Landslide Susceptibility Assessment: GIS Application to a Complex Mountainous Environment

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Abstract This study attempts to quantify landslide susceptibility in the upper Putna River basin in the Romanian Carpathians Bend using GIS techniques and logistic regression. First, a detailed landslide inventory was carried out and a GIS database was built, comprising potential predictors of landslide occurrence. The GIS database included 11 quantitative predictors, mostly geomorphometric parameters, and 4 qualitative predictors which were transformed into quantitative variables using landslide density approach. The logistic regression analysis, combined with a stepwise selection of the predictors, showed that landslide occurrence is best explained by slope inclination class, altitude, soil class, distance to drainage network and surface geology. The results show that the potentially unstable terrains, displaying high and very high landslide susceptibility values, cover an area about 3 times greater than the mapped landslide area.

1 Introduction

Landslides are a very common geomorphic hazard with considerable economic and ecological consequences. In Romania, significant landslide areas occur in hilly and mountain regions, especially those underlain by molasse and flysch formations. The studies carried out to date have tried to explain manifestation, typology and evolution of landslides as well as the relations between geology and landslide

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distribution. Recent studies attempt to apply new research methods and techniques, such as landslide susceptibility assessment and appropriate mapping (Micu and Bălteanu 2009; Bălteanu et al. 2010; Grozavu et al. 2010).

At international level, landslide susceptibility assessment has recently been a subject of numerous studies; however, the application of this knowledge utilizes various conceptual and methodological approaches. Several authors provide good reviews of the recent methodology and evaluations of the subsequent approaches (Mantovani et al. 1996; Soeters and van Westen 1996; Aleotti and Chowdhury 1999; Guzzetti et al. 1999; Castellanos Abella and Van Westen 2008; Corominas and Moya 2008; Grozavu et al. 2010).

Generally, landslide susceptibility is defined as a quantitative and qualitative assessment of the classification, volume (or area) and spatial distribution of landslides which exist or potentially may occur in an area (Fell et al. 2008). Therefore, the purpose of landslide susceptibility mapping is to highlight the regional distribution of potentially unstable slopes based on a detailed study of the factors responsible for landsliding. Thus, the focus is on the recognition of landslide-prone areas achieved by mapping susceptibility.

One of the problems related to the accountability of landslide susceptibility maps is the lack of standardization in analytical methods (Ayalew et al. 2005) and consequently, the need for a common language and standard procedures in landslide risk zoning (Fell et al. 2008).

This chapter focuses on the evaluation of landslide susceptibility by applying a logistic regression analysis, to a typical region in the Romanian Carpathians Bend area. Here, the extension of built-up areas as a consequence of a clear intensification of touristic activities during the last two decades has complex, systemic implications at the local level. Our main goal is to identify, weigh and integrate the different parameters determining landslide susceptibility and to achieve an adequate spatial model for the study area.

2 Study Area

The studied region is located in the Romanian Carpathians Bend, in the upper Putna River basin (Fig. 1). The area of the region is 210.15 km^2 and the altitude ranges from 460 to 1,588 m with an average of around 900 m.

Geologically, the study region belongs to the outer flysch, known by its active tectonics, structural diversity and lithological heterogeneity (Dumitrescu et al. 1970). The geological layers are of Cretaceous (Senonian), Paleogene (Eocene and Oligocene) and lower Miocene (Aquitanian and Burdigalian) age. They form two major structural units separated by Tarcău fault: Vrancea Nappe, which appears in a tectonic window, south from Tarcău fault, and Tarcău Nappe, to the north of the fault (Fig. 2).

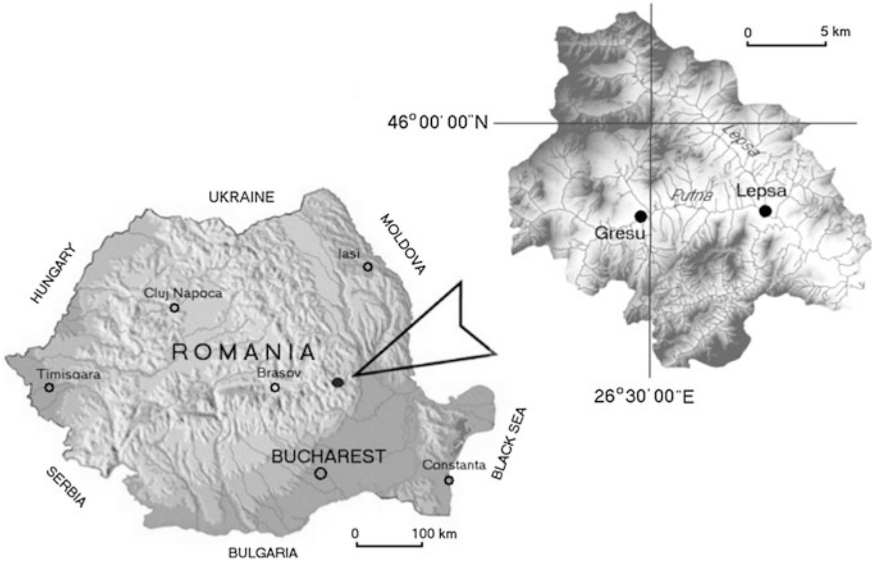

Fig. 1 Location of the study area

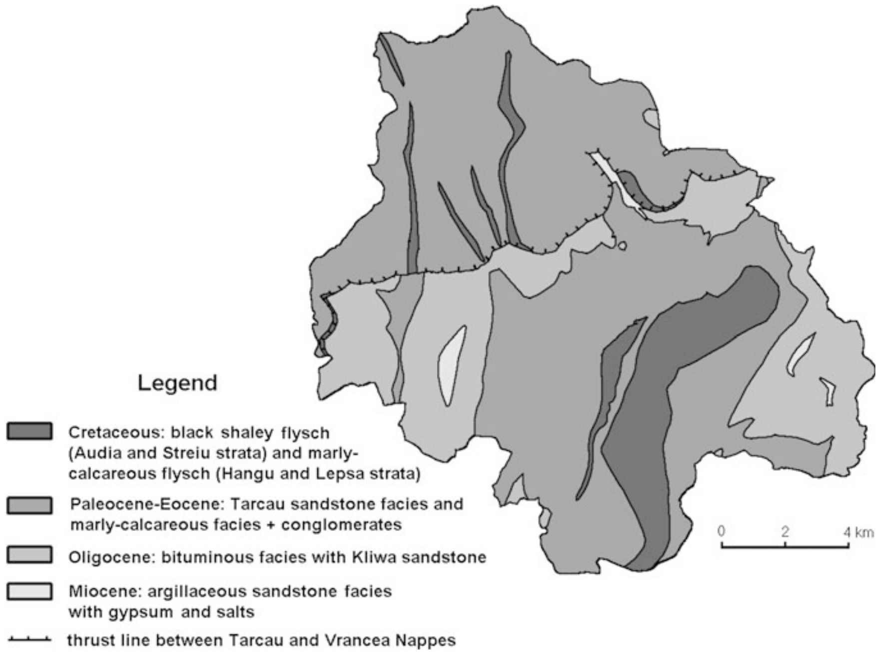

Fig. 2 Schematic lithological and structural map of the study area

The following main lithofacies occur in the study area (Ichim et al. 1998):

- black shaley flysch (Streiu strata) of Cretaceous age, occurring only in the Vrancea Nappe, composed by bituminous schistous shales with conglomerates, marls and limestones,
- marly limestone facies, including Cretaceous Hangu and Lepşa strata and Paleocene-Eocene lateral variation of Tarcău Sandstone deposits,
- Tarcău Sandstone facies (Paleocene-Eocene), consisting of sandstones with mica, forming massive beds with thin intercalations of marls,
- bituminous facies with Kliwa sandstone of Oligocene age, composed of thick-bedded, white quartzouse sandstones with intercalations of conglomerates, menilites, bituminous marls and disodilic shales,
- shaley sandstone facies with gypsum and salt of Miocene age.

Morphologically, the region is dominated by steep slopes, frequently affected by intense denudation processes, while flat areas (terraces and floodplains) occupy minor surfaces (Tufescu 1966; Ichim et al. 1996).

The area is drained by the east-flowing Putna River and its main tributaries: Lepşa, Greşu and Tişiţa.

The region is characterized by a high variety of hydrogeological conditions, due to the diverse lithology, with springs occurring on valley bottoms and slopes (Ichim et al. 1998).

Geological conditions, geomorphometric parameters, climate characteristics and human activities, especially construction on slopes, favor slope processes such as landslides. Large-scale mass movements can also be triggered by powerful earthquakes and the Romanian Carpathians Bend area is well-known for its high seismicity. For example, after the March 1977 earthquake, the volume of the material mobilized on slopes was 20–50 times greater than a multi-year average (Bălteanu 1979).

3 Methods and Materials

3.1 Methodological Review

Various methods for landslide susceptibility assessment can be encountered in the scientific literature. Qualitative methods, such as ranking and rating (Anbalagan 1992) or analytical hierarchy process, AHP (Barredo et al. 2000; Ayalew et al. 2005; Komac 2006), are simple and rely on subjective assessment. Quantitative methods, such as bivariate statistical analyses, BSA (Yin and Yan 1988; Binaghi et al. 1998) or multivariate statistical analyses, MSA (Carrara et al. 1991), are based on complex mathematical concepts. These initial efforts were followed by many multivariate statistical studies based on the application of multiple regression and discriminant analysis. Among these, logistic regression is a frequently used method, considered particularly suitable as it reduces the subjectivity in the landslide susceptibility analysis (e.g. Aleotti and Chowdhury 1999; Malczewski 1999; Süzen and Doyuran 2004a, b; Van Westen et al. 2006; Thiery et al. 2007; Nefeslioglu et al. 2008; Van Den Eeckhaut et al. 2010).

A third category of methods providing good results in landslide susceptibility analysis is represented by hybrid methods, including index-based methods, such as BSA + AHP (Ayalew et al. 2004) and training-based methods, such as BSA + Neural Networks (Lee et al. 2004; Borgogno Mondino et al. 2009).

3.2 Materials, Database and Methodological Approach

The primary input data consisted of ortophotos, 1:5,000 topographic maps, 1:100,000 geological map and 1:100,000 soil map. Based on this input, a landslide causative factors database was built in GIS environment, including the following information layers:

- geology, soil, land use (as qualitative variables),
- Digital Elevation Model (DEM) derived from 1:5,000 topographic maps at a resolution of 5×5 m,
- geomorphometric parameters (slope angle, slope height, slope aspect, mean curvature, plan curvature, profile curvature, wetness index, modified catchment area),
- distance to drainage network, distance to roads.

The data on geology, soil and land use were digitized from the respective maps and terrains with particular parameters were grouped into 5 susceptibility classes (very low, low, medium, high and very high) according to their susceptibility for landsliding. Next, these classes were intersected with landslide polygons and landslide density for each class was computed (Bai et al. 2010). In this manner, qualitative variables were transformed into quantitative variables and further used as predictors in the logistic regression approach.

We also tested the use of landslide density for slope inclination classes, taking into account that the relation between landslide distribution and slope inclination is not linear, with most of the landslides occurring on moderately steep slopes (7–20^{o}).

The other potential predictors (DEM, slope aspect, mean curvature, plan curvature, profile curvature, wetness index, distance to drainage network and roads) were used as continuous variables.

The susceptibility mapping started with the preparation of a landslide inventory map. We identified 198 landslides with the total area of 2,326.06 ha covering 11.07 % of the study area. The inventory was performed by means of large-scale mapping, using topographic maps (1:25,000, 1:5,000), orthophotos and field surveys for validation of landslide areas. Landslides were classified according to their activity into active landslides, semi-active landslides (the most frequent ones) and stabilized landslides (recently forested).

Useful information regarding the typology, stage of landslide evolution and the relations between geology and landslide distribution in the region is provided by Ichim et al. (1996) and Ursu (2006). The first category distinguished by these authors comprises the old and large landslides with a dominant translational character, which affect the in situ geological structures, reaching depths up to 80–90 m. The second category includes shallow landslides with a rotational character, which affect surface deposits. Most of the landslides belong to this category, but they have a small extent and represent approximately 20 % of the total landslide area. Our analysis also takes into account the sections affected by rocky landslides and soil landslides, encountered along steep slopes.

Descriptive statistics for landslide area and the potential predictors are given in Table 1.

Spatial analysis was performed using TNTmips 6.9 software and ArcGIS 9.3 software, while statistical analysis was carried out using Excel 2003 and XLSTAT 2010 software.

From the wide variety of methods potentially useful for quantifying landslide susceptibility, we chose a multivariate statistical approach based on the application of the logistic regression model. This method links the presence/absence of a phenomenon to a set of quantitative or qualitative variables, generating a continuous spatial probability model:

$$P = \frac{1}{1 + e^{-z}} \tag{1}$$

Table 1 Descriptive statistics for landslide area and potential predictors

Variables	Minimum	Maximum	Mean	Standard deviation
Landslide area (ha)	0.014	524.555	11.748	56.872
DEM (m)	459.22	1588.09	899.39	165.76
Slope inclination (degree)	0	68.483	19.974	10.143
Slope height (m)	0.39	377.93	40.21	42.74
Slope aspect (degree)	0.15	359.99	176.36	98.57
Modified catchment area (ha)	0.0025	227.329	0.701	5.073
Curvature (rad/m)	− 0.053	0.045	0.00	0.008
Plan curvature (rad/m)	− 0.036	0.039	0.00	0.005
Profile curvature (rad/m)	− 0.047	0.034	0.00	0.005
Wetness index	4.184	17.465	8.187	1.766
Distance to roads (m)	0	3881	617	619
Distance to drainage (m)	0.03	1064.3	172.8	160.1
Geology class (landslide density)	0.547	1.259	1.027	0.249
Soil class (landslide density)	0.116	1.754	1.057	0.315
Land use class (landslide density)	0.651	2.040	1.058	0.436
Slope class (landslide density)	0.154	1.976	1.025	0.694

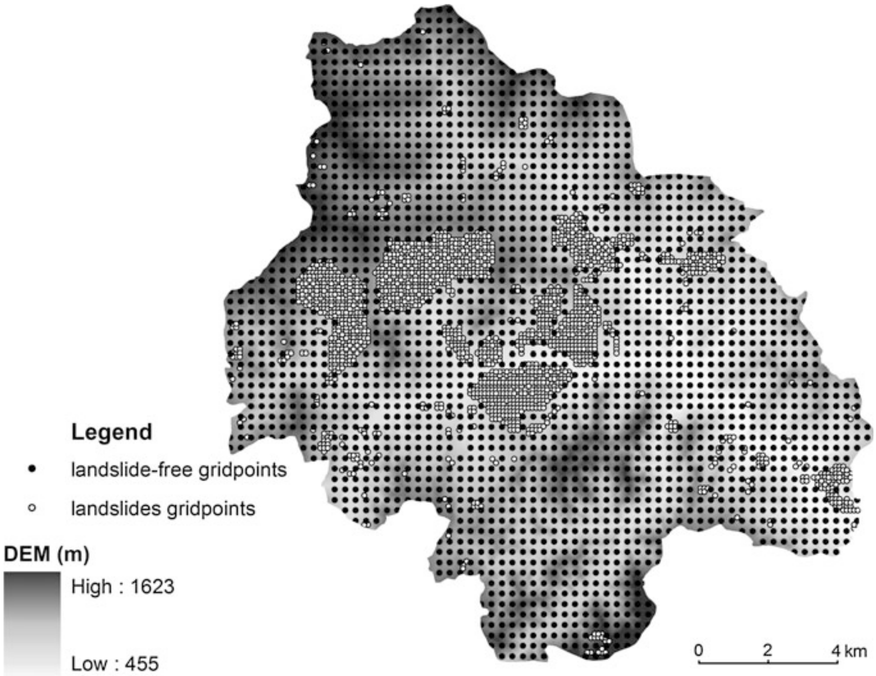

Fig. 3 Locations of grid points inside and outside the landslide area

where P is the probability of an event (landslide) to occur, which varies from 0 to 1 on an S-shaped curve, computed on the basis of a linear combination (z) of predictors ($x_1 \ldots x_n$):

$$z = b_0 + \sum_{i=1}^{n} b_i \cdot x_i \qquad (2)$$

where b_0 is the intercept of the model and b_i are the regression coefficients.

In order to extract predictors' values from a raster layer, a total number of 3,999 equally distanced grid points were generated for the landslide and landslide-free areas (Fig. 3). For the reason of preserving the relative equality of the two point samples, required by the nature of the statistical analysis, the density of points inside landslide area is markedly higher than in the landslide-free area.

4 Results and Discussion

A comparison of the logistic regression models analyzing landslide densities in either continuous slope inclination values or slope inclination classes indicated that the latter model explains greater proportion of the variance. The stepwise selection

Table 2 Standard regression coefficients of the logistic regression model using slope classes instead of slope continuous values

Predictors	Standardized regression coefficients	Standard error	Wald chi square	Pr > chi square
DEM	−0.348	0.025	189.572	< 0.0001
Slope height[a]	*0.000*	*0.000*		
Slope aspect	0.038	0.021	3.519	0.061
Modified catchment area[a]	*0.000*	*0.000*		
Curvature[a]	*0.000*	*0.000*		
Plan curvature[a]	*0.000*	*0.000*		
Profile curvature	0.098	0.022	19.431	< 0.0001
Wetness	0.053	0.024	4.821	0.028
Distance to roads	−0.048	0.027	3.222	0.073
Distance to drainage	0.163	0.021	59.189	< 0.0001
Geology	0.152	0.021	50.701	< 0.0001
Soil	0.221	0.024	85.279	< 0.0001
Land use	0.114	0.022	26.149	< 0.0001
Slope inclination classes	0.406	0.025	255.324	< 0.0001

[a] Variables excluded from the model by the stepwise selection procedure are shown in italics

of the predictors eliminated slope height, modified catchment area, plan and mean terrain curvature. According to the standardized regression coefficients (Table 2), landslides occurrence is best explained by slope inclination class, altitude, soils (soil class), distance to drainage network, and geology (Fig. 4), with land use, profile curvature, wetness index, distance to roads and terrain aspect being less significant predictors.

The logistic regression analysis showed that the spatial distribution of landslide occurrence probability is determined by the following combination of linear relationships:

$$\begin{aligned} Z = {} & -1.659 - 3.813\mathrm{E}{-03} \cdot \mathit{DEM} + 7.069\mathrm{E}{-04} \cdot \mathit{ASPECT} + 37.714 \cdot \mathit{PROFILEC} \\ & + 5.502\mathrm{E}{-02} \cdot \mathit{WETNESS} - 1.406\mathrm{E}{-04} \cdot \mathit{DIST\_ROADS} + 1.846\mathrm{E}{-03} \cdot \mathit{DIST\_DRAINAGE} \\ & + 1.107 \cdot \mathit{GEOLOGY} + 1.287 \cdot \mathit{SOIL} + 0.478 \cdot \mathit{LAND\_USE} + 1.058 \cdot \mathit{SLOPE\_CLASS} \end{aligned}$$

The outcome of the application of the logistic regression equation in GIS environment is displayed in Fig. 5. Considering the high complexity of the analyzed mountainous area, the quality regression parameters indicate a fairly good model using a cutoff value of 0.5 (Tables 3 and 4). The percentage of correctly classified points is 74.93 % in the landslide area and 70.74 % in the landslide-free area, while the overall prediction accuracy of the model is 72.84 %, with an area under the Receiver Operating Characteristic (ROC) curve of 0.802.

Landslide susceptibility was classified into five classes (very low, low, medium, high and very high susceptibility), using the natural breaks (Jenks) method (Fig. 6). The method identifies significant changes in the histogram distribution

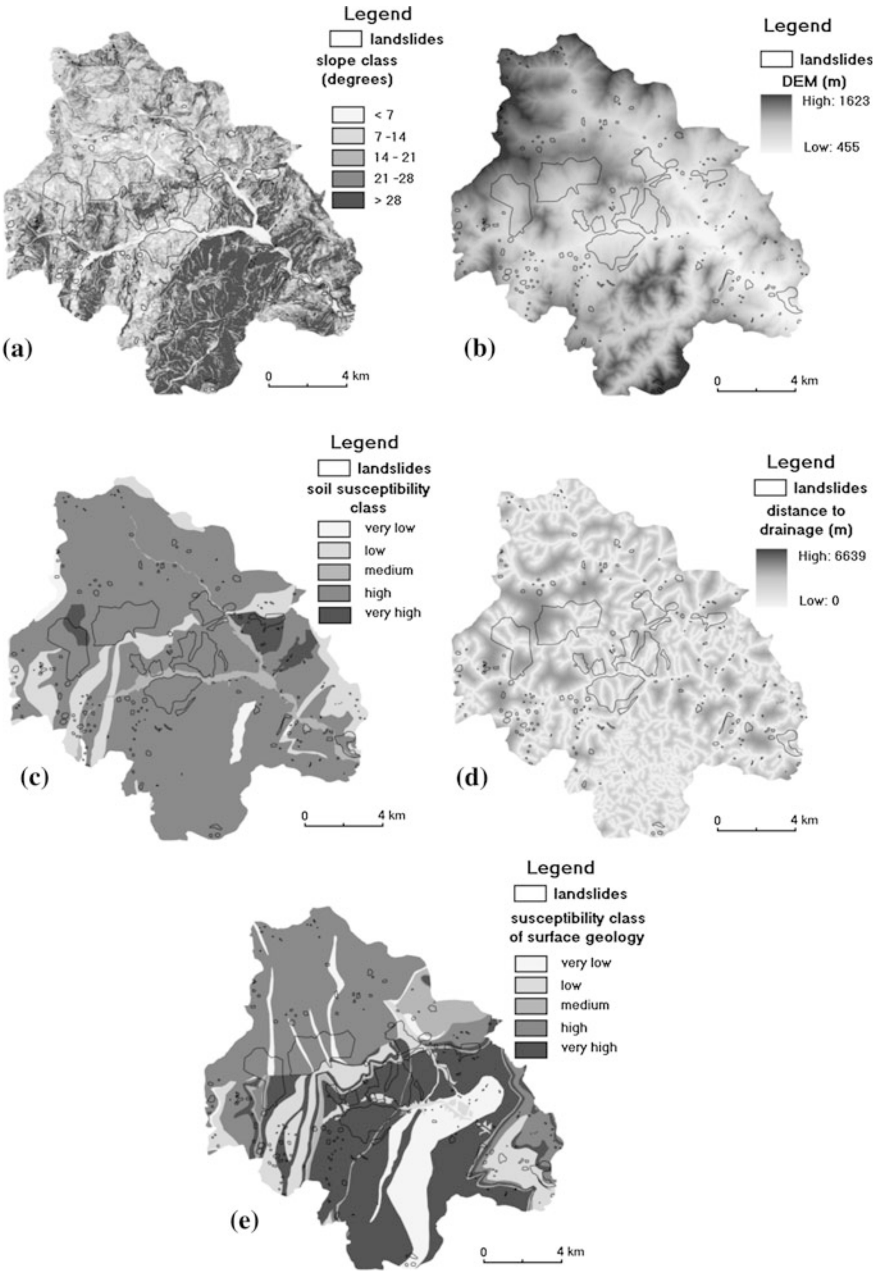

Fig. 4 Distribution in the study area of the main predictors used for deriving landslide susceptibility index: **a** slope classes, **b** DEM, **c** soil classes, **d** distance to drainage network, **e** surface geology

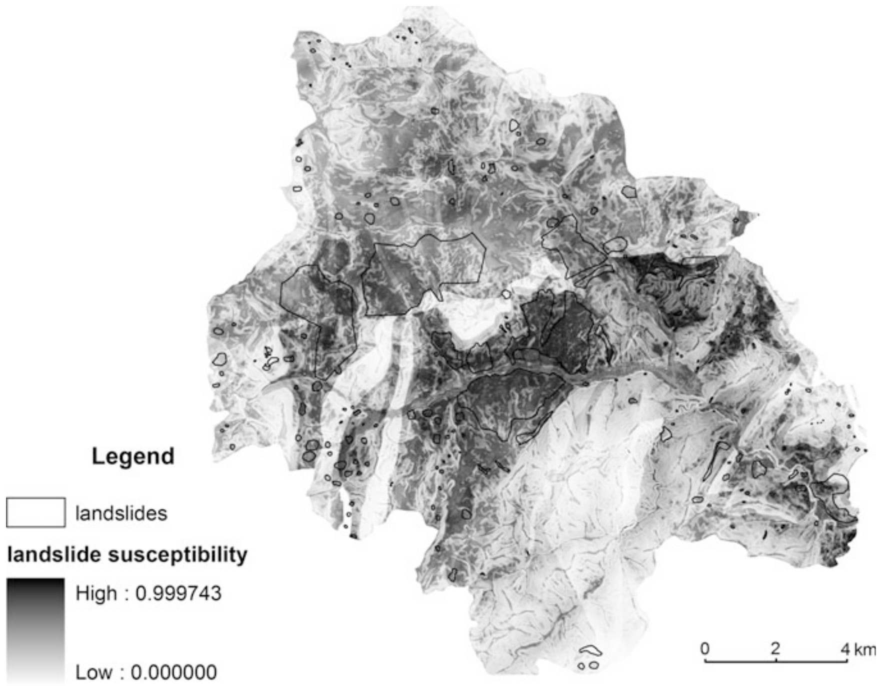

Fig. 5 Distribution of the landslide susceptibility index in the study area

Table 3 Quality parameters of the logistic regression model

Quality parameters	Values
-2 Log(Likelihood)	4,337.806
R^2 (McFadden)	0.218
R^2 (Cox and Snell)	0.260
R^2 (Nagelkerke)	0.307

and sets class breaks which best group similar values and maximize the differences between classes.

According to this classification, 31.3 % of the study region (nearly 6,600 ha), falls into high and very high susceptibility classes. Considering that about 25 % of this area could be misclassified (Table 4), there still remain about 4,900 ha correctly classified. Comparing this value to the actual extent of landslides (2,326 ha) indicates the occurrence of about 2,600 more hectares of the terrain showing high and very high susceptibility for landsliding.

However, comparing our results to those from a previous study that used the same approach for a cuesta front area in the Moldavian Plateau (Grozavu et al. 2010) indicates that the logistic regression is less appropriate for mountainous areas, mainly due to the non-linearity of the relations between landslide occurrence and quantitative and qualitative terrain characteristics.

Table 4 Numbers and percentages of correctly classified points

From\to	0[a]	1[a]	Total	% correct
0[b]	1,407	582	1,989	70.74 %
1[b]	504	1,506	2,010	74.93 %
Total	1,911	2,088	3,999	72.84 %

[a] points corresponding to predicted landslide-free (0) and landslide area (1)
[b] points corresponding to actual landslide-free (0) and landslide area (1)

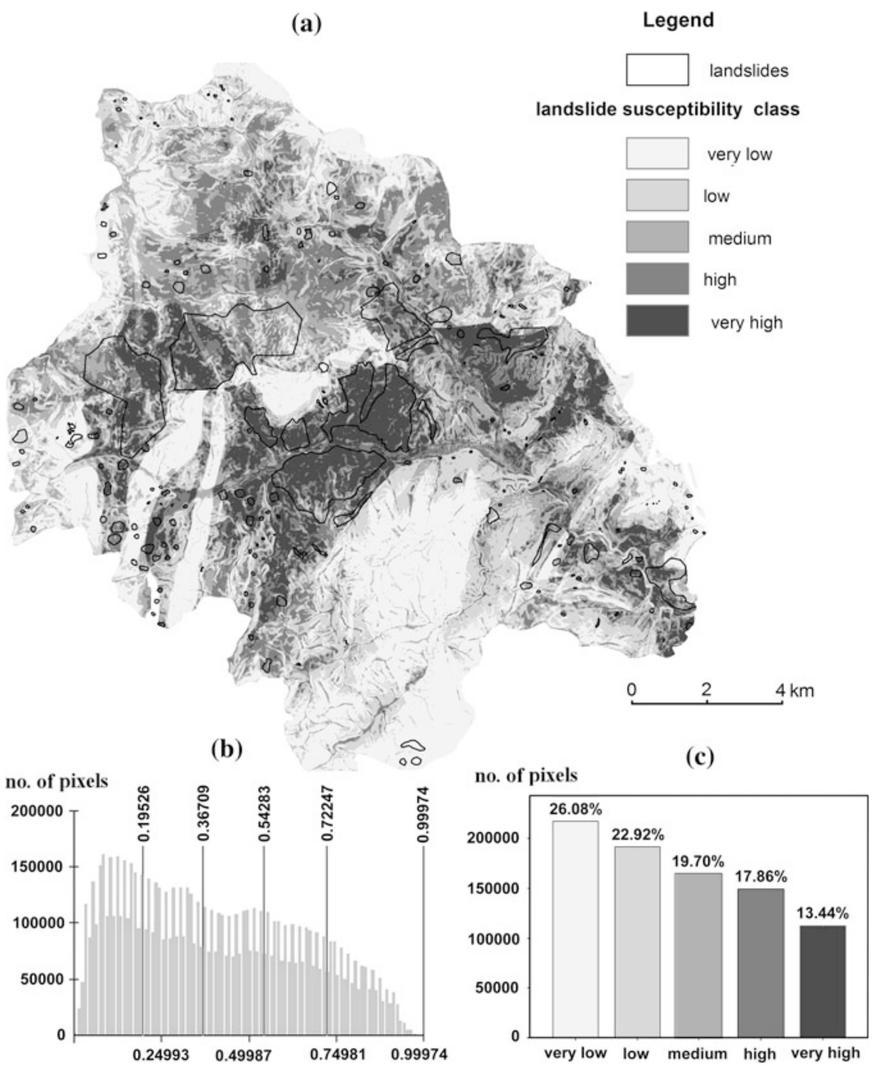

Fig. 6 Classes of the landslide susceptibility index for the study area: **a** spatial distribution, **b** classification method, **c** histogram of landslide susceptibility classes

5 Conclusions

This study has indicated that logistic regression approach is an adequate tool for the evaluation of landslide susceptibility and that the application of GIS techniques facilitates data processing and spatial visualization of the results.

Application of this model to a complex mountainous environment, characterized by a high structural diversity and lithologic heterogeneity and constituting a favorable context for slope processes, reveals that over 30 % of the 210 km^2 region (about three times more than the mapped landslide area) displays high and very high susceptibility for landsliding.

The model indicates that present and future landslides are mainly determined by slope inclination class, altitude, soil classes, distance to drainage network and geology.

Considering the spatial resolution (i.e. 5×5 m) of the classified landslide susceptibility map obtained from logistic regression, this model may be a tool for landslide susceptibility analysis at a large scale.

The study also emphasizes the importance of a correct characterization of the processes leading to landsliding for producing reliable susceptibility zonation map.

The resulting map allows delineating zones where precaution measures should be implemented, establishing standards and requirements for the use of land on and around slopes that are likely to fail and, also, assessing the risk that a proposed use of land will affect the slope stability of the studied area.

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