Application of a perialpine landslide susceptibility model in the Alpine region (Slovenia)

Uporabnost predalpskega modela verjetnosti pojavljanja plazov na alpskem območju

Marko KOMAC

Geološki zavod Slovenije, Dimičeva 14, SI - 1000 Ljubljana, marko.komac@geo-zs.si

Keywords: landslide, susceptibility model, spatial factor, factor weight, Alps, Slovenia *Ključne besede:* plazovi, verjetnost pojavljanja, model, prostorski dejavniki, uteži, Alpe, Slovenija

Abstract

A very good landslide susceptibility prediction model was developed for the area in the perialpine region in the central western Slovenia. Using multivariate statistics the interactions between spatial factors and landslide distribution were tested, and the importance of individual factor to the landslide susceptibility was defined. On the basis of the statistical results several landslide prediction models were developed using the Analytical Hierarchy Process (AHP) method. These models gave very different results, with a prediction error ranging from 6,89 % to 31,8 %. As a final result of the research, weights of different spatial factors from the best models calculated with the AHP method were derived. The results showed that the lithology (31 % variance), the slope inclination (21,2 % variance), and cover type (13,7 % variance), the terrain roughness (10,1 % variance), and the terrain curvature (8,6 % variance) play an important role in landslide susceptibility in general. Minor roles also play the distance to streams and the distance to structural elements. These factors weights values were later used as input values in a simple linear weighted landslide susceptibility prediction model for the area in the Alpine region (north-western Slovenia). The fact is that the ideal weight's value of a factor differs from area to area. Each original weight value used in the new (Alpine) model presented only the mean of the new weight's range/distribution, which was used as an input to the linear model. The analysis of the ideal factors weights in the Alpine area included several analytical trials, where different factors with different weight distribution were used. Altogether, almost 65 000 different models were calculated and tested to the landslide distribution. The best prediction results gave the model, where lithology played the major role in the landslide susceptibility (30 %), slope inclination contributed less (22 %), and land cover type contributed 20 % to the landslide susceptibility. The terrain curvature c

Kratka vsebina

Za območje v predalpskem svetu osrednje Slovenije je bil s pomočjo multivairatne statistike razvit kvaliteten model napovedi verjetnosti pojavljanja plazov. Pri izdelavi

modela je bil določen vpliv posameznih prostorskih dejavnikov na pojavljanje plazov, njihovo medsebojno delovanje in pomembnost dejavnikov pri pojavljanju plazov. Na podalagi statističnih rezultatov je bilo z uporabo metode Analytical Hierarchy Process (AHP) izdelanih več modelov napovedi verjetnosti pojavljanja plazov, ki so dali zelo različne rezultate napovedi. Natančnost napovedi se je gibala med 6,89 % in 31,8 %. Z metodo AHP so bili za najboljše modele izračunani deleži vpliva prostorskih dejavnikov na pojavljanje plazov. Rezultati so pokazali, da igra pri napovedi pojavljanja plazov litologija najpomembnejšo vlogo (31 % variance), sledijo ji naklon pobočij (21,2 % variance), raba tal (13,7 % variance), razgibanost terena (10,1 % variance) in ukrivljenost terena (8,6 %). Manjši vlogi pripadata dejavnikoma oddal jenosti od površinskih tokov in od strukturnih elementov (prelomov in narivov). Ti podatki o pomembnosti prostorskih dejavnikov so bili nato uporabljeni kot vhodni utežni podatki pri izdelavi modela napovedi verjetnosti pojavljanja plazov za območje v alpskem svetu severo-zahodne Slovenije. Pričakovati je, da se vrednosti uteži prostorskih dejavnikov razlikujejo od lokacije do lokacije, kar postavlja pod vprašaj uporabnost modela napovedi oz. vrednosti uteži predalpskega območja pri izdelavi modela napovedi za alpsko območje. Uporabljene vrednosti uteži predalpskega modela so v novem, alpskem modelu linearno utežene vsote predstavljale srednje vrednosti razponov uteži. Iskanje idealnih uteži vplivnih dejavnikov na pojavljanje plazov v Alpskem svetu je bilo sestavljeno iz več analitičnih poskusov, pri katerih so bili uporabljeni različni razponi uteži za različne prostorske dejavnike. Skupaj je bilo izdelanih in testiranih na pojavljanje plazov skoraj 65.000 različnih matematičnih modelov. Modeli z najboljšimi rezultati napovedi so pokazali, da igra pri napovedi verjetnosti pojavljanja plazov v alpskem modelu, tako kot pri predalpskem modelu, litologija najpomembnejšo vlogo (30 %), z 22 % ji sledi n

Introduction

The occurrence of spatially distributed events or phenomena is the result of numerous interacting spatial and temporal factors. To predict these events is always a tricky task. Even trickier is the application of the prediction results from one research area to another without loosening the rules that model is based on. It is not very difficult to apply a model to some other area than the learning one, if model's rules are universal. When predicting landslide susceptibility this is a rare case, since the combinations of different factors that influence the spatial distribution and those that govern the triggering conditions are numerous and site specific. Or aren't they?

In the most ideal circumstances of course, only one model for each type of phenomenon would be enough for a prediction of the same phenomenon anywhere. There are several reasons/obstacles that indicate the restrictions of model applicability. Those reasons are (1) spatial and temporal diversity of the pheno-

menon governing factors, (2) inexact definitions of phenomena, (3) misclassification of phenomena, and (4) inaccuracy of the data on governing factors. Since it is almost impossible to overcome all the obstacles given above, the prediction models' usefulness' is limited.

The paper will show the development of linear weighted landslide susceptibility prediction model using multivariate statistics and Analytical Hierarchy Process (AHP), its accuracy testing in the same area, and its application to the non-related, distant area. The testing of the landslide susceptibility prediction applicability will be carried out with numerous models with varying factors' weights values. The results will show the level of the applicability of perialpine landslide susceptibility model to the Alpine area.

The research will only take into account the causal factors, since the triggering factors are rather difficult to predict and to model, due to their temporal variation. Despite their complexity some researchers did try to tackle the problem (Kojima & Obayashi, 2002; 2004).

Study area and data used

The landslide susceptibility prediction model was developed in the perialpine area in the central Slovenia. The area that spreads approximately 1220 square kilometres (35×35 km) and lies in the central part of Slovenia, west of Ljubljana, its capital. The model was later applied to the municipality of Bovec (367 km²) that lies in the Alpine region in the north-western part of Slovenia. Both areas are shown in Figure 1.

elevation model (DEM) data were obtained from the national 25 m resolution InSAR DEM 25 (Survey and Mapping Administration, 2000). All the additional data on the terrain morphology (curvature, elevation, slope, aspect, basins, and primary slope-units) were derived from the DEM. The "Basic Geological Map at the scale of 1:100 000" served as a source for the geologic data of the perialpine area, and for the Alpine area the 1:25 000 scaled geological map was used. For the land use and the vegetation cover in

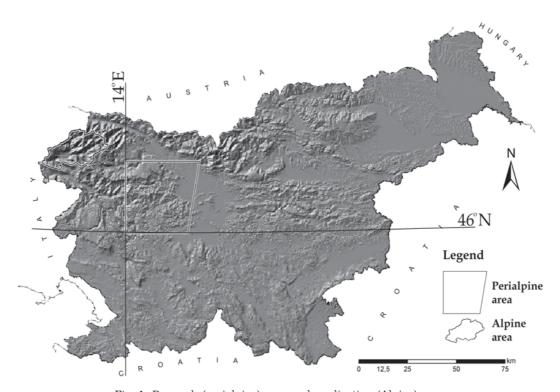


Fig. 1. Research (perialpine) area and application (Alpine) area. Slika 1. Obravnavano predalpsko območje in alpsko območje uporabe razvitega modela.

For the purpose of model development the spatial factors' data that have already been proven by many authors (Carrara, 1983; Carrara, at al. 1991; Kojima et al., 2000; Fabbri et al., 2003; Crozier & Glade, 2005) to be relevant to the landslide susceptibility were gathered. The landslide data were obtained from the landslide database that was constructed at Geological Survey of Slovenia. For the perialpine area, it consists of the data on 614 landslides, and 27 landslides for the Alpine area. The digital

the perialpine region, satellite images from different sources were used and combined, using PCA (Principal Component Analysis) merging method, where the first principal component image from the multi-spectral satellite data was replaced with the first principal component image of the high-resolution part. 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. For the land use and the vegetati-

on cover in the Alpine region, already classified and interpreted data from orthophoto were used (Ministry of Agriculture, Forestry and Nutrition, 2004). The topologic map in scale 1:50 000 was used as a source of the surface water data (Survey and Mapping Administration, 1994).

Methodology

The whole process was divided into two phases. In the first phase the models were developed and tested on the data from the learning area (perialpine area) and in the second phase, the developed models were applied to the Alpine area, and their accuracy and applicability was assessed. Figure 2 presents the whole process of model development and its application.

Perialpine area modelling

Univariate statistical analyses (Kolmogorov-Smirnov test and Chi-square test) were performed to confirm the role of a specific factor or to rule it out. Prior to the multivariate statistical analysis, the study area was automatically divided to 78365 slope units (Carrara, 1983; Carrara et al., 1991; Van Westen, 1993; Ardizzone et al., 2002), for which 24 new statistical variables were calculated. The division of the area into the slope units was necessary step due to the point nature of the landslide data. Based on its temporal distribution the perialpine landslide data set was divided into the learning set (65 %) and into the testing set (35 %). Using multivariate statistical analysis, the interactions between factors and landslide learning set distribution were tested. As a result the importance of individual factors on the landslide occurrence was defined. The results from the multivariate statistical analyses were used for defining the relations between spatial factors prior to the AHP (Analytical Hierarchy Process) model development. For the model development, the results from multivariate analyses, both linear regression and factor analysis, were used. One part of the models was developed using the values from statistical analyses for defining subjectively the relationship values between different factors. The rest of the

models were developed by importing the calculated relationship values between different factors, based on their statistical function values, into the AHP matrixes. The application of the AHP method, developed by Saaty (1977), on the landslide prediction has been shown before (Barredo et al., 2000; Mwasi, 2001; Nie et al., 2001) and it was used to more transparently define the factors that govern the landslide occurrence. For all the models, where AHP was used, the CR (Consistency Ratio) was calculated and those with CR higher than 0.1 were immediately eliminated. For more details refer to Komac (2005).

Taking into account the normal distribution of the results, an approximation was done, where in each of the model, the highest value represents the highest landslide susceptibility, and vice versa, the lowest value represents the lowest landslide susceptibility. Considering the normal distribution, the mean represents the crude boundary between the landslide "safe" and landslide prone areas. Models were then tested for their landslide susceptibility accuracy on the testing set. The slope unit(s) with landslide(s) where the landslide susceptibility was lower than the model's mean value represented the error.

Alpine area modelling

For each spatial factor the weigh value from the best perialpine model represented the mean value of the weights' uniform distribution in the model application phase in the Alpine area. All the models calculated for the Alpine area were tested for their accuracy to the known landslide distribution in the same area. For the test areas, the upper 20 % of the landslide area was taken. The estimation was made that roughly upper one fifth of the landslide area represents the triggering area that actually represents the area influenced by causal factors. Prior to the model calculation each spatial factor's data were classified according to landslide susceptibility and standardised since the calculations are based on linear weighted equations. After the model calculation and prior to the test, all the models were normalised, like in the case of perialpine area model testing. Almost 65 000 models

were calculated and tested. The landslide cells that occurred in areas below the model's mean value represented the error. For the landslide susceptibility factor classification random 2/3 (671 cells) of the Alpine landslide population was taken. The rest, 1/3 (269 cells) of the population was used for the susceptibility model testing.

ble 1 shows the modelling results for the perialpine area.

Various factor combinations and weight values for the seven Alpine modelling trials are presented in the Table 1. There are three statistical variables used in the perialpine models that were not applied to the Alpine are, at least not directly. Variables terrain

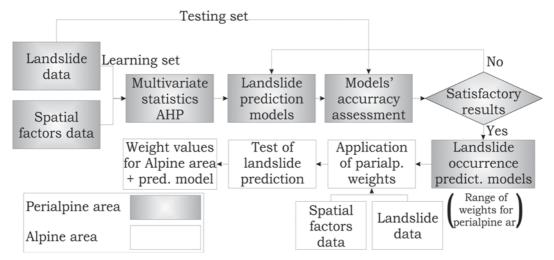


Fig. 2. Flowchart of the development and application process.

Slika 2. Diagram procesa izgradnje modela napovedi verjetnosti pojavljanja plazov in prenosa rezultatov na drugo območje.

Results and discussion

Model's prediction capability of the landslide susceptibility is expressed in the term of error, in other words, in the term of number of landslide cells that fall in the areas of low landslide susceptibility. The errors of perialpine landslide susceptibility models ranged from 6,89 % to 31,8 %. The best model, based on the results of the factor analysis, showed that lithology plays the most important role (31 % of variance) in the landslide susceptibility. Slope inclination is also important and accounts for 21,2 % of variance, land cover type accounts for 13,7 % of variance, the terrain roughness for 10,1 % of variance. The terrain curvature is responsible for 8,6 % of variance, lithologic diversity for 5,5 %, and land cover diversity for 3,9 % of variance. Distance to streams and distance to structural elements (faults and thrusts) also play a role, but a minor one. They account for 3,6 % and 2,3 % of variance respectively. The second row of Taroughness, lithologic diversity and land cover diversity are in the case of Alpine area incorporated into terrain curvature or slope inclination, lithology, and land cover respectively. There is also one variable that was introduced to the Alpine prediction model and it was not analysed in the perialpine prediction model, the synchronism between the strata dipping and slope orientation and angle. The purpose of the inclusion was to test the importance of the synchronicity in the landslide susceptibility modelling.

For every combination the model error was calculated based on the principle that is given in the previous chapter. Table 2 lists the range of error for each trial. The span of the errors is between 4,07 % and 66,4 %. The results in Table 2 clearly show that the errors of the Alpine models are smaller in trials, where the weights' values were similar to the weights' values of perialpine area. Results of the 8th, 9th and 13th trial, where all the factors used, except the elevation factor that was used only in the 8th trial, confirm

Table 1. Weights' values for perialpine and Alpine area.

Preglednica 1. Vrednosti uteži za predalpski model in za alpski model napovedi.

Area	No. models	Spatial factor	Litho	Slope	LC	Rough	Curv	Litho. divers.	LC divers.	Dist. streams	Dist. struct. el.	Synchro	Asp	Elev
Perialpine area	28	Weight	0,31	0,212	0,137	0,101	0,086	0,055	0,039	0,036	0,023	-	-	-
Alpine area – trial 1		Max	0,39	0,34	0,19	-	0,08	-	-	-	-	0,19	ı	
	2435	Min	0,2	0,15	0,1	-	0,05	-	-	-	-	0,1	-	-
		Step	0,01	0,01	0,01	-	0,01	-	-	-	-	0,01	1	-
Alpine area – trial 2	460	Max	0,38	0,33	0,2	-	0,07	-	-	-	-	0,2	-	-
		Min	0,2	0,15	0,1	-	0,05	1	-	-	-	0,1	ı	-
		Step	0,02	0,02	0,02	-	0,02	ı	-	-	-	0,02	1	-
Alpine area – trial 3		Max	0,5	0,5	-	-	0,5	-	-	0,5	0,5	0,05	1	-
	9308	Min	0	0	-	-	0	1	-	0	0	0	ı	-
		Step	0,05	0,05	-	-	0,05	-	-	0,05	0,05	0,05	-	-
Alpine area		Max	0,38	0,38	0,38	-	0,38	-	-	-	-	0,38	-	-
– trial 4	17654	Min	0,1	0,1	0,1	-	0,1	-	-	-	-	0,1	-	-
		Step	0,02	0,02	0,02	-	0,02	-	-	-	-	0,02	-	-
Alpine area		Max	1	1	1	-	1	-	-	1	1	-	1	1
- trial 5	12199	Min	0	0	0	-	0	-	-	0	0	-	0	0
		Step	0,1	0,1	0,1	-	0,1	-	-	0,1	0,1	-	0,1	0,1
Alpine area	3219	Max	0,45	0,35	0,3	-	0,15	-	-	0,1	0,1	-	0,02	0,15
– trial 6		Min	0,2	0,1	0,1	-	0,05	-	-	0	0	-	0	0
		Step	0,05	0,05	0,05	-	0,05	-	-	0,05	0,05	-	0,01	0,05
Almino onco	1711	Max	0,4	0,3	-	-	0,1	-	-	0,1	0,1	0,3	-	-
Alpine area – trial 7		Min	0,2	0,1	-	-	0,05	-	-	0	0	0,1	-	-
		Step	0,05	0,05		-	0,05	-	-	0,05	0,05	0,05	-	-
Alpine area	909	Max	1	1	1	-	1	-	-	1	1	1	1	1
– trial 8		Min	0	0	0	-	0	-	-	0	0	0	0	0
		Step	0,2	0,2	0,2	-	0,2	-	-	0,2	0,2	0,2	0,2	0,2
	3016	Max	0,7	0,7	0,7	-	0,7	-	-	0,7	0,7	0,7	1	-
Alpine area		Min	0	0	0	-	0	-	-	0	0	0	0	-
– trial 9		Step	0,1	0,1	0,1	-	0,1	-	-	0,1	0,1	0,1	0,1	-
Alpine area – trial 10		Max	1	1	-	-	1	-	-	-	-	1	-	-
	273	Min	0	0	_	-	0	-	_	-	_	0	-	-
		Step	0,1	0,1	-	-	0,1	-	-	-	-	0,1	-	-
Alpine area – trial 11	273	Max	-	1	1	-	1	-	-	-	-	1	-	-
		Min	-	0	0	-	0	-	_	-	_	0	-	_
		Step	-	0,1	0,1	-	0,1	-	-	-	-	0,1	-	-
	273	Max	-	1	-	-	1	-	-	1	1	-	-	-
Alpine area – trial 12		Min	-	0	_	-	0	-	-	0	0	-	-	-
		Step	-	0,1	-	-	0,1	-	-	0,1	0,1	-	-	-
Alpine area – trial 13	9000	Max	1	1	1	-	1	-	-	1	1	1	1	-
		Min	0	0	0	-	0	-	-	0	0	0,1	0	-
		Step	0,1	0,1	0,1	-	0,1	-	-	0,1	0,1	0,1	0,1	-
		Max	0,42	0,3	0,2	-	0,2	-	-	0,1	0,1	-	-	-
Alpine area – trial 14	4872	Min	0,3	0,2	0,1	-	0,1	-	-	0	0	-	-	-
– ırıaı 14		Step	0,02	0,02	0,02	-	0,02	-	-	0,02	0,02	_	_	-

Explanation to the Table 1 / Razlaga k Preglednici 1: Perialpine area / predalpsko območje; Alpine area / alpsko območje; No. models / št. modelov; Spatial factor / Prostorski dejavnik; Weight / Utež; Max – Maximum value / Največja vrednost; Min – Minimum value / Najmanjša vrednost; Step / Korak; Litho – Lithology / Litologija; Slope – Slope inclination / Naklon pobočij; LC – Land cover type / Raba tal; Rough – Terrain roughness / Razgibanost terena; Curv – Terrain curvature / Ukrivljenost pobočij; Litho. divers. – Lithologic diversity / Litološka raznolikost; LC divers. – Land cover type diversity / Raznolikost rabe tal; Dist. streams – Distance to streams / Oddaljneost od površinskih tokov; Dist. struct. el. – Distance to structural elements / Oddaljenost od strukturnih elementov; Synchro – Strata dip/slope orientation synchronism / Sinhronost vpadov plasti z usmerjenostjo pobočij; Asp – Slope aspect / Usmerjenost pobočij; Elev – Elevation / Nadmorska višina.

that the factors' weights are important, and that random selection of the values gives worst results

Where lithology, slope inclination and land use cover were excluded or played minor roles in models, models gave the worst prediction results with error around 66 %. Vice versa, the best results of models, where synchronism was not included but also slope aspect and elevation factors were included, showed that in the case of coarse weights (5th trial) the land-cover factor played the most important role (80 %) with the lithology playing a minor role (20 %). When analysis was done on more precise weight values (6th trial), the results were different. The lithology accounted for 23 %, the slope inclination for 20 %, the land-cover type for 30 %, the terrain curvature and distance to streams each for 10 %, the elevation for 5 %, and the slope aspect accounted for 2 %.

Results of the 14th trial, where the same factors were used for the susceptibility model development as for the perialpine landslide susceptibility model, showed that the lithology accounts for 30 % of the susceptibility model, slope inclination for 22 %, and land cover type for 20 %. The terrain curvature covers for 16 %, and the rest is split between the distance to streams (10 %) and the distance to structural elements (2 %).

Where lithology was not included, results were surprisingly good. In the 11^{th} trial the land-cover factor accounted for 90 % and the terrain curvature for 10 %. The results of the 12^{th} trial show that slope inclination and distance to streams play an equal role (50 %).

When the synchronism was included in the modelling landslide susceptibility, it accounted for the 18 % - 22 % (1st, 2nd and 4th trial). The rest of the included spatial factors bore more or less the same importance as in the model where synchronism between the strata dipping and slope orientation was not included. When the two "distance to" factors were excluded from the model, the lithology accounted for 12 % - 30 %, the slope inclination for 18 % - 33 %, the landcover type for 18 % - 36 %, and the terrain curvature for 5 % - 10 %. When the landcover factor was excluded from the model, the lithology accounted for 25 % - 40 %, the slope inclination for 5 % - 30 %, the terrain curvature for 10 % - 50 %, the distance to

streams for 5 % - 10 %, and the distance to structural elements for 0 % - 10 %.

The best overall results (4,6% - 6,5%) error) were achieved when the land-cover factor played the most important role (70% - 90%), and the rest was accounted for the lithology, the slope aspect, the terrain curvature, or for the synchronism.

The factors' weights values for the best models, calculated in $1^{\rm st}$, $4^{\rm th}$, $7^{\rm th}$ and $14^{\rm th}$ trial are shown in the Table 3 under rows "Alpine M1", "Alpine M4", "Alpine M7" and "Alpine M14" respectively.

The factors' weights values of the best models for the Alpine area are compared in the Table 3. For comparison also the weights' values for the best perialpine model are given (Perialpine PM1). If it is assumed that the factors "Lithological diversity", "Land cover diversity" and "Terrain roughness" can be represented with factors "Lithology", "Land cover", and "Terrain curvature" or "Slope inclination" respectively, it is clear, that the correlation between the spatial factors of the two comparable models exists (Spearman R = 0.942857; for PM1 and M14).

Figure 3 shows the area distribution of the landslide susceptibility classes for the model, in which the perialpine factors' weight values were directly applied to the Alpine model (PM1; error = 22,98 %), the best Alpine models, from trials where the synchronism factor was included (M1; error = 17.34 %, M4; error = 6.78 %), the best Alpine model, from trials where the synchronism was included and land-cover factor was excluded (M7; error = 21,95 %), and the best Alpine model, in which the synchronism was not included (M14; error = 17,07 %). LSP1, LS1, LS4, LS7, and LS14 represent the cumulative distribution of landslides for models M1 to M14 respectively.

The Alpine (M14) model and perialpine model are shown in Figure 4. Darker areas represent higher landslide susceptibility.

The results suggest that same spatial factors with slightly different importance govern the landslide occurrence in the Alpine region in comparison to the perialpine region. The role of land-cover factor is definitely an important one, but some facts have to be considered. The land-cover data was obtained from the Ministry of Agriculture, where the importance is focused on agricul-

Alpine area		Error	Error (%)	Alpine area		Error	Error (%)
Trial 1	Max	90	24,39%	Trial 8	Max	245	66,40%
Poskus 1	Min	64	17,34%	Poskus 8	Min	24	6,50%
Trial 2	Max	90	24,39%	Trial 9	Max	245	66,40%
Poskus 2	Min	55	14,91%	Poskus 9	Min	24	6,50%
Trial 3	Max	162	43,90%	Trial 10	Max	174	47,15%
Poskus 3	Min	24	6,50%	Poskus 10	Min	68	18,43%
Trial 4	Max	116	31,44%	Trial 11	Max	154	41,73%
Poskus 4	Min	25	6,78%	Poskus 11	Min	245 66,40% 24 6,50% 245 66,40% 24 6,50% 174 47,15% 68 18,43% 154 41,73% 15 4,07% 145 39,30% 51 13,82% 245 66,40% 24 6,50% 102 27,64%	4,07%
Trial 5	Max	176	47,70%	Trial 12	Max	145	39,30%
Poskus 5	Min	24	6,50%	Poskus 12	Min	51	13,82%
Trial 6	Max	101	27,37%	Trial 13	Max	245	66,40%
Poskus 6	Min	36	9,76%	Poskus 13	1 Min 15 4,07% Max 145 39,30% 2 Min 51 13,82% Max 245 66,40% Min 24 6,50%		
Trial 7	Max	96	26,02%	Trial 14	Max	102	27,64%
Poskus 7	Min	81	21,95%	Poskus 14	Min	63	17,07%

Table 2. Error range for each trial. Preglednica 2. Razpon napak napovedi za posamezni analtični poskus

Explanation to the Table 2 / Razlaga k Preglednici 2:Error -Prediction error of model / Napaka

tural land and the rest land-cover types are not defined in detail. Hence the generalisation effect of the land-cover data and the resulted over-estimated importance of the factor. Considering the fact of the over-estimation of the land-cover factor, the best Alpine model (M14) gives similar results as the one developed for the perialpine region. Nevertheless the relations between weights of spatial factors in the perialpine model (PM1) and Alpine model (M14) are very similar, which gives a confirmation to the universality of the landslide susceptibility modelling.

Concluding remarks

It has been shown that some uniform principles of interaction between the spatial factors that govern the landslide occurrence and the landslide susceptibility do exist, inde-

pendently of the location. If simplified, these interactions can be represented in a form of linear weighted equations or models. Landslide susceptibility is governed by numerous spatial factors that can be cut down to several important ones, the lithological properties, the slope inclination, the land use, the curvature, the distance to streams and the distance to structural elements. When the synchronism between strata dipping and slope orientation was used in the modelling of landslide susceptibility, the results have shown that this factor was as important as the land-cover type (M1), or as important as the terrain curvature and the distance to streams (M14), or even more important than lithology (M4). In the case of the Alpine susceptibility models, the independency and correlation between spatial factors were not analysed, but it is clear that they exist. This is also the important but unfortunately missing part of most landsli-

Table 3. Weight values of best models for perialpine and Alpine area.

Preglednica 3. Vrednosti uteži pri najboljših modelih napovedi (predalpski in alpski).

Model	Litho	Slope	LC	Curv	Dist. struct. el.	Dist. streams	Asp	Elev	Synchro	Rough.	Litho. divers.	LC divers.
Perialpine PM1	36,5 %	26,25 %	17,6 %	13,65 %	3,6 %	2,3 %	-	-	ı	In Slope & Curv	In Litho	In LC
Alpine M1	28 %	30 %	18 %	6 %	ı	-	-	-	18 %	1	-	-
Alpine M4	12 %	5 %	50 %	10 %	-	-	-	-	22 %	-	-	-
Alpine M7	40 %	30 %	-	10 %	0 %	10 %	0 %	-	10 %	-	-	-
Alpine M14	30 %	22 %	20 %	16 %	2 %	10 %	-	-	-	-	-	-

The acronyms are the same as in Table 1. / Razlaga je enaka tisti za Preglednico 1.

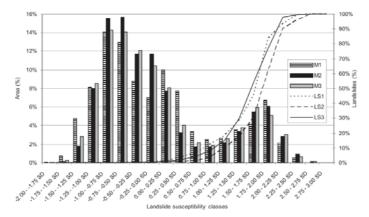


Fig. 3. Distribution of area for susceptibility models (PM1, M1, M4, M7 and M14) and cumulative distribution of landslides (LSP1, LS1, LS4, LS7 and LS14) according to the normalised landslide susceptibility classes of models PM1, M1, M4, M7 and M14 respectively.

Slika 3. Porazdelitev površin razredov verjetnosti pojavljanja plazov za modele (PM1, M1, M4, M7 in M14) in kumulativna porazdelitev plazov (LSP1, LS1, LS4, LS7 in LS14) glede na normalizirane razrede verjetnosti pojavljanja plazov za modele PM1, M1, M4, M7 in M14.

de susceptibility analyses done in recent years by numerous researchers. The analyses for the purpose of assessment of model applicability were done based on the absolute simplification of the landslide susceptibility model. The interaction or correlation between the synchronism and other spatial factors remains to be analysed.

The results would be even more realistic and reliable if more landslides would be included in the study, since the landslide population would be more representative.

The rock-fall phenomena was not analysed in this research since it is clearly governed by slightly different spatial factors' interactions and by additional spatial factors, like frosting/thawing process etc.

The results of the research are interesting from several aspects. They give a good overview of the models' inter-spatial applicability, and at the same time give an overview of factor's influence to model errors due to the change in the factor's value.

Successful inter-spatial application of the landslide susceptibility models to some extent has been shown. The differences between diverse regions still pose problems to model's simple application from one region to another. To a certain degree of error, these inter-spatial models are applicable. For more accurate or even for a universal landslide susceptibility model these obstacles will probably be overcome only when really abundant, detailed and sufficient spatial data will

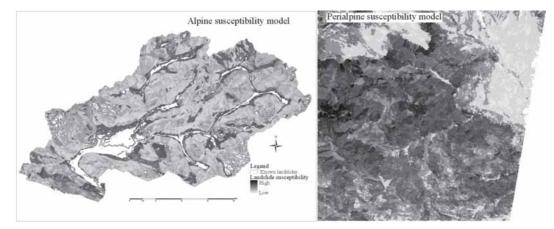


Fig. 4. Alpine landslide susceptibility model M14 (left) and perialpine landslide susceptibility model (right).

Slika 4. Alpski model napovedi verjetnosti pojavljanja plazov M14 (levo) in predalpski model napovedi verjetnosti pojavljanja plazov (desno).

be available. Until then the uncertainty of the interpolated spatial data is too big and the phenomena observed too complex to easily overcome the problem of its diversity in space and time.

Acknowlegments

The author would like to thank Mr. Marko Tukič, the student of the Faculty for Computer and Information Science at University of Ljubljana for making "that loopy script" work.

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 (1/2), 3-14.

Barredo, J. I., Benavides, A., Hervas, J.

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.- Int. Journal of Applied Earth Observation and Geoinformation, 2/1, 9-23.

Carrara, A. 1983: Multivariate models for

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.

Crozier, M.J. & Glade, T. 2005: Landslide hazard and risk: Issues, concepts and approach.—In Glade, T., Anderson, M.G., Crozier, M.J., eds., Landslide Hazard and Risk, John Wiley & Sons, p. 1–40, New York.

Fabbri, A.G., Chung, C.F., Cendreo, A. & Remondo, J. 2003: Is Prediction of Future Landslides Possible with a GIS? - Natural Hazards, 30, 287-499.

Kojima, H., Chung, C.F. & Van Westen, C.J. 2000: Strategy on the landslide type analysis based on the expert knowledge and the quantitative prediction model. - International Archives of Photogrammetry & Remote Sensing, Vol. 33/Part-B7, p. 701-708.

Kojima, H. & Obayashi, S. 2002: An inverse analysis of unobserved trigger factors of the slope failures based on structural equation modeling. - International Archives of Photogrammetry & Remote Sensing, 34/4, "GeoSpatial Theory, Processing and Applications". (http://www.isprs.org/commission4/proceedings/pdfpapers/207.pdf).

Kojima, H. & Obayashi, S. 2004: Decompositional analysis of unobserved trigger factors of slope failures based on structural equation modelling. - In Brebbia, C.A. (ed.), Risk analysis IV, (Management information systems, 9), WIT, 307-318, Southampton.

Komac, M. 2005: Napoved verjetnosti pojavljanja plazov z analizo satelitskih in drugih prostorskih podatkov = Landslide occurrence probability prediction with analysis of satellite images and other spatial data. - Geološki zavod Slovenije, 284 p., Ljubljana.

Ministry of Agriculture, Forestry and Nutrition 2004: Landuse cover (derived from orthophoto). - Ministrstvo za kmetijstvo, gozdarstvo in turizem, Ljubljana.

Mwasi, B. 2001: Land use conflicts resolution in a fragile ecosystem using multi-criteria evaluation (MCE) and a GIS-based decission support system (DSS). In International Conference on Spatial Information for Sustainable Development, Nairobi, Kenya: Proceedings.- Fédération Internationale des Géomètres, 11 p., Frederiksberg.

nationale des Géomètres, 11 p., Frederiksberg. 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. In 22nd Asian Conf. on Remote Sensing: Proceedings, 1, 660–665, Singapore

Saaty, T. L. 1977: A scaling method for priorities in hierarchical structures. - Journal of Mathematical Psychology, 15, Society for Mathematical Psychology, Academic Press, 234–281, New York

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 2000: In-SAR DMV 25 (Digitalni model višin) = InSAR DEM 25 (Digital Elevation Model).- Geodetska uprava Republike Slovenije. Liubliana.

uprava Republike Slovenije, Ljubljana. Van Westen, C. J. 1993: GISSIZ - training package for geographic information systems in slope instability zonation. 1, Theory. - ITC, 1993, ITC, 245 pp., Enschede.