4. Landslide susceptibility map of Burdur province

**Distance to Streams:** Drainage density is an additional conditioning factor connected with landslide formation. Surface changes induced by stream erosion and the undercutting of slope toes can affect landslide initiation. The proximity of the slope in relation to streams can negatively affect the stability of the slope. In this study, five different buffer zones were created: 0–1000 m, 1000–2000 m, 2000–3000 m, 3000–4000 m, and >4000m (Figure 3d). *Rainfall;* Most landslides occur following sudden, intense rain and snow melt; increases the degree of saturation, underground hydrostatic level, and water pressure, which increases the potential for landslide occurrence. Annual total precipitation from 1950 to 2014 observed in six meteorological stations located within the research area were used to make a precipitation map, including four categories (Figure 3e).

Distance to Road: Landslides can occur on the sides of slopes intersected by roads (Yalcin et al., 2011). The slope might normally be steady, but the roads might change the dynamics of the topography and reduce the load on the heel of slope, thus destabilising it. In addition, frequency vibrations produced by vehicles can cause landslides. In this study, a distance to road map was created with five different buffer zones at 1000 m intervals, in order to determine the effect of the road on the stability of the slope (Figure 3f). Curvature; Curvature represents the morphology and is parallel to the direction of the highest slope (Kayastha et al., 2013). A negative value represents convex, a positive value represents concave, and a value of zero indicates that the surface is linear. Curvature has an effect on the acceleration or deceleration of flow over the surface, and convex slopes can lead to more erosion because of the acceleration of the fluid. The study area was classified as convex, concave, and flat as shown in Figure 3g. Land Cover; The effect of land cover in slope stability is one of the most important factors, and it has been studied since the 1960s.

Human implementation of the land could play an important role in the occurrence of landslides as land cover absorbs the water of the terrain and reduces the potential for landslide. The land use maps in this study were obtained from MTA (1992), and six different land cover classes were described (Figure 3h). Slope; Slope is the main parameter that affects landslide occurrence, and thus, it is widely used in landslide susceptibility analysis. In this study, a slope gradient map was obtained from DEM and divided into six different classes: 0°-10°, 10°-20°, 20°-30°, 30°-40°, 40°-50°, and >50°. Almost 35% of the study area consists of slopes in the  $0-10^{\circ}$  range, and 28% consists of slopes in the 30-40° range. Less than 1% of the study area has a slope angle >50° (Figure 3i). *Lithology;* This parameter has been regarded as the most crucial factor in landslide susceptibility, and thus, it was assigned the highest weight value among the parameters (Table 5). Numerous studies (Kayastha et al., 2013; Shahabi et al., 2014) (Kayastha et al., 2013, Song et al., 2012, Shababi et al., 2014) have used lithology as an input parameter to designate landslide susceptibility. Eight litho logical units were determined in the study area, which was digitised from 1/100000-scale geological maps from MTA (1997) (Figure 3j).

### Analysis of landslide susceptibility

In the AHP method, each layer is divided into smaller factors and these factors are composed according to their importance. Each factor is valued between 1 and 9 in comparison with other factors. The preference values for the study are given in Table 1. A significant advantage provided by AHP is, it can determine the rating inconsistencies by the consistency index (CI). As seen in table 3, all obtained CR values are less than 0.10, which is considered the highest value (34). The values given in the last column of Table 1, yield weight values for each causative factor. These weight values indicate the degree of importance of the factor or class.

According to the results, lithology had the highest value, 0.321; followed by land cover and slope, which were of equal importance with a value of 0.187. Distance to streams (0.024) and distance to fault (0.026) had the lowest values among the criteria. Finally, landslide susceptibility index (LSI) was calculated by a procedure based on the weighted linear sum. The overlay analysis method was then used to generate landslide susceptibility maps in Arc GIS Spatial Analyst, classifying areas into four categories of different landslide susceptibility zones: low, medium, high, and very high. The susceptibility map shows that 38.28% (2679 km<sup>2</sup>) of the area has low susceptibility, 48.52% (3395 km<sup>2</sup>) has medium susceptibility, 11.63% (815 km<sup>2</sup>) has high susceptibility, and 1.57% (110 km<sup>2</sup>) has very high susceptibility (Figure 4). It was noted that the very high landslide susceptibility areas are located mainly in the east side of Burdur province, in Bucak County, and around the towns of Tefenni and Karamanlı. According to the resulting map; slope wash, high slope and northward facing slopes are the areas where landslide formation is most common.

### Conclusions

As with other natural disasters, it is not easy to estimate where and when a landslide will occur. GIS combined with AHP is an effective technique for identifying landslide hazard zones. This method was implemented in Burdur province with a 30m cell size. In this study, ten criteria-distance to fault, wetness index, aspect, distance to stream, precipitation, distance to road, curvature, land cover, slope, and lithology-were considered and mapped using the GIS techniques of buffer zoning, overlay analysis, and interpolation. According to pair wise comparisons, lithology, land cover, and slope were weighted the highest in influencing landslides. Ultimately, landslide susceptibility zones were determined and classified from low to very high. According to this study, 11.63% (815 km<sup>2</sup>) of the investigation area has high susceptibility and 1.57% (110 km<sup>2</sup>) has very high susceptibility. This type of preliminary study and comprehensive feasibility analysis of the determined area can be helpful for planners, engineers, and policy makers in mitigating damage risks, planning disaster management, avoiding risk areas when building cities, and building retaining walls in appropriate zones.

### REFERENCES

AFAD (Başbakanlık Afet ve Acil Durum Yönetimi Başkanlığı), 2015. Bütünleşik tehlike haritalarının hazırlanması heyelan-kaya düşmesi temel kılavuz. https://www.afad.gov.tr/Dokuman/TR/184-2015070617353-kutle-hareketleri-temel kilavuz tr.pdf.

Accessed 25 December 2015

- Ayalew, L. and Yamagishi, H. 2005. The application of GISbased logistic regression for landslide susceptibility mapping in the Kakuda-Yahiko Mountains, Central Japan. *Geomorphology*, 65, 15–31.
- Bai, S.B., Wang, J., Lü, G.N., Zhou, P.G., Hou, S.S. and Xu, S.N. 2010. GIS-based logistic regression for landslide susceptibility mapping of the Zhongxian segment in the Three Gorges area, China. *Geomorphology*, 115, 23-31.
- Barrile, V., Cirianni, F., Leonardi, G. and Palamara, R. 2016. A fuzzy based methodology for Landslide Susceptibility Mapping. *Procedia Social and Behavioral Sciences*, 223, 896-902.

- Chaudhary, P., Chhetri, S.K., Joshi, K.M., Shrestha, B.M. and Kayastha, P. 2016. Application of an Analytic Hierarchy Process (AHP) in the GIS interface for suitable fire site selection: A case study from Kathmandu Metropolitan City, Nepal. Socio-Economic Planning Sciences, 53, 60-71
- Chen, W., Xie, X., Wang, J., Pradhan, B., Hong, H., Tien Bui, D., Duan, Z. and Ma, J. 2017. A comparative study of logistic model tree, random forest, and classification and regression tree models for spatial prediction of landslide susceptibility. *Catena*, 151, 147-160.
- Choi, J., Oh, H.-J., Lee, H.-J., Lee, C. and Lee, S. 2012. Combining landslide susceptibility maps obtained from frequency ratio, logistic regression, and artificial neural network models using ASTER images and GIS, *Engineering Geology*, 124,12-23.
- Cruden, D.M. 1991. A Simple Definition of a Landslide. Bulletin of the International Association of Engineering Geology, 43, 27-29.
- Dragicevic, S., Terence, L. and Shivanand, B. 2015. GISbased multicriteria evaluation with multiscale analysis to characterize urban landslide susceptibility in data-scarce environments. *Habitat International*, 45, 114-125.
- Ercanoglu, M. and Gokceoglu, C. 2002. Assessment of landslide susceptibility for a landslide-prone area (north of Yenice, NW Turkey) by fuzzy approach. *Environmental Geology*, 41,720–730.
- Ercanoglu, M., Kasmer, O. and Temiz, N. 2008. Adaptation and comparison of expert opinion to analytical hierarchy process for landslide susceptibility mapping. *Bulletin of the International Association of Engineering Geology*, 67, 565-578.
- Esmaeil, T., Zahra, J., Mohsen, B., Abdolali, R. and Seyed, K.A. 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*, 15, 267-272.
- Hong, H., Xu, C. and Tien Bui, D. 2015. Landslide Susceptibility Assessment at the Xiushui Area (China) Using Frequency Ratio Model. *Procedia Earth and Planetary Science*, 15, 513-517.
- Ilanloo, M. 2011. A comparative study of fuzzy logic approach for landslide susceptibility mapping using GIS: An experience of Karaj dam basin in Iran. *Procedia Social and Behavioral Sciences*, 19, 668-676.
- Kayastha, P., Dhital, M.R. and De Smedt, F. 2013. Application of the analytical hierarchy process (AHP) for landslide susceptibility mapping: A case study from the Tinau watershed, west Nepal. *Computers and Geosciences*, 52, 398-408.
- Lee, S. and Evangelista, D.G. 2006. Earthquake-Induced Landslide-Susceptibility Mapping Using An Artificial Neural Network. *Natural Hazards and Earth System Sciences*, 6, 687–695.
- Lee, S., Ryu, J.H. and Kim, I.S. 2007. Landslide susceptibility analysis and its verification using likelihood ratio, logistic regression, and artificial neural network models: case study of Youngin, Korea. *Landslides*, 4, 327-338.
- Lee, S. and Talip, J.A. 2005. Probabilistic landslide susceptibility and factor effect analysis. *Environmental Geology*, 47, 982-990.
- Malczewski, J. and Rinner, C. 2015. Multicriteria decision analysis in geographic information science. *Springer science business media*, New York

- Mancini, F., Ceppi, C. and Ritrovato, G. 2010. GIS and statistical analysis for landslide susceptibility mapping in the Daunia area, Italy. *Natural Hazards and Earth System Sciences*, 10,1851-1864.
- MGM (Meteoroloji Genel Müdürlüğü), 2015. Resmi İstatistikler, https://www.mgm.gov.tr/veridegerlendirme/ilve-ilceler-istatistik.aspx?m=BURDUR, 30 Eylül 2016.
- Mohammady, M., Pourghasemi, H.R. and Pradhan, B. 2012. Landslide susceptibility mapping at Golestan Province, Iran: A comparison between frequency ratio, Dempster– Shafer, and weights of evidence models. *Journal of Asian Earth Sciences*, 61, 221-236.
- Moore, I.D., O' Loughlin, E.M. and Burch, G.J. 1988. A contour-based topographic model for hydrological and ecological applications. *Earth Surface Process and Landforms*, 14(4), 305–320.
- MTA., 1997. 1:100000 The scale Geological Map of Turkey, Isparta layouts. *MTA General Directorate*, Ankara.
- Oh, H.J. and Pradhan, B. 2011. Application of an euro-fuzzy model to landslide-susceptibility mapping for shallow landslides in a tropical hilly area. *Computers and Geosciences*, 37,1264-1276.
- Ohlmacher, G.C. and Davis, J.C. 2003. Using multiple logistic regression and GIS technology to predict landslide hazard in northeast Kansas, USA. *Engineering Geology*, 69, 331–343.
- Owen, L.A., Kamp, U., Khattak, G.A., Harp, E.L., Keefer, D.K. and Bauer, M.A. 2008. Landslides triggered by the 8 October 2005 Kashmir earthquake. *Geomorphology*, 94, 1– 9.
- Ozdemir, A. and Altural, T. 2013. A comparative study of frequency ratio, weights of evidence and logistic regression methods for landslide susceptibility mapping: Sultan Mountains, SW Turkey. *Journal of Asian Earth Sciences*, 64,180-197.
- Patriche, C.V., Pirnau, R., Grozavu, A. and Rosca, B. 2016. A Comparative Analysis of Binary Logistic Regression and Analytical Hierarchy Process for Landslide Susceptibility Assessment in the Dobrovat River Basin, Romania. *Pedosphere*, 26, 335-350.
- Pistocchi, A., Luzi, L. and Napolitano, P. 2002. The use of predictive modeling techniques for optimal exploitation of spatial databases: a case study in landslide hazard mapping with expert system-like methods. *Environmental Geology*, 41, 765–775.

- Pradhan, B. 2010. Landslide Susceptibility mapping of a catchment area using frequency ratio, fuzzy logic and multivariate logistic regression approaches. *Journal of the Indian Society of Remote Sensing*, 38, 301-320.
- Saaty, T.L. 1977. A scaling method for priorities in hierarchical structures. *Journal of mathematical psychology*, 15, 234-281.
- Saaty, T.L. 1980. The Analytic Hierarchy Process. McGraw-Hill, New York
- Shahabi, H., Khezri, S., Ahmad, B.B. and Hashima, M. 2014. Landslide susceptibility mapping at central Zab basin, Iran: A comparison between analytical hierarchy process, frequency ratio and logistic regression models. *Catena*, 115, 55-70.
- Süzen, M.L. and Doyuran, V. 2004. Data driven bivariate landslide susceptibility assessment using geographical information systems: a method and application to Asarsuyu cathment, Turkey. *Engineering Geology*, 71, 303-321.
- Trigila, A., Ladanza, C., Esposito, C. and Mugnozza, G.S. 2015. Comparison of Logistic Regression and Random Forests techniques for shallow landslide susceptibility assessment in Giampilieri (NE Sicily, Italy). *Geomorphology*, 249, 119-136.
- Upreti, B.N. and Dhital, M,R. 1996. Landslide studies and management in Nepal. *International mountain development (ICIMOD)*, Katmandu Nepal.
- Wang, L.-L., Sawada, K. and Moriguchi, S. 2013. Landslide susceptibility analysis with logistic regression model based on FCM sampling strategy. *Computers & Geosciences*, 57, 81-92.
- Westen, V. 1993. Application of geographical information system to landslide hazard zonation. PhD, Enschede Nederlands.
- Yalcin, A., Reis, S., Aydinoglu, A.C. and Yomralioglu, T. 2011. A GIS-based comparative study of frequency ratio, analytical hierarchy process, bivariate statistics and logistics regression methods for landslide susceptibility mapping in Trabzon, NE Turkey. Catena, 85, 274-287.

\*\*\*\*\*\*