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LANDSLIDE SUSCEPTIBILITY EVALUATION USING GIS. CASE STUDY: SILVANIA HILLS (ROMANIA)

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ABSTRACT. – Landslide Susceptibility Evaluation Using GIS. Case Study: Silvania Hills (Romania). Landslides are destructive natural or human-induced hazards, therefore an assessment of landslide susceptibility becomes essential in an area that is prone to landslide through its geographical features. Landslide susceptibility maps provide valuable information for disaster mitigation works and land planning strategies. Silvania Hills are highly prone to landslide due their lithological and geomorphological structure. The purpose of this paper is to prepare a reliable landslide susceptibility map, which was obtained using the maximum entropy model. The model was run considering twelve environmental factors: lithology, slope, aspect, land use, land cover type, precipitation, temperature, terrain roughness, depth of fragmentation, drainage density, profile and plan curvature. The resulting map was grouped into five landslide susceptibility classes: very low, low, moderate, high and very high class. The results indicated that the land use and -cover type, slope and depth of fragmentation are the three most influential landslide predisposing factors. The accuracy of the resulted map was verified by generating a receiver operating characteristic (ROC) curve. The area under the curve (AUC) showed a good performance (0.847) of the analysis.

Keywords: *natural hazard, landslide, susceptibility analysis, mapping susceptibility, database, MaxEnt model, Silvania Hills, GIS, ROC curve.*

1 INTRODUCTION

Landslides are destructive natural or man-induced hazards caused by a sudden rapid movement of a cohesive mass of bedrock that is saturated with moisture. This damaging disaster can affect properties and land use, thus threatening the economic system and infrastructure. In Romania, landslides represent the natural hazards with the highest occurrence frequency and they have the widest manifestation area (Surdeanu, 1998).

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Landslide susceptibility maps describe the tendency of a territory for landslides, using appropriate, accurate methods and data (known causing factors of the local terrain conditions). Therefore, the purpose of landslide susceptibility mapping is to highlight the regional distribution of potentially unstable slopes (Grozavu et al., 2013). Spatial analysis is particularly significant and often used in mapping susceptibility. Thus, these maps provide valuable information for infrastructure and land planning strategies, land use, hazard mitigation design, protection of environment and responsible resource exploitation.

In the recent years, many methods were applied and evaluated for preparing landslide susceptibility assessments. These methods include bivariate (Bilașco et al., 2011, Conforti et al., 2011), fuzzy logic (Schernthanner, 2005), multivariate logistic regression, artificial neural network (Pradhan and Lee, 2010; Grozavu et al., 2013) and maximum entropy analysis (Davis and Sims, 2013).

Due to its particular structural, geomorphological and geological setting, the Silvania Hills is widely affected by landslides. The main objective of the present study is to prepare an accurate landslide susceptibility map which will help reducing the risks caused by landslides in the Silvania Hills. The map was prepared by using GIS analysis and maximum entropy model, taking into consideration twelve landslide causing factors.

2 STUDY AREA

2.1 Literature review

Previously, few studies were carried out on landslide susceptibility, hazard and risk analysis on the Silvania Hills. Geomorphological studies, landslides processes and their impacts have been investigated by Posea (2005), Bilașco (2006), Filip (2008), Blîdiță (2009), Arghiuș (2010), Zaharia, Driga & Chendeș (2011), Pop (2014) in this area, at a local scale. These studies were investigating environmental components and their relations between each other in order to predict important areas that could be affected by geomorphological hazards. Another aim of these studies was to recognize the cause of such failures and to bring to attention the fact that measures must be taken in order to prevent further hazards. For this purpose, the researchers used GIS spatial analysis models and classical identification, inventory and mapping methodology.

2.2 Description of the study area

The area under investigation is part of the Western Hills, located in the north-western hilly region of Romania (fig. 1). The area of the region is 3960 km^2, altitudes range from 126m to 670m with an average of around 400m.

From a regional point of view, the studied area is divided into the following main subdivisions: Basin of Baia Mare, Basin of Sălaj, Basin of Crasna, Basin of Barcău, Basin of Zalău, Codru Hills, Crasna Hills, Sălaj Hills, Șimleu Hills (Ielenicz and Pătru, 2005).

Geologically, the Silvania Hills are mostly composed by sedimentary rocks (clay, gravel, marl, sands) from the Mio-Pliocene (Posea et al., 1974). The sedimentary rocks were formed by the accumulation of the gravel and sands carried by rivers, which had their sources in the Carpathian Mountains (Ielenicz and Pătru, 2005).

Morphologically, the region is characterized by steep slopes (the slope varies from 0^0 to 41^0), thus the region is affected by intense denudation processes. The slope angle is the most important factor which influences the dynamics of the down-slope movement.

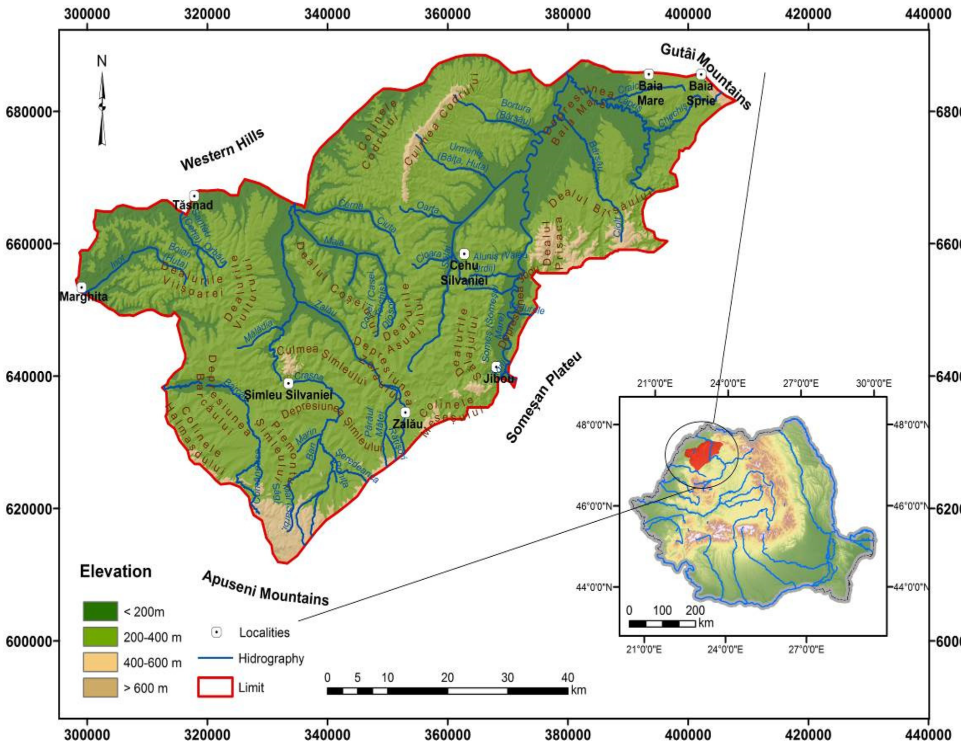

Fig. 1. Geographical position of the study area

Mass movements are also triggered by climate characteristics and human activities. Sudden, intense rains can cause landslides, but the present human activities in the study area, like mining, edifice and road construction, deforestation, over-grazing and over-cultivation are main factors that have significant role in landslide occurrence.

3 METHODOLOGY AND DATA COLLECTION

3.1 Spatial database

The first steps in landslide susceptibility zonation are identifying the causative factors of landslide hazards and preparing the corresponding data sets. In order to generate relevant factor maps, GIS software was used, which allowed for the setting up of spatial analyses. By using this technology, it was possible to investigate qualitative and quantitative information specific for the identified natural hazard.

For this research we used a wide range of data, represented by spatialized geographic elements. Based on these, a spatial database (table 1) that considers the causative factors of the landslides was created for the area under investigation. This database includes twelve landslide predisposing agents: lithology, land use (qualitative information), NDVI (Normalized Difference Vegetation Index), precipitation, temperature distribution and DEM (Digital Elevation Model) derived factors - slope aspect, slope angle, depth of fragmentation, drainage density, profile and plan curvature, terrain roughness (quantitative information).

Table 1. Spatial database

No.	**Name**	**Type**	**Structure**	**Source**
1	Landslide inventory	Vector	Polygon	Aerial orthophotograms and satellite imagery
2	Lithology	Vector	Polygon	Geology Map 1:100000
3	Land use	Vector	Polygon	Corine Land Cover 2006
4	NDVI	Raster	Grid	Landsat TM imagery
5	Precipitation	Raster	Grid	National Administration of Meteorology, Romania
6	Temperature	Raster	Grid	National Administration of Meteorology, Romania
7	Slope	Raster	Grid	DEM (30x30) derived
8	Aspect	Raster	Grid	DEM (30x30) derived

No.	Name	Type	Structure	Source
9	Depth of fragmentation	Raster	Grid	DEM (30x30) derived
10	Drainage density	Raster	Grid	DEM (30x30) derived
11	Profile and plan curvature	Raster	Grid	DEM (30x30) derived
12	Terrain roughness	Raster	Grid	DEM (30x30) derived

3.1.1 Landslide inventory

Landslide related data must be collected accurately, thus a valid landslide susceptibility analysis can be carried out. Landslide inventories offer essential information for evaluating landslide vulnerability, hazards or risks. These maps show the spatial distribution of existing landslides and the potential for future ones.

The research began with the preparation of a landslide inventory map (fig. 2) based on high resolution satellite imagery, aerial photographs (source: ANCPI, 1:5 000; Google Earth) and large-scale topographical maps (1:25 000). A number of 622 landslides were identified and mapped in the study area. They occupy 18.12 km^2 and correspond to 0.45% of the total area.

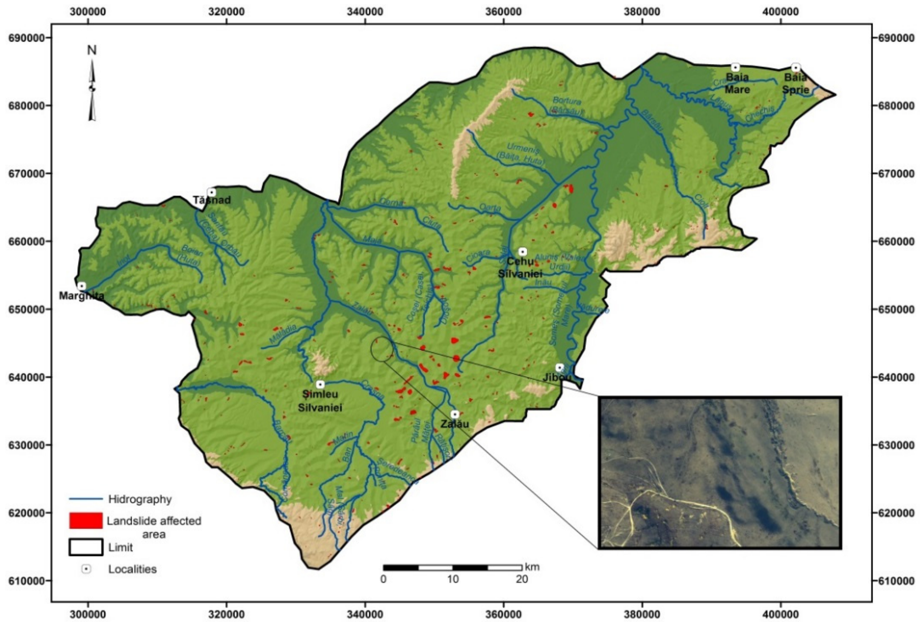

Fig. 2. Landslide inventory

3.1.2 Landslide influencing factors

In the study, twelve possible landslide predisposing factors (fig. 3) were analyzed. From these landslide-related factors, thematic layers were generated using the Spatial Analysis Tool in ArcGIS 10.2 software.

One of the most important and frequently used factors which affects the occurrence of landslides is the *slope of the terrain*. All mass movements occur on slopes under the influence of the gravitational force. A requirement in landslide occurrence is the existence of a minimum slope angle to enable sliding. Without it, the unstable deposits might be affected only by subsidence and resetting (Bilașco et al., 2011). The slope angle map was created from the digital elevation model, which had 30x30 m resolution. The raster map was grouped into 7 classes: 0^0-2^0, 2^0-5^0, 5^0-10^0, 10^0-15^0, 15^0- 25^0, 25^0-35^0, 35^0-41^0. Most of the landslides occurred between 5^0 and 10^0, but over 35^0 any of them were identified.

Another essential predisposing agent is *geology*. This factor induces the process of land sliding through its lithological and structural features and characteristics. These types of geomorphological processes mostly occur on sedimentary rocks (clay, marls, poorly consolidated sands). When their surface becomes wet, they deform, in the lack of solid base, in the direction of movement. Thus, a large amount of material is failing simultaneously. Analyzing the geology map of the studied area, the most widespread lithology is Mio-Pliocene sedimentary rock (67.66%), which explains the high occurrence of landslides.

Land use and -cover type are significant causative factors because sparsely vegetated areas are more exposed to faster denudation processes and instability than forests. Vegetation through their root system has a soil-binding power, thus the soil becomes more resistant to erosion. Using these two factors, environmental and human-induced impacts can be identified, such as deforestation, exploitation of natural resources, road cuts, construction activities and over-grazing. These activities can contribute to a major loss of vegetation thus the exposure to landslides becomes higher.

The database used in the spatial analyses was derived from the vector layer Corine Land Cover 2006 and from the raster layer Normalized Difference Vegetation Index (NDVI).

Landsat TM (30-m resolution) imagery was used to create the NDVI. The NDVI is a numerical indicator that represents the relative density of vegetation, thus the indicator assesses whether the observed area contains live green vegetation or not. NDVI values range from -1.0 to +1.0 and were obtained by the combination of visible red band and near-infrared band. The equation of the indicator is as follows:

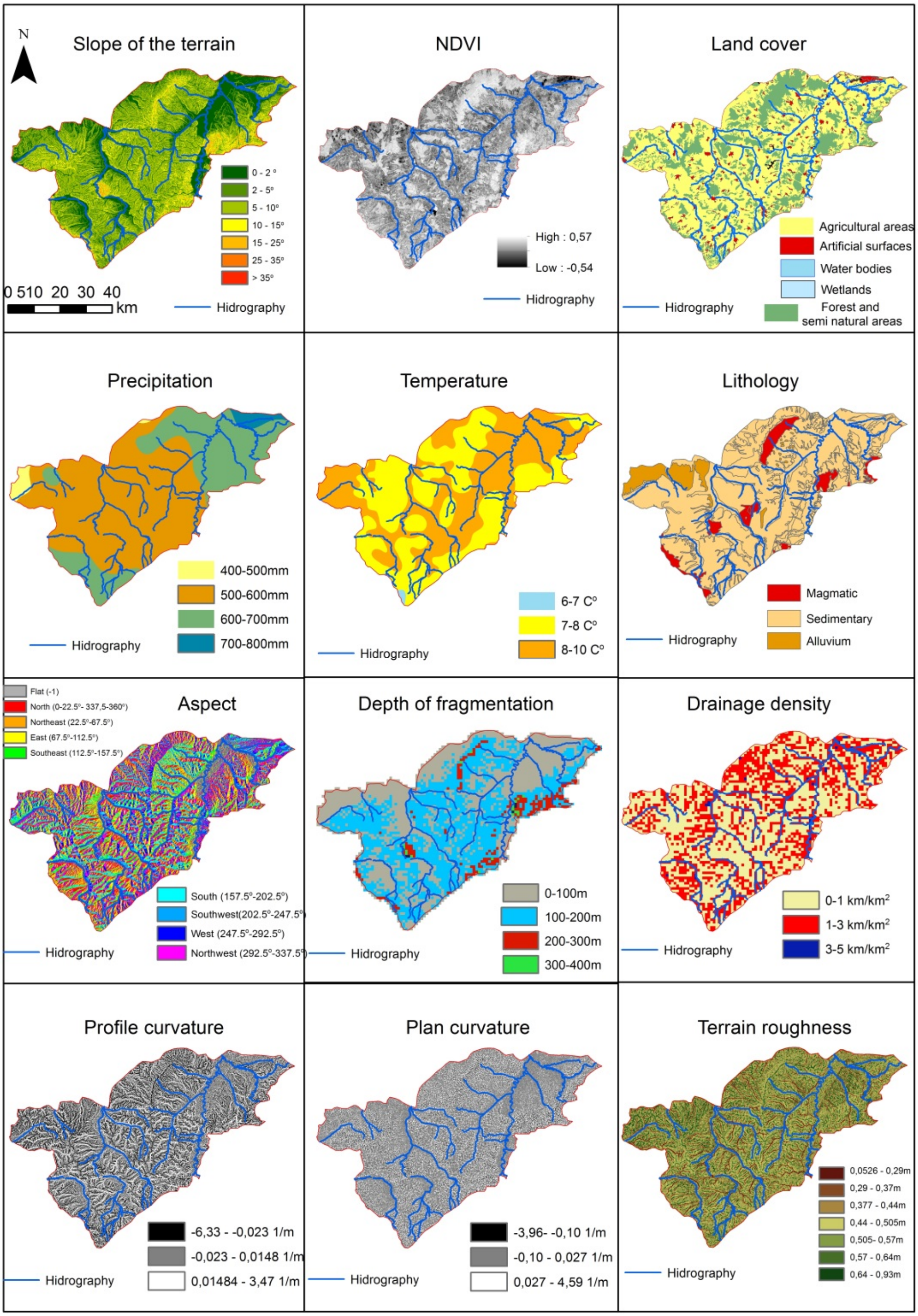

Fig. 3. Landslide predisposing factors

NDVI=(NIR-RED)/NIR+RED)

where NIR= near infrared band and RED= visible red band. High NDVI value indicates higher density of vegetation, low NDVI value indicates artificial and water surfaces, snow, sand or rock (Bayes et al., 2015).

The land use, based on the Corine Land Cover 2006 database, was grouped into 5 classes: agricultural areas, artificial surfaces, forests and natural areas, water bodies and wetlands. Analyzing this factor map, it is observed the fact that 96.08% of landslides occur near artificial surfaces and 3.54% of landslides appear on agricultural and natural areas. This is explained by the human-induced impacts presented in the description of the study area.

Precipitation influences the down-slope movement process by sudden, intense rains and snow melting. Landslide occurrence is favoured by significant rainfalls that follow a drought period when the existing fissures enable water penetration (Bilașco et al., 2011). The precipitation map was reclassified into four groups: 400-500mm, 500-600mm, 600-700mm, 700-800m. The highest average precipitation values were identified in the hilly areas, between 400-600m elevation.

Temperature has an effect on the freeze-thaw and wetting-drying processes, thus contributing to slope instability and down-slope movement. The raster map was reclassified into three classes: 6^0-7^0, 7^0-8^0, 8^0-10^0.

Aspect derives from the DEM. As a landslide-conditioning factor, it describes the direction of slope (Chen et al., 2016). The orientation of slope produces major differences in climatic parameters that are unevenly distributed on the surface: insolation, solar radiation, precipitation. Thus, slopes with south and south-west orientation receive more solar energy. The slope aspect map was reclassified into eight directional classes: flat (-1), north (337.5^0- 360^0, 0^0-22.5^0), north-east (22.5^0–67.5^0), east (67.5^0–112.5^0), south-east (112.5^0–157.5^0), south (157.5^0–202.5^0), south-west (202.5^0–247.5^0), west (247.5^0–292.5^0), and north-west (292.5^0–337.5^0). Differences were observed between the south, south-west facing slopes and the north facing slopes: 28.9% of landslides occur on the south, south-west exposed slopes and 24.9% of landslides occur on the north faced slopes.

Depth of fragmentation is a geomorphological indicator and expresses the relative altitudinal difference for a certain area. This factor has an important influence in the instability of slopes: the higher is the depth of fragmentation, the greater becomes the slopes angle, therefore down-hill mass movement becomes predisposed. The map was grouped into 4 major classes: 0-100m, 100-200, 200-300m, 300-400m. A significant part of the landslide affected areas (97.9%) were identified between 0-200m.

Drainage density is another geomorphological indicator and expresses the total length of all the streams and rivers in a drainage basin divided by the total area of the basin. Thus, this indicator measures the horizontal fragmentation of a drainage basin. Highly fragmented territories have high slope terrain values, therefore the steeper is the slope, the higher the probability for mass movement. The map was divided into three classes: 0-1 km/km^2, 1-3 km/km^2, 3-5 km/km^2. Most of the existing landslides (61.22%) were identified in the second class.

Profile and plan curvature were calculated via the curvature tool. Profile curvature is parallel to the direction of the maximum slope and it measures the rate of change of the slope. Plan curvature is perpendicular to the direction of maximum slope, thus influencing the convergence or divergence of downhill flowing water. The maps were classified in three groups using the natural jenks method. Positive profile and plan curvature values indicate high concavity, therefore the landslide occurrence probability is high (Petrea et al., 2014). The plan curvature was classified into the following groups: -3.966 - -0.106 1/m; -0.106 – 0.027 1/m; 0.027 – 4.59 1/m. Most of the landslide affected areas (71.17%) were identified in the second group. The profile curvature was classified into the following classes: -6.33- -0.1 1/m; -0.1 – 0.053 1/m; 0.053 – 3.47 1/m. 79.78% of the existing landslides were identified in the second class.

The concept of *terrain roughness* was introduced by Riley et al. (1999), and it indicates terrain ruggedness and a local elevation index. Terrain ruggedness is useful for identifying landscape patterns. The raster was classified into seven groups using the natural breaks method: 0.05-0.29m; 0.29-0.37m; 0.37-0.44m; 0.44-0.50m; 0.50- 0.57m; 0.57-0.64m; 0.64-0.93m. A significant part of the landslide affected areas (38.98%) were identified in the fourth class.

3.2 Spatial analyses

In order to prepare a landslide susceptibility map, there was used the maximum entropy model. The landslide susceptibility map was generated by the MaxEnt software using all the generated thematic maps.

Maximum entropy was used in the analysis of a variety of earth system processes, like species distribution. The presence-only nature of landslides—or the limited knowledge of absence locations—makes maximum entropy methods designed for species habitat analysis appealing (Davis et al., 2013). MaxEnt compares the conditional density function of covariates (predictor variables) at presence sites $f_1(z)$ to the marginal (background) density of covariates in the study area $f(z)$, to derive the conditional occurrence probability $Pr(y=1|z)$ (Elith et al. 2011). Also, in the recent years, MaxEnt was used for creating landslide susceptibility maps.

The maximum entropy model has many advantages and a few drawbacks. The advantages are the following: it requires only presence data, together with environmental information for the whole study area; it can utilize both continuous and categorical data; the MaxEnt probability distribution has a concise mathematical definition, and is therefore amenable to analysis; MaxEnt is a generative approach, which can be an inherent advantage when the amount of training data is limited (Philips et al., 2005).

The MaxEnt model was run using the thematic layers. The resulted values were grouped into five classes, using the natural jenks distribution: very low, low, moderate, high and very high susceptibility class of landslides (fig. 4).

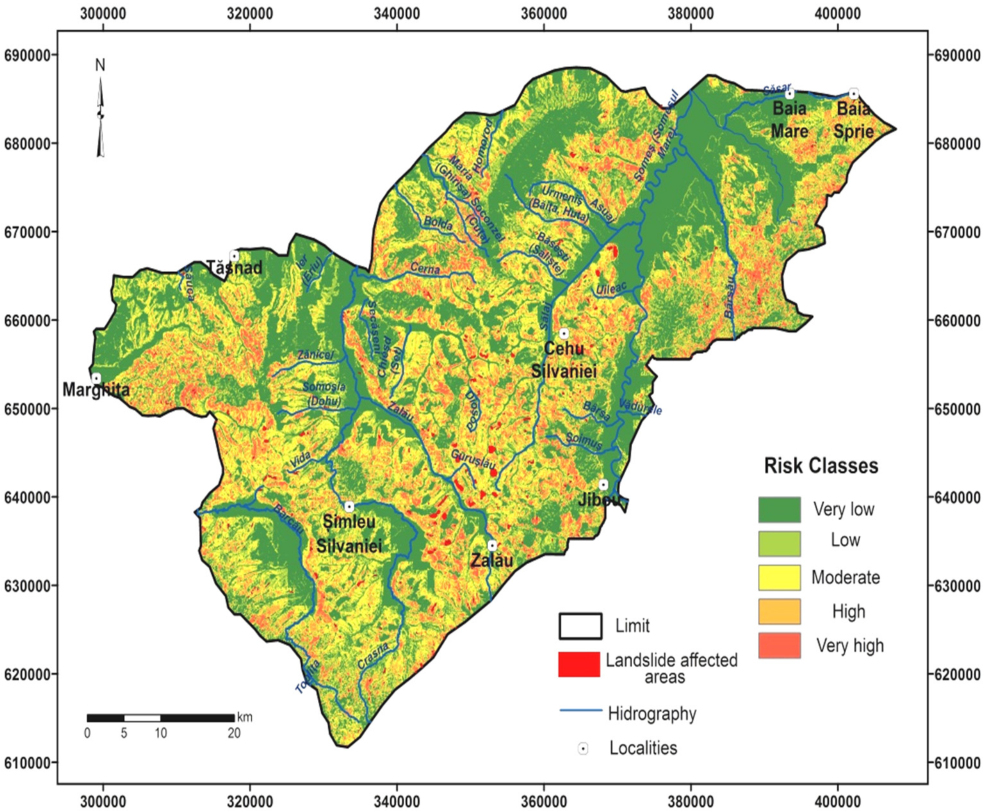

Fig. 4. Landslide susceptibility map

4 RESULTS AND VALIDATION

Analyzing the results, 74.29% of the mapped landslides are included in the high and very high susceptibility category, 16.8% in the moderate category, and less than 9% of the areas affected by this natural hazard are situated outside the area characterized by a high susceptibility for landslides.

According to the susceptibility map classification, areas with very high and high susceptibility (22.9%) are located mainly in the north, north-eastern and north-western part of the hills (Sălaj, Prisaca, Bîrsău, Vulturul Hills), followed by areas with moderate susceptibility (17.9%) located in the south and south-western part of the studied territory. Areas classified into low and very low susceptibility categories represent 59.2% of the total area (fig. 5). They are located mostly in the Someșul Mare, Zalău and Sălaj Corridor (caused by the large extension of the flat floodplains) and at the contact between slopes and floodplains.

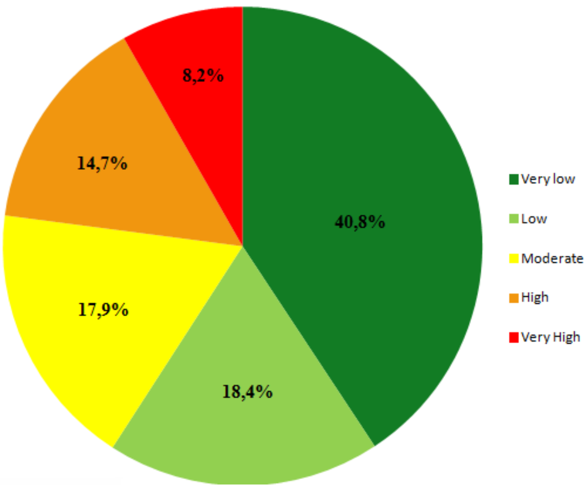

Fig. 5. Percentage distribution of the susceptibility classes

The MaxEnt software calculated the contribution (in percentage) of each landslide predisposing factor. The results showed that the land use and -cover type, slope and depth of fragmentation are the three most influential landslide causative agents of the study area (table 2). Analyzing these three factors, it can be concluded that the most predisposed areas are located near artificial surfaces. Agricultural lands are also threatened (caused by human impact). Slopes between 5^0-15^0 and 0-100m depth of fragmentation are the most favorable values for the occurrence of further landslides.

Table 2. Factor contribution

Landslide predisposing factor	Percent contribution (%)
Land cover	37.5
Slope	26.8
Depth of fragmentation	14.3
Plan curvature	8.5
Topograpghic roughness	4.2
Precipitation	2.4
Profile curvature	1.7
Lithology	1.6
Aspect	1.4
Temperature	1.2
Drainage density	0.3

Validation of landslide susceptibility models is an essential requirement to check the predictive capabilities of the landslide susceptibility map produced (Chung and Fabbri, 2003). In order to test the reliability of the resulted susceptibility map, a receiver operating characteristic curve (ROC curve) was generated with the MaxEnt software. The ROC method tests the predictability rate of the method applied for the study area by comparing the map of susceptibility with the landslide inventory.

For the validation of the susceptibility analysis, area under the ROC curve (AUC) was also applied. The values on the X axis represent the false positive rate (areas with high susceptibility rate, but with no landslides). The values on the Y axis represent the true positive rate (areas with high susceptibility rate where landslides occur). While AUC values between 0.7 and 0.9 indicate reasonable discrimination ability, values higher than 0.9 are typical of highly accurate classification models (Swets, 1988). Values under 0.5 indicate poor performance of the applied method.

The AUC value for the maximum entropy was estimated at 0.847 (fig.6), which indicates reasonable discrimination ability. Therefore, it can be concluded that the selected landslide predisposing factors are relevant for the model applied.

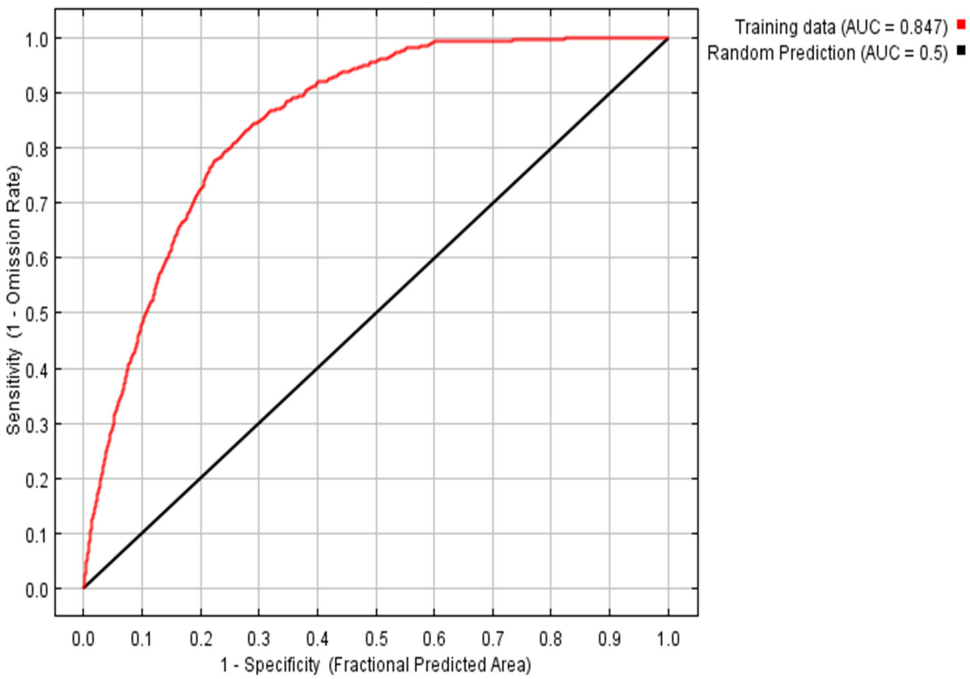

Fig. 6. ROC curve

5 CONCLUSIONS

Landslides are devastating natural or human-induced hazards, affecting a significant number of people, threatening economy and damaging properties. Therefore, a statistically valid susceptibility map should be used for territories where landslide occurrence is very high, thus analyzing this map, it can be possible the prevention of further land sliding. The prevention of further landslides requires a complex analysis of the causative factors. The most sever predisposing factors are human induced impacts, such as exploitation of natural resources, road cuts, construction activities, over-grazing, deforestation. As we know, the soil is the most important natural resource for the entire humanity. It is very important to understand the severity of the possible consequences. Thus, the prevention of landslides becomes possible just by protecting our natural resources and by responsible human activity.

The aim of this article was to prepare a valid susceptibility map, using an optimal combination of landslide causing factors, for the Silvania Hills. Analyzing the Silvania Hills, 622 landslides were identified, and considering that the geology, in a high percentage, is made up of sedimentary rocks, this territory becomes predisposed for further land sliding.

A maximum entropy model was run using twelve landslide causing factors. The results indicated that the most influential landslide predisposing factors are the land use and -cover type, slope and depth of fragmentation. This fact can be explained by the high rate of human impact in this area.

The model was validated using a ROC curve, its high AUC (0.847) value shows a good performance of the analysis. Thus, the applied model has a very good correlation with the chosen predisposing factors.

The validation shows that the model has a good predictability, thus becoming useful for further analyses and research. Based on the resulted map, it can be concluded that the implementation of land planning strategies are necessary to reduce the risk caused by landslide hazards in the Silvania Hills.

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