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Landslide Susceptibility Mapping in Bitlis Province using GIS-based AHP method

CBS Tabanlı AHP Yöntemi Kullanılarak Bitlis İlinin Heyelan Duyarlılık Haritalaması

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Abstract

This study presents the landslide susceptibility assessment of the region by considering the landslide-susceptible hazard factors such as slope, precipitation, soil, lithology, distance to the river, land use, elevation, aspect, and distance to active faults as well as historical landslide events and population throughout the province of Bitlis. For this purpose, a GIS-based Analytical Hierarchy Process (AHP) was used as an effective method in multiple decision-making methods. The results showed that approximately 25% of the study area has moderate to high landslide susceptibility. Accordingly, the landslide susceptibility of the study area is high, especially in the southwest and southeast parts of the study area which have mountainous and deep river valleys, and the partially mountainous regions in the north. Compared with previous landslide records and similar susceptibility maps in the literature, the results were found to be quite successful in determining landslide susceptibility of the study area. However, risk assessment wasn't made within the scope of the study.

Keywords: *Landslide susceptibility, Analytical Hierarchy Process (AHP), GIS*

Özet

Bu çalışma, Bitlis ili genelinde eğim, yağış, toprak, litoloji, akarsuya olan mesafe, arazi kullanımı, yükseklik, bakı ve aktif faylara olan uzaklık gibi heyelana duyarlı tehlike faktörlerinin yansıra tarihsel heyelan olayları ve nüfus yoğunluğu dikkate alarak bölgenin heyelan duyarlılık değerlendirmesini sunmaktadır. Bu amaçla çoklu karar verme yöntemlerinde etkin bir yöntem olarak CBS tabanlı Analitik Hiyerarşi Süreci (AHS) kullanılmıştır. Sonuçlar, çalışma alanının yaklaşık %25'inin orta ila yüksek heyelan duyarlılığına sahip olduğunu göstermiştir. Buna göre, çalışma alanının özellikle dağlık ve derin akarsu vadilerinin bulunduğu güneybatı ve güneydoğu kesimlerinde ve kuzeyde kısmen dağlık bölgelerde heyelan duyarlılığı yüksektir. Literatürdeki önceki heyelan kayıtları ve benzer duyarlık haritaları ile karşılaştırıldığında, sonuçların çalışma alanının heyelan duyarlılığını belirlemede oldukça başarılı olduğu görülmüştür. Ancak çalışma kapsamında risk değerlendirmesi yapılmamıştır.

Anahtar kelimeler: *Heyelan duyarlılık, Analitik Hiyerarşi Süreci (AHS), CBS*

1. Introduction

Landslide is one of the natural disasters that cause the most loss of life and property in the world. It poses a significant hazard source, especially for loos, steep and mountainous terrain. It is stated that landslides can be induced by the interactivity of several factors such as earthquakes, intense rainfall, geology, land cover, slope geometry, groundwater saturation, vegetation cover, and human influences (Pradhan et al., 2011; Rawat and Joshi, 2012).

Hasekioğulları and Ercanoğlu (2012) aimed to investigate the parameter effects in preparing landslide susceptibility maps with a data-driven approach and to adapt this approach to AHP. They considered a total of 13 input parameters such as slope, aspect, plan curvature, topographical elevation, vegetation cover index, land use in the AHP assessment methodology for the landslide susceptibility of their study area in the Western Black Sea region of Turkey.

Mansouri Daneshvar (2014) aimed to map landslide susceptibility using AHP for recognition of a hazardous zone in northeast of Iran. Althuwaynee et al. (2016) introduced three main methods for landslide-susceptibility analysis based on the literature as the deterministic, the qualitative/ heuristic and the probabilistic approach. Qualitative methods are based entirely on the opinion of the expert who makes the risk assessment and therefore can be evaluated subjectively (Aleotti and Chowdhury, 1999). One of the most effective and preferred methods in qualitative methods for susceptibility assessment is the analytical hierarchy process (AHP). Many researchers in the literature used different versions of AHP approach for successful landslide susceptibility analysis. Özşahin (2015) conducted the landslide susceptibility analysis of Ganos Mountain (Tekirdağ) with the help of GIS and determined that the landslide potential in Ganos Mountain is at a moderate level. However, he identified areas of the mountain area with very low, low, high and very high landslide susceptibility. This study showed that GIS techniques give more effective results than AHP method in the preparation of landslide susceptibility maps. Althuwaynee et al. (2016) used an integrated methodology combining an automatic interaction detection model with analytic hierarchy process (AHP) to assess a medium-scale landslide susceptibility for their study area. Chen et al. (2016) aimed to map the landslide susceptibility using the AHP and certain factor (CF) models based geographic information system (GIS) for a region in China. They considered slope degree, slope aspect, plan curvature, altitude, geomorphology, lithology, distance from faults, distance from rivers and precipitation as landslide conditioning factors. Their results showed the accuracy of the AHP was approximately 78%. Kumar and Anbalagan (2016) presented a study of AHP method in landslide susceptibility mapping (LSM) for a region of Tehri reservoir in India. The results obtained from the study reached a reasonable accuracy of approximately 79%. Myronidis et al. (2016) developed a landslide susceptibility model by coupling the AHP and the frequency ratio method in a GIS environment for a landslide-prone site of Cyprus. Rahim et al. (2018) generated a landslide susceptibility map based on twelve causative factors such as slope, aspect, elevation, drainage network, stream power index, topographic witnesses, lithology, fault lines, rainfall, road network, land cover and soil texture using GIS-based AHP. In the study, nine topographic, geomorphological, and climatic parameters affecting landslide susceptibility were considered. Mokarram and Zarei (2018) applied a GIS-based fuzzy-AHP approach to determinate the landslide susceptibility mapping in a region of Iran. They considered some input criteria for the model such as the digital elevation model, lithology, slope, land use, river, road, fault, and precipitation. Acar (2019) analyzed the landslide susceptibility map of the Inebolu basin in Turkey with the help of a GIS-based AHP, taking into account decision-making criteria such as slope, aspect, elevation, curvature, land use, lithology, and distance to the river. El Jazouli et al. (2019) produced a landslide susceptibility map using GIS-based AHP approach, considering some landslide-related factors, including land cover, lithology, distance to road, distance to fault, distance to drainage network, elevation, aspect, and slope gradient. Nguyen and Liu (2019) proposed a new approach for AHP combining of bivariate analysis with correlation statistics to evaluate the importance of the pairwise comparison. Rather than scaling expert opinions, they aimed to establish a correlation between actual landslide events and relevant criteria.

In recent years, artificial neural network techniques have been used in the determination of natural disaster susceptibility in many areas. Ermini et al. (2005) aimed to define a method with the ability to forecast landslide susceptibility through the application of artificial neural networks, which allows black-box models to be implemented, similar to some other statistical approaches (Carrara et al., 1991 and 1995). Such studies encouraged systematic approaches such as ANN-based statistical methods in landslide susceptibility and mapping. Reichenbach et al. (2018), based on a comprehensive review, stated that the range of thematic data types used for susceptibility assessment has not changed significantly with time. They also pointed out that the most common statistical methods for landslide susceptibility modelling are logistic regression, neural network analysis, data-overlay, index-based and machine learning methods with an increasing preference in the recent years. Machine learning techniques have become a method frequently preferred by researchers in recent years. Merghadi et al. (2020) presented an overview of the most popular machine learning techniques available for landslide susceptibility studies. They performed an extensive comparison analysis between different machine learning techniques using a case study from Algeria, and they stated that tree-based ensemble algorithms achieve excellent results compared to other machine learning algorithms and that the Random Forest algorithm offers robust performance for accurate landslide susceptibility mapping with only a small number of adjustments required before training the model (Merghadi et al., 2020). In order to determine the height ranges of landslides, the effect of elevation on landslides was examined by reviewing the grade ranges and elevation values used by Çellek (2020) and applied to the map sections selected from Turkey.

This brief literature review shows that the AHP is a highly capable approach in the analysis of landslide susceptibility because it involves multi-criteria decision-making process. Some researchers such as Göksu (2017) and Ekinci (2020a) studied the landslide susceptibility and natural disaster diversity of the same region (Bitlis), but no study has been carried out in this context for the region before.). This study presents a susceptibility analysis of the Bitlis province of Turkey using GIS-based AHP and considering some hazard and susceptibility factors.

2. Study Area

The province of Bitlis, chosen as the study area, is one of the regions with the highest landslide susceptibility in Turkey due to its topographic, geological, and climatic properties (Figure 1). Especially the southern parts of the study area are mountainous, stems and deep valleys. The settlements and access roads in the mountainous south are generally located in deep river valleys. The upper geological structure of the region consists of lava and ignimbrite layers originating from the Nemrut Caldera (Ulusoy et al., 2019). In these areas, ignimbrite layers loosen due to meteorological conditions such as snow, rain, frost, and groundwater, causing rockfall. On the other hand, alluvial loose soil layer collected in hard lava rock beds and valleys is very sensitive to landslides. Three main tectonostratigraphic units are observed in the region, which are located on top of each other with tectonic contact (Göncüoğlu and Turhan, 1983). The uppermost part of these units is called as Bitlis metamorphic zone. On the other hand, the study area has a very variable structure in terms of seasonal climate change. Aydın et al. (2015) explained the reason for this as a micro-climatic feature display in which climate transitions occur in the region. Due to the collision of the cold and humid air in the north with the hot air in the south, sudden precipitation with significant temperature differences between seasons can trigger landslides in the region. In addition, the study area is in the Eastern Anatolia Region, which is a very active region in terms of seismicity. The region is mainly controlled by the northward movement of the Arabian plate and the collision of the Anatolian plate along the deformation zone called the Bitlis zone. These seismic features cause major earthquakes in the region (Işık, 2010; Işık et al., 2012; Işık et al., 2020; Ekinci et al., 2020b). All these situations make the study area highly susceptible to landslides. The study area is among the provinces in Turkey where landslide/rockfall events occur the most with 412 events between 1950 and 2019.

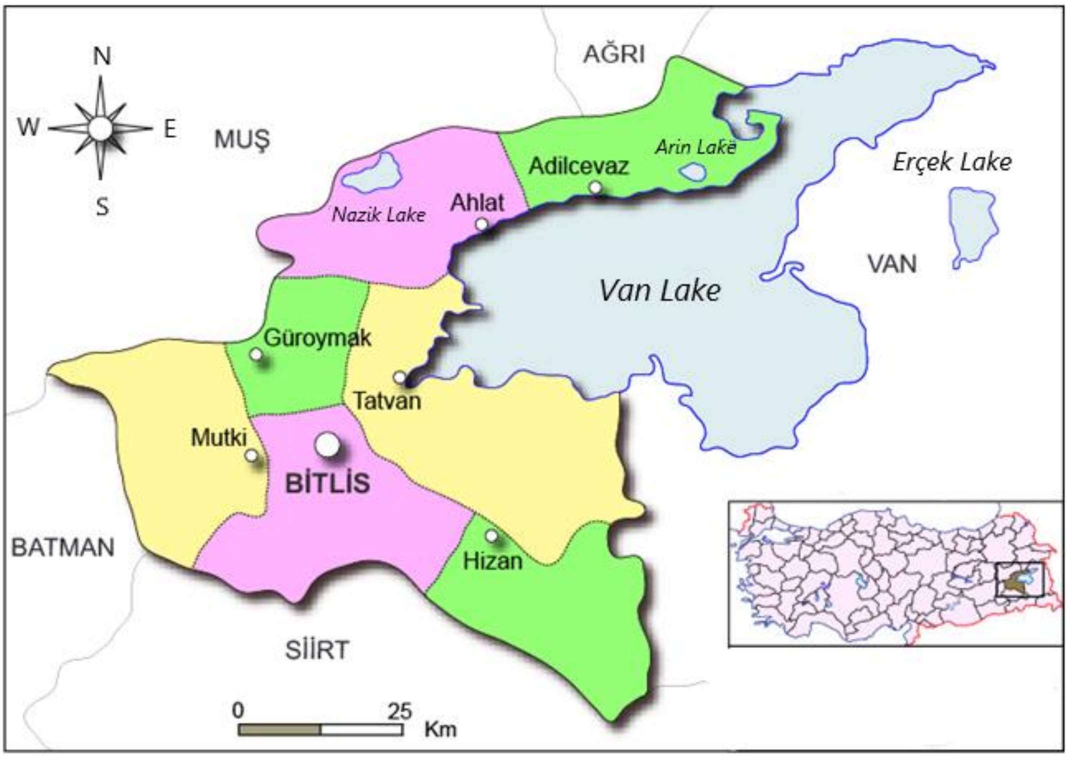

Figure 1. Location map of the study area (after Saygılı, 2015)

3. Methodology

The study area is a mountainous region with extreme climatic conditions, various soil, seismic and geological (such as volcanic and tectonic) structures. Therefore, many factors can trigger the landslide event. For this reason, a multiple decision-making method such as AHP was chosen as a very suitable method for determining the landslide susceptibility of the study area.

AHP, introduced by Saaty (1980), is a flexible approach that can be adapted to many different multi-criteria decision-making problems. To manage the decision-making process, this method includes some layers such as decision stages in which the selected criteria are scored and the stages of determining alternative values. Once the AHP schema is established, pairwise comparison matrices are defined between the effective criteria. Each criterion is scored in accordance with Table 1 considering the importance level of the comparison pairs.

Table 1. Importance intensities for pairwise comparison in AHP (Saaty, 1990; Wang et al., 2008)

Importance intensity (Scores)	Definition
1	Equal importance
3	Moderate importance of one over another
5	Strong importance of one over another
7	Very strong importance of one over another
9	Extreme importance of one over another
2, 4, 6, 8	Intermediate values
Reciprocals	Reciprocals for inverse comparison

Saaty (1980) presented the principal right eigenvector method to determine weight vector for AHP. The normalized matrix is derived by dividing each element of the comparison matrix by the sum of the corresponding columns. Each vector in the normalized matrix is averaged to obtain the weight vector. The priorities matrix is obtained by multiplying the comparison matrix and the weight vector as;

$$[AW_i] = [A][W_i] \tag{1}$$

The maximum eigenvalue (λmax) can be also formulized as below:

$$\lambda_{max} = \frac{1}{n}\sum_{i=1}^{n}\frac{AW_i}{W_i} \tag{2}$$

where, n is criteria number, A is the pairwise comparison matrix, W is the weight vector. The consistency ratio of the pairwise comparison matrix define by CR should have an acceptable ratio (Wang et al. 2008):

$$CR = \frac{\lambda_{max}-n}{(n-1)RI} \tag{3}$$

In which, the CI is the consistency index, RI is the random inconsistency index taken from Table 2.

Table 2. RI values according to numbers of criteria (n = 1 – 15) (Saaty, 1990)

n	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
RI	0.00	0.00	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49	1.51	1.48	1.56	1.57	1.59

For acceptable consistency, the decision-making process should be repeated until this ratio of CR drops below 0.10. CR = 0.00 represents the best consistency for the decision-making process (Saaty, 1990; Subramanian and Ramanathan, 2012).

4. Susceptibility Analysis

The success of AHP largely depends on the correct selection of the criteria affecting the event and the accuracy in the scoring of the decision makers. In this study, some factors that affect and are affected by the landslide event in the study area are considered. The criteria that can trigger the landslide event can be defined as hazard, and that can be affected can be described as vulnerability factors. The hazard factors in the study were slope, precipitation, soil, lithology, distance to river, land use, elevation, aspect, and distance to fault. The data of all these criteria were collected from the relevant institutions (HGM, 2021; USGS, 2021; Geofabrik, 2021; TAD, 2021; Copernicus, 2021; MTA, 2021; MGM, 2021; Climate-Data, 2021; AFAD, 2021). For each criterion, these data sets were divided into subclasses and mapped with the help of GIS as shown in Figure 2.

Each zone on the maps in Figure 2 was scored according to landslide susceptibility (Figure 3). While selecting these criteria in Figures 2 and 3, all relevant institutions' open databases were scanned in detail, and important factors that could affect landslide susceptibility were taken into account. Thus, a multi-faceted and more sensitive study on the landslide susceptibility of the region was aimed.

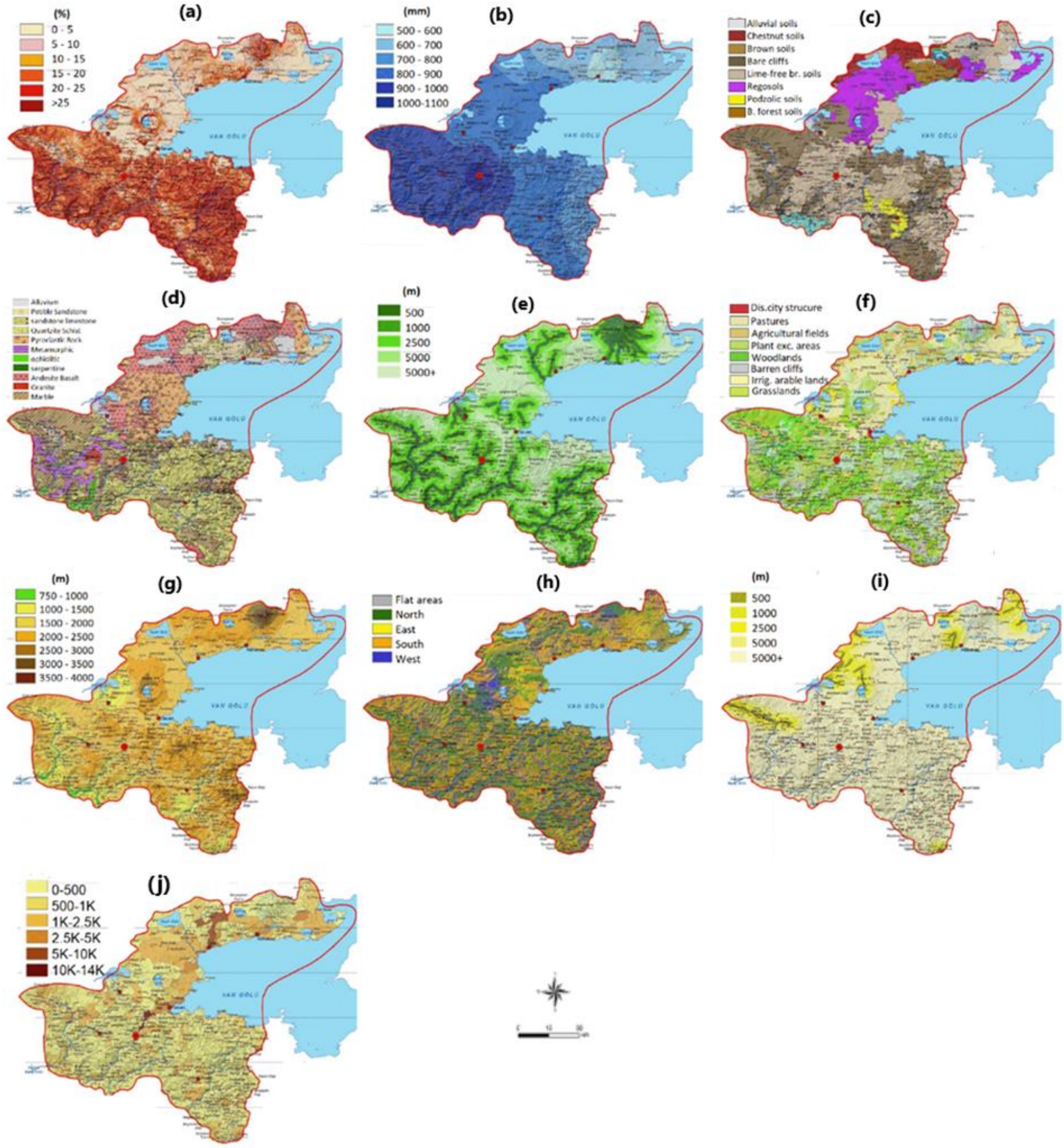

Figure 2. Sub-classification maps of each criterion prepared according to the data obtained from the relevant institutions: a) slope, b) precipitation, c) soil, d) lithology, e) distance to rivers, f) land use, g) elevation, h) aspect, i) distance to active faults, j) population

In Figure 3a, landslide events that occurred in the past in the study area are shown. According to this, the landslides are concentrated in the north, but generally spread in the southern regions. This map with past records will enhance the final map. One of the most important factors that can affect landslide susceptibility is slope. Therefore, in the map given in Figure 3b, zones with high slopes were scored high. Another important criterion that triggers landslides is precipitation. Water seeping into the ground due to precipitation may trigger landslides. For this reason, the northwest region with high precipitation was scored high as seen in Figure 3c. As the soil structure, especially barren brown soils, chestnut-colored soils, and river oil zones were evaluated as high sensitivity.

The landslide susceptibility of the regosols located on a relatively flat land in the middle region and the forest soils located in the river valleys in the west and southeast were evaluated as low (Figure 3d). In terms of lithology, rocks such as marble, granite, andesite basalt and metamorphic rocks in the southern part of the study area have low landslide susceptibility. On the other hand, the susceptibility of alluvial, conglomerate, sandstone, etc. formations in the northern parts are higher (Figure 3e). River valleys are zones where slopes are high.

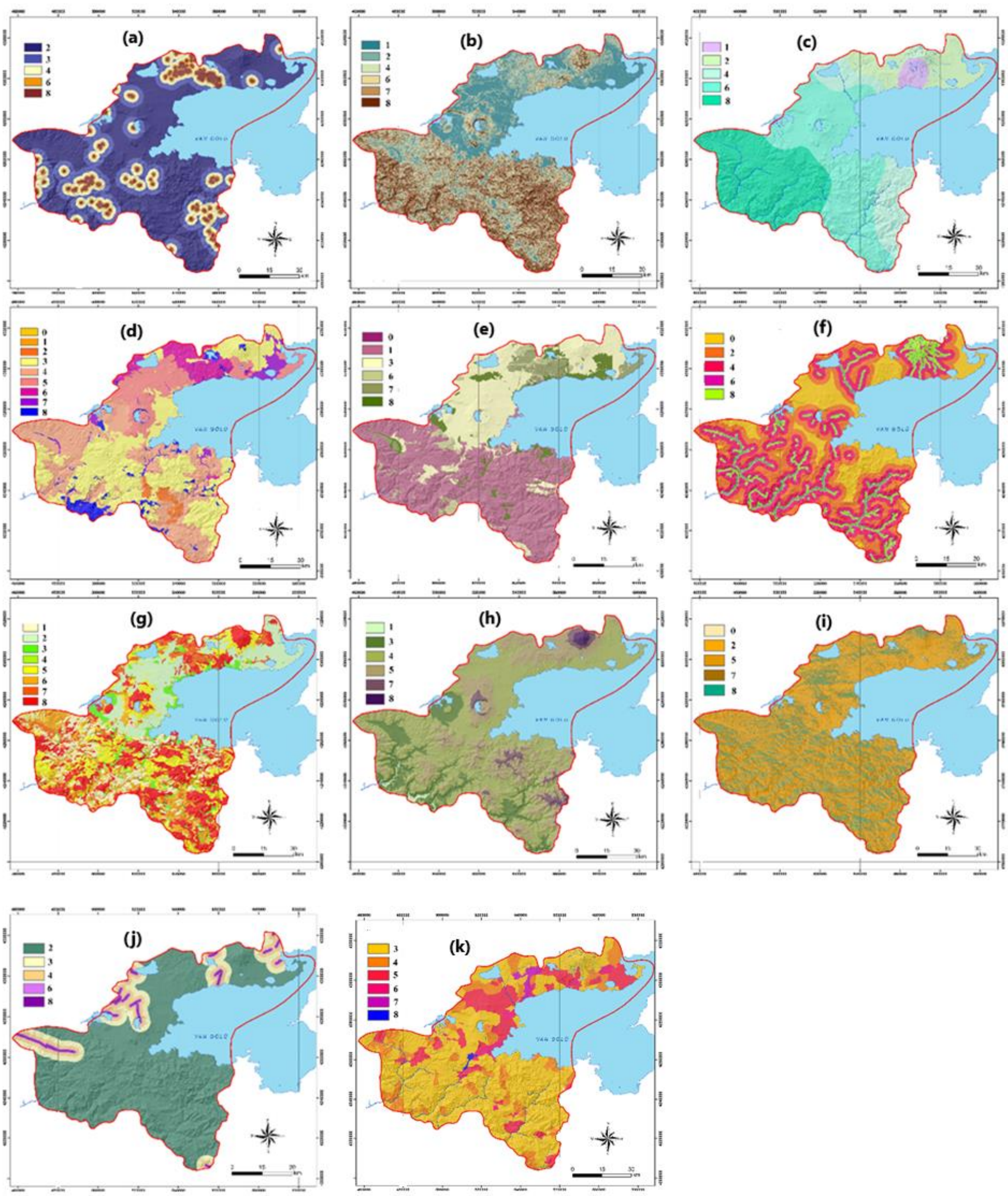

Figure 3. Scored maps a) landslide events, b) slope, c) precipitation, d) soil, e) lithology, f) distance to rivers, g) land use, h) elevation, i) aspect, j) distance to active faults, k) population of the criteria for landslide susceptibility

The closer to the river, the higher landslide susceptibility (Figure 3f). Figure 3g shows the scoring of land use on landslide susceptibility. In this map, vegetation with deep root structure such as forests and wooded areas was selected with low sensitivity.

However, sections with relatively lower slopes such as pastures and irrigable areas were also considered to have an average sensitivity. The areas with weak vegetation or bare lands were highly susceptible to landslides.

As can be seen in Figure 3h, the elevation is scored as a factor that increases landslide susceptibility. In the aspect map in Figure 3i, the landslide susceptibility is higher in south-facing zones than in the north since freeze-thaw would be more common in southern regions. Another factor that can trigger a landslide is an earthquake. The areas close to the active fault line given in Figure 3j is more susceptible to landslides. Finally, the population density is given in Figure 3k as a factor increasing the landslide susceptibility.

Human activities such as excavation, construction and un-planting may increase the landslide susceptibility on the ground, as well as increase the landslide vulnerability in the areas due to population density. The superiority of each criterion of the comparison matrix over the other was scored using the scale in Table 3, and thus the pairwise comparison matrix is obtained as in Table 3. Then, each element of this matrix is divided by the corresponding column sum to gain the normalized matrix given in Table 4.

Table 3. The pairwise comparison matrix for landslide susceptibility of the region (a-landslide events, b-slope, c-precipitation, d-soil, e-lithology, f-distance to rivers, g-land use, h-elevation, i-aspect, j-distance to active faults, k-population)

A	a	b	c	d	e	f	g	h	i	j	k
a	1	2	3	3	3	3	3	4	5	5	7
b	1/2	1	3	3	3	4	5	5	5	7	7
c	1/3	1/3	1	3	3	5	5	7	7	7	7
d	1/3	1/3	1/3	1	1	2	3	3	7	7	5
e	1/3	1/3	1/3	1	1	3	3	4	4	4	5
f	1/3	1/4	1/5	1/2	1/3	1	3	3	5	2	5
g	1/3	1/5	1/5	1/3	1/3	1/3	1	2	2	2	5
h	1/4	1/5	1/7	1/3	1/4	1/3	1/2	1	2	2	3
i	1/5	1/5	1/7	1/7	1/4	1/5	1/2	1/2	1	1	3
j	1/5	1/7	1/7	1/7	1/4	1/2	1/2	1/2	1	1	3
k	1/7	1/7	1/7	1/5	1/5	1/5	1/5	1/3	1/3	1/3	1
TOTAL	3.96	5.14	8.64	12.65	12.62	19.57	24.70	30.33	39.33	38.33	51.00

Table 4. Process of the weight vector from the normalization matrix (a-landslide events, b-slope, c-precipitation, d-soil, e-lithology, f-distance to rivers, g-land use, h-elevation, i-aspect, j-distance to active faults, k-population)

A	a	b	c	d	e	f	g	h	i	j	k	Wi
a	0.253	0.389	0.347	0.237	0.238	0.153	0.121	0.132	0.127	0.130	0.137	**0.206**
b	0.126	0.195	0.347	0.237	0.238	0.204	0.202	0.165	0.127	0.183	0.137	**0.197**
c	0.084	0.065	0.116	0.237	0.238	0.256	0.202	0.231	0.178	0.183	0.137	**0.175**
d	0.084	0.065	0.039	0.079	0.079	0.102	0.121	0.099	0.178	0.183	0.098	**0.102**
e	0.084	0.065	0.039	0.079	0.079	0.153	0.121	0.132	0.102	0.104	0.098	**0.096**
f	0.084	0.049	0.023	0.040	0.026	0.051	0.121	0.099	0.127	0.052	0.098	**0.070**
g	0.084	0.039	0.023	0.026	0.026	0.017	0.040	0.066	0.051	0.052	0.098	**0.048**
h	0.063	0.039	0.017	0.026	0.020	0.017	0.020	0.033	0.051	0.052	0.059	**0.036**
i	0.051	0.039	0.017	0.011	0.020	0.010	0.020	0.016	0.025	0.026	0.059	**0.027**
j	0.051	0.028	0.017	0.011	0.020	0.026	0.020	0.016	0.025	0.026	0.059	**0.027**
k	0.036	0.028	0.017	0.016	0.016	0.010	0.008	0.011	0.008	0.009	0.020	**0.016**

Result mapping and classification processes were performed with ArcGIS, a GIS software. For this, raster data was reclassified by means of Arctoolbox -3D Analyst Tools - Raster - Reclass. After the classification process, the data was converted into vector data via Conversion Tools – From Raster – Raster to Polygon. Then, vector data was integrated with Data Management Tools – Generalization – Dissolve. Data Management Tools- Fields – Add Field tool is used to enter the scoring values into the attribute table of each criterion.

The average of each row of the normalized matrix is calculated in the last column as the weights of the criteria representing this row. According to the determined weights, the maximum eigenvalue was calculated as $\lambda max=12$ from Eq. (2). The consistency ratio, CR, was also calculated as 0.07 from Eq. (3), and since this value is less than 0.10, it can be said that the comparison matrix has an acceptable consistency. Consequence, the weights of the criteria on landslide susceptibility were calculated as follows: 20.6% for landslide, 19.7% for slope, 17.5% for precipitation, 10.2% for soil, 9.6% for lithology, 7.0% for distance to rivers, 4.8% for land use, 3.6% for elevation, 2.7% for aspect, 2.7 for fault distance and 1.6% for population. These weights were implemented to layers of the criteria maps in GIS environments to create the result maps of landslide susceptibility.

5. Results and Discussion

The raster map layers in Figure 3 were weighted with the ratios obtained from the AHP, and the landslide susceptibility map was obtained in the GIS environment. In the map shown in Figure 4, the landslide susceptibility is colored in five different degrees, as very low susceptible, low susceptible, moderate susceptible, high and very high susceptible. According to this map, approximately 8% of the study area is susceptible to landslides at very low levels, 66% at low levels, 25% at medium and high levels, and 1% at very high levels (Table 5). Accordingly, especially the mountainous southwestern parts of the study area are high-susceptible areas, while the central and northern parts are considered low-susceptible areas. Steep sections with deep aquifer valleys are areas with high landslide susceptibility. A similar situation is also valid for the river valley in the southeast of the study area. In addition, relatively mountainous areas with a sandstone lithological structure in the northern parts are susceptible to landslides.

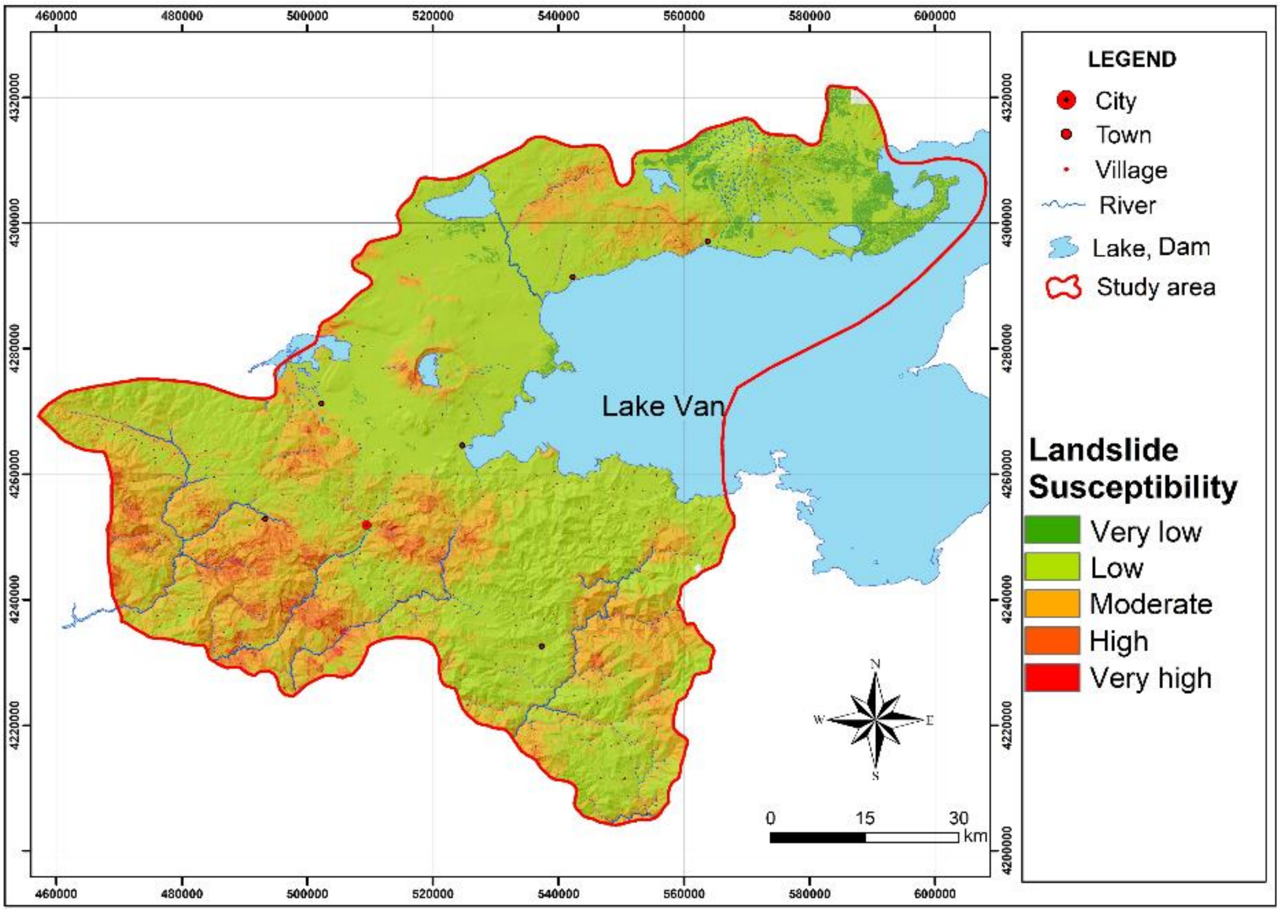

Figure 4. Final landslide susceptibility map of the study area

To test the accuracy of the map, it was also compared with some maps from the literature given in Figure 5. Figure 5a shows the landslide susceptibility map of the study area prepared by Göksu (2017). Ekinci et al. (2020a) also showed the historical landslides in the study area on the map in Figure 5b. Since there is no accuracy analysis or comparison about Göksu's (2017) map, the reliability of this map is not completely known, but it is seen that especially the parts with high landslide susceptibility overlap with the results of this study (Figures 4 and 5a). On the other hand, the landslide susceptibility map obtained from this study is in good agreement with the observed landslide records on the map presented by Ekinci et al. (2020a) (Figures 4 and 5b). In general, Figures 4 and 5 showed that the landslide susceptibility is concentrated in the southeast and southwest and partially in the north. Although no comprehensive accuracy assessment or analysis were performed, these comparisons demonstrate the validity and reasonable accuracy of the results obtained for the study area.

Table 5. Spatial distribution of landslide susceptibility classes and ranges

<table>
<tr><th>Landslide Susceptibility Classes</th><th>Landslide Susceptibility Ranges</th><th>Area (km^2)</th><th>Ratio (%)</th></tr>
<tr><td>Very Low</td><td>0 – 0.19</td><td>536.56</td><td>8</td></tr>
<tr><td>Low</td><td>0.20 – 0.39</td><td>4426.62</td><td>66</td></tr>
<tr><td>Moderate</td><td>0.40 – 0.59</td><td rowspan="2">1676.75</td><td rowspan="2">25</td></tr>
<tr><td>High</td><td>0.60 – 0.79</td></tr>
<tr><td>Very High</td><td>0.80 – 0.99</td><td>67.07</td><td>1</td></tr>
<tr><td colspan="2">TOTAL</td><td>6707</td><td>100</td></tr>
</table>

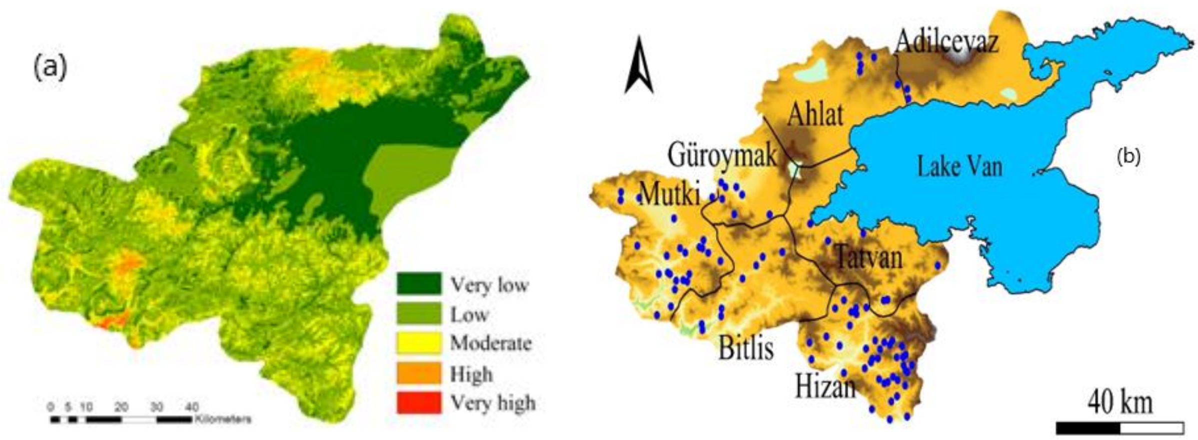

Figure 5. Literature records on landslide susceptibility of the study area: a) landslide susceptibility map (Göksu, 2017), b) past landslide records in the study area (Ekinci et al., 2020a)

6. Conclusions

In this study, landslide susceptibility maps of Bitlis province, located in the Eastern Anatolia Region of Turkey, where relatively mountainous and landslide events are common, were obtained by applying GIS-based AHP. The important factors in the landslide susceptibility of the region are slope, precipitation, soil structure and lithology as well as past landslide events (inventory) and population. The results indicate that approximately 25% of the study area has moderate to high landslide susceptibility. Accordingly, the landslide susceptibility of the study area is high, especially in the southwest and southeast parts of the study area (Mutki, Bitlis and Hizan) due to the mountainous structures and deep river valleys, and in the partially mountainous regions in the north (the region between Ahlat and Adilcevaz). The landslide susceptibility in the middle parts of the region where Güroymak, Ahlat and Tatvan districts are located is low. Although the previous landslide records and some other studies in the literature support the results of the study, this study reflects the landslide susceptibility of the area much better. The main reason for this is that eleven different criteria were considered with a logical filter in the used method. It is expected that the results obtained will contribute to the disaster management of the region.

Some limitations, advantages and disadvantages of this study can be presented as follows. First, it depends on the accuracy of the results and the availability of sufficiency and the accuracy of the data sets. The field of study and expertise of the decision makers and the scoring of the criteria are the most important factors on the robustness of the results. In addition, the selection of effective criteria on the event is important. For this reason, the effective criteria on the event should be selected and defined correctly. With this method, which offers a qualitative approach, the deterministic and probabilistic aspects of the event are ignored. On the other hand, it is possible to get very simple, effective, fast and accurate results thanks to AHP with accurate data set usage, multiple-decision mechanism and flexible expert opinions. In addition, it should be noted that the accuracy of the results in this study was not tested with any Accuracy Assessment technique, their validity was checked only by comparing them with similar studies and real event records. For better accuracy analysis, it is recommended to test the model accuracy with the techniques such as ROC curve in the literature.

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References

Acar, E. (2019). *Production of landslide susceptibility maps by using AHP method and GIS analyses* (Master's thesis). Hacettepe University, Graduate School of Natural and Applied Sciences, Department of Geological Engineering, Ankara.

AFAD. (2021, July 01). 2020 yılı doğa kaynaklı olay istatistikleri. Retrieved from https://www.afad.gov.tr/kurumlar/afad.gov.tr/e_Kutuphane/Istatistikler/2020yilidogakaynakliolayistatistikleri.pdf

Aleotti, P., & Chowdhury, R. (1999). Landslide hazard assessment: summary review and new perspectives. *Bulletin of Engineering Geology and the Environment, 58*(1), 21–44.

Althuwaynee, O.F., Pradhan, B., & Lee, S. (2016). A novel integrated model for assessing landslide susceptibility mapping using CHAID and AHP pair-wise comparison. *International Journal of Remote Sensing*, *37*(5), 1190–1209.

Aydın, M.C., & Işık, E. (2015). Evaluation of Ground Snow Loads in the Micro-climate Regions. *Russian Meteorology and Hydrology, 40*(11), 741–748.

Birincioğlu-Sevgi, E. (2021). *Disaster risk analysis of Bitlis province using geographical information systems and analytical hierarchy method* (Master's thesis). Bitlis Eren University Graduate Education Institute, Department of Emergency and Disaster Management, Bitlis.

Carrara, A., Cardinali, M., Detti, R., Guzzetti, F., Pasqui, V., & Reichenbach, P. (1991). GIS techniques and statistical models in evaluating landslide hazard. *Earth Surface Processes and Landforms, 16*, 427– 445.

Carrara, A., Cardinali, M., Guazzetti, F., & Reichenbach, P. (1995). GIS techniques in mapping landslide hazard. In A. Carrara, & F. Guzzetti (Eds.), *Geographical Information Systems in Assessing Natural Hazards* (pp. 135–175). The Netherlands: Kluwer Academic Publishers.

Chen, W., Li, W., Chai, H., Hou, E., Li, X., & Ding, X. (2016). GIS-based landslide susceptibility mapping using analytical hierarchy process (AHP) and certainty factor (CF) models for the Baozhong region of Baoji City, China. *Environmental Earth Sciences, 75*(1), 63. doi: 10.1007/s12665-015-4795-7.

Climate-Data. (2021, December 16). Climate data for cities around the world. Retrieved from https://tr.climate-data.org

Copernicus. (2021, December 16). Data of land use from Copernicus Land Monitoring Service. Retrieved from https://land.copernicus.eu.

Çellek, S. (2020). Morphological parameters causing landslides: a case study of elevation. *Bulletin of the Mineral Research and Exploration, 162*, 197-224.

Ekinci, R., Büyüksaraç, A., Ekinci, Y.L., & Işık, E. (2020a). Bitlis ilinin doğal afet çeşitliliğinin değerlendirilmesi. *Doğal Afetler ve Çevre Dergisi, 6*(1), 1-11.

Ekinci, Y.L., Büyüksaraç, A., Bektaş, O., & Ertekin, C. (2020b). Geophysical Investigation of Mount Nemrut Stratovolcano (Bitlis, Eastern Turkey) Through Aeromagnetic Anomaly Analyses. *Pure and Applied Geophysics, 177*, 3243–326.

El Jazouli, A., Barakat, A., & Khellouk, R. (2019). GIS-multicriteria evaluation using AHP for landslide susceptibility mapping in Oum Er Rbia high basin (Morocco). *Geoenvironmental Disasters*, *6*(1), 3. doi: 10.1186/s40677-019-0119-7.

Ermini, L., Catani, F., & Casagli, N. (2005). Artificial Neural Networks applied to landslide susceptibility assessment. *Geomorphology, 66*, 327–343.

Geofabrik. (2021, December 16). Maps and Data. Retrieved from https://www.geofabrik.de/data.

Göksu, A. E. (2017). Landslide Susceptibility Analysis Report. Disaster and Emergency Management Presidency (AFAD), Bitlis, Turkey.

Göncüoğlu, M. C., & Turhan, N. (1983). New Results on the Age of Bitlis Metamorphics. *Bulletin of the Mineral, Research and Exploration, 95-96*, 44-48.

Hasekioğulları, G. D., & Ercanoğlu, M. (2012). A new approach to use AHP in landslide susceptibility mapping: a case study at Yenice (Karabük, NW Turkey). *Natural Hazards, 63*(2), 1157-1179.

HGM. (2021, December 16). Republic of Türkiye Ministry of National Defense General Directorate of Mapping. Turkish administrative borders data. Retrieved from https://www.harita.gov.tr.

Işık, E. (2010). *Bitlis City Earthquake Performance Analysis* (Doctoral dissertation). Sakarya University, Graduate School of Natural and Applied Science, Sakarya.

Işık, E., Aydın, M. C., Bakış, A., & Özlük, M. H. (2012). The faults near Bitlis and seismicity of the region. *BEU Journal of Science, 1*(2), 153-169.

Işık, E., Aydın, M. C., & Büyüksaraç, A. (2020). 24 January 2020 Sivrice (Elazığ) earthquake damages and determination of earthquake parameters in the region. *Earthquakes and Structures*, *19*(2), 145-156.

Kumar, R., & Anbalagan, R. (2016). Landslide susceptibility mapping using analytical hierarchy process (AHP) in Tehri reservoir rim region, Uttarakhand. *Journal of the Geological Society of India, 87*(3), 271-286.

Mansouri Daneshvar, M. R. (2014). Landslide susceptibility zonation using analytical hierarchy process and GIS for the Bojnurd region, northeast of Iran. *Landslides, 11*(6), 1079-1091.

Merghadi, A., Yunus, A. P., Dou, J., Whiteley, J., ThaiPham, B., Bui, D. T., Avtar, R., & Abderrahmane, B. (2020). Machine learning methods for landslide susceptibility studies: A comparative overview of algorithm performance. *Earth-Science Reviews, 207*, 103225. doi: 10.1016/j.earscirev.2020.103225.

MGM. (2021, December 16). Precipitation Data, Climate-Data, Turkish State Meteorological Service. Retrieved from https://www.mgm.gov.tr.

Mokarram, M., & Zarei, A.R. (2018). Landslide susceptibility mapping using fuzzy-AHP. *Geotechnical and Geological Engineering, 36*(6), 3931-3943.

Myronidis, D., Papageorgiou, C., & Theophanous, S. (2016) Landslide susceptibility mapping based on landslide history and analytic hierarchy process (AHP). *Natural Hazards*, *81*(1), 245-263.

MTA. (2021, December 16). Data of geological structure from geoscience map viewer and drawing editor, General Directorate of Mineral Research and Exploration of Turkey. Retrieved from http://yerbilimleri.mta.gov.tr/anasayfa.aspx.

Nguyen, T. T. N., & Liu, C. C. (2019). A new approach using AHP to generate landslide susceptibility maps in the Chen-Yu-Lan Watershed, Taiwan. *Sensors*, *19*(3), 505. doi: 10.3390/s19030505.

Özşahin, E. (2015). Coğrafi Bilgi Sistemleri yardımıyla heyelan duyarlılık analizi: Ganos Dağı örneği (Tekirdağ). *Harita Teknolojileri Elektronik Dergisi, 7*(1), 47-63.

Pradhan, B., Mansor, S., Pirasteh, S., & Buchroithner, M. F. (2011). Landslide Hazard and Risk Analyses at a Landslide Prone Catchment Area Using Statistical Based Geospatial Model. *International Journal of Remote Sensing, 32*, 4075–4087.

Reichenbach, P., Rossi, M., Malamud, B. D., Mihir, M., & Guzzetti, F. (2018). A review of statistically based landslide susceptibility models. *Earth-Science Reviews, 180*, 60-91.

Rahim, I., Ali, S. M., & Aslam, M. (2018). GIS Based landslide susceptibility mapping with application of analytical hierarchy process in District Ghizer, Gilgit Baltistan Pakistan. *Journal of Geoscience and Environment Protection, 6*(2), 34-49.

Rawat, J. S., & Joshi, R. C. (2012). Remote-Sensing and GIS-Based Landslide-Susceptibility Zonation Using the Landslide Index Method in Igo River Basin, Eastern Himalaya, India. *International Journal of Remote Sensing*, *33*(12), 3751–3767.

Saaty, T. L. (1980). *The analytic hierarchy processes*. New York, NY: McGraw-Hill.

Saaty, T. L. (1990). How to make a decision: The analytic hierarchy process. *European Journal of Operational Research*, *48*(1), 9–26.

Saygılı, R. (2015). Coğrafya şekil. Retrieved from https://www.harita.gov.tr.

Subramanian, N., & Ramanathan, R. (2012). A review of applications of Analytic Hierarchy Process in operations management. *International Journal of Production Economics*, *138*, 215-241.

TAD. (2021, December 16). Agricultural Land Evaluation Portal (TAD Portal), Republic of Turkey Ministry of Agriculture and Forestry General Directorate of Agricultural Reform. Retrieved from https://www.tarimorman.gov.tr.

Ulusoy, İ., Çubukçu, H.E., Mouralis, D., & Aydar, E. (2019). Nemrut Caldera and Eastern Anatolian Volcanoes: Fire in the Highlands. In C. Kuzucuoğlu, A. Çiner & N. Kazancı (Eds.), *Landscapes and Landforms of Turkey* (pp. 589–599). Springer, Cham.

USGS. (2021, December 16). EarthData and Digital Elevation Model (DEM) for Bitlis province, United States Geological Survey (USGS). Retrieved from https://www.usgs.gov.

Wang, Y., Liu J., & Elhag, T. (2008). An Integrated AHP-DEA methodology for bridge risk assessment. *Computers and Industrial Engineering*, *54*(3), 513-525.