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EVALUATION OF FOREST ROAD NETWORK PLANNING IN LANDSLIDE SENSITIVE AREAS BY GIS-BASED MULTI-CRITERIA DECISION MAKING APPROACHES IN IHSANGAZI WATERSHED, NORTHERN TURKEY

PLANIRANJE MREŽE ŠUMSKIH PROMETNICA U PODRUČJIMA PODLOŽNIM KLIZIŠTIMA KORISTEĆI VIŠEKRITERIJSKI PRISTUP ODLUČIVANJA TEMELJEN NA GIS-U U SLIVU IHSANGAZI U SJEVERNOJ TURSKOJ

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SUMMARY

Forest roads are one of the fundamental infrastructures in carrying out forestry activities and services. According to FAO, approximately 20 percent of the world's forest lands are covered mountain forests. Since forests are generally located also in mountainous areas with steep slope in Turkey, difficulties experienced in these mountainous conditions render the provision of services difficult while increasing the costs. The aim of this study is to evaluate forest road planning alternatives which are to be developed in landslide sensitive mountainous areas based on the Landslide Susceptibility Mapping (LSM). For this purpose, a total of 12 models were generated with different multi-criteria decision making (MCDM) approaches including Modified Analytical Hierarchy Process (M-AHP), Fuzzy Inference System (FIS), and Logistic Regression (LR). As a result of the study, the best model was Model 3 obtained with LR approach (area under the curve (AUC)=76.6%) value followed by LR-Model 4 (AUC=75.7%) and FIS-Model 4 (AUC=73.4%). Model 3 (AUC=71%) was the most successful M-AHP approach. Consequently, the application of these methods will provide an advantage in making more accurate and more rational decisions during road network planning in landslide sensitive forest areas.

KEY WORDS: Landslide susceptibility, forest roads, modified-AHP, fuzzy inference system, logistic regression

INTRODUCTION
UVOD

According to World Bank's report (Dilley et al. 2005), Landslide has been occurred in an area of approximately in 3.5 million square km every year owing to increasing of population, climate change and the other factors. Besides, 820,000 km square areas have been determined to have the highest landslide risk, and 300 million people are under landslide risk, and also 60 million people live in high-risk

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areas (Dilley et al. 2005). The landslide is force of natural and also triggered by environmental events, such as earthquake (Evans et al. 2009), high rainfall and large waves (Hapke and Green 2006), (typhoon-induced floods) Acosta et al. 2016), forest loss (Bathurst et al. 2007, Pfeil-McCullough et al. 2015). In addition to, landslide, adversely affects the environment and people (Brabb 1991, Petley 2012, Van der Geest 2018, Zumpano et al. 2018). As such, it is of great importance to determine landslide sensitive areas in advance.

Monitoring, determination of effective factors and modelling are required for take measures against landslide. In this context, in recent years, an increasing number of Landslide Susceptibility Mapping (LSM) (Corominas et al. 2014) studies have been carried out in many countries all around the world (i.e. Austria, China, India, Iran, Ireland, Italy, Korea, Nepal, Portugal, Taiwan, Turkey, and USA). In these studies, many different modelling were developed via Geographic Information System (GIS) and Remote Sensing (RS) techniques such as Logistic Regression (LR) (Eker and Aydın 2016; Lin et al. 2017; Pourghasemi et al. 2018), Adaptive Neuro Fuzzy Inference System (ANFIS) (Bui et al. 2012; Aghdam et al. 2016; Jaafari et al. 2017), Frequency Ratio (FR) (Lee and Talib 2005; Lee et al. 2015), Kernel Logistic Regression (KLR)- Alternating Decision Tree (ADT)- Support Vector Machine (SVM) (Yao et al. 2008; Hong et al. 2015), Step-wise Weight Assessment Ratio Analysis (SWARA) (Dehnavi et al. 2015), Analytic Hierarchy Process (AHP) (Ercanoğlu et al. 2008; Shahabi et al. 2014), Artificial Neural Networks (ANN) (Ermini et al. 2005; Choi et al. 2012; Conforti et al. 2014), Weighted Linear Combination (WLC) (Feizizadeh and Blaschke 2013), Ordered Weighted Average (OWA) (Feizizadeh and Blaschke 2013), bivariate statistics (BS) (Yalçın et al. 2011), Statistical Index (Wi) (Yalçın et al. 2011; Aghdam et al. 2016), Fuzzy Logic (FL) (Akgün and Türk 2010; Akgün et al. 2012; Aksoy and Ercanoğlu 2012), Back Propagation Algorithm (BPA) (Vahidnia et al. 2010), Weighting Factor (Wf) (Yalçın 2008), GIS Based Road-Pegging Tool (PEGGER) (Jaafari et al. 2015), Bayesian (Jaafari et al. 2015), Modified- Analytic Hierarchy Process (M-AHP) (Nefeslioğlu et al. 2012), Machine Learning (ML) (Steger et al. 2016; Kavzoglu et al. 2019), Multi-layer Perceptron Neural Network (MLP-NN) (Pham et al. 2017), Logistic Regression (GLM)- Generalized Additive Models (GAM), Weights of Evidence (WoE)- Support Vector Machine (SVM)- Random Forest Classification (RF)- Bootstrap Aggregated Classification Trees (Bundling) with penalized Discriminant Analysis (BPLDA) (Goetz et al. 2015), Logistic Model Tree (LMT) (Truong et al. 2018), Prompt Assessment of Global Earthquakes for Response (PAGER) (Tanyaş et al. 2017). Due to the climatic-topographic-social characteristics, the factors used in these models vary.

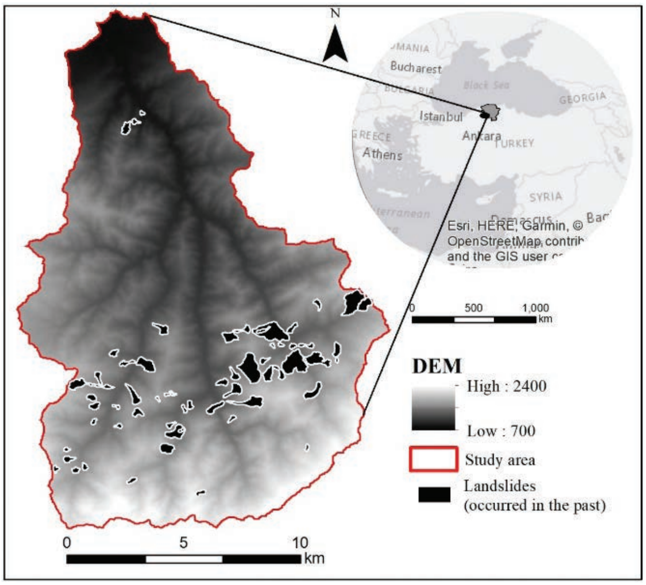

Figure 1. Location of Ihsangazi Watershed
Slika 1. Položaj Ihsangazi Watershed

Landslides take place by actuation of various factors such as elevation (Gorsevski et al. 2006; Lu et al. 2011; Feizizadeh and Blaschke 2013; Eker and Aydın 2016), slope (Pantha et al. 2008; Nefeslioğlu et al. 2012; Dehnavi et al. 2015; Lee et al. 2015; Martinovic et al. 2016), aspect (Vahidnia et al. 2010; Hong et al. 2015), lithology (Conforti et al. 2014; Jaafari et al. 2015; Zezere et al. 2017), distance to faults (Saha et al. 2005; Vahidnia et al. 2010), distance to streams (Yalçın et al. 2011; Pham et al. 2017), distance to roads (Yalçın 2008; Shahabi et al. 2014; Steger et al. 2016), Topographic Wetness Index (TWI) (Goetz et al. 2015; Jacobs et al. 2018) and Stream Power Index (SPI) (Akgün and Türk 2010; Conforti et al. 2014).

The aim of this study is the determination of the most appropriate model among the different models in the planning of forest road network in the landslide sensitive areas. For this purpose, 12 models were developed using three different approaches, M-AHP, FIS, and LR. In the solution process, the models were generated by evaluating specific factors such as elevation, slope, aspect, lithology, distance to stream, distance to roads, TWI, and SPI.

MATERIAL AND METHODS
MATERIJAL I METODE

Study Area – *Prostorno područje*

The study area is İhsangazi Watershed in İhsangazi district of Kastamonu province located in the northwest of Turkey. İhsangazi Watershed has an area of 21,863 ha and it is located between the latitude of 41°12' 01" and 41°02' 31" and longitude of 33°31' 36" and 33°39' 25" (Figure 1). The study area is covered with forests. The most of the roads within the watershed are forest roads and there is a total of 321.4 km of roads as of the end of 2017. Forest roads are defined as B-type low volume roads with 6 m platform width.

Landslide Factors – *Čimbenici razorenja*

Nine factors; elevation, slope, aspect, lithology, distance to faults, distance to streams, distance to roads, TWI, and SPI; were evaluated in developing models for LSM. The elevation is a negative factor in forest road planning since the cost of road construction increases as the elevation increases in the mountainous area. Elevation also negatively effects the periodic maintenance works. The slope is another important factor that directly affects the costs in forest road construction (Akay 2006; Akay et al. 2008; Hong et al. 2015). In this study, IUFRO (International Union of Forest Research Organizations) slope classes were utilized as in five different grades 0-5.71, 5.71-13.80, 13.80-21.88, 21.88-31.99 and > 32 degrees (Erdaş 2008). Aspect is also one of the topographical factors affects soil properties and thereby the growing habitat (Dehnavi et al. 2015). Aspect has been examined according to eight different directions in this study. Lithology is a factor which affects the cost of construction of forest roads as it reveals the bedrock characteristics (Conforti et al. 2014). The lithology was evaluated in six groups in this study. Distance to faults is one of the factors have a significant role in triggering the landslides (Vahidnia et al. 2010). In this study, distance to faults analysis was made by expressing 1 km zones. Distance to the streams is also one of the factors utilized commonly in LSM studies when the proximity relation is significant (Pourghasemi et al. 2014; Aghdam et al. 2016; Wang et al. 2016). The distances to the streams are expressed as zones with interval distance of 100 m in this study. One of the significant factors triggering the landslide is the distance to roads (Yalçın 2008). They have been expressed as zones with interval distance of 100, 300, 500, and 1000 m. TWI is utilized widely in order to determine the location and size of water-saturated areas at the topographic level (Moore et al. 1991; Goetz et al. 2015) (Equation 1):

$$TWI = \ln\left(\frac{As}{tan\beta}\right) \qquad (1)$$

A_s = Specific basin area (m^2)/ Specifično područje bazena
β = Incline of slope / Nagib nagiba

SPI is defined as the power of flowing water to erode the topography by taking the assumption that the current (q) is proportional to the specific basin area (Ace) (Moore et al., 1991; Akgün and Türk, 2010) (Equation 2):

$$\text{SPI} = \text{As} \times tan\beta \qquad (2)$$

A_s = Specific basin area (m^2) / Specifično područje bazena
B = Incline of slope / Nagib nagiba

Landslide Susceptibility Mapping – *Mapiranje osjetljivosti*

12 models were generated with different MCDM approaches including M-AHP, FIS, and LR for evaluation of the LSM. M-AHP approach, the first method in this study, was considered as the most preferred a multidisciplinary decision method in forestry studies. The M-AHP approach, not require expert opinion, has been developed, due to the fact that the analysis can be subjective in classical AHP method. Moreover, M-AHP normalizes the factors thereby making criteria comparison more successful at the decision phase. Another method utilized in the study was Fuzzy-Logic method (Mamdani) (FIS) which has been first expressed by Zadeh (1965). FIS is successful in solving complex problems. Fuzzy logic is one of the approaches which has a mathematical methodology in which the variable values are not only utilized as 0 or 1 but also the intermediate values are taken into consideration. The last method, Logistic Regression (LR) approach was preferred as it is used in such sensitivity analysis in many studies and it gives the chance to make comparisons.

In this study, NetCAD GIS 7.6 software was employed for evaluation of the factors M-AHP, FIS and LR methods. For the validation of the models, information as regarding with the landslides, which have occurred in the past, was obtained from the General Directorate of Mineral Research and Explorations institution (Duman et al. 2011) and tested

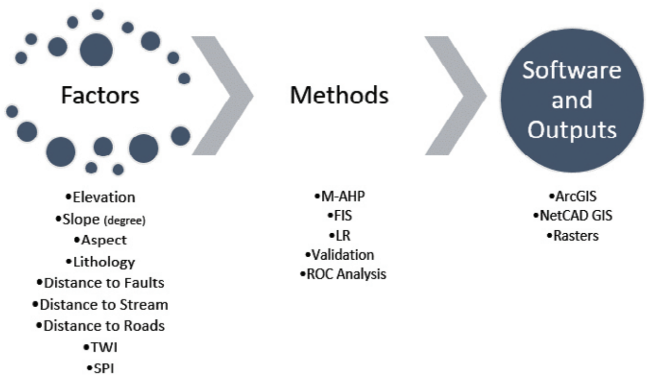

Figure 2. Flowchart of LSM in forested area
Slika 2. Dijagram toka LSM-a na šumovitom području

through Receiver Operating Characteristic (ROC) analysis and Area Under the Curve (AUC) value. Obtained model outputs were recorded as a raster data layers. The workflow of this study is provided in Figure 2.

RESULTS
REZULTATI

The maps of landslide factors (i.e. elevation, slope, aspect, lithology, distance to faults, distance to stream, distance to roads, TWI, and SPI) are listed in Figure 3. It was found

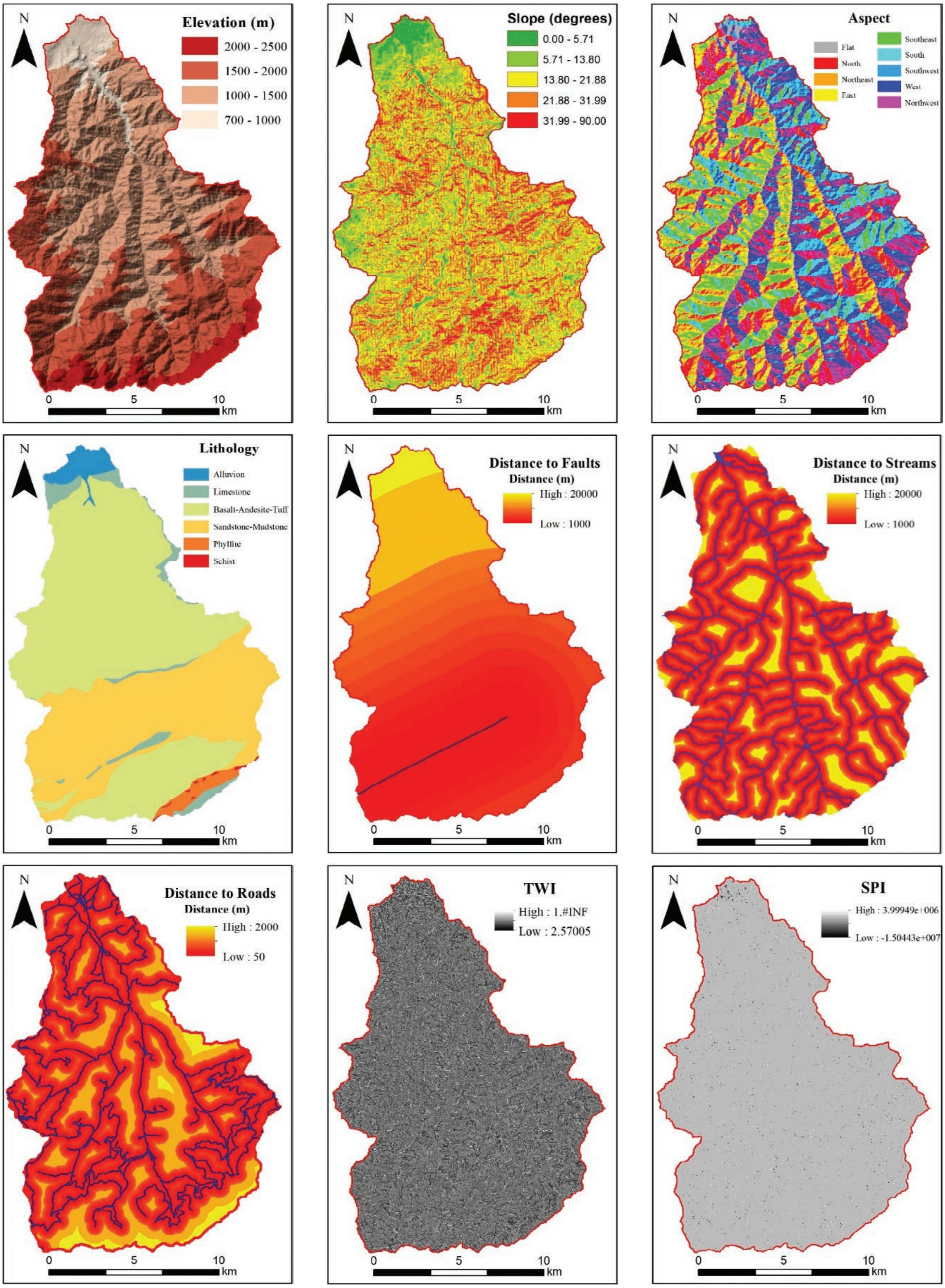

Figure 3. LSM factors in forested area; (a) elevation, (b) slope, (c) aspect, (d) lithology, (e) distance to faults, (f) distance to stream, (g) distance to roads, (h) TWI, (i) SPI.

Slika 3. LSM čimbenici u šumovitom području; (a) visina, b) nagib, (c) aspekt, (d) litologija, (e) udaljenost do kvarova, (f) udaljenost do potoka, (g) udaljenost do cesta, (h) TWI, (i) SPI.

Table 1. Factors and models in LSM process
Tablica 1. Čimbenici i modeli u LSM procesu

Factors / Čimbenici	Model 1	Model 2	Model 3	Model 4
Elevation/Visina	✓	✓	✓	✓
Slope (degree)/ Nagib	✓	✓	✓	✓
Aspect / Aspekt				✓
Lithology / Litologija	✓	✓	✓	✓
Distance to Faults / Udaljenost do kvarova	✓	✓	✓	✓
Distance to Stream / Udaljenost do potoka	✓	✓	✓	✓
Distance to Roads / Udaljenost do cesta	✓		✓	✓
TWI	✓			
SPI			✓	

that the elevation of the study area ranged between 700 m and 2400 m and the average elevation was 1380 m. The average slope of the area was 15.51 degrees with the maximum slope of 54.60 degree in the study area. The dominant aspect of the study area was found to be south. Elevation, slope, and aspect factors were obtained through utilization of ArcGIS 10.3 TM and NetCAD GIS 7.6 software. This was performed as a result of generating the equal curves of height from the base provided free from Digital Elevation Model ASTER-GDEM by limiting of the work area with 10-meter interval.

In this study, 12 models were developed according to M-AHP, FIS and LR approaches with different combinations of nine factors. The factors distributions of the models formed in LSM process are provided in Table 1. Factors used in M-AHP method and score values for factors were given in Table 2.

The elevation factor for M-AHP scoring was evaluated in four groups and the highest score was given to the lowest height areas with 7 points in this study. This was followed by higher areas which received 5, 3, and 1 points, respectively. Slope (degree) factor was evaluated in five groups according to IUFRO and the highest score was given 9 point to lowest degree areas, and the highest areas to 1 point. Since sunny areas may be more prone to landslide, aspect factor in sunny areas was given a maximum value of 11 points, and was given a minimum value of 1 point to shaded

Table 2. The scores used in M-AHP method
Tablica 2. Rezultati korišteni u M-AHP metodi

Factors/ Čimbenici	Class/Klasa	Score/ Postići	Factors /Čimbenici	Class/Klasa	Score/ Postići
Elevation/ Visina	700 - 1000	7	Distance to Faults/ Udaljenost do kvarova	1000 - 2000	9
	1000 - 1500	5		2000 - 5000	5
	1500 - 2000	3		5000 - 10000	3
	2000 - 2500	1		10000 -20000	1
Slope (degree)/ Nagib	0 – 5.71	9	Distance to Stream/ Udaljenost do potoka	1000 - 2000	9
	5.71 – 13.80	7		2000 - 4000	5
	13.80 – 21.88	5		4000 - 8000	3
	21.88 – 31.99	3		8000 - 20000	1
	32<	1			
Aspect/ Aspekt	Flat	1	Distance to Roads/ Udaljenost do cesta	100 - 200	9
	North	5		200 - 500	5
	Northeast	5		500 - 1000	3
	East	5		1000 - 2000	1
	Southeast	3	TWI	1.39 - 4.77	9
	South	5		4.77 - 8.15	7
	Southwest	7		8.15 - 11.53	5
	West	11		11.53 - 14.91	3
	Northwest	7		14.91 - 18.29	1
Lithology/ Litologija	Alluvion	1	SPI	3.89 - 1.04	9
	Limestone	1		1.04 - 1.8	7
	Basalt-Andesite-Tuff	1		1.8 - 4.6	5
	Sandstone-Mudstone	9		4.6 - 7.5	3
	Phyllite	5		7.5 - 10.35	1
	Schist	3			

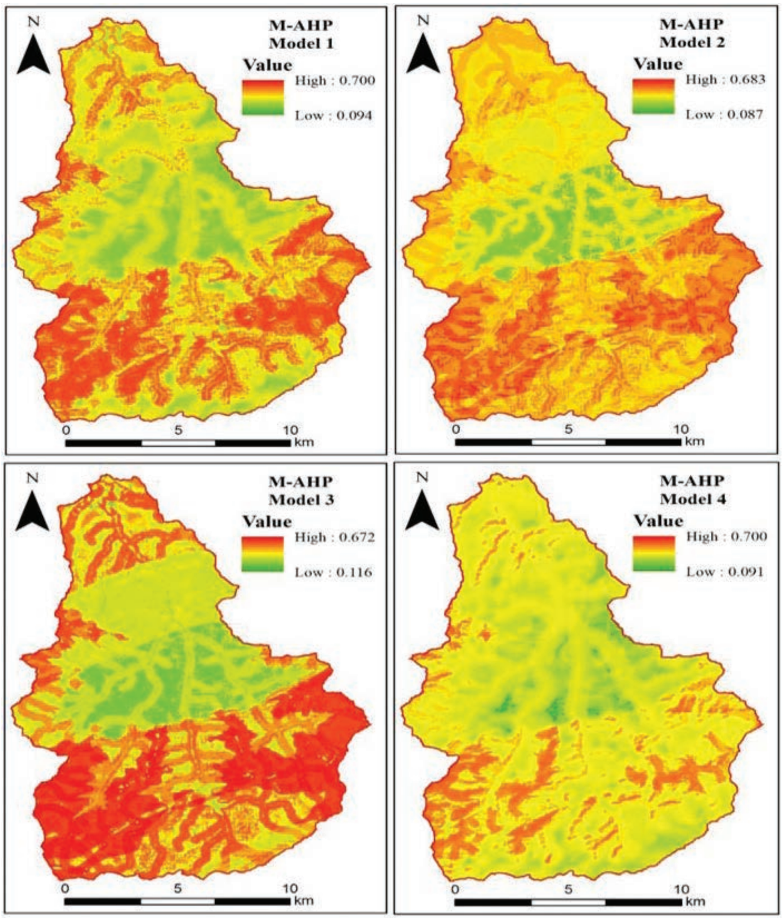

Figure 4. M-AHP analysis results
Slika 4. Rezultati M-AHP analize

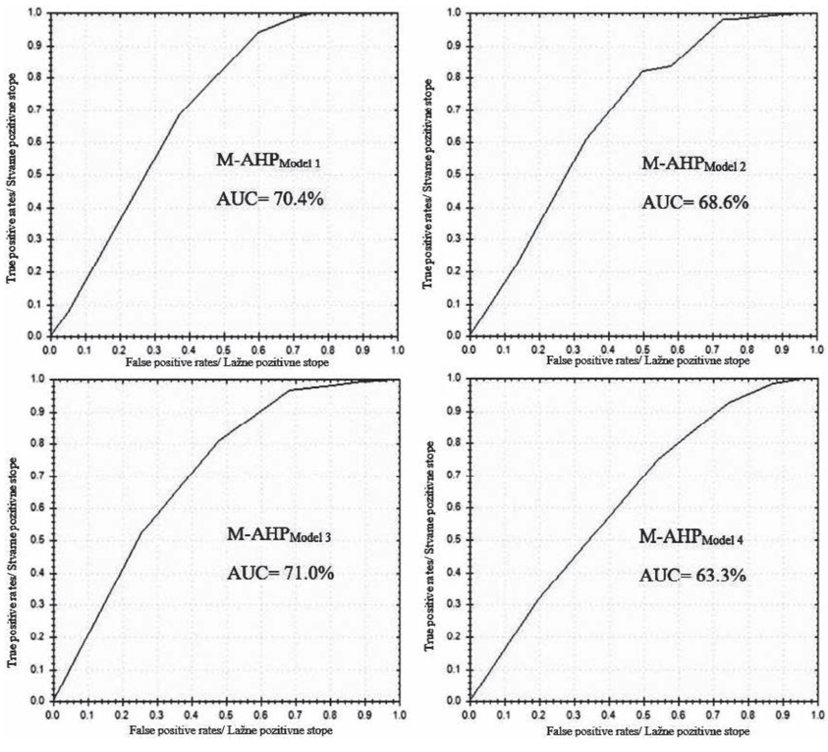

Figure 5. ROC and AUC results for M-AHP
Slika 5. ROC i AUC rezultati za M-AHP

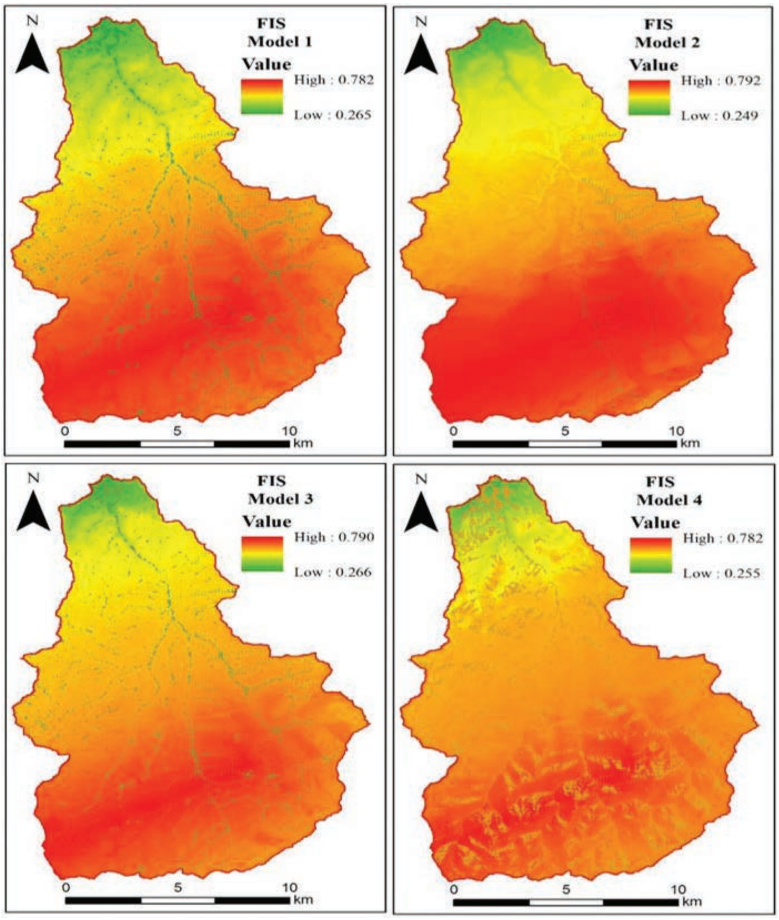

Figure 6. FIS analysis results
Slika 6. Rezultati FIS analize

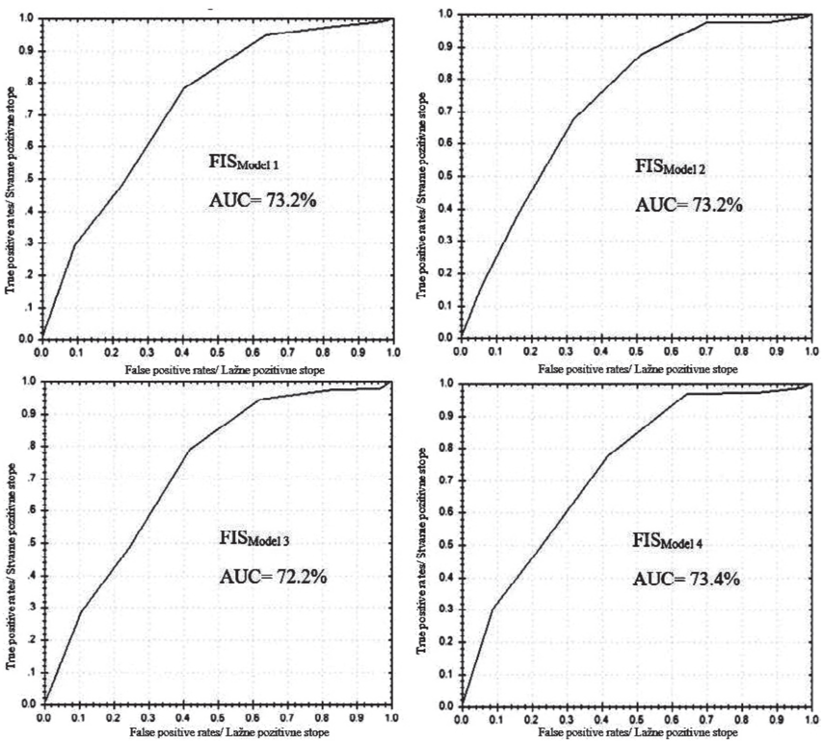

Figure 7. ROC and AUC results for FIS
Slika 7. Rezultati ROC i AUC za FIS

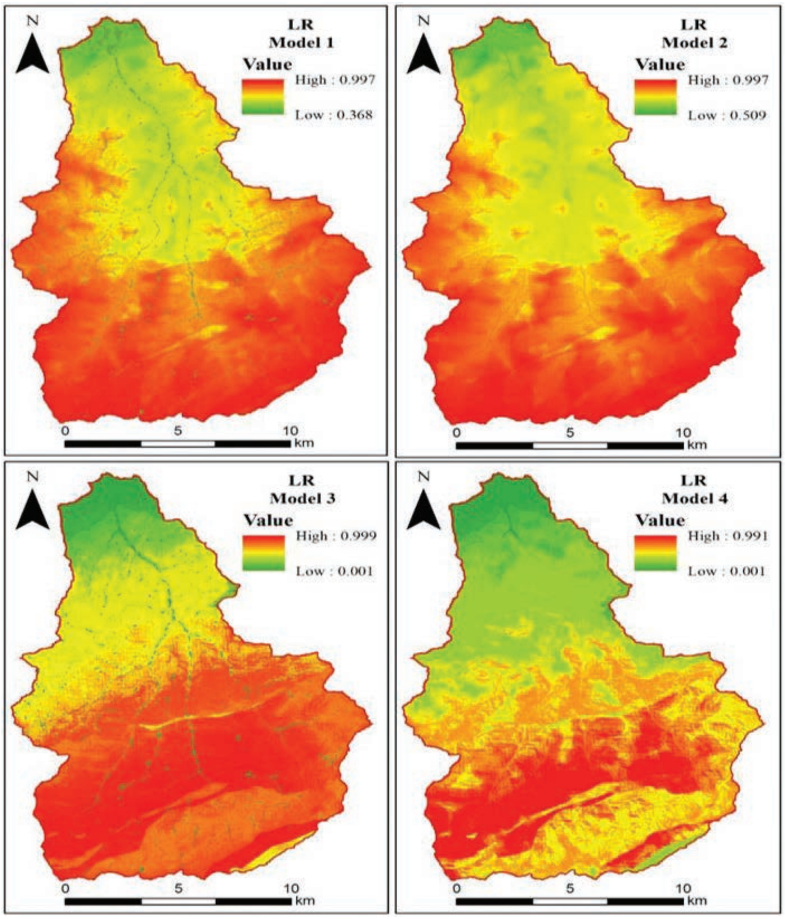

Figure 8. LR analysis results
Slika 8. Rezultati LR analize

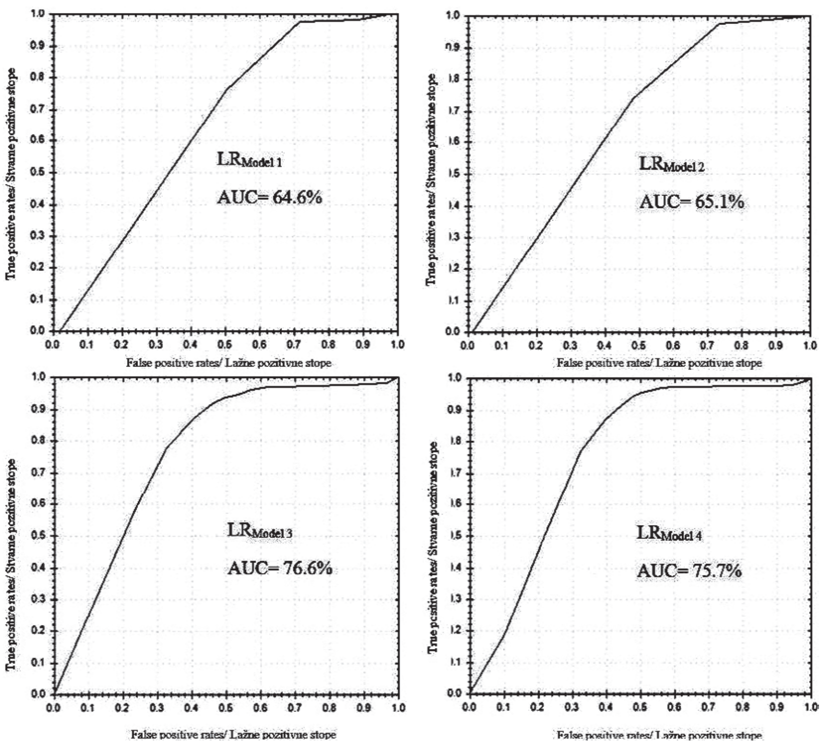

Figure 9. ROC and AUC results for LR
Slika 9. ROC i AUC rezultati za LR

areas. Points for lithology factor was assigned as 9 to Sandstone-Mudstone areas, 5 point to Phyllite areas, 3 point to Schist areas and other areas were scored as 1 point. Distance to faults factor is grouped in five classes as 1-2 km, 2-5 km, 5-10 km and 10-20 km zones and the nearest distance is 9 points and the longest distance is 1 points. Distance to streams factor is grouped in four classes as 2 km, 4 km, 8 km and 20 km zones and the shortest distance is 9 points and the longest distance is 1 points. Distance to roads factor is grouped in four classes as 200 m, 500 m, 1000 m and 2000 m zones and the nearest distance is 9 points and the longest distance is 1 points. The TWI and SPI factor was evaluated in five different groups and the scores were the highest 9 point and the lowest 1 point.

The FIS method was implemented via the toolbar found in the software GIS 7.6. Three different membership functions, low, medium and high, were assigned for the configuration of desired range values. The last method, LR, was obtained by joining the raster of each factor via the toolbar in the software and then joining them subsequently. The models in this study and the validation values of the models were provided in Figure 4-9.

The LSM index value in the models generated in line with the M-AHP method was between 0.087 as the lowest value and 0.700 as the highest value. Models' successes were found to be AUC-Model $1_{M\text{-}AHP}$ = 70.4%, AUC-Model $2_{M\text{-}AHP}$ = 68.6%, AUC-Model $3_{M\text{-}AHP}$ = 71.0%, AUC-Model $4_{M\text{-}AHP}$ = 63.3%, respectively, according to the M-AHP method (Figure 5).

The LSM index value in the models developed in line with the FIS method was between 0.249 as the lowest value and 0.792 as the highest value (Figure 6). Models' successes were found to be AUC-Model 1_{FIS} = 73.2%, AUC-Model 2_{FIS} = 73.2%, AUC-Model 3_{FIS} = 72.2%, AUC-Model 4_{FIS} = 73.4%, respectively, according to the FIS method (Figure 7).

The LSM index value in the models generated in line with the LR method was between 0.001 as the lowest value and 0.999 as the highest value (Figure 8). Models' successes were found to be AUC-Model 1_{LR} = 64.6%, AUC-Model 2_{LR} = 65.1%, AUC-Model 3_{LR} = 76.6%, AUC-Model 4_{LR} = 75.7%, respectively, according to the LR method (Figure 9).

The general road density of the study area is 14.7 $m.ha^{-1}$. It was determined that the landslide risk was high in the southern part of İhsangazi Watershed as a result of the approaches utilized in the study (i.e. M-AHP, FIS and LR). As such, the density of the roads (i.e. all of the forest roads) located in the south of the watershed was computed again and found to be 14.6 $m.ha^{-1}$ (Figure 10). This computed value is much below the 25 $m.ha^{-1}$ value (Erdaş 1997), which is the road density value desired to be reached. However, it should be taken into consideration that the average road density should not be increased in terms of not triggering the landslide formation as the foregoing area is close to the fault line and located in very susceptible areas to landslide in LSM models.

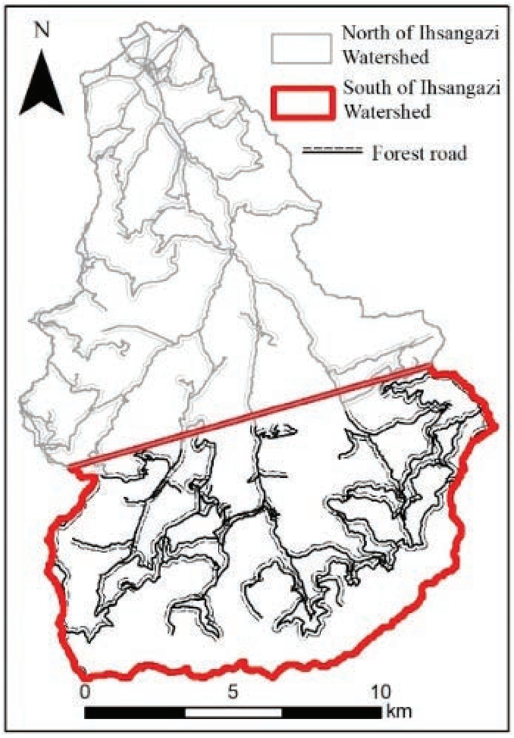

Figure 10. Forest roads to the south of IW
Slika 10. Šumske ceste na jugu IW-a

DISCUSSION AND CONCLUSION
RASPRAVA I ZAKLJUČAK

It has great importance to determine areas susceptible to landslide in advance by virtue of GIS techniques and to integrate them into planning stages made for such areas. Plans can be more rational when evaluated in this respect. 12 models have been established according to three different approaches (M-AHP, FIS and LR) by using nine factors which can be used in practice and can help to decide the determination of alternative routes. The validations of the models were calculated by comparing the data of the previous landslide areas and the results of the models. All the model successes ranged from 64.6% to AUC and 76.6% to AUC in this study. In previous studies, Yalçın et al. (2011) determined the AUC value of 42.58 % based on seven factors while Shahabi et al. (2014) reported the AUC value of 89.41% considering the eight factors. In most recent studies, Eker and Aydın (2016) found the AUC value of 85% based on eight factors and Jacobs et al. (2018) reported the AUC value of 78% according to seven factors. Comparing with the results from the similar studies, the successes of the models revealed in this study were at acceptable levels. In addition to number and combination of factors in LSM studies, obtaining quality data are as well important. The high-resolution DEM data, where many factors such as height, slope, aspect and etc. are calculated, also increases the success of the models (Jacobs et al. 2018).

It was determined from the model results that there will be an intense risk of landslide in the southern part of the study area. The roads planned to be built in this area have to be made in a more meticulously planned way and in such a way that they neither cause nor trigger landslides. It is seen that the current road density value in the study area is not adequate in terms of forest management since it is below the target density aimed to be achieved (25 $m.ha^{-1}$) by General Directorate of Forestry. It will be essential to increase the existing road density to the desired levels in order to manage and protect the forests, and also to carry out other essential forestry activities. It is very substantial that the roads to be built should be planned carefully in areas with landslide risk and priority should be given to the selection of routes which need minimum excavation. In this way, the potential damage on the environment will be kept at a minimum level. It is also important that the integrity and duration of the existing roads in landslide sensitive areas should be improved through stabilization works and by installation of necessary road structures in a more environmentally way.

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REFERENCES
LITERATURA

- Acosta, L. A., Eugenio, E. A., Macandog, P. B. M., Magcale-Macandog, D. B., Lin, E. K. H., Abucay, E. R., Primavera, M. G. 2016: Loss and damage from typhoon-induced floods and landslides in the Philippines: community perceptions on climate impacts and adaptation options. International Journal of Global Warming, 9(1), 33-65.
- Aghdam, I. N., Varzandeh, M. H. M., Pradhan, B. 2016: Landslide susceptibility mapping using an ensemble statistical index (Wi) and adaptive neuro-fuzzy inference system (ANFIS) model at Alborz Mountains (Iran). *Environmental Earth Sciences*, *75*(7), 553.
- Akay, A. E. 2006: Minimizing total costs of forest roads with computer-aided design model. Sadhana, 31(5), 621-633.
- Akay, A.E., Erdas, O., Reis, M., Yuksel, A. 2008: Estimating Sediment Yield from a Forest Road Network by Using a Sediment Prediction Model and GIS Techniques. Building and Environment. 43, 687–695.
- Akgun, A., Türk, N. 2010: Landslide susceptibility mapping for Ayvalik (Western Turkey) and its vicinity by multicriteria decision analysis. Environmental Earth Sciences, 61(3), 595–611. https://doi.org/10.1007/s12665-009-0373-1
- Akgun, A., Sezer, E.A., Nefeslioglu, H.A., Gokceoglu, C., 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.
- Aksoy, B., Ercanoğlu, M. 2012: Landslide Identification and Classification by Object- Based Image Analysis and Fuzzy Logic: An example from the Azdavay region (Kastamonu, Turkey). Computers & Geosiciences, 38, 87-98.
- Bathurst, J. C., Moretti, G., El-Hames, A., Beguería, S., García-Ruiz, J. M. 2007: Modelling the impact of forest loss on shallow landslide sediment yield, Ijuez river catchment, Spanish Pyrenees. *Hydrology and Earth System Sciences*, *11*(1), 569-583.
- Brabb, E. E. 1991: The world landslide problem. Episodes, 14(1), 52-61.
- Bui, D.T., Pradhan, B., Lofman, O., Revhaug, I., Dick, O.B. 2012: Landslide susceptibility mapping at Hoa Binh province (Vietnam) using an adaptive neuro-fuzzy inference system and GIS, Computers & Geosciences, 45, 199-211.
- Choi, J., Oh, H.-J., Lee, H.-J., 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, Engineering Geology, 124,12-23.
- Conforti, M., Pascale, S., Robustelli, G., Sdao, F. 2014: Evaluation of prediction capability of the artificial neural networks for mapping landslide susceptibility in the Turbolo River catchment (northern Calabria, Italy). Catena, 113, 236–250. https://doi.org/10.1016/j.catena.2013.08.006
- Corominas, J., van Westen, C., Frattini, P., Cascini, L., Malet, J. P., Fotopoulou, S., and Smith, J. T. 2014: Recommendations for the quantitative analysis of landslide risk. Bulletin of Engineering Geology and the Environment, 73(2), 209–263. https://doi.org/10.1007/s10064-013-0538-8
- Dehnavi, A., Aghdam, I. N., Pradhan, B., Varzandeh, M. H. M. 2015: A new hybrid model using step-wise weight assessment ratio analysis (SWARA) technique and adaptive neuro-fuzzy inference system (ANFIS) for regional landslide hazard assessment in Iran. Catena, 135, 122-148.
- Dilley, M., Chen, R. S., Deichmann, U., Lerner-Lam, A. L., Arnold, M. 2005: Natural disaster hotspots: a global risk analysis. The World Bank.
- Duman, T.Y., Çan, T., Emre, Ö. 2011: 1/1.500.000 Türkiye Heyelan Envanteri Haritası, Maden Tetkik ve Arama Genel Müdürlüğü Özel Yayınlar Serisi -27, Ankara, Türkiye. ISBN:978-605-4075-85-3.
- Eker, R., Aydın, A. 2016: Landslide Susceptibility Assessment of Forest Roads. European Journal of Forest Engineering, 2(2), 54-60.
- Ercanoğlu, M., Kaşmer, Ö., Temiz, N. 2008: Adaptation and comparison of expert opinion to analytical hierarchy process for landslide susceptibility mapping. Bulletin of Engineering Geology and the Environment, Vol:67, No:4, 565-578.
- Erdaş, O.1997: Orman Yolları–Cilt I. KTÜ Orman Fakültesi Yayınları, 187, 25.
- Erdaş, O. 2008: Transport Tekniği. KSÜ Rektörlüğü, Kahramanmaraş, Yayın No: 130/20 554s.

- Ermini, L., Catani, F., Casagli, N. 2005: Artificial Neural Networks applied to landslide susceptibility assessment, Geomorphology, 66, 327–343.
- Evans, S. G., Roberts, N. J., Ischuk, A., Delaney, K. B., Morozova, G. S., Tutubalina, O. 2009: Landslides triggered by the 1949 Khait earthquake, Tajikistan, and associated loss of life. Engineering Geology, 109(3-4), 195-212.
- Feizizadeh, B., Blaschke, T. 2013: GIS-multicriteria decision analysis for landslide susceptibility mapping: Comparing three methods for the Urmia lake basin, Iran. Natural Hazards, 65(3), 2105–2128. https://doi.org/10.1007/s11069-012-0463-3
- Goetz, J. N., Brenning, A., Petschko, H., Leopold, P. 2015: Evaluating machine learning and statistical prediction techniques for landslide susceptibility modeling. Computers and Geosciences, 81, 1–11. https://doi.org/10.1016/j.cageo.2015.04.007
- Gorsevski, P. V., Gessler, P. E., Foltz, R. B., Elliot, W. J. 2006: Spatial prediction of landslide hazard using logistic regression and ROC analysis. Transactions in GIS, 10(3), 395-415.
- Hapke, C. J., Green, K. R. 2006: Coastal landslide material loss rates associated with severe climatic events. Geology, 34(12), 1077-1080.
- Hong, H., Pradhan, B., Xu, C., Tien Bui, D. 2015: Spatial prediction of landslide hazard at the Yihuang area (China) using two-class kernel logistic regression, alternating decision tree and support vector machines. Catena, 133, 266–281. https://doi.org/10.1016/j.catena.2015.05.019
- Jaafari, A., Najafi, A., Rezaeian, J., Sattarian, A., Ghajar, I. 2015: Planning road networks in landslide-prone areas: A case study from the northern forests of Iran. Land Use Policy, 47, 198–208. https://doi.org/10.1016/j.landusepol.2015.04.010
- Jaafari, A., Rezaeian, J., Omrani, M.S., 2017: Spatial Prediction of Slope Failures in Support of Forestry Operations Safety. Croatian Journal of Forest Engineering 38(1): 107-118.
- Jacobs, L., Dewitte, O., Poesen, J., Sekajugo, J., Nobile, A., Rossi, M., Kervyn, M. 2018: Field-based landslide susceptibility assessment in a data-scarce environment: The populated areas of the Rwenzori Mountains. Natural Hazards and Earth System Sciences, 18(1), 105–124. https://doi.org/10.5194/nhess-18-105-2018
- Kavzoglu, T., Colkesen, I., Sahin, E. K. 2019: Machine Learning Techniques in Landslide Susceptibility Mapping: A Survey and a Case Study. In Landslides: Theory, Practice and Modelling (pp. 283-301). Springer, Cham.
- Lee, M. J., Park, I., Lee, S., 2015: Forecasting and validation of landslide susceptibility using an integration of frequency ratio and neuro-fuzzy models: a case study of Seorak mountain area in Korea. Environmental Earth Sciences, 74(1), 413-429.
- Lee, S., Talib, J. A. 2005: Probabilistic landslide susceptibility and factor effect analysis. Environmental Geology, 47(7), 982-990.
- Lin, L., Lin, Q., Wang, Y. 2017: Landslide susceptibility mapping on a global scale using the method of logistic regression. *Natural Hazards and Earth System Sciences*, *17*(8), 1411-1424.
- Lu, S. Y., Lin, C. Y., Hwang, L. S. 2011: Spatial Relationships between Landslides and Topographical Factors at the Liukuei Experimental Forest, Southwestern Taiwan after Typhoon Morakot, 26(4), 399-408.
- Martinović, K., Gavin, K., Reale, C. 2016: Development of a landslide susceptibility assessment for a rail network. Engineering Geology, 215, 1-9.
- Moore, I. D., Grayson, R. B., Ladson, A. R. 1991: Digital Terrain Modelling: A Review of Hydrological, Geomorphological, and Biological Applications. Hydrological Processes, 5(1), 3-30.
- Nefeslioglu, H.A., San, T., Gokceoglu, C., Duman, T.Y., 2012: An assessment on the use of Terra ASTER L3A data in landslide susceptibility mapping. Int. J. Appl. Earth Obs. Geoinf. 14 (1), 40–60.
- Pantha, B. R., Yatabe, R., Bhandary, N. P. 2008: GIS-based landslide susceptibility zonation for roadside slope repair and maintenance in the Himalayan region. Episodes, 31(4), 384–391.
- Petley, D. 2012: Global patterns of loss of life from landslides. Geology, 40(10), 927-930.
- Pfeil-McCullough, E., Bain, D. J., Bergman, J., Crumrine, D. 2015: Emerald ash borer and the urban forest: Changes in landslide potential due to canopy loss scenarios in the City of Pittsburgh, PA. Science of the Total Environment, 536, 538-545.
- Pham, B. T., Tien Bui, D., Prakash, I., Dholakia, M. B. 2017: Hybrid integration of Multilayer Perceptron Neural Networks and machine learning ensembles for landslide susceptibility assessment at Himalayan area (India) using GIS. Catena, 149, 52–63. https://doi.org/10.1016/j.catena.2016.09.007
- Pourghasemi, H. R., Moradi, H. R., Aghda, S. F., Gokceoglu, C., Pradhan, B. 2014: GIS-based landslide susceptibility mapping with probabilistic likelihood ratio and spatial multi-criteria evaluation models (North of Tehran, Iran). Arabian Journal of Geosciences, 7(5), 1857-1878.
- Pourghasemi, H. R., Yansari, Z. T., Panagos, P., Pradhan, B. 2018: Analysis and evaluation of landslide susceptibility: a review on articles published during 2005–2016 (periods of 2005–2012 and 2013–2016). Arabian Journal of Geosciences, 11(9), 193.
- Saha, A. K., Arora, M. K., Gupta, R. P., Virdi, M. L., Csaplovics, E. 2005: GIS-based route planning in landslide-prone areas. International Journal of Geographical Information Science, 19(10), 1149–1175. https://doi.org/10.1080/13658810500105887
- Shahabi, H., Khezri, S., Ahmad, B. Bin, Hashim, 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. https://doi.org/10.1016/j.catena.2013.11.014
- Steger, S., Brenning, A., Bell, R., Petschko, H., Glade, T. 2016: Exploring discrepancies between quantitative validation results and the geomorphic plausibility of statistical landslide susceptibility maps. Geomorphology, 262, 8–23. https://doi.org/10.1016/j.geomorph.2016.03.015
- Tanyaş, H., Van Westen, C. J., Allstadt, K. E., Jessee, M. A. N., Görüm, T., Jibson, R. W., Hovius, N. 2017: Presentation and analysis of a worldwide database of earthquake-induced landslide inventories. *Journal of Geophysical Research: Earth Surface*, *122*(10), 1991-2015.
- Truong, X., Mitamura, M., Kono, Y., Raghavan, V., Yonezawa, G., Do, T., Lee, S. 2018: Enhancing Prediction Performance of Landslide Susceptibility Model Using Hybrid Machine Learning Approach of Bagging Ensemble and Logistic Model Tree. *Applied Sciences*, *8*(7), 1046.
- Vahidnia, M. H., Alesheikh, A. A., Alimohammadi, A., Hosseinali, F. 2010: A GIS-based neuro-fuzzy procedure for integrating knowledge and data in landslide susceptibility mapping. Computers and Geosciences, 36(9), 1101–1114. https://doi.org/10.1016/j.cageo.2010.04.004

- Van der Geest, K. 2018: Landslide Loss and Damage in Sindhupalchok District, Nepal: Comparing Income Groups with Implications for Compensation and Relief. International Journal of Disaster Risk Science, 1-10.
- Wang, Q., Li, W., Wu, Y., Pei, Y., Xie, P. 2016: Application of statistical index and index of entropy methods to landslide susceptibility assessment in Gongliu (Xinjiang, China). Environmental Earth Sciences, 75(7), 599.
- Yalcin, A. (2008). GIS-based landslide susceptibility mapping using analytical hierarchy process and bivariate statistics in Ardesen (Turkey): Comparisons of results and confirmations. Catena, 72(1), 1–12. https://doi.org/10.1016/j.catena.2007.01.003
- Yalçın, 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(3), 274–287. https://doi.org/10.1016/j.catena.2011.01.014
- Yao, X., Tham, L. G., Dai, F. C. 2008: Landslide Susceptibility Mapping Based on Support Vector Machine: A Case Study on Natural Slopes of Hong Kong, China. Geomorphology, 101(4), 572-582.
- Zadeh, L. A. 1965: Information and control. Fuzzy sets, 8(3), 338-353.
- Zêzere, J. L., Pereira, S., Melo, R., Oliveira, S. C., Garcia, R. A. C. 2017: Mapping landslide susceptibility using data-driven methods. Science of the Total Environment, 589, 250–267. https://doi.org/10.1016/j.scitotenv.2017.02.188
- Zumpano, V., Pisano, L., Malek, Ž., Micu, M., Aucelli, P. P., Rosskopf, C. M., Belteanu, D., Parise, M. 2018: Economic Losses for Rural Land Value Due to Landslides. Frontiers in Earth Science, 6, 97.

SAŽETAK

Šumske ceste jedna su od temeljnih infrastruktura u obavljanju šumarskih djelatnosti i usluga. Budući da su šume općenito smještene u planinskim područjima sa strmim nagibom u Turskoj, teškoće koje se događaju u ovim planinskim uvjetima povećavaju troškove. Cilj ove studije je procijeniti alternative planiranja šumskih cesta koje će se razvijati u planinskim područjima koja se nalaze na osjetljivim klizištima, na temelju mapiranja mapa osjetljivosti na terenu (LSM). U tu svrhu generirano je ukupno 12 modela s različitim pristupima višestrukog odlučivanja (MCDM), uključujući Modificirani analitički hijerarhijski proces (M-AHP), Fuzz sustav (FIS) i logističku regresiju (LR). Kao rezultat studije, najbolji model bio je Model 3 dobiven uz LR pristup (područje ispod krivulje (AUC) = 76,6%), a zatim LR-Model 4 (AUC = 75,7%) i FIS-Model 4 (AUC = 73.4%). Model 3 (AUC = 71%) bio je najuspješniji M-AHP pristup. Slijedom toga, primjena ovih metoda pružit će prednost u donošenju točnijih i racionalnih odluka tijekom planiranja cestovne mreže u osjetljivim šumskim područjima.

KLJUČNE RIJEČI: Podvodna osjetljivost, šumske ceste, modificirani AHP, sustav neizrazitog zaključivanja, logistička regresija