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Assessing the spatial variability of coefficients of landslide predictors in different regions of Romania using logistic regression

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Abstract. In landslide susceptibility assessment, an important issue is the correct identification of significant contributing factors, which leads to the improvement of predictions regarding this type of geomorphologic processes. In the scientific literature, different weightings are assigned to these factors, but contain large variations. This study aims to identify the spatial variability and range of variation for the coefficients of landslide predictors in different geographical conditions. Four sectors of 15 km × 15 km (225 km^2) were selected for analysis from representative regions in Romania in terms of spatial extent of landslides, situated both on the hilly areas (the Transylvanian Plateau and Moldavian Plateau) and lower mountain region (Subcarpathians). The following factors were taken into consideration: elevation, slope angle, slope height, terrain curvature (mean, plan and profile), distance from drainage network, slope aspect, land use, and lithology. For each sector, landslide inventory, digital elevation model and thematic layers of the mentioned predictors were achieved and integrated in a georeferenced environment. The logistic regression was applied separately for the four study sectors as the statistical method for assessing terrain landsliding susceptibility. Maps of landslide susceptibility were produced, the values of which were classified by using the natural breaks method (Jenks). The accuracy of the logistic regression outcomes was evaluated using the ROC (receiver operating characteristic) curve and AUC (area under the curve) parameter, which show values between 0.852 and 0.922 for training samples, and between 0.851 and 0.940 for validation samples. The values of coefficients are generally confined within the limits specified by the scientific literature. In each sector, landslide susceptibility is essentially related to some specific predictors, such as the slope angle, land use, slope height, and lithology. The study points out that the coefficients assigned to the landslide predictors through logistic regression are capable to reveal some important characteristics in landslide manifestation. The study also shows that the logistic regression could be an alternative method to the current Romanian methodology for landslide susceptibility and hazard mapping.

1 Introduction

Landslides are widespread gravitational processes, controlled by various factors related to geology, geomorphology, hydrology, climate and land use, all of them having a significant potential impact on the environment and human society. Generally, they are defined as down slope movements of rock mass, debris, or earth under the direct influence of gravity (Cruden, 1991).

As in the case of any type of risk phenomena, the analysis of landslide risk assumes the use of "observations about what we know to make predictions about what we don't know" (Paustenbach, 2002). For landslide risk evaluation, recent studies take into account several components such as landslide susceptibility, landslide hazard, landslide vulnerability and consequently, the elements at risk.

Landslide susceptibility is defined as the spatial occurrence probability of landslides. Compared to the other components of landslide risk, it can be modelled with a relatively high degree of accuracy. The assessment of different probability degrees is based on the assumption that slope failures in the future will be more likely to occur under the conditions that led to past and present slope movements (Varnes, 1984;

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Carrara et al., 1995; Guzzetti et al., 1999; Ercanoglu, 2008). Because the temporal factor is not taken into account (Dai and Lee, 2002; Zêzere et al., 2002), landslide susceptibility relies on a rather complex knowledge of slope movements and their controlling factors (Ayalew and Yamaghishi, 2005). The manner in which these conditions combine themselves spatially and temporally, leading to landslide manifestations, is still in an early stage of exploration.

Landslide susceptibility assessment can be approached by means of qualitative or heuristic methods (which are partially subjective and essentially based on expert knowledge), quantitative methods (based on numerical expressions of the relations between controlling factors and landslide activities), or combinations of qualitative and quantitative (hybrid) methods. The quantitative methods have developed rapidly during the last two decades due to the growing accessibility of geoinformation tools, including geographic information systems (GIS), remote sensing, digital photogrammetry, and global positioning systems (van Westen et al., 2008; Guzzetti et al., 2012). The application of statistical tools and new research techniques facilitate a fast and accurate computation and give more insights into the landsliding process, including its mapping (Guzzetti et al., 1999; van Westen et al., 2006). Statistical methods include bivariate analysis, like weights of evidence (WOE), which approaches the relations between the controlling factors individually (Thiery et al., 2007), and multivariate analysis, which evaluates the relative importance of each instability factor with respect to the others, allowing a better understanding of the interrelationships between the controlling factors (Falaschi et al., 2009).

One of the most popular statistical methods used for landslide susceptibility assessment is the binary logistic regression (BLR), with numerous applications for this purpose, especially at regional scales (Süzen and Doyuran, 2004; Zhu and Huang, 2006; Mathew et al., 2009; Bai et al., 2010, 2011; Rossi et al., 2010; Van Den Eeckhaut et al., 2010; Atkinson and Massari, 2011; Ercanoglu and Temiz, 2011; Akgun, 2012). The main advantage of this method is its capability to eliminate unrelated causative factors and evaluate the significance of the related ones (Yesilnacar and Topal, 2005; Falaschi et al., 2009; Chauhan et al., 2010; Ghosh et al., 2011).

The identification and selection of the predictors plays an essential role in landslide susceptibility assessment (Aleotti and Chowdury, 1999). However, the selection of parameters is far from being "standardized". It usually depends on expert knowledge, size of the area, time, scale, landslide types, methodology to be applied, budget, data availability and reliability (Glade and Crozier, 2005). BLR provides, as well as other multivariate methods, numerical weights for the predictors, as expressions of the degree in which their spatial combinations influence landslide manifestations.

In Romania, prior to the year 2000, the assessment of landslide susceptibility and hazard was based on geomorphological mapping and expert knowledge (Bălteanu et al., 1994; Constantin, 2008). Starting from 2003, a semi-quantitative approach has been implemented at a national level, including standards for landslide hazard mapping (Romanian Government Decision no. 477/2003). This approach assigns the same weight to a number of eight factors, regardless of their position inside the various geomorphological units from Romania. In recent years there have been several contributions concerning landslide susceptibility mapping such as those that exploit statistical bivariate methods (Armaş, 2011; Constantin, 2011), multivariate methods (Micu and Bălteanu, 2009; Bălteanu et al., 2010; Şandric et al., 2011; Mărgărint et al., 2011; Armaş, 2012; Grozavu et al., 2012) and geotechnical based approaches (Nicorici et al., 2012).

The present study employs the BLR method in order to achieve an accurate image concerning the spatial variability and range of variation of coefficients of landslide predictors and to evaluate the landslide susceptibility in different geographical areas, using the same predictors. For this purpose, four sectors were chosen belonging to different geographical regions from Romania, located both in hilly areas (Transylvanian Plateau, Moldavian Plateau) and in lower mountain region (Subcarpathians). In all these sectors, the landslides, either old or recent, have important extents, constituting the main land degradation form.

2 Study areas

As previously mentioned, four sectors were selected for analysis, namely Căpuşu de Câmpie, Şipote, Lungani and Helegiu, located in representative regions of Romania in terms of spatial extent of landslides (Fig. 1). Each sector has a square shape with sides of 15 km (225 km^2), corresponding to the rectangular grid of the Romanian 1 : 25 000 topographic map. Two of them – Căpuşu de Câmpie and Lungani – have already been subject to landslide susceptibility evaluation within a previous study (Mărgărint et al., 2011).

2.1 Căpuşu de Câmpie sector

The Căpuşu de Câmpie sector is located in the central part of the country, within the Transylvanian Depression, on the Comlod Basin (right-side tributary of Mureş River). This sector is developed on a series of saliferous domes and brachyanticlines with mean flank slopes of 3–6° (Irimuş, 1998). The lithology is represented by Neogene deposits, including clays and marls with sand intercalations, incorporating loose sandstones and volcanic tuffs. In the south-western part of the sector, there are more recent deposits of Pannonian age, represented by clays with sand intercalations. From a morphologic perspective, the Comlod Valley and its tributaries cut into a hilly area with broad interfluves and various slopes. The altitude varies between 283 and 572 m a.s.l., the relief energy is below 150 m and the density of relief fragmentation reaches 1.0–1.2 km km^{-2}. From the climatic perspective the

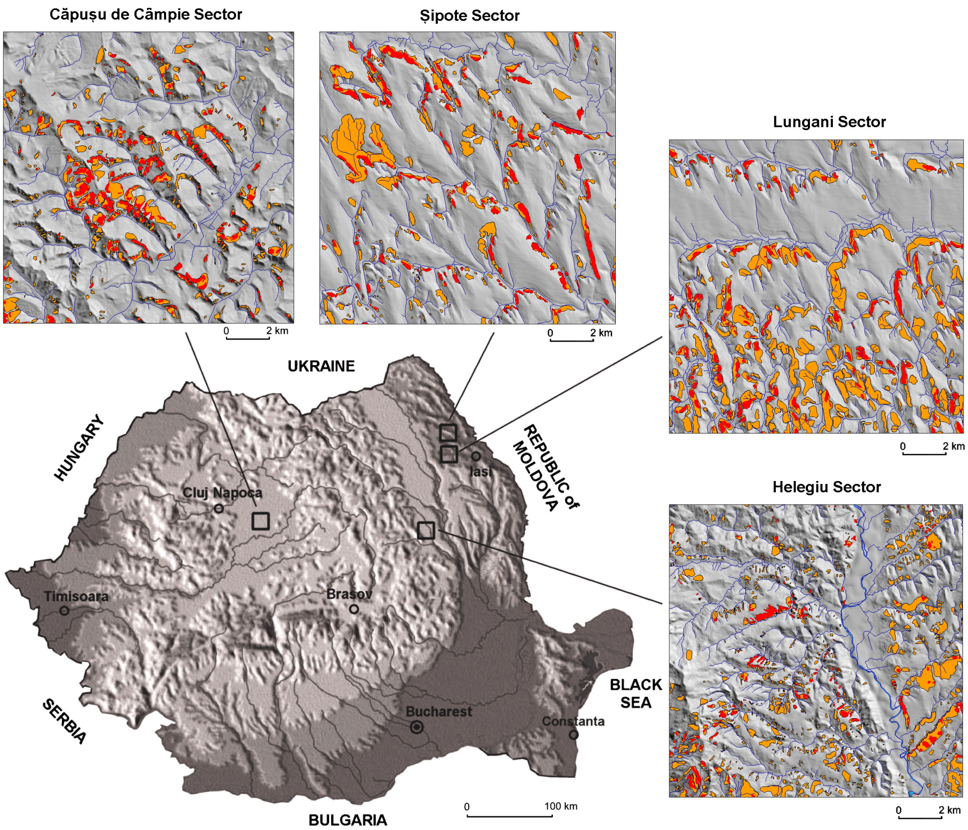

Fig. 1. Location of study areas, with landslide distribution (in orange), and active landslides (in red) overlaid on terrain hillshade.

mean annual temperature is 8.5–9 °C, and the mean annual precipitations are around 600–630 mm yr^{-1}, their monthly distribution presenting a peak within the April–July period. The agricultural lands dominate the sector (about 90 % of the total surface), the proportion of arable lands reaching 70 %.

Landslides are the dominant slope modelling processes, affecting important slope areas. Generally, they are shallow landslides, with deluvial depths between 2 and 5 m, and surfaces between 0.1 and 20 ha. Deep seated landslides are also present, which is typical for the Transylvanian Depression, locally named *glimee* (Morariu & Gârbacea, 1968; Surdeanu et al., 2011). These are large rotational landslides, with thickness normally of more than 30 m, showing usually steps-like and hummocky morphology (Fig. 2). The *glimee*'s distribution within the Transylvanian Depression denotes a causal relationship between their occurrence and particular structural-lithologic patterns such as the inclined position of geologic strata (in monoclinal or slightly folded deposits such as those found in domes and anticlinal folds); the presence of alternate permeable and impermeable deposits; and considerable thickness of permeable strata (usually sand and gravels). Basically, the development mechanism of this type of landslide could be explained by the occurrence of a deep landslide in the upper part of the slope, followed by the successive retreat of the scarp. This generates the detachment of new masses and the pushing of deluvial deposits towards the base of the slope. Old step-like detached masses evolve through erosion and shallow landslides, becoming more and more fragmented, while the frontal part receives a gentle undulating shape (Fig. 2). Generally, it is accepted that the development of *glimee* was favoured by climatic conditions from late Pleistocene – early Holocene (Preboreal and Boreal ages). Nevertheless, the exceptional precipitation amounts, recorded for instance in 1970 and 1975, proved that these landslides continue to evolve under the present climatic conditions, as numerous reactivations were recorded. Without a doubt, a slope affected by *glimee* continues to evolve nowadays, through the formation of new scarps, new landslide bodies overlaying the old ones (Surdeanu et al., 2011).

2.2 Şipote and Lungani sectors

Şipote and Lungani sectors are located in north-eastern Romania, in the central part of the Moldavian Plateau, belonging to the extensive east European geostructural platform. The lithology presents monoclinic structure with an inclination of 4–8 m km^{-1} along the NNW–SSE direction (Ionesi, 1994), comprising alternating Neogene rocks: marls, clays, sandstone and sand complexes. Morphologically, the Şipote sector is represented by a succession of large interfluves

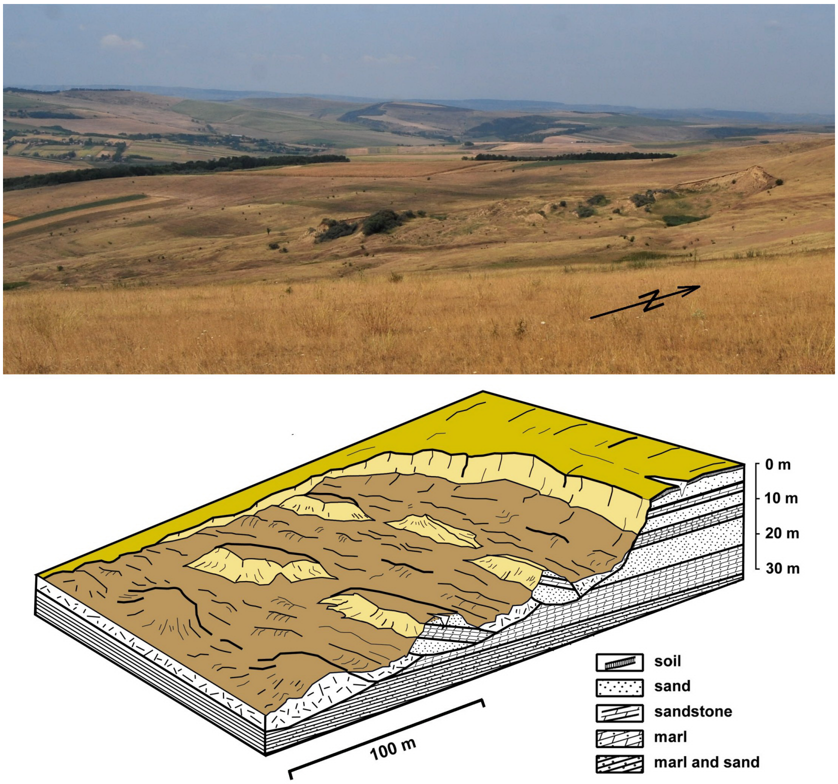

Fig. 2. Deep-seated landslide (*glimee*) in the Transylvanian Plateau (Căpuşu de Câmpie sector) and associated block diagram.

separated by valleys, while the Lungani sector occupies a part of the Bahluiet floodplain and its right-side cuesta scarp. The altitudes vary between 45 and 218 m a.s.l. for the Şipote sector, and between 50 and 212 m a.s.l. for the Lungani sector. The relief energy reaches 80–120 m (for the Şipote sector) and 60–100 m (for the Lungani sector), while the relief fragmentation presents, for both sectors, similar values to those from the Căpuşu de Câmpie sector. The mean annual precipitations are around 530–560 mm yr^{-1}, being unevenly distributed within the year (more than half of the annual quantity falls from May to August).

These natural characteristics, along with the land use dynamics (deforestations, crops cultivated on slopes, dense network of ponds) and the extent of roads and settlements, have overall influenced the stability of the slopes (Mărgărint et al., 2010). Important slope areas, mostly the cuesta escarpments, are affected by translational landslides, with thickness between 3 and 5 m and also rotational landslides with thickness greater than 5 m (Fig. 3). A particular type of slope morphology, known as *hârtoape*, resembles an amphitheatre, being located on the slopes or at the origin of torrential valleys (Fig. 4). This morphology is characteristic for an important part of the Moldavian Plateau. *Hârtoape* evolution was done over a long time with the participation of complex geomorphological processes, especially landslides and erosion processes. Significant parts within this morphology are associated with old, dormant, landslides which have thicknesses of 10–20 m, but are in turn affected by recent processes, such as shallow landslides (Fig. 5), slumps and surface erosion.

2.3 Helegiu sector

The Helegiu sector is located in the Moldavian Subcarpathians, which constitute a complex structural unit bordering the Carpathian Mountains. Characteristic are the Paleogene and Neogene deposits with frequent deep and shallow alternance of various lithology such as clays, marl-clays, sandstones, sands, gravel, loams, volcanic tuffs, gypsum, etc. The geological structure (tectonic nappes) and the diverse lithology have conditioned the formation of a fragmented relief on the Tazlău Valley and its tributaries. The altitudes vary between 194 and 979 m a.s.l., the relief energy is 200–280 m, and the density of relief fragmentation reaches 1.5–2.0 km km^{-2}. The mean annual precipitations vary around 530–670 mm yr^{-1}, heavy rainfalls being characteristic. All these are conditions that favour mass movement processes like collapse, slump and, especially, landslides which often put their mark on the landscape, with different ages, morphologies and intensities. Often, when favourable conditions are met, the old slope deposits, with average thickness of 3–5 m in relative equilibrium to the substrate, can be reactivated or can support active sliding. Slope modelling processes of this sector could be linked with an intense

Fig. 3. Deep seated landslide in the Moldavian Plateau (Şipote sector).

hydrographical activity of the Tazlău River and its tributaries, and also with deforestations during the last two centuries. In this period, the forest surface decreased by half, sometimes even more, especially around villages, being replaced by secondary meadows, orchards, or by the extension of settlements (Ungureanu, 1993). Also, after social and economic transformations in 1989, important deforestations have been produced as a result of changes in property status.

3 Methodology

In order to fulfil the purpose of the present study we chose the BLR method. For modelling terrain landsliding susceptibility we created a spatial database (landslide inventory, digital elevation model (DEM), and thematic layers of the predictors considered to be potential factors for landslide occurrence for each of the four study sectors) and integrated it in a georeferenced environment. For the evaluation of the accuracy of BLR outcomes we used the classification accuracy tables, the receiver operating characteristic (ROC) curve and the area under the curve (AUC) parameter.

3.1 The logistic regression method

The BLR method belongs to the group called the generalized linear models (GLM). The natural logarithm of the odds ratio, that is the ratio between the probability for an event to occur and the probability for an event not to occur, $\ln[P/(1-P)]$, is called logit. If this quantity can be expressed as a linear combination of predictors (x), then the probability for an event to occur can be further derived:

$$P = 1/(1+e^{-x}). \quad (1)$$

In this manner, the probability of an event (landslide) to occur is linked to a linear combination of predictors through a logistic function. The regression coefficients are computed using the maximum likelihood estimation (Süzen and Doyuran, 2004; Bai et al., 2010). Compared to linear regression, there is no unique solution for logistic regression coefficients. That is why the maximum likelihood estimation follows an iterative algorithm. Though the regression coefficients are not readily interpretable, one can use the standardized coefficients to assess the relative importance of predictors.

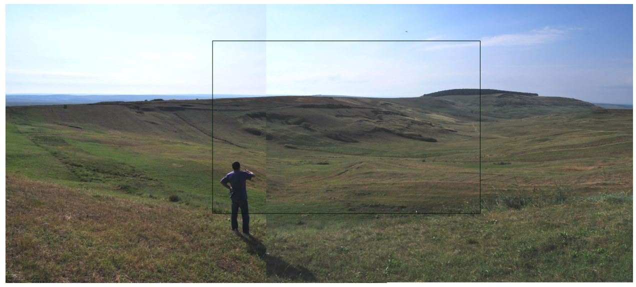

Fig. 4. Semicircular depression shaped by complex geomorphological processes (*hârtop* in the Moldavian Plateau, Şipote sector).

3.2 Data

The necessary data for landslide susceptibility computation were acquired from cartographic and aerial photographic materials, the primary basis for spatial data acquisition being the 1 : 25 000 Romanian topographic map, with Gauss–Krüger transversal polycylindric projection, printed in 1984.

In a first stage, the landslide inventories were created for all sectors, based on interpretation of the 2006 orthophotos with a spatial resolution of 0.5 m, which were further checked and validated by field campaigns. The inventory has considered only areas with obvious manifestation of sliding processes. The old, relict, large landslides sites (*glimee* and *hârtoape*) were not entirely included in the landslide inventory and, consequently, in the regression equation, but only those surfaces within them which present a distinctive landsliding morphology, and clearly defined boundaries (Atkinson and Massari, 1998; Ohlmacher and Davis, 2003). The overall landslide inventory summarizes 528 landslides for the Căpuşu de Câmpie sector, 284 for the Şipote sector, 286 for the Lungani sector and 851 for the Helegiu sector (Fig. 1). Table 1 presents the landslide synthetically for the four considered study areas: number of polygons, and the landslide surface considering the activity status (average, minimum and maximum surfaces). The second column (number of polygons) shows the landslides inventoried for this study. Table 2 shows the types of landslides, which have been classified into two main categories: shallow landslides, which are translational, the depth of which does not exceed 5 m; and deep seated landslides with depths exceeding 5 m, generally characterized also by rotational movements. Where the landslides spread over large areas and a clear differentiation of

Table 1. Landslide characteristics for the study sectors.

Sector	Landslides - total						Active landslides				
	No. of polygons	Sample size in depletion areas	Area (ha)			% from total area	No. of polygons	Area (ha)			% from total area
			Med.	Min.	Max.			Med.	Min.	Max.	
Căpuşu de Câmpie	528	845	4.41	0.01	76.88	10.34	272	2.21	0.08	26.97	2.67
Şipote	284	782	9.69	0.06	561.90	12.22	143	4.97	0.16	45.45	3.16
Lungani	286	801	14,55	0.01	232.38	18.49	159	4.50	0.19	40.23	3.18
Helegiu	851	1027	2.10	0.01	118.06	10.10	197	1.51	0.05	33.42	1.33

Table 2. Landslide types for the study sectors.

Sector	Shallow landslides			Deep seated landslides			Complex landslides		
	No. of polygons	Mean area (ha)	Total area (ha)	No. of polygons	Mean area (ha)	Total area (ha)	No. of polygons	Mean area (ha)	Total area (ha)
Căpuşu de Câmpie	409	1.88	769.96	93	11.09	1031.27	14	36.84	515.81
Şipote	215	3.52	755.96	64	18.44	1180.33	5	162.72	813.59
Lungani	206	8.17	1682.31	71	25.98	1844.66	7	90.64	634.44
Helegiu	712	1.38	980.13	126	7.63	962.42	9	58.95	530.58

the two subtypes was not possible, we chose to introduce a third class of complex landslides.

Next, starting from the digitized elevation isolines, the DEM of each sector was computed at a spatial resolution of 20 m × 20 m. The DEMs were further used to derive the thematic layers representing a part of the predictors required in the analysis. The geomorphometrical predictors (continuous variables), such as elevation, slope angle, mean curvature, plan curvature, profile curvature, and distance from drainage network were computed using ArcGIS 9.3 software, while slope height, representing the altitudes above river channels, was derived in SAGA-GIS 2.0.8 software. We also computed three categorical predictors (categorical variables) such as slope aspect, land use, and lithology. The slope aspect was computed using ArcGIS 9.3 software, its values being grouped into four classes (north, east, south, and west). The land use layer was created by vectorization and classification of land use polygons on the basis of high resolution 2006 orthophotos, which were georeferenced using the 1 : 5000 topographic maps. The following land use categories were depicted by photo interpretation and named according to Romanian cadastral terminology: arable, pastures, arable and pastures, forest, water, built areas, and unproductive land (which refers to the excessive degraded areas that are virtually devoid of vegetation like gullies, ravines, streams, boulders, rocks, etc.). Finally, the predictor lithology was acquired from the geological map of Romania at scale 1 : 200 000, because sources that are more detailed were not available for this parameter. At this scale, only the Helegiu mountainous sector reveals a high geological complexity.

3.3 The modelling strategy

For modelling the landslide susceptibility the integration of predictors (both continuous and categorical ones) must be done in the logistic regression model. As for the categorical variables, they can be integrated in two ways: one approach is to express the classes of each categorical parameter as dummy variables (Guzzetti et al., 1999; Dai and Lee, 2002; Ohlmacher and Davis, 2003; Nefeslioglu et al., 2008); the other approach is to compute landslide densities for categorical parameters and use them as predictors (Zhu and Huang, 2006; Yilmaz, 2009). The present study exploits the latter approach in order to avoid the creation of an excessively high number of dummy variables. Consequently, landslide densities were computed for slope aspect, land use and lithology, according to the following formula (Bai et al., 2010):

$$\mathrm{LD}_i = \frac{(\mathrm{LA}_i/\mathrm{A}_i)}{(\mathrm{LA}/\mathrm{A})}, \tag{2}$$

where LD_i is the landslide density value for class i, LA_i and A_i are the landslide area in class i and the total area of class I, respectively, and LA and A are the total landslide area in the study region and the total area of the study region, respectively. In order to achieve the landslide density raster layers, the zonal histogram procedure from the ArcGIS 9.3 Spatial Analyst extension was employed using the landslide polygons as the zone data set. The results were exported and processed in Excel software in order to obtain the landslide density values for each class. These values were then recorded into the attribute tables of the categorical factors, which were further converted into raster layers.

Fig. 5. Shallow landslide in the Şipote sector, detail from Fig. 4.

Because a certain amount of redundancy is present among the considered predictors, a selection procedure must be applied. In the present study, the XLSTAT 2010 trial version software was used to apply the logistic regression and the selection of the relevant predictors was performed by the stepwise (forward) procedure implemented into the logistic regression module. This procedure adds the variables one by one, checking at each step if the contribution of the new variable, assessed through the Wald chi-square test, is statistically significant. After the third variable is added, the procedure checks if removing any of the variables improves the model. We used this procedure in order to avoid the multicollinearity problem.

It is generally acknowledged that the application of logistic regression requires fairly equal number of presences (1) and absences (0) in the input data set (Nefeslioglu et al., 2008; Bai et al., 2010; Ayalew and Yamagishi, 2005; García-Rodríguez et al., 2008; Gorum et al., 2008). In the present study, the depletion areas of each landslide were semi-automatically identified and mapped by using a geomorphometrical parameter called mass balance index (Hensel and Bork, 1988; Böhner and Selige, 2006). This parameter was derived in SAGA-GIS using the DEM and vertical distance to channel network as input layers. As the mass balance index has higher values on steep slopes and exposed convex upper slope positions, it can be used to map landslide depletion areas. It was found that values greater than 0.1 correspond largely to these areas. Grid points were then generated in the areas with mass balance index values greater than 0.1 and inside landslide polygons. Finally, the resulting point sample was visually inspected and corrected when necessary. These samples contain about 800–1000 points, the number being specified in Table 1. Small landslides often received a single point in the depletion zone, while larger landslides received several points. After the depletion areas were sampled, we generated random samples of similar sizes outside the depletion areas and outside landslide polygons. A part of the

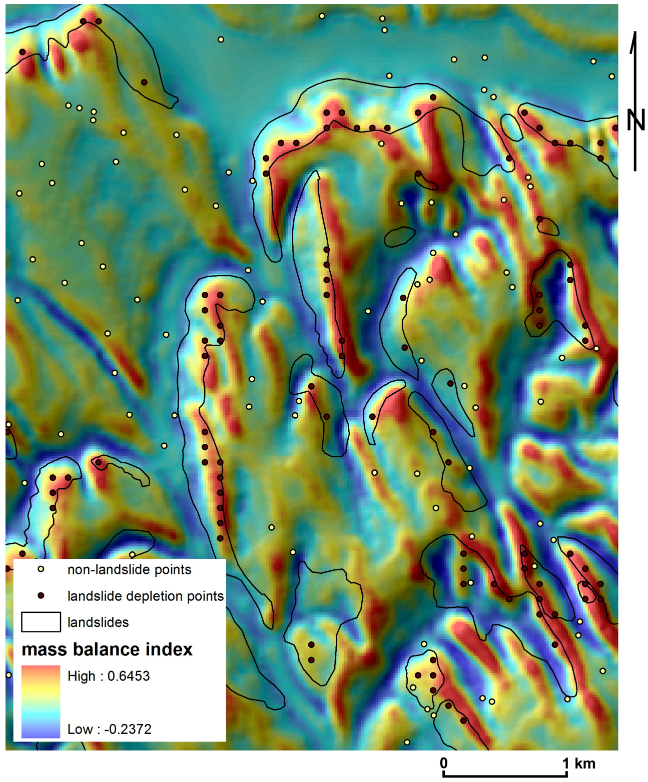

Fig. 6. The mass balance index used for sampling the landslide depletion areas (detail of the Lungani sector).

Lungani sector is shown in Fig. 6 as an example for this procedure.

For susceptibility modelling we used 80 % of the landslide and non-landslide points, representing the training samples. Consequently, 20 % of the samples, randomly selected, were used as independent data sets for validation and for testing the predictive potential of the models.

Next, we obtained continuous susceptibility values (from 0 to 1), which we classified thereafter into five classes. This is an important issue and as far as we know there is no agreement concerning the best approach. There are several possible approaches to achieve this: equal intervals, standard deviation based separations, natural breaks method, quantiles, etc. The use of equal intervals has the disadvantage of emphasizing one class relative to others (Ayalew and Yamagishi, 2005). Some authors recommend the standard deviation approach as the best choice for class separation (Ayalew and Yamagishi, 2005). The natural breaks algorithm (Jenks, 1977) performs the classification by grouping similar values while maximizing the differences between classes. It gives good results when the landslide susceptibility index (LSI) histogram shows evident breaks. This method was preferred here, so we separated five landslide susceptibility classes: very low, low, medium, high and very high (Table 5).

Finally, we tested the quality of the logistic regression model. Although other procedures exist, such as the likelihood ratio, or the pseudocoefficients of determination (e.g. McFadden, 1973; Cox and Snell, 1989; Nagelkerke, 1991), we used for validation the classification accuracy tables and the ROC methodology for both training and test samples. Applied in various fields, such as medicine, meteorology, etc., including geomorphology and particularly landslide susceptibility assessment (Chauhan et al., 2010; Mancini et al., 2010; Guns and Vanacker, 2012), the ROC curve is a useful tool for assessing the accuracy of predictions issued by a binary classifier system. It represents a graphical plot of true positive rate (known also as sensitivity) and false positive rate (known also as 1-specificity).

In the context of the current research, the BLR classifies the points as belonging to landslide depletion areas if the probability value is greater than the specified threshold (0.5). Otherwise, they are classified as non-landslide depletion points. The group of points representing landslide depletion areas is the "positive" group, while the other points represent the "negative" group. A true positive prediction is therefore the correct assignment of a point to the landslide depletion area group. A false positive prediction is the wrong assignment of a point to this group. A correct assignment to the non-landslide depletion group is called true negative or sensitivity. The number of false positive predictions is equal with 1 minus the number of true negatives. Plotting the fraction of true positives out of the positives (true positive rate) against the fraction of false positives out of the negatives (false positive rate) for all possible values of the threshold parameter (from 0 to 1), results in the ROC curve. The point (0,1), corresponding to the upper left of the plot represents the perfect classification, when all points are correctly classified.

The AUC is an indicator of the model quality, seen as one of the most useful tools for evaluating the BLR model fit (Gorsevski et al., 2006). For a perfect classification, the AUC is 1. For a random model, the AUC is 0.5. Generally, a good model must have an AUC value greater than 0.7 and an excellent model an AUC value greater than 0.9 (XLSTAT tutorial).

4 Results

Landslide densities were computed for slope aspect classes, land use, and lithology (Table 3), the values of which were further used in logistic regression analysis. Within the slope aspect classes, the analysis of landslide density reveals the fact that the highest values correspond to the western and northern slopes, where the surface deposits keep a high degree of humidity. In the case of the Căpuşu de Câmpie sector, the hierarchy is changed, where the highest values belong to the southern class. Considering the land use, the highest densities belong to the degraded land class (the landslides themselves contributing to the individualization of this specific class). The following classes are pastures and forest (for Căpuşu de Câmpie, Şipote and Lungani sectors), an issue that will be discussed below. Considering the lithology, the highest values belong to marls and clays, especially when they are mixed with sands and sandstones (the sectors within the plateau units) or with calcareous sandstones and conglomerates (Helegiu sector). Consequently, the lowest values are associated to the Quaternary deposits regardless of their granulometry (these deposits occupy almost entirely all the alluvial plains and fluvial terraces).

Through the stepwise filtering procedure of logistic regression method, the relevant predictors for landslide susceptibility assessment were selected for each of the four analysed sectors. The logistic regression coefficients are shown in Table 4, the predictors being arranged in order of decreasing importance according to the standardized coefficient values. The graphic representations of the standardized coefficients' values are presented in Fig. 7. They prove to be useful for better understanding the relations between the spatial distribution of landslide susceptibility classes and the influence of each factor in landsliding.

Though this procedure aims to avoid the multicollinearity problem, the correlation matrices were analysed as well. It was found that most of the predictors are statistically independent, showing R^2 values generally lower than 0.16, which assures the reliability of the results. High correlations were found between mean curvature, on one hand, and plan and profile curvature, on the other hand. The mean curvature was however eliminated by the stepwise filtering procedure in all sectors. Figure 8a–f shows the spatial distribution of the six predictors in the case of the Helegiu sector. We chose to display the thematic maps for this sector because this is characterized by a high geomorphologic and lithologic complexity, which have the potential of emphasizing better the spatial relations between landslide occurrence, the values of main predictors and the susceptibility classes.

Following the susceptibility modelling, we obtained the maps for all four sectors, which show five classes: very low, low, medium, high and very high. Classified landslide susceptibility maps are displayed in Fig. 9. Though the limits of classes vary slightly from one sector to another when using the natural breaks method (Jenks) algorithm, the differences are insignificant. As the threshold values separating the susceptibility classes present little variations among the four sectors, they allow an objective assessment of class percentages (Table 5). Also, this table presents the percentages of susceptibility classes for each sector. Very low and low susceptibility classes group 70–75 % of the Căpuşu de Câmpie, Şipote and Lungani sectors, while these classes represent about 57 % in the case of the Helegiu sector. The high and very high susceptibility classes represent 14–18 % in the Căpuşu de Câmpie, Şipote and Lungani sectors and about 27 % in the case of the Helegiu sector.

Table 3. Landslide density (LD) for lithology, slope aspect and land use classes.

Sectors	Lithology	LD	Slope aspect	LD	Land use	LD
Căpuşu de Câmpie	Alluvial and colluvial deposits – Quaternary	0.196	North	0.710	Built area	0.001
	Clays and marls, sand, sandstones, volcanic tuffs – Sarmatian	2.526	East	0.696	Arable land	0.200
	Clays, sands, volcanic tuffs – Pannonian	1.058	South	1.226	Pastures	3.709
			West	1.574	Forest and pastures	4.100
					Forest	0.889
					Waters and wetlands	0.000
Şipote	Gravels, sands – Quaternary	0.472	North	1.638	Built area	0.084
	Marls, clays, sandstones and sand complexes – Sarmatian	1.123	East	0.781	Arable land	0.268
			South	0.494	Pastures	2.744
			West	1.275	Forest	2.604
					Waters and wetlands	0.005
					Degraded land	5.053
Lungani	Gravels, sands (fluvial terraces) – Quaternary (Pleistocene)	0.065	North	1.138	Built area	0.321
	Sands, clays – Quaternary (Holocene)	0.328	East	0.861	Arable land	0.498
	Marls, clays, sandstones and sand complexes – Sarmatian	1.200	South	0.466	Pastures	1.911
			West	1.618	Forest	1.950
					Waters and wetlands	0.003
Helegiu	Gravels, sands – Quaternary	0.279	North	1.138	Built area	0.021
	Sandstones, volcanic tuffs – Tortonian	1.048	East	0.736	Arable land	0.065
	Sandstones, marls, gypsum – Helvetian	1.161	South	0.852	Arable land and pastures	1.462
	Sandstones, clays – Volhinian	1.189	West	1.316	Pastures	1.998
	Marls, clays, salt – Badenian	0.902			Forest	0.221
	Sandstones, menilite, dysodilic shales – Latorfian-chattian	1.196			Waters and wetlands	0.000
	Argilaceous shales, clays, sandstones – Priabonian	0.814			Degraded land	3.268
	Calcareous sandstones, marls, conglomerates – Lutetian	1.888				

The spatial distribution of the LSI points out tight relations between landslides and the main terrain morphological and land use features. In all sectors, the high and very high susceptibility classes correspond to the slopes most affected by landslides. In the Căpuşu de Câmpie sector, these classes clearly reveal the upstream areas of the semi-circular basins developed along the already mentioned dome flanks, the configuration of which is mainly the result of their evolution through landsliding processes. In the Şipote sector, the two classes are distributed along three alignments oriented NW–SE, along the cuesta scarps. In the western part of this sector, the LSI values delineate a major landslide basin of *hârtop* type. A general W–E orientation is observed in the northern part of the Lungani sector, where the long-term fluvial processes have individualized two cuesta-like slopes, separated by a sector of terraces with low LSI values. In the southern part of this sector, the dense hydrographic network, generally oriented S–N, is well exposed by these high and very high classes of LSI. Apparently randomly distributed in the Helegiu sector, the two LSI classes correspond greatly to the spatial patterns of land use, in the central and north-eastern part, and of lithology, in the south-western part.

As for the models' validation, the classification accuracy tables indicate good and stable logistic regression models. The percentages of correctly classified points, for a cut-off value of 0.5, were achieved for both training and validation samples, and are presented in Table 6. Higher model accuracy is noticed for the plateau sectors, especially for Şipote and Lungani (with an overall accuracy of 86.86 and 86.88 %, respectively).

Table 4. Logistic regression (standardized) coefficients with predictors listed in order of decreasing importance.

Sectors	Predictors	Regression coefficients	Standardized regression coefficients	Standard error	Wald chi-square	Pr > Chi2	Wald lower bound (95 %)	Wald upper bound (95 %)
Căpuşu de Câmpie	Slope angle	0.211	0.587	0.054	118.302	< 0.0001	0.481	0.692
	Land use class	0.604	0.581	0.046	160.728	< 0.0001	0.491	0.670
	Slope height	0.026	0.420	0.072	34.182	< 0.0001	0.279	0.561
	Profile curvature	−5.333	−0.392	0.056	49.818	< 0.0001	−0.501	−0.283
	Elevation	−0.011	−0.255	0.072	12.370	0.000	−0.397	−0.113
	Lithological class	0.720	0.120	0.048	6.199	0.013	0.026	0.215
	Plan curvature	1.727	0.105	0.048	4.866	0.027	0.012	0.199
Şipote	Slope angle	0.275	0.746	0.060	152.809	< 0.0001	0.628	0.864
	Land use class	0.903	0.686	0.054	162.138	< 0.0001	0.581	0.792
	Slope height	0.070	0.513	0.063	65.288	< 0.0001	0.389	0.637
	Elevation	0.009	0.138	0.060	5.223	0.022	0.020	0.256
Lungani	Slope angle	0.293	0.665	0.062	113.718	< 0.0001	0.543	0.787
	Slope height	0.046	0.499	0.106	22.370	< 0.0001	0.292	0.706
	Profile curvature	−7.291	−0.460	0.060	59.287	< 0.0001	−0.577	−0.343
	Plan curvature	8.378	0.436	0.055	61.773	< 0.0001	0.327	0.545
	Distance from drainage	−0.004	−0.314	0.080	15.326	< 0.0001	−0.471	−0.157
	Land use class	0.597	0.237	0.047	24.998	< 0.0001	0.144	0.330
	Lithological class	1.362	0.236	0.074	10.072	0.002	0.090	0.381
	Elevation	−0.013	−0.208	0.094	4.913	0.027	−0.392	−0.024
Helegiu	Land use class	1.374	0.634	0.042	225.937	< 0.0001	0.552	0.717
	Profile curvature	−3.811	−0.351	0.041	73.132	< 0.0001	−0.431	−0.270
	Slope angle	0.111	0.324	0.040	67.281	< 0.0001	0.247	0.402
	Lithological class	1.455	0.275	0.042	41.996	< 0.0001	0.192	0.358
	Plan curvature	2.153	0.205	0.038	29.504	< 0.0001	0.131	0.279
	Aspect class	1.391	0.180	0.035	26.024	< 0.0001	0.111	0.249
	Distance from drainage	0.001	0.115	0.037	9.906	0.002	0.043	0.187

Table 5. Upper thresholds values (TV), derived by Jenks' method, and percentages of landslide susceptibility classes from the total area of each sector.

Sector	Very low		Low		Medium		High		Very high	
	TV	%	TV	%	TV	%	TV	%	TV	%
Căpuşu de Câmpie	0.110	50.08	0.282	21.85	0.512	9.85	0.762	8.68	0.999	9.54
Şipote	0.112	55.60	0.272	19.57	0.490	10.37	0.743	7.29	0.999	7.16
Lungani	0.109	52.92	0.289	17.60	0.512	11.45	0.758	9.09	0.999	8.95
Helegiu	0.137	36.46	0.320	21.12	0.527	15.65	0.742	14.16	0.999	12.61

The area under the ROC curves, in the case of training samples (Fig. 10a), indicates high degree of accuracy for all landslide susceptibility models, while their predictive abilities are proven by the high AUC values computed for the validation samples (Fig. 10b). It should be noted that the Şipote sector followed by Căpuşu de Câmpie and Lungani sectors, present higher AUC values, of 0.922 and 0.912 respectively, compared to the mountainous sector of Helegiu (0.852). The AUC values are even higher in the case of the validation samples (0.940 for Şipote and 0.921 for Lungani and Căpuşu de Câmpie), excepting the Helegiu sector for which the value is similar to the one computed for the training sample (0.851).

5 Discussions

In general, in every analysed sector, the landslide susceptibility is determined mostly by certain predictors such as slope angle, land use, slope height, and lithology, while other predictors play a secondary role (profile curvature, plan curvature, elevation, and distance from drainage network). The least relevant predictors are the mean curvature (which was eliminated from the analysis by the stepwise procedure for all study sectors, due to redundancy, as it is well correlated with plan and profile curvatures) and slope aspect (which was removed in the case of three sectors – Căpuşu de Câmpie, Şipote and Lungani).

Table 6. Percentages of correctly classified points with respect to training and validation samples, using a cut-off value of 0.5.

Sector	Training sample			Validation sample		
	% correct for landslide-free points	% correct for landslide points	Overall accuracy (%)	% correct for landslide-free points	% correct for landslide points accuracy	Overall (%)
Căpuşu de Câmpie	82.42	85.48	83.95	82.14	85.29	83.73
Şipote	84.38	88.19	86.26	86.49	87.20	86.86
Lungani	82.33	88.11	85.18	84.64	88.82	86.88
Helegiu	72.59	84.02	78.44	77.34	78.61	77.97

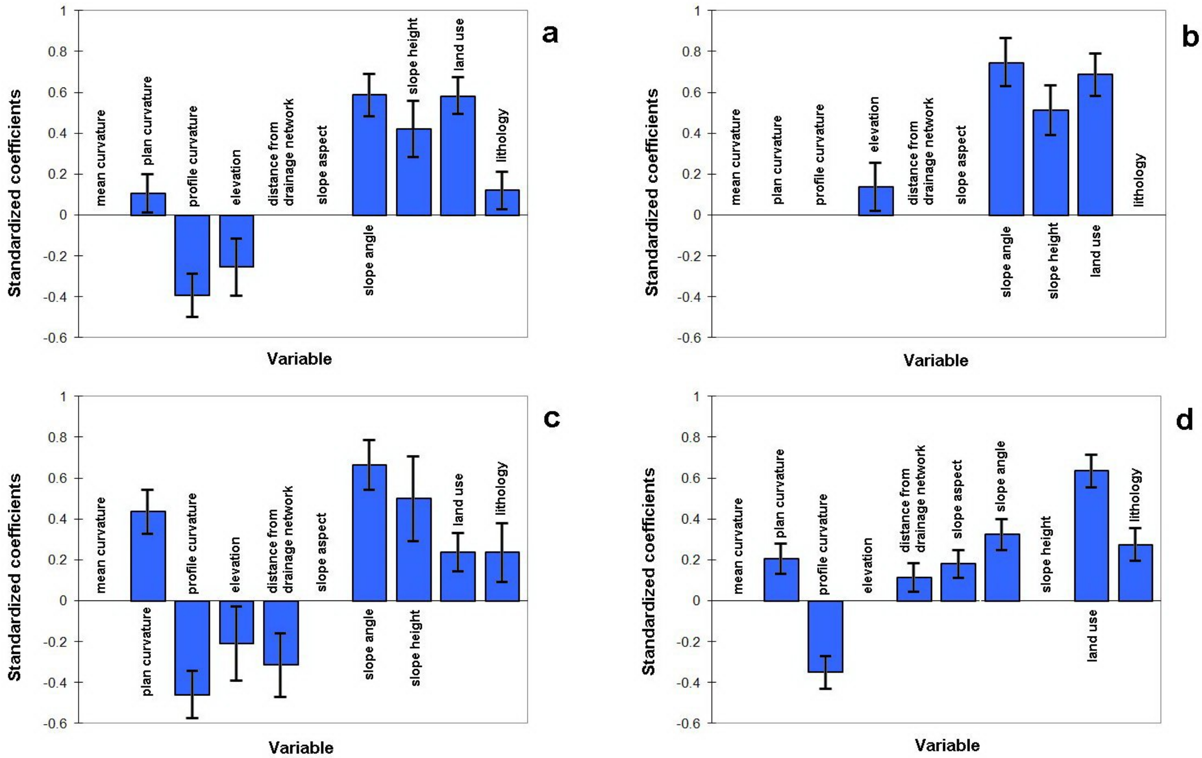

Fig. 7. Standardized coefficients' values of predictors (with bars showing 95 % confidence interval): **(a)** Căpuşu de Câmpie sector; **(b)** Şipote sector; **(c)** Lungani sector; **(d)** Helegiu sector.

Slope angle is the most important factor for the Căpuşu de Câmpie, Şipote and Lungani sectors. This is the predictor that is almost constantly found among the most important three factors within many of the studies applying a similar methodology assessment at regional scale (Ayalew et al., 2005; Gorsevski et al., 2006; Bai et al, 2010; Chauhan et al., 2010; Dominguez-Cuesta et al., 2010; Pradhan and Lee, 2010; Van den Eeckhaut et al., 2010; Yalcin et al., 2011). The great influence of slope factor highlights the high and very high susceptibility classes, which are clearly positioned along the cuesta escarpments. For the Şipote and Lungani sectors, though the overall correlation between slope and lithology is not significant, high slope values are locally associated with the occurrence of hard rocks which form the monostructural plateaus. As a consequence, the areas with high landslide susceptibility occur mostly in the upper part of slopes. This aspect is also documented in literature, especially in the monoclinal regions affected by landslides in western Europe: Belgium and France (van den Eeckhaut et al., 2009, 2010). For the Helegiu sector, we can affirm that slope angle is less effective because of the lithological characteristics which did not favour the accumulation of deep slope deposits. This explains the low values for mean surface of landslides and, at the same time, the large number of small landslides, the occurrence of which links with the higher density of lithological contacts.

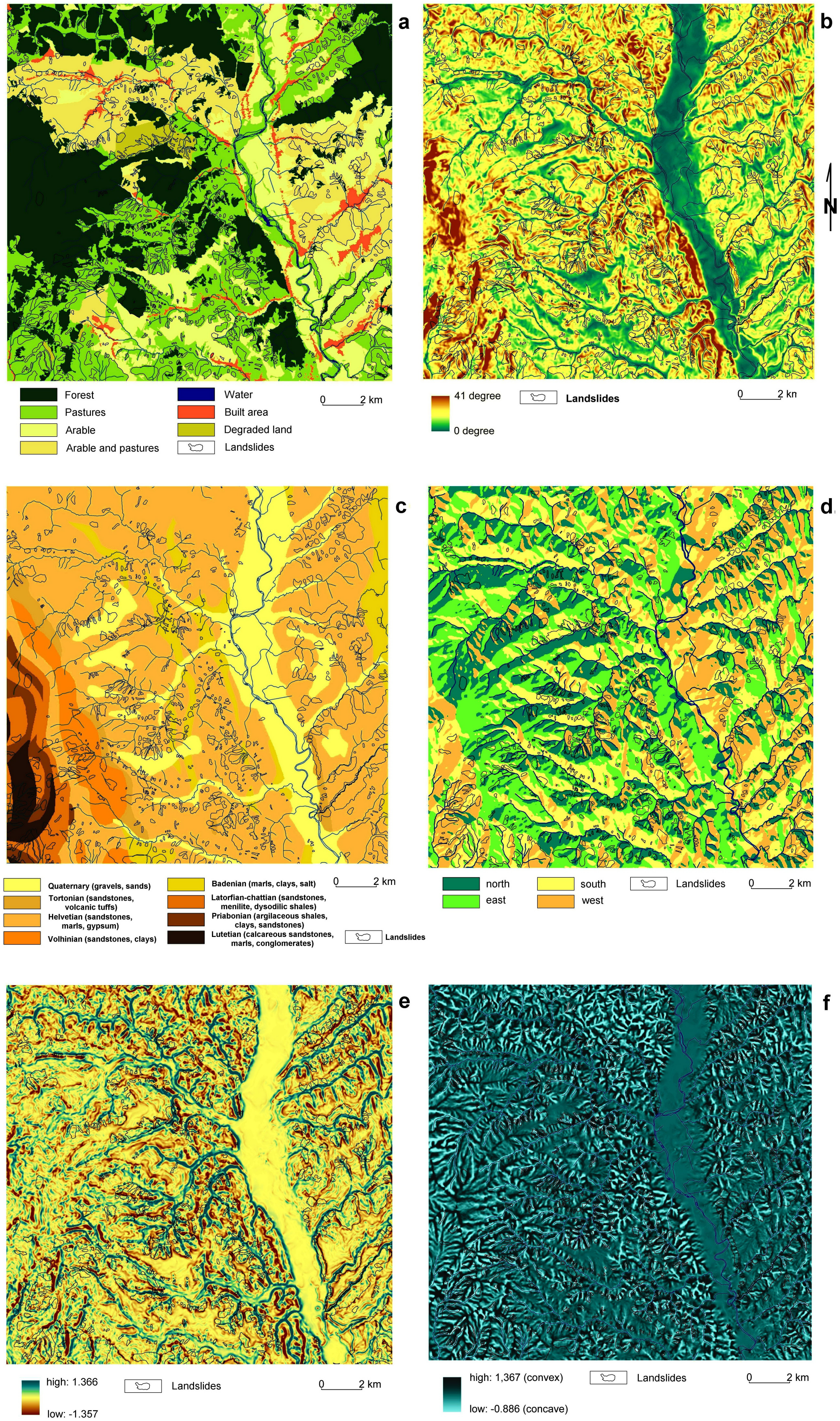

Fig. 8. Significant predictors for the Helegiu sector: **(a)** land use; **(b)** slope angle; **(c)** lithology; **(d)** slope aspect; **(e)** profile curvature; **(f)** plan curvature.

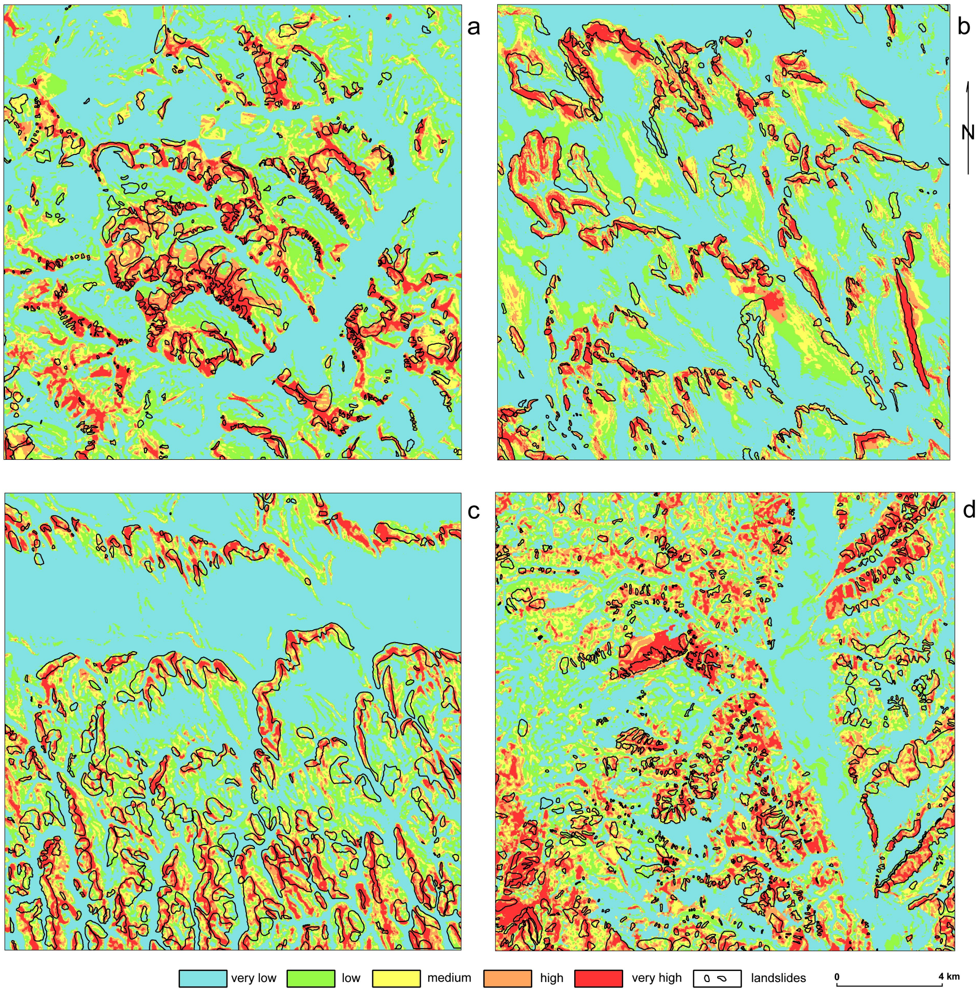

Fig. 9. Classified landslide susceptibility maps: **(a)** Căpuşu de Câmpie sector; **(b)** Şipote sector; **(c)** Lungani sector; **(d)** Helegiu sector.

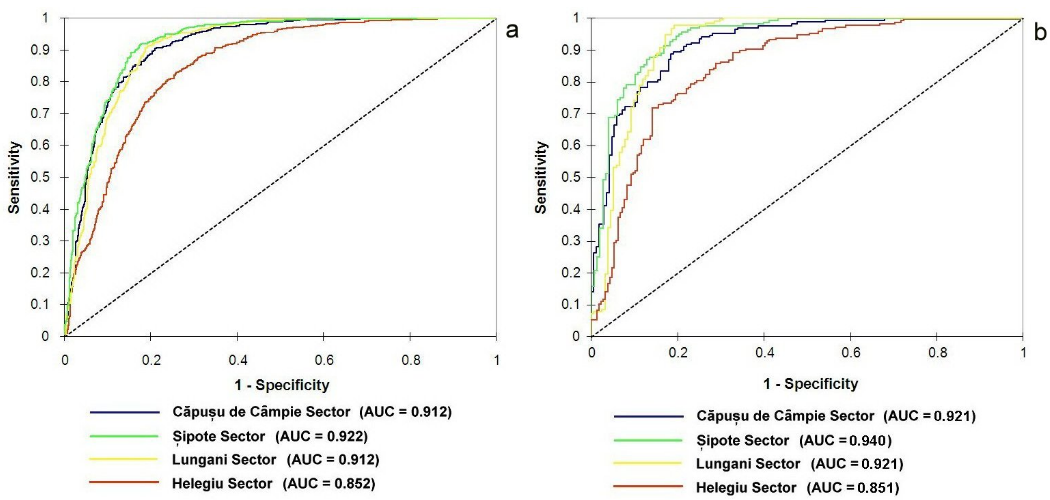

Fig. 10. ROC curves with associated AUC values computed from training samples **(a)** and validation samples **(b)**.

Land use is the most important factor for the Helegiu sector and is placed in the second position in the case of Căpuşu de Câmpie and Şipote sectors. It may be possible that the results are influenced by the consideration of present land use and not by the one prior to the occurrence of landslides (Atkinson and Massari, 1998). Since our database does not have a multitemporal nature, we cannot make judgments on the temporal relationships between landslides and land use change. We can affirm that the changes in the land use (such as deforestation, grazing expansion, afforestation) are highly reflected in landslide evolution. Given that the highest densities of landslides are associated with land covered with pasture and forest, we can define the following two circumstances: first, the landslides were favoured by deforestation (currently being present mainly on terrains with pastures); and second, where the lands affected by landslides have been afforested (now being found as stabilized landslides). For the Helegiu sector, the land use factor stands out because of its much higher coefficient relative to the other factors, due to the massive deforestations from the last two centuries which led to the great extension of landslides on terrains currently used as pastures. Yet another possible explanation is the integration of the degraded land class which has the biggest value of landslide density. For the plateau sectors (Căpuşu de Câmpie and Şipote), land degradation processes, including landsliding, were favoured, among others, by long-term subsistence agricultural practices, with no agrotechnical conservation measures, and high degree of land property fragmentation and tillage along the maximum slope gradient direction. The persistence and the shifting on parallel tracks of agricultural exploitation roads have constituted, in many situations, favourable conditions for the extension of landslides. For the Lungani sector, the lower relative importance of this parameter is explained by the presence of the Bahlueţ floodplain (in the central-northern part), which is mostly covered with pastures, but where landslides are missing.

The slope height is the next important factor, being the second in the case of the Lungani sector and the third for Căpuşu de Câmpie and Şipote sectors. Its significant influence is explained by the high relative altitude of landslide depletion areas, on which the models are based. For the Helegiu sector the slope height is not significant, because the landslides are distributed over a lager altitudinal variance within the slopes, by comparison with the other three sectors.

The lithology factor occupies the fourth position in the predictors' hierarchy in the case of the Helegiu sector. The landslide density values reveal the influence of some sequences of marl, sandstone and conglomerate strata in increasing the landslide susceptibility values. For the other sectors, this factor has a lower influence due to the relatively high geological uniformity.

The other factors, as already mentioned, proved to be less important predictors for landslide susceptibility assessment in all study sectors.

Regarding the spatial variability of the predictor coefficients, we could mention the difference between Şipote and Lungani sectors, both of them belonging to the same geographical unit – the Moldavian Plateau. We consider that the higher fragmentation degree in the Lungani sector, due to a higher density of rivers, is the main cause for shallow landslide occurrence. As such, in this sector the plan and profile curvature predictors have higher values of these coefficients. In addition, the distance from drainage network predictor has the highest value among the four sectors.

Despite its high predictive power, as in the case of any statistical method, our susceptibility models have some inherent limitations: (i) in all the landslide types being analysed (shallow and deep seated), the calculus of susceptibility values could have an important degree of generalization; (ii) being medium scale models, they do not consider the large spatial variability of local conditions that could influence landslide occurrence (especially the geotechnical ones); these models are mainly build upon the mappable parameters from cartographic sources and those that are derived from the DEM; and (iii) the models assume that landslides will occur under the influence of the same combination of predictors, whereas field observations indicate that some landslides are influenced by local conditions in conjunction with other factors, such as the slope angle (Che et al., 2012).

The application of a wide range of methods for landslide susceptibility assessment is beneficial, as the current official Romanian methodology has some important limitations: (i) the absence of landslide inventory as a very important layer to correlate spatial distribution of landslides and causal factors (Guzzetti, 2000; van Westen et. al., 2003) and also to validate the results; (ii) the absence of the DEM and geomorphometrical parameters from the spatial database, such as slope angle, slope aspect, topographical curvatures, distance to drainage network, etc.; (iii) the assignment of the same weights to contributing factors of landslides in all Romanian regions, while neglecting the major geomorphological units; (iv) combining different databases which refer to contributing factors at different scales (between 1 : 500 000 and 1 : 5000), while the final map is achieved at 1 : 25 000 for county level and 1 : 5000 for the local one; and (v) the absence of a time factor in hazard evaluation (Manea and Surdeanu, 2012).

In Romania, the continuous development of geospatial databases, including both contributing factors and the complete inventory of landslides, will allow wide applications of statistical methods for landslide susceptibility assessment, such as the logistic regression. This will be beneficial for the creation of accurate landslide susceptibility maps, an essential tool for effective land-use management, which should become a standard tool to support land management decision-making (Akgun, 2012; Park et al., 2013).

Compared to our mentioned previous study on landslide susceptibility in the Căpuşu de Câmpie and Lungani sectors (Mărgărint et al., 2011), the results of the present study are close, despite some small methodological differences, like the predictors used and landslide inventory. In our previous study we used a different number of predictors (nine predictors versus ten predictors in this study). As for the landslide inventory, this was based only on topographical maps at 1 : 25 000 scales, therefore the generalization degree was higher.

Considering the higher values of the AUC obtained both in our previous study and in the present study, we can affirm that the logistic regression could be an important alternative to the current Romanian methodology and could improve the landslide susceptibility mapping at medium to large scales.

6 Conclusions

The scientific literature provides several hierarchies of predictors with respect to their influence on landslide susceptibility assessment, having a large range of variation. In most cases, certain predictors occupy the first ranks: slope angle, lithology, land use, and slope aspect. The present study concurs with these findings, placing the coefficients of predictors within the limits that are specified in other similar studies.

For all study sectors, high values of predictors' coefficients are noticed for slope angle and land use. The influence of lithology, in the case of the Helegiu mountainous sector, confirms the fact that, under high geological diversity conditions, the predictor lithology has a significant relevance in landslide susceptibility.

The ranks and coefficients associated with the other predictors show high degrees of variability from one sector to another. It is obvious that the selection of common predictors in landslide susceptibility assessment leads to more generalized analyses. The variation of the coefficients of predictors may suggest the existence of other factors, with local influences, which are probably considered redundant in some cases, but which should be evaluated as they reflect the regional traits of landslide manifestation process. This variability could also be related to the spatial scale and to the level of detail of input materials, on the basis of which the data acquisition is performed.

The results of this paper allow us to consider that the logistic regression method could represent an alternative for the landslide susceptibility and hazard mapping in Romania. This paper's method uses some essential elements that are not found in the existent methodology (landslide inventory, DEM and geomorphometrical parameters, and land use), and which can make possible a better differentiation of landslide susceptibility. The results of this study may help to improve the accuracy of landslide susceptibility and hazard mapping by the taking into account new landslide predisposal factors and the differentiation of their weights within major geographical units.

Supplementary material related to this article is available online at http://www.nat-hazards-earth-syst-sci.net/13/3339/2013/nhess-13-3339-2013-supplement.pdf.

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