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Assessment of alternative forest road routes and landslide susceptibility mapping using machine learning

Ender Buğday [1✤iD], Abdullah Emin Akay [2iD]

[1] Çankırı Karatekin University, Faculty of Forestry, Forest Engineering Department, Çankırı, Turkey
[2] Bursa Technical University, Faculty of Forestry, Forest Engineering Department, Bursa, Turkey

FOREST MANAGEMENT

ABSTRACT

Background: Forest roads are among the most basic infrastructure used for forestry activities and services. To facilitate the increased amount of biomass harvesting adequately, the existing road network may require modifications to allow forest transportation within harvesting units that are not yet accessed by the roads. The construction of a forest road can trigger landslides, so the necessary constraints should be considered when the road is being planned to preclude such problems. Landslide Susceptibility Mapping (LSM) has become an integral part of the growing process of machine learning (ML), providing a more effective platform for practitioners, planners, and decision-makers. This study aims to reveal the most suitable alternative routes for a forest road, especially in areas susceptible to landslides, and to provide an effective tool for decision-makers.

Results: For this purpose, two models were developed through ML: Logistic Regression (LR) and Random Forest (RF). Elevation, slope, aspect, curvature, Topographic Wetness Index (TWI), Stream Power Index (SPI), distance from the fault, the road, and the stream, and lithology were considered as the main landslide susceptibility factors in these models. The best model was obtained by the RF approach with an Area Under ROC Curve (AUC) value of 81.9%, while the LR model was 78.2%. LSM data was used as a base, and alternative routes were obtained through CostPath analysis.

Conclusion: It has been shown that the ML methods used in this study can positively contribute to decision-making by providing more effective LSM calculations in studies to determine alternative routes in a forest road network.

Keywords: Roads routing problem, random forest, logistic regression, R software

HIGHLIGHTS

Route determination that can be passed with the least damage in landslide sensitive areas Innovative approach to computer aided forest road routing .
Planning of an environmentally friendly alternative forest road.

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✤Corresponding author e-mail: enthere@gmail.com
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INTRODUCTION

Landslides, which can occur almost anywhere in the world, are mass movements of land ranging from small areas to ones of considerable scale that threaten people and the environment and cause various degrees of loss and damage (Glade and Crozier, 2005). Landslides also have negative short and long-term economic consequences for those affected and may incur heavy costs (Klose et al., 2015). Many factors affect the formation of landslides. They include elevation (Sarma et al., 2020), slope (degree) (Saha and Saha, 2020), aspect (Lee and Min, 2001), curvature (Pourghasemi et al., 2018), the TWI (Nhu et al., 2020), the SPI (Gholami et al., 2019), distance from the fault (Shirzadi et al., 2017), distance from the road (Sun et al. 2020), distance from the stream (Wubalem and Meten, 2020), and lithology (Rosi et al., 2018). However, areas susceptible to landslides can be effectively classified in advance using GIS techniques. Therefore, having identified these susceptible areas, more detailed planning may be conducted, and measures taken to prevent negative outcomes. (Raja et al., 2017; Bugday and Akay, 2019).

In Turkey, forests are in mountainous, sloping regions with higher rainfall levels than the surrounding landscape and the removal of vegetation for road construction increases the risk of further landslides. With an increasing demand for wood as a raw material, new methods of construction are required. This is especially true in areas susceptible to landslides, where greater detail should be included in planning new forest roads to prevent damage and loss from landslides. Road construction also has a direct effect on the landslide since it results in an increase in all elements of the risk equation (Risk = Hazard × Exposure × Vulnerability) (Lummen and Yamada, 2014), while landslides damage various infrastructure facilities, such as roads and buildings (Cascini et al., 2013). It is vital, therefore, that Remote Sensing (RS) techniques and GIS are employed to minimize these damaging and negative effects or to avoid these risky areas while providing positive alternatives.

Landslide Susceptibility Mapping (LSM) modeling studies have grown in number and location throughout the world during the past 20 years, with the success rates of the models generated at between 65% and 98%. (Kavzoglu et al., 2019). Approaches to LSM modeling vary widely, and some of the most common approaches are highlighted in this study: AHP (Kayastha et al., 2013; Roccati et al., 2021; Grozavu and Patriche, 2021), ANFIS (Paryani et al., 2020; Chen et al., 2021), ANN (Chen et al., 2017), PSO-ANN (Moayedi et al., 2019), Weighting Factor (Yalcin, 2008; Hussain et al., 2021), Bayesian (Sun et al., 2021; Lee et al., 2020), Deep Learning (Dao et al., 2020; Ngo et al., 2021), Frequency Ratio (Senanayake et al., 2020; Berhane et al., 2020), Fuzzy Logic (Tsangaratos et al., 2018; Razifard et al., 2019), Logistic Regression (Schlögel et al., 2018; Chen et al., 2019), Machine Learning (Ghorbanzadeh et al., 2019, Kavzoglu et al., 2019, Mohammady et al., 2021), M-AHP (Nefeslioglu et al., 2012; Bugday and Akay, 2019), Multilayer Perceptron Neural Network (Li et al., 2019; Hong et al., 2020), SWARA (Dehnavi et al., 2015; Pourghasemi et al., 2019).

The main aim of the study was to reveal the most suitable LSMs to use when planning road construction projects in forests located in steep and sloping areas and to create a support system to determine the limitations of alternative routes. To this end, two different models were created through LR and RF modeling. Elevation, slope (degree), aspect, curvature, TWI, SPI, distance from the fault, the road, the stream, and lithology, were used in the modeling. Using data obtained from the models, suitable routes were created automatically by computer with the help of least CostPath analysis using ArcGIS software. The results were compared with those obtained from a traditional approach to route planning.

MATERIAL AND METHODS

Study Area

The study area is located in the central border of Zonguldak province in the north of Turkey and in Devrek Forest District (Figure 1). It is also located in an area where forest areas are widespread and landslides are experienced in Karadere locality. The study area is 29095 ha and located between the latitude of 41°16’22” and 41°20’24” and longitude of 31°47’40”, 31°56’18”. In the study area, there are pure and mixed stands of beech, hornbeam, sessile oak, black pine forests, which are generally in maturity for harvesting. These forests are managed according to the principles of Ecosystem-Based Functional Planning (ETFOP) according to their various functions (Zengin et al., 2011). The existing forest roads in the study area are low-standard B-type roads (6m road width and 4m road surface) which are defined according to the geometric classification of the General Directorate of Forestry (GDF).

Landslide Susceptibility Factors

The landslide susceptibility factors evaluated in this study include elevation, slope (degree), aspect, curvature, Topographic Wetness Index (TWI), Stream Power Index (SPI), distance from the fault, the road, and the stream, and lithology. Elevation is an effective factor in forest road planning because it increases both landslide sensitivity and cost in the performance of road construction (Akay, 2006). As elevation also means an increase in the distance to settlements, it additionally reduces the costs of periodic maintenance works (Bugday and Akay, 2019). Aspect is one of the factors that affects soil properties and the growing environment. Aspect was studied in eight different directions (Lee and Talib, 2005). The slope is one of the most effective factors in landslide formation (Ma et al., 2020). It is also an important factor as it has a direct effect on the construction costs for forest roads (Akay et al., 2008). In this study, International Union of Forest Research Organizations (IUFRO) slope classes

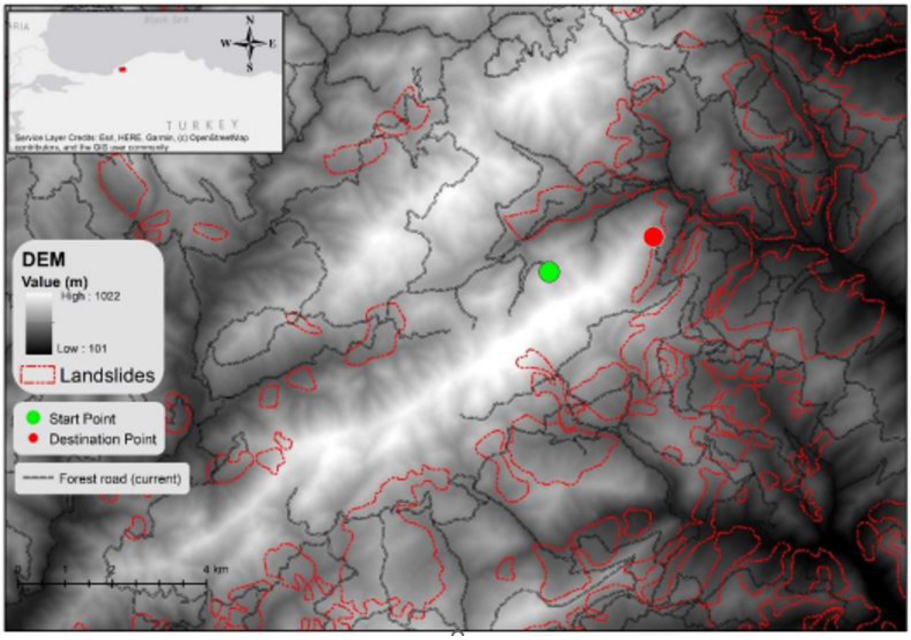


Figure 1. Location of landslides in the study area.

were expressed in five different degree classes, 0–5.71, 5.71–13.80, 13.80–21.88, 21.88–31.99, and >32. Curvature is among the factors that affect both the direction and severity of the landslide (Ohlmacher, 2007). The TWI is widely used to determine the location and size of areas saturated with water at the topographic level (Zhang et al., 2020). SPI is defined as the ability of flowing water to erode topography, considering the assumption that the flow is proportional to the specific basin area (Sameen et al., 2020). Distance from the fault is one of the factors that is widely used in landslide susceptibility studies and it plays an important role in triggering landslides (Demir, 2019). In this study, it was analyzed in five zones including 0.5 km, 1 km, 2 km, 5 km, and 10 km. Another important factor in triggering the landslide is the distance from the road (Sur et al., 2021). In this study, it was evaluated in six zones with intervals of 100 m, 250 m, 500 m, 1,000 m, 1,500 m, and 2,000 m. Distance from the stream is commonly used in studies where proximity relationship is important (Wang et al., 2017). In this study, stream distances were considered in four zones including 0.5 km, 1 km, 2 km, and 5 km. Lithology affects the cost of construction of forest roads because it reveals characteristics of the bedrock (Tang et al., 2021). In this study, lithology was evaluated in six different groups (Figure2).

The Digital Elevation Model (DEM) was obtained free of charge from ASTER GDEM, published on the web, and elevation, aspect, slope (degree), curvature, TWI, and SPI factors were generated using ArcGIS 10.3 TM software. Distance from the road was obtained by using forest subdistrict databases where the study area was located. The field data of lithology, distance from the fault and stream, and landslides that had occurred in the past, were obtained from the General Directorate of Mineral Research and Explorations (GDMRE) (Duman et al., 2011).

Generating LSM

In this study, the LSM tool pack developed by Sahin et al. (2020), working with R integration in an ArcGIS environment, was used to develop LSM. According to this tool pack, with LR and RF modeling, effective and more accurate LSM estimates can be made by using the above factors. Out of 108 landslides, 80% (86 landslides) of the data was used for training purposes and 20% (22 landslides) for testing.

ArcGIS 10.3 software was used to evaluate the factors with LR and RF methods. To validate the models obtained by these approaches, information on landslide events that had occurred in the past was tested. Models developed according to LR and RF were tested with Receiver Operating Characteristic (ROC) analysis and AUC value. The AUC score was classified as 0.9–1.0 (excellent), 0.8–0.9 (very good), 0.7–0.8 (good), 0.6–0.7 (moderate), and 0.5–0.6 (weak) (Swets, 1988). The model outputs were recorded as raster images.

Determination of Forest Road Routes

ArcGIS-CostPath analysis was used in automatically determining alternative roads' routes, which was the final stage of the study. This analysis included a methodology that allowed for an objective comparison of alternative scenarios for weighting factors (i.e. slope length, elevation, slope, positive cardinal points, production amount, etc.) that determine the location of a route (ESRI, 2016). The methodology used three scenarios to identify alternative routes that were compared to determine the effectiveness and susceptibility of this approach.

First, the route study started with the determination of the two points that were outside the existing roads that needed to be connected to each other and the alternative routes to be planned. Route limitation was made by the positioning of the starting and destination points. Planning

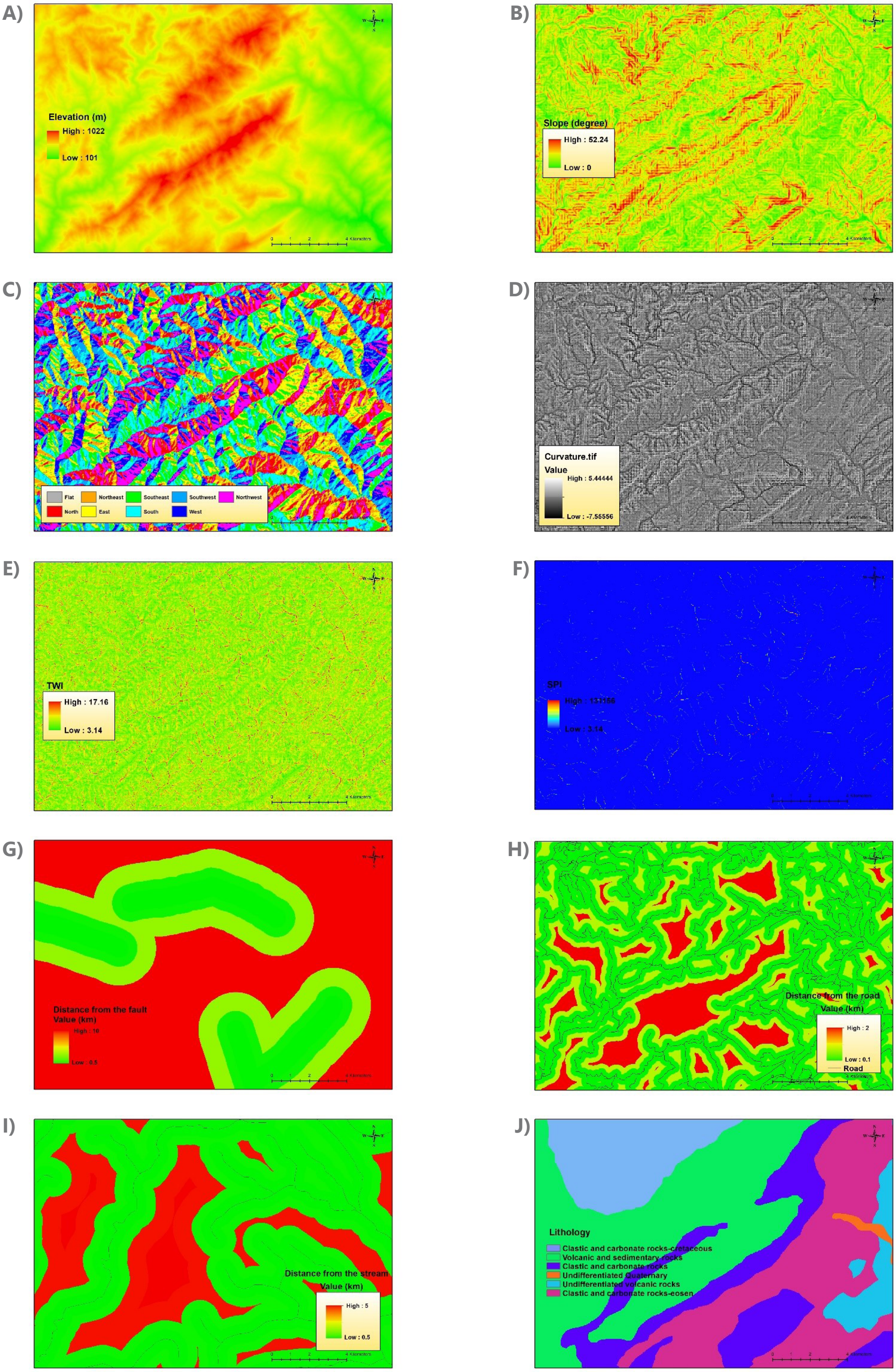


Figure 2. SM factors in forested area; (a) elevation, (b) slope (degree), (c) aspect, (d) curvature, (e) Topographic Wetness Index (TWI), (f) Stream Power Index (SPI), (g) distance from the fault, (h) distance from the road, (i) distance from the stream, and (j) lithology.

for the road was based on the slope criteria, which were obtained by traditional methods. In the next stage, the route was recalculated with the help of CostPath analysis, with consideration given to the data on landslide sensitivity that was obtained through the LR and RF methods. The workflow for this study is summarized in Figure 3.

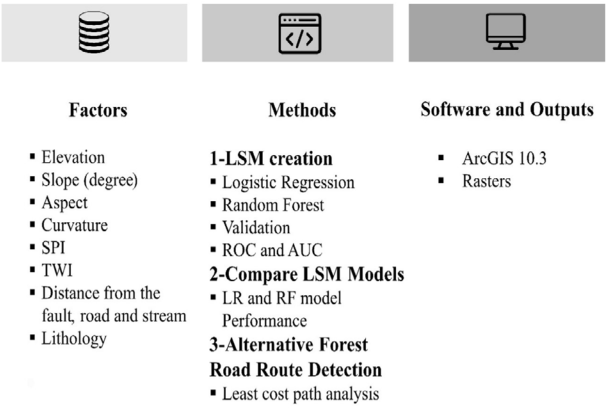


Figure 3. Flowchart of the study.

RESULTS

Digital Maps of Landslide Susceptibility Factors

Study area elevation values varied between 100 m and 1,020 m, with an average elevation of 500 m (Figure 3a). The dominant aspect of the study area was to the south. The average slope of the area was 16.1 ° and in the working area it was determined as 52.2 °. The length of the roads in the study area was calculated as 514 km in a total area of 29,094.6 ha.

LSM modeling and validation

In this study, models with ten factors were developed according to LR and RF modeling. The ROC, which highlights the model's performance in LSM studies, and the AUC, which expresses the area under this graph, were used for the validation. First, the importance of each factor was analyzed by the application of widely used statistical methods, chi-square, information gain, and random forest importance. Table 1 lists the results from high to low significance levels. As the table shows, each method produced different feature weights. In the rankings, it was observed that the first four factors were in the same order in this study, and there were differences in the rankings of other factors according to the statistical approach.

The next step was to evaluate the effects of these features on the performance of the prediction model. For this purpose, factors were included in the iterative estimation process in the LSM tool pack by placing them in ascending order according to their estimated importance. Estimates were made for a data set with an increasing number of factors at each iteration. From these estimates, the best subset, which included factors that provided high or equal estimation, was selected and the best models were determined. Various binary statistical tests (Wilcoxon signed-rank test, F-Test, Kolmogorov Smirnov test, and One Sample T-Test) are presented in the LSM tool pack (Table 2). In this study, the scenario using chi-square as the feature sorting algorithm and the F-Test to analyze the differences in the performance of the prediction algorithm in the best subset selection is discussed. All possible scenarios, which consider factor selection and statistical approaches, are shown in Table 2.

Logistic regression analysis

LR is a widely used modeling approach in studies on landslide susceptibility. The most successful models out of a total of ten factors using this approach are shown in Table 2. The AUC value (91.2172) of the Case 1 model was selected as the most successful according to the LR approach; estimate, standard error, z-value, and Pr values of the factors are given in Figure 4. This image presents a positive correlation between aspect, curvature, slope, SPI, lithology factors, elevation, TWI, and distance from the fault, the stream, and the road to the landslide formation. In addition, when the p-values were examined in terms of statistical significance in the study area, it was calculated that the factors of aspect, elevation, slope, lithology, distance from the fault, and distance from the stream were more important.

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

Nº	Factors	Chi-Squared	Factors	Information Gain	Factors	Random Forest Importance
1	Aspect	0.4521	Aspect	0.3882	Aspect	303.7328
2	Lithology	0.3385	Lithology	0.1246	Lithology	82.0112
3	Elevation	0.2444	Elevation	0.0983	Elevation	74.0761
4	Slope	0.1987	Slope	0.0217	Slope	58.8738
5	Dis.stream	0.1459	Dis.stream	0.0108	Dis.stream	32.6708
6	SPI	0.1307	SPI	0.0097	Dis.fault	29.2779
7	TWI	0.1140	TWI	0.0085	TWI	25.5365
8	Dis.road	0.1041	Dis.road	0.0077	SPI	23.3148
9	Dis.fault	0.0961	Dis.fault	0.0071	Dis.road	21.5252
10	Curvature	0.0739	Curvature	0.0055	Curvature	16.5537

Table 2. Best feature subset size by Chi-Square, Information Gain, and Random Forest Importance.

Feature ranking method	Case nº	Statistical test used for subset selection	Model Nº: The best subset size selected by performance of LR	Features in the best subset
Chi-Square	Case 1	F-test	Model 9	Aspect, Lithology, Elevation, Slope, Dis.stream, SPI, TWI, Dis.road, Dis.fault
	Case 2	Kolmogorov Smirnov test	Model 8	Aspect, Lithology, Elevation, Slope, Dis.stream, SPI, TWI, Dis.road
	Case 3	One Sample T-Test	Model 5	Aspect, Lithology, Elevation, Slope, Dis.stream
	Case 4	Wilcoxon signed-rank test	Model 9	Aspect, Lithology, Elevation, Slope, Dis.stream, SPI, TWI, Dis.road, Dis.fault
Information Gain	Case 5	F-test	Model 9	Aspect, Lithology, Elevation, Slope, Dis.stream, SPI, TWI, Dis.road, Dis.fault
	Case 6	Kolmogorov Smirnov test	Model 9	Aspect, Lithology, Elevation, Slope, Dis.stream, SPI, TWI, Dis.road, Dis.fault
	Case 7	One Sample T-Test	Model 8	Aspect, Lithology, Elevation, Slope, Dis.stream, SPI, TWI, Dis.road
	Case 8	Wilcoxon signed-rank test	Model 9	Aspect, Lithology, Elevation, Slope, Dis.stream, SPI, TWI, Dis.road, Dis.fault
RF-Importance	Case 9	F-test	Model 9	Aspect, Lithology, Elevation, Slope, Dis.stream, SPI, TWI, Dis.road, Dis.fault
	Case 10	Kolmogorov Smirnov test	Model 9	Aspect, Lithology, Elevation, Slope, Dis.stream, SPI, TWI, Dis.road, Dis.fault
	Case 11	One Sample T-Test	Model 5	Aspect, Lithology, Elevation, Slope, Dis.stream, SPI
	Case 12	Wilcoxon signed-rank test	Model 8	Aspect, Lithology, Elevation, Slope, Dis.stream, SPI, TWI, Dis.road

Random Forest analysis

RF is one of the most commonly used modeling approaches in studies on landslide susceptibility. Again, ten factors were used, and the most successful model obtained (Case 1) and the order of importance of the factors are shown in Figure 5.

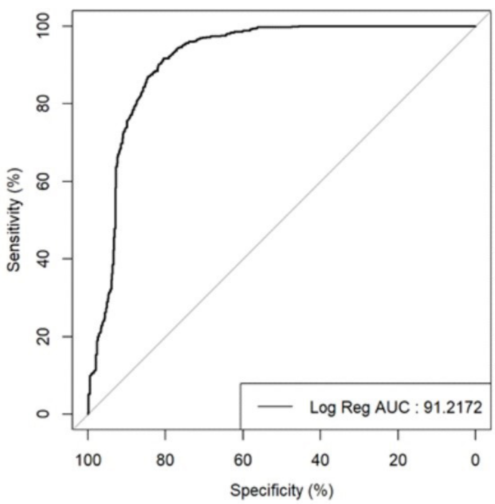
According to the results obtained here, the ranking based on the LR approach differed from the RF method. Ranking according to the RF approach was aspect, lithology, elevation, slope, distance from the stream, distance from the fault, TWI, SPI, distance from the road, and curvature. According to this rating and the IncNodePrutiy measure, it was calculated that the importance levels of the factors, aspect, lithology, elevation, and slope, were quite high when compared with other factors.

Performance Comparison of LR and RF modeling approaches

At this stage, the best performing LSM model (Case 1, Model 9) was compared according to LR and RF. The performance results are presented as a graphic and a table in Figure 6. Considering the results, it was determined that the best model was 9 in both approaches and it had good to very good model success with a RF-AUC score of 0.81 and a LR-AUC score of 0.78.

Alternative forest road route detection

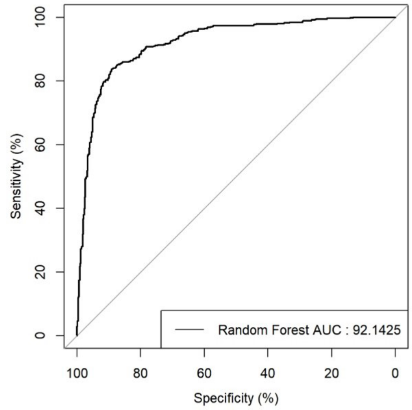
The study area generally consisted of beech stands that were at the cutting age. This area is among several locations that will not be opened for production in the



Coefficients:	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	-2.44E+03	4.34E+02	-5.618	1.93e-08 ***
Aspect	1.50E+01	6.19E-01	24.236	< 2e-16 ***
Curvature	1.15E+02	6.56E+01	1.747	0.08066
Elevation	-2.17E+00	3.92E-01	-5.523	3.34e-08 ***
Slope	4.91E+01	7.49E+00	6.561	5.36e-11 ***
SPI	3.12E-02	3.07E-02	1.015	0.31025
TWI	-3.75E+00	3.57E+01	-0.105	0.91639
Dis.from the fault	-1.19E+02	1.86E+01	-6.390	1.66e-10 ***
Lithology	6.08E+02	3.15E+01	19.342	< 2e-16 ***
Dis.from the stream	-2.15E+02	7.33E+01	-2.940	0.00328 **
Dis.from the road	-2.32E+02	2.03E+02	-1.143	0.25314

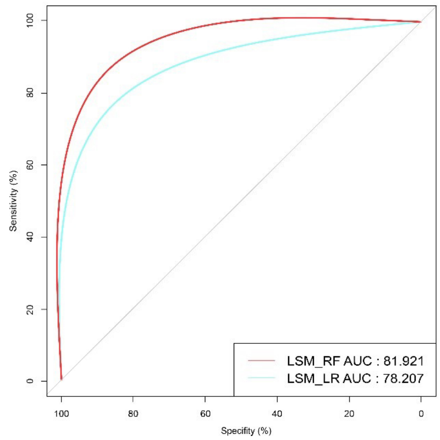
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
(Dispersion parameter for binomial family taken to be 1) - Null deviance: 4791.0 on 3455 degrees of freedom Residual deviance: 2680.6 on 3445 degrees of freedom - AIC: 2702.6 - Number of Fisher Scoring iterations: 5

Figure 4. LR model AUC score and statistics of factors.



Factors	IncNodePurity
Aspect	303.7328
Lithology	82.01112
Elevation	74.07609
Slope (Degree)	58.87383
Distance from the stream	32.67083
Distance from the fault	29.27797
TWI	25.53648
SPI	23.31486
Distance from the road	21.52524
Curvature	16.55361

Figure 5. RF model AUC score and statistics of factors.



	LSM_LR	LSM_RF
Accuracy	0.593731	0.649924
AUC.Classified	0.782068	0.819214
AUC.NonClassified	0.930554	0.995498
MAE	0.406269	0.350076
RMSE	0.637393	0.591672
Kappa	0.078754	0.10094
Precision	0.999051	1
Recall	0.580942	0.638429
F1	0.734675	0.779318

Figure 6. Models performance results of LR and RF approaches.

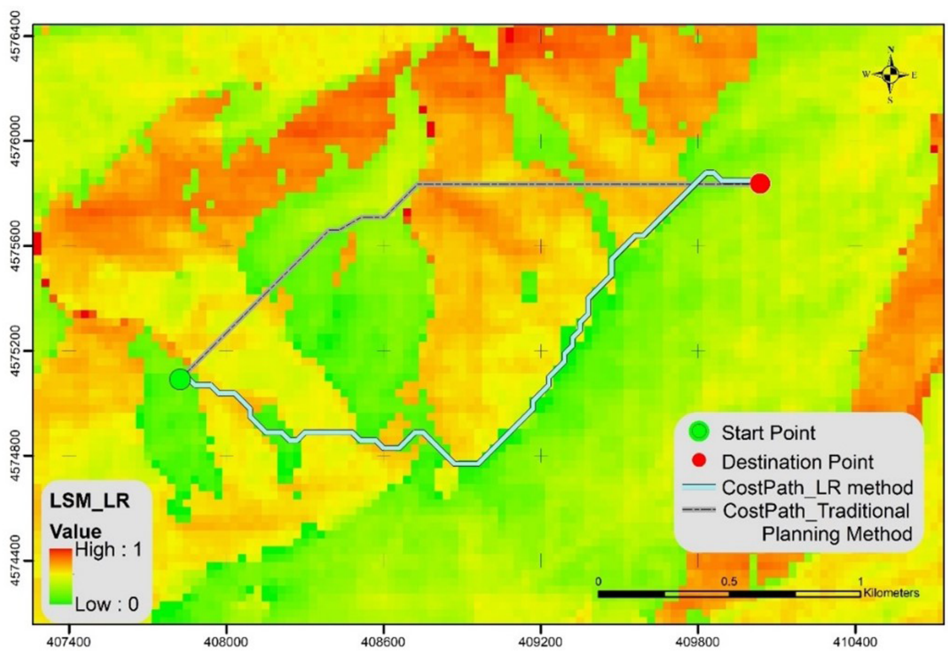


Figure 7. LSM generated from the LR method and CostPath road route.

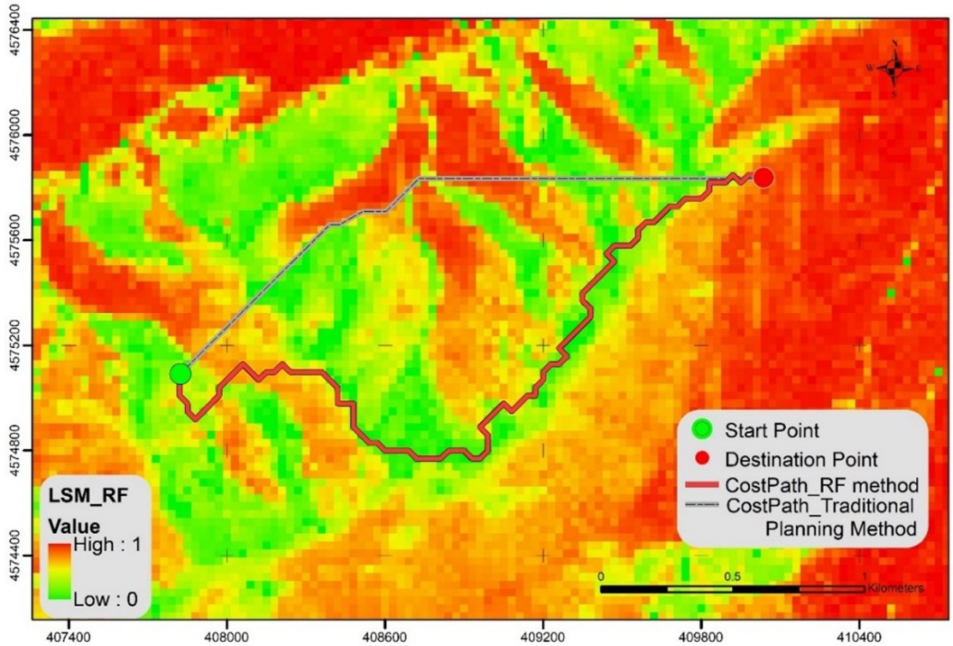


Figure8. LSM generated from the RF method and CostPath road route.

near future. Instead, it is planned to develop the stands to their optimum through continuing forest maintenance with the aim of producing quality timber product for the market. Results from the LR and RF approaches in the study showed that landslide susceptibility was quite high in the northern and eastern parts of the study area (Figures 7 and 8). Road construction was required in the study area. In this study, CostPath analysis was conducted using ArcGIS software. As a result of the planning, it was discovered that the route developed by traditional methods would pass through the middle of the area with high landslide susceptibility. In the analysis of route determination using LR and RF LSMs produced in this study, it was determined that alternative routes should pass through areas with very low susceptibility to landslides.

DISCUSSION

Forest road planning studies in Turkey have accelerated since the 1960s (Erdaş, 1997). With the widespread use of developing technologies, the determination of road routes and the construction works have been modernized. In addition to these developments, there has been a significant increase in software and the number of expert users of this technology. As in other sectors, GIS software is used for multi-criteria path planning and alternative routes in the forestry sector. The software contributes greatly to more effective decision-making in the planning process. It is especially important in providing advance information when determining which areas are susceptible to landslides and for providing a basis for studies to be carried out in those areas. The GIS system, therefore, is a convenient tool for decision-makers and planners in providing this transfer of information. In this study, LSM was developed according to two different approaches, LR and RF. The achievements of models in national and international literature vary according to approaches between approximately 65% and 98% AUC (Kavzoglu et al., 2019). The main factors affecting the success rates are the sensitivity and quality of the data, the size of the area studied, and the advantages of the approach used. In similar studies, Roccati et al. (2021) found the AUC value to be 73% according to nine factors; Grozavu and Patriche (2021) reported 75% according to three factors; Mohammady et al. (2021) found 73.8% according to 12 factors; and Kavzoglu et al. (2019) reached 96% according to eight factors.

The determination of alternative routes is generally searched to provide the location of the line required to optimally connect the starting and ending points (Bast et al., 2016). This study aimed to reveal alternative routes in a forest area that required location of a new forest road network. For this purpose, three different forest road routes (based on traditional method, LR, and RF methods) were introduced (Figure 7 and 8). As in this study, CostPath analysis is widely used in determining alternative routes. The difference in this study, however, is that the analysis of determining alternative routes was applied to the forest road. In a related study, Kadi et al. (2019) used AHP as a multi-criteria decision method and the route planning was made in MATLAB software. Picchio et al. (2018) implemented alternative road planning method, similar to present study, was used, but the landslide criteria were not considered by them. In another related study, Bugday and Akay (2019) evaluated landslide criteria in forest road planning, but alternative routes were not systematically searched.

CONCLUSION

Results from the model showed a susceptibility to landslide throughout the study area. Therefore, the introduction of alternative routes in such sensitive areas acquires greater importance. For effective planning, it is essential that the elements and stages of a plan are evaluated in greater detail to provide clearer information to the decision-maker. Considering the landslide criteria will provide a goal-oriented environment where costs can be calculated more consistently depending on the purpose of the road and its geometric features. The traditional length of the route determined by this study was approximately 2,500 m; while it was approximately 3,080 m according to the LR method, and 3,650 m according to RF. Depending on the purpose of the road, LR or RF routes may be preferred. Unplanned and inappropriately implemented forest roads may cause environmental damages, thus, it is important to minimize the possible damages through conducting detailed planning and proper implementation in the field. In addition, it is considered that multi-criteria planning with the help of GIS will be beneficial in the short and long term, especially in areas with landslide susceptibility, so that the service expected from forest roads can be ensured without interruption throughout the year.

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AUTHORSHIP CONTRIBUTION

Project Idea: EB, AEA
Database: EB, AEA
Processing: EB, AEA
Analysis: EB, AEA
Writing: EB, AEA
Review: EB, AEA

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