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A landslide susceptibility model using the Analytical Hierarchy Process method and multivariate statistics in perialpine Slovenia

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Abstract

Landslides cause damage to property and unfortunately pose a threat even to human lives. Good landslide susceptibility, hazard, and risk models could help ~~mitigate~~ or even avoid the unwanted consequences resulted from such hillslope mass movements. For the purpose of landslide susceptibility assessment the study area in the central Slovenia was divided to 78 365 slope units, for which 24 statistical variables were calculated. For the land-use and vegetation data, multi-spectral high-resolution images were merged using Principal Component Analysis method and classified with an unsupervised classification. Using multivariate statistical analysis (factor analysis), the interactions between factors and landslide distribution were tested, and the importance of individual factors for landslide occurrence was defined. The results show that the slope, the lithology, the terrain roughness, and the cover type play important roles in landslide susceptibility. The importance of other spatial factors varies depending on the landslide type. Based on the statistical results several landslide susceptibility models were developed using the Analytical Hierarchy Process method. These models gave very different results, with a prediction error ranging from 4.3% to 73%. As a final result of the research, the weights of important spatial factors from the best models were derived with the AHP method. Using probability measures, potentially hazardous areas were located in relation to population and road distribution, and hazard classes were assessed.

Keywords: Landslide susceptibility; Multivariate analysis; Analytical Hierarchy Process; Slovenia

1. Introduction

Recent natural disasters in Europe, like the floods in 2002 (BBC, 2002) and numerous hillslope mass movements that have occurred in the course in recent years, have augmented the need for a better understanding of these natural phenomena. Geohazards, such as landslides, floods or earthquakes, are a source of concern around the world and Slovenia is no exception. Such events are generally the result of natural forces, seldom the consequence of human action. Whatever the cause, their prevention or mitigation is an important step towards the preservation of

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the environmental quality. Hence the need for a better understanding of these phenomena, especially when their triggering factors can be to some measure controlled, as in the case of landslides.

Landslides are the result of two interacting sets of forces; *the precondition factors*, generally naturally induced, which govern the stability conditions of slopes, and *the preparatory and the triggering factors*, induced either by natural factors or by human intervention. These triggers are usually intensive, geologically speaking short-term processes that irreversibly change the slope and cause the landslide (Glade and Crozier, 2005).

The scope of the paper is to examine the long-term factors, and to define their relations to landslide occurrence in the studied area. The primary goal was to study spatial factors that conjointly influence the occurrence of landslides, and to statistically establish the multivariate relations of the independent factors with the spatial distribution of landslides. The second goal was to create a landslide susceptibility model, based on the statistical relationships that would help to predict the landslide prone areas with a high reliability, not only in the studied area. Additionally, the results of such a study would define hazardous areas, where landslides might occur over short-term timescales. As a final goal of the research, superimposing the population density map and the infrastructure map on the resulting landslide susceptibility maps helps assess the distribution of the two according to the landslide hazard.

2. Area description and data collection

The study area occupies approximately 1220 km^2 (35 × 35 km) in the central part of Slovenia, west of Ljubljana (Fig. 1). The area belongs to a perialpine region, it extends from an elevation of 247 m in eastern part, in the Sava and Sora River plain, to 1663 m a.s.l. in the western part, in the perialpine mountainous area.

Successful prediction of landslide occurrence and the production of a map of the landslide-prone areas ~~calls for~~ the collection of the relevant spatial data. More details can be found in Crozier (1989) and Guzzeti et al. (1999). The fact that data needed for the research were obtained from different institutions and on different scales (from 1 : 50 000 to 1 : 100 000) puts the data accuracy issue under some doubt. The landslide data were obtained from the point landslide database that was constructed at Geological Survey of Slovenia. For the study area, it consists of data on 614 shallow translation landslides, dating from 1964 to

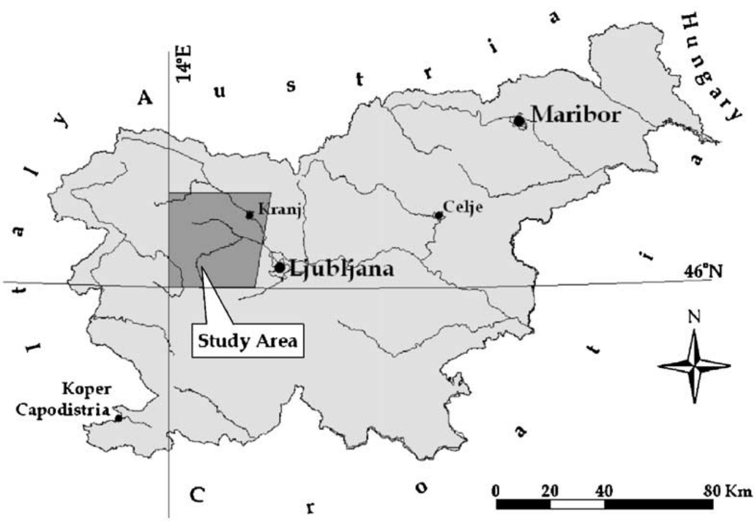

Fig. 1. The study area in the western part of central Slovenia. It lies in the perialpine region and it extends over 1220 km^2. The range of the 30-years average annual rainfall is between 1200 and 2500 mm/year. The range of the maximum 24-h rainfall with the return period of 100 years is between 300 and 500 mm. The terrain gradually changes from river plains in the east to the perialpine region in the west.

2001. In the database landslides were classified into four types; fossil or remnant landslides (68), dormant landslides (413), creeping (57), and slides (60). Approximate velocity equivalents (after Glade and Crozier, 2005) for the four types are extremely slow, very slow, slow, and very to extremely fast, respectively. Sixteen landslides were classified as unknown type. The digital elevation model (DEM) data were obtained from the national 25 m resolution InSAR DEM 25 (Survey and Mapping Administration, 2000a). All the additional data on the terrain morphology (terrain curvature, elevation, slope, aspect, basins, and primary slope-units) were derived from the DEM. The "Basic Geological Map of Yugoslavia at the scale of 1 : 100 000" served as a source for the geological data (Buser et al., 1967; Buser, 1968, 1987; Grad and Ferjanĉiĉ, 1974). For the land use and the vegetation cover (cover type) reconnaissance, satellite images from two different satellites were used and combined, using a PCA (Principal Component Analysis) merging method as explained in the next section. The multi-spectral part of the satellite data was obtained from the Landsat-5 TM images, and the high-resolution part was obtained from the Resurs-F2 MK-4 images. The topographic map at a scale of 1 : 50 000 was used as a source of the surface water data (Survey and Mapping Administration, 1994). The population density data were obtained from National Office of Spatial Planning and Survey and Mapping Administration (1997) and infrastructure data from Survey and Mapping Administration (2000b). In the research area there are around 135 000 inhabitants and over 12 000 km of roads.

3. Methods

3.1. Satellite data

The multi-spectral satellite data, obtained from the Landsat-5 TM images, were merged with the high-resolution satellite data, obtained from the Resurs-F2 MK-4 images, using the principal component analysis (PCA) joining method (Cliché et al., 1985; Chavez et al., 1991; Sanjeevi et al., 2001; Vani et al., 2001). Principal component analysis is a linear dimensionality reduction technique, which identifies orthogonal directions of maximum variance in the original data, and projects the data into a lower-dimensionality space formed of a sub-set of the highest-variance components (Bishop, 1995). The principle of the PCA joining method is that the first principal component derived from the multi-spectral satellite data, which relates to the data on surface albedo, is replaced with the first principal component of the high-resolution satellite data, which also relates to the data on surface albedo, but at a higher resolution. After the merge, the principal components of multi-spectral satellite data are retransformed back into the original images but with a resolution of the high-resolution images. Prior to the landslide susceptibility assessment, the landslide population was split into the learning (293 landslides) and the testing sets (321 landslides) based on the temporal distribution of the landslide population. The relation between the two is not an ideal one, but the temporal boundary was defined by the date of the acquisition of the satellite images in September 1993. Since the learning set of landslides, used in the susceptibility model development, had to be "visible" on the satellite images, the landslides that occurred after the image acquisition could not be used as a learning set. Next, all joined images were classified according to landslide susceptibility rate (areas or cover-types where more landslides have occurred have a higher possibility of future landslide occurrence) using either the unsupervised classification or the advanced red-green-blue (RGB) clustering method (ERDAS, 1999), which works better on spherically clustered data. The RGB clustering method was used only on the images that were transformed from orthogonal RGB colour model to spherical CIE L*a*b* colour model (CIE, 1986). Each of the 418 different colour composites was classified into 1024 classes that were tested for landslide occurrence using Classification Success Index (Komac, 2005). Based on the results of the χ^2 test for their landslide susceptibility the 1024 classes of the best colour composite were finally merged into 33 classes of different cover types that actually represent different landslide susceptibilities.

3.2. Statistical analyses

To efficiently, and with lower costs, identify the landslide-prone areas a better and more precise understanding of the relationship between the spatial factors is necessary. Carrara (1983) and Carrara et al. (1991) have shown that statistical analyses of contributing spatial factors can be successfully used for predicting landslide prone areas. First, individual spatial factors for the different landslide types and for landslides generally, were tested with various statistical tests. The Kolmogorov–Smirnov test and χ^2 test were used for categorical and continuous variables (lithology, cover type, slope inclination (slope), elevation, aspect, terrain curvature, distance to geological boundaries, distance to structural elements, and distance to rivers) and Student's t test was used for the continuous variables (the same variables as above, except for lithology and the cover type). The confidence limits of the analyses were set to 95%. The univariate analyses were done on the whole landslide population to determine the significance of each factor for landslide susceptibility.

For the purpose of multivariate analyses, the learning set of landslides was randomly chosen from the landslide population (394 or 64.2% of landslides with similar portions for each landslide type) disregarding the temporal component. Here the learning set is almost twice as big as the testing set. Such a relation between the learning and the testing set enables more representative analytical results.

Multiple relations between the factors and the landslide distribution were tested with factor analysis (FA) and multiple regression analysis (MRA). The importance of the individual factors or groups of factors on landslide susceptibility was defined. For the purpose of the multivariate analysis, the area was automatically subdivided into the 78 365 slope units, for which 24 statistical variables were calculated. The high number of slope units resulted from the division of computer-derived basins that were further subdivided into smaller units according to different slope aspects. Table 1 lists all the variables that were calculated for each slope unit. A similar, but manual approach of terrain division into slope units has been shown before (Carrara, 1983; Carrara et al., 1991; Van Westen, 1993; Ardizzone et al., 2002). Only those slope units, where landslides were mapped, were analysed with multivariate statistics. As a dependant variable, the spatial frequency of landslides in a slope unit was used. Due to the wide range of slope unit areas, the frequency values were log transformed prior to the analyses.

3.3. Model developing process with AHP based on the multivariate analyses results

After having analysed all the spatial data, different models were developed, using the AHP (Analytical Hierarchy Process) method. The application of the AHP method, developed by Saaty (1977), for landslide susceptibility has been shown before (Barredo et al., 2000; Mwasi, 2001; Nie et al., 2001) and it was

Table 1
List of the statistical variables, calculated for each of the 78 365 slope units

#	Variable	#	Variable	#	Variable
1	Maximum slope inclination	9	Mean cosine of slope orientation (aspect)	17	Maximum distance to closest surface water (ln of the distance)
2	Mean slope inclination	10	Minimum distance to closest geological boundary (ln of the distance)	18	Mean distance to closest surface water (ln of the distance)
3	Standard deviation of slope inclination	11	Maximum distance to closest geological boundary (ln of the distance)	19	Variety of lithology
4	Mean elevation	12	Mean distance to closest geological boundary (ln of the distance)	20	Majority of lithology
5	Absolute maximum of curvature	13	Minimum distance to closest structural element (ln of the distance)	21	Median of lithology
6	Convex/concave type	14	Maximum distance to closest structural element (ln of the distance)	22	Variety of classified satellite data — land use and vegetation cover
7	Mean of terrain curvature	15	Mean distance to closest structural element (ln of the distance)	23	Majority of classified satellite data — land use and vegetation cover
8	Standard deviation of terrain curvature	16	Minimum distance to closest surface water (ln of the distance)	24	Median of classified satellite data — land use and vegetation cover

used to define the factors that govern landslide occurrence more transparently and to derive their weights. For the model development, the results from the multivariate analyses, both MRA and FA, were used. One set of the models was developed using the values from the statistics to manually define the relationships between the different factors according to the AHP methodology. These values were later imported into the AHP matrixes. The other set of the models was developed by automatically importing the calculated relationship values between different factors, based on the statistical values, into the AHP matrixes. For all the models, where AHP was used, the CR (*Consistency Ratio*) was calculated (see Saaty, 1977). The models with the CR greater than 0.1 were automatically rejected. With the AHP method, the values of spatial factors weights were defined. Using a weighted linear sum procedure (Voogd, 1983) the acquired weights were used to calculate the landslide susceptibility models.

To effectively compare the calculated models, the normalisation of the results had to be done. Taking into account the normal distribution of the results, an approximation was done, where in each of the model, the highest value represented the highest landslide susceptibility, and the lowest value represented the lowest landslide susceptibility. Considering the normal distribution, the mean represented the crude boundary between the landslide "safe" and landslide prone areas. This division served for the model error estimation. Of course, the reality is far from that, either because of model errors, or because of variations in the factors. After normalisation, the error for each model was estimated by defining the proportion of slope units with landslides whose landslide susceptibility was lower than the mean value of the model.

The models that produced best results were used to determine potentially hazardous areas in relation to landslide occurrence. For the hazard map (nominally classified landslide susceptibility map with defined prediction error possibility), the normalised model values were classified into several "fuzzy" classes that follow the gradual transition between the landslide-"safe" and the landslide-prone areas. We propose the "fuzzy" classification of the landslide hazard, based on the standard deviation values (Fig. 2). This classification resulted in 8 levels of landslide hazard and the mean value (Table 2). The probability of future landslide occurrence is much higher in the areas with higher landslide susceptibility. Simple descriptive statistical measures/parameters were used as a foundation for defining the hazard classes as described in the following text. Here only the upper half of the distribution and landslide hazard, con-

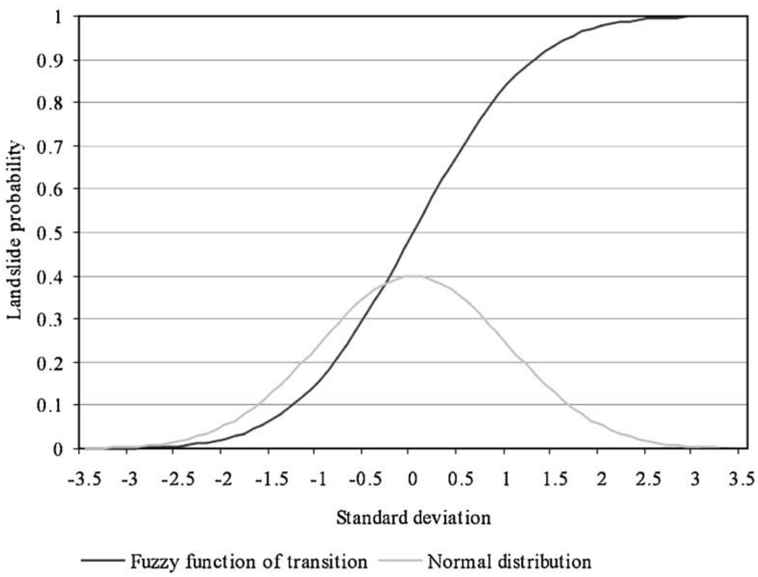

Fig. 2. "Fuzzy" function of the landslide occurrence probability. The value zero represents the mean.

Table 2
"Fuzzy" classification of the landslide susceptibility based on the standard deviation (SD) values

Statist. descript.	Hazard	Statist. descript.	Hazard
< − 1.75 SD	Very small	>MV–1 SD	Moderately high
− 1.5 to − 1.75 SD	Small	1–1.5 SD	Relatively high
− 1 to − 1.5 SD	Relatively small	1.5–1.75 SD	High
− 1 SD to <MV	Moderately small	>1.75 SD	Very high
Mean value	Boundary		

The result are eight landslide hazard classes.

nected to the distribution, will be discussed. The other half is its mirror counterpart. Values from mean to standard deviation (SD) (moderately high) represented the lowest landslide hazard class (~0.5–0.84 probability of landslide occurrence) since it is highly possible that if errors (misclassifications) exist in the model, they would occur in this class. The class of values from 1 to 1.5 SD represented relatively high hazard due to a small possibility of the model error occurrence (~0.84–0.933 probability of landslide occurrence). Values from 1.5 to 1.75 SD (~0.933–0.96 probability of landslide occurrence) represented high hazard due to a very small possibility of model error occurrence, and values higher than 1.75 SD (~0.96–1 probability of landslide occurrence) of the landslide-prone area population represented a very high level of hazard. Here, the error of the model was negligible.

4. Results and discussion

The results of the satellite image analyses showed that the best result of the landslide-susceptible area prediction was achieved with the merged image that was the composite of channels 3, 4 and 5, transformed to the CIE L*a*b* colour model and was classified with the advanced RGB clustering method (Fig. 3). The landslide-susceptible area prediction error was 12.6%(α error — portion of the area that was classified as non-landslide, but where current landslides do occur) and the non-landslide area prediction error was 8.1% (β error — portion of the area that was classified as landslide-prone, but where no landslides can be found). The overall success of the landslide-suscepti-

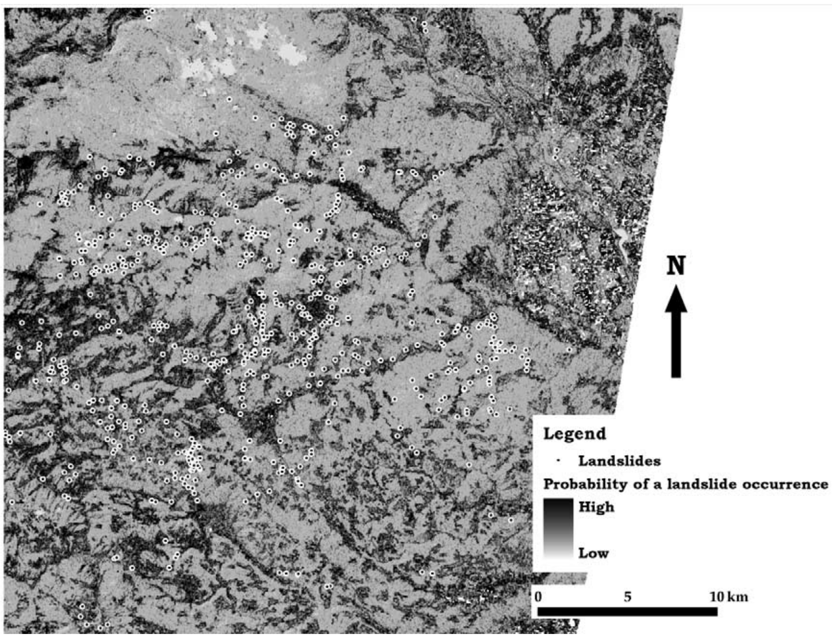

Fig. 3. The most suitable satellite image for the landslide susceptibility modelling (colour composite of channels 3, 4 and 5 of the merged high resolution multi-spectral images). The image was classified into the 33 classes of probability of landslide occurrence, from light colours with low probability to dark colours with high probability. Landslide locations ($n = 614$) are represented by points.

ble area classification of the best model was 79.2%. The result represents the classification of the vegetation/land-use type (cover type) according to landslide susceptibility and does not deal with vegetation or land-use types. The merged multi-spectral high-resolution satellite images proved to convey useful information on landslide occurrence, without having detailed knowledge about the land cover type of the terrain under investigation.

The univariate analyses results showed that the following factors proved to play an important role (in brackets the significance classes are given): the slope (>14°), the terrain curvature (concave from -2 to -0.5), the distance to the geological boundaries (2.5–50 m), the distance to rivers (7.5–150 m), the lithology (shale; scree deposits; graywacke, sandstone, shale, marly shale, and tuff; sandstone, shale, siltstone, conglomerate, and marl; sandstone, argillite, and tuff; pyroclastites), and the cover type (not defined, since the type was not assessed). The slopes above 14° tend to be much more unstable than the less steep ones, although analyses have also shown that also the class from 11° to 14° tends to be very unstable, especially in looser materials (gravel and sand). The terrain curvature indicates that landslides tend to occur in concave areas where the concentration of pore water is higher. Closeness of landslide occurrence to geological boundaries might be the consequence of the contacts between overlying more and underlying less permeable rocks resulting in abundance of springs and hence more soil moisture, or the consequence of the difference in behaviour in case of the earthquakes. The distance to rivers clearly indicates two possible reasons. One is the presence of groundwater, and the other is the undercutting process by running surface waters. Considering lithological units, landslide occurrence is expected in the lithological units, given above, due to their geomechanical properties, either due to the friction angles or due to the presence of pore water.

Comparing the results of multivariate analyses, the FA (principal component) proved to be the most appropriate and reliable method for landslide susceptibility assessment. Table 3 shows the proportions of the variance, explained by various factors that are represented by one or more variables. Each individual variable is numbered and its description is explained in Table 1. At the bottom, the total explained variance is shown. The explained variance values indicate that the factors chosen for the landslide susceptibility analyses represent around 80% of landslide occurrence governing factors. In other words, these results may suggest that precondition factors represent roughly 80%, and the preparatory and the triggering factors represent the rest of the influence on landslide occurrence.

Table 4 shows the values for the weights for the spatial factors in the most suitable susceptibility models for different landslide types. The last row shows the error for each of the models. For all types of landslides the susceptibility models developed with the FA gave the best results, except for slides where the MRA model achieved the same success rate as the FA model. The best susceptibility model for all landslides ($n = 614$) showed that the most important precondition factors were the lithological properties (36.5%), followed by the slope (21.2%), the cover type properties (17.6%), the terrain roughness (10.1%), the terrain curvature (8.6%), the distance to

Table 3
Proportions of the variance, explained by factor loadings (factor analysis — principal component method)

	All landslides	Fossil landslides	Dormant landslides	Creeping	Slides
F1	1, 2, 5 & 8 (22%)	3, 20 & 21 (26%)	1, 2, 3, 5 & 8 (24%)	20 & 21 (23%)	1, 2, 3, 5 & 8 (27%)
F2	20 & 21 (15%)	1, 2 & 8 (19%)	18 & 22 (14%)	1, 2, 5 & 8 (19%)	6, 12 & 19 (16%)
F3	7 & 18 (12%)	7 & 22 (12%)	9, 23 & 24 (12%)	7 & 18 (15%)	20 & 21 (14%)
F4	9, 23 & 24 (10%)	15 & 19 (9%)	20 & 21 (10%)	9, 23 & 24 (12%)	23 & 24 (10%)
F5	19 & 22 (7.5%)	23 & 24 (8%)	15 (8%)	15 & 19 (6.5%)	7 (7.5%)
F6	15 (6%)	18 (7%)	6 (6%)	6 (5.5%)	15 (6%)
F7	6 (5.5%)	–	12 & 19 (5.5%)	–	–
Sum	78.3%	80.2%	79.2%	80.4%	80.5%

Numbers in fields represent the variables, listed in the Table 1. In brackets the proportion of the explained variance by variables in given field is given. The first column represents factors and the last row represents the sum of the explained variance of the best susceptibility model for all the landslides and for each landslide type.

Table 4
Values of weights of spatial factors in the best models for all landslides and for each landslide type (fossil landslides, dormant landslides, creeping, and slides)

Spatial factor	All landsld.	Spatial factor	Fossil landsld.	Spatial factor	Dormant landsld.	Spatial factor	Creeping	Spatial factor	Slides
Lithologic properties	31.0%	Lithologic properties	21.8%	Lithologic properties	30.2%	Slope	21.3%	Lithologic properties	33.4%
Slope	21.2%	Slope	15.7%	Slope	20.8%	Lithologic properties	19.4%	Slope	26.1%
Cover type	13.7%	Terrain roughness	15.2%	Cover type	13.1%	Lithologic diversity	15.2%	Terrain roughness	11.6%
Terrain roughness	10.1%	Cover type	14.8%	Terrain roughness	10.4%	Cover type	14.6%	Cover type	11.1%
Terrain curvature	8.6%	Cover type diversity	7.8%	Lithologic diversity	5.4%	Terrain curvature	11.7%	Terrain curvature	6.7%
Lithologic diversity	5.5%	Lithologic diversity	6.8%	Distance to geologic boundaries	5.0%	Distance to surface water	5.2%	Lithologic diversity	6.2%
Cover type diversity	3.9%	Distance to geologic boundaries	6.1%	Cover type diversity	4.7%	Aspect	4.8%	Distance to tectonic elements	2.9%
Distance to surface water	3.6%	Distance to surface water	6.1%	Distance to surface water	4.0%	Distance to tectonic elements	3.4%	Distance to geologic boundaries	1.8%
Distance to tectonic elements	2.3%	Distance to tectonic elements	5.7%	Distance to tectonic elements	3.5%	Distance to geologic boundaries	3.0%		
				Aspect	1.7%	Terrain roughness	1.7%		
				Terrain curvature	1.3%				
No. of landslides	614[a]		68		413		57		60
No. of landslides in testing set	394		46		268		34		37
Error (misclassified landslides)	10.66%		4.35%		8.58%		11.76%		13.51%

For each landslide type first the important spatial factors are listed and one column to the right, the weights are given for each spatial factor. The last three rows represent the number of landslides, number of landslides included in the testing set, and error of susceptibility models, respectively.

[a] 16 landslides were classified as unknown type, so they were only included in the over-all landslide analyses.

surface waters (3.6%), and the distance to tectonic elements (2.3%). Fig. 4 shows the FA susceptibility model for all landslides (M1). In the best model in the case of fossil landslides ($n=68$) the lithological properties also played the most important role (28.6%). The second most important factors in the case of fossil landslides were cover type properties (22.6%), followed by the slope, the terrain roughness, the distance to surface waters, and the distance to tectonic elements with 15.7%, 15.2%, 6.1% and 5.7%, respectively. The most important precondition factors for the dormant landslide ($n=413$) occurrence were the lithological properties (35.6%), the slope (20.8%), the cover type properties (17.8%), the terrain roughness (10.4%), the distance to geologic boundaries (5%), the distance to surface waters (4%), the distance to tectonic elements (3.5%), the aspect (1.7%), and the terrain curvature (1.3%). When modelling creeping susceptibility ($n=57$), the following factors proved to be the most important: the lithological properties (34.6%), the slope (21.3%), the cover type (14.6%), the terrain curvature (11.7%), the distance to surface waters (5.2%), the aspect (4.8%), the distance to tectonic elements (3.4%), the distance to geologic boundaries (3%), and the terrain roughness (1.7%). The MRA model for slides showed that the terrain roughness factor was the most important one (58%), the second was the terrain curvature (32.1%), the third was the cover type diversity (5.8%), and only 4% were assigned to the lithological properties. The FA model for slides resulted in somewhat different results from the MRA model, but similar to other landslide types models. The primary role was again taken by the lithological properties (39.6%), the secondary role by slope (26.1%), the tertiary role the terrain roughness (11.6%), followed by the cover type (11.1%), the curvature (6.7%), the distance to tectonic elements (2.9%), and by the distance to geologic boundaries (1.8%). The results of landslide susceptibility models, expressed in the term of the error, ranged from 4.35% to 72.97%. The models showed that the most important precondition factors are the lithology and slope inclination as natural fac-

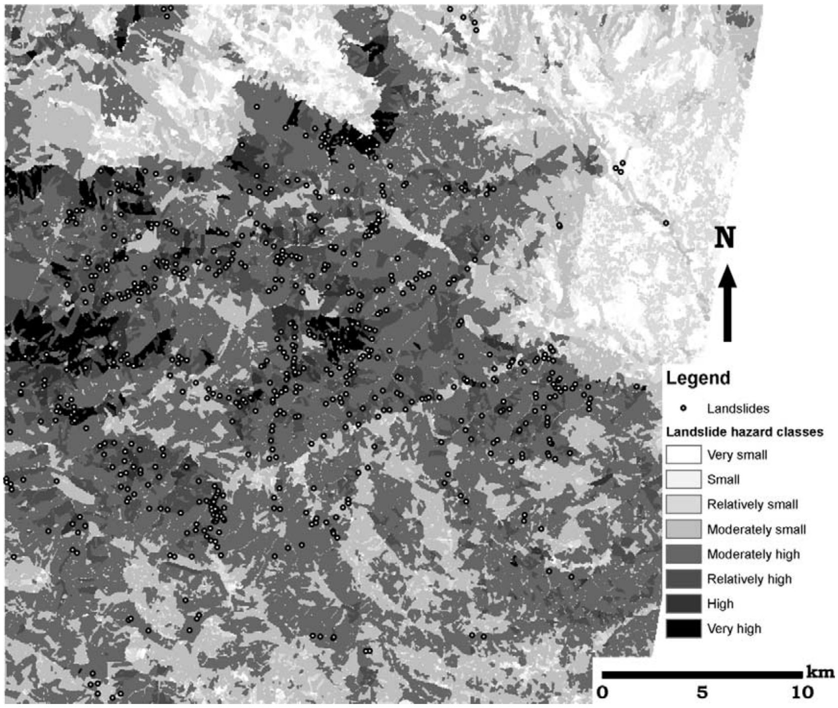

Fig. 4. Landslide susceptibility model (M1), derived with factor analysis, (principal component method — a varimax rotation method). The eight classes represent the landslide hazard, from very small to very high. Landslide locations ($n=614$) are represented by points. The error of the model was 10.66%.

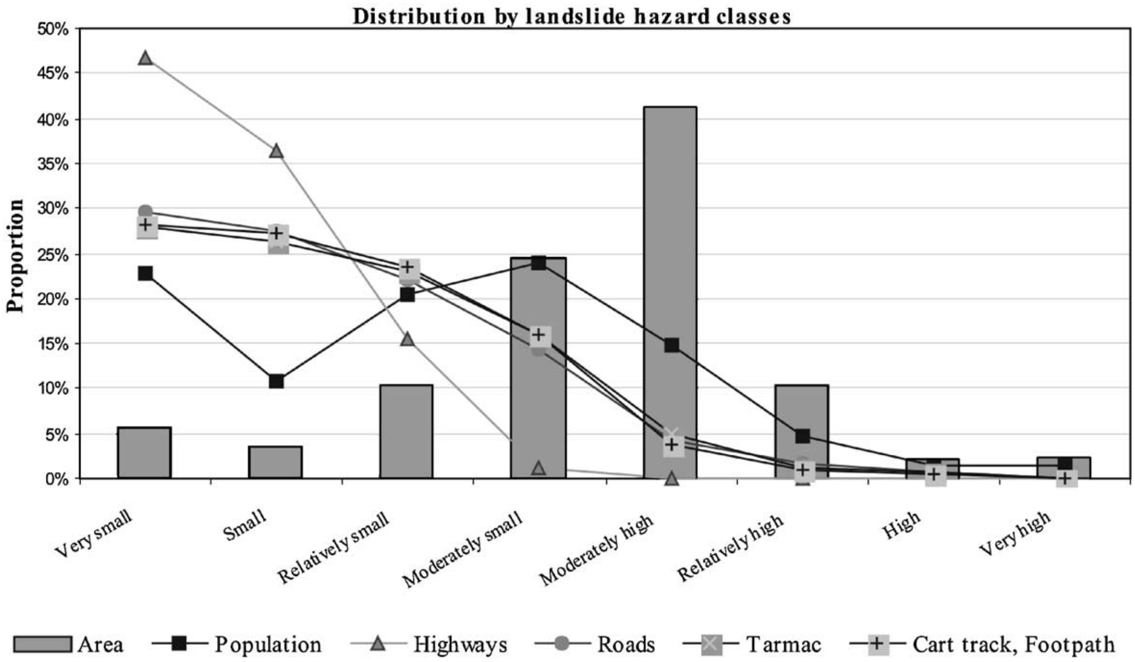

Fig. 5. The distribution of the study area according to landslide hazard classes, and the distribution of the population and the infrastructure according to the eight landslide hazard classes. The imaginary line between Moderately small class and Moderately high class represents the crude boundary between the landslide-prone areas (right) and landslide "safe" areas (left).

tors, and the land use and the vegetation cover as a mixed, anthropogenic-natural factor.

The simple overlay of the infrastructure and populated areas with the hazard maps enabled the assessment of the two distributions by hazard classes. Fig. 5 represents the distribution of model M1 according to landslide hazard classes, the distribution of population and different road classes according to landslide hazard classes of model M1. The proportions are shown in Table 5.

The results of the hazard analysis showed that approximately 2.7% of the population live on highly hazardous landslide-prone areas, but almost 20% live on the areas where landslides pose at least a moderate hazard (Table 5). Almost 78% of population lives in low landslide hazard areas. In the case of the infrastructure the trend shows an ordered association of the less important classes with areas of higher hazard. All the highways have been constructed on areas of low landslide hazard, while in

Table 5
Distribution of the area, different road classes (highways, roads, paths, cart tracks footpaths, and jointly for all roads), and the population according to eight landslide hazard classes

Hazard class	Area (%)	Highways (%)	Roads (%)	Tarmac roads (%)	Cart track, footpath (%)	All roads (%)	Population (%)
Very small	5.59	46.75	29.55	27.86	28.28	28.51	22.72
Small	3.53	36.48	27.45	26.34	27.15	27.03	10.86
Relatively small	10.39	15.61	22.15	22.95	23.44	22.99	20.44
Moderately small	24.48	1.16	14.39	16.02	16.08	15.63	23.92
Moderately high	41.20	0	4.18	4.84	3.74	4.13	14.83
Relatively high	10.32	0	1.53	1.28	0.90	1.15	4.63
High	2.15	0	0.75	0.70	0.41	0.57	1.29
Very high	2.34	0	0	0	0	0	1.39

the case of other tarmac roads less than 1% lie in the areas of high landslide hazard, and around 6.5% in the areas with at least a moderate landslide hazard. Just over 5% of cart tracks and footpaths lie in the areas with at least a moderate landslide hazard, and less than 0.5% in areas of high landslide hazard.

5. Conclusions

Landslide occurrence and behaviour are governed by numerous spatial factors that can be, for the purpose of regional susceptibility assessment, cut down to several important ones. These factors can be relatively easily acquired from geological maps, topographic maps, DEMs, and satellite imagery. Using these data, good landslide susceptibility models were developed. It has been shown that using merged multi-spectral high-resolution satellite images landslide-prone areas can be effectively defined and later used for landslide susceptibility model development. The results of the univariate statistics proved to be useful in assessing the importance of each individual factor. The univariate statistics results have indicated the same important factors as the multivariate analyses, but they cannot be simply used for susceptibility model development, since neglecting the existing interactions between factors results in wrong predictions. Multivariate statistics were used instead and factor analysis proved to be the most effective multivariate statistical tool in developing a landslide susceptibility model. It has been shown that the use of the AHP method gives a mean to define the factor weights in the linear landslide susceptibility model. Based on simple descriptive statistical measures like standard deviation and occurrence probability, hazard maps were derived from susceptibility maps. Unfortunately the frequency of the triggering event could not be determined due to insufficient data hence the frequency of landslide occurrence could not be clearly defined. It is not clear whether the high number of landslides that occurred after September 1993 in comparison to those that occurred before indicates that the occurrence frequency is growing or that the high number is simply the result of a more systematic approach to landslide mapping.

References

Ardizzone, F., Cardinali, M., Carrara, A., Guzzeti, F., Reichenbach, P., 2002. Impact of mapping errors on the reliability of landslide hazard maps. Natural Hazards and Earth System Sciences 2, 3–14.

Barredo, J.I., Benavides, A., Hervas, J., Van Westen, C.J., 2000. Comparing heuristic landslide hazard assessment techniques using GIS in the Tirajana basin, Gran Canaria Island, Spain. International Journal of Applied Earth Observation and Geoinformation 2, 9–23.

BBC, 2002. Floods Wreak Havoc in Germany. (http://news.bbc.co.uk/2/hi/europe/2194395.stm, 28th June, 2005).

Bishop, C., 1995. Neural Networks for Pattern Recognition. University Press, Oxford.

Buser, S., 1968. Osnovna geološka karta SFRJ, lista Gorica, 1 : 100,000 = basic geological map of Yugoslavia, Map Gorica, scale 1 : 100,000. Zvezni geološki zavod, Belgrade.

Buser, S., 1987. Osnovna geološka karta SFRJ, list Tolmin in Videm, 1 : 100,000 = basic geological map of Yugoslavia, Map Tolmin and Udine, scale 1 : 100,000. Zvezni geološki zavod, Belgrade.

Buser, S., Grad, K., Pleniär, M. 1967. Osnovna geološka karta SFRJ, list Postojna, 1 : 100,000 = basic geological map of Yugoslavia, Map Postojna, scale 1 : 100,000. Zvezni geološki zavod, Belgrade.

Carrara, A., 1983. Multivariate models for landslide hazard evaluation. Mathematical Geology 15, 403–426.

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

Chavez Jr., P.S., Slides, S.C., Anderson, J.A., 1991. Comparison three different methods to merge multiresolution and multispectral data: Landsat TM and SPOT panchromatic. Photogrammetric Engineering and Remote Sensing 57, 295–303.

CIE, 1986. Colorimetry, Second edition. Commission Internationale de L'Eclarirage, Paris.

Cliché, G., Bonn, F., Teillet, P., 1985. Integration of the SPOT pan channel into its multispectral mode for image sharpness enhancement. Photogrammetric Engineering and Remote Sensing 51, 311–316.

Crozier, M.J., 1989. Landslides: Causes, Consequences and Environment. Routledge, London.

ERDAS, 1999. ERDAS Field Guide. ERDAS, Inc., Atlanta.

Glade, T., Crozier, M.J., 2005. The nature of landslide hazard impact. In: Glade, T., Anderson, M.G., Crozier, M.J. (Eds.), Landslide Hazard and Risk. Wiley, Chichester, pp. 43–74.

Grad, K., Ferjanĉiĉ, L., 1974. Osnovna geološka karta SFRJ, list Kranj, 1 : 100,000 = basic geological map of Yugoslavia, Map Kranj, scale 1 : 100,000. Zvezni geološki zavod, Belgrade.

Guzzeti, F., Carrara, A., Cardinali, M., Reichenbach, P., 1999. Landslide hazard evaluation: a review of current techniques and their application in a multi-scale study, central Italy. Geomorphology 31, 181–216.

Komac, M., 2005. Napoved verjetnosti pojavljanja plazov z analizo satelitskih in drugih prostorskih podatkov (Landslide occurrence prediction with analysis of satellite images and other spatial data). Geological Survey of Slovenia, Ljubljana, pp. 136 – 138.

Mwasi, B., 2001. Land use conflicts resolution in a fragile ecosystem using Multi-Criteria Evaluation (MCE) and a GIS-based Decision Support System (DSS). Int. Conf. on Spatial Information for Sustainable Development, Nairobi, Kenya, FIG — International Federation of Surveyors. 11 pp.

National Office of Spatial Planning and Survey and Mapping Administration, 1997. Population density per hectare by classes. Database 1,28 MB, Ljubljana.

Nie, H.F., Diao, S.J., Liu, J.X., Huang, H., 2001. The application of remote sensing technique and AHP-fuzzy method in comprehensive analysis and assessment for regional stability of Chongqing City, China. Proc. of the 22nd Asian Conf. on Remote Sensing, Vol. 1, Centre for Remote Imaging, Sensing and Processing (CRISP), National University of Singapore, Singapore Institute of Sorveyors and Valuers (SISV) and Asian Association on Remote Sensing (AARS), Singapore, pp. 660 – 665.

Saaty, T.L., 1977. A scaling method for priorities in hierarchical structures. Journal of Mathematical Psychology 15, 234 – 281.

Sanjeevi, S., Vani, S., Lakshmi, K., 2001. Comparison of conventional and wavelet transformation techniques for fusion of IRS-1C LISS-III and PAN images. Proc. of the 22nd Asian Conf. on Remote Sensing, Vol. 1, Centre for Remote Imaging, Sensing and Processing (CRISP), National University of Singapore, Singapore Institute of Sorveyors and Valuers (SISV) and Asian Association on Remote Sensing (AARS), Singapore, pp. 140 – 145.

Survey and Mapping Administration, 1994. Skanogrami TK 50 — topografske karte merila 1 : 50,000. Datum vira: 1978–1987 = TK 50 — topographic maps at scale 1 : 50,000, acquisition date 1978–1987. Geodetska uprava Republike Slovenije, Ljubljana.

Survey and Mapping Administration, 2000a. InSAR DMV 25 (digitalni model višin) = InSAR DEM 25 (digital elevation model). Geodetska uprava Republike Slovenije, Ljubljana.

Survey and Mapping Administration, 2000b. Generalizirana kartografska baza v M 1 : 25,000—ceste. Datum vira: 1994–2000 = generalised cartographic database, scale 1 : 25,000 — roads, acquisition date 1994–2000. Geodetska uprava Republike Slovenije, Ljubljana.

Van Westen, C.J., 1993. GISSIZ — training package for geographic information systems in slope instability zonation. Theory, vol. 1. ITC, Enschede.

Vani, K., Shanmugavel, S., Marruthachalam, M., 2001. Fusion of IRS-LISS and pan images using different resolution ratios. Proc. of the 22nd Asian Conf. on Remote Sensing, Vol. 1, Centre for Remote Imaging, Sensing and Processing (CRISP), National University of Singapore, Singapore Institute of Sorveyors and Valuers (SISV) and Asian Association on Remote Sensing (AARS), Singapore, pp. 146 – 151.

Voogd, H., 1983. Multicriteria Evaluation for Urban and Regional Planning. Pion Ltd., London.