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Assessment of Forest Road Networks for Landslide Susceptibility: A Case Study of Northern Forest Area in Türkiye

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Abstract

Landslides, which usually occur in mountainous and hilly areas, occur as a result of the soil or rock material forming a slope moving down under the influence of gravity. Forested areas, mostly in mountainous regions, are susceptible to landslides. Forest roads are important infrastructure facilities to protect forest resources and to achieve sustainable management objectives. Forest roads provide many benefits such as facilitating the transportation of wood raw materials, preventing fires and providing access to areas where recreational activities are carried out. However, inappropriately opened forest roads in forest areas cause problems such as landslides, which cause both serious destruction of road networks and serious deformations in forest areas. Landslide-prone forest roads also cause serious economic losses due to disruption of product transport and road maintenance costs. Within the scope of this study, landslide susceptibility maps (LSMs) were produced to determine the relationship between landslides and landslide-causing factors in Handüzü Forest Management Unit of Kastamonu Regional Directorate of Forestry (KRDF) located in the Central Black Sea Region of Türkiye. Land use, altitude, slope, aspect, plan and profile curvature, topographic wetness index (TWI), distance to forest road, drainage networks and fault, crown closure and lithology were used as conditioning factors in the study. Logistic Regression (LR) and Support Vector Machine (SVM) based machine learning models were used to generate LSMs. The receiver operating characteristics (ROC) curve and area under the ROC curve (AUC) method were used to compare the performance of landslide susceptibility models. In the accuracy assessment using the prediction rate curve, the AUC value was 0.968 for the SVM model and 0.668 for the LR model. The AUC values confirmed that SVM performed much better than LR. In addition, the susceptibility of newly planned forest roads (not currently available in the field) in LSMs were determined in the study. As a result of the study, it was determined that the most effective factors affecting landslides in Handüzü Forest Management Directorate are distance to forest roads and drainage networks. In the analyses, it was found that 28.28% of the existing forest roads in the LSM produced with SVM and 56.57% in the LSM produced with LR were found to be in »high« and »very high« landslide susceptible areas. Similarly, 38.43% of the newly planned roads in the LSM produced with SVM and 52.23% in the LSM produced with LR were found to be in »high« and »very high« landslide susceptible areas. These findings showed that forest roads are the main factor in the occurrence of landslides in the study area. Therefore, taking LSMs into account in the planning of forest roads will contribute to reducing the damages that may occur in forest areas due to landslides.

Keywords: landslide susceptibility mapping, Handüzü forest management unit, Logistic Regression (LR), support vector machine (SVM), distance to forest roads, Kastamonu

1. Introduction

Türkiye is situated in a risk-prone geographical area where many natural disasters occur. Landslides, forest fires, floods and inundations, erosion and soil slips, droughts and earthquakes are among the most common natural disasters encountered in Türkiye and worldwide (Görüm and Fidan 2021, Chang and Ross 2024, Lestari et al. 2024). In Türkiye, landslide is the most frequent natural disaster after earthquake (Özşahin 2015). Landslides are mass movements in which soil, rock, or a combination of these materials move downward and outward on a slope, triggered by factors such as human activities, improper land use, heavy rainfall and seismic activities (Soeters and Van Western 1996, Varnes 1978). Landslides are more dangerous than many other natural disasters because they can damage natural resources and manmade structures, leading to loss of life and property (Saha et al. 2002). Landslides caused an average of 838 deaths per year worldwide between 2002 and 2021 (CRED 2023). Therefore, the issues caused by landslides should not be underestimated.

Although forests generally effectively prevent shallow landslides, they can have negative effects in areas prone to deep-seated landslides. An ideal forest may not completely prevent shallow landslides but can significantly reduce their occurrence (Chiaradia 2016). However, as forests are generally located in steep areas, their effectiveness in mitigating landslides significantly decreases when the slope reaches very high angles (Fang et al. 2023, Castellazzi and Previtali 2024, Hong–In et al. 2024, Phillips et al. 2024). In the context of natural slopes, shallow landslides typically occur at slopes ranging from 15 to 25° for earth flows and from 20 to 45° for debris flows. Slopes exceeding 45° in gradient are often characterised by a paucity of soil, thereby hindering the occurrence of sliding. Rockfalls, a landslide phenomenon as defined by Varnes (1978), manifest on exceedingly steep slopes, defined as those with a gradient of 45° or greater (FAO 2013). In forested areas, factors contributing to landslides include natural causes, such as slope gradient, cut-fill ratio, soil type, regional geology, climate, elevation, earthquakes, vegetation and rock type. Human-induced factors such as improper selection of settlement areas, unplanned and irregular urbanisation, incorrect land use, property issues and deforestation also play a role (Highland and Bobrowsky 2008, Sarker and Rashid 2013, Sarma et al. 2020, Bao et al. 2023, Moon et al. 2024). However, as landslides are influenced by multiple factors, predicting their occurrence remains challenging despite ongoing research efforts (Ma et al. 2021, Sreelakshmi et al. 2022, Casagli et al. 2023).

Forest roads are the most important infrastructure facilities in forestry (Türk 2022). Forest roads enable the economical transportation of products resulting from production activities, provide access to compartments and sub-compartments for silvicultural interventions, facilitate continuous movement of personnel and materials for forest protection activities and help resolve transportation issues between forest villages. In this context, forest road infrastructure that provides economic, social and cultural benefits to the country and society should be planned considering various environmental and forestry-related factors (Laschi et al. 2019, Akay et al. 2021).

Landslides are among the major factors that damage forest roads, which are crucial to forestry operations (Türk et al. 2024). Considering these developments, identifying suitable forest road routes is crucial for developing forest policies. The planning of road networks starts with a study of the topographic and geological conditions. Designing forest road networks while considering numerous factors is crucial for ensuring road continuity, as well as for the country's economy and environmental impact (Akay et al. 2020, Toscani et al. 2020, Acosta et al. 2023).

Given that landslides cause economic losses and loss of life, susceptibility studies aimed at reducing landslide damage and informing land use planning are crucial. Landslide susceptibility maps (LSM), which are critical for preventing or mitigating landslide damage, show the distribution and likelihood of areas prone to landslides after identifying the factors causing these events and by representing past landslide occurrences in an inventory. This is achieved through various analyses (Raja et al. 2017, Bugday and Akay 2019). Geographic information system (GIS) technologies are widely used for storing large amounts of data, evaluating it through statistical analyses and applying machine learning (ML) and artificial intelligence methods in landslide susceptibility analysis (Aleotti and Chowdhury 1999, Dikshit et al. 2020). To produce LSMs, statistical methods, such as frequency ratio (FR), and ML techniques, such as logistic regression (LR) and artificial neural networks (ANN), are widely used because of their effectiveness. In this context, numerous studies have evaluated ML methods for producing LSMs and assessing forest roads affected by landslides based on various factors. Sur et al. (2021) determined the areas with higher landslide susceptibility using the ensemble model of GIS-based multi-criteria decision making through fuzzy landslide numerical risk factor model along the Kalsi-Chakrata road corridor of Uttarakhand. Eker and Aydın (2014) created a landslide susceptibility map considering eight factors identified for their study area. The produced map was then overlaid with the road network map of the area to evaluate the conditions of forest roads in terms of landslide risk. Ghorbanzadeh et al. (2020), Kavzoglu et al. (2019), Arabameri et al. (2020), Shahabi et al. (2015) and Thanh et al. (2020) conducted landslide susceptibility analyses using ML methods to create LSMs. Mumcu Kucuker (2024) conducted a study in which landslide susceptibility analyses and maps were produced using ArcGIS software, and landslide-prone forest roads were identified using the analytical hierarchy process (AHP).

Pham et al. (2016) used various ML techniques (support vector machine [SVM], LR, Fisher's linear discriminant analysis, Bayesian network and naive Bayes) to assess landslide susceptibility in 930 landslide areas. Wang et al. (2016) proposed a landslide prediction model using LR, FR, decision trees, weights of evidence (WoE) and ANNs. Chen et al. (2018) proposed a landslide vulnerability model using the random forest (RF) algorithm based on digital elevation models and Landsat 8 data. Xiao et al. (2020) proposed a landslide vulnerability model using hybrid models that combine RF, FR, the certainty factor and the index of entropy (IOE).

In the present study, LSMs were produced for the Handüzü Forest Management Unit, which is part of the Karadere Forest Management Directorate under the Kastamonu Regional Directorate of Forestry (KRDF) in the north-western region of Türkiye. In LR and SVM based landslide susceptibility models, conditioning factors such as altitude, aspect, crown closure, distance to drainages, distance to faults, distance to roads, land use, lithology, plan curvature, profile curvature, slope and topographic wetness index (TWI) were considered. The results obtained showed that the existing forest roads are effective in the occurrence of landslides in the study area. As in many countries, major repair works are carried out on forest roads in Türkiye, and 702 km of forest roads were subjected to major repair in the investment programme of the General Directorate of Forestry in 2021 with a budget of 15,939,000 TL (1,797,000 $, according to the average dollar exchange rate of the Central Bank of 2021) (Türk 2022). Therefore, it is predicted that considering landslide susceptibility in the determination of new forest road routes to be opened will reduce major repair costs. Our study will contribute to the literature in taking measures against the factors affecting landslides by using reliable landslide susceptibility models for different regions with landslide risk worldwide.

2. Materials and Methods

2.1 Study Area

Handüzü Forest Management Unit is located within the Kastamonu Province, Central District. It is ad-

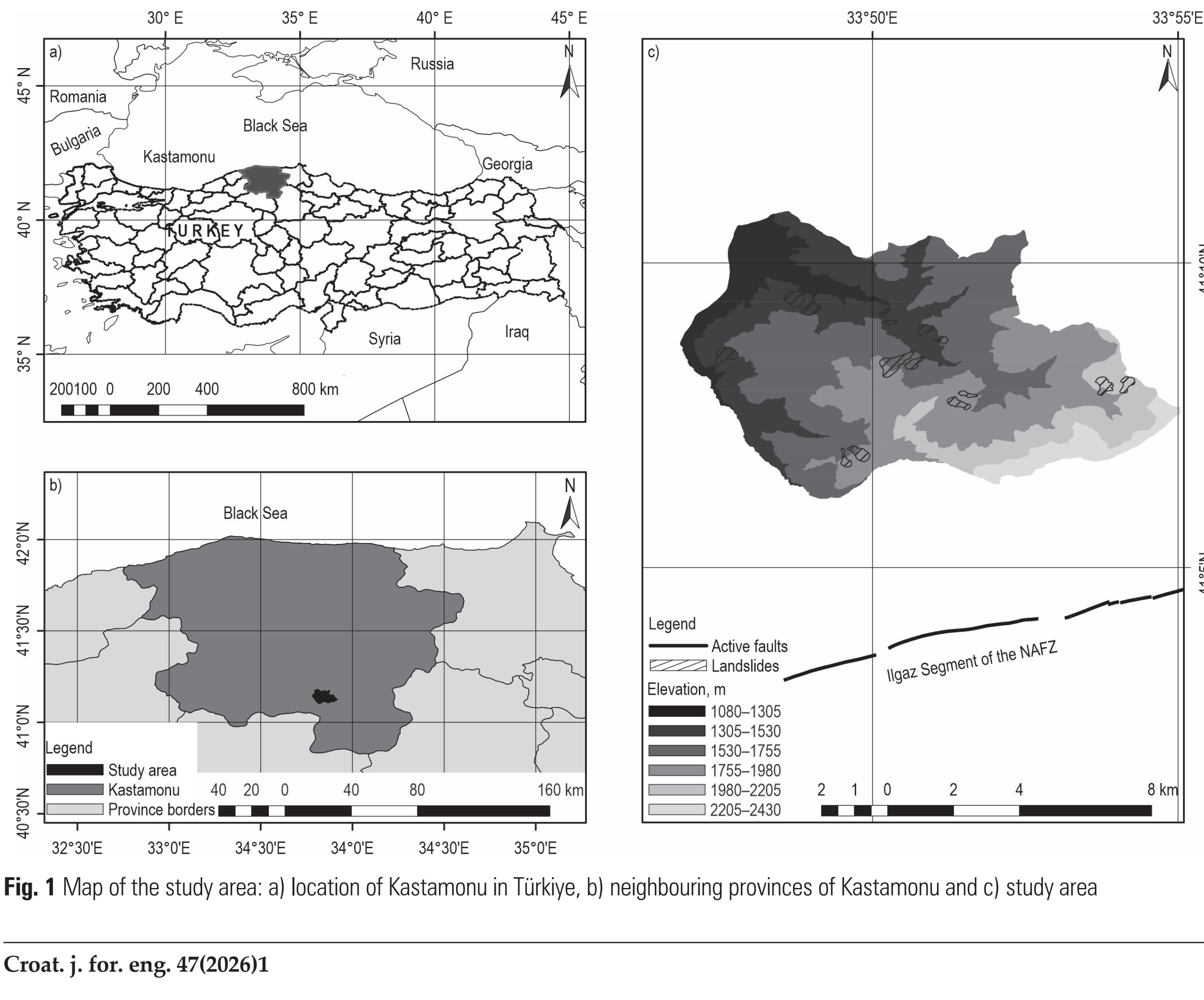

Fig. 1 Map of the study area: a) location of Kastamonu in Türkiye, b) neighbouring provinces of Kastamonu and c) study area

ministratively affiliated to KRDF, Karadere Forest Management Directorate. The study area covers 6093.48 ha located between latitudes 41°06'4.01'' and 41°10'47.72'' North, and longitudes 33°46'49.79'' and 33°55'1.82'' East (Fig. 1).

The study area, with elevations ranging from 1080 m to 2430 m and slopes varying between 0° and 61.19° (181.8%), has mountainous and rugged terrain. The average slope is 20.19° (36.77%), and approximately 51% of the area has slopes exceeding 20° (36.4%). According to the KRDF data, the study area consists of 76.8% coniferous forests, 0.87% broadleaf forests, 6% mixed forests, 13.3% forest clearings, 1.69% degraded forests, 1.1% agricultural lands, 0.13% settlement areas and 0.11% forest warehouses.

There are seven lithological units in the study area (Fig 2). The Triassic-Liassic Bekirli Formation (TRJb), consisting of sedimentary fill; schist; gneiss; and blocks of limestone, marble, metaserpentine, metadiorite, metagabbro and metaquartzite, is the oldest unit in the study area. The Upper Jurassic-Lower Cretaceous Susuz Formation (JKsu) comprises sandstone, siltstone, claystone, sandy-clayey limestone and volcanic rocks

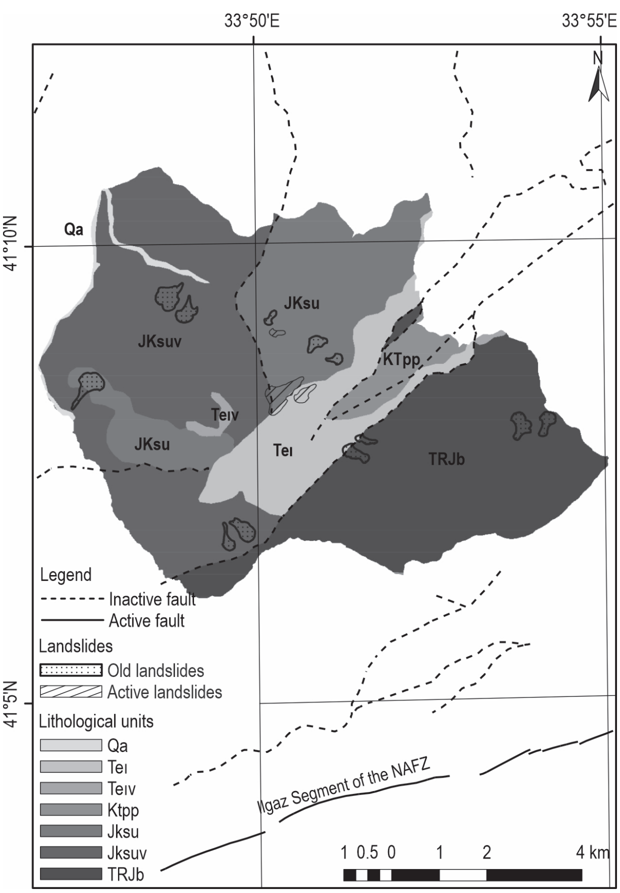

Fig. 2 Lithological map of the study area

(diorite, andesite, diabase and tuff). The Early Cretaceous-Turonian Volcanic Member (JKsuv) of the Susuz Formation, appearing as intercalated contributions, primarily consists of volcanic rocks. The dominant rocks in this unit are andesite, basalt, diabase, dacite, spilite and tuff, along with granodiorite, diorite, dacite and diabase dykes cutting through these formations. The Maastrichtian-Palaeocene Pervanekaya Formation (KTpp) comprises conglomerate, gravelly sandstone, sandy limestone and limestone. The Lutetian Ilıca Formation (Teı) comprises conglomerate, sandstone, sandy limestone, limestone and volcanic rocks. The Lutetian Akyörük Volcanic Member (Teıv) comprises basalt-andesite, tuff and agglomerates. Quaternary alluvium (Qa), represented by river and floodplain sediments, comprises gravel, sand and silt-clay deposits (Sevin and Uğuz 2011).

According to the Earthquake Zone Map published in 1996, Kastamonu Province is located in the North Anatolian Fault Zone (NAFZ) and has a total population of 388,990, with 46% of its surface area in Seismic Zone I, 22% in Seismic Zone II, 24% in Seismic Zone III and 8% in Seismic Zone IV (Özmen 2011). According to the 1996 Earthquake Zone Map, the areas under the responsibility of the Karadere Forest Management Unit are also in Seismic Zone I. The 39 km long Ilgaz Segment, which lies on the NAFZ and is responsible for major earthquakes and loss of life, passes 5 km south of the study area (Fig. 2). The right-lateral strike-slip NAFZ is one of the most destructive fault fractures among active faults in the world. NAFZ, a significant fault system on the continental crust, starts from the Karlıova Triple Junction in the east and extends approximately 1200 km westward to the Saros Gulf, forming a broadly convex, northward-curving structure that roughly parallels the Black Sea coast (Ketin 1948, Barka 1996). The destructive seismic activity of the NAFZ was first recognised in the 1939 Erzincan earthquake (Ms=7.8). Since then, notable earthquakes have occurred along the NAFZ, including Niksar-Erbaa in 1942 (Ms=7.1); Ladik in 1943 (Ms=7.3); Bolu, Gerede and Cerkes in 1944 (Ms=7.3); Kursunlu in 1951 (Ms=6.8); Abant in 1957 (Ms=6.8); Mudurnu in 1967 (Ms=7.0); and Düzce in 1999 (Ms=7.2) (Sarp et al. 2013). The Kargı-Ilgaz segment, located 5 km south of the study area, is one of the segments in the NAFZ that has the potential to produce earthquakes with magnitudes ranging between 4–6 (Erturanç and Tüysüz 2010).

2.2 Landslide Inventory

In the present study, a 1:25,000–scale landslide inventory produced by the General Directorate of Mineral Research and Exploration (GDMRE) was used. According to the inventory data, 15 landslides occurred in the study area. Of these landslides, 12 are classified as old (inactive or passive) and three as active (Fig. 2). When the distribution of landslides according to lithological units is analyzed, it is seen that 36.56% occurred in the Early Cretaceous-Turonian aged Volcanic Member (JKsuv), 32.16% in the Susuz Formation (JKsu), 22.01% in the Bekirli Formation (TRJb) and 9.27% in the Ilica Formation (Teı). When the distribution of landslides according to slope classes was analysed, it was found that 16.35% of the landslides occurred between 10–15° slope range, 28.09% between 15–20° slope range, 25.93% between 20–25° slope range, 15.48% between 25–30° slope range and 7.68% between 30–35° slope ranges. The average area of the landslide polygons is 10.56 ha, ranging from 6.50 ha to 26.29 ha. The total area of landslides is 158.35 ha. This constitutes approximately 2.6% of the study area. This ratio is suitable for landslide susceptibility modelling, as it is possible to come across studies in the literature where landslides constitute approximately 2% or 3% of the study area. For example, in the landslide susceptibility study conducted by Usta et al. (2024), it was reported that landslide polygons cover 2% of the study area. Another landslide susceptibility mapping study conducted by Akinci et al. (2022) in Şavşat district of Artvin province (Türkiye) reported that landslides covered approximately 3% of the study area.

The landslide polygons comprise 15,819 pixels with 10 m spatial resolution. During the training and validation phases of ML models, both landslide and non-landslide pixels are required (Yao et al. 2023). Therefore, 15,819 non-landslide pixels were randomly selected from the study area. In accordance with similar previous studies, 70% of the landslide (positive) and non-landslide (negative) pixels were used for model training, whereas 30% were used for model validation (Pourghasemi et al. 2021, Kavzoglu and Teke 2022, Yavuz Ozalp et al. 2023, Usta et al. 2024).

2.3 Landslide Conditioning Factors

Because of their varying topographic, geological, environmental and climatic characteristics, landslides have occurred in various regions of the world (Zhou et al. 2024). There are no widely accepted guidelines for selecting conditioning factors. Liu et al. (2022) conducted a bibliometric analysis and stated that there are 12 factors commonly used in LSM studies. These factors include slope, aspect, lithology, elevation, distance to rivers, distance to faults, land cover/use, distance to roads, precipitation, TWI, plan curvature and profile curvature. In this study, the following 12 factors were used for landslide susceptibility analysis based on the literature and the geo-environmental characteristics of the study area: altitude, slope, aspect, plan curvature, profile curvature, TWI, land use, lithology, distance to drainages, distance to faults, distance to roads and crown closure (Fig. 3, Fig. 4).

Digital topographic maps of the study area were obtained from the General Directorate of Mapping. The digital elevation model (DEM) with 10 m spatial resolution was produced from the topographic maps. Slope, aspect, plan curvature, profile curvature and TWI were generated from the DEM. The drainage network of the study area was obtained from the DEM using SAGA GIS 9.0.1 software. The distance to the drainage map was produced using the »Euclidean Distance« function in ArcGIS 10.5 software. A geological map of the study area was obtained from GDMRE (Table 1). Lithology and faults data were obtained from the geological map. The distance to faults map for the study area was generated using the »Euclidean Distance« function in ArcGIS 10.5 software. The forest management plan of the study area was obtained from the KRDF. Land use and crown closure were derived from this dataset. Using the road network data in the forest management plan, the distance to the roads map of the study area was produced using the »Euclidean Distance« function in ArcGIS 10.5 software.

Table 1 Landslide conditioning factors used in this research

Original data	Factors	Scale	Source
Topographical maps	Altitude	1:25000	General Directorate of Mapping (GDM)
	Slope		
	Aspect		
	Plan curvature		
	Profile curvature		
	Distance to drainages		
	TWI		
Forest management plan	Land use	1:25000	Kastamonu Regional Directorate of Forestry (KRDF)
	Crown closure		
	Distance to roads		
Geological map	Lithology	1:25000	General Directorate of Mineral Research and Exploration (GDMRE)
	Distance to faults		

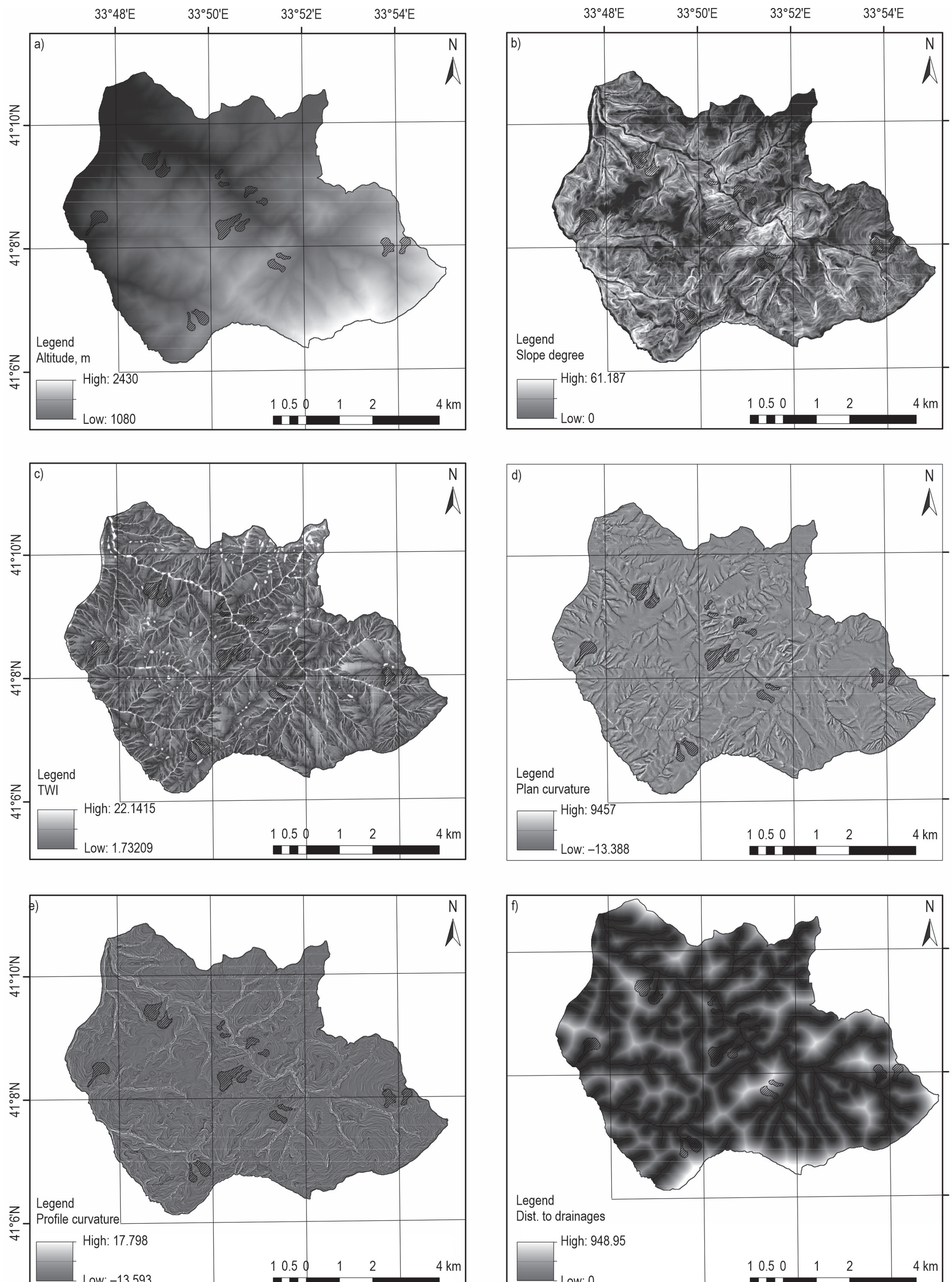

Fig. 3 Conditioning factor maps: a) altitude, b) slope, c) topographic wetness index (TWI), d) plan curvature, e) profile curvature and f) distance to drainage

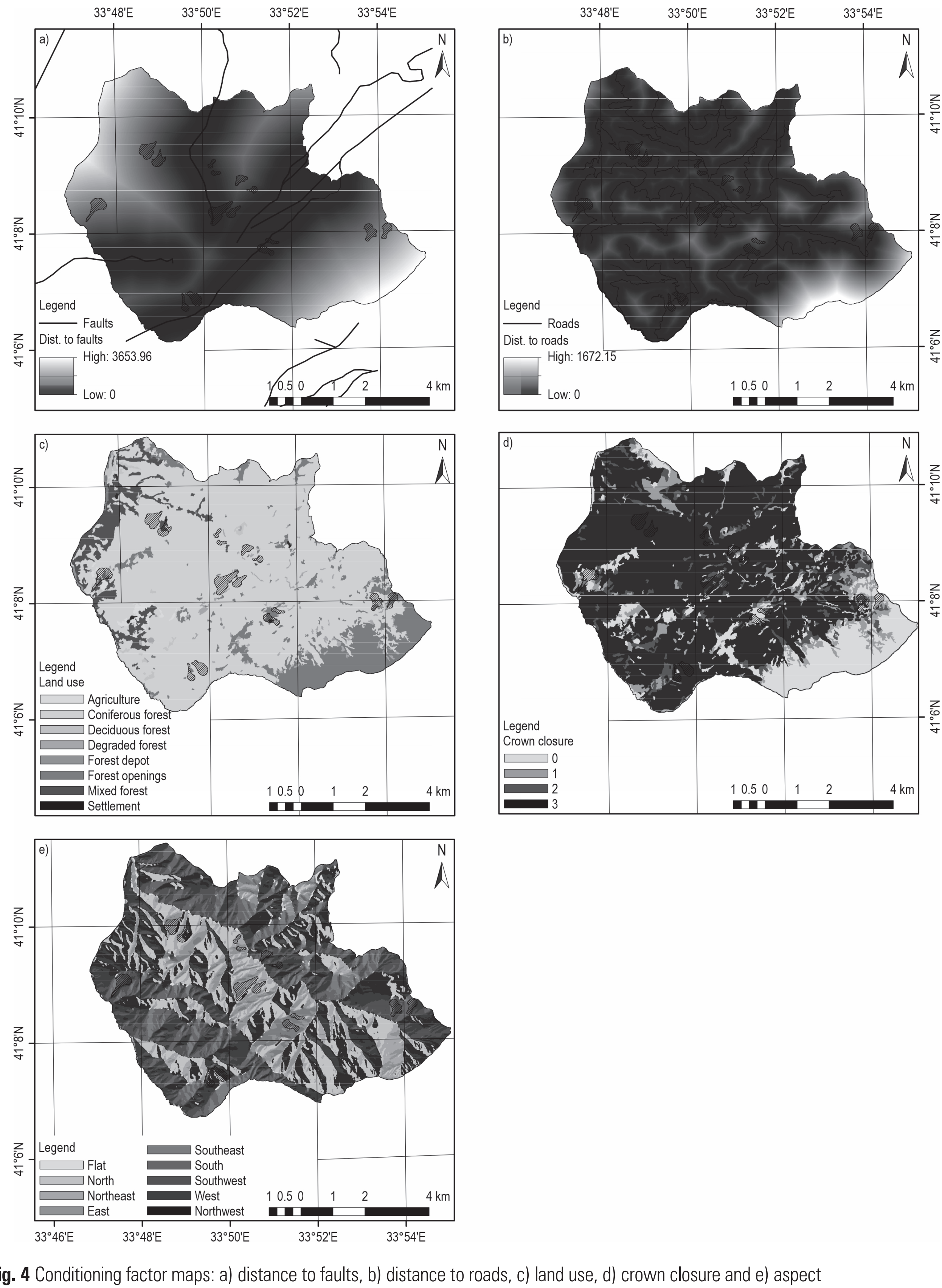

Fig. 4 Conditioning factor maps: a) distance to faults, b) distance to roads, c) land use, d) crown closure and e) aspect

2.4 Methodology

The aim of this study was to produce landslide susceptibility maps of Handüzü forest management unit and to determine the factors affecting the occurrence of landslides in the study area. The study generally followed the following methodology:

- ⇒ collection of spatial data (topographic maps, forest management plan, geological map) from public institutions
- ⇒ production of Digital Elevation Model (DEM) of the study area
- ⇒ production of conditioning factor maps
- ⇒ obtaining landslide inventory data, creating training and test data sets
- ⇒ performing multicollinearity analysis to test whether there is a strong correlation between the factors
- ⇒ applying LR and SVM models in R program, generating LSMs, determining the importance of conditioning factors and comparing the performance of the models using test data set.

The operations under the first four items are explained in detail in sections 2.2 and 2.3. Detailed information about Multicollinearity analysis, LR and SVM models are given in the following sections (Sections 2.4.1, 2.4.2 and 2.4.3).

2.4.1 Multicollinearity Analysis

Multicollinearity occurs in a regression model when there is a relationship or correlation between two or more independent variables (explanatory variables), which can cause problems in the model results (Daoud 2017, Kim 2019). The problem of multicollinearity reduces the predictive accuracy of the model, which leads to misleading results, decreases the statistical significance of the independent variables, and thus causes incorrect interpretation of the model results (Kim 2019, Chen and Chen 2021, Kavzoglu and Teke 2022).

As with all regression analysis studies, it is important to verify the independence of variables in ML-based landslide susceptibility mapping studies. In this context, the selection of proper variables is achieved through multicollinearity analysis (Chen et al. 2018, Aslam et al. 2023). Variance inflation factors (VIF) and tolerance (TOL) are widely accepted as the most common statistical indicators for determining multicollinearity (Daoud 2017, Pourghasemi et al. 2018, Nohani et al. 2019, Akinci and Yavuz Ozalp 2021). VIF indicates the increase in the variance of a regression coefficient because of multicollinearity. TOL, the inverse of the VIF value, represents the amount of variation in an independent variable that is not explained by other independent variables. TOL values <0.10 indicate multicollinearity. Variables with a VIF value >10 or a TOL value <0.1 are considered multicollinear and should be removed from the model (Daoud 2017, Wang et al. 2019, Dağ et al. 2020, Hong et al. 2020, Wei et al. 2022).

2.4.2 Logistic Regression

LR enables the establishment of a multivariate regression relationship between a dependent variable and more than one independent variable (Lee and Pradhan 2007). The LR model can be used to evaluate the spatial relationship between the occurrence of landslides and the conditioning factors that influence landslides (Lee et al. 2007). The purpose of LR in landslide susceptibility mapping is to find the most appropriate model for describing the relationship between the presence or absence of a landslide and a number of independent factors, such as lithology, slope and distance to fault (Ayalew and Yamagishi 2005, Shahabi et al. 2015). The LR model can be calculated using the following Eq. 1.

$$P = \frac{1}{(1 + e^{-z})} \tag{1}$$

Where:

P is the probability of landslide occurrence. The value of P varies between 0 and 1 and z varies between −∞ and +∞

Z is defined by the following Eq. 2.

$$z = b_0 + b_1 x_1 + b_2 x_2 + \cdots + b_n x_n \tag{2}$$

Where:

b_0 is the intercept of the model

n is the number of independent variables

x_i (i = 1, 2, 3,..., n) are independent variables

b_i (i = 1, 2, 3,..., n) are coefficients measuring the contribution of independent variables (Kavzoglu et al. 2014).

In this study, the »glm« method of the »caret« package (Kuhn 2008) in RStudio Desktop (Version: 2023.12.1) was used to perform LR.

2.4.3 Support Vector Machine

SVM, which is used in many supervised learning tasks and is theoretically based on solid foundations, was first designed by Cortes and Vapnik (1995). In SVM, which is commonly used for classification problems and extended to solve regression tasks, the fundamental idea is to find a hyperplane that separates the data in a sample dataset into two classes when considered in the context of binary classification (Boswell 2002). In cases in which the data cannot be linearly separated, SVM uses kernel functions such as linear kernels, polynomial kernels, sigmoid kernels, or radial basis function (RBF) kernels to achieve linear separation. The kernel function commonly used in landslide susceptibility mapping studies is the RBF (Akinci and Zeybek 2021, Akinci et al. 2022, Ye et al. 2023). In this study, the »svmRadial« method of the »caret« package (Kuhn 2008) was used in RStudio Desktop (Version: 2023.12.1) to implement the SVM algorithm. In most ML algorithms, there are parameters known as hyperparameters that need to be adjusted before the model training phase to construct a robust model. The RBF-based SVM has two important hyperparameters. These are *c*, also known as cost parameter, and gamma (γ). The caret package uses sigma (σ) instead of γ to control the shape of the separating hyperplane (Bhatia and Chiu 2017, Akinci et al. 2022). In the caret package, there are two ways to tune the hyperparameters of an algorithm: tuneLength and tuneGrid. The tuneLength allows the system to tune the algorithm (i.e., the hyperparameters) automatically. In this study, the tuneLength approach was used to tune the hyperparameters. In practice, the tuneLength value was set to 6, and the parameters were c=8 and σ=0.065.

3. Results

3.1 Results of Multicollinearity Analysis

The results of the multicollinearity analysis conducted for the study area are presented in Table 2. As the VIF values of the factors were <10, there was no multicollinearity among the conditioning factors and all factors were used in the susceptibility analyses.

Table 2 Results of multicollinearity analysis for landslide conditioning factors

Conditioning factors	VIF	TOL
Altitude	1.81023	0.55242
Aspect	1.04235	0.95937
Crown closure	1.66855	0.59932
Distance to drainages	1.25534	0.79659
Distance to faults	1.39802	0.71529
Distance to roads	1.53196	0.65276
Land use	1.45700	0.68634
Lithology	1.06071	0.94276
Plan curvature	1.25031	0.79980
Profile curvature	1.08854	0.91866
Slope	1.24923	0.80049
TWI	1.34909	0.74124

3.2 Landslide Susceptibility Mapping

The landslide susceptibility index (LSI) values calculated by LR and SVM based ML models for each pixel were classified into five subclasses – very low, low, moderate, high and very high – using the natural breaks classification method, and thus the susceptibility maps of the study area were obtained (Fig. 5).

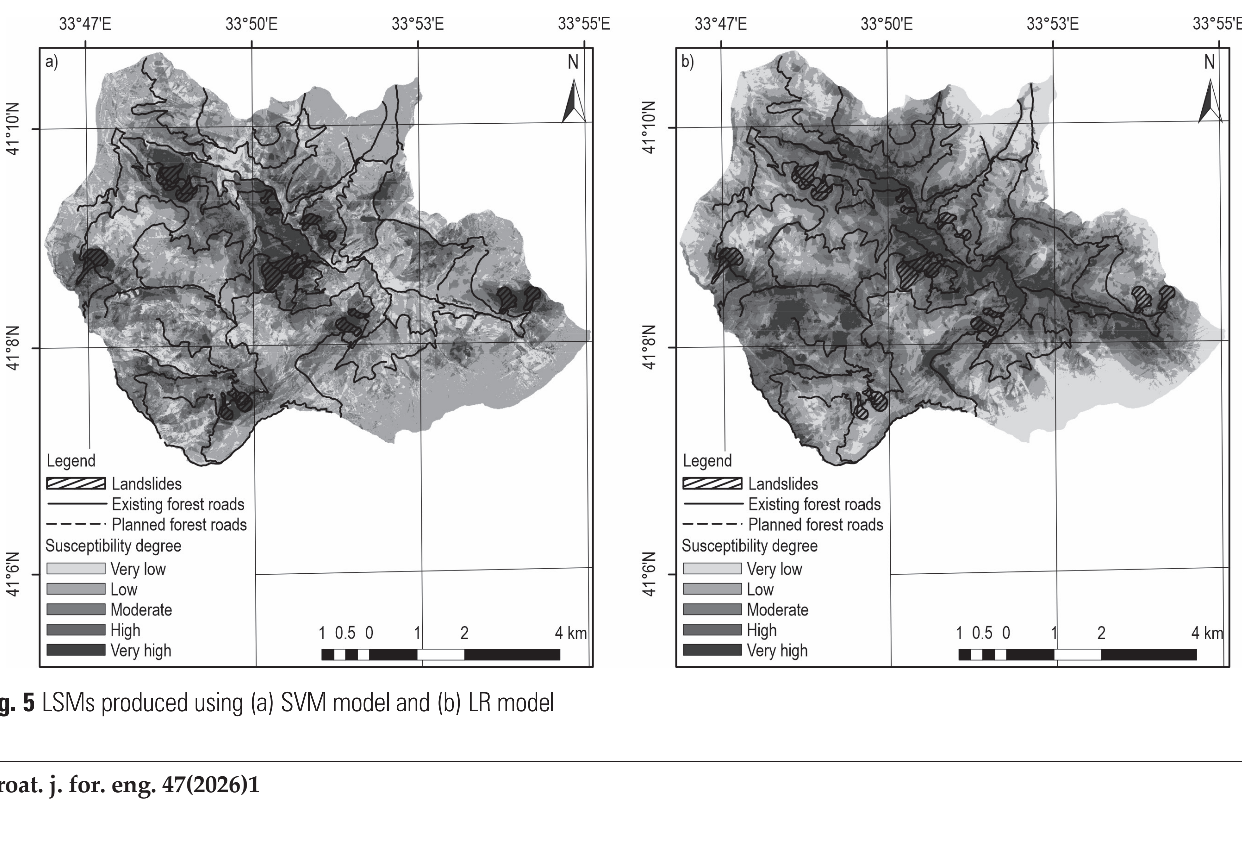

Fig. 5 LSMs produced using (a) SVM model and (b) LR model

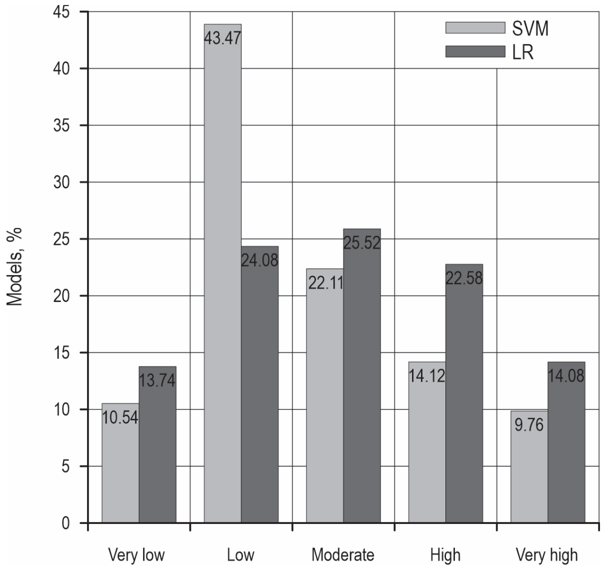

Fig. 6 Percentage distribution of susceptibility classes

According to the SVM model, 10.54% of the study area was classified as very low, 43.47% as low, 22.11% as moderate, 14.12% as high and 9.76% as very high in terms of landslide susceptibility. According to the LR model, 13.74% of the study area was classified as very low, 24.08% as low, 25.52% as moderate, 22.58% as high and 14.08% as very high in terms of landslide susceptibility (Fig. 6). According to the SVM model, a total of 23.88% of the study area was classified as high and very high susceptibility to landslides, whereas this figure was 36.66% for the LR model.

3.3 Importance of Conditioning Factors

The importance levels of the 12 factors used in susceptibility analyses are shown in Fig. 7. In both models, distance to roads and distance to drainages emerged as the most influential factors in the occurrence of landslides in the study area. After these two factors, the third and fourth most influential factors were aspect and distance to faults in the SVM model and crown closure and distance to faults in the LR model. In contrast, land use and profile curvature were the least influential factors on landslides in both models.

Existing roads are forest roads in the study area that are already actively used. Newly planned roads are roads that are included in the forest road network plans but have not yet been opened or constructed in the area. The existing forest roads in the study area are 116.06 km long in total. The length of the new forest roads planned to be opened is 20.87 km. The susceptibility levels of existing forest roads and new forest roads planned to be opened in both models are presented in Fig. 8 and Fig. 9. According to the LSM generated by the SVM model, 28.28% (32.82 km) of the existing roads are located in areas with high and very high susceptibility to landslides. In contrast, the LR model showed that 56.57% (65.6 km) of the existing roads are situated in areas with high and very high susceptibility to landslides (Fig. 8). For planned forest roads, the SVM and LR models showed that 38.43% (8.02 km) and 52.23% (10.9 km) were situated

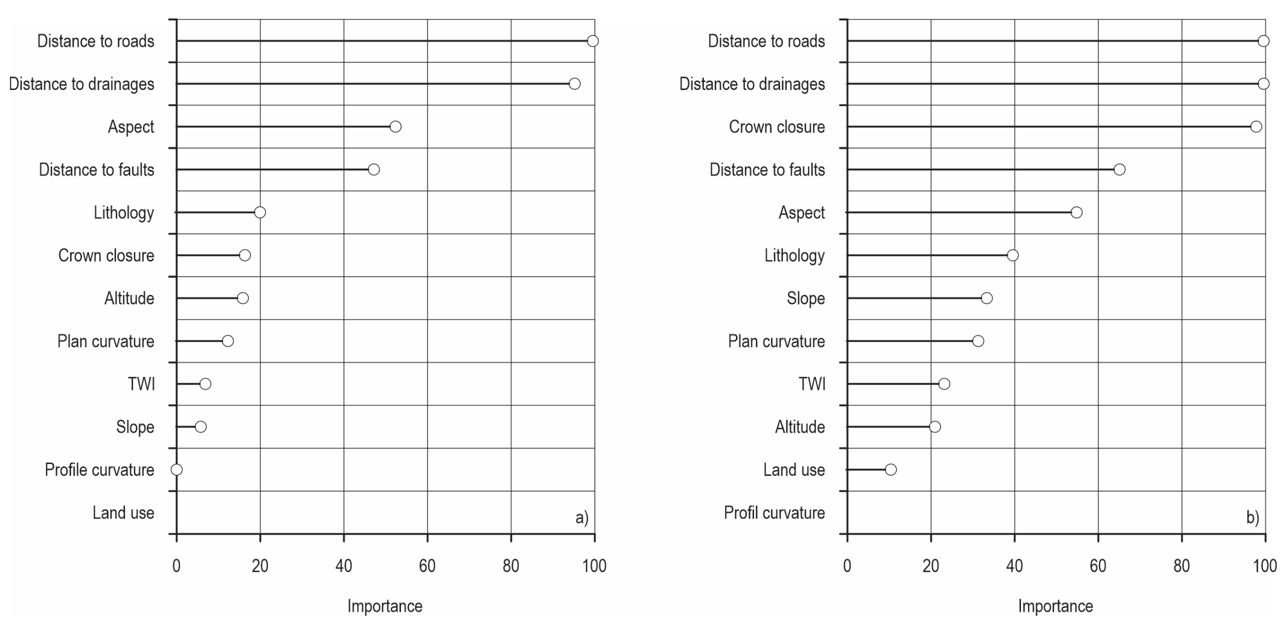

Fig. 7 Importance of conditioning factors for (a) SVM model and (b) LR model

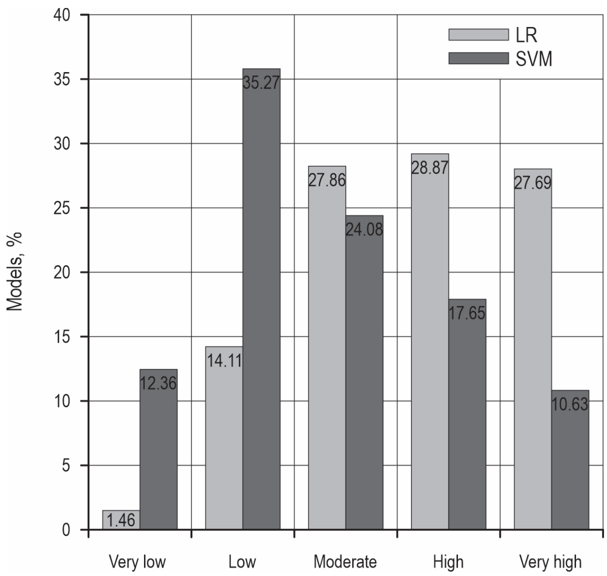

Fig. 8 Susceptibility distribution of existing forest roads in LSMs

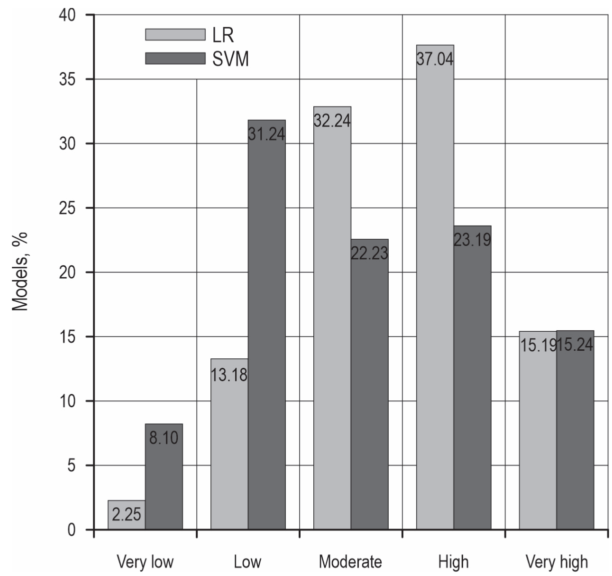

Fig. 9 Susceptibility distribution of planned forest roads in LSMs

in areas with high and very high susceptibility to landslides, respectively (Fig. 9).

The frequency ratios of the subclasses of the two factors identified to be the most influential in the occurrence of landslides in the study area are given in Table 3. Upon examining the data, 54.05% of the landslides in the study area occurred within 150 m of roads. Furthermore, 95.67% of the landslides in the

Table 3 Frequency ratios of subclasses of two factors determined to be most effective in landslide occurrence

Factors	Subclasses	No. of landslide pixels		No. of pixels in domain		FR
		A	PLO, %	C	PIF, %	
Distance to roads, m	0–150	8556	54.05	283,300	46.49	1.1626
	150–300	4351	27.49	156,080	25.61	1.0731
	300–450	2236	14.13	79,972	13.12	1.0763
	450–600	629	3.97	36,045	5.92	0.6718
	600–750	57	0.36	16,912	2.78	0.1297
	750–900	0	0	10,326	1.69	0.0000
	900–1050	0	0	8520	1.40	0.0000
	1050–1200	0	0	7211	1.18	0.0000
	1200–1350	0	0	5101	0.84	0.0000
	1350–1672.15	0	0	5881	0.97	0.0000
Distance to drainage, m	0–100	5491	34.69	194,976	32.00	1.0841
	100–200	3948	24.94	161,009	26.42	0.9439
	200–300	2832	17.89	123,733	20.31	0.8811
	300–400	2217	14.01	73,861	12.12	1.1555
	400–500	964	6.09	35,962	5.90	1.0319
	500–600	376	2.38	14,158	2.32	1.0223
	600–700	1	0.01	3598	0.59	0.0107
	700–800	0	0	1542	0.25	0.0000
	800–948.95	0	0	509	0.08	0.0000

inventory occurred within 450 m of existing roads. These findings clearly indicate that forest roads are a fundamental factor triggering landslides in the study area. When the existing landslides were evaluated in terms of proximity to drainage networks, 34.69% of the landslides occurred within 100 m of drainage networks (Table 3). Similar to roads, 91.53% of the landslides occurred within 400 m of the drainage networks (Table 3). This also indicates that proximity to drainage networks is an effective factor in landslide occurrences in the study area.

3.4 Validation and Performance Comparison of Susceptibility Models

The most commonly used methods for comparing the performance of landslide susceptibility models are the receiver operating characteristics (ROC) curve and area under the ROC curve (AUC) (Usta et al. 2024, Xu et al. 2024, Zhou et al. 2024). The AUC value ranges between 0 and 1, and the closer the AUC value is to 1, the better the performance of the model (Yavuz Ozalp et al. 2023, Yu et al. 2023, Zhou et al. 2024). ROC curves and AUC values of the ML models used in the present study are shown in Fig 10.

Fig 10 shows that the AUC value for the SVM model was 0.968, while the AUC value for the LR model was 0.668. According to the AUC values, SVM outperformed LR. In many previous studies, models with AUC values ranging from 0.6 to 0.7 are considered to have average performance, whereas models with AUC values between 0.9 and 1.0 are considered to have excellent performance (Wu et al. 2020, Akinci and Yavuz Ozalp 2021, Akinci and Zeybek 2021). According to this evaluation, the SVM model exhibited excellent performance, whereas the LR model showed average performance.

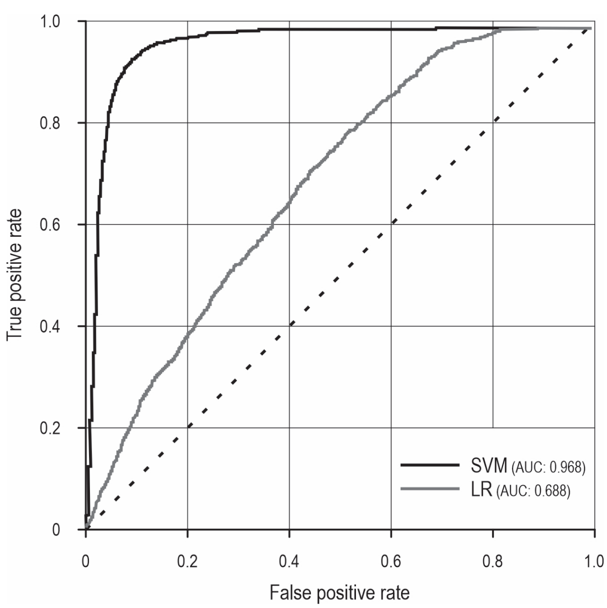

Fig. 10 AUC values for LR and SVM models

4. Discussion

This study aimed to produce LSMs for the region within the administrative boundaries of the Handüzü Forest Management Unit under the KRDF. Other aims of the study were to overlay the planned new forest roads with the LSMs, identify the road routes located in areas highly susceptible to landslides and inform the authorities to ensure these routes are moved to safer areas.

In the production of LSMs of the study area, 12 conditioning factors were used. Distance to roads and distance to drainages were found to be the most influential factors in the occurrence of landslides in this study area. This finding of our study is consistent with the literature. For example, in the landslide susceptibility study conducted by Eker and Aydın (2014) in Yığılca Forest Directorate (Türkiye), logistic regression (LR) method was used and it was found that very high landslide frequency was associated with areas located 0–200 m from roads and 0–100 m from streams. On the other hand, Arabameri et al. (2020) combined Analytic Hierarchy Process (AHP), statistical index (SI) and linear discriminant analysis (LDA) methods to identify landslide susceptible areas in Nekaroud watershed, a forested region in Mazandaran province of Iran and showed that distance to roads was the most influential factor in landslide occurrence.

In the present study, the determination of optimal routes for newly planned forest roads was not addressed. This is the primary limitation of this study. Thus, optimal road routes based on landslide susceptibility should be determined in future studies. Previous studies have focused on this topic. For example, Buğday and Akay (2022) mentioned that the construction of a forest road could trigger landslides in the area and emphasised that landslide susceptibility should be considered during road planning to prevent damage to the forest ecosystem caused by landslides. Buğday and Akay (2022) produced LSMs of the study area using LR and RF ML models. Unlike the present study, alternative road routes were determined using the CostPath analysis function of ArcGIS software. In another study by Kadi et al. (2021) in Maçka Forest Management Unit (Trabzon, Türkiye), 37% of the existing forest roads were highly susceptible to landslides and 2% were extremely susceptible. The researchers produced the landslide susceptibility map of the study area using the AHP method and developed an optimal road generation algorithm to generate optimal road routes with minimum landslide risk.

LR and SVM models were used to generate LSMs of the study area. SVM performed much better than LR. With an AUC of 0.688, LR showed an average performance, while SVM with an AUC of 0.968 showed an excellent performance. This difference is explained by the fact that the method used by the SVM algorithm for prediction is quite different from LR. LR, which uses a weighted least squares algorithm, is basically a linear classifier. The prediction is based on constructing a regression line that best fits the data points and minimising the weighted sum of squared distances to this line. The major drawback of LR is that if there are complex (non-linear) relationships between variables in the dataset, the method cannot identify these non-linear relationships (Pochet and Suykens 2006). SVM, on the other hand, performs better on complex data sets compared to LR because it uses kernel functions (e.g. RBF) to classify data that cannot be linearly separated (Verplancke et al. 2008). In addition, SVM can generalise better in landslide susceptibility mapping studies, such as in this study area, when the classes (landslide and non-landslide samples) are unevenly distributed. Therefore, there are many landslide susceptibility studies in the literature where SVM outperforms LR (Kavzoglu et al. 2014, Lin et al. 2017, Orhan et al. 2022).

The difference in the classification logic of SVM and LR algorithms causes a difference in the distribution of landslide susceptibility classes in LSMs. Looking at the distribution of landslide susceptibility classes in Fig. 6, it is seen that the LSM produced according to the LR model has a higher percentages of moderate, high and very high susceptibility classes than the LSM produced according to the SVM. On the other hand, SVM has a higher percentage in the low susceptibility class. The distribution in Fig. 6 shows that for this study area, the LR model fails to correctly identify the non-linear relationships between the dependent and independent variables, the model fails to classify the areas with low landslide susceptibility and classifies these areas with moderate, high or very high landslide susceptibility. Therefore, this situation leads to different susceptibility distributions of existing forest roads and new forest roads planned to be opened in the LSMs produced by LR and SVM (Figs. 8, 9).

There are 15 landslide polygons in the 6093.48 ha study area. Readers may think that 15 polygons may be insufficient for landslide susceptibility modelling. However, landslide polygons with a total area of 158.35 ha are represented by 15,819 pixels at 10 m spatial resolution. The overall dataset of 31,618 pixels (15,819 landslides + 15,819 non-landslides) is quite sufficient for training and validation of ML models. When the landslide susceptibility mapping literature is examined, it is possible to find studies with much fewer pixels than this. For example, in the landslide susceptibility mapping study conducted by Shahabi et al. (2023), researchers used 64 landslide locations. The researchers used 45 of the 64 landslide locations in the training and 19 in the validation phase. Moon et al. (2024) aimed to prepare landslide vulnerability maps in mountainous areas with forest roads and to determine the effective factors necessary for the establishment of disaster prevention measures. In this study, the researchers used 40 landslide and 45 non-landslide locations.

Forest roads should be avoided in areas with high landslide risk, and alternative routes should be designed. To achieve sustainable and precision forestry, it is crucial to consider landslide susceptibility when designing road networks. By minimising the negative environmental impacts of landslides and considering the high costs associated with road construction, it is possible to balance economic objectives effectively.

5. Conclusions

Forest roads are one of the important infrastructure facilities that enable the realisation of forestry activities. In current practice, forest roads are planned without considering the landslide risk and are opened uncontrolled. However, advances in information technology nowadays allow landslide susceptibility to be assessed and mapped with high accuracy using machine learning models. LSMs are effectively used both in mitigating damages caused by landslides and in decision-making and planning processes for land use. In this study, LSMs of Handüzü Forest Management Unit were produced using LR and SVM models. Both models showed that the main factors affecting the occurrence of landslides in the study area are distance to forest roads and drainage networks. Forested areas are mostly located in mountainous areas. Therefore, uncontrolled excavation activities carried out to open roads in these areas with high slopes may destabilise the slopes and increase the risk of landslides. Therefore, in order to prevent degradation of forested areas due to landslides and to ensure sustainable forest management, the landslide susceptibility of the region should be taken into account when planning forest road networks. Forest roads should be constructed on low slopes and stable ground as much as possible, slopes adjacent to roads should be made more stable by terracing, effective surface drainage channels should be constructed along the road to prevent uncontrolled accumulation of rainwater, and forest roads and surrounding slopes should be regularly checked for landslide risk. In addition, in order to prevent landslides due to proximity to drainage networks, sloping lands close to the drainage network should be landscaped with appropriate terracing methods, natural vegetation should be preserved in areas with extreme slopes and landslide risk should be reduced by planting the edges of river beds. Finally, the authors point out that the main limitation of this study is that only two models were used. In this context, tree-based ensemble learning algorithms such as CatBoost, XGBoost and LightGBM as well as deep learning algorithms such as CNN and RNN may provide more promising results in explaining the complex relationships between landslides and conditioning factors.

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Conflicts of Interest

The authors declare no conflict of interest. The founding sponsors had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, and in the decision to publish the results.

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