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EFFECT OF THE INPUT PARAMETERS ON THE SPATIAL VARIABILITY OF LANDSLIDE SUSCEPTIBILITY MAPS DERIVED BY STATISTICAL METHODS. CASE STUDY OF THE VALTELLINA VALLEY (ITALIAN CENTRAL ALPS)

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Effect of the input parameters on the spatial variability of landslide susceptibility maps derived by statistical methods. Case study of the Valtellina valley (Italian Central Alps).

This study is aimed at assessing different spatial patterns of predicted values of landslide susceptibility maps with almost similar success and prediction rate curves. Our approach is applied to an alpine environment (Italian Central Alps) where debris flows represent a frequent damaging phenomenon. The Weights of Evidence modelling technique (a data driven Bayesian method) was applied using ArcSDM (Arc Spatial Data Modeler) an ArcGIS extension. The output prediction maps were reclassified in the same way to compare the predicted results: a relative classification, based on the proportion of the area classified as susceptible, was made. The thresholds among different susceptibility classes were put at each 10 % of the study area, classified decreasingly from the highest to the lowest susceptibility values. After applying Kappa Statistic, Cluster Analysis, and Principal Component Analysis (PCA), we analysed the spatial variability of the predicted maps. The results have shown great differences within the output spatial patterns of the predicted maps, and also within the highest susceptibility classes.

Key words: landslide susceptibility mapping, Weights of Evidence, spatial variability, Kappa Statistic, Cluster Analysis, Principal Component Analysis

INTRODUCTION

Landslide susceptibility assessment is based on analysis of terrain conditions in those sites where previous landslides happened (Carrara et al. 1995). Slope instabilities are among the most significant natural damaging events; they are one of the primary causes of injury to life and property damage, resulting in enormous casualties and huge economic losses (Schuster 1996). Susceptibility assessment has shown significant improvements in recent years by using indirect statistically-based methods implemented within GIS (Aleotti and Chowdhury 1999). Statistical methods are being widely used to analyse landslide prone areas mainly in Europe, for example Pauditš et al. (2005) analysed the territory of the Liptovská kotlina basin in Slovakia and Klimeš (2002) examined landslide susceptibility in the Vsetín district in Czechia. Although spatial data analysis techniques are now widely adopted as effective tools for independent validation of predicted results in post-processing operations (Beguería 2006), poor at-

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tention is often paid to the evaluation of the spatial variability of the predicted results.

The relationships between past events and predisposing factors may give us information on the likely spatial distribution of future occurrences. However, it seems that the quality of predicted results does not automatically increase with the number of predisposing factors used in the modelling procedures, and the significance of such conditioning factors is frequently not thoroughly evaluated. In our study we focus on the different spatial patterns of susceptibility maps derived by the same statistical method, but with different combinations of predisposing factor maps (geology, land use, slope, aspect, etc.). To achieve this goal the same methodology for generation of landslide susceptibility maps was applied, using different combinations of factor maps classified in the same way. After that we compared the obtained maps using Kappa Statistic, Cluster Analysis and Principal Component Analysis.

STUDY AREA

The study was done in Valtellina valley (Fig. 1). Valtellina is a typical Italian alpine valley lying in northern Italy (Lombardy Region). The axis of the valley is formed by the Adda River, flowing through Bormio, Tirano and Sondrio

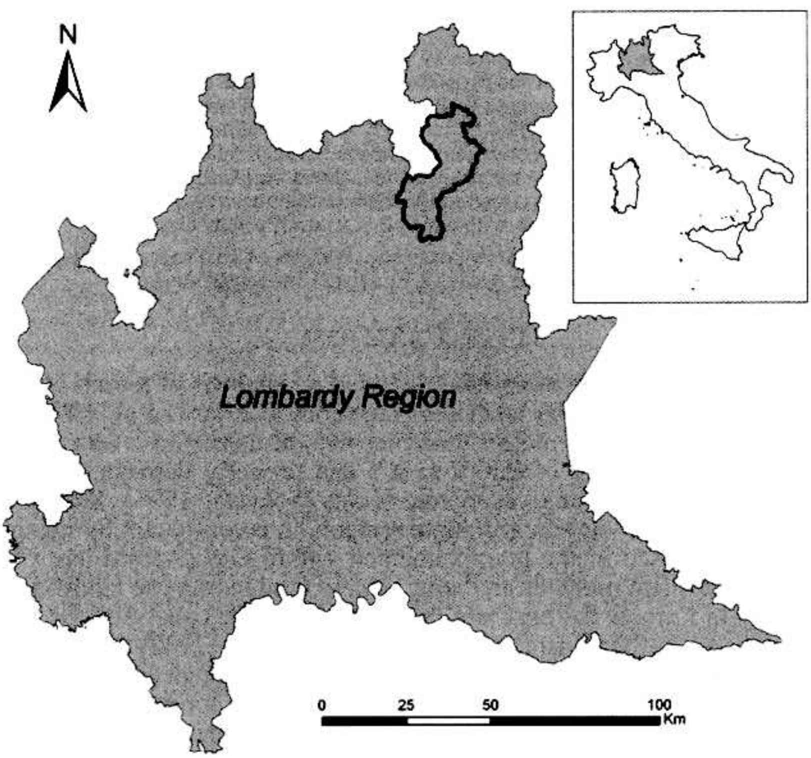

Fig. 1. Location of the study area

to Lake Como. The valley has prevalently an E-W orientation from Dubino to Teglio, where it takes an N-E turn for few kilometres, and then turns almost to N around Sondalo. The orientation is determined by the tectonic setting. Valley is superimposed on a regional fault that sharply separates the proper Alps (Austroalpine, Penninic and Helvetic nappes) to the north from the Variscan basement of the Southern Alps to the south. The Periadriatic Fault (or so called Insubric Line or Tonale Fault) runs on the northern slopes of Valtellina, some 500 m above the Adda river floodplain, then goes on towards the NE to the Tonale Pass to Merano and Mules near Vipiteno, where it turns back to the E-W direction, running along Val Pusteria up to Klagenfurt and beyond. The bedrock is mainly composed of metamorphic rocks (gneiss, mica schist, phyllite and quartzite) and intrusive rock units, with subordinate sedimentary rocks. Due to the proximity of the tectonic lineament, cataclastic and mylonitic zones are present.

Valtellina has a U-shaped valley profile derived from Quaternary glacial activity. The lower part of the valley flanks are covered with glacial, fluvioglacial, and colluvial deposits of variable thickness. The alluvial plain of the Adda River is up to 3 km wide and alluvial fans at the outlet of tributary valleys can reach a considerable size, with a longitudinal length up to 3 km.

The study area about 450 km^2 lies in a Mountain Consortium of Municipalities in Valtellina di Tirano (Fig. 2). The territory is subdivided among 12 municipalities and it has about 29,000 inhabitants (mostly living on the bottom of the valley). The elevation of the study area ranges from 350 m a.s.l. – San Giacomo di Teglio, up to 3,370 m a.s.l. – Cima Viola.

Valtellina has an unenviable history of intense and diffused landsliding. Statistical analysis (Crosta et al. 2003) shows that a large percentage of landslides is represented by rainfall-induced, small size and thickness slides (up to 1.5 m) with volumes ranging from a few up to some hundreds of cubic metres. Field surveys mapped mainly shallow soil slips and/or soil slips – debris flows and slumps affecting Quaternary covers. These phenomena remove portions of cultivated areas (one of the most important source of sustenance for people), cause the interruption of transportation corridors and disruptions in inhabited areas, and sometimes require the temporary evacuation of people. The study area suffered from intense rainfall and consequent landslides several times in the past. The major events occurred in 1983, 1987 and 2000. The flood and landslides in 1987 caused a lot of fatalities, many of them by fast moving soil slips – debris flows.

METHODOLOGY

The methodology applied consists of several steps. Firstly a database of explanatory variables (factor maps) and training points (debris flow scarp areas) was prepared. To predict the locations of future landslides and to evaluate these predictions we used the 1,478 debris-flows scarp areas from the National Italian Landslide Inventory (IFFI 2008). These scarp areas were than used to prepare a statistical model of landslide susceptibility comparing the scarp areas with seven geo-referenced explanatory variables: geology (7 classes), land use (7 classes), and topography – input as five separate data layers: slope gradient (8 classes), slope aspect (4 classes), internal relief (7 classes, $\Delta h/625\ m^2$), slope

Fig. 2. Mountain Consortium of Municipalities in Valtellina di Tirano: the debris flow scarps are represented by dots

planar (3 classes) and profile curvature (3 classes) obtained from a digital elevation model (DEM) of 5 meter resolution. A single value was assigned to each pixel in each data layer.

In the next step a random subdivision of the scarp areas in two mutually exclusive subsets (training and evaluation subsets) was made by a random spatial criterion. One group (training subset) was used to prepare the susceptibility model comparing locations of the training points with explanatory variables. The second (evaluation) subset was used to evaluate the predictive power of the created susceptibility maps.

Thirdly the Weights of Evidence modelling technique was applied to assess the debris flow susceptibility. This statistical method was firstly used in medicine (Spiegelhater and Kill-Jones 1984) and then applied in mineral resources prospecting (Bonham-Carter et al. 1988 and 1990, Agterberg et al. 1989). In the 1990's this method started to be used in landslide susceptibility evaluation (Van Westen 1993, Van Westen et al. 2003, Süzen and Doyuran 2004). The Weights of Evidence (WofE) modelling technique utilizes a combination of different spatial datasets (evidential themes or factor maps) in order to analyse and describe their interactions and generates predictive models (Bonham-Carter 1994, Raines et al. 2000). WofE is a data-driven process that uses known occurrences (training points or response variables) as model training sites to produce predictive probability maps (response theme) from multiple weighted evidence (Raines 1999). Training points are used in WofE to calculate prior probability, weights of each evidential theme, and posterior probabilities of the response theme. The WofE model uses a log-linear form of the Bayesian probability model. The prior probability P_{prior} that an event $\{D\}$ could occur per unit area is calculated as the total number of events over the total area (1). This initial estimate can be later increased or diminished in different areas by the use of available explanatory variables $\{B\}$(2,3). The method is based on the calculation of positive and negative weights by which the degree of spatial association among events and explanatory variables may be modelled (4,5).

$$P_{\Pr ior} = \frac{Landslide\_Area}{Total\_Area} \tag{1}$$

$$P\{D|B\} = P\{D\}\frac{P\{B|D\}}{P\{B\}} \tag{2}$$

$$P\{D|\overline{B}\} = P\{D\}\frac{P\{\overline{B}|D\}}{P\{\overline{B}\}} \tag{3}$$

$$W^{+} = \log_e \frac{P\{B|D\}}{P\{B|\overline{D}\}} \tag{4}$$

$$W^{-} = \log_e \frac{P\left\{\overline{B}\middle|D\right\}}{P\left\{\overline{B}\middle|\overline{D}\right\}} \quad (5)$$

The over bar sign "¯" represents the absence of an event and/or explanatory variable. The ratio of the probability of D presence to that of D absence is called odds (Bonham-Carter 1994). The WofE for all Ds is combined using the natural logarithm of the odds (logit), in order to estimate the conditional probability of landslide occurrence. When several Ds are combined, areas with high or low weights correspond to high or low probabilities of the presence of the D (Thierry et al. 2007). Other statistics could be automatically calculated by SDM extension – Spatial Data Modeller (Sawatzky et al. 2008) as a useful measure of the spatial correlation between explanatory variables and the occurrence of an event (Bonham-Carter 1994). This modelling technique was applied eleven times changing the number and combination of the explanatory variables – factor maps in each experiment. So each final map depends on a different combination of factor maps.

As a next step the goodness-of-fit was assessed using success rate curves – SRC (Van Westen et al. 2003). SRC were built by plotting on the X axis the cumulative percentage of susceptible areas (starting from the highest susceptibility values to the lowest ones) and on the Y axis the cumulative percentage of training points. The steeper was the curve, the better was the capability of the model to describe the distribution of landslides. This step was aimed at analysing how well the model fits the occurrences of 739 mapped debris-flow scarps (training subset) in terms of the explanatory variables used in each experiment. The degree of fit does not express how well the predictions locate future landslides because the landslides in the training subset were used to construct the prediction map.

The fifth step was aimed to evaluate the predictive power of the maps using a predictive subset: prediction rate curve method – PRC (Chung and Fabbri 2003) to strengthen the model prediction power. The PRC were built in a same way as the SRC, but instead of using training subset, we used a prediction subset of debris-flow scarps that did not enter into the model calculation. A count of landslides in the predictive subset that fall into the susceptibility classes of the prediction map yields prediction rates, which are used here to estimate the reliability and power of the map generated for predicting locations of future landslides.

After obtaining 11 susceptibility maps and evaluating their success and prediction rates, a reclassification of the predictive maps into 10 classes was made (Fig. 3) in order to spatially compare the resulting maps by using Kappa Statistic, Cluster Analysis, and Principal Component Analysis. A 10-classes equal area classification was applied so that the set of susceptibility classes has the characteristics as follows: 1) all 10 classes include the same number of pixels and therefore each class covers the same area on the ground (one tenth of the entire study area (about 45 km^2), 2) the 1st class is the less susceptible, and 3) it is relatively simple to compare the spatial distribution of the susceptibility classes.

Finally Kappa Statistic, Cluster Analysis and Principal Component Analysis were applied to the 11 susceptibility maps classified into 10 classes. K is a statistical measure of inter-class reliability. It is generally considered a more robust measure than simple percent agreement calculation (6), since K takes into account the agreement occurring by chance. Cohen's Kappa measures the agreement between two rates, each one classifying N items into C mutually exclusive classes (Rossiter 2004):

$$K = \frac{P(a) - P(e)}{1 - P(e)} \tag{6}$$

Where $P(a)$ is the relative observed agreement among rates, and $P(e)$ is the probability that the agreement is due to chance. If the rates are in complete agreement then $K = 1$. In case there is no agreement among these rates other than what would be expected by chance, then $K \leq 0$ (Tab. 1).

Tab. 1. Relative agreement between rates used by Kappa Statistic (after Rossiter 2004)

K	Interpretation
0	No agreement
0 – 0.2	Very low agreement
0.2 – 0.4	Low agreement
0.4 – 0.6	Moderate agreement
0.6 – 0.8	High agreement
0.8 – 1	Very high agreement

After applying Kappa Statistic we used Cluster Analysis and Principal Component Analysis to strengthen and to visualize the results obtained from Kappa Statistic. PCA can be used for a dimensionality reduction of the dataset by retaining those characteristics of the dataset that contribute most to its variance, by keeping lower-order principal components and ignoring higher-order ones. It is also useful as it can provide a simple way to plot complex multivariate data structures.

RESULTS AND DISCUSSION

The performance of eleven susceptibility maps, obtained by different combinations of factor maps, was assessed with standard evaluation and validation techniques by the computation of the area under SRC and PRC (AUC) (Beguería 2006).

According to AUC under SRC, the best working model was represented by map R_08 (84.04%). This map was calculated using a combination of geology, land use, slope, planar and profile curvature factor maps. The second best working model was model R_09 (83.98%) composed of these factor maps: geology, land use, slope and planar curvature. The third best working model was model n. 6 (83.34%) built with a combination of geology, land use, slope, internal relief, profile curvature and planar curvature factor maps. The difference of AUC among these maps is almost negligible.

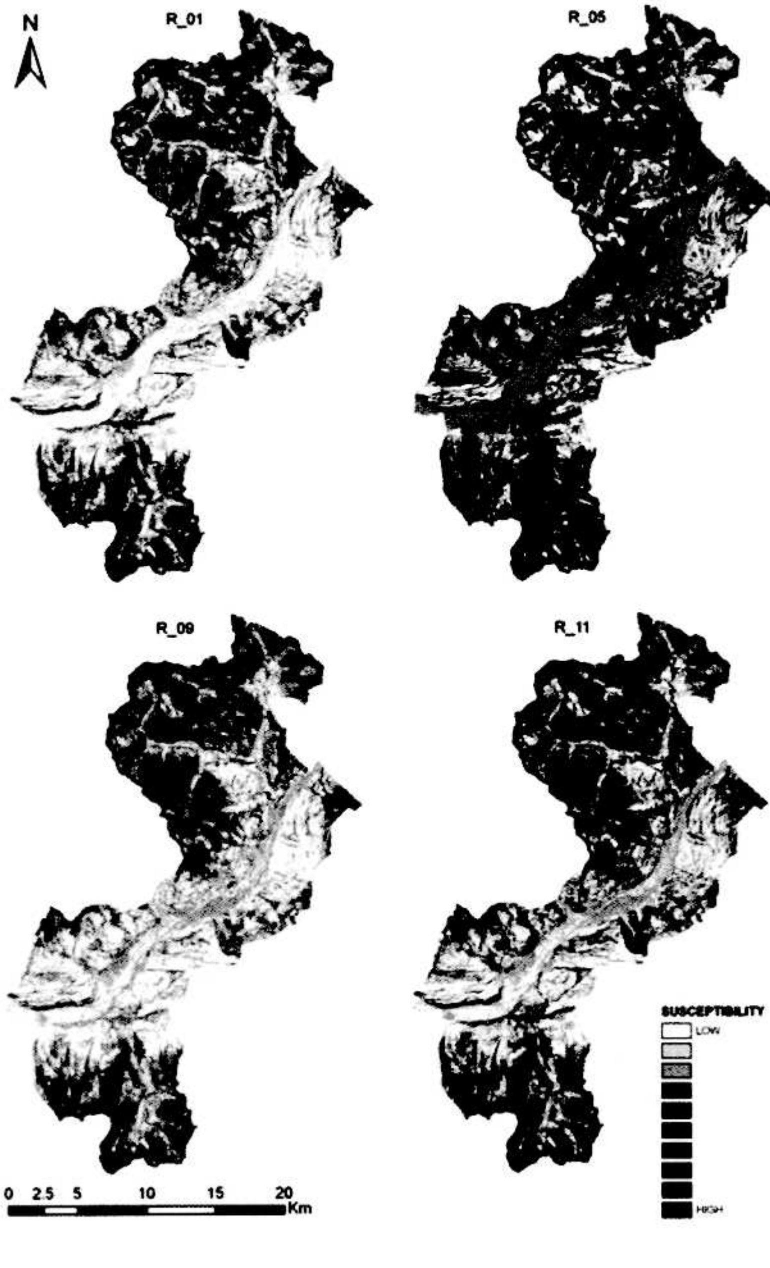

Fig. 3. Four of the eleven predicted maps calculated by the WofE

Susceptibility classes are represented by a grey scale ramp ranging from light grey (low susceptibility) to dark grey tones (high susceptibility). On each map, the debris flows scarp areas of the predictive subset are superimposed. R_01, R_05, R_09 and R_11 are the model numbers.

In relation to AUC for PRC, again the best performing map was R_09 (83.65%). This map was, as mentioned before, composed of geology, land use, slope and planar curvature factor maps. The second and third best performing maps were R_08 (83.57%) and R_11 (82.89%). Map R_08 was made by combination of geology, land use, slope, planar and profile curvature; while map R_11 was made from geology, land use, slope, internal relief and planar curvature.

The other maps have very similar results in SRC and PRC (Tab. 2), except map R_05 that was made by combining only the geology and slope factor maps (Fig. 4 and 5). This result has lower SRC and PRC and shows that the land use factor map has great added information value to the model. The difference between the AUC of all the produced maps is 6.32% in SRC and 5.96% in PRC.

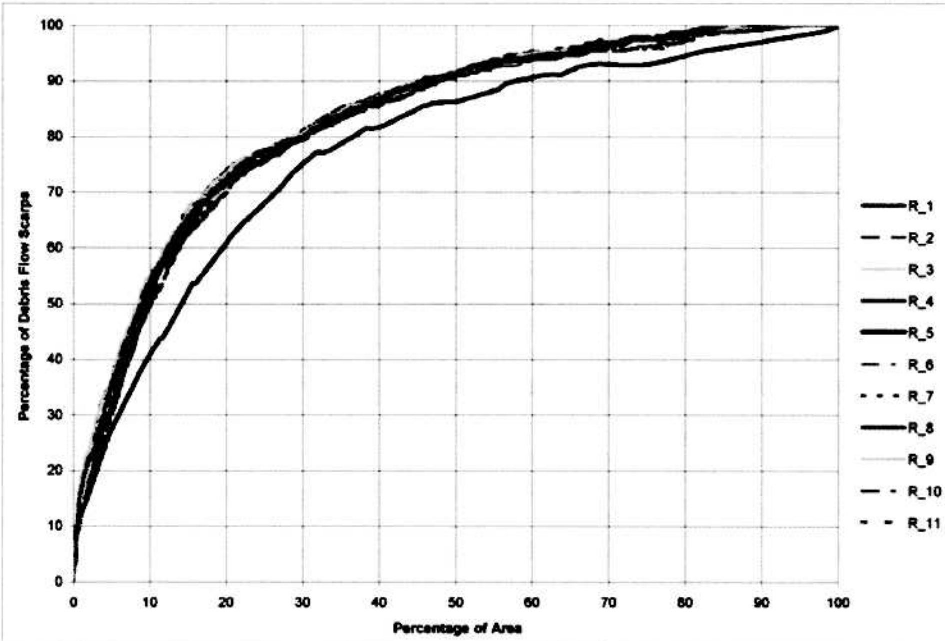

Fig. 4. SRC for the 11 susceptibility maps. Ten models show almost similar results and make individual curves hard to distinguish. Only model R_5 shows much lower values

For assessment of spatial variability among susceptibility maps, we calculated the K values. The results are shown in Fig. 6 and 7 where the K-values of whole susceptibility maps and the highest susceptibility classes are compared. To easily interpret the results from Kappa statistic we performed a Cluster Analysis that shows the proximity between different maps. The analysis shows that only 6 maps have a reliable class consistency (with K-values above 0.6). This feature is most striking when compared with the results from SRC and PRC. Excluding map R_05, the other maps (all with almost similar success and prediction rate values) show levels of proximity really variable (many situations are characterized by low level of inter-class correlation). This means that maps

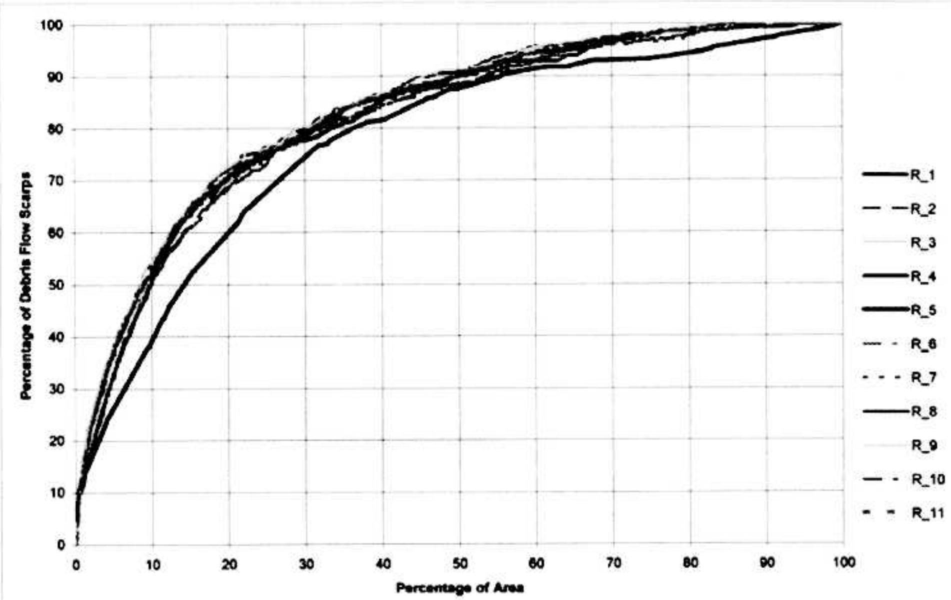

Fig. 5. PRC for the 11 susceptibility maps. Ten models show almost similar results and make individual curves hard to distinguish. Only model R_5 shows much lower values.

Tab. 2. Results of the success and prediction rate capabilities for the eleven models

Model	AUC SRC (%)	AUC PRC (%)	Factor maps
R_01	83.30	82.78	slope, geology, land use, aspect, internal relief, planar, profile curvature
R_02	82.07	81.44	slope, geology, land use, aspect, internal relief
R_03	82.70	82.01	slope, geology, land use, aspect
R_04	82.68	81.99	slope, geology, land use
R_05	77.72	77.70	slope, geology
R_06	83.34	82.81	slope, geology, land use, internal relief, planar, profile curvature
R_07	82.09	81.43	slope, geology, land use, internal relief
R_08	84.04	83.57	slope, geology, land use, planar curvature, profile curvature
R_09	83.98	83.65	slope, geology, land use, planar curvature
R_10	82.76	81.99	slope, geology, land use, profile curvature
R_11	83.32	82.89	slope, geology, land use, internal relief, planar curvature

with similar prediction rates could have a different spatial class distribution. Inter-class accuracy increases when only the most susceptible areas are taken into account, as shown in Fig. 7. This could be seen as a positive result given that a high accuracy for the higher susceptible classes avoids the problem of false negatives. Anyway the inter-map accuracy is still low for many combinations.

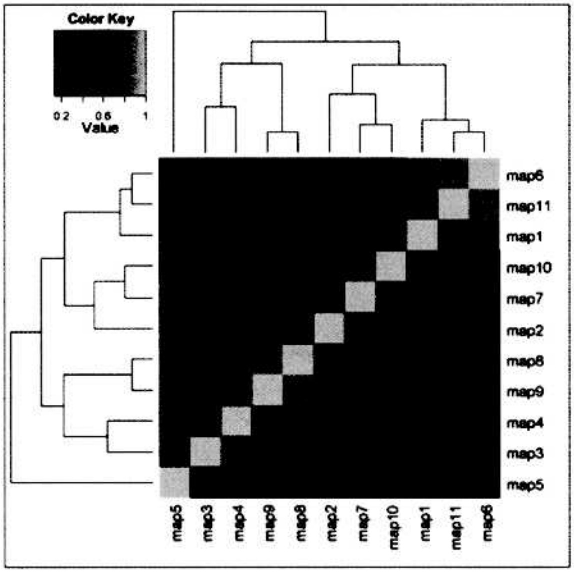

Fig. 6. Classification agreement among the susceptibility maps (all classes)

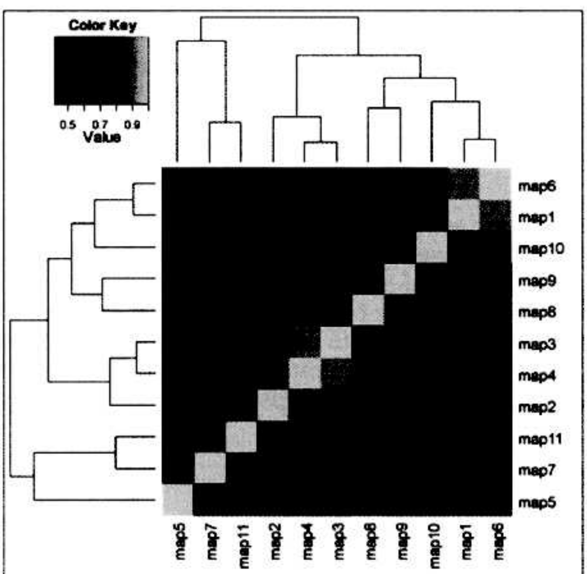

Fig. 7. Classification agreement among the highest susceptibility class

A Principal Component Analysis was also performed to strength the results mentioned above. The result from the PCA shows us two main clusters in comparing whole map variability (Fig. 8). Their difference is due to the presence and absence of the internal relief factor map. This result is very important because the effect of the presence and absence of one single factor map could have very strong influence on the results. Moreover the map R_05 seems to be completely different from the two main clusters. When assessing only the highest susceptibility classes the results from PCA seem to be much more diffused (Fig 9).

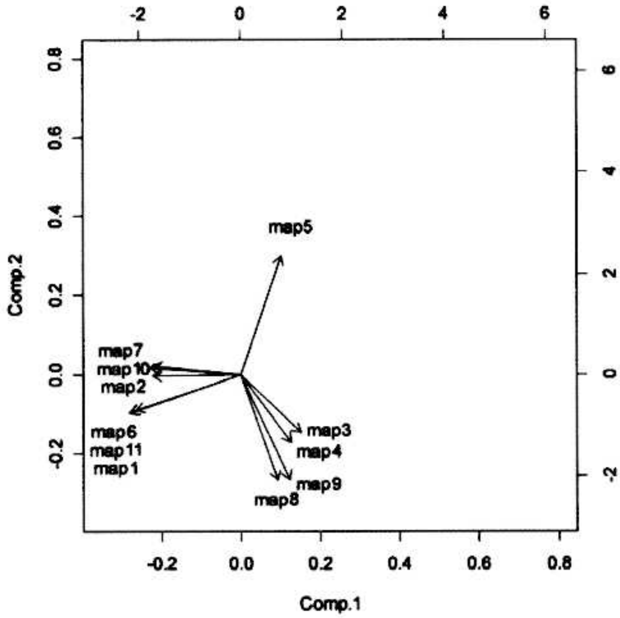

Fig. 8. PCA results of class variability among the susceptibility maps

The results from our analysis have serious implications for which combination of factor maps to choose, if the results from standard evaluation procedures are very similar but the spatial pattern of these maps is very different. The process of the correct reclassification of the factor maps also plays an important role in the susceptibility assessment. The maps calculated using an inappropriate selection of factor maps could show results quite far from reality. On the other hand with a good selection of factor maps reliable susceptibility maps could be obtained.

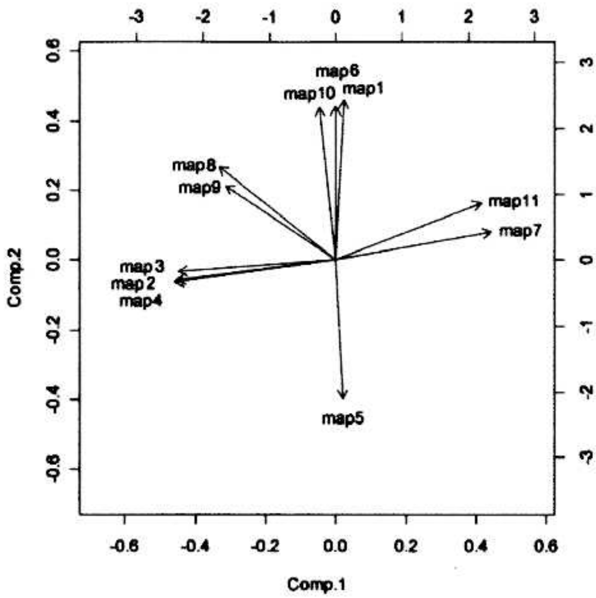

Fig. 9. PCA results of class variability among the highest susceptibility class

CONCLUSIONS

Landslide susceptibility maps are essential tools for spatial planning and contributions to public safety worldwide (Guzzetti et al. 1999, Glade et al. 2005). Predictive methods can be based on sophisticated mathematical models operating on complex databases with advanced software and hardware technologies. Potential users may face some problems of interpretation of the predicted information. Some effective approaches to testing the accuracy of the spatial predictions by cross-validation techniques are now available. In our opinion when we transpose predicted values from a map to a graph (for evaluating the predictive power of that map) we loose the spatial location of those values. So, two predictive maps with similar predictive power may not have the same meaning. To achieve this aim, the same approach was applied several times changing the combination of factor maps. As we can observe, success-rate curves and prediction-rate curves (excluding the experiment R_05) show very similar results, testifying to similarities in susceptibility maps. Application of Kappa Statistics, Cluster Analysis, and Principal Component Analysis calls for a really different situation. A careful evaluation of automatically obtained susceptibility maps with the real conditions in the study area and other available information is essential. Moreover cautious selection of relevant factor maps seems to be the most crucial step in the susceptibility assessment on a regional scale using statistically based methods.

Despite its limitations, statistically based landslide susceptibility maps are a useful tool to analyse large areas where usually limited geotechnical knowledge is available to perform physically based modelling.

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PRIESTOROVÁ VARIABILITA MÁP NÁCHYLNOSTI ÚZEMÍ NA VZNIK ZOSUVOV. PRÍKLADOVÁ ŠTÚDIA ÚDOLIA VALTELLINA (TALIANSKE CENTRÁLNE ALPY)

Hodnotenie náchylnosti území na vznik svahových pohybov pomocou pravdepodobnostno-štatistických metód implementovaných do prostredia GIS sa v posledných rokoch významne zdokonalilo. Napriek tomu, že sa v súčasnosti analýza priestorových dát pri spracovávaní výsledkov široko využíva ako efektívny nástroj na nezávislú kontrolu a validáciu, pomerne malá pozornosť sa venuje hodnoteniu priestorovej variability získaných výsledkov. Súčasné modelovanie vychádza z premisy vzťahu medzi minulými svahovými pohybmi a predispozičnými faktormi, ktoré sa používajú na modelovanie budúceho výskytu zosuvov. Potvrdilo sa, že kvalita predpovedaných výsledkov nerastie automaticky s množstvom vstupných informácií (geologické pomery, sklon a orientácia svahu, land use atď.) a význam jednotlivých faktorov nie je vždy správne vyhodnotený. Predložená štúdia vyhodnocuje rozdielny priestorový vzorec (pattern) predpovedaných hodnôt rôznych máp náchylnosti na vznik mur s takmer zhodnými krivkami predpovedaných hodnôt.

Študovaná oblasť leží v údolí Valtellina v talianskych Centrálnych Alpách, na území 12 obcí s rozlohou približne 450 km^2. Údolie Valtellina mnohokrát zasiahli silné a vytrvalé zrážky, ktoré spôsobili povodne a množstvo zosuvov. Asi najznámejšia je udalosť z júla 1987, keď počas troch dní spadlo až 511 mm zrážok a došlo k rozsiahlym záplavám a výskytu mur. K ďalších významným zrážkovým udalostiam, po ktorých nasledovali hlinito-kamenité prúdy, došlo v rokoch 1983 a 2000.

Na vyhodnotenie náchylnosti terénu na vznik hlinito-kamenitých prúdov bola použitá metóda Weights of Evidence (Bayesianská pravdepodobnostná metóda), ktorá je implementovaná v prostredí ArcGIS pomocou extenzie SDM (Sawatzky et al. 2008). Výsledné mapy náchylnosti terénu, ktoré vznikli rôznou kombináciou predispozičných faktorov, boli klasifikované rovnakým spôsobom. Prahy medzi jednotlivými triedami náchylnosti terénu boli umiestnené každých 10 % študovaného územia zoradeného od najväčšmi po najmenej náchylné. Na takto klasifikovaných mapách náchylnosti bola analyzovaná priestorová variabilita rozloženia jednotlivých tried náchylnosti pomocou Kappa štatistiky, zhlukovej analýzy a analýzy hlavných komponentov. Výsledky ukazujú veľké rozdiely v rozložení všetkých tried náchylnosti jednotlivých máp aj v rámci najnáchylnejšej triedy.

Mapy náchylnosti terénu na vznik zosuvov sú nevyhnutným nástrojom územného plánovania a prispievajú k bezpečnosti obyvateľstva na celom svete (Guzetti et al. 1999, Glade et al. 2005). Metódy predpovedania náchylnosti môžu byť založené na sofistikovaných matematických a štatistických modeloch pracujúcich s rozsiahlymi a komplexnými databázami pri použití moderných hardvérových a softvérových technológií. Potenciálni užívatelia týchto máp sa však môžu stretávať s problémom správnej interpretácie predpovedaných informácií. V súčasnosti sú k dispozícii efektívne prístupy k vyhodnocovaniu presnosti priestorových predpovedí. Problémom je, že transponovaním priestorových informácií (predpovedaných hodnôt) do grafu strácame priestorovú zložku informácie. Dve mapy predpovedajúce náchylnosť tak môžu vykazovať zhodné hodnoty kriviek predpovedaných hodnôt, ale môžu mať veľmi odlišný význam. Na analýzu tejto problematiky sa použili rovnaké vstupné údaje (faktorové mapy, súbor odlučných oblastí), následne boli vytvorené rôzne kombinácie jednotlivých faktorových máp. Mapy náchylnosti boli potom zhodne klasifikované. Ako vyplýva z výsledkov pri jednotlivých modeloch, sú SRC a PRC (okrem modelu č. 5) takmer totožné. Pokiaľ sa výsledky posudzujú štandardnými technikami, jednotlivé modely sa zhodujú. Aplikáciou Kappa štatistiky, zhlukovej analýzy a analýzy hlavných komponentov však prídeme k úplne odlišnému výsledku. Z tohto dôvodu je dôležité opatrne pristupovať k výsledkom automaticky vypočítaných modelov. Nevyhnutné je overovať ich a porovnávať so skutočnou situáciou v teréne a využívať ostatné možné zdroje informácií.

Napriek svojim obmedzeniam zostávajú štatistické metódy hodnotenia náchylnosti území na zosuvy dôležitým nástrojom na analýzu rozsiahlych oblastí, pre ktoré nie sú k dispozícii dostatočne presné geotechnické informácie, umožňujúce fyzikálne založenú analýzu náchylnosti na zosuvy.