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Landslide susceptibility assessment of the part of the North Anatolian Fault Zone (Turkey) by GIS-based frequency ratio and index of entropy models

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Abstract: In the present study, landslide susceptibility assessment for the the part of the North Anatolian Fault Zone is made using index of entropy models within geographical information system. At first, the landslide inventory map was prepared in the study area using earlier reports, aerial photographs and multiple field surveys. 63 cases (69 %) out of 91 detected landslides were randomly selected for modeling, and the remaining 28 (31 %) cases were used for the model validation. The landslide-trigerring factors, including slope degree, aspect, elevation, distance to faults, distance to streams, distance to road. Subsequently, landslide susceptibility maps were produced using frequency ratio and index of entropy models. For verification, the receiver operating characteristic (ROC) curves were drawn and the areas under the curve (AUC) calculated. The verification results showed that frequency ratio model (AUC=75.71%) performed slightly better than index of entropy (AUC=75.43%) model. The interpretation of the susceptibility map indicated that distance to streams, distance to road and slope degree play major roles in landslide occurrence and distribution in the study area. The landslide susceptibility maps produced from this study could assist planners and engineers for reorganizing and planning of future road construction.

Keywords: Landslide susceptibility, GIS, Nort Anatolian Fault Zone, İndex of Entropy, Reşadiye, Tokat.

1. Introduction

Among various natural hazards, landslides are the most widespread and damaging. Potentials landslide-prone areas should, therefore, are identified in advance in order to reduce such damage. In this respect, landslide susceptibility assessment can provide valuable information essential for hazard mitigation through proper project planning and implementation. The main goal of landslide susceptibility analysis is to identify dangerous and high risk areas and thus landslide damage can be reduced through suitable mitigation measures (Solaimani *et al.* 2013). Different methods to prepare landslide susceptibility and hazard maps using statistical methods and GIS tools were developed in the last decade (Van Westen et al. 2003; Guzzetti et al. 2005). Many of these studies have applied statistical models such as logistic regression(Akgun 2012; Ozdemir and Altural 2013; Solaimani et al. 2013;Demir et al. 2015), bivariate(Bednarik et al. 2010; Pareek et al. 2010; Pradhan and Youssef 2010) and multivariate (Pradhan 2010a, b; Choi et al. 2012). Probabilistic models such as frequency ratio (FR), weight of evidence (WOE), etc. have been used in landslide susceptibility mapping (Akgun et al. 2008; Oh et al. 2012; Yilmaz and Keskin 2009; Youssef et al. 2009, 2013; Pradhan and Youssef 2010; Pradhan et al. 2011; Akgun et al 2012; Saponaro et al. 2014; Sujatha et al. 2014; Demir et al. 2015, Bourenane et al 2016, Chen et al. 2016b). Other different methods such as, analytical hierarchy process (AHP) (Yalcin et al. 2011; Pourghasemi

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et al. 2012a; Park et al. 2013, Demir et al. 2013, Myronidis et al. 2016, Wu et al. 2016, Chen et al. 2016a), index of entropy (IOE) model(Mihaela et al.2011; Devkota et al. 2013, Jaafari et al 2013, Youssef et al. 2015, Wang et al. 2016), certainty factor (CF) model (Devkota et al. 2013), artificial neural network model (Chauhan et al. 2010; Pouydal et al. 2010; Pradhan and Buchroithner 2010; Park et al. 2013),, spatial multicriteria decision analysis (MCDA) approach (Akgun and Turk 2010; Akgun 2012), fuzzy logic and neuro-fuzzy (Vahidnia et al. 2010; Sezer et al. 2011), decision-tree methods (Nefeslioglu et al. 2010; Pradhan 2013), fuzzy logic (Pourghasemi et al. 2012a, 2012b, 2012c; Sharma et al. 2013), support vector machine (SVM) (Yilmaz 2010; Pradhan 2013) have also been employed for the purpose of landslide susceptibility mapping.

This study aims to develop landslide susceptibility maps of the part of the North Anatolian Fault Zone, southeast Resadiye-Koyulhisar Turkey, (Fig. 1), using index of entropy (IOE) model. To achieve this, index of entropy analysis methodology, to obtain landslide susceptibility map using the geographic information system was developed, applied, and verified in the study area.

Figure 1. Study Area

2. Study area

The study area is located in the the North Anatolian Fault Zone, between the southeast Resadiye to Koyulhisar Sivas province. The area lies between 44^{o}70’64’’ and 44 ^{o} 56’84 latitude and 36 ^{o} 21’87 and 41 ^{o} 47’09’’ longitude, and covers an area about of 720 km^2.

According to a geological map prepared by General Directory of Mineral Research and Exploration, north of the NAFZ there are, from old to young, Upper Cretaceous-age volcanic and sedimentary units, Maastrichtian-age limestone, and Pliocene-age basalt

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and other volcanic units. While the Upper Cretaceous volcanic and sedimentary units on the lower slopes have a gentle slope morphology, Maastrichtian limestones present a very steep morphology. While the dip of the lower beds of the limestone varies over short distances due to the effect of the NAFZ, it is generally to the northeast (Gokceoglu et al. 2005). Landslides are common natural hazards in the seismically active North Anatolian Fault Zone (NAFZ), which is 1,100 km in length and is moving westward with the rate of 2.5 cm every year according to geological and GPS data(Demir et al 2013) The latest catastrophic event occurred on March 17, 2005 at Kuzulu (Sivas) in the valley. The landslide was initiated within highly weathered volcanics in the mode of sliding and then transformed to an earth flow. It killed 15 people, and more than 30 houses and a mosque were buried and damaged by the earth flow material. A second but smaller landslide originated from the same source areas after 4 days and caused additional damages (Gokceoglu et al. 2005; Ulusay et al. 2007; Yılmaz 2009). After the main event, the governor needed landslide susceptibility maps of the landslide area.

3. Data production

The study began with the preparation of a landslide inventory map based on field work, earlier reports and satellite images. Landslide inventory maps show the areal distribution of existing landslide areas and their characteristics. These maps indicate the landslides, which are perceptible on site (Cevik and Topal 2003). In total, 321 landslides were mapped (Fig. 2) and subsequently digitized for further analysis. The mapped landslides cover an area of 47.81 km2, which constitutes 6.68 % of the entire study area. From these landslides, 63 (69 %) randomly selected instabilities were taken for making landslide susceptibility models and 28 (31 %) were used for validating the models.

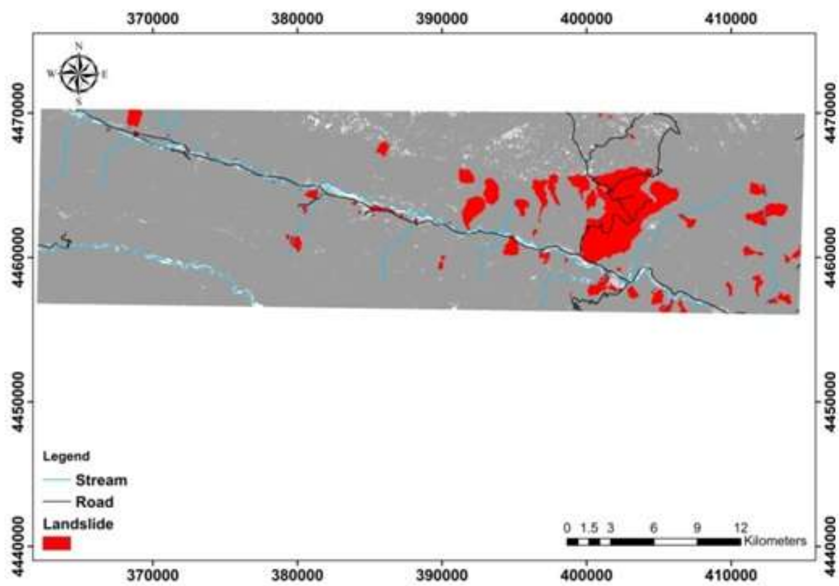

Figure 2. Landslide inventory map

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The number of landslide-conditioning factors may range from only a few numbers to several (Mohammady et al. 2012; Pourghasemi et al. 2012d; Papathanassiou et al. 2012). The selection of these factors mainly depends on the availability of data for the study area and the relevance with respect to landslide occurrences (Papathanassiou et al.2012). According to the Ayalew and Yamagishi (2005), in GIS-based studies, the selected factors should be operational, complete, non-uniform, measurable, and non-redundant. We prepared six thematic data layers representing the following landslide conditioning factors: slope degree, aspect, elevation, distance to faults, distance to streams, distance to road (Figure 3).

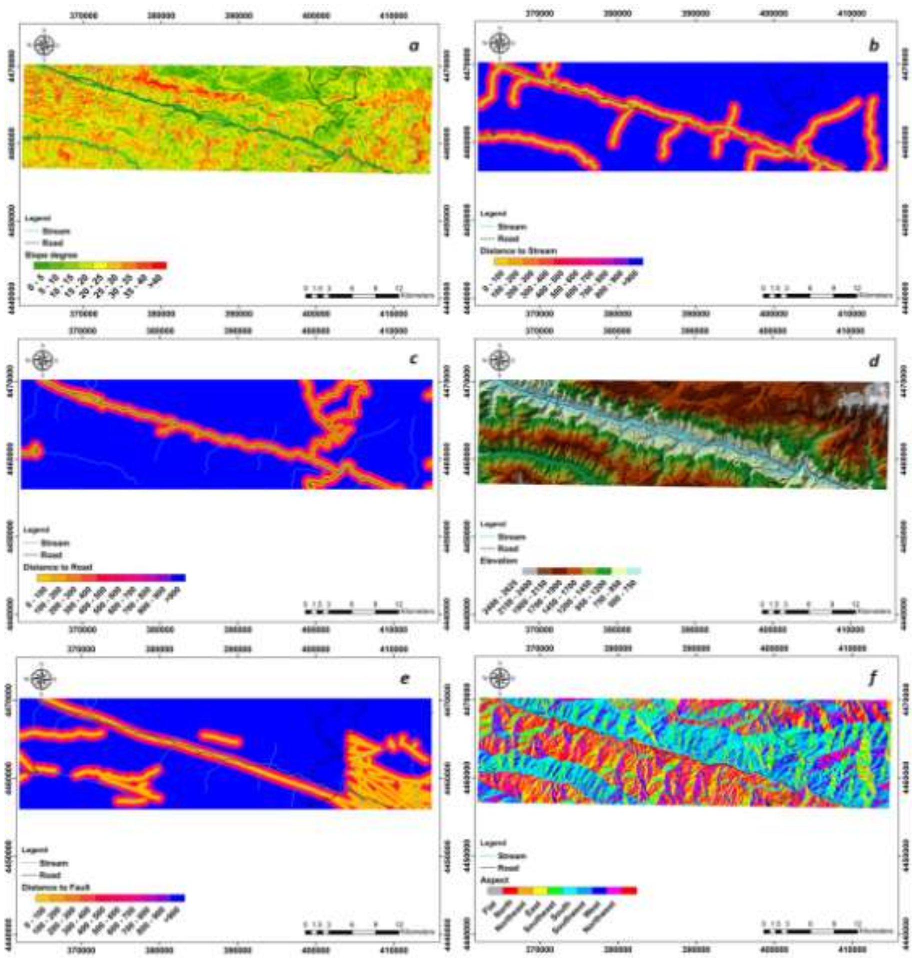

Figure 3. Conditioning Factors(a.slope degree, b.distance to stream, c.distance to road, d.elevation, e.distance to faults,f.aspect.)

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The main parameter of the slope stability analysis is the slope degree(S. Lee and K. Min 2001). Because the slope degree is directly related to the landslides, it is frequently used in preparing landslide susceptibility maps[S. Lee, J. H. Ryu, J. S. Won and H. J. Park (2004), M. Ercanoglu, C. Gokceoglu, T. W. J. Van Asch (2004, A. Clerici, S. Perego, C. Tellini and P. Vescovi (2002) . For this reason, the slope degree map of the study area is prepared from the digital elevation model (DEM) and divided into nine slope classes with an interval of 5°(Figure 3). Aspect and elevation also were extracted from the DEM. Aspects are grouped into 9 classes such as flat (-1), north (337.5°–360°, 0°–22.5°), 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°).In the study area, the elevation ranges between 500 and 2,625 m. The elevation values were divided into nine classes (Figure 3). The distance from faults, road and stream is calculated at 100m intervals using the geological map (Figure 9). An important parameter that controls the stability of a slope is the saturation degree of the material on the slope(Yalçın 2008, Yalçın and Bulut 2007). The closeness of the slope to drainage structures is another important factor in terms of stability. Streams may adversely affect stability by eroding the slopes or by saturating the lower part of material resulting in water level increases(Pourghasemi et al. 2012a, Gökçeoğlu 1996, Saha et al. 2002). For this reason, ten different buffer zones were created within the study area to determine the degree to which the streams affected the slopes. A road constructed can cause a disturbance of the slopes that lead to increase in stress on the back of the slope, because of changes in topography and decrease of load on toe, some tension cracks may develop. Although a slope is balanced before the road construction, some instability may be happened because of negative effects of excavation. In the current study many landslides were recorded along the roads in the study area that is due to road construction. The distance from roads was calculated and reclassified into ten classes.

4. Landslide Susceptibility Analysis

a. Application of Index of Entropy Model

In this study index of entropy model was used for landslide susceptibility analysis using six landslide conditioning factors.

The entropy indicates the extent of the instability, disorder, imbalance, and uncertainty of a system (Yufeng and Fengxiang, 2009). The entropy of a landslide refers to the extent that various factors influence the development of a landslide (Pourghasemi et al., 2012b; Jaafari et al., 2013). Several important factors provide additional entropy into the index system. Therefore, the entropy value can be used to calculate objective weights of the index system. The equations used to calculate the information coefficient Wj representing the weight value for the parameter as a whole (Bednarik et al., 2010; Constantin et al., 2011) are given as follows:

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$$P_{ij} = \frac{b}{a} \tag{1}$$

$$(P_{ij}) = \frac{P_{ij}}{\sum_{j=1}^{S_j} P_{ij}} \tag{2}$$

$$H_j = -\sum_{i=1}^{S_j} (P_{ij}) \log_2 (p_{ij}),\ j = 1,..,n \tag{3}$$

$$H_{j\max} = \log_2 S_j S_j - number\ of\ classes \tag{4}$$

$$I_j = \frac{H_{j\max} - H_j}{H_{j\max}},\ I = (0,1),\ j = 1,...,n \tag{5}$$

$$W_j = I_j . P_{ij} \tag{6}$$

where a and b are the domain and landslide percentages, respectively, (Pij) is the probability density, Hj and Hj max represent entropy values, Ij is the information coefficient and Wj represents the resultant weight value for the parameter as a whole.
The final landslide susceptibility map was prepared by the summation of weighted products of the secondarily parametric maps. The final landslide susceptibility maps using index of entropy model was developed using the following equation:

$$\begin{aligned} Y_{iIE} = {} & ((Slope\ degree * 0{,}110) + (Aspect * 0{,}080) + \\ & (Elevation * 0{,}136) + (Distance\ to\ Road * 0{,}023) + \\ & (Distance\ to\ Stream * 0{,}023) + (Distance\ to\ Fault) * 0{,}005)) \end{aligned} \tag{7}$$

where Y is the value of landslide susceptibility (Fig. 4). The result of this summation is a continuous interval of values from 0.7297 to 6.1861, which represents the landslide susceptibility index. A natural break classification method was used to divide the interval into four classes and a susceptibility map was prepared (Bednarik et al., 2010; Constantin et al., 2011; Erner et al., 2010; Falaschi et al., 2009; Ram Mohan et al., 2011; Xu et al., 2012a, 2012b). According to the landslide susceptibility map generated with the IOE model (Fig. 4 and Table 1), it was found that 24.87% and 23.50% of the total landslides falls in the very low and low susceptibility zones respectively. Moderate, high, and very high susceptible zones represent 20.37%, 16.42%, and 14.83% of the landslides pixels, respectively.

Table.1 Spatial relationship between each landslide conditioning factor and landslides using index of entropy model.

Factor (Parameter)	Class	Percentage of pixels in the class (%) (a)	Percentage of landslide pixels(%) (b)	Pij	(Pij)	Hj	Hjmax	Ij	Wj
Elevation (m)	500-750	11.324	10.406	0.919	0.147	2.551	3.170	0,195	0,136
	750-950	13.048	16.226	1.244	0.199				
	950-1200	18.265	21.566	1.181	0.189				
	1200-1450	18.478	24.770	1.341	0.214				
	1450-1700	19.762	20.921	1.059	0.169				

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	1700-1900	12.213	6.021	0.493	0.079				
	1900-2150	4.096	0.091	0.022	0.004				
	2150-2400	2.115	0.000	0.000	0.000				
	2400-2625	0.699	0.000	0.000	0.000				
Slope degree (°)	0-5	7.093	7.888	1.112	0.142	2.770	3.170	0.126	0,110
	5-10	11.692	24.212	2.071	0.265				
	10-15	15.430	26.660	1.728	0.221				
	15-20	16.929	17.950	1.060	0.136				
	20-25	16.714	11.004	0.658	0.084				
	25-30	15.076	6.438	0.427	0.055				
	30-35	10.864	4.399	0.405	0.052				
	35-40	4.870	1.338	0.275	0.035				
	>40	1.331	0.111	0.083	0.011				
Aspect	FLAT	1.043	0.302	0.290	0.034	2.871	3.170	0,094	0,080
	NORTH	13.922	5.270	0.378	0.045				
	NORTHEAST	12.046	4.593	0.381	0.045				
	EAST	9.461	5.779	0.611	0.072				
	SOUTHEAST	10.956	11.476	1.047	0.124				
	SOUTH	15.267	25.409	1.664	0.196				
	SOUTHWEST	13.818	24.351	1.762	0.208				
	WEST	11.493	15.909	1.384	0.163				
	NORTHWEST	11.994	6.911	0.576	0.068				
Distance to Stream (m)	0-100	3.692	7.789	2.110	0.152	3.266	3.322	0,017	0,023
	100-200	3.630	7.086	1.952	0.140				
	200-300	3.584	5.757	1.606	0.115				
	300-400	3.614	5.274	1.459	0.105				
	400-500	3.522	4.877	1.384	0.100				
	500-600	3.440	4.510	1.311	0.094				
	600-700	3.307	3.666	1.108	0.080				
	700-800	3.133	3.451	1.101	0.079				
	800-900	3.110	3.400	1.093	0.079				
	>900	68.968	54.190	0.786	0.056				
Distance to Road (m)	0-100	6.937	12.505	1.803	0.142	3.262	3.322	0,018	0,023
	100-200	6.445	10.563	1.639	0.130				
	200-300	6.258	9.866	1.577	0.125				
	300-400	6.179	9.075	1.469	0.116				
	400-500	5.825	7.848	1.347	0.106				
	500-600	5.016	5.799	1.156	0.091				
	600-700	5.813	6.422	1.105	0.087				
	700-800	5.801	5.880	1.014	0.080				
	800-900	6.566	6.414	0.977	0.077				
	>900	45.159	25.628	0.568	0.045				
Distance to	0-100	6.331	4.788	0.756	0.079	3.305	3.322	0,005	0,005

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Fault (m)					
	100-200	5.193	4.444	0.856	0.090
	200-300	4.245	3.980	0.938	0.098
	300-400	3.682	3.346	0.909	0.095
	400-500	3.261	3.676	1.127	0.118
	500-600	2.940	3.592	1.222	0.128
	600-700	2.984	3.167	1.061	0.111
	700-800	2.899	2.548	0.879	0.092
	800-900	2.805	2.153	0.768	0.080
	>900	65.660	68.306	1.040	0.109

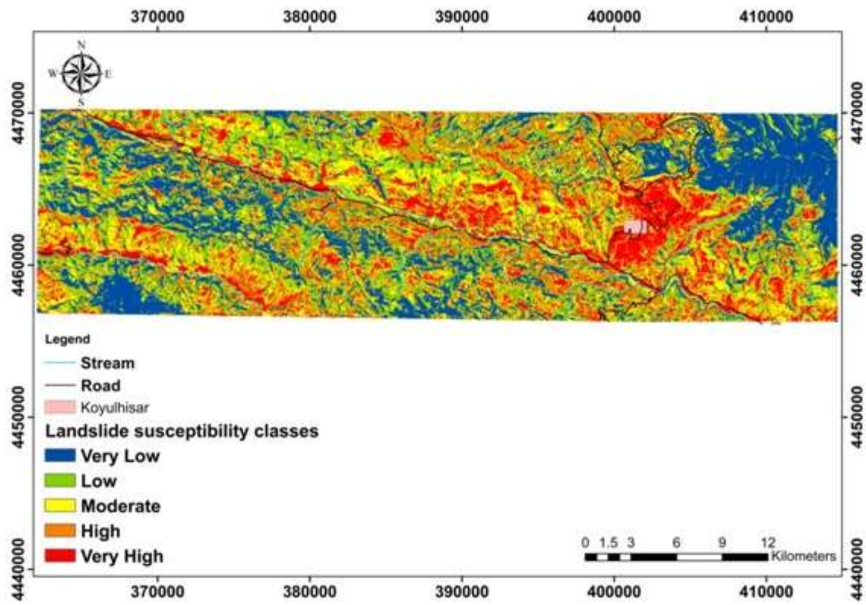

Figure 4. Landslide susceptibility map IOE

b. Application of Frequency ratio method

Frequency ratio method is a simple and understandable probabilistic model, and the model is based on the observed relationships between distribution of landslides and each landslide-causative factor, to reveal the correlation between landslide locations and the factors in the study area (Lee and Pradhan, 2007). To calculate the frequency ratio, the ratio of landslide occurrence to non-occurrence (Regmi et al., 2013) was calculated for each factor's class. Therefore, the frequency ratio for each factor's class was calculated from its relationship with landslide events. The frequency ratio is defined as shown in Equation (8).

$$FR = \frac{PLO}{PIF} \quad (8)$$

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Here, PLO is the subcategory percentage of each factor conditioning landslide in a landslide area, while PIF is the category percentage of each factor conditioning landslide (Table 2).

Table.2 Frequency ratio values of the landslide-trigerring parameters.

Factor (Parameter)	Class	Number of pixels in class	Percentage of pixels in the class (%) (a)	Number of landslide pixels	Percentage of landslide pixels(%) (b)	FREQUENCY RATIO (FR) (b/a)
Elevation (m)	500-750	130386	11.324	5166	10.406	0.919
	750-950	150242	13.048	8055	16.226	1.244
	950-1200	210313	18.265	10706	21.566	1.181
	1200-1450	212763	18.478	12297	24.770	1.341
	1450-1700	227550	19.762	10386	20.921	1.059
	1700-1900	140627	12.213	2989	6.021	0.493
	1900-2150	47161	4.096	45	0.091	0.022
	2150-2400	24348	2.115	0	0.000	0.000
	2400-2625	8044	0.699	0	0.000	0.000
Slope degree (°)	0-5	81676	7.093	3916	7.888	1.112
	5-10	134628	11.692	12020	24.212	2.071
	10-15	177671	15.430	13235	26.660	1.728
	15-20	194923	16.929	8911	17.950	1.060
	20-25	192448	16.714	5463	11.004	0.658
	25-30	173594	15.076	3196	6.438	0.427
	30-35	125095	10.864	2184	4.399	0.405
	35-40	56076	4.870	664	1.338	0.275
	>40	15323	1.331	55	0.111	0.083
Aspect	FLAT	12005	1.043	150	0.302	0.290
	NORTH	160305	13.922	2616	5.270	0.378
	NORTHEAST	138703	12.046	2280	4.593	0.381
	EAST	108940	9.461	2869	5.779	0.611
	SOUTHEAST	126147	10.956	5697	11.476	1.047
	SOUTH	175786	15.267	12614	25.409	1.664
	SOUTHWEST	159110	13.818	12089	24.351	1.762
	WEST	132340	11.493	7898	15.909	1.384
	NORTHWEST	138098	11.994	3431	6.911	0.576
Distance to Stream (m)	0-100	42513	3.692	3867	7.789	2.110
	100-200	41798	3.630	3518	7.086	1.952
	200-300	41271	3.584	2858	5.757	1.606
	300-400	41614	3.614	2618	5.274	1.459
	400-500	40558	3.522	2421	4.877	1.384
	500-600	39604	3.440	2239	4.510	1.311
	600-700	38082	3.307	1820	3.666	1.108
	700-800	36070	3.133	1713	3.451	1.101
	800-900	35807	3.110	1688	3.400	1.093
	>900	794117	68.968	26902	54.190	0.786
Distance to Road (m)	0-100	79875	6.937	6208	12.505	1.803

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	100-200	74209	6.445	5244	10.563	1.639
	200-300	72053	6.258	4898	9.866	1.577
	300-400	71146	6.179	4505	9.075	1.469
	400-500	67076	5.825	3896	7.848	1.347
	500-600	57759	5.016	2879	5.799	1.156
	600-700	66937	5.813	3188	6.422	1.105
	700-800	66800	5.801	2919	5.880	1.014
	800-900	75608	6.566	3184	6.414	0.977
	>900	519971	45.159	12723	25.628	0.568
Distance to Fault (m)	0-100	72894	6.331	2377	4.788	0.756
	100-200	59789	5.193	2206	4.444	0.856
	200-300	48884	4.245	1976	3.980	0.938
	300-400	42392	3.682	1661	3.346	0.909
	400-500	37545	3.261	1825	3.676	1.127
	500-600	33854	2.940	1783	3.592	1.222
	600-700	34362	2.984	1572	3.167	1.061
	700-800	33376	2.899	1265	2.548	0.879
	800-900	32301	2.805	1069	2.153	0.768
	>900	756037	65.660	33910	68.306	1.040

Therefore, the greater the ratio above unity, the stronger the relationship between landslide occurrence and the given factor's class attribute, and the lower the ratio below unity, the lesser the relationship between landslide occurrence and the given factor's class attribute (Lee and Pradhan, 2006; Yalcin et al., 2011). To calculate the landslide susceptibility index (LSI), each factor's frequency ratio values were summed as shown in Equation 9.

$$LSI = \sum_{i=1}^{n} FR \quad (9)$$

The LSI map was reclassified using the equal interval method in GIS, and as a result, the study area was divided into five susceptibility classes: very low, low, moderate high, and very high (Fig. 5). According to this landslide susceptibility map, 24.67 % of the total area was determined to be very low susceptible. Low, moderate, and high susceptible zones constitute 23.08 %, 19.70 %, and 16.85 % of the area, respectively. The very high susceptible area is 15.69 % of the total area.

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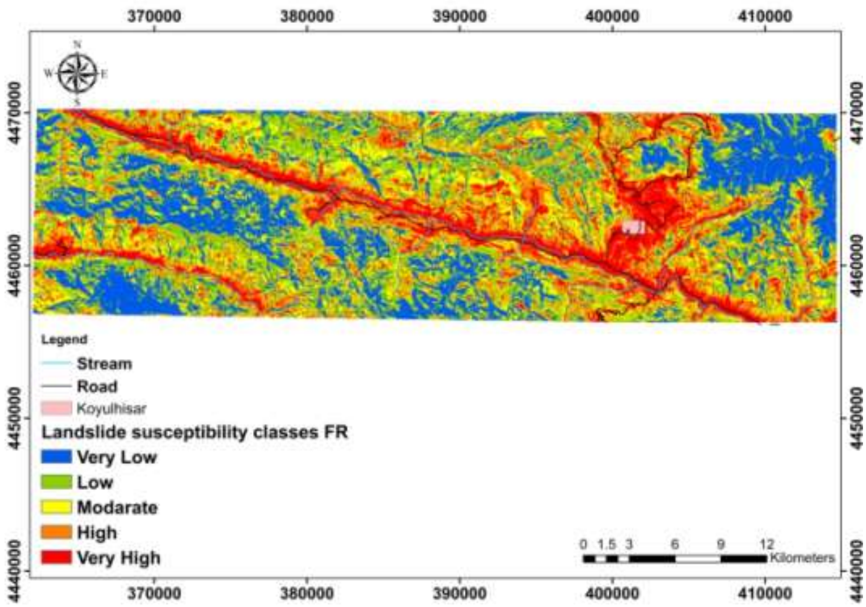

Figure 5. Landslide susceptibility map FR

5. Validation of Landslide Susceptibility map

Landslide susceptibility maps without validation are less meaningful (Chung and Fabbri 1998). In the current study, validation of the landslides susceptibility maps was checked by using receiver operating characteristics (ROC) (Akgun et al., 2012; Tien Bui et al., 2012a, b, 2013; Regmi et al., 2014; Ozdemir and Altural, 2013). The ROC curve is a useful method for representing the quality of deterministic and probabilistic detection and forecast systems. The ROC plots the different accuracy values obtained against the whole range of possible threshold values of the functions, and the ROC serves as a global accuracy statistic for the model, regardless of a specific discriminate threshold (Pourghasemi et al., 2012). In the ROC curve, the sensitivity of the model (the percentage of existing landslide pixels correctly predicted by the model) is plotted against 1-specificity (the percentage of predicted landslide pixels over the total study area) (Mohammady et al., 2012; Jaafari et al., 2013). The area under the ROC curve (AUC) represents the quality of the probabilistic model to reliably predict of the occurrence or non-occurrence of landslides. A good fit model has an AUC values range from 0.5–1, while values below 0.5 represent a random fit. The success rate results were obtained by comparing the landslide training data with the susceptibility maps (Fig. 6).
AUC plot assessment results showed that the AUC values were 0.7571 and 0.7543 for FR and IOE models and the training accuracy were 75.71 and 75.43 %, respectively. From the results of the AUC evaluation, it is seen that both the success rate curve show almost similar result. All the models employed in this study showed reasonably good accuracy in predicting the landslide susceptibility of the study area.

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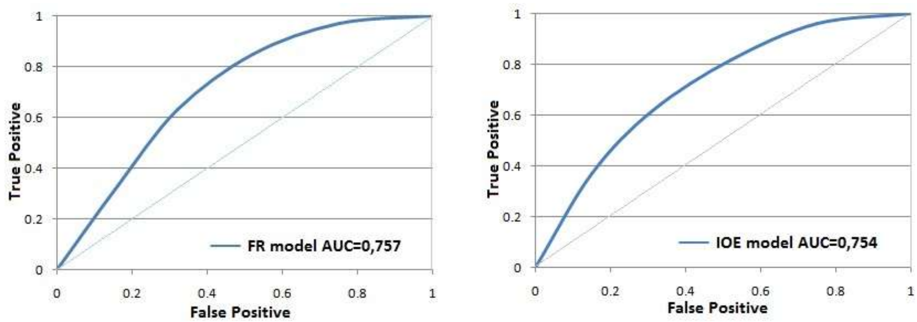

Figure 6. Success rate curves of FR and IOE models of the study area.

6. Conclusion

In this study, the accepted models, frequency ratio and index of entropy, within a GIS environment for the aim of LSM have been used. For this purpose, six trigerring factors, i.e., slope degree, aspect, elevation, distance to faults, distance to streams and distance to road were used. A total of 91 landslides were identified and mapped. Out of which, 63 (69 %) were randomly selected for generating a model and the remaining 28 (31 %) were used for validation purposes. In this study, five landslide susceptibility classes, i.e., very low, low, moderate, high, and very high susceptibility for landsliding, were derived with equal interval method. The validation has been determined by using the ROC method in which the accuracy of the LS maps produced by the frequency ratio and index of entropy models was 0.757 and 0.754, respectively for success rate technique. This shows that all the models employed in this study showed reasonably good accuracy in predicting the landslide susceptibility of the part of the North Anatolian Fault Zone (Turkey). All susceptibility zones require further engineering geological and geotechnical considerations. The increasing population pressure has forced people to concentrate their activities on steep mountain slopes. Thus, to safeguard the life and property from landslides, the susceptibility map can be used as basic tools in land management and planning future construction projects in this area. The landslide susceptibility map produced in this study can be used for optimum management by decision makers and land use planners, and also avoidance of susceptible regions in study area.

7. References

Akgun, A., (2012). A comparison of landslide susceptibility maps produced by logistic regression, multi-criteria decision, and likelihood ratio methods: a case study at İzmir, Turkey. Landslides 9 (1), 93–106. http://dx.doi.org/10.1007/s10346-011- 0283-7.

Akgun A, Turk N. (2010). Landslide susceptibility mapping for Ayvalik (Western Turkey) and its vicinity by multi-criteria decision analysis. Environmental Earth Science; 61(3): 595-611

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Discussions

Akgun, A., Sezer, E.A., Nefeslioglu, H.A., Gokceoglu, C., and Pradhan, B., (2012). An easy-to-use MATLAB program (MamLand) for the assessment of landslide susceptibility using a Mamdani fuzzy algorithm. Computers & Geosciences, 38, 23–34

Akgün, A., Dag, S., Bulut, F., (2008). Landslide susceptibility mapping for a landslideprone area (Findikli, NE of Turkey) by likelihood-frequency ratio and weighted linear combination models. Environmental Geology 54, 1127–1143.

Ayalew, L. and Yamagishi, H., (2005). The application of GIS-based logistic regression for landslide susceptibility mapping in the Kakuda-Yahiko mountains, Central Japan. Geomorphology, 65, 15–31.

Bednarik, M., Magulová, B., Matys, M., Marschalko, M., (2010). Landslide susceptibility assessment of the Kral˘ovany–Liptovsky´ Mikuláš railway case study. Physics and Chemistry of the Earth 35, 162–171.

Bourenane H., Guettouche M. S., Bouhadad Y., Braham M.,2016. Landslide hazard mapping in the Constantine city, Northeast Algeria using frequency ratio, weighting factor, logistic regression, weights of evidence, and analytical hierarchy process methods.Arab J Geosci (2016) 9: 154 DOI 10.1007/s12517-015-2222-8

Cevik, E. and Topal, T., (2003). GIS-based landslide susceptibility mapping for a problematic segment of the natural gas pipeline, Hendek (Turkey). Environmental Geology, 44, 949–962.

Chauhan, S., Sharma, M., Arora, M.K., Gupta, N.K., (2010). Landslide susceptibility zonation through ratings derived from artificial neural network. International Journal of Applied Earth Observation and Geoinformation 12, 340–350.

Choi J, Oh HJ, Lee HJ, Lee C, Lee S (2012). Combining landslide susceptibility maps obtained from frequency ratio, logistic regression, and artificial neural network models using ASTER images and GIS. Eng Geol 124:12–23

Clerici A, Perego S, Tellini C, Vescovi P (2002). A procedure for landslide susceptibility zonation by the conditional analysis method. Geomorphology 48:349–364

Constantin, M., Bednarik, M., Jurchescu, M.C., Vlaicu, M., (2011). Landslide susceptibility assessment using the bivariate statistical analysis and the index of entropy in the Sibiciu Basin (Romania). Environmental Earth Science 63, 397–406.

Chen W., Li W., Chai H., Hou E., Li X., Ding X., (2016a) GIS-based landslide susceptibility mapping using analytical hierarchy process (AHP) and certainty factor (CF) models for the Baozhong region of Baoji City, China. Environ Earth Sci 75:63 DOI 10.1007/s12665-015-4795-7

Chen W., Chai H., Sun X., Wang Q., Ding X.,Hong H., (2016b). A GIS-based comparative study of frequency ratio, statistical index and weights-of-evidence models in landslide susceptibility mapping. Arab J Geosci 9: 204 DOI 10.1007/s12517-015-2150-7

Chung CJ, Fabbri AG (1998) Probabilistic prediction models for landslide hazard mapping. Photogramm Eng Rem S 65(12):1389–1399

Demir G, Aytekin M, Akgün A, İkizler SB, & Tatar O (2013). A comparison of landslide susceptibility mapping of the eastern part of the North Anatolian Fault Zone (Turkey) by likelihood-frequency ratio and analytic hierarchy process methods. Natural hazards, 65(3), 1481-1506

© Author(s) 2016. CC-BY 3.0 License.

Demir, G., Aytekin, M., Akgun, A., (2015). Landslide susceptibility mapping by frequency ratio and logistic regression methods: an example from Niksar–Resadiye (Tokat, Turkey). Arab. J. Geosci. http://dx.doi.org/10.1007/s12517-014-1332-z.
Ercanoglu M, Gokceoglu C, van Asch TWJ (2004). Landslide susceptibility zoning north of Yenice (NW Turkey) by multivariate statistical techniques. Nat Hazards 32:1–23
Erner, A., Sebnem, H., Duzgun, B., (2010). Improvement of statistical landslide susceptibility mapping by using spatial and global regression methods in the case of More and Romsdal (Norway). Landslides 7, 55–68.
Falaschi, F., Giacomelli, F., Federici, P.R., Puccinelli, A., D'Amato Avanzi, G., Pochini, A., Ribolini, A., (2009). Logistic regression versus artificial neural networks: landslide susceptibility evaluation in a sample area of the Serchio River valley, Italy. Natural Hazards 50, 551–569.
N. T. Long and D. S. Florimond (2012). Application of an analytical hierarchical process approach for landslide susceptibility mapping in A Luoi district, Thua Thien Hue Province, Vietnam," Environmental Earth Science, vol. 66, no. 7, pp. 1739-1752.
Gokceoglu C. and Aksoy H. (1996). Landslide susceptibility mapping of the slopes in the residual soils of the Mengen region (Turkey) by deterministic stability analyses and image processing techniques," Engineering Geology, vol. 44, no. 1-4, pp. 147-161.
Gokceoglu C, Sönmez H, Nefeslioglu HA, Duman TY, Can, T. (2005). The March 17, 2005 Kuzulu landslide (Sivas, Turkey) and landslide susceptibility map of its near vicinity. Engineering Geology;81 (1): 65-83.
Guzzetti, F., Reichenbach, P., Cardinali, M., Galli, M., and Ardizzone, F., (2005). Landslide hazard assessment in the Staffora basin, Northern Italian Apennines. Geomorphology, 72, 272–299.
Jaafari, A., Najafi, A., Pourghasemi, H.R., Rezaeian. J., and Sattarian, A., (2013). GIS-based frequency ratio and index of entropy models for landslide susceptibility assessment in the Caspian forest, northern Iran. International Journal of Environmental Science and Technology, DOI: 10.1007/s13762-013-0464-0.
Kannan M, Saranathan E, & Anabalagan R (2013). Landslide vulnerability mapping using frequency ratio model: a geospatial approach in Bodi-Bodimettu Ghat section, Theni district, Tamil Nadu, India. Arabian journal of Geosciences, 6(8), 2901-2913
Mihaela C, Martin B, Marta CJ, & Marius V (2011). Landslide susceptibility assessment using the bivariate statistical analysis and the index of entropy in the Sibiciu Basin (Romania). Environ Earth Sci 63:397-406
Mohammady, M., Pourghasemi, H.R., and Pradhan, B., (2012). Landslide susceptibility mapping at Golestan Province Iran: a comparison between frequency ratio, Dempster-Shafer, and weightsof evidence models. Journal of Asian Earth Sciences, 61, 221–236.
Myronidis D., Papageorgiou C., Theophanous S.,2016. Landslide susceptibility mapping based on landslide history and analytic hierarchy process (AHP).Nat Hazards (2016) 81:245–263 DOI 10.1007/s11069-015-2075-1
Oh, H.J., Park, N.W., Lee, S.S., Lee, S., (2012). Extraction of landslide-related factors from ASTER imagery and its application to landslide susceptibility mapping. International Journal of Remote Sensing 33 (10), 3211–3231.
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

© Author(s) 2016. CC-BY 3.0 License.

Pourghasemi HR, Pradhan B, & Gokceoglu C (2012a). Application of fuzzy logic and analytical hierarchy process (AHP) to landslide susceptibility mapping at Haraz watershed, Iran. Nat Hazards 63:965-996

Pourghasemi HR, Pradhan B, Gokceoglu C, & Moezzi, KD (2012b). Landslide susceptibility mapping using a spatial multi criteria evaluation model at Haraz Watershed, Iran. In Terrigenous Mass Movements (pp. 23-49). Springer Berlin Heidelberg

Pourghasemi, H.R., Pradhan, B., Gokceoglu, C., Mohammadi, M., Moradi, H.R., (2012c). Application of weights-of-evidence and certainty factor models and their comparison in landslide susceptibility mapping at Haraz watershed, Iran. Arabian Journal of Geosciences. http://dx.doi.org/10.1007/s12517-012-0532-7.

Pourghasemi, H.R., Gokceoglu, C., Pradhan, B., Deylami Moezzi, K., (2012d). Landslide susceptibility mapping using a spatial multi criteria evaluation model: case study at Haraz Watershed, Iran. In: Pradhan, B., Buchroithner, M. (Eds.), Terrigenous Mass Movements. Springer-Verlag, Berlin Heidelberg, pp. 23–49. http:// dx.doi.org/10.1007/978-3-642-25495-6-2.

Pareek N, Sharma ML, & Arora MK (2010). Impact of seismic factors on landslide susceptibility zonation: a case study in part of Indian Himalayas. Landslides 7(2):191-201

Park, N.W., (2011). Application of Dempster–Shafer theory of evidence to GIS-based landslide susceptibility analysis. Environmental Earth Science 62, 367–376.

Pouydal CP, Chang C, Oh HJ, & Lee S (2010). Landslide susceptibility maps comparing frequency ratio and artificial neural networks: a case study from the Nepal Himalaya. Environ Earth Sci 61:1049-1064

Pradhan, B., (2013). A comparative study on the predictive ability of the decision tree, support vector machine and neuro-fuzzy models in landslide susceptibility mapping using GIS. Computers & Geosciences, 51, 350–365.

Pradhan, B. and Lee, S., (2010a). Delineation of landslide hazard areas using frequency ratio, logistic regression and artificial neural network model at Penang Island, Malaysia. Environmental Earth Sciences, 60, 1037–1054

Pradhan, B., Lee, S., (2010b). Landslide susceptibility assessment and factor effect analysis: back propagation artificial neural networks and their comparison with frequency ratio and bivariate logistic regression modelling. Environmental Modelling and Software 25 (6), 747–759.

Pradhan, B., Lee, S., Buchroithner, M.F., (2010c). Remote sensing and GIS-based landslide susceptibility analysis and its cross-validation in three test areas using a frequency ratio model. Photogrammetrie Fernerkundung Geoinformation 1, 17–32. http:// dx.doi.org/10.1127/14328364/2010/0037.;

Pradhan, B., Mansor, S., Pirasteh, S., Buchroithner, M., (2011). Landslide hazard and risk analyses at a landslide prone catchment area using statistical based geospatial model. International Journal of Remote Sensing 32 (14), 4075–4087. http://dx.doi.org/ 10.1080/01431161.2010.484433

Ram Mohan, V., Jeyaseelan, A., Naveen Raj, T., Narmatha, T., Jayaprakash, M., (2011). Landslide susceptibility mapping using frequency ratio method and GIS in South eastern part of Nilgiri District, Tamilnadu, India. International Journal of Geomatics and Geoscience 1 (4), 951–961.

Regmi, A.D., Devkota, K.C., Yoshida, K., Pradhan, B., Pourghasemi, H.R., Kumamoto, T., and Akgun, A., (2014). Application of frequency ratio, statistical index, and

© Author(s) 2016. CC-BY 3.0 License.

weights-of-evidence models and their comparison in landslide susceptibility mapping in Central Nepal Himalaya. Arabian Journal of Geosciences, 7, 725–742.

Lee S, Min K (2001) Statistical analyses of landslide susceptibility at Yongin, Korea. Environ Geol 40:1095–1113

Lee S, Ryu JH, Won JS, Park HJ. (2004). Determination and application of the weights for landslide susceptibility mapping using an artificial neural network, Engineering Geology 2004; 71: 289–302.

Saha A.K., Gupta R. P. and Arora M. K. (2002). GIS-based landslide hazard zonation in the Bhagirathi (Ganga) valley, Himalayas, International Journal of Remote Sensing, vol. 23, no. 2, pp. 357-369.

Saponaro A, Pilz M, Wieland M, Bindi D, Moldobekov B, & Parolai S (2014). Landslide susceptibility analysis in data-scarce regions: the case of Kyrgyzstan. Bulletin of Engineering Geology and the Environment, 1-20.

Sezer, E.A., Pradhan, B., Gokceoglu, C., (2011). Manifestation of an adaptive neuro-fuzzy model on landslide susceptibility mapping: Klang valley, Malaysia. Expert Systems with Applications 38 (7), 8208–8219.

Sharma LP, Nilanchal Patel, Ghose MK, & Debnath P (2013). Synergistic application of fuzzy logic and geo-informatics for landslide vulnerability zonation-a case study in Sikkim Himalayas, India. Appl Geomat 5:271-284

Solaimani K, Mousav SZ, & Kavian A (2013). Landslide susceptibility mapping based on frequency ratio and logistic regression models. Arabian Journal of Geosciences, 6(7), 2557-2569

Sujatha ER, Rajamanickam V, Kumaravel P, Saranathan E (2013). Landslide susceptibility analysis using probabilistic likelihood ratio model—a geospatial-based study. Arab J Geosci 6(2):429–440

Tien Bui, D., Pradhan, B., Lofman, O., Revhaug, I., and Dick, O.B., (2012). Spatial prediction of landslide hazards in Hoa Binh province (Vietnam): a comparative assessment of the efficacy of evidential belief functions and fuzzy logic models. Catena, 96, 28–40.

Tien Bui, D., Pradhan, B., Revhaug, I., Nguyen, D.B., Pham, H.V., and Bui, Q.N., (2013). A novel hybrid evidential belief functionbased fuzzy logic model in spatial prediction of rainfall-induced shallow landslides in the Lang Son city area (Vietnam). Geomatics Natural Hazards & Risk, doi:10.1080/19475705.2013.843206.

Ulusay, R., Aydan, Ö., and Kılıç, R., (2007). Geotechnical Assessment of the 2005 Kuzulu landslide (Turkey). Engineering Geology, 89 (1), 112-128.

Vahidnia, M.H., Alesheikh, A.A., Alimohammadi, A., Hosseinali, F., (2010). A GIS-based neurofuzzy procedure for integrating knowledge and data in landslide susceptibility mapping. Computers and Geosciences 36 (9), 1101–1114.

Van Westen CJ, Lulie GF (2003). Analyzing the evolution of the Tessina landslide using aerial photographs and digital elevation models. Geomorphology 54(1–2):77–89

Wu Y., Li W., Liu P., Bai H., Wang Q., He J., Liu Y., Sun S. 2016, Application of analytic hierarchy process model for landslide susceptibility mapping in the Gangu County, Gansu Province,China. Environ Earth Sci (2016) 75:422 DOI 10.1007/s12665-015-5194-9

Xu, C., Dai, F.C., Xu, X.W., and Lee, Y.H., (2012a), GIS-based support vector machine modeling of earthquake-triggered landslide susceptibility in the Jianjiang River watershed, China. Geomorphology, 145–146, 70–80.

Nat. Hazards Earth Syst. Sci. Discuss., doi:10.5194/nhess-2016-327, 2016
Manuscript under review for journal Nat. Hazards Earth Syst. Sci.
Published: 18 October 2016
© Author(s) 2016. CC-BY 3.0 License.

Xu, C., Xu, X.W., Dai, F.C., and Saraf, A.K., (2012b), Comparison of different models for susceptibility mapping of earthquake triggered landslides related with the 2008 Wenchuan earthquake in China. Computers & Geosciences, 46, 317–329.

Yalcin A. and Bulut F. (2007). Landslide susceptibility mapping using GIS and digital photogrammetric techniques: a case study from Ardesen (NE-Turkey), Natural Hazards, vol. 41, no. 1, pp. 201-226

Yalcin A., (2008). GIS-based landslide susceptibility mapping using analytical hierarchy process and bivariate statistics in Anderson (Turkey): comparision of results and confirmations, Catena, vol. 72, no. 1, pp. 1-12.

Yalcin, A., Reis, S., Aydinoglu, A.C., 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.

Yilmaz I., (2009a). Landslide susceptibility using frequency ratio, logistic regression, artificial neural networks and their comparison: a case study from Kat landslides (Tokat-Turkey). Comput Geosci 35(6):1125–1138

Yilmaz, I., (2010). Comparison of landslide susceptibility mapping methodologies for Koyulhisar, Turkey: conditional probability, logistic regression, artificial neural networks, and support vector machine. Environmental Earth Sciences

Yılmaz, I. and Keskin, İ. (2009). GIS based statistical and physical approaches to landslide susceptibility mapping (Şebinkarahisar, Turkey). Bullettin of Engineering Geology and Environment, 68:4; 459-471.

Youssef, A.M., Pradhan, B., and Gaber, A.F.D., and Buchroithner, M.F., (2009). Geomorphological Hazards Analysis along The Egyptian Red Sea Coast between Safaga and Quseir. Natural Hazards & Earth System Sciences, 9, 751–766.

Youssef, A.M., Pradhan, B., and Maerz, H.N., (2013). Debris flow impact assessment caused by 14 April 2012 rainfall along the Al- Hada Highway, Kingdom of Saudi Arabia using high-resolution satellite imagery. Arabian Journal of Geosciences, DOI: 10.1007/ s12517-013-0935-0.

Youssef, A.M., Al-Kathery M., Pradhan, B.,(2015). Landslide susceptibility mapping at Al-Hasher Area, Jizan (Saudi Arabia) using GIS-based frequency ratio and index of entropy models Geosciences Journal Vol. 19, No. 1, p. 113 – 134.

Yufeng, S., Fengxiang, J., (2009). Landslide Stability Analysis Based on Generalized Information Entropy. 2009 International Conference on Environmental Science and Information Application Technology, pp. 83–85