Optimal use of thematic maps for landslide susceptibility assessment by means of statistical analyses: Case study of shallow landslides in fine grained soils

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ABSTRACT: Landslide zoning by means of statistical analyses may be carried out in two successive steps, respectively producing: a landslide susceptibility computational map; a susceptibility map for zoning purposes. The procedure proposed herein is relevant for the first step of the analysis, as it allows to select the optimal territorial variables (i.e. independent variables of the statistical analysis) derived from significant thematic maps available over the territory to be zoned. To this aim, different classification schemes and focal statistics techniques are adopted. The selection process of the variables is based on a series of bivariate analyses between a set of different independent variables derived from the same significant thematic map and an inventory of landslides (i.e. dependent variable of the bivariate analysis). At the end of the process, one optimal independent variable for each significant thematic map is selected on the basis of performance indicators taking into account: the contribution to the success of the analysis; the discriminant capability of the classification; the accuracy of the analysis. The proposed method is applied to a case study of shallow landslides in fine grained soils, in a test area located in the province of Catanzaro of the Calabria region (southern Italy).

1 INTRODUCTION

Susceptibility assessment is one of the fundamental ingredients of landslide risk estimation and zoning. The literature offers many definitions of landslide susceptibility (e.g., Brabb, 1984; Soeters and Van Westen, 1996; Fell et al., 2008). The underlying principles in these definition, as expressed by Varnes (1984), are: the past and present are keys to the future; the main conditions that cause landsliding can be identified. These concepts imply that future landslides are highly likely to occur in the same geological, geomorphological and hydrological processes that have led to instability in the past. Numerous studies exist in the international literature able to zone landslide susceptibility over large areas by means of data driven methods (e.g., Guzzetti et al., 1999; Lee et al., 2007). According to Calvello et al. (2013), susceptibility zoning by statistical analyses at regional scale must be carried out in two successive steps, respectively producing: a landslide susceptibility computational map; a susceptibility map for zoning purposes. Within statistical analyses performed to produce landslide susceptibility computational maps, the procedure proposed herein allows to derive, starting from a series of thematic maps available over the territory to be zoned, the optimal set of independent numerical variables to be used for the analyses. An application of the proposed methodology is provided, with reference to shallow landslides in fine grained soils, at 1:5000 scale within a test area located in the province of Catanzaro of the Calabria region (southern Italy).

2 MATERIALS AND METHOD

2.1 Case study and dataset

The test area is located in southern Italy, in the province of Catanzaro of the Calabria region (Figure 1). The territory analyzed, covering an area of approximately 8 km², is located on the left bank of the Corace river. Within this area, 429 phenomena classified as shallow earth slides or earth slides‒earth flows (Varnes, 1978) were inventoried in 2010. Their width is ranging from 3 m to 20 m, their length from 10 m to 100 m and their depth from few decimetres to 3 m. The geomorphological data used in the case study are derived from an available Digital Elevation Model (DEM) with grid cell sizes equal to 5 × 5 m². The other datasets used for the analyses are reported in Figure 2. Figure 2a highlights the presence of: holocene alluvial deposits, colluvial deposits and landslide debris; pliocene light blue-grey silty clays partially affected by intercalations of pleistocene sandstone; plio‐pleistocene sands and clays. The figure also reports
some faults overlapping the NW-SE and NE-SW fault systems (Cascini et al., 2015). All the phenomena involve weathered clayey rocks characterized by variable thickness gradually increasing from the top towards the foot of the slopes (Figure 2b), with low values on sharply defined ridges—up to 0.5 m—and at the top of the slopes—from 0.5 m to 1.5 m—and maximum thickness depths higher than 5 m in correspondence of the valley bottom.

2.2 Statistical analyses for landslide susceptibility computation and zoning

Statistical analyses have long been used to evaluate landslide susceptibility at regional scale (Brabb et al., 1972; Guzzetti et al., 1999; among many others). These methods rely on information provided by a landslide event map derived from a landslide inventory and a series of thematic independent variables identified as possible causal factors for landslide events. Examples of statistical models used in landslide susceptibility and hazard zoning are: likelihood ratios (Chung, 2006); weights of evidence; information value (Yin and Yan, 1988); favourability functions (Fabbri et al., 2002); discriminant analysis (Carrara et al., 1991); factor analysis (Fernandez et al., 1999); logistic regression (Budimir et al., 2015); artificial neural networks. Landslide susceptibility zoning is based on the discretization of a territory Terrain Mapping Units (TMUs) containing a set of ground conditions that differ from the adjacent units across definable boundaries (Hansen, 1984). Calvello et al. (2013) propose a distinction between terrain computational units, or TCUs, which refer to territorial domains used to define, calibrate and/or validate a model for landslide analyses, and terrain zoning units, or TZUs, which are units used to produce a landslide map for zoning purposes. This distinction introduces the following principle: when dealing with geo-statistical analyses developed for zoning purposes at a given scale, the terrain units that are suitable to be used within a geostatistical model (TCUs) are not necessarily suitable for the discretization of the zoning map derived from the results of that model (TZUs).

2.3 Proposed method

The statistical analyses carried out herein are based on bivariate correlations, over the test area, between each available independent variable and a dichotomous dependent variable derived from the available inventory of landslides. Independent variables may be either categorical or numerical. In the first case, the variables are generally classified according to the heuristic classification of the related thematic information. In the second case, the variables can be classified according to several classification methods (e.g., quantile, natural breaks, equal intervals, geometrical intervals). The method herein proposed to determine how to derive and choose a set of optimal independent variables from a set of thematic maps only addresses numerical variables.

Figure 3 shows a scheme of the proposed procedure. The input data are: a set of thematic maps, a landslide inventory, the subdivision of the test area into Terrain Computation Units (TCUs). The information contained within each available thematic map is used a given number of times to produce a series of independent variables for the statistical analysis. To check the influence of the information related to the spatial discretization of each thematic map, a focal statistics technique is employed to calculate, for each TCU, the mean of
the values within a specified neighbourhood around it. The shape of the neighborhood is circular with neighbourhood radius, \( D_k \), ranging, in the analyses performed herein, from 1 (i.e. native variable) to 32 cells. All the independent variables obtained by focal statistics, \( V_i \), need to be classified. Herein, they are always classified into 8 classes \( (j = 1, \ldots, 8) \) following both the quantile and the natural breaks methodologies.

The statistical method herein employed to relate the independent variables to the landslide location (i.e. dependent variable derived from a landslide inventory) is derived from the “information value method” (e.g. Yin and Yan, 1988). The statistical weight assigned to each class, \( j \), of each variable, \( V_i \), is computed using the following formula:

\[
W_{ij} = \log \left( \frac{D_{ij}}{D^*} \right) = \log \left( \frac{F_{ij} / N_{ij}}{F_{tot} / N_{tot}} \right)
\]  

(1)

where: \( W_{ij} \) is the weight assigned to the class \( j \) of the independent variable \( V_i \); \( D_{ij} \) is the density of landslides within class \( j \) of the independent variable \( V_i \); \( D^* \) is the average density of landslides within the test area; \( F_{ij} \) is the number of TCUs with landslides belonging to the class \( j \) of the independent variable \( V_i \); \( N_{ij} \) is the number of TCUs belonging to the class \( j \) of the independent variable \( V_i \); \( F_{tot} \) is the total number of TCUs with landslides within the test area; \( N_{tot} \) is the total number of TCUs within the test area.

High positive values of the weight of a given class of a given variable mean high probability that TCUs belonging to that class are affected by landslides; on the contrary, low negative values of the weight mean low probability for TCUs belonging to a given class of a given variable to be affected by landslides. It is important to notice that Eq. 1 cannot be used to compute weight values when landslides are not inventoried in that class. In such cases, the class weight is set to a value equal to the closest negative integer inferior to the minimum computed weight for all classes of all variables.

In a first phase, the computed weights are used to select the independent variables most relevant for the analysis. The performance assessment of the bivariate correlation between the independent and the dependent variables is based on the criteria proposed by Ciurleo et al. (2015), which use two indicators, \( \beta_i \) and \( \sigma_i \), defined as follows:

\[
\beta_i = \frac{TPR_i}{FPR_i} = \frac{\text{Sensitivity}_i}{1 - \text{Specificity}_i} = \frac{TP_i / (TP_i + FN_i)}{FP_i / (FP_i + TN_i)}
\]  

(2)

\[
\sigma_i = \sqrt{\frac{\sum_{j=1}^{n} (W_{ij}^* - W_i)^2}{n-1}}
\]  

(3)

\[
W_{ij}^* = W_j \left( \frac{N_{ij}}{N_{tot}} / n \right)
\]  

(4)

where: \( TPR_i \) is the true positive rate (sensitivity of the bivariate model) for the independent variable \( V_i \); \( FPR_i \) is the false positive rate for the independent variable \( V_i \) (1 – specificity of the bivariate model); \( TP_i \) is the number of TCUs with landslides belonging to the classes of variable \( V_i \) for which the weight index assumes a positive value; \( FN_i \) is the number of TCUs with landslides belonging to the classes of variable \( V_i \) for which the weight index assumes a negative value; \( FP_i \) is the number of TCUs without landslides belonging to the classes of variable \( V_i \) for...
which the weight index assumes a positive value; \( T_{n_i} \) is the number of TCUs without phenomena belonging to the classes of variable \( V_i \) for which the weight index assumes a negative value; \( W_{ij}^\ast \) is the normalized value of the weight assigned to the class \( j \) of variable \( V_i \); \( W_i \) is the average value of the weights assigned to the classes of variable \( V_i \); \( n \) is the number of classes of variable \( V_i \).

The performance indicator \( \beta \) (Eq. 2) quantifies the contribution of the independent variable to the success of the bivariate analysis; the performance indicator \( \sigma \) (Eq. 3) quantifies the discriminant capability of the classification of the independent variable. Only the variables showing values of \( \beta \) and \( \sigma \) higher than the two specified thresholds are considered statistically relevant for the analysis.

In a second phase, each one of the relevant variables identified in the previous step is, once more, independently tested in order to select its best performing spatial discretization, herein called “optimal discretization”. This step is carried out by considering the focal statistics implementation which maximises the area under curve, AUC, of the related receiver operating characteristic curve, ROC (Swets, 1988). Finally, the third and last phase of the procedure consists in the selection of the multivariate “optimal

![Figure 4](image-url)

**Figure 4.** Numerical variables tested for their bivariate statistical correlation with the dependent variable: natural breaks classification in 8 classes and application of focal statistics with characteristic dimensions \( D_k \) ranging from 1 (i.e. native variable) to 32 cells: a) \( D_1 = 1 \); b) \( D_2 = 2 \); c) \( D_4 = 4 \); d) \( D_8 = 8 \); e) \( D_{16} = 16 \); f) \( D_{32} = 32 \).
combined combination” of the variables identified in the previous step. In particular, the latter are used to derive a series of landslide susceptibility computational maps, one for each considered combination. The number of combinations tested is equal to the number of relevant variables selected, starting from the one showing the best bivariate correlation and then adding the rest of the variables, one by one, following their order of importance. Each map is drawn considering the values of a multivariate computational susceptibility index, \( IS_{TCU} \), which is assigned to each TCU according to the following formula:

\[
IS_{TCU} = \sum W_{ik(i)}
\]  

where: \( W_{ik} \) is the weight index of the relevant independent variable \( V_i \) related to the TCU belonging to class \( k(i) \) of that variable.

As already stated, Eq. 5 is applied several times, one for each considered combination of the optimal discretization of the relevant variables. The results of the multivariate analyses are then evaluated considering two new statistical indicators related to the shape of the ROC curve, \( S_{10} \) and \( E_{90} \), defined as follows:

\[
S_{10} = TPR_i(\text{at} \ FPR_i = 0.1)
\]  

\[
E_{90} = FPR_i(\text{at} \ TPR_i = 0.9)
\]  

where: \( TPR_i \) (at \( FPR_i = 0.1 \)) is the value of true positive rate on the ROC curve (i.e. sensitivity) when the false positive rate is 0.1; \( FPR_i \) (at \( TPR_i = 0.9 \)) is the value of false positive rate on the ROC curve (1 – specificity) when the true positive rate is 0.9.

The performance indicator \( S_{10} \) (Eq. 7) quantifies the success of the multivariate analysis in correspondence with a fixed value of the computed false positive rate, herein set equal to 10%; the performance indicator \( E_{90} \) (Eq. 7) quantifies the overestimation error of the multivariate analysis in correspondence with a fixed value of the computed true positive rate, herein set equal to 90%.

### 3 ANALYSES AND RESULTS

All the variables employed in the statistical model have been expressed in raster format using square grid cells, whose size is equal to 5 × 5 m², as Terrain Computational Units (TCUs). The number of TCUs over the test area is equal to 316,302. The dichotomous dependent variable is derived from the available landslide inventory, reporting 429 phenomena occurred in 2010. The TCUs affected by landslides ever the test area are 7835. The independent variables used in the analysis are the following eight: elevation zone (V1); slope curvature (V2); slope gradient (V3); slope aspect (V4); distance from river network (V5); distance from faults (V6); geological unit (V7); thickness of weathered rock (V8). The categorical variables (V7, V8) are divided, following the classification reported in the employed thematic maps, in six and eight classes, respectively. The numerical variables (V1 to V6) are classified according to quantile and natural breaks criteria employing eight classes and are processed by focal statistics with a \( D_k \) ranging from 1 (i.e. native variable) to 32. As shown in Figure 4, six different

### Table 1. Example of classification of the independent variables employed in the statistical analysis: variable V3 (slope curvature).

<table>
<thead>
<tr>
<th>Focal statistics ( D_k )</th>
<th>( Q^* )</th>
<th>( C^* )</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0–1.26</td>
<td>0–1.44</td>
</tr>
<tr>
<td>2</td>
<td>1.26–3.53</td>
<td>1.44–3.91</td>
</tr>
<tr>
<td>3</td>
<td>3.53–7.31</td>
<td>3.91–7.62</td>
</tr>
<tr>
<td>4</td>
<td>7.31–11.34</td>
<td>7.62–11.33</td>
</tr>
<tr>
<td>5</td>
<td>11.34–15.87</td>
<td>11.33–15.86</td>
</tr>
<tr>
<td>6</td>
<td>15.87–20.16</td>
<td>15.86–19.98</td>
</tr>
<tr>
<td>7</td>
<td>20.16–24.69</td>
<td>19.98–24.30</td>
</tr>
<tr>
<td>8</td>
<td>24.69–64.25</td>
<td>23.81–45.64</td>
</tr>
</tbody>
</table>

* M - methods; C – Classes, Q – quantile criterion, NB – natural breaks criterion.
variables can be tested for each native variable. The maps show that the focal statistics manipulation produces, for all variables, a smoother transition among the different classes when $D_k$ increases. The variables most sensitive to this discretization are slope curvature and slope aspect.

Table 1 shows an example of the values assumed by each class of variable V3, when both $D_k$ in the focal statistics and the classification scheme vary. The result of the discretization by focal statistics entails a significant variation of the minimum and maximum absolute values of V3; the latter, for instance, varies from 64.25° to 29.98°. The effect of the classification scheme on the classes’ thresholds is also very apparent. Table 2 shows that three variables can be defined as relevant for the analysis (V1, V2, V3). Indeed, their values of $\beta$ and $\sigma$ are, as suggested by Ciurleo et al. (2015), simultaneously higher than 1.7 and 0.4.

In order to identify the optimal variables, the AUC values were also calculated for each discretization of each relevant variable (Figure 5). The overall maximum AUC, equal to 0.93, is attributed to variable V3 obtained considering a $D_k$ equal to 4 cells and classified in 8 classes following the natural breaks method. For V1 and V2 the maximum AUC values are 0.87 and 0.75, respectively obtained with $D_k = 32$ cells and 4 cells. It is also worth highlighting that for V1 the AUC values range from 0.86 to 0.87, so the optimal discretization is the one that maximizes the values of both $\beta$ and $\sigma$.

In order to stress the role played by each relevant variable in the multivariate analysis, three different combinations have been performed: C1) considering only V3; C2) combining V3 and V1; C3) combining all three variable (Table 3). Figure 6 shows the related landslide susceptibility computational maps, obtained by using both the optimal discretization by focal statistics (C1opt, C2opt, C3opt) and the native variables (C1nat, C2nat, C3nat). The Figure reports six maps classified on the basis of the values assumed by the multivariate computational susceptibility index, $IS_{TCu}$, as follow: not susceptible, for $IS_{TCu} \leq 0$; susceptible for $IS_{TCu} > 0$. A pairwise comparison between the resulting maps always designate the maps obtained by focal statistics as better than those obtained considering the native variables.

Table 3 shows that the difference of $S_{10}$ values between the “optimal” combinations (C1opt, C2opt, C3opt) and the other ones (C1nat, C2nat, C3nat) is always higher than or equal to 10%. The better result was found for combination C3opt, for which this difference is equal to 20% while the value of $E_{10}$ is only 20%. A final landslide susceptibility computational map derived from “C3opt” is shown in Figure 7; the map is created by adding the information contained in the two categorical variables V7 and V8 (geology and weathering thickness), as defined by Ciurleo et al. (2015). The success of this last analysis is testified by the very high value assumed by the Area Under Curve (AUC), which is equal to 93.2%.

4 CONCLUDING REMARKS

A method has been proposed to evaluate both the most relevant independent variables and their optimal discretization to be used within a statistical analysis aiming at computing landslide susceptibility maps over large portions of territory. The proposed method has been applied within a test area in southern Italy. To build the database of input

<table>
<thead>
<tr>
<th>Thematic map</th>
<th>Focal Statistics $D_k$</th>
<th>Quantile (Q)</th>
<th>Natural breaks (NB)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\beta$</td>
<td>$\sigma$</td>
<td>$B_i$</td>
</tr>
<tr>
<td>V1 Elevation</td>
<td>1</td>
<td>2.78</td>
<td>1.67</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>2.82</td>
<td>1.70</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>2.85</td>
<td>1.72</td>
</tr>
<tr>
<td></td>
<td>8</td>
<td>2.87</td>
<td>1.72</td>
</tr>
<tr>
<td></td>
<td>16</td>
<td>2.95</td>
<td>1.73</td>
</tr>
<tr>
<td></td>
<td>32</td>
<td>3.06</td>
<td>1.81</td>
</tr>
<tr>
<td>V2 Curvature</td>
<td>1</td>
<td>2.18</td>
<td>0.86</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>1.88</td>
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</tr>
<tr>
<td></td>
<td>4</td>
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</tr>
<tr>
<td></td>
<td>8</td>
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<td>0.42</td>
</tr>
<tr>
<td></td>
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<td>2.09</td>
<td>0.38</td>
</tr>
<tr>
<td></td>
<td>32</td>
<td>2.02</td>
<td>0.70</td>
</tr>
<tr>
<td>V3 Slope</td>
<td>1</td>
<td>4.05</td>
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</tr>
<tr>
<td></td>
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<tr>
<td>V4 Aspect</td>
<td>1</td>
<td>1.24</td>
<td>0.24</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>1.32</td>
<td>0.25</td>
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<tr>
<td></td>
<td>4</td>
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</tr>
<tr>
<td></td>
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<td></td>
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</tr>
<tr>
<td></td>
<td>32</td>
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<td>V5 Distance from river</td>
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<td></td>
<td>2</td>
<td>1.60</td>
<td>0.28</td>
</tr>
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<td>0.29</td>
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<td>0.28</td>
</tr>
<tr>
<td></td>
<td>32</td>
<td>1.58</td>
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<tr>
<td>V6 Distance from fault</td>
<td>1</td>
<td>1.45</td>
<td>0.18</td>
</tr>
<tr>
<td></td>
<td>2</td>
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<td>0.18</td>
</tr>
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</table>
The best classification criterion, of the two adopted herein, is natural breaks; ii) $\beta$ and $\sigma$ values related to the focal statistics discretization of the variables (i.e. $d_k$ higher than 1) almost always assume values substantially higher than those obtained from the native variables (i.e. $d_k$ equal to 1); iii) for each significant independent variable, the values of AuC are not considerably influenced by the classification criterion nor by the value assumed by $d_k$; iv) the landslide susceptibility computational maps obtained with and without focal statistics processing (in the various analysed combinations) showed significant differences in terms of success of analysis, as testified by the changes in values of the two indicators $S_{10}$ and $e_{90}$. The overall success of the analyses is further proved by the very high value attained by the AuC of the ROC curve for the final landslide susceptibility computational map. This value is indeed higher than 90%, thus the

variables, a series of independent thematic maps has been processed employing two different classification criteria (quantile and natural breaks) and focal statistics techniques (using $d_k$ ranging from 1 to 32 cells). At the end of the process, one optimal discretization for each relevant independent variable has been selected on the basis of the values assumed by three statistical indicators ($\beta$, $\sigma$, AuC). The results of the performed analyses showed that: i) the best classification criterion, of the two adopted herein, is natural breaks; ii) $\beta$ and $\sigma$ values related to the focal statistics discretization of the variables (i.e. $d_k$ higher than 1) almost always assume values substantially higher than those obtained from the native variables (i.e. $d_k$ equal to 1); iii) for each significant independent variable, the values of AuC are not considerably influenced by the classification criterion nor by the value assumed by $d_k$; iv) the landslide susceptibility computational maps obtained with and without focal statistics processing (in the various analysed combinations) showed significant differences in terms of success of analysis, as testified by the changes in values of the two indicators $S_{10}$ and $E_{90}$. The overall success of the analyses is further proved by the very high value attained by the AuC of the ROC curve for the final landslide susceptibility computational map. This value is indeed higher than 90%, thus the

<table>
<thead>
<tr>
<th>C1opt</th>
<th>C1nat</th>
<th>C2opt</th>
<th>C2nat</th>
<th>C3opt</th>
<th>C3nat</th>
</tr>
</thead>
<tbody>
<tr>
<td>V1</td>
<td>opt</td>
<td>nat</td>
<td>opt</td>
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</tr>
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<td>V2</td>
<td>opt</td>
<td>nat</td>
<td>opt</td>
<td>nat</td>
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<td>V3</td>
<td>opt</td>
<td>nat</td>
<td>opt</td>
<td>nat</td>
<td>opt</td>
</tr>
<tr>
<td>$S_{10}$</td>
<td>50%</td>
<td>40%</td>
<td>50%</td>
<td>40%</td>
<td>60%</td>
</tr>
<tr>
<td>$E_{90}$</td>
<td>20%</td>
<td>30%</td>
<td>20%</td>
<td>20%</td>
<td>20%</td>
</tr>
</tbody>
</table>
analysis can be considered, following the original ROC curve proposal by Swets (1988), as having a high accuracy. As a final remark, it is worth stating that the analyses carried out and the obtained results have to be referred to landslide susceptibility analyses of shallow landslide source areas at 1:5000 scale. Therefore, a generalization of the findings discussed herein is not straightforward. Indeed, the results of statistical analyses are always strongly dependent on the quantity and quality of the information provided in relation to the relevant landslide predisposing factors over the study area.

ACKNOWLEDGEMENTS

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REFERENCES


