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Landslide susceptibility assessment of the Asi watershed, southern Türkiye

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Abstract: Landslides constitute recurrent natural hazards worldwide with greater socioeconomic impacts in low-income places. Landslide susceptibility studies are carried out to determine the potential for landslides to occur in a region, to predict possible risks in the future and to integrate this information into sustainable planning and management strategies. Slip-type landslides occur in limited areas of less than 1% of the Asi watershed in Southern Türkiye. Therefore, meaningful estimations cannot be made with classical statistical models. So, using the maximum entropy approach (MaxEnt), a technique for estimating based on a small number of observations, a landslide susceptibility assessment was constructed. The association between the locations where landslides are detected and environmental variables is modeled using the best probability density in the maximum entropy technique. The analyses were repeated with three different random selection methods using two-thirds of the landslide dataset to analyse it and one-third as validation data. The accuracy and precision of the obtained models were evaluated with the area under the receiver operating characteristic curves and success prediction curves. Hence, we performed a susceptibility assessment based on a maximum entropy method in the 7893 km^2 Asi watershed. The area under the receiver operating characteristic curves was 0.76 as a result, and 72% of the landslides occurred in areas with a total area of 28% that were high and extremely high susceptible areas. The determination of the landslides that will develop in the region over time and the susceptibility assessments to be repeated will contribute to the more effective planning of mitigation studies. This method can be applied in other watersheds with localized landslide processes that affect human activities. Landslide susceptibility studies are a fundamental tool for understanding landslide risks at a regional scale and predicting future hazards. These studies have a central role in regional planning, infrastructure management, crisis response, and the formulation of sustainable development strategies.

Key words: Asi watershed, slip-type landslides, maximum entropy method, receiver operating characteristic curve, success-prediction curve, Landslide susceptibility

1. Introduction

Landslides are one of the most common disasters in the world resulting in large death tolls and economic losses every year. In addition, mass movements occur at every latitude and altitude with variable magnitude and frequency (García et al., 2020; Pandey et al., 2020). Although losses are increasing worldwide, the socioeconomic consequences are much higher in developing countries than in the developed world (Turner, 2018; Emberson et al., 2020; Quesada Román, 2021 a,b; Tekin and Çan, 2022; Chang et al., 2023). Contemporarily, rapidly changing climatic conditions and increasing urban development make the potential effects of landslides even more important (Quesada Román et al., 2021; Quesada Román and Mata Cambronero, 2021). Landslides are among the disasters that cause great damage and threaten human life. In this context, landslide susceptibility studies have a strategic importance in order to understand and evaluate the landslide risk at the regional scale and to predict possible future threats.

Earth scientists provide specific, and often different, definitions of the term landslide (Kornejady et al., 2017). Hungr et al. (2014) proposed a new classification of 32 landslide-type keywords which remains simple compared to the globally known Varnes' classification of 29 mass movement types from 1978. Landslide susceptibility mapping can be regarded as an important preliminary step for assessing the risk of future landslides (Park, 2015; Carrión et al., 2021; Duman and Çan 2023). Methods to characterize potential landslide areas can be basic, intermediate, and sophistical adding heuristic or empirical models, statistical analyses, and/or deterministic models (van Westen et al., 2006). Moreover, to validate landslide areas quantitatively and/or quantitively, there are knowledge-driven, data-driven, and physically based methods (Corominas et al., 2014).

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A prediction-based approach, the MaxEnt (maximum entropy) machine learning method is observation-based. (Dwivedi et al., 2022; Achu et al., 2023). A maximum entropy model provides the ability to incorporate many variables that cannot be incorporated in a physical model alone (Davis and Blesius, 2015). MaxEnt model can be applied as an efficient technique in susceptibility assessment for landslides (Javidan et al., 2021). Moreover, the method has been applied in several regions with high landslide susceptibility with successful results (Kurilla and Fubelli, 2022; Peng et al., 2022; Conforti et al., 2023).

Türkiye is located in a geography where the risk of landslides is high with its rich geological structure, diverse topography, and variable climatic conditions. Therefore, the potential impacts of landslides are of great importance both from an environmental and socioeconomic perspective. Disasters that can be caused by landslides can adversely affect critical sectors such as infrastructure, agriculture, energy, and transportation, as well as threaten human life. In this article, Türkiye's unique geographical features and risk profile indicate that landslide susceptibility studies play a vital role in terms of the country's sustainable development goals. In this article, a landslide susceptibility study was conducted in order to understand the landslide risk and predict future risks in the Asi watershed, which is one of the 25 largest catchments in Türkiye. How these studies can be used in the country's urban planning, infrastructure management, emergency preparedness, and environmental protection strategies will be discussed. Taking effective measures against these risks arising from Türkiye's geographical richness stands out as a vital step for the safety and sustainable development of future generations.

The Asi watershed is characterized by its densely populated areas, intensive farming, and frequent landslide incidence. It is crucial to assess the factors that play a role in causing slope failure and to reduce their socioeconomic effects by creating a landslide susceptibility map. In this study, a comparison of the maximums is performed, using the receiver operating characteristic curve, and the accuracy of landslide susceptibility maps produced with statistical approaches was assessed (ROC). The resulting maps will be used for regional land use planning and landslide mitigation.

2. Study area

The Asi watershed, is located in the southern part of Türkiye and the Eastern Mediterranean Region. It lies between latitudes 36°21' North, 35°48' South, and longitudes 36°41' East and 35°53' West. The section of the Asi Basin within the borders of Türkiye, 70.4% Hatay, 18.6% Gaziantep, 8.6% Kilis, 1.3% Osmaniye, 0.9% Adana, and 0.2% of them are located within the borders of Kahramanmaraş provinces. The entire province of Hatay is located within the Asi River watershed (Figure 1). With an area of approximately 25,000 km^2, 69% of the Asi

Sources: Esri, GEBCO, NOAA, National Geographic, Garmin, HERE, Geonames.org, and other contributors; Esri, Garmin, GEBCO, NOAA NGDC, and other contributors

Figure 1. Location map of the study area.

watershed's area is located in Syria, 23% in Türkiye, and 8% within the borders of Lebanon. The origin of Asi River starts from the eastern slopes of the Lebanon mountains and plays a key role in the irrigation of agricultural lands (Homus, Hama, and Ghab plains) in Syria. The Asi River flows in Türkiye for 88 km. With the drying of Amik Lake in Türkiye, Karasu takes the Küçük Asi branch, which turns into a stream formed by the merger of Balıklı Lake channel and Afrin Stream (Dalar, 2010). In addition, the stream draws an administrative border of 3.5 km between Reyhanlı and Antakya districts (Atasoy, 2012). The river that irrigates the Amik Plain alters its route from south to north and curves to the west there. It generates the Harbiye waterfalls as it enters a confined strait in an east-west direction close to Hatay. Additionally, it creates a delta beginning 6 km to the southwest of the town of Samandağ in Antakya and empties into the Mediterranean Sea (Azarkan, 2003; Dursun, 2006; Usun and Geçen 2017). The basin is one of the most important water collection basins in the world, both economically and geographically because it is located within the borders of 3 countries. The Asi Basin, shows its influence in Lebanon, Syria, and Türkiye with relevant natural risk disaster potential. It is an active area for earthquakes and landslides, especially in the Turkish region. The Amanos fault in the lower places of the East Anatolian Fault zone, especially in the middle part of the Asi basin, constitutes one of the faults with high earthquake hazards.

The CORINE land cover map has been prepared at 3 different levels since 1985 (URL-1 2019). Within the scope of the CORINE Project, it is aimed to determine the land changes that occurred in many countries by using the same standards in 1990, 2006, 2012, and 2018. In the Asi River basin, it is notable that artificial masses and water bodies increase, while agricultural areas and wetlands decrease according to the land changes that occurred between 1990 and 2018 (Figure 2). Most of the landslides are in agricultural areas and artificial areas.

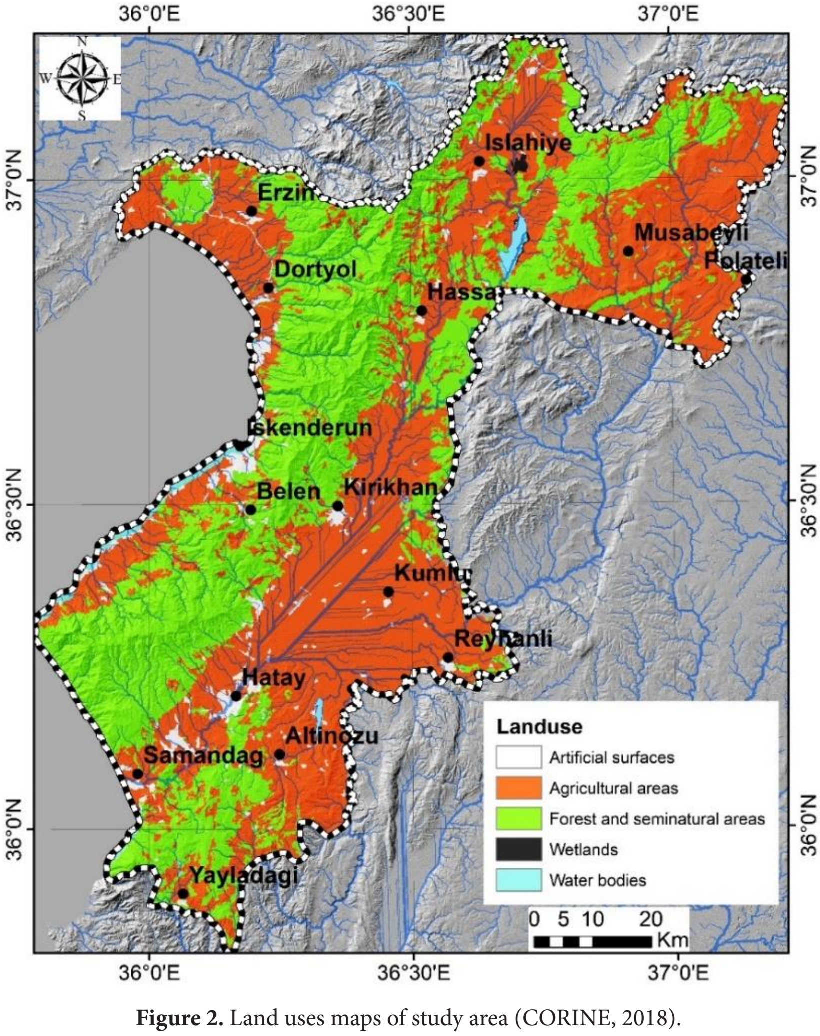
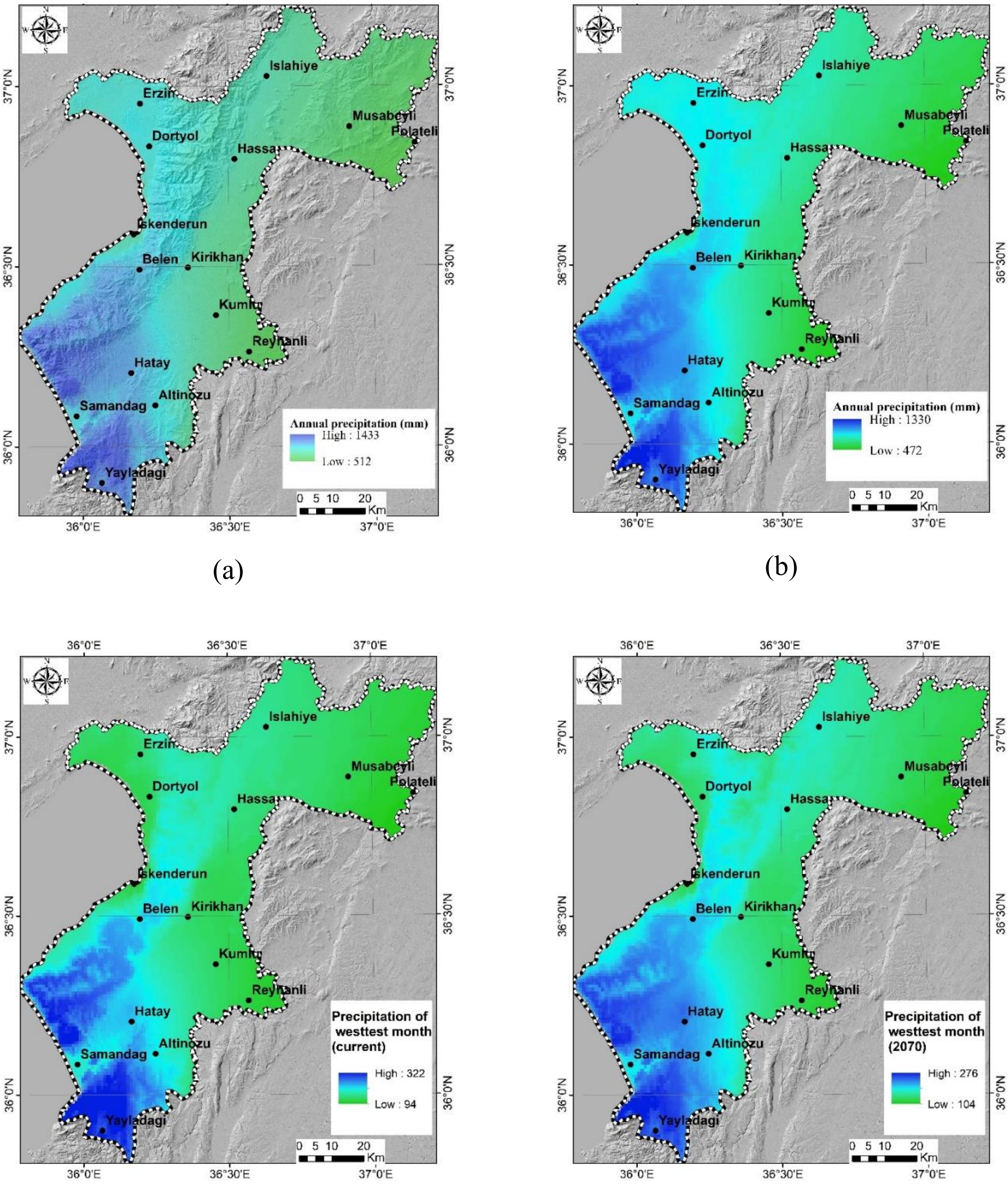


Figure 2. Land uses maps of study area (CORINE, 2018).

Due to the Mediterranean climate that prevails throughout the basin, there is almost no seasonal variation between autumn and winter, especially in terms of agricultural activities. Climate data prepared by Worldclim (URL-3 2020) for a series of global climate layers with a spatial resolution of about one km were examined for the study area. In light of the data obtained from the meteorology stations between 1960–1990, future prediction models were prepared. According to these data, it is seen that the annual average precipitation values in the study area between 1960 and 1990 were 1433 mm (Figure 3a), 1330 mm (Figure 3b) according to the scenario foreseen for the year 2070, therefore there will be a decrease of 100 mm. When we look at the average precipitation data of the wettest months from the world's climate scenarios, it is seen that the annual precipitation values of 322 mm (Figure 3c) have been reached, especially in the southeast regions of the study area according to today's data. It is estimated that there will be a decrease of approximately 140 mm in these values in 2070 (Figure 3d).



(a) (b)

(c) (d)

Figure 3. Annual precipitation 1970–1990 Current (a), 2070 (b), precipitation of wettest month current (c), 2070 (d).

There are magmatic, sedimentary, and metamorphic rocks formed from the Paleozoic to the present in the Asi Basin (Figure 4). Undifferentiated Paleozoic metamorphic units are in the Asi Basin. Sadan formation (Paleozoic aged) consists of sandstone-siltstone intercalated shales. Zabuk formation comprises silica cemented medium-thick bedded quartz and feldspar sandstones. Seydişehir Formation has a shale-siltstone alternation. Bedinan formation comprises different clastic rocks with different characteristics. Limestone-shale intercalation conformed the Stacked formation while the Köprülü formation consists of limestone and sandstone interlayers. Mesozoic Geological Formations consist of ophiolitic mélange cumulate gabbros. General characteristics of Mesozoic-aged ophiolitic units consist of siliceous shale, argillaceous limestone, cherty limestone, radiolarite, and chert intercalation. Intermediate layers of thick-bedded, chert, and fine-grained sandstone are observed in the complex. Limestones cover partly silicified and partly igneous rock blocks. The Karadut Complex is tectonically overlain by the Sayındere and Kastel formations and the Koçali Complex and is tectonically overlain by the Koçali Complex. The thickness of the unit is between 800–2000 m (Açıkbaş and Baştuğ, 1975). Neogene aged Eocene, Pliocene and Paleocene-aged units generally consist of terrestrial sediments and are generally in conglomerate sandstone lithology. Quaternary Alluvial units are generally seen in plain areas and along river branches.

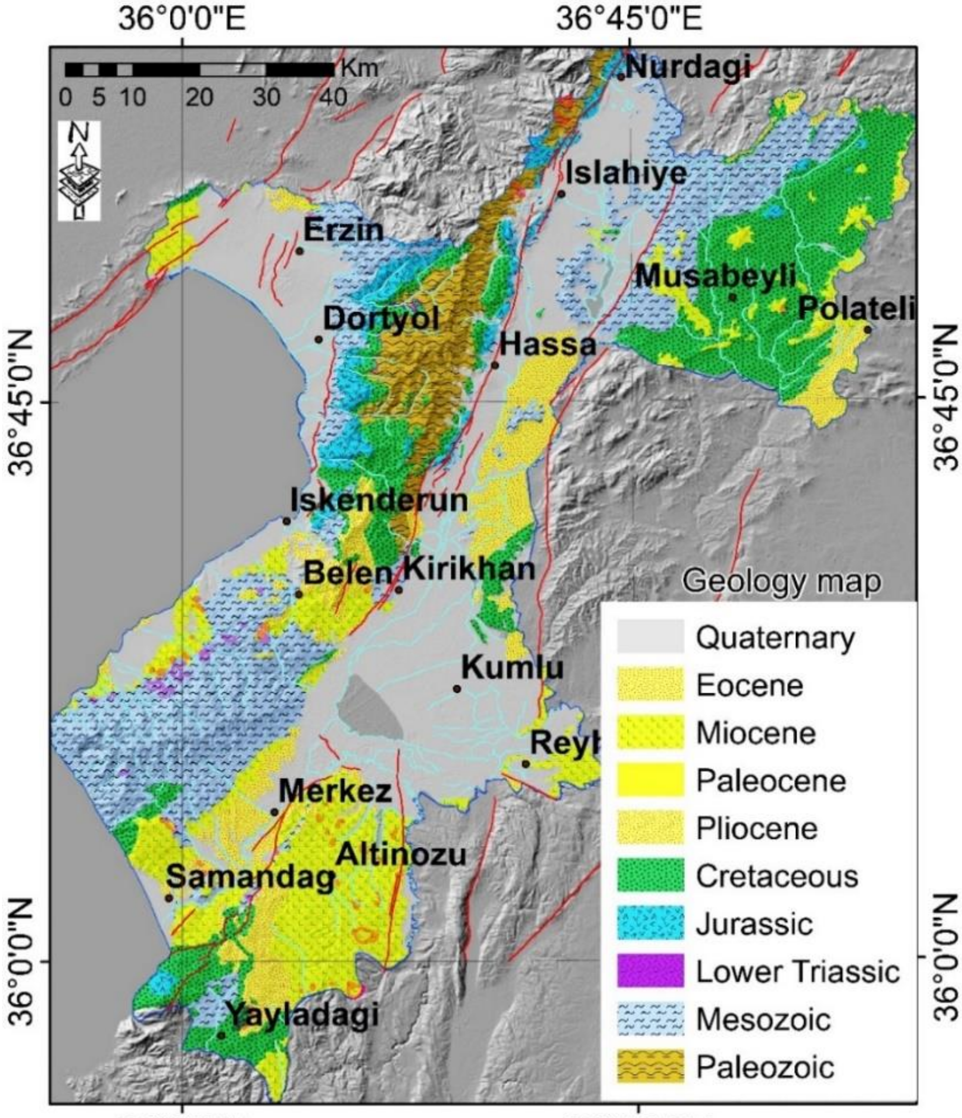


Figure 4. Geology map of study area (Akbaş et al., 2011).

3. Material and methods

For the landslide susceptibility study performed using the maXent method, a three-stage approach was followed. In the first stage, Digital Elevation Model (DEM), Slope, Plan curvature, Profile curvature, Curvature, Slope/Aspect transformation (Sat_Trasp), Slope/Aspect transformation (Satsin), Slope/Aspect transformation (Sat_Cos), Mean slope, Heat load index (HLI), Topographic wetness index (TWI), Dissection, Roughness, Surface/Area Ratio (SAR), Surface relief ratio (SRR), were used as predisposing factors for landslides. These were prepared in the form of thematic maps using the digital elevation model data created from 100 × 100 m grid cells in the ArcGIS environment. The size and scale of the study area play an important role in choosing pixel dimensions. One of the most important factors in choosing the pixel dimensions of 100 m is the large working area. At the same time, choosing pixel sizes on a smaller scale can cause greater data collection and processing difficulties. Pixel sizes of 100 m can make data collection and processing more manageable and faster. Then, these variables were transformed into high-resolution geographic information systems (GIS) data using appropriate data sources. In the last stage, the distribution of landslide areas was modeled using the MaXent method.

MaXent enables the creation of a landslide susceptibility map by analyzing the relationships between the determined variables. At this stage, important parameters such as slope, elevation, and lithology played a key role in determining the landslide potential. The results obtained thanks to the MaXent method provide valuable guidance in identifying landslide susceptibility areas and predicting future risks.

3.1. Landslide inventory

Landslide inventory maps showing the type and spatial distribution of landslides are maps that help understand landslide events per region, select the target areas that require detailed studies, and form the basis of landslide mitigation studies. The methods used in the preparation of landslide inventory maps vary depending on the purpose of the study, the size of the study area, the scale of the topographic maps where landslides will be processed and the aerial photographs used, the spatial resolution of the satellite images, and the existing infrastructure and financial possibilities.

Because of the geological structure and geographical features of the Asi region, landslide events frequently generate disasters in the Asi watershed. The scattered construction of rural settlements, the low standard transportation network in parallel with the dispersed construction, and the uncontrolled surface drainage systems of the transportation network are among the factors that prepare and trigger landslides (Duman and Çan, 2023). The spatial distribution of landslides, which are effective regionally, should be mapped in detail to reduce the losses caused by landslides. The size, distribution, superstructure, and infrastructure elements of the landslides were recorded in detail. Accordingly, there are 103 slide types of landslides in the study area, varying in size from 0.0017 km^2 to 4.04 km^2. The slide types of landslides can be translational or rotational and be present in different materials such as rocks, debris, and soils (Hungr et al., 2014). Elevation values start from sea level and reach a maximum of 2215 m, and landslides are generally observed in the middle and lower parts of the basin in the higher parts (Figure 5). A total of 15 variables produced from the digital elevation model and derivative maps were used in the susceptibility assessments.

It is known that landslides in the Asi watershed are generally triggered by precipitation and earthquakes. Some examples of landslides that occurred after extreme precipitation are shown in Figure 6. Such examples are very important in order to observe the effects of climate change. Especially after the earthquakes that took place in Türkiye on February 6, 2023, the landslide that occurred in the olive grove of 35 ha resulted in huge cleavages (Figure 6). The landslides observed in the basin are concrete examples emphasizing, how vital environmental awareness and sustainable development are. Despite the precautions taken in the past, new landslides continue to occur due to heavy rainfall in the region.

3.2. The maximum entropy method (MaxEnt)

The maximum entropy principle, which is based on the idea that a probability distribution with maximum entropy is the best approximation to an unknown distribution with respect to certain known restrictions, was initially developed in statistical mechanics and information theory (Jaynes, 1957; Sivia and Skilling, 2006).

The maximum entropy method is a machine learning approach used to obtain the widest probability distribution based on some known properties of a particular system. This method offers some important advantages over other methods. First of all, the maximum entropy method allows to obtain objective and information-oriented results even in the presumed lack of information. This is extremely useful, especially when limited data or attributes are missing. Moreover, the maximum entropy can include previously unknown information with the least bias so that predictions can be created in a more balanced and realistic way. This method can also be used effectively in complex and multivariate systems because it does not require overly specific assumptions that are not data-based. As a result, the maximum entropy method offers a unique advantage in statistical predictions, providing flexibility, stability, and general validity even in limited information situations. MaxEnt is a method that can perform well even when

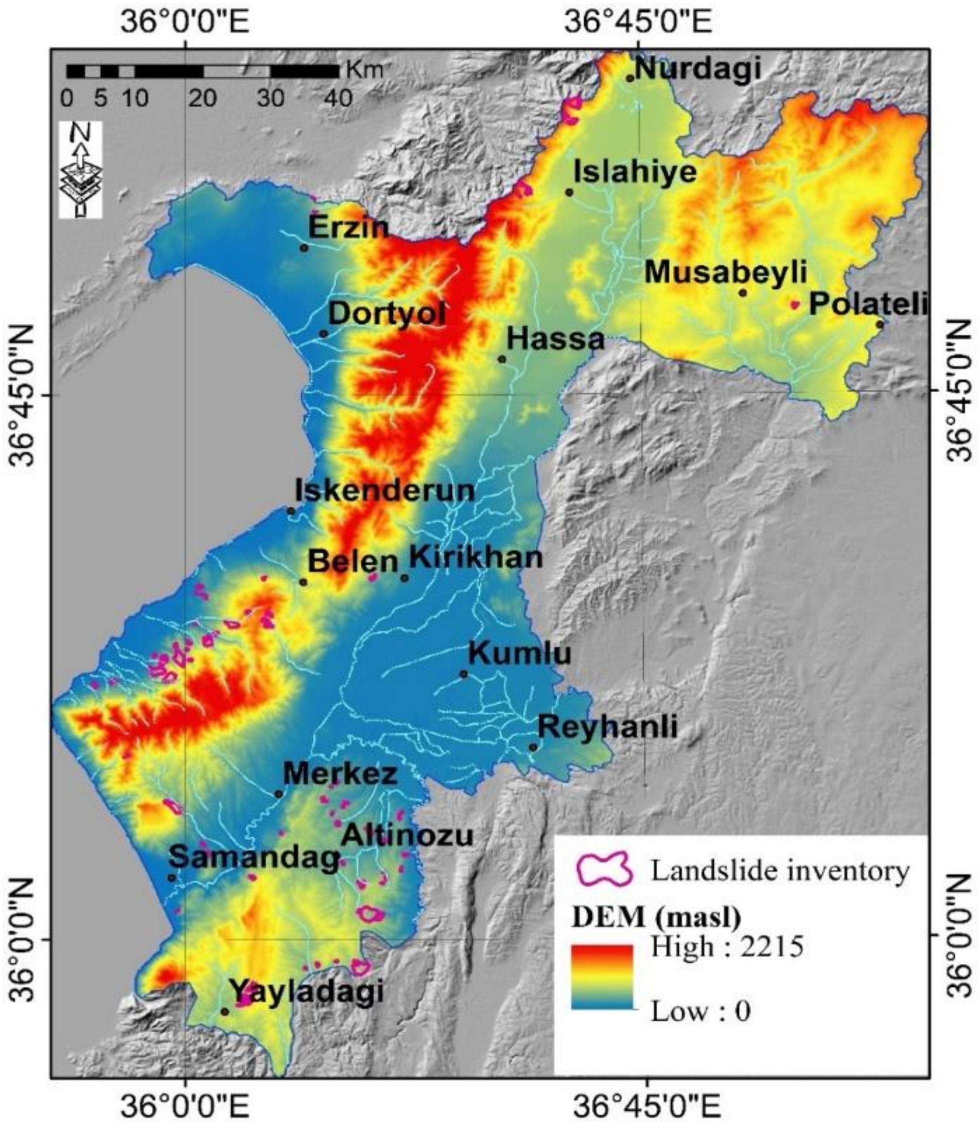


Figure 5. Landslide inventory and digital elevation model of Asi watershed.

there is an imbalance or lack of data between classes. In situations where class distributions are uneven, it can make predictions by focusing on rare classes. MaxEnt can be applied to various data types and problem types. It can be applied not only to numerical data but also to categorical data. MaxEnt is a method that can keep the risk of overfitting low. Overfitting means that the model fits too much to the training data and produces poor results on new data. MaxEnt can reduce this risk as it works with a limited set of parameters. MaxEnt is a model that can capture nonlinear relationships. Thanks to this feature, it can explore complex relationships and interactions between data.

Finding the probability distribution (p) of target occurrences over the specified sites for landslides within the study region is the aim of maximum entropy modeling. The moment restrictions on the distribution p are defined in terms of causal components or characteristics. The values of the causative components at each presence location are used to define the instant, similar to how the mean is defined. For instance, the estimated distribution's predicted slope value ought to be rather near the average slope value overall presence sites (Park, 2015). There may be a wide range of distributions that meet the aforementioned restrictions. The most uniform distribution is chosen from among these different possible distributions by using the maximum entropy concept. (Phillips and Dudík, 2008). MaxEnt is a presence-only method which deals with landslide locations. This property, besides its privileges to refrain from further judgment about the uninspected

Figure 6. Some examples of landslides in the watershed.

locations, could expose the model to more biased inputs, where reconnaissance may take place only on nearby pathways or other accessible routes (Chen et al., 2017). Studies to determine where it will occur spatially in the future play an important role in disaster reduction studies and investments of local governments.

The characteristic features and environmental effects of landslides can be revealed with thematic maps. In this study, the digital elevation model (DEM), which is effective in landslide formation in the region, and its 16 geomorphometric values (Slope, Slope/Aspect transformation (Sat_Trasp), Slope/Aspect transformation (Satsin), Slope/Aspect transformation (Sat_Cos), Mean slope, Heat load index (HLI), Topographic wetness index (TWI), Dissection, Roughness, Surface/Area Ratio (SAR), Surface relief ratio (SRR), Curvature, Plan Curvature, Profile Curvature) raster-based map were calculated (Table 1).

Table 1. Descriptive statistics of the geomorphometric variables used in the model.

Study area	**Minimum**	**Maximum**	**Mean**	**Std. Deviation**
Sat_Trasp	0	1	0.53	0.3
Satsin	–1	1	0	0.16
Sat_Cos	–1.01	1.01	–0.01	0.16
Mean slope	0	53.14	9.62	8.18
HLI	4266	9891	5137.64	504.62
TWI	3.43	15.78	6.74	1.38
Dissection	0	1	0.49	0.14
Roughness	0	12.46	3.63	1.66
SAR	10,000	21,240.1	10,286.85	470.03
SRR	0	0.81	0.5	0.07
Plan curvature	–0.82	0.95	0	0.11
Profile curvature	–1.34	1.31	0	0.11
Curvature	–1.75	1.61	0	0.19
Slope	0	61.9	9.62	8.53
Dem	0	2204	521.31	404.84
Landslide area				
Sat_Trasp	0	1	0.41	0.33
Satsin	–0.069	0.67	0.05	0.18
Sat_Cos	–0.74	0.63	0.02	0.2
Mean slope	2.1	35.27	13.37	6.57
HLI	4468	7414	5366.66	528.75
TWI	4.04	11.42	6.37	1.14
Dissection	0.08	0.93	0.48	0.12
Roughness	1.62	8.45	4.44	1.21
SAR	10,002.9	13,133.9	10,388.42	413.95
SRR	0.27	0.68	0.5	0.05
Plan curvature	–0.61	0.43	–0.01	0.1
Profile curvature	–0.52	0.65	0.01	0.12
Curvature	–0.8	0.77	–0.02	0.18
Slope	1.18	39.41	13.35	7.12
Dem	24	1433	536.17	269.64

The MaxEnt method is a data mining technique that has been widely used in recent years to solve many complex classification and regression problems in regions with limited and reliable landslide data (Brzezińska et al., 2021). MaxEnt version 3.4.4 was used in this study. The landslide inventory data with spatial data definition was converted to csv format and the preparatory environmental factors were converted to ASCII format to be used in the analyses (Figure 7). In the landslide susceptibility analysis with the maximum entropy method landslides were evaluated as 80% analysis and 20% test data. However, the maximum number of iterations was determined as 500, provided that the threshold value fell below 0.0001 before stopping the sensitivity model configuration. Finally, to determine the Maximum Entropy distribution, 10,000 landslide pixels were determined in the background together with landslide pixels. Results will be presented in very low, low, medium, high, and very high based on an equal intervals statistical distribution.

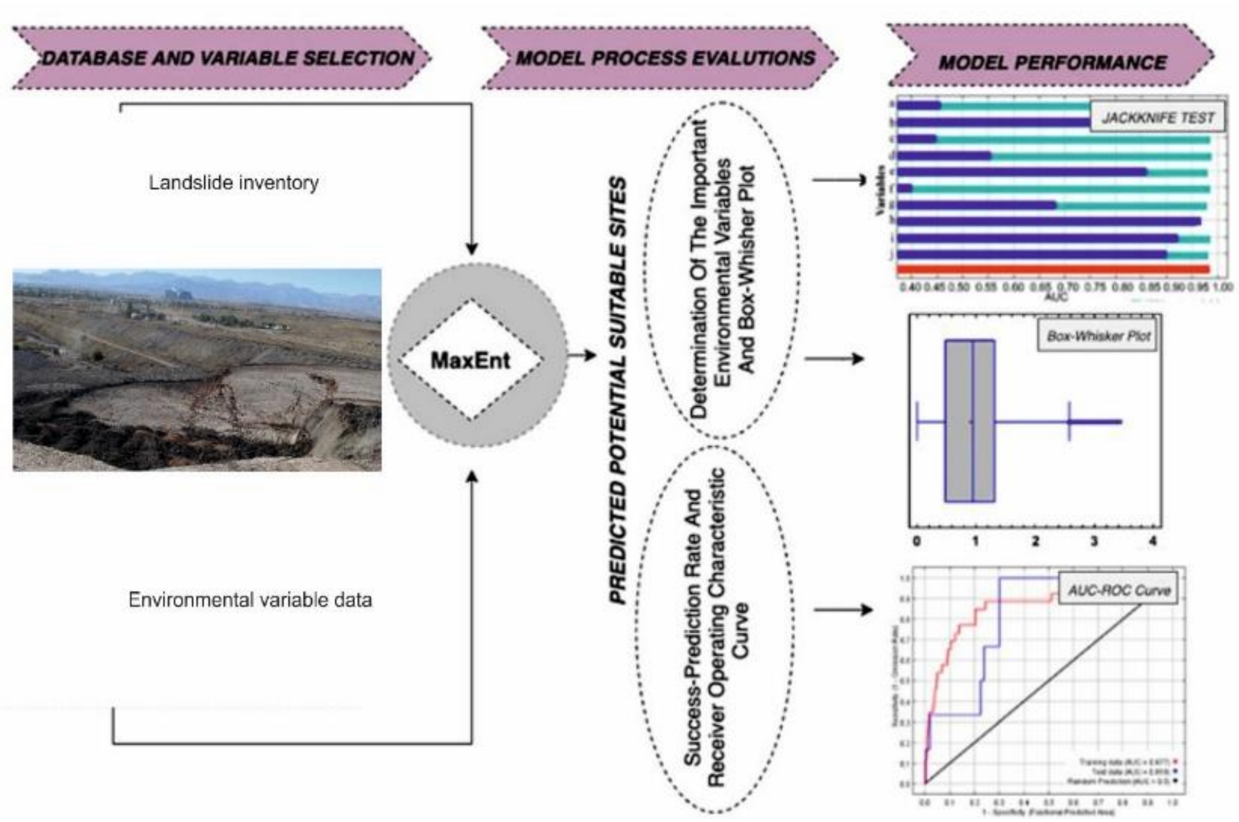


Figure 7. Flowchart of the MaxEnt models.

4. Results

To prevent natural events such as earthquakes, landslides, or floods from turning into natural disasters with physical, socio-economic, and other environmental effects that reduce or destroy the resistance of the society, evaluation, preparation, and risk assessments based on scientific foundations and structural and nonstructural measures should be taken, especially in a long period must be taken. This study concentrated on the MaxEnt model, which was used to forecast the potential distribution of landslide locations. In this study, the susceptibility analysis of landslides used a total of 15 environmental variables (Sat_Trasp, Satsin, Sat_Cos, Mean slope, HLI, TWI, Dissection, Roughness, SAR, SRR, Plan curvature, Profile curvature, Curvature, Slope, DEM). In the study region, 103 landslide localities were accessible. This study evaluated the model's capacity to forecast the locations of landslide-prone areas. 80% of the data should be used for training and the remaining 20% for testing to achieve this goal. These processes were given a total of 10 iteration runs, or they were kept going until a convergence threshold of 0.00001 was reached. The analysis of the study area because of the landslide susceptibility map and the probability values of the study area were evaluated in 5 categories between very low and very high through the consideration of the equal intervals (Figure 8).

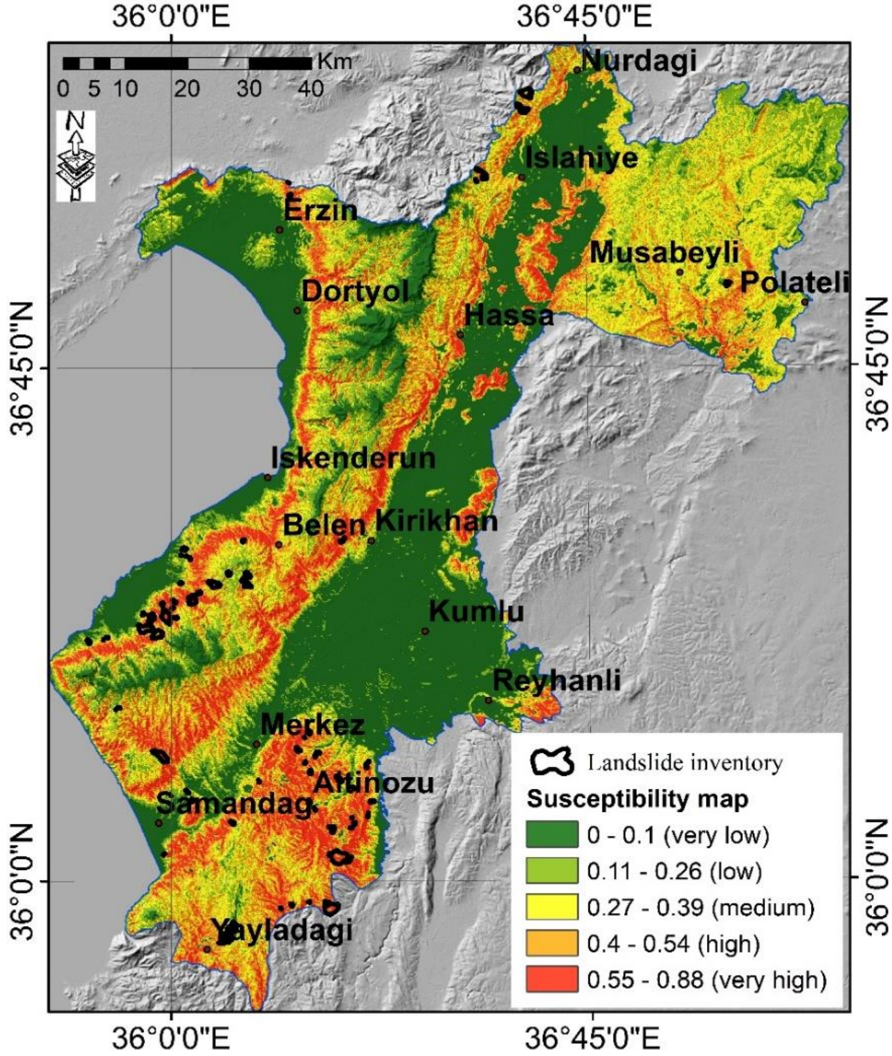


Figure 8. Landslide susceptibility map of Asi watershed area.

The accuracy of the model on the training and test data was evaluated by the receiver operating characteristic curve and the area under the curve (AUC). Accordingly, the AUC values were determined as 0.799 and 0.784, respectively. According to the training and test data (Figure 9a), the percentages are as follows: 34.85% very low, 15.63% low, 21.65% medium, 18.02% high, and 9.86% very high in the study area. It is observed that the landslides are within the susceptible class range of 0.50% very low, 3.30% low, 16.33% medium, 33.82% high, and 44.06% very high (Figure 9b).

MaxEnt software was used to conduct Jackknife test methods to assess the effectiveness of the model and the significance of each environmental variable. The importance levels of a total of 15 environmental variables considered in landslide susceptibility assessments were evaluated with the Jackknife test according to training and test data (Figure 10). Accordingly, mean slope, (mnslope), roughness, and surface/map area ratio (Sar) parameters were found to have the highest contribution to the susceptibility model.

5. Discussion

Maps showing the likelihood of landslides in certain areas can forecast or provide critical information. This is a result of the interaction between an earlier landslide and the local environment. These maps also display the expected landslides' spatial distribution in the areas where they will probably happen. The maps, however, cannot predict the amount of material to be displaced, the timing, or the frequency of the landslides. Our results indicated values area under the curve (AUC) using MaxEnt were between 0.799 and 0.784. Similar or higher values have been found in Northern Pakistan (Shahzad et al., 2022), China (Liu

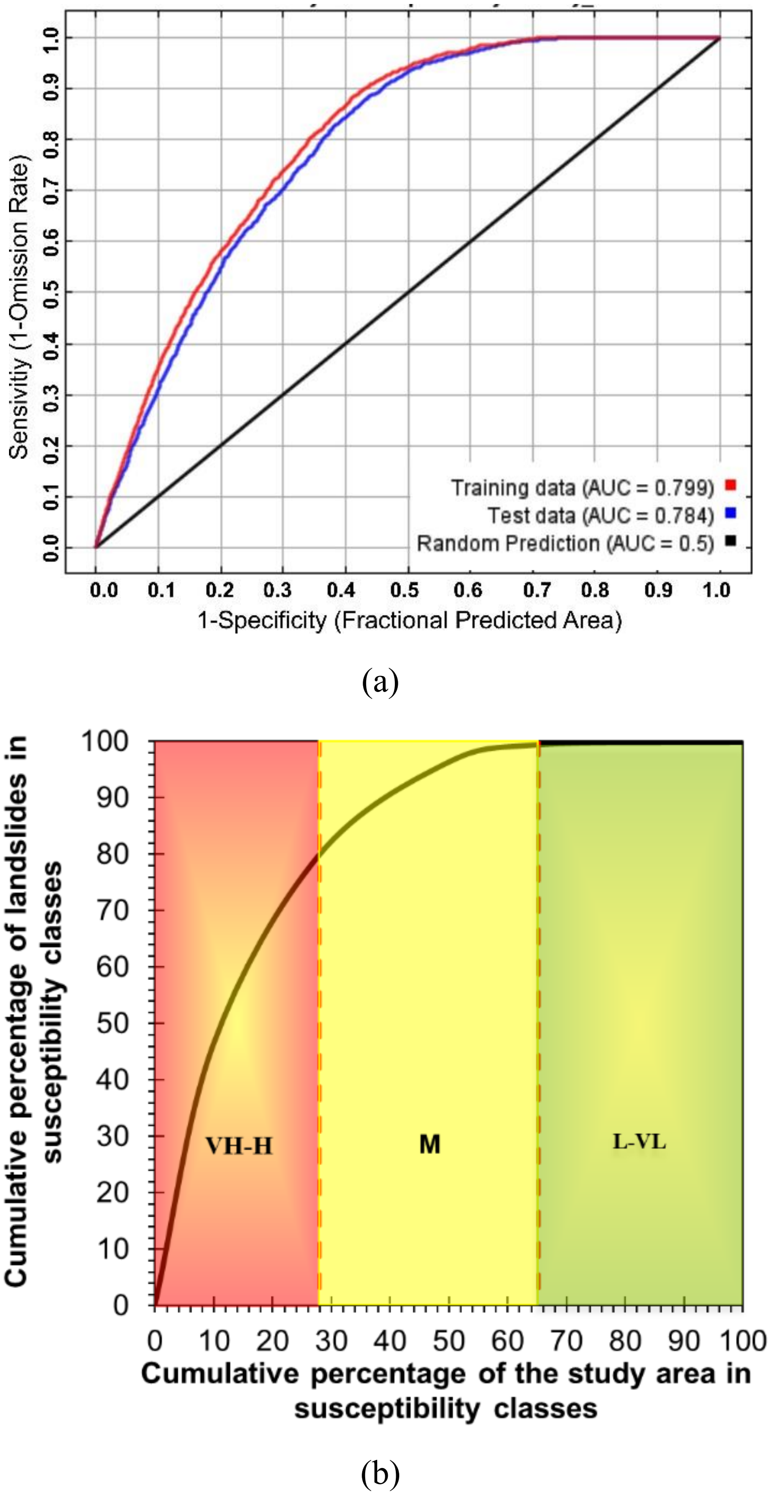


Figure 9. Landslides ROC curves and AUC values (a) and success and prediction rate (b) landslide susceptibility map.

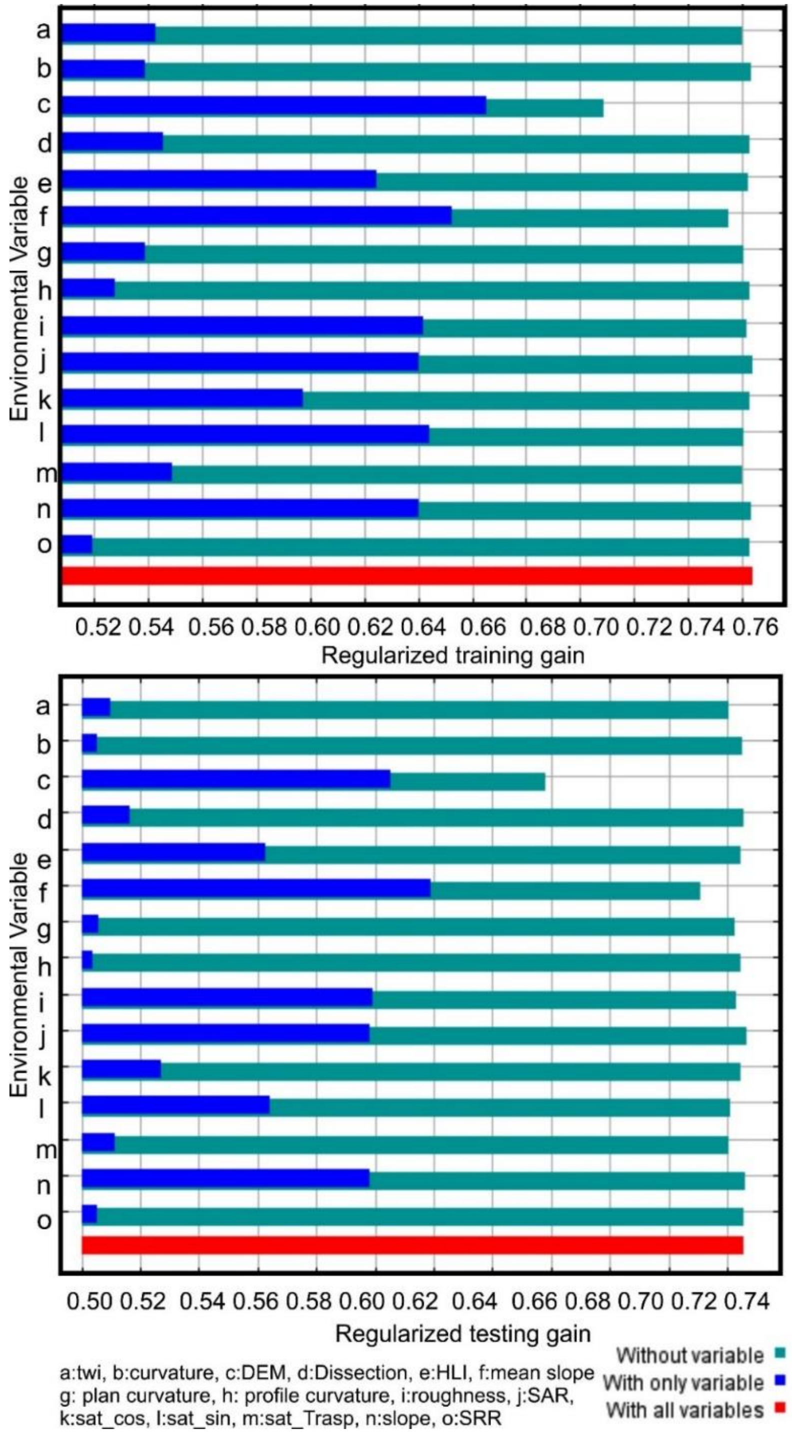


Figure 10. Jackknife test for AUC of individual environmental variable importance for landslide susceptibility map.

et al., 2021; Liu et al., 2022), Iran (Kornejady et al., 2017; Rafiei Sardooi et al., 2021; Memarian et al., 2022), and other mostly Asian countries. MaxEnt have been found a very confident model for determining landslides. Felicísimo et al. (2013) compared four statistical techniques for modelling landslide susceptibility in northern Spain. MaxEnt showed the most stable confidence intervals, and it was one of the best methods for producing smoother patterns. Park (2015) found in Korea that the maximum entropy model showed better predictive performance compared with the logistic regression modelling landslide susceptibility. Chen et al. (2018) found that the entropy model had the highest AUC value compared to support vector machine (SVM) by four kernel functions to explain landslides susceptibility in Shaanxi, China. The nonparametric nature of entropy may account for the entropy model's higher performance. There are no distributional assumptions required for entropy. According to Pourghasemi et al. (2012), conditional probability models performed marginally worse than entropy models when used in Iran to map the susceptibility of landslides. Another benefit is that it does not presume a linear model, allowing it to choose the most influencing aspects of the likelihood of a landslide using the appropriate model.

6. Conclusions

This study determined the landslide susceptibility of the Asi watershed in southern Türkiye, using a MaxEnt method. These landslide susceptibility maps can be used to identify the precise locations for slope stabilization measures. Susceptibility assessment and hazard zonation are critical for effective landslide mitigation and management. Several inherent causal and external triggering elements that differ greatly from location to place have an impact on landslides. These aspects must be well evaluated in further landslide research. Each of these variables has the potential to affect the landslide process and, when combined, they cause landslide activity. Additionally, different methodologies used for landslide evaluation studies can be roughly categorized into qualitative and quantitative methodologies. Geomorphological analysis (an inventory approach) and heuristic procedures (a knowledge-based approach) are examples of qualitative approaches while statistical and deterministic techniques are examples of quantitative approaches. Hence, our results and the applied method can be implemented in several countries with limited baseline data. MaxEnt models can enhance our capacity to identify susceptible areas for landslides worldwide.

The landslide susceptibility study conducted in the Asi watershed is an important base map for examining the effects of the geological, topographic, climatic, and soil characteristics of the region on the landslide risk. This study is a fundamental step in understanding how regional characteristics affect landslide events. The geographical, geological, and environmental conditions of the Asi watershed differ from other regions. Therefore, developing site-specific landslide susceptibility maps and strategies offers more effective and tailored protection and management solutions. This study can provide an important watershed, for identifying and assessing potential landslide risks in the region. These data are of high accuracy, and can be used to determine future risk reduction measures and emergency management strategies. Climate change plays an active role in the development of landslide events. This study, carried out in the Asi watershed is a key feature for understanding how climate change may affect landslide susceptibility in the region. This type of study can help local people understand landslide risk and contribute to management processes. Conscious communities can support more effective risk reduction and contingency plans. This kind of original work can offer opportunities for academic researchers and practitioners to make new scientific discoveries and develop new solutions. Landslide susceptibility study is one of the important data sources for regional development projects and land use planning. Plans that take into account the landslide risk can support the sustainable development of the region.

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