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Generating Landslide Susceptibility Maps Using Mathematical Models and UAV data: The Case of Çankırı Region in Türkiye

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Abstract

Landslides are natural disasters that affect not only residential areas but alos forest ecosystems. In order to determine the areas with high landslide risk and take necessary measures in risky areas, landslides susceptible should analyzed and susceptible map (LSM) should be developed in advance. In this study, a LSM was produced for two study areas with different sizes including Çankırı province and in the Ilısılık Village of Çankırı in Türkiye. Analytical Hierarchy Process (AHP) and Logistic Regression Modeling (LRM) methods were used to generate LSM based on the main factors including elevation, slope, lithology, distance to faults - streams and roads. For Çankırı province, 30 m resolution Digital Elevation Model (DEM) was used to produce the map while one-meter resolution Digital Terrain Model (DTM), generated by using Unmanned Aerial Vehicle (UAV), was used for Ilısılık Village. As a result of the study, AHP model success was calculated as 73.9% and 91.7% for Çankırı and Ilısılık, respectively, considering the previous landslides occurred in the region. On the other hand, LRM model success was 75.2% and 93.1%, respectively. It was also indicated that DTM data is advantageous to DEM data by offering a more precise and detailed usage opportunity. The sensitivity is revealed more clearly and effectively in precision planning studies such as risk mapping of natural disasters that requires special measurement in small areas.

Keywords: Natural disaster, landslide, unmanned aerial vehicle, susceptibility mapping, modeling

1. Introduction

There are many natural disasters in the world and landslide is one of these natural disasters that damages environments and threats the human life. Landslide is expressed as the downslope of the material originating from the gravity of earth parts such as soil and rock, earthquake, water, volcanic eruptions, and various construction works done by people on the earth's surface (WHO, 2021).

Considering Turkey's geological and topographic structure, the landslide is the second most common natural disaster after earthquakes (Ergünay, 2007). Landslides negatively affect the environment and cause billions of dollars worth of material damage (Brabb, 1991; Yalçın, 2007). Landslides are likewise evaluated in mass movements; slope movement is caused by the gravitational effect of soil, rubble, or rock masses or by human intervention (Cruden, 1991).

In the classification of landslides, there are different systems implemented by researchers in the literature for different purposes. Varnes's (1978) classification is the most widely accepted worldwide (Hungr et al., 2014). This classification system considers parameters such as the morphology of the slope instability, the mechanism of failure, the material type, and the type of movement (Çan et al., 2013). Landslide susceptibility studies are defined as the relative classification of landslide susceptibility by considering the input parameters, that is, the predisposing factors that may cause landslide formation in a region.

Landslides are caused by various factors including elevation (Eker et al., 2012), slope (Nefeslioğlu et al., 2012), aspect (Hong et al., 2015), lithology (Jaafari et al., 2015), and distance to faults (Saha et al., 2005). In addition, landslides may occur depending on the other factors such as distance to streams (Yalçın et al., 2011), distance to roads (Yalçın, 2008), Topographic Wetness Index (TWI) (Jacobs et al., 2018) and Stream Power Index (SPI) (Akgun and Turk, 2010). With the development of today's technology and software possibilities, researchers can make landslide susceptibility analyses for large areas (e.g., city-wide, basin-wide, etc.) using mathematical models and remote sensing images. In sustainable management of natural resources, the Analytical Hierarchy Process (AHP) and Logistic Regression Modeling (LRM) methods are widely used for large areas (Ayalew, and Yamagishi, 2005; Lee and Sambath, 2006; Yalçın, 2007; Yalçın,

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2008; Pourghasemi et al., 2012; Park et al. 2013; Myronidis et al., 2016; Bugday, and Akay, 2019). The satellite images are widely used in developing such susceptibility maps while UAV based data also provides quick and cost effective remote sensing data.

In this study, landslide susceptibility was categorized and mapped within the administrative borders of Çankırı province according to landslide susceptibility degrees. The Analytical Hierarchy Process (AHP) and Logistic Regression Modeling (LRM) were used to generate a landslide susceptibility maps (LSMs) based on specified factors (i.e. elevation, slope, aspect, lithology, distance to faults, distance to rivers, and distance to road factors). In data collection, multi-copter type UAV was used in the field which is the prominent aspect of this study.

2. Material and Methods

2.1. Study Area and Data

The study was carried out in the administrative borders of Çankırı province, within 40° 50' 20" - 40° 16' 30" northern latitudes and 32° 34' 40" - 34° 02' 29" east longitudes (Figure 1). The size of this study area is 749613.5 hectares. The second study area with small size is Ilısılık Village where UAV was used to generate DTM (Figure 2). The size of the second study area is 7.7 hectares. According to the previous landslide data, provided by General Directorate of Mineral Research and Exploration (MTA), there are 100 landslides in the Çankırı Province and eight landslides in the Ilısılık Village (Duman et al., 2011).

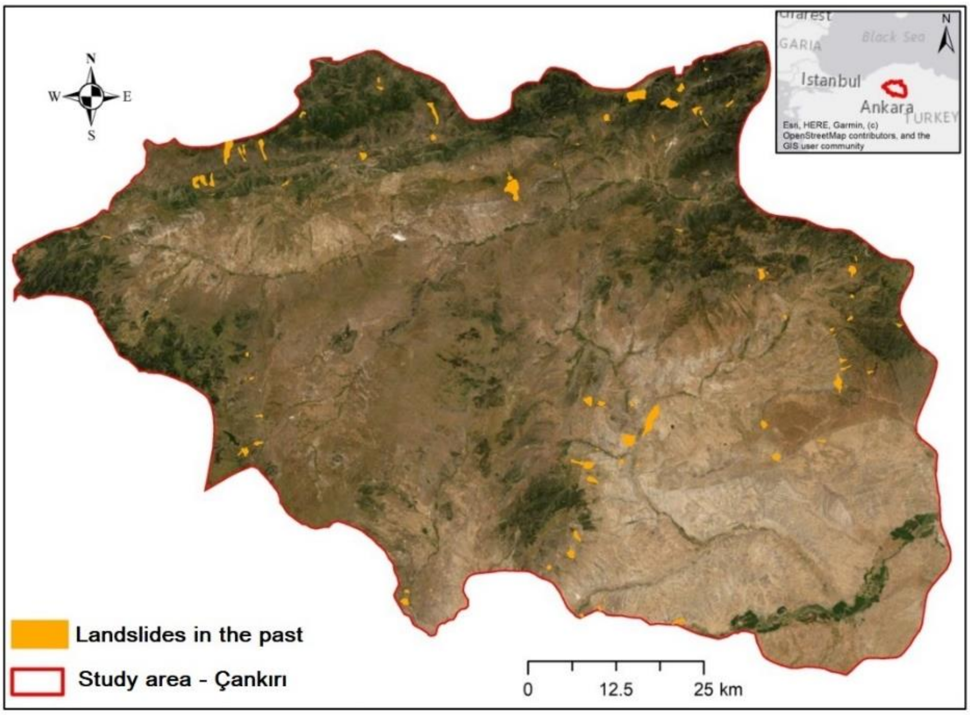

Figure 1. The border of Çankırı province and previous landslides

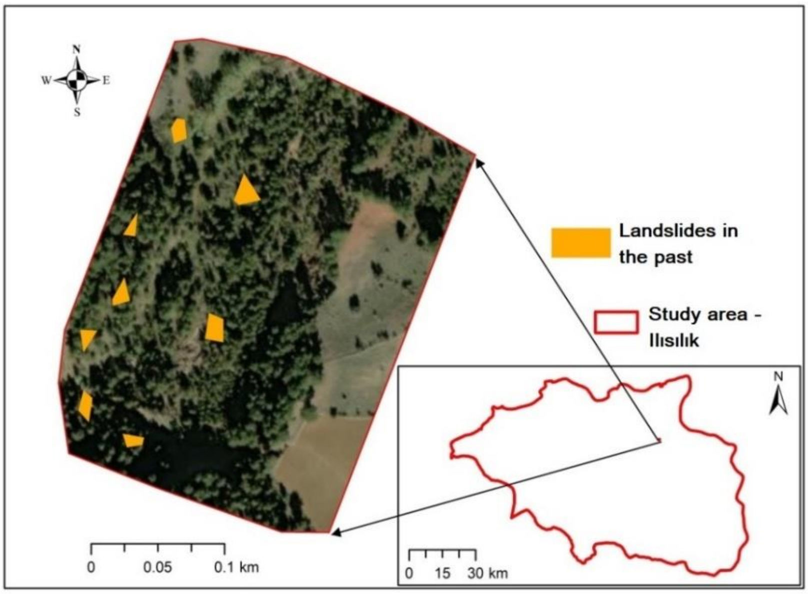

Figure 2. Location of Ilısılık Village in Çankırı province and previous landslides

In the study, fault information was obtained from the database of the MTA (Emre et al., 2013). Then, lithology information was obtained from Çankırı Province AFAD Provincial Directorate (AFAD, 2015). The DEM (30 m) of the Çankırı Province study area was obtained from www.usgs.gov address free of charge. DTM (0.04 m resolution) of Ilısılık Village study area was generated based on UAV data collected by using DJI Phantom 4 model device. Some technical specifications of DJI Phantom 4 device are given in Table 1. ArcGIS 10.3 TM (ESRI, 2018) was used to produce digital layers for the susceptibility factors (including DEM and DTM) and previous landslides data and to generate susceptibility maps in the solution processes.

Table 1. Technical specifications of DJI Phantom 4 device

Specifications & Values	
Weight: 1350 g-1400 g	Flight Time: 26-30 minutes
GPS Mode: Yes	Sensor Type: CMOS
Flight Distance: 5000 m-6000 m	Size: 36cm-40cm
Aperture: 2.8/f	Maximum Speed: 40 kmp-50 kmp
Effective Pixels: 12 MP	Angle of View: 94°
Battery: 5870 mAH LiPo	Sensor Size: 1/2.3 inch
Camera: 4K	

2.2. AHP Model

It is a very common method used in landslide susceptibility studies. Weight for each factor is assigned using AHP based on its effect on landslide occurrence (Abedini et al., 2017). The landslide susceptibility map was derived using the weighted overlap method and divided into five; very low, low, medium, high, and very high susceptibility classes. Using the AHP model, the landslide susceptibility map was generated using the following equation:

$$AHP = ((elevation \times W_1) + (slope \times W_2) + (lithology \times W_3) + (distance\ to\ faults \times W_4) + (distance\ to\ streams \times W_5) + (distance\ to\ roads \times W_6) \quad (1)$$

In this formula, "W_{AHP}" is the weight of the factor affecting landslide. The raster pixel values were then used to determine the class ranges on the landslide susceptibility map, to very low (0-0-2), low (0.2-0.4), medium (0.4-0.6), high (0.6-0.8) and very high (0.8-1.0).

Elevation is a factor used in landslide susceptibility studies and is frequently included in national-international assessments. It is known that the land becomes susceptible to landslides with the increase in altitude. The slope is one of the most commonly used factors in landslide susceptibility studies. In this study, slope data was produced and analyzed in degrees. Lithology is frequently used in landslide susceptibility studies because it includes parameters that can predict landslides' occurrence and severity. The distance to faults factor is one of the frequently used factors in the international literature in terms of being the trigger of the landslide. In this study, the distance factor to the faults was classified as 0.2 km, 0.5 km,1 km, 5 km, 10 km, 20 km and 50 km. The distance factor to the streams is one of the effective factors in the formation of landslides. In this study, the distance factor to the rivers was classified as 0.2 km, 0.5 km, 1 km, 5 km and 10 km. The distance to roads factor is a factor that is widely used in landslide susceptibility studies and increases the susceptibility to landslides negatively. This study classified the distance to the roads as 0.2 km, 0.5 km, 1 km, 5 km, and 10 km.

2.3. Logistic Regression Modeling (LRM)

LRM model is used to determine the cause and effect relationship with the explanatory variables in cases where the response variable is observed in categorical and double, triple, and multiple categories. It is a regression method in which the expected values of the response variable are obtained as probabilities according to the explanatory variables (Gorsevski et al., 2006, Lee and Pradhan, 2007). Logistic regression involves adjusting the dependent variable using an equation in the following form (Duman et al., 2006):

$$Y = logit\ (p) = \ln[p\,/(1-p)] = C_0 + C_1X_1 + \cdots + C_nX_n \quad (2)$$

In this equation, "p" is the probability that the dependent variable (Y) is 1. "p/(1-p)" is the nominal (expected) probability or probability ratio. "C_0" intersection point "C_n" are coefficients that measure the contribution of independent factors (X_1,…X_n) to changes in Y. In this study, the dependent variable is defined as the presence or absence of landslides, while the independent variables are the factors that are thought to affect landslide susceptibility.

3. Results

3.1. Çankırı Province

The landslide susceptibility maps were produced based on AHP and LRM modeling approaches. The digital data layers were produced for the main factors including elevation (Figure 3-a), slope (Figure 3-b), lithology (Figure 3-c), distance to faults (Figure 3-d), distance to streams (Figure 3-e), and distance to roads (Figure 3-f).

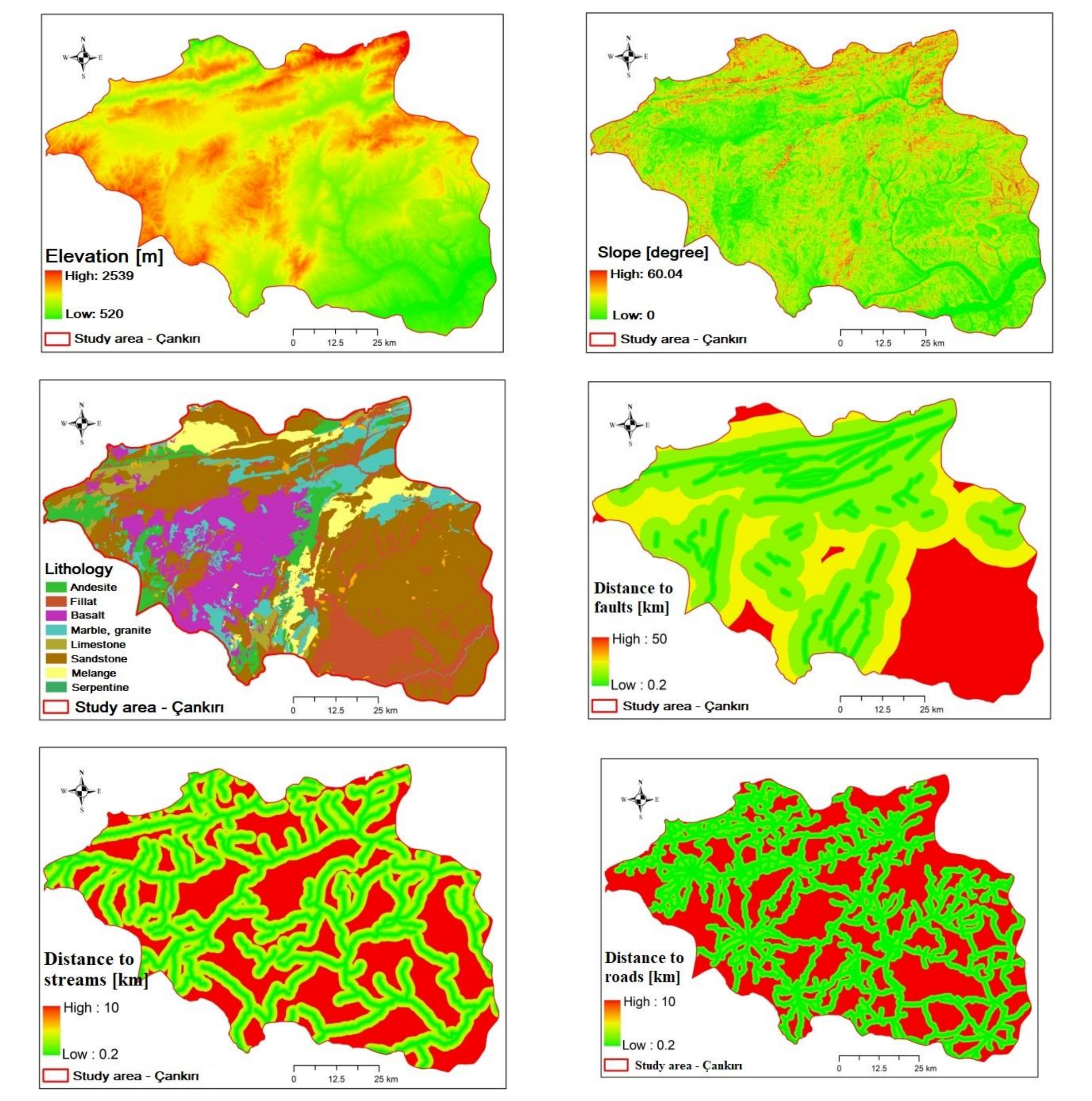

Figure 3. The maps of main factors: a-elevation, b-slope, c-lithology, d-distance to faults, e-distance to streams, f-distance to roads

The elevation of the study area was between 520 m and the 2539 m, with the average of 1173 m. The average slope in the study area was 10.9^o, within the range of 0^o and 60^o. The geological types in the area included abyssal basin, terrestrial, terrestrial-self, self-slope and slope-absal basin characteristics. In Çankırı province, andesite, basalt, marble, granite, sandstone, limestone, clayey limestone, serpentine and fillat structures are presents. In this study, lithological data were categorized as hard and non-hard rocks. The hard rocks included andesite, basalt, marble, granite and sandstone while the non-hard rocks were limestone, clayey limestone, serpentine and fillat.

3.1.1. AHP model results

In the AHP approach, a score between 1 and 9 was given to each factor regarding the degree of importance. The first-factor superiority over the second factor was evaluated by scoring up to 9. Each factor was scored according to the other paired factor. Then, the weighted values formed from the scores of the factors are given in Table 2. It was found that the factors with the highest weight value was distance to faults, and followed by the slope. Finally, landslide susceptibility map generated by AHP model is indicated in Figure 4. Based on the landslide records data, the success of the model was calculated as AUC=73.9% (Figure 4).

3.1.2. LRM model

The landslide susceptibility map generated based on the LRM model was obtained according to the main factors (elevation, slope, lithology, distance to faults, rivers, and roads) is given in Figure 5. In this approach, the success of the model was calculated as AUC=75.2%.

Table 2. The weighted values of the factors in AHP approach

Factors	%
Elevation	5,6
Slope (degree)	27.4
Lithology	7.6
Distance to faults	54.5
Distance to streams	2.2
Distance to roads	2.7

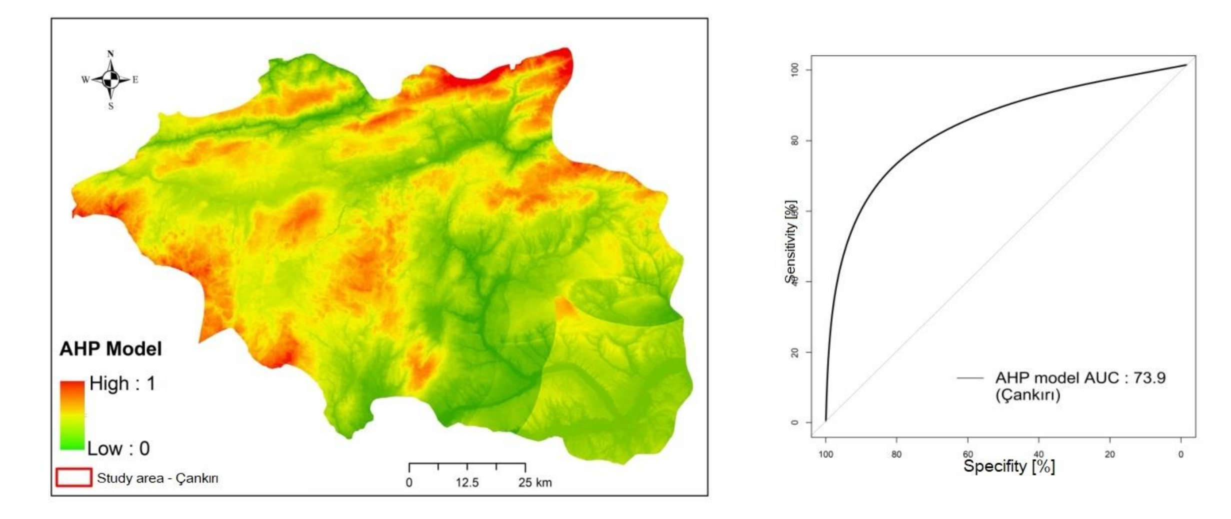

Figure 4. LSM obtained using the AHP approach and ROC – AUC model success in Çankırı province

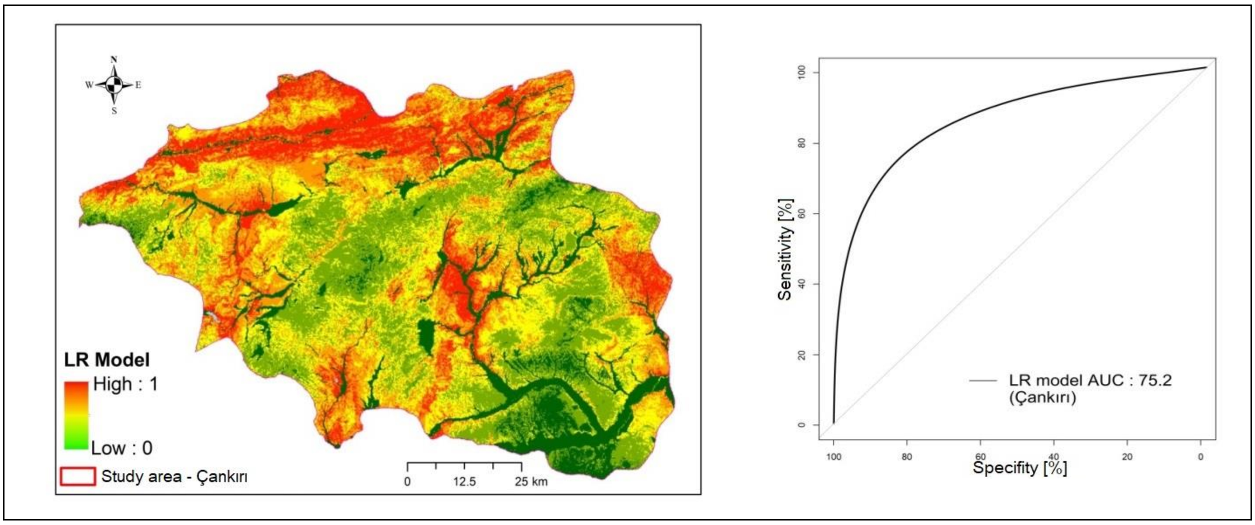

Figure 5. LSM obtained using the LRM approach and ROC – AUC model success in Çankırı province

3.2. Ilısılık Village

The landslide susceptibility maps were also generated for Ilısılık Village using AHP and LRM modeling approaches. The factors of elevation (Figure 6a), slope (Figure 6b), lithology (Figure 6c), distance to faults (Figure 6d), distance to streams (Figure 6e), and distance to roads (Figure 6f) were used in the generation of these maps, as they were carried out in the Çankırı province.

The elevation of the Ilısılık study area was between 1298 m and 1371 m, with an average elevation of 1333 m. The slope in the study area was between 0^o and 61^o degrees, and the average slope was 15.1^o. The lithology data was included in the analysis as hard and non-hard rocks in the study area. The hard rocks were sandstone, conglomerate, and mudstone, while the non-hard rocks are mixed structures (mélange) consisting of limestone and clayey limestone.

3.2.1. AHP model

The scores of the main factors were same as the ones given in the study area of Çankırı Province. The AHP model obtained according to the factors of elevation, slope, lithology, distance to faults - streams, and roads used. The model's success was calculated as AUC=91.7% (Figure 7).

3.2.2. LRM model

The landslide susceptibility map generated based on the LRM model was obtained according to the main factors (elevation, slope, lithology, distance to faults, rivers, and roads) is given in Figure 6. In this approach, the success of the model was calculated as AUC=93.1% (Figure 8).

3.3. Comparison of AHP and LRM Models

Furthermore, DEM and DTM data processing was carried out according to the AHP and LRM modeling approaches, both within the borders of Çankırı Province and within the study areas of Ilısılık Village (Figure 9 and 10). In the light of the findings, it was found that generating landslide susceptibility maps with drones requires more precise measurement.

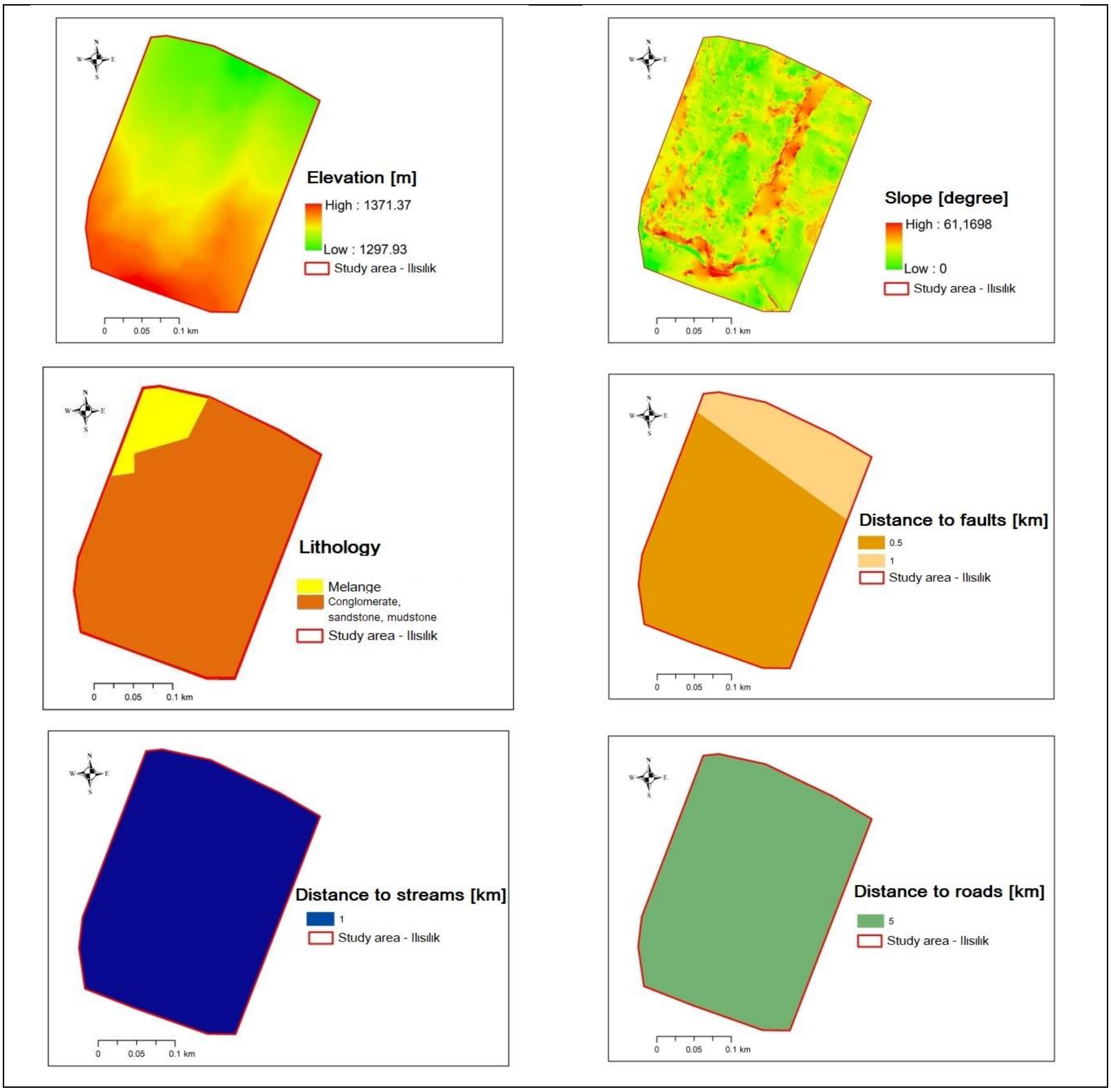

Figure 6. The maps of main factors: a-elevation, b-slope, c-lithology, d-distance to faults, e-distance to streams, f-distance to roads

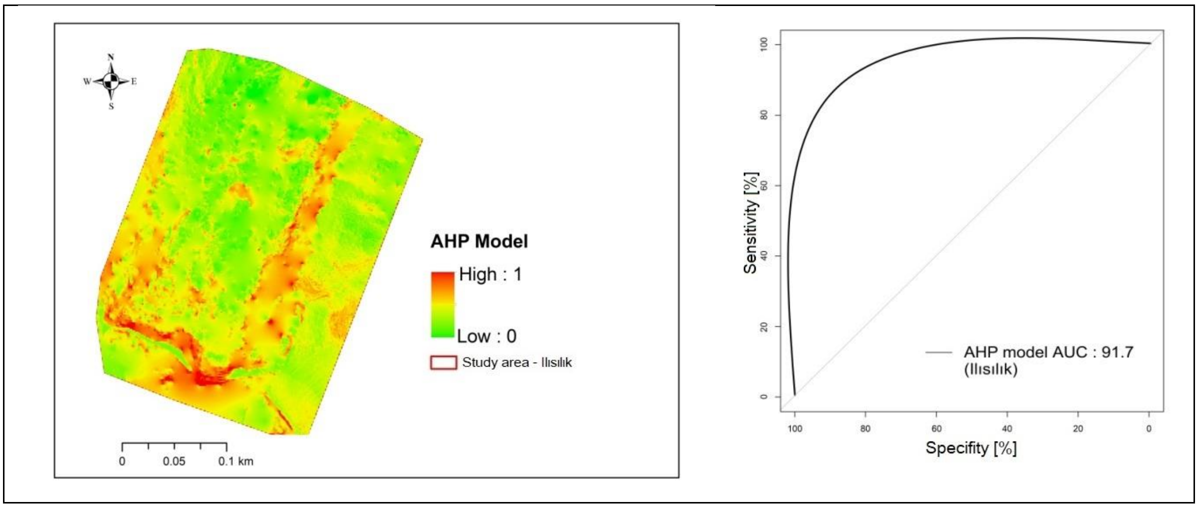

Figure 7. LSM obtained using the AHP approach and ROC – AUC model success in Ilısılık Village

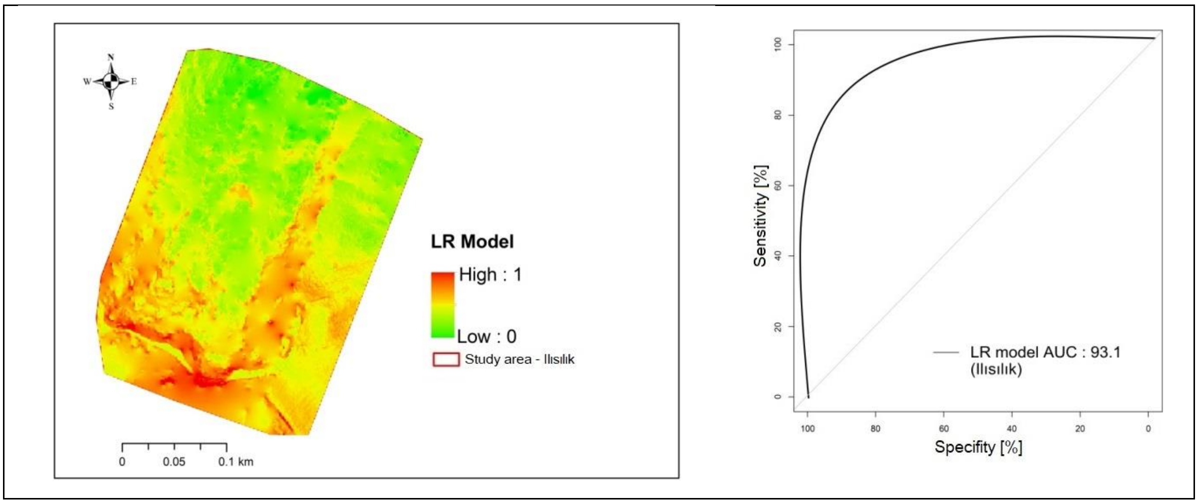

Figure 8. LSM obtained using the LRM approach and ROC – AUC model success in Ilısılık Village

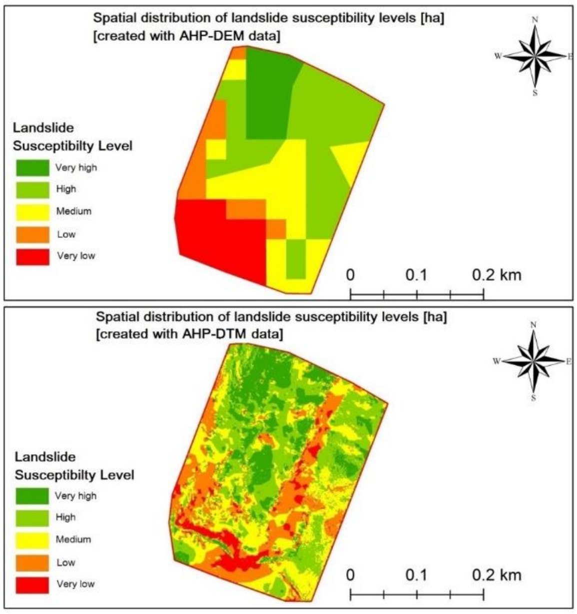

Figure 9. LSMs obtained using the AHP approach

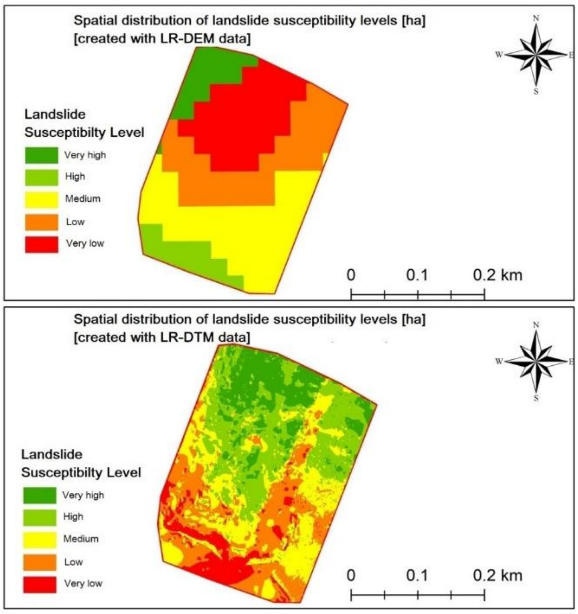

Figure 10. LSMs obtained using the LRM approach

As a result of the analysis using AHP-DEM data, the area with a landslide susceptibility level of "Very Low" covered 11.94% (0.92 ha) of the entire area. The area with a "Low" landslide susceptibility level covered 36.69% (2.84 ha) of the entire area. At the "medium" sensitivity level, the area covered 25.84% (2.0 ha) of the entire area. The area with a landslide susceptibility level of "High" covered 9.68% (0.75 ha) of the entire area. The area with a landslide susceptibility level of "Very High" covered 15.82% (1.22 ha) of the entire area (Figure 11).

According to the analysis carried out using AHP-DTM data, the area with a landslide susceptibility level of "Very Low" covered 17.46% (1.35 ha) of the entire area. The area with a "Low" landslide susceptibility level covered 30.14% (2.33 ha) of the entire area. At the "medium" sensitivity level, the area covered 26.39% (2.04 ha) of the entire area. The area with a "High" landslide susceptibility level covered 20.31% (1.57 ha) of the entire area. And, the area with a landslide susceptibility level of "Very High" covered 5.69% (0.44 ha) of the entire area (Figure 11).

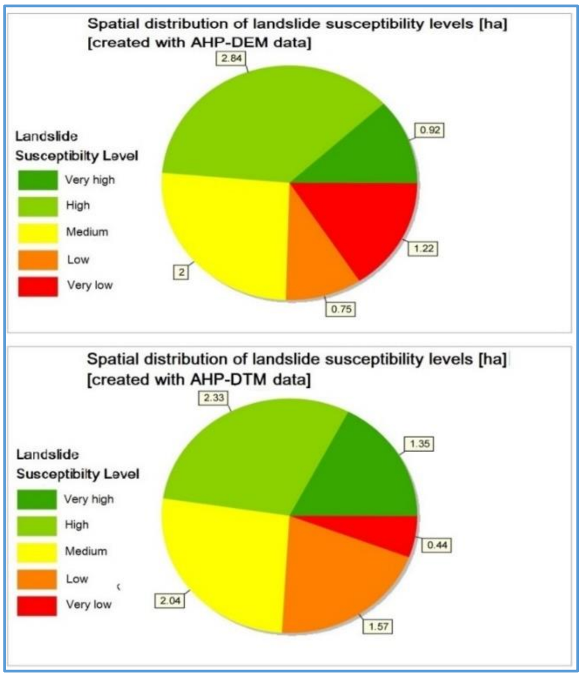

Figure 11. Landslide susceptibility distributions according DEM and DTM data based AHP approach

The analysis carried out using LR-DEM data indicated that the area with a landslide susceptibility level of "Very Low" covered 8.66% (0.67 ha) of the entire area. The area with a "Low" landslide susceptibility level covered 7.88% (0.61 ha) of the entire area. At the "medium" sensitivity level, the area covered 32.04% (2.48 ha) of the entire area. The area with a "High" landslide susceptibility level covered 26.61% (2.06 ha) of the entire area. The area with a landslide susceptibility level of "Very High" covered 24.81% (1.92 ha) of the entire area (Figure 12).

As a result of the analysis carried out using LR-DTM data, the area with a landslide susceptibility level of "Very Low" covers 15.12% (1.17 ha) of the entire area. The area size with a "Low" landslide susceptibility level covers 27.52% (2.13 ha) of the entire area. The area size at the "medium" sensitivity level covers 26.49% (2.05 ha) of the entire area. The area size with a landslide susceptibility level of "High" covers 22.48% (1.74 ha) of the entire area. The area size with the landslide susceptibility level "Very High" covers 8.40% (0.65 ha) of the entire area (Figure 12). In the light of the findings obtained as a result of the study, both modeling approaches have high success rates and can be used effectively in the detection of areas susceptible to landslides.

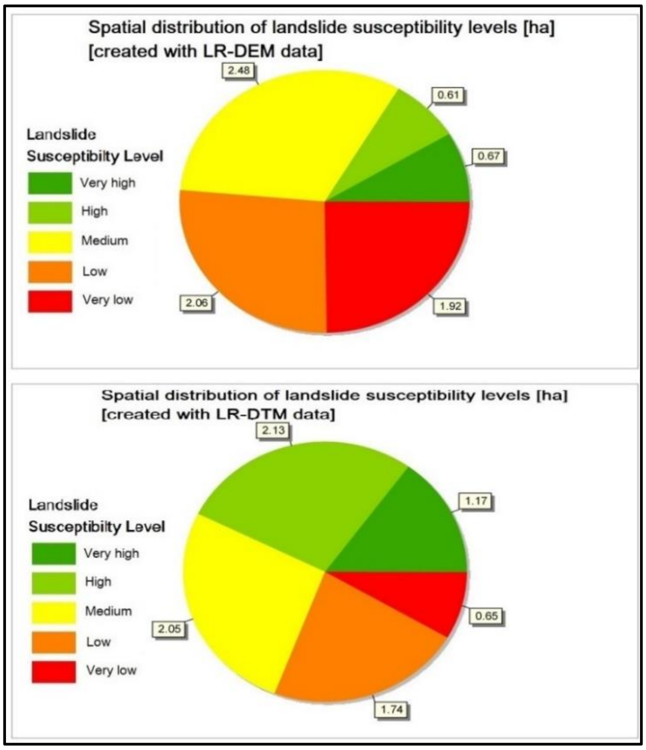

Figure 11. Landslide susceptibility distributions according DEM and DTM data based LR approach

4. Discussion and Conclusion

Considering international literature, landslide susceptibility studies have gained momentum, especially in the last ten years. In addition, landslide susceptibility studies are also used often in practice. Various institutions and organizations benefit from modern approaches and systems, especially within the scope of an effective fight against disasters. The use of dynamic platforms in the decision-making processes of planners, decision-makers, and practitioners is important to eliminate or minimize the damages that may occur. For these reasons, it is an important step in achieving the goals in management studies that the areas sensitive to natural disasters, which may adversely affect people, are supported by modeling studies to be carried out with the help of GIS and obtaining high-accuracy results.

In this study, two different models were presented according to the AHP and LR modeling approaches and a total of six different landslide triggering factors. The success of the model, which was obtained as a result of the analysis carried out according to the AHP approach using the same factors, was calculated as the landslide susceptibility of the areas within the borders of Çankırı province (using DEM data) to be 73.9% and the area within the border of Ilısılık Village to be 91.7% (using DTM data). The success of the model obtained as a result of the analysis carried out according to the LR model approach was determined to be 75.2% for the Çankırı province study area and 93.1% for the Ilısılık study area. As a result of the similar modelling studies implemented the AHP approach; AHP model success value was 84% in Yalçın (2007), 81.3% in Yalçın (2008), 81.1% in Pourghasemi et al. (2012), 73.9% in Myronidis et al. (2016), and 78.9% in Park et al. (2013). Likewise, as a result of the modelling studies created according to the LR approach; LR model success value was 86.37% in Lee and Sambath (2006), 76.6% in Bugday and Akay (2019), 83.58% in Ayalew and Yamagishi (2005), 88% in Görüm and Gönençgil (2006), and 86.37% in Lee and Sambath (2006).

When the aforementioned studies are compared with this study, it is seen that similar success rates are calculated. In this study, it was also determined that landslide susceptibility could be calculated more effectively and more clearly as a result of modeling with high-resolution factors produced from UAV data based DTM and the success rates of the models presented were high. The use of data obtained from satellite vehicles in large areas is considered appropriate in terms of forming a general idea. However, making use of UAV for smaller areas and areas that need special work has supportive features in decision-making, as more detailed and more sensitive data can be produced, at a high level of confidence.

As a result of more sensitive and detailed measurement, GIS techniques and computer-based approaches provide an advantageous environment for plan makers, practitioners, and decision-makers. The more reliable and multi-purpose use of the data obtained as a result of this kind of precision measurement allows a large number of studies in this field. It is thought that more effective and detailed planning can be done by using this advantageous potential of technological tools. Niethammer et al. (2011) emphasized in their study that there will be innovations in the field of software with the development of technology. The continuous development of existing technologies also encourages development in the field of software. It is thought that processing the data obtained from technological devices with new software and transforming them into useful-quality information will contribute to the use of new approaches in practice for different sectors (forest, construction, mining, geology, etc.). In future studies, the data obtained from UAV with different technical features with different modelling approaches can be compared, and which tools are needed in the axis of aim-data resolution and software combinations can be revealed. The area subject to this study is classified as arid areas with very low annual precipitation. It is thought that for areas with high annual precipitation, model combinations including climate and precipitation parameters may yield more effective results.

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