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Landslide Susceptibility Mapping Using Different Modeling Approaches in Forested Areas (Sample of Çankırı-Yapraklı)

Ender Buğday

Çankırı Karatekin University, Faculty of Forestry, 18100 Çankırı, Turkey

Abstract

The effective management of forest resources is very important for the future of the forest and to meet both ecological and economic needs. In this study, it is aimed to contribute to the applicability of modeling in practice by identifying regions that may be landslide in forest areas via different modeling approaches. A total of six models were created by using four criteria (elevation, slope, aspect and stream power index) and using Fuzzy Inference System (FIS) and Modified-Analytic Hierarchy Process (M-AHP) approaches in this study. The model's performance was measured using the Receiver Operating Characteristic (ROC) curve and Area Under Curve (AUC). According to the results of study, the most successful model was determined as FIS Model 1 with the AUC value of 82.1% and M-AHP Model 1 with the AUC value of 80.9%. This study provides important outputs that indicates the potential benefits of using landslide susceptibility mapping in the fields of forest harvesting, road network planning and forest management.

Keywords: Landslide, forest-planner, forest modeling

1. Introduction

Forestry activities consist of many sub-plans close relations with each other in a very wide area, such as forest harvesting planning, the road network planning, management planning. Forestry activities are multi-purpose and multi-benefit oriented tasks. Forest is a limited natural resource, and re-forestation requires long-term efforts. Therefore, the effects of the factors that may have a negative impact on planning should be minimized. For this purpose, effective factors need to be effectively modeled. Today's technological opportunities provide a great advantage in creating fast and efficient modeling and decision support system. Modeling approaches are frequently used in forestry for various purposes such as landslide modeling in forested areas.

Many criteria can be used in the creation of landslide susceptibility mapping (LSM) models, such as elevation (Gokceoglu and Aksoy, 1996), distance to roads (Yesilnacar and Topal, 2005), land use (Fell et al., 2008), slope (Cevik and Topal, 2003), distance to faults (Pourghasemi et al., 2013), lithology (Van Westen et al., 2003), distance to streams (Ercanoglu and Gokceoglu, 2004), aspect (Yalcin, 2008), plan curvature (Regmi et al., 2014) and Stream Power Index (Jaafari et al., 2014).

There are many LSM modeling studies in the literature. The focus of these studies is the simultaneous evaluation of multiple factors. The studies differ in terms of modeling methods, such as Adaptive Neuro-Fuzzy Inference System (Sezer et al., 2017; Ghorbanzadeh et al., 2018), Analytical Hierarchy Process (Intarawichian and Dasananda, 2010; Quan and Lee, 2012), Artificial Neural Networks (Ermini et al., 2005; Park et al., 2013), Frequency Ratio (Pradhan, 2010; Park et al., 2013), Fuzzy Inference System (Park et al., 2012; Osna et al., 2014; Buğday and Özel, 2019), Logistic Regression (Lee 2005; Felicísimo et al., 2013), Machine Learning (Pradhan, 2013; Micheletti, 2014), Modified-Analytical Hierarchy Process (Sezer et al., 2017; Pourghasemi and Rossi, 2017), Random Forest (Youssef et al,. 2016; Catani et al., 2013) and Support Vector Machine (Özdemir and Altural, 2013; Pourghasemi et al., 2013).

Interpretation of results obtained from modeling studies and transferring them to planner and implementer by "susceptibility mapping" is quite common method (Yesilnacar and Topal, 2005; Pradhan, 2013). In this study, four models are presented according to two different modeling approaches for LSM in forest area. The landslide susceptibility map in the forest area was made by using elevation, slope, aspect and Stream Power Index factors, in order to create a basis for the planning of forestry activities, using Fuzzy Inference System (FIS) and Modified-Analytic Hierarchy Process (M-AHP) approaches. Besides, various suggestions have

*Corresponding author: Tel: +90 376 218 3263 E-mail: ebugday@karatekin.edu.tr
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been made for planner and practitioner in terms of the LSM using in forest area.

2. Material and Methods

2.1. Study Area

Yapraklı Forest Enterprise Chief (29407.3 ha) in Çankırı Forest Enterprise Directorate affiliated with Ankara Regional Directorate of Forestry was chosen a study area. This area is located between 40° 47' 10"- 40° 40' 99" northern latitude and 33° 35' 01"- 33° 52' 14" eastern longitude. Since there have been various landslides of various number and sizes in the study area, it has been used as research area in this study (Figure 1). The average slope of the study area is 12 degrees, the dominant aspect is the southeast and the average elevation is 1310 m (between 850 m and 1885 m).

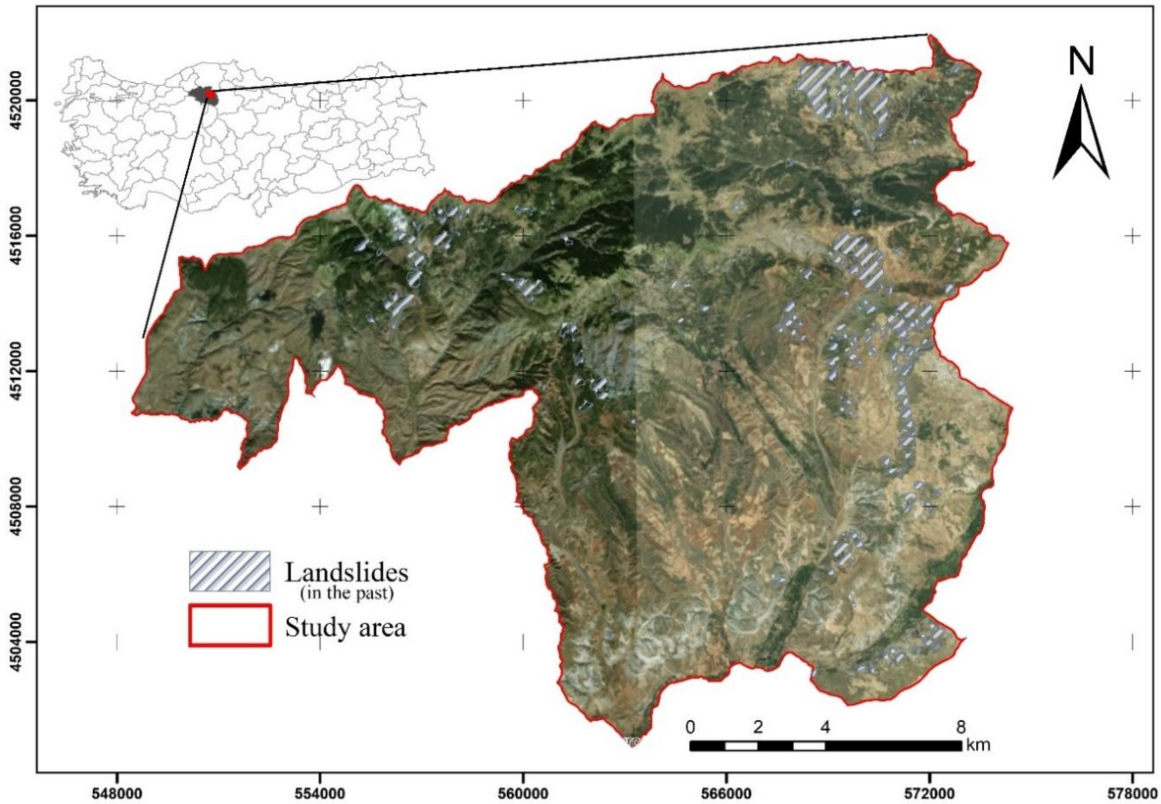

Figure 1. The study area border and landslides

2.2. Landslide Mapping

The main objective of modeling studies is to achieve the highest success with minimum criteria (Agarwal and Rathod, 2006). In each LSM modeling study, combinations of different criteria are used. Many factors are used as criteria in LSM studies and there are no specific criteria that are widely used (Sahin et al., 2018). The characteristics of the study area and the quality of the available data can affect the success of the models created with different criteria combinations. The most important feature affecting these combinations is the availability of the data. This situation, which is to affect the success of the direct models, leads researchers to carry out modeling in different landslide areas using different criteria and their combinations. For these reasons, all criteria used in this study were obtained from ASTER - GDEM free of charge at 12.5 m x 12.5 m high resolution (NASA, 2019). The criteria used in this study were elevation, slope, aspect and Stream Power Index (Figure 2).

The elevation is one of the most commonly used criteria in LSM studies. The average elevation in the study area was 1310 m, with minimum elevation of 850 m and the maximum elevation of 1885 m. In this study, the elevation was divided in five classes (850-1000 m, 1000-1150 m, 1150-1300 m, 1300-1500 m, and 1500-1885 m).

Another important criteria is slope (degree) in LSM studies. The average slope of the study area was 14.33°, ranging from 0° to 65.8°. In this study, the slope was classified into five different groups (0-5°, 5-12°, 12-18°, 18-22°, and 22-65.8°).

The aspect factor is one of the factors included in such studies and it is generally classified in nine different groups (Flat, North, Northeast, East, South, Southeast, West, Northwest, and Southwest). The main aspect of the study area was the southeast aspect.

SPI (ranging from -1 to 17) is an index commonly used in LSM studies. SPI was used to express topography erosion (triggering landslides) based on the assumption that the basin area and current are proportional (Moore et al., 1991).

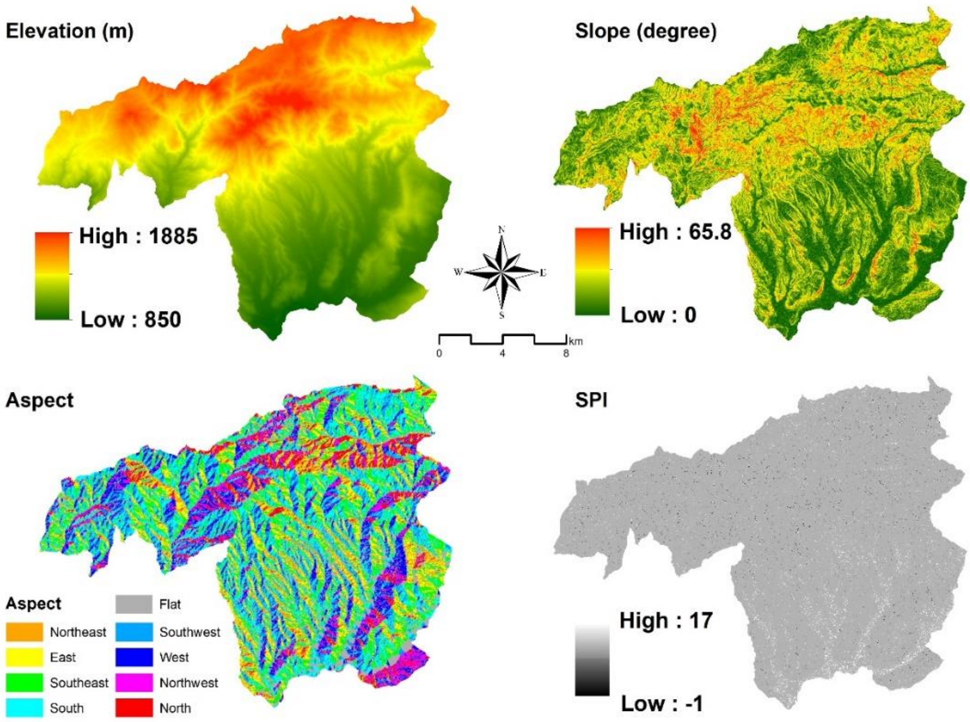

Figure 2. The criteria used in the study

The LSM process and the steps taken to generate the LSM in this study were given in the flow chart of Figure 3. This study consists of deciding of criteria, determination of modeling methods and validation, creation of models and evaluation of results.

The landslides locations and sizes (Duman et al., 2011) were gained from the General Directorate of Mineral Research and Exploration (MTA). The models were generated according to FIS and M-AHP approaches in this study. FIS is a commonly used approach to model simulation. The values of FIS are the values between 0 and 1 numbers, so the data for the criteria were normalized. In the FIS approach, membership functions are defined and learning rules are created. In this way, areas with landslide possibility are sorted from low to high sensitivity. The data obtained from the modeling were all converted to raster data format.

The M-AHP approach eliminates the user experience which is the main characteristic of the AHP approach (Sezer et al., 2017). The value of the criteria after being normalized and scored according to percentage of the landslides affecting the sensitivity was given in Table 1. The scores given to the factors were 1, 3, 5, 7 and 9. Then, these criteria were calculated in GIS and merged with each other to obtain models for LSM.

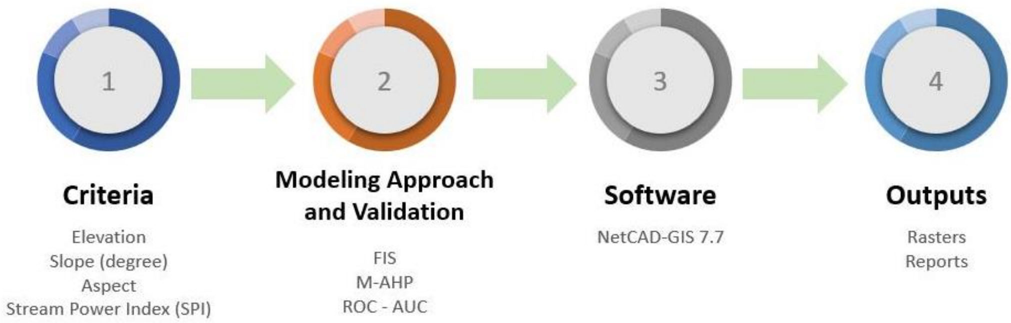

Figure 3. Flow chart of the study

Table 1. Criteria group scores for M-AHP

Factors	Classes	Score	Factors	Classes	Score
Elevation (m)	850-1000	1	Slope (degree)	0 - 5	1
	1000-1150	3		5 - 12	3
	1150-1300	5		12 - 18	5
	1300-1500	7		18 - 22	7
	1500-1885	9		22 - 66	9
Aspect	Flat	1	SPI	-1	9
	North and Northwest	3		5	7
	East, Northeast	3		10	5
	South and Southeast	7		13	3
	West and Southwest	5		17	1

In the study, two different models were formed by using four specified factors. The combinations of the factors used in the models were formed according to FIS and M-AHP approaches used in this study (Table 2).

Table 2. Combinations of factors used in models

Factors	Model 1	Model 2
Elevation	✓	✓
Slope (degree)	✓	✓
Aspect	✓	✓
SPI	✓	-

The reliability of the models produced was tested with the Receiver Operating Characteristic (ROC) curve and the success rates of the models were calculated by the Area Under Curve (AUC). The ROC curve is generally used as the threshold value for binary classification systems as 0.50 (Nandi and Shakoor 2010). In this study, Netcad 7.7 software was used for implementations FIS and M-AHP approach, and ROC-AUC calculations.

3. Results and Discussion

According to the MTA landslide inventory, a total of 124 landslides occurred in the study area. The size of these landslides varied between a minimum of 0.2 ha and a maximum of 116 ha. The landslide sensitivity of the study area was relatively high. In this study, a total of four models have been developed (Figure 4). The value range varies between 0 and 0.8 in the developed FIS models. In M-AHP models, the values vary between 0 and 0.9.

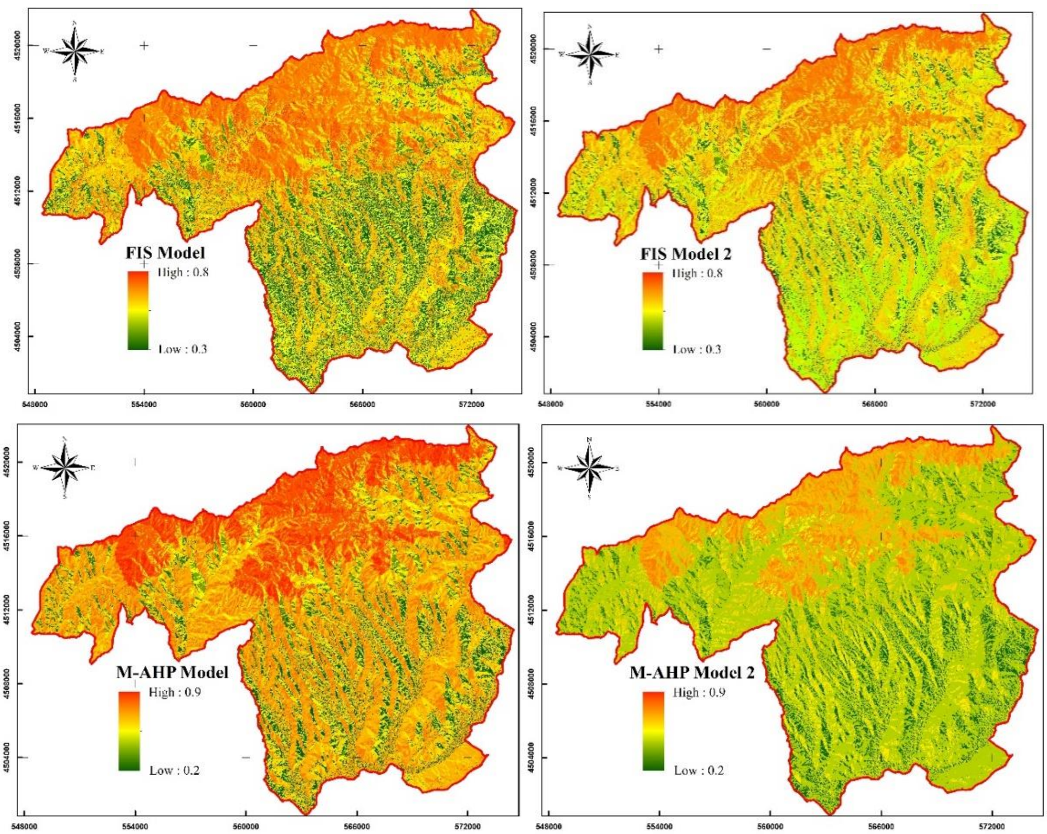

Figure 4. Model raster outputs (FIS and M-AHP)

For modeling validation, past landslides have been used. Models were tested with ROC and success rates were determined with AUC. According to this; FIS Model 1 AUC=82.1% and FIS Model 2 AUC=79.8%, M-AHP Model 1 AUC=80.9% and M-AHP Model 2 AUC=78.3% (Figure 5).

In this study, the modelling approach using of advanced GIS methods to create a decision support platform in planning before the forestry activities in the landslide sensitive forest areas was carried out. Four criteria were used in this study and four different models were obtained. It was found that FIS and M-AHP approaches can be preferred since they have practical use for planners and practitioners. The most successful model was Model 1 (AUC=82.1%) obtained by the FIS approach. In Model 2, a lower success rate was achieved due to three criteria.

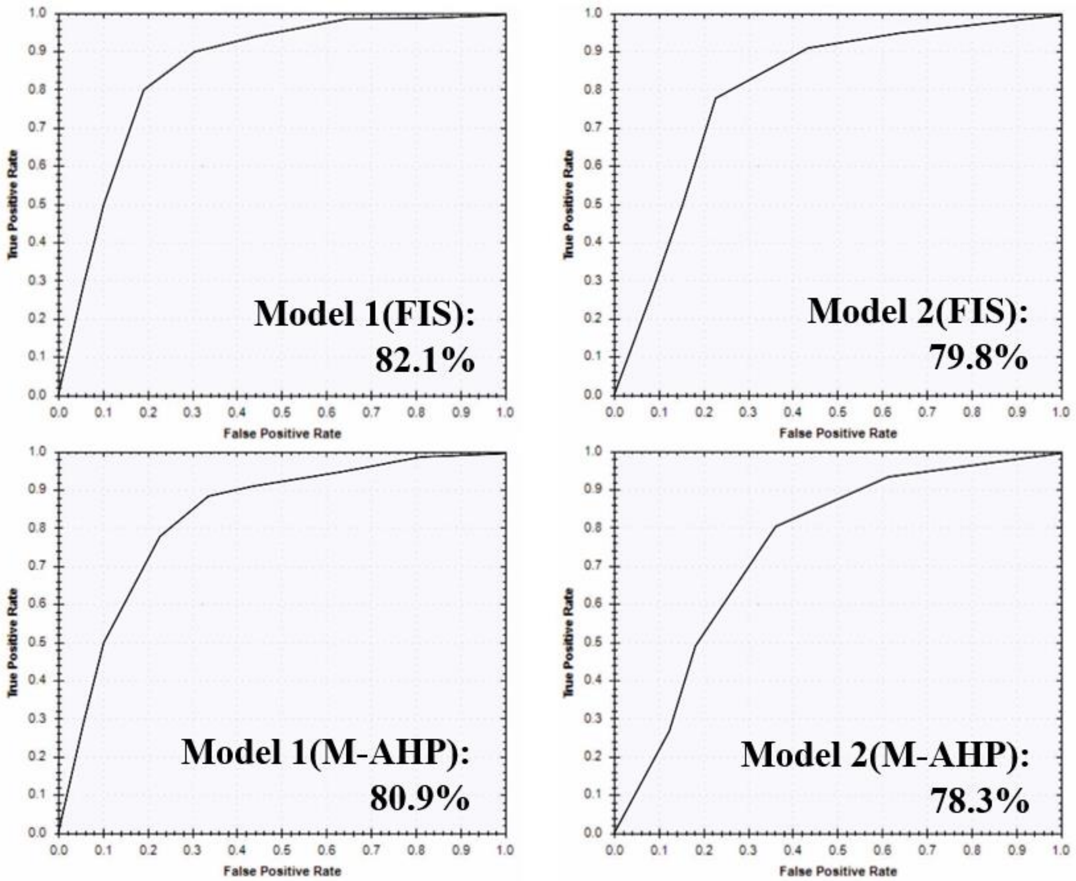

Figure 5. AUC success values of the Models

The models created by FIS provided more successful results than M-AHP models in this study. In a similar study conducted by Sezer et al. 2017, using FIS and M-AHP approaches (seven factors), it was reported that AUC values ranged between 0.66 and 0.82. Buğday and Özel (2019) conducted a study using FIS and M-AHP (nine factors) and they found that AUC values ranged between 0.62 and 0.71. The values obtained from these studies were similar to the analysis results in this study.

4. Conclusion

In forestry activities carried out according to the principles of sustainable forest management, planning is even more important than before. Knowing the negative impacts that will affect the success of planning, identifying and modeling the possible impacts increases the success and applicability of planning. In this study, the factor of the landslide which has a negative impact on planning in forestry applications in landslide sensitive areas was effectively modeled considering slope, aspect, elevation, and SPI criteria. In the follow up studies; the most suitable modeling methods can be determined for forestry applications by evaluating different criteria and models in landslide sensitive forest areas.

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