

# A GIS BASED LANDSLIDE SUSCEPTIBILITY MAPPING USING MACHINE LEARNING AND ALTERNATIVE FOREST ROAD ROUTES ASSESSMENT IN PROTECTION FORESTS

## MAPIRANJE OSJETLJIVOSTI NA KLIZIŠTA NA TEMELJU GIS-A KORIŠTENJEM STROJNOG UČENJA I PROCJENE ALTERNATIVNIH ŠUMSKIH PUTOVA U ZAŠTITNIM ŠUMAMA

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### SAŽETAK

Šumarske aktivnosti treba provoditi u okviru održivog šumarstva, dok se ubiru blagodati šumarstva. U skladu s tim, izgradnju cesta kroz šume treba pažljivo planirati, posebno u zaštitnim šumama. Šumska područja u Turskoj općenito su široko rasprostranjena u planinskim i visoko nagnutim područjima koja su osjetljiva na klizišta – osjetljivost na klizišta jedan je od najvažnijih kriterija za odabir zaštićenih šuma. Kao takvo, važno je procijeniti detaljne i primjenjive alternative u pogledu posebnih područja i privatnih šuma. Cilj ovoga istraživanja je utvrditi alternativne pravce za šumske ceste u zaštićenim šumama korištenjem geografskih informacijskih sustava (GIS), posebno u područjima s velikom osjetljivošću na klizišta. U tu svrhu izrađena je karta osjetljivosti na klizišta (LSM) korištenjem metoda modeliranja logističke regresije (LR) i slučajnih šuma (RF), koje se široko koriste u strojnom učenju (ML). Odabrana su dva modela s najvišim radnim karakteristikama prijavnika (ROC) i površinom ispod krivulje (AUC), te deset čimbenika (nagib, nadmorska visina, litologija, udaljenost od ceste, udaljenost do greške, udaljenost od rijeke, zakrivljenost, indeks snage struje, korišteni su indeks topografskog položaja i indeks vlažnosti topografije). Najbolja metoda modeliranja LSM bila je AUC. Vrijednost AUC bila je 90,6% s RF pristupom i 80,3% s LR pristupom. Stvoreni LSM-ovi korišteni su za određivanje alternativnih putova koji izračunavaju analizu putanja troškova. Nadamo se da će osjetljivost na klizišta i odabir alternativnih putnih pravaca šumskih puteva utvrđenih pristupima i tehnikama u ovoj studiji biti od koristi planiranju šumskih cesta, kao i donositeljima planova i odluka.

**KLJUČNE RIJEČI:** Šumarstvo, otkrivanje alternativnih ruta, put troškova, slučajna šuma, logistička regresija

### INTRODUCTION

#### UVOD

Ideally, the continuity of goods and services provided by forestry should be ensured while the integrity of forest ecosystems is preserved (Colchester, 1994; Dorren et al. 2004; Blaser and Gregersen 2013). Greater importance sho-

uld be given to protection forests due to the challenges they face (Lamsal 2011). Protection forests are defined through a general framework of regulations both in Turkey and throughout the globe (Weiss 2000; Bauer et al. 2004; Varmola et al. 2004; GDF 1984). Certain criteria must be met for a forest to qualify as a protection forest, including ava-

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lanches, landslides, and areas with high erosion sensitivity. They should prevent the filling of dams, lakes and river beds, and its adverse effect on the environmental health of settlements (GDF 1984). Forest road construction falls under the category of construction works that can harm the environment (Boston, 2016); harm that is mostly the result of defective planning (Gumus et al. 2008; Bugday 2018).

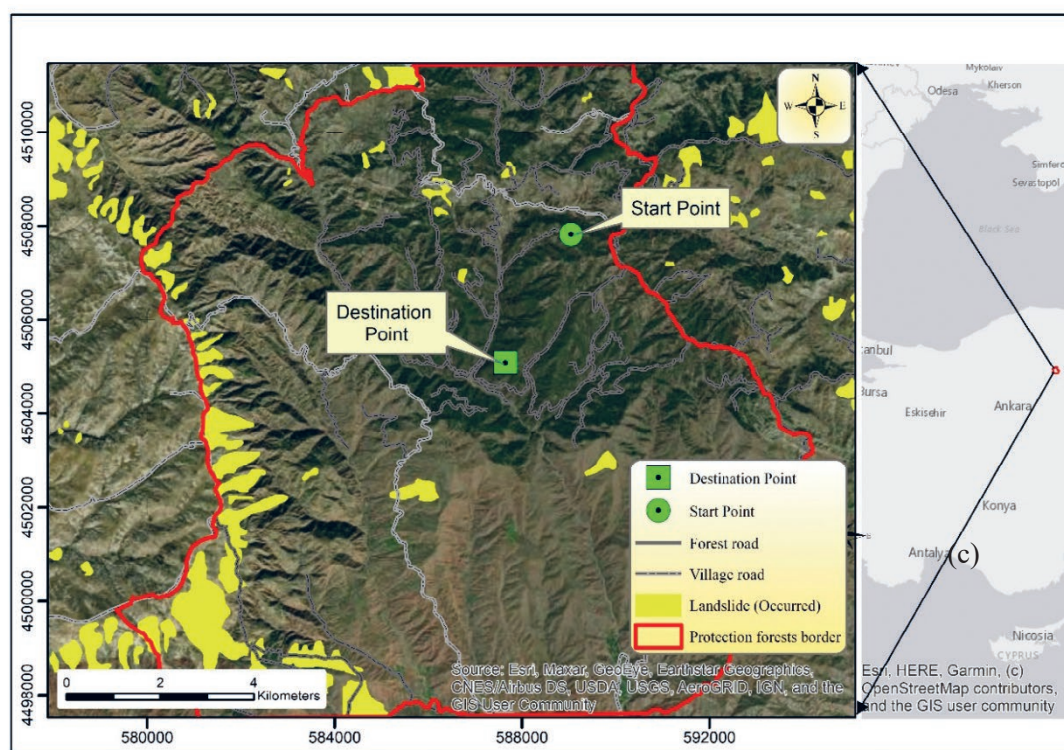
In order to prevent further damage to protection forests in areas with topographical and spatial challenges (Hayati et al. 2012; Akay et al. 2014), it is important to carefully plan and implement those plans in a manner that minimizes the destructive environmental effects of forest road construction.

Geographic Information Systems (GIS) software has proved advantageous in decision-making and planning processes (Phua and Minowa 2005). Multicriteria analysis, which informs GIS-based decisions in spatial and temporal contexts for both national and international studies, can be highly accurate and time-efficient by leveraging computers (Tan et al. 2021), and various modeling approaches can be used to generate GIS-based LSMs. Some of these approaches include: Fuzzy Logic (Stanley and Kirschbaum, 2017), Support Vector Machine (Kavzoglu et al. 2015), Frequency Ratio (Yilmaz and Keskin 2009), Logistic Regression (Zhou et al. 2021), Weights of Evidence (Pradhan et al. 2010), Adaptive Neuro-Fuzzy Inference System (Bui et al. 2012), Decision Tree (Arabameri et al.

2021), Machine Learning (Kavzoglu et al. 2019), Analytic Hierarchy Process (Laschi et al. 2016; Kadi et al. 2019) Artificial Neural Network (Jesudasan and Saravanan 2021). In addition, although there is no settled understanding in LSM modeling studies, generally aspect (Yan et al. 2019), slope (Sun et al. 2020), elevation (Du et al. 2017), curvature (Wang et al. 2020), distance to fault (Demir 2018) - road (Tang et al. 2021) - stream (Kalantar et al. 2018), land-use (Nohani et al. 2019), lithology (Paryani et al. 2020), NDVI (Pourghasemi et al. 2020), Stream Power Index (SPI) (Hong et al. 2018), Topographic Position Index (TPI) (Xie et al. 2021), and Topographic Wetness Index (TWI) (Gheslaghi et al. 2021) etc. factors are widely used.

Forest roads include not only the basic facilities but also the structures required for the execution of forestry activities (Demir 2007). Forest roads should be well designed (Akay et al. 2019), because they can negatively affect underground (Haskell, 2000) and aboveground (Fallahchai et al. 2018) elements. As such, it is vital, both in terms of ecological and nature-friendly engineering, that plans for roads in protection forests with high landslide susceptibility and topographically negative features are detailed and provide alternatives in order to ensure roads are built in line with their purpose.

The aim of this study is to generate LSMs that can be used during planning phases as the basis for the determination of forest road routes in protection forests and establish a



**Figure 1.** Location of landslides in the study area

**Slika 1.** Položaj klizišta na istraživanom području

platform for planners and decision makers to identify alternative routes by using modern methods. Sixteen different models were created through two different ML approaches: LR and RF modeling. Alternative forest roads were computed using the same approaches. Curvature, distance to fault, lithology, distance to road, slope (degree), stream power index (SPI), distance to stream, topographic position index (TPI), and topographic wetness index (TWI) factors were used for the modeling. The two models with the highest AUC value were used to calculate alternative routes by using least cost path analysis and ArcGIS software. During the last phase of this study, the alternative routes were compared with a route created through the classical approach.

## MATERIAL AND METHODS

### MATERIJAL I METODE

#### Study Area – *Prostorno područje*

The study area was conducted in the Erikli region, Yapraklı District, of the Çankırı province in northern Turkey. The area falls under the administrative responsibility of the Erikli Forestry Operations Directorate, which is affiliated to the Çankırı Forestry Operations Directorate of Ankara Regional Directorate of Forestry. This area has a history of landslide events. The protection forests have an area of 149.38 km<sup>2</sup> and are located at a latitude between 40° 37' 47" and 40° 44' 46" and a longitude between 33° 56' 34" and 34° 05' 25". Black pine (*Pinus nigra* Arnold) forests dominate this area while there are also stands. These forests have been named as protection forests by the General Directorate of Forestry (GDF). Almost all roads in the studied area are forest roads with road formation width of 6 m, and their total length is 157.96 km. The general forest road density is 10.57 m/ha. The area's altitude varies between approximately 790 m and 1,520 m with an average elevation of 1,210 m. The maximum slope is 67.6 degrees, and the average is 16.5 degrees. During the training phase, data on 70% (61 landslides) of the total 87 landslides that occurred in the studied area were selected, and data on the remaining 30% (26 landslides) were used during the testing phase.

#### LSM Modeling Process – *LSM Proces modeliranja*

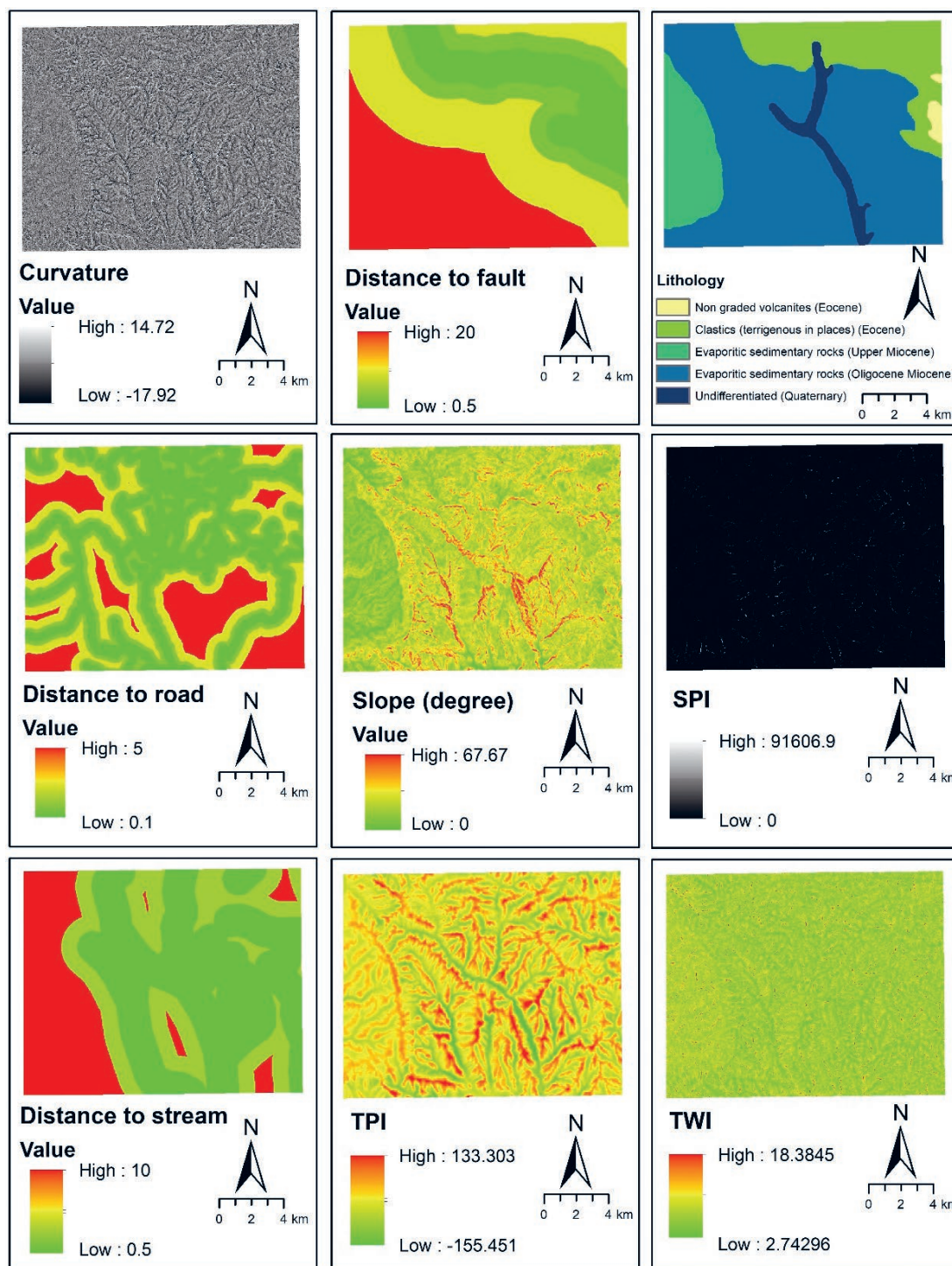
The digital elevation model (DEM) was obtained free of charge from ASTER-GDEM (published on the web) and elevation, curvature, slope, SPI, TPI, and TWI factors were created using ArcGIS 10.3 TM software. Distance to road was obtained from the Forest Subdistrict databases. Lithology, distance to fault, and distance to stream factors, as well as field data of past landslides, were obtained from the General Directorate of Mineral Research and Explorations (GDMRE) (Duman et al. 2011).

Curvature (Figure 2a) is commonly used in LSM modeling studies because it helps predict the direction and severity of landslides (Dou et al. 2019). Distance to fault is an important and significant factor in the triggering of landslides (Massey et al. 2020). In the studied area, the distances were 0.5, 1, 3, 5, 10, and 20 km (Figure 2b). The lithology factor has high significance; it determines both landslide susceptibility and cost of forest road construction since it provides information on the characteristics of the bedrock (Boroughani et al. 2020). For this study, lithology was evaluated for five different groups (Figure 2c). Distance to road is an artificial factor affecting landslide formation that is frequently used in national and international literature to determine landslide susceptibility (Li and Chen 2020; Bugday and Akay 2019) (Figure 2d). Slope is a main factor in landslide formation (Pourghasemi et al. 2021) and, similar to the lithology factor, also affects cost. Five different classes (0°–5.71°, 5.71°–13.80°, 13.80°–21.88°, 21.88°–31.99° and > 32°) were added to the analysis based on the International Union of Forest Research Organizations (IUFRO) slope classes (commonly used in Turkey) (Figure 2e). The stream power index (SPI) was computed with the assumption that the flow (q) is proportional to the specific catchment area (As) and is expressed as the ability of the current water flow in the basin to cause erosion (Achour and Pourghasemi 2020) (Figure 2f). Distance to stream is a factor commonly employed in studies that consider the significance of proximity relations in landslide susceptibility (Senouci et al. 2021). Distances are expressed as zones with 0.5, 1, 2, 5 and 10 km intervals (Figure 2g). Topographic Position Index (TPI) is used in landslide susceptibility studies to determine the cell position relative to ridges and valleys, where positive values represent ridges, negative values represent valleys, and zero values represent flat areas (Jenness 2006) (Figure 2h). The TWI factor is used to express the location and spatial dimensions of water-saturated areas (Eiras et al., 2021) (Figure 2i).

#### LSM Process – *LSM proces*

In this study, the LSM Tool Pack, developed by Sahin et al. (2020), was used to create an LSM. LSM prediction models were created using the factors shown in Figure 2, using LR and RF modeling methods.

ArcGIS 10.3 software used LR and RF methods to evaluate the factors for this study. Information on past landslide events and on areas where landslides have never occurred was tested to validate the models. The validation of the models created by LR and RF methods was tested using receiver operating characteristic (ROC) analysis and the Area Under ROC Curve (AUC) value. In the literature, the AUC score is expressed as follows: 0.9–1.0 = excellent; 0.8–0.9 = very good; 0.7–0.8 = good; 0.6–0.7 = moderate; 0.5–0.6 = poor (Bradley, 1997).



**Figure 2.** LSM factors in forested area; (a) curvature, (b) distance to fault, (c) lithology, (d) distance to road, (e) Slope(degree), (f) Stream Power Index (SPI), (g) distance to stream (h) Topographic Position Index (TPI), and (i) Topographic Wetness Index (TWI)

**Slika 2.** LSM faktori u šumovitom području; (a) zakrivljenost, (b) udaljenost do rasjeda, (c) litologija, (d) udaljenost do ceste, (e) nagib (stupanj), (f) indeks snage struje (SPI), (g) udaljenost do struje (h) Indeks topografskog položaja (TPI) i (i) indeks vlažnosti topografije (TWI)

### Detection of Alternative Forest Road Routes – Otkrivanje alternativnih šumskih puteva

The last phase of the study was the generation of alternative road routes. ArcGIS-Cost Path analysis was carried out on a computer. Bases of single or multiple criteria (weighted and unweighted) can be employed in the analysis of routes

(ESRI 2016). This methodology was applied to three alternative scenarios in order to identify alternative road routes that were compared in order to determine the effectiveness and sensitivity of this approach.

The route determination study started by determining two points outside existing roads that connect to each other and

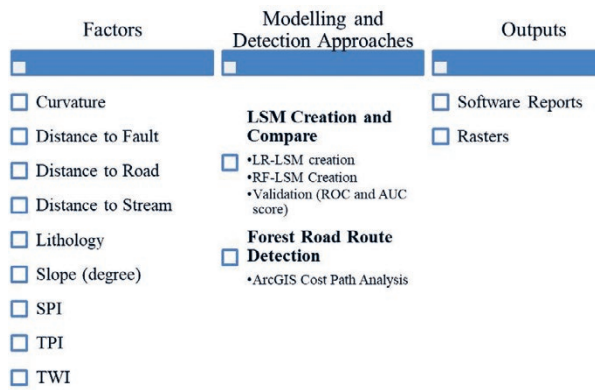


Figure 3. Study flowchart

Slika 3. Dijagram toka studije

to the planned alternatives, and route limitation was made by positioning the starting and destination points. First, road planning was carried out using the slope criterion used by the traditional approach. Second, the route was recalculated using ArcGIS Cost Path analysis, taking into account the landslide susceptibility obtained through the LR and RF methods. This study's workflow is summarized in Figure 3.

## RESULTS REZULTATI

During the first phase, according to the importance of each factor as given by Sahin et al. (2020), chi-square, information gain, and random forest importance were applied from high to low importance as listed in Table 1. The table shows that each method and factor produced different feature

weights and are in different rankings, according to the statistical method. There are differences between the first three factors in the chi-square ranking and in the factor rankings of information gain and random forest importance. Selections were based on the values obtained from the chi-square to determine the models and modeling that was carried out.

To determine the effects of the factors on the performance of the prediction model (Sahin et al. 2020), the factors' importance values were ranked in ascending order. The factors that provided high performance (by choosing the best subset) were estimated in order to determine the highest AUC values. Various statistical tests (Wilcoxon signed-rank test, F-Test, Kolmogorov Smirnov test, and One Sample T-Test) were used by the LSM Tool Pack (Table 2). For this study, the Case 1 model-7 scenario was chosen. The best possible scenarios, using combinations of factors, are shown in Table 2.

### Logistic Regression – Logistička regresija

The LR modeling approach has been frequently and widely used in landslide-susceptibility studies. The most successful combinations, using nine factors in total, are shown in Table 2. The AUC value (97.5522) of the Case 1 model-7 scenario, which was selected as the most successful LR approach, the estimated factors, std. Error, z-value, and Pr values are shown in Figure 4. The curvature factor correlated negatively with landslide formation, while the remaining eight factors (distance to fault, lithology, distance to road, slope, SPI, distance to stream, TPI, and TWI) correlated positively. Furthermore, slope, TPI, lithology, distance

Table 1. Feature importance's of the feature ranking algorithms

Tablica 1. Značaj značajke algoritama za rangiranje značajki

No Br	Factors Čimbenici	Chi-Squared Hi-Kvadrat	Factors Čimbenici	Information Gain Dobivanje Informacija	Factors Čimbenici	Random Forest Importance Značaj Slučajnih Šuma
1	Curvature (Zakrivljenost)	0,48363	Dis.to stream (Udaljenost do streama)	0,27114	Dis.to stream (Udaljenost do streama)	113,43418
2	Dis.to fault (Udaljenost do greške)	0,40660	TPI (Indeks topografskog položaja)	0,23300	TPI (Indeks topografskog položaja)	91,65237
3	Dis.to road (Udaljenost do ceste)	0,35962	Slope (Degree) (Nagib (stupanj))	0,11658	Slope (Degree) (Nagib (stupanj))	74,57421
4	Dis.to stream (Udaljenost do streama)	0,24392	Lithology (Litologija)	0,08317	Lithology (Litologija)	57,42980
5	Lithology (Litologija)	0,23980	Dis.to fault (Udaljenost do greške)	0,05243	Dis.to road (Udaljenost do ceste)	53,71091
6	Slope (Degree) (Nagib (stupanj))	0,22645	Dis.to road (Udaljenost do ceste)	0,03330	Dis.to fault (Udaljenost do greške)	49,56295
7	SPI (Indeks snage strujanja)	0,22143	SPI (Indeks snage strujanja)	0,02611	SPI (Indeks snage strujanja)	33,59275
8	TPI (Indeks topografskog položaja)	0,11068	Curvature (Zakrivljenost)	0,01192	TWI (Indeks Topografska vlažnost)	23,84570
9	TWI (Indeks Topografska vlažnost)	0,08544	TWI (Indeks Topografska vlažnost)	0,00740	Curvature (Zakrivljenost)	11,12684

**Table 2.** Best factors combinations according to Chi-Square, Information Gain, and Random Forest Importance**Tablica 2.** Najbolje kombinacije čimbenika prema Chi-Squareu, dobitku informacija i slučajnoj važnosti šuma

Feature ranking method Način rangiranja značajki	Case no Slučaj br	Statistical test used for subset selection Statistički test koji se koristi za odabir podskupa	Model No: The best subset size selected by performance of LR Broj modela: Najbolja veličina podskupa odabrana prema performansama LR	Features in the best subset Značajke u najboljem podskupu
Chi-Square Hi-Kvadrat	<b>Slučaj 1</b>	F-test F-test	Model 7 Model 7	Dis.to Stream, TPI, Slope, Lithology, Dis.to Fault, Dis.to Road, and SPI <i>Udaljenost do streama, Indeks topografskog položaja, Nagib, Litologija, Udaljenost do greške, Udaljenost do ceste, Indeks snage strujanja</i>
	<b>Slučaj 2</b>	Kolmogorov Smirnov test	Model 7 Model 7	Dis.to Stream, TPI, Slope, Lithology, Dis.to Fault, Dis.to Road, SPI <i>Udaljenost do streama, Indeks topografskog položaja, Nagib, Litologija, Udaljenost do greške, Udaljenost do ceste, Indeks snage strujanja</i>
	<b>Slučaj 3</b>	One Sample T-Test	Model 5 Model 5	Dis.to Stream, TPI, Slope, Lithology, and Dis.to Fault <i>Udaljenost do streama, Indeks topografskog položaja, Nagib, Litologija, Udaljenost do greške</i>
	<b>Slučaj 4</b>	Wilcoxon signed-rank test	Model 8 Model 8	Dis.to Stream, TPI, Slope, Lithology, Dis.to Fault, Dis.to Road, SPI, Curvature <i>Udaljenost do streama, Indeks topografskog položaja, Nagib, Litologija, Udaljenost do greške, Udaljenost do ceste, Indeks snage strujanja, Zakrivljenost</i>
Information Gain Dobivanje Informacija	<b>Slučaj 5</b>	F-test	Model 7 Model 7	Dis.to Stream, TPI, Slope, Lithology, Dis.to Fault, Dis.to Road, SPI <i>Udaljenost do streama, Indeks topografskog položaja, Nagib, Litologija, Udaljenost do greške, Udaljenost do ceste, Indeks snage strujanja</i>
	<b>Slučaj 6</b>	Kolmogorov Smirnov test	Model 6 Model 6	Dis.to Stream, TPI, Slope, Lithology, Dis.to Fault, Dis.to Road <i>Udaljenost do streama, Indeks topografskog položaja, Nagib, Litologija, Udaljenost do greške, Udaljenost do ceste</i>
	<b>Slučaj 7</b>	One Sample T-Test	Model 8 Model 8	Dis.to Stream, TPI, Slope, Lithology, Dis.to Fault, Dis.to Road, SPI, Curvature <i>Udaljenost do streama, Indeks topografskog položaja, Nagib, Litologija, Udaljenost do greške, Udaljenost do ceste, Indeks snage strujanja, Zakrivljenost</i>
	<b>Slučaj 8</b>	Wilcoxon signed-rank test	Model 5 Model 5	Dis.to Stream, TPI, Slope, Lithology, Dis.to Fault <i>Udaljenost do streama, Indeks topografskog položaja, Nagib, Litologija, Udaljenost do greške</i>
RF-Importance ZS-Šuma	<b>Slučaj 9</b>	F-test	Model 7 Model 7	Dis.to Stream, TPI, Slope, Lithology, Dis.to Fault, Dis.to Road, SPI <i>Udaljenost do streama, Indeks topografskog položaja, Nagib, Litologija, Udaljenost do greške, Udaljenost do ceste, Indeks snage strujanja</i>
	<b>Slučaj 10</b>	Kolmogorov Smirnov test	Model 5 Model 5	Dis.to Stream, TPI, Slope, Lithology, Dis.to Fault <i>Udaljenost do streama, Indeks topografskog položaja, Nagib, Litologija, Udaljenost do greške</i>
	<b>Slučaj 11</b>	One Sample T-Test	Model 8 Model 8	Dis.to Stream, TPI, Slope, Lithology, Dis.to Fault, Dis.to Road, SPI, Curvature <i>Udaljenost do streama, Indeks topografskog položaja, Nagib, Litologija, Udaljenost do greške, Udaljenost do ceste, Indeks snage strujanja, Zakrivljenost</i>
	<b>Slučaj 12</b>	Wilcoxon signed-rank test	Model 6 Model 6	Dis.to Stream, TPI, Slope, Lithology, Dis.to Fault, Dis.to Road <i>Udaljenost do streama, Indeks topografskog položaja, Nagib, Litologija, Udaljenost do greške, Udaljenost do ceste</i>

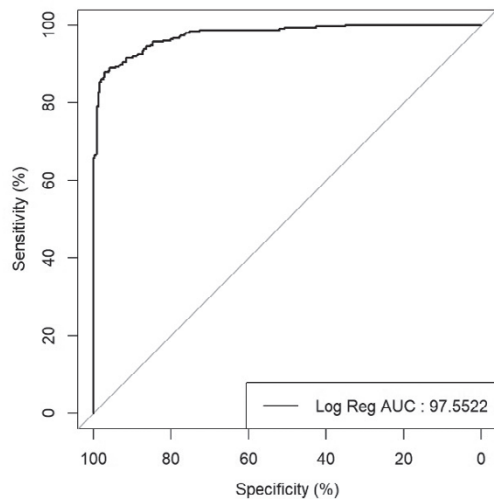
to fault, road and stream, and the TWI factors were more important than other factors (curvature and SPI) in terms of statistical significance.

### Random Forest – Slučajna šuma

The RF approach was used for modeling, employing the same nine factors to make comparisons. The most successful model (Case 1 model-7) was calculated to have an

AUC value of 99.9862. The AUC value computed through this modeling approach and the factors' order of importance are shown in Figure 5.

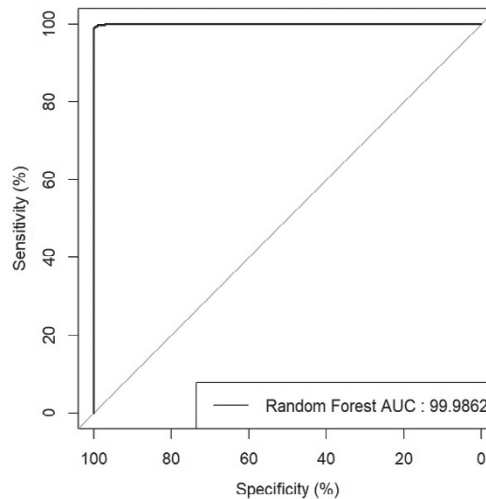
The ranking was found to be distance to stream, TPI, slope, lithology, distance to road, distance to fault, SPI, TWI, and curvature. The three factors with the highest importance in this ranking were distance to stream, TPI, and slope.



Coefficients	Estimate	Std. Error	z value	Pr(> z )
(Intercept)	-8.51E+00	7.84E-01	-10.859	< 2e-16 ***
Slope	2.69E-01	2.13E-02	12.617	< 2e-16 ***
TPI	1.12E-01	8.81E-03	12.709	< 2e-16 ***
Curvature	-5.40E-02	1.08E-01	-0.501	0.6162
Lithology	8.28E-01	8.71E-02	9.501	< 2e-16 ***
Fault	1.14E-01	3.48E-02	3.265	0.00109 **
Road	2.09E+00	2.66E-01	7.859	3.87e-15 ***
SPI	5.24E-05	6.87E-05	0.763	0.44566
Stream	2.34E-01	6.15E-02	3.808	0.00014 ***
TWI	4.49E-01	7.74E-02	5.805	6.43e-09 ***

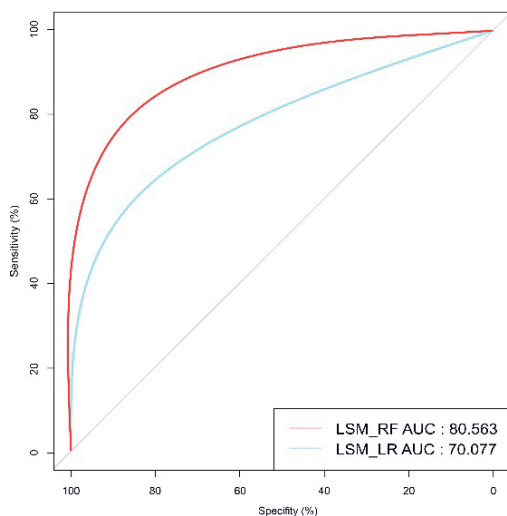
Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
 (Dispersion parameter for binomial family taken to be 1) - Null deviance: 1987.95 on 1433 degrees of freedom Residual deviance: 614.25 on 1424 degrees of freedom - AIC: 634.29 - Number of Fisher Scoring iterations: 7

**Figure 4.** Best LR model AUC score and statistics on factors  
**Slika 4.** Ocjena AUC najboljeg modela LR i statistika o faktorima



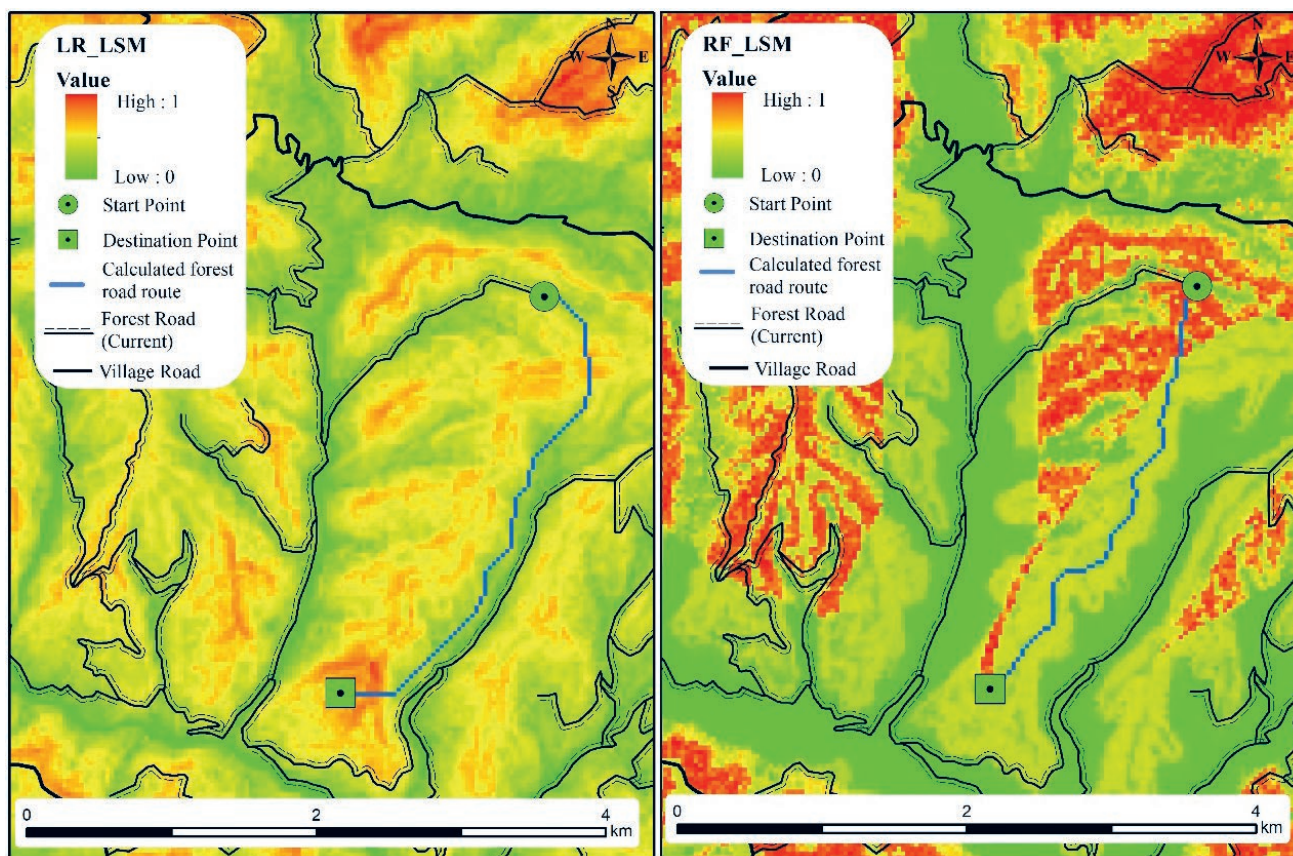
Factors	IncNodePurity
Dis.to Stream	130.86419
TPI	92.72004
Slope(degree)	45.57829
Lithology	22.42328
Dis.to Road	18.00387
Dis.to Fault	17.62894
SPI	12.03630
TWI	8.89416
Curvature	3.92871

**Figure 5.** Best RF model AUC score and order of importance of factors  
**Slika 5.** Ocjena AUC najboljeg RF modela i redoslijed važnosti čimbenika



	LR_LSM	RF_LSM
Accuracy	0.45788	0.64529
<b>AUC.Classified</b>	<b>0.70077</b>	<b>0.80563</b>
AUC.NonClassified	0.90962	0.97664
MAE	0.54212	0.35471
RMSE	0.73629	0.59557
Kappa	0.09294	0.19251
Precision	0.99735	0.99923
Recall	0.41518	0.61711
F1	0.58630	0.76300

**Figure 6.** Models performance results of LR and RF  
**Slika 6.** Modeliraju rezultati izvedbe LR i RF



**Figure 7.** LSM generated from the LR and RF methods and calculated CostPath road route

**Slika 7.** LSM generiran iz LR i RF metode i izračunata CostPath cestovna ruta

#### Performance Comparison of The Best Model – *Usporedba izvedbe najboljeg modela*

During this phase, the performance of the best LSM models (model 7) produced through the LR and RF approaches was compared. According to the test results (Figure 6), the best model in both approaches was model 7, with an LR-AUC score = 0.70 and an RF-AUC score = 0.80. The LR and RF approaches are at good and very good model success levels, respectively.

#### Detection of Alternative Forest Road Routes – *Otkrivanje alternativnih šumskih puteva*

The study area was restricted to the area determined by the forest district chief. This was to increase accessibility during the execution of protection activities and to meet the road requirement. This area consists of Black Pine (*Pinus nigra* Arnold) stands. The results of the LR and RF approaches show that the landslide susceptibility of the study area was higher in the northeast and southwest axis compared with other areas (Figure 7). LSMs produced through each modeling approach were employed, and ArcGIS Cost Path analysis showed that alternative routes could be designed to pass through areas with very low landslide susceptibility.

## DISCUSSION RASPRAVA

Most forest road planning studies in Turkey were completed in 1979 (Erdaş 1997). Planning studies have gained pace since the introduction of Geographic Information Systems (GIS) software for civilian use, and its use by institutions is widespread. Furthermore, a clear decision-making tool has emerged for plan and decision makers. GIS software has become a decision-support platform for numerous branches of study, for example, landslide susceptibility mapping. Mapping areas susceptible to landslides by expressing them through reliable modeling approaches is effective. There are factors that affect model success in LSM modeling studies: the size of the study area, the sensitivity of the landslide data employed, the resolution of the DEM data, and the methodology of the preferred modeling approach. In this study, the model success level is good to very good. Although model success varies in the national and international literature, the overall model success ranges from 65% to 98.5% AUC for LSM studies (Kavzoglu et al. 2019). Studies with similar characteristics can be compared with this study: Kavzoglu et al. (2015) used nine factors to determine the AUC value as 98.5%; Zhou et al. (2021) used ten factors to determine the AUC value as



78.2%, and Pradhan et al. (2010) used nine factors to determine the AUC value as 97%.

In this study, alternative routes for a forest area in need of a forest road were determined through ArcGIS Cost Path analysis, and the LSM was obtained through LR and RF methods (Figures 7). Other studies also use ArcGIS Cost Path analysis for alternative route detection (Sari and Sen, 2017; Liampas et al. 2019). The difference between this and other studies is that it was conducted with the intention of determining route options that meet the need for roads in forest areas. Forest road alternative routes have been a subject of interest both nationally and internationally. Studies carried out with a similar approach, but using different methods and software, are as follows: Akay and Sessions (2005) determined GIS-supported three-dimensional routes by using TRACER software; Laschi et al. (2016) used the AHP approach for alternative road planning, but did not consider the landslide criterion used for this study; Bugday and Akay (2019) evaluated the landslide criterion for forest roads in landslide areas but did not determine any alternative routes, and Kadi et al. (2019) planned routes using MATLAB software and the AHP approach.

## CONCLUSION ZAKLJUČAK

In order to continue with uninterrupted forestry works throughout the year, it is important to make detailed road plans from the start and evaluate the advantages and disadvantages of the areas in terms of sustainability. Modern methods of determining alternative routes are vital in particularly sensitive areas. Plan and decision makers can make better decisions using detailed data obtained as a result of sensitive forestry studies. The length of the routes determined by this study are calculated to be approximately 2730 m, using the LR method, and 2850 m, using the RF method. More detailed and precise planning is needed in order to keep environmental damage caused by forest road construction to a minimum. Further studies that use multicriteria planning approaches and GIS software will be beneficial to forestry and forest management. It is clear that diversifying multifactor analyses in future studies, and making the results available to practitioners, planners, and decision makers, is important in terms of maximizing ecosystem health and minimizing human impact.

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## SUMMARY

Forestry activities should be carried out within the purview of sustainable forestry while reaping the benefits of forestry. Accordingly, the construction of forest roads through forests should be carefully planned, especially in protection forests. Forest areas in Turkey are generally widespread in mountainous and high sloping areas that are susceptible to landslides-landslide susceptibility is one of the most important criteria for the selection of protected forests. As such, it is important to evaluate detailed and applicable alternatives regarding special areas and private forests. The aim of this study is to determine alternative routes for forest roads in protected forests through the use of geographic information systems (GIS), particularly in areas with high landslide susceptibility. To this end, a landslide susceptibility map (LSM) was created using logistic regression (LR) and random forest (RF)

modeling methods, which are widely used in machine learning (ML). Two models with the highest receiver operating characteristic (ROC) and area under curve (AUC) values were selected, and ten factors (slope, elevation, lithology, distance to road, distance to fault, distance to river, curvature, stream power index, topographic position index, and topographic wetness index) were used. The best LSM modeling method was AUC. The AUC value was 90.6% with the RF approach and 80.3% with the LR approach. The generated LSMs were used to determine alternative routes that were calculated through cost path analysis. It is hoped that the susceptibility to landslides and selection of alternative forest road routes determined through the approaches and techniques in this study will benefit forest road planning as well as plan and decision makers.

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**KEY WORDS:** Forestry, alternative route detection, cost-path, Random Forest, Logistic regression