Susceptibility zoning of shallow landslides in fine grained soils by statistical methods
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A B S T R A C T
The paper proposes a methodology, in two successive steps, to zone the susceptibility to shallow landslides in fine grained soils by means of statistical methods. The first step of the methodology, aiming at defining, calibrating and validating the statistical analysis, ends with a landslide susceptibility computational map; the second step of the methodology is employed to produce a susceptibility map for zoning purposes. This structured methodology arises from the need to distinguish, at any given scale of analysis, between the spatial discretization needed to perform the statistical computations (terrain computational units) and terrain units useful for zoning purposes (terrain zoning units). The applicability of the proposed methodology is tested, at two different scales (1:25,000 and 1:5000), in two areas of southern Italy, the test area for the larger scale being a portion of the test area used for the analysis at the smaller scale. This allows for the generalization of the obtained results through the comparison, for the same phenomena in the same geo-environmental context, of the predisposing factors at two scales of analysis. In both analyses, the relevant variables for the susceptibility assessment are: elevation zone, slope gradient, slope curvature and geology; in the analysis at large scale also the weathered rock thickness, available only at this scale, assumes a relevant role. In both cases, the aggregation of multiple terrain computational units (TCU) into a larger terrain zoning unit (TZU) works best when focal statistic techniques are used with a characteristic dimension of the area of influence equal to 16 TCUs.

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1. Introduction
Shallow landslides in fine-grained soils typically involve the upper layer of slopes affected by weathering processes. They generally occur during the wet season and quickly evolve following mechanisms classified as shallow earth slides or earth slides–earth flows (Cascini et al., 2015). The morphometric features of these phenomena mainly depend on the spatial distribution of the weathered rock thickness along the slope, where a diffuse pattern of cracks, due to alternate processes of wetting and drying and insolation and frost, is generally observed. In spite of the small size of these phenomena they usually occur over wide areas, often causing serious economic damages (Crozier, 2005; Glade et al., 2005; Antronico et al., 2013). Susceptibility zoning of these landslides is thus becoming an important topic in the scientific literature (Gullà et al., 2008), especially in relation to land-use planning and management (Soeters and van Westen, 1996; Fell et al., 2008a). Soeters and van Westen (1996) classify the methods employed to derive landslide maps for zoning purposes in three classes: heuristic, statistical and deterministic. Fell et al. (2008a) propose a correlation among the same methods (classified as basic, intermediate and advanced), scales of analysis and zoning purposes to define three zoning levels: preliminary, intermediate and advanced. For instance, when using basic methods exclusively, only a preliminary zoning level can be obtained; while the use of intermediate and advanced methods can allow reaching intermediate or advanced level of zoning (Fell et al., 2008a). The choice on the most appropriate zoning method to adopt, at a given scale for a given purpose, also depend on other factors, such as the characteristics of the phenomena (typology, area and/or volume, etc.), the quality and accuracy of the available data within the area to be zoned, and the know-how and expertise of the analysts. Indeed, depending on their area and/or volume, landslides may be represented by dots with attributes at small scale, by polygons at medium scale, whereas they can be mapped at large scale distinguishing minor and lateral scarps as well as retrogressive deformations such as tension cracks or minor landslides (Cascini et al., 2015). It is also worth stressing that the accuracy of the input data is deeply linked to the accuracy of the obtained results, thus cost–benefit analyses are needed to identify the amount and type of soil investigations which increase the quantity and quality of the available data.

All that considered, we propose a methodology based on statistical analyses in order to identify the most relevant predisposing factors for
shallow landslides in fine grained soils. The proposed methodology may be defined, following the terminology introduced by Fell et al. (2008a), an intermediate method pursuing an intermediate level of susceptibility zoning at both medium and large scales. Medium scale zoning should be seen as both an advanced analysis for information and advisory purposes (typically pursued at small scale) and a preliminary analysis for statutory purposes. An application of the proposed methodology is provided with reference to a 136 square kilometers test area, the Catanzaro isthmus in southern Italy, which was already analysed at small scale by Cascini et al. (2015) and is herein analysed at medium scale (1:25,000). To further test the potentiality of the methodology, two hydrological basins within the test area are also analysed and zoned at large scale (1:5000). This allows the comparison, for the same phenomena in the same geo-environmental context, of the identified predisposing factors at each scale of analysis.

2. Materials and methods

2.1. Statistical analyses for landslide susceptibility assessment

The framework for landslide risk analysis proposed by Fell et al. (2005) indicates susceptibility as one of the fundamental ingredients of landslide risk estimation and zoning. Numerous studies exist in the international literature evaluating landslide susceptibility over large areas by means of data driven statistical methods, typically implemented at medium to small scales (Brabb et al., 1972; Carrara et al., 1977; Guzzetti et al., 1999; Dai and Lee, 2002; Chung and Fabbri, 2003; Van Westen, 2004; Thiery et al., 2007; Pourghasemi et al., 2012; Pardeshi et al., 2013; Sarkar et al., 2013; Kavzoglu et al., 2015; among others). Statistical analyses may be classified in two main categories according to whether they employ bivariate and multivariate techniques. The main difference between the two classes of analyses concerns the possible inter-relationships among the causal factors (independent variables of the analyses). Bivariate techniques derive weight values from statistical indicators based on the causal relationship between landslide events (dependent variable of the analyses) and each one of the independent variables, thus assumed as not inter-related. Multivariate techniques employ a statistical model which is able to exploit all the information provided by the set of thematic variables, thus explicitly considering the possible interaction among the independent variables in their causal relationship with the dependent variable. Examples of bivariate statistical models used in landslide susceptibility and hazard studies are: likelihood ratios (Chung, 2006; Lee et al., 2007; Dewitte et al., 2010); weights of evidence (Neuhäuser and Terhorst, 2007; Dahal et al., 2008); information value (Yin and Yan, 1988); favourability functions (Fabbri et al., 2002; Tangestani, 2009). Examples of multivariate statistical models are: discriminant analysis (Carrara et al., 1991; Baeza and Corominas, 2001); factor analysis (Fernandez et al., 1999; Ercanoglu et al., 2004); logistic regression (Atkinson and Massari, 2011; Budimir et al., 2015); artificial neural networks (Ermini et al., 2005; Nefeslioglu et al., 2008).

2.2. The proposed methodology

The multivariate statistical methodology employed herein to zone the susceptibility to shallow landslides in fine grained soils includes two successive steps. The first step includes the definition, calibration and validation of the statistical analysis, and it ends with the production of a landslide susceptibility computational map. The second step is the production of a susceptibility map for zoning purposes. Differently from most of the statistical methods used in the literature to derive landslide susceptibility maps, the proposed approach is based on a clear distinction between landslide susceptibility computational and zoning maps. Indeed, the discretization of the test area employed in the final cartographic product of the statistical analysis, which is perfectly suitable for statistical purposes (e.g., terrain units equal to square cells, whose size is related to the scale of analysis), is not necessarily suitable for zoning purposes. The main conceptual innovation of the proposed procedure is the explicit definition, at the end of the statistical analysis, of a zoning algorithm which deals with this issue.

Fig. 1 shows a flow chart of the proposed two-step procedure. In the first step, the statistical analysis is defined on the basis of a series of spatial variables derived from significant thematic maps (i.e. independent variables of the multivariate analysis) and an inventory of shallow landslides (i.e. dependent variable of the multivariate analysis). During this step, the model is calibrated and validated and the independent variables most relevant for the susceptibility analysis are selected. The first step ends with the production of a landslide susceptibility computational map over the study area. In the second step, the computational map is used as an input for producing the final landslide susceptibility zoning map of the area on the basis of appropriately defined terrain zoning units. Fell et al. (2008a), within their ‘Guidelines for landslide susceptibility, hazard and risk zoning for land use planning’ define zoning as follows: the division of land into homogeneous areas or domains and their ranking according to degrees of actual or potential landslide susceptibility, hazard or risk. The two-step statistical methodology introduced herein is based on the previous definition as well as on the distinction, proposed by Calvello et al. (2013), between terrain computational units, TCUs, and terrain zoning units, TZUs. The first ones refer to the spatial domains used to define, calibrate and validate a model for landslide analyses, the second ones are spatial domains used to produce a landslide map for zoning purposes. The level of discretization of the area is based, for both spatial domains, on the scale of the analysis. In particular, the size of TCUs is related to the spatial resolution of the map, whereas the size of TZUs is related to the desired informative resolution of the zoning. For instance, when a regular square grid is used in a GIS environment, a common dimension
of the elementary pixel is 1/1000 of the scale factor. The information associated to such elementary pixel, however, is inadequate to be directly used in a zoning map at that scale, because the associated level of discretization of the spatial domains would be too small. For instance, Fell et al. (2008b) state that the minimum area covered by an inventoried and mapped landslide should be higher than 1600 m² for local zoning (scale 1:10,000 to 1:25,000) and 0.4 km² for regional zoning (scale 1:50,000 to 1:100,000); Calvello et al. (2013) suggest that the minimum dimension of the TZU is set to 16 elementary pixels corresponding to, regardless of scale, an area of 16 mm² on paper. The zoning algorithm proposed herein derives the TZUs from multiple TCUs following two approaches: aggregating multiple TCUs into a larger TZU; employing focal statistic techniques to get TZUs having the same dimensions of the TCUs yet containing information related to a larger area around them.

The proposed methodology is herein applied to a case study in southern Italy. The statistical analyses and susceptibility zoning have been carried out at two scales, 1:25,000 and 1:5000. The test area for the larger scale is a portion of the test area used for the analysis at medium scale.

2.2.1. Statistical analysis

The statistical analyses are based, at the two considered scales, on bivariate correlations over the test area between each available independent variable (e.g., elevation zone, slope gradient, slope aspect) and a dichotomous dependent variable derived from inventories of shallow landslides. The independent variables are either numerical or categorical. In the first case, the variables are classified according to a quantile criterion employing 8 classes; in the second case, the number...
The statistical indicator employed to quantify the individual contribution to the success of the analysis of each variable, $V_i$, is a bivariate success index, $\beta_i$, which is computed using the terms of a $2 \times 2$ contingency table according to the following formula:

$$\beta_i = \frac{TPR_i}{1 - Specificity_i} = \frac{TP_i}{(TP_i + FN_i)}$$

where: $TPR_i$ is the true positive rate, also called sensitivity, of the bivariate model for the independent variable $V_i$; $FPR_i$ is the false positive rate of the bivariate model for the independent variable $V_i$, complementary to what is often referred to as specificity; $TP_i$ is the number of TCUs with phenomena belonging to the classes of the independent variable $V_i$ for which the weight index assumes a positive value; $FN_i$ is the number of TCUs with phenomena belonging to the classes of the independent variable $V_i$ for which the weight index assumes a negative value; $FP_i$ is the number of TCUs without phenomena belonging to the classes of the independent variable $V_i$ for which the weight index assumes a positive value; $TN_i$ is the number of TCUs without phenomena belonging to the classes of the independent variable $V_i$ for which the weight index assumes a negative value.

The statistical indicator employed to evaluate the discriminant capability of the weight values assigned to the classes of each independent variable, $V_i$, is the bivariate standard deviation index of the normalized weights, $\sigma_i$, which is computed according to the following formulas:

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

$$W_{ij} = W_i \frac{N_{ij}}{N_{tot}}$$

where: $W_{ij}$ is the normalized value of the weight assigned to the class $j$ of the independent variable $V_i$; $W_i$ is the average value of the weights assigned to the classes of the independent variable $V_i$; $n$ is the number of classes of the independent variable $V_i$.
Fig. 6. Variables employed in the statistical analysis at medium scale. Independent variables: (a) elevation zones, V1; (b) slope gradient, V2; (c) slope aspect, V3; (d) slope curvature, V4; (e) distance from rivers, V5; (f) geology, V6; (g) morpho-structures, V7. Dependent variable: (h) landslide inventory, year 2010. Legend for (f): 1. Holocene alluvial deposits and Aeolian sands; 2. Pleistocene sands, gravels, and brown and red-brown conglomerates; 3. Pliocene sands and sandstones; 4. Pliocene light blue-grey silty clays; 5. Miocene evaporitic limestones; 6. Miocene sandstones and sands; 7. Miocene conglomerates; 8. Palaeozoic schists.

Table 1
Classification of the independent variables employed in the statistical analysis at medium scale.

<table>
<thead>
<tr>
<th>Class</th>
<th>V1 Elevation zone (m)</th>
<th>V2 Slope gradient (°)</th>
<th>V3 Slope aspect (°)</th>
<th>V4 Slope curvature (m⁻¹)</th>
<th>V5 Distance from rivers (m)</th>
<th>V6 Geological unit (-)</th>
<th>V7 Morpho-structures (-)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.00 to 33.08</td>
<td>0.00 to 0.01</td>
<td>1.00 to 35.81</td>
<td>-0.75 to -0.07</td>
<td>0.00</td>
<td>Holocene alluvial deposits and Aeolian sands</td>
<td>1.3</td>
</tr>
<tr>
<td>2</td>
<td>33.09 to 58.51</td>
<td>0.01 to 2.50</td>
<td>35.81 to 79.69</td>
<td>-0.06 to -0.04</td>
<td>0.01 to 22.46</td>
<td>Pleistocene sands, gravels, and brown and red-brown conglomerates</td>
<td>2.2</td>
</tr>
<tr>
<td>3</td>
<td>58.52 to 80.76</td>
<td>2.51 to 6.59</td>
<td>79.69 to 120.75</td>
<td>-0.03 to -0.02</td>
<td>22.47 to 59.90</td>
<td>Pliocene sands and sandstones</td>
<td>2.4</td>
</tr>
<tr>
<td>4</td>
<td>88.77 to 104.60</td>
<td>6.60 to 10.45</td>
<td>120.75 to 157.56</td>
<td>0.00 to 0.02</td>
<td>59.91 to 93.59</td>
<td>Pliocene light blue-grey silty clays</td>
<td>3.1</td>
</tr>
<tr>
<td>5</td>
<td>104.61 to 133.21</td>
<td>10.46 to 14.32</td>
<td>157.56 to 195.78</td>
<td>0.00 to 0.02</td>
<td>93.60 to 134.77</td>
<td>Miocene evaporitic limestones</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>133.22 to 171.36</td>
<td>14.33 to 18.86</td>
<td>195.78 to 235.42</td>
<td>0.03 to 0.05</td>
<td>134.78 to 194.66</td>
<td>Miocene sandstones and sands</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>171.37 to 233.34</td>
<td>18.87 to 25.00</td>
<td>235.42 to 290.63</td>
<td>0.06 to 0.09</td>
<td>194.67 to 291.99</td>
<td>Miocene conglomerates</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>233.35 to 403.41</td>
<td>25.01 to 57.95</td>
<td>290.63 to 356</td>
<td>0.10 to 1.11</td>
<td>292.00 to 954.59</td>
<td>Palaeozoic schists</td>
<td></td>
</tr>
</tbody>
</table>
The bivariate standard deviation index of the normalized weights, $\sigma$, quantifies the ability of the variable’s classification to differentiate the TCUs in relation to the density of landslides. To this aim, normalization of the weights is needed when the TCUs are not equally distributed among the classes, i.e. when the variable’s classes have different numbers of elements, $N_{ij}$.

The two indexes computed with Eqs. (2) and (3) are used to select the independent variables which are considered to be relevant for the statistical analysis. To this aim, two threshold values are specified, one for each index, and only the variables showing values higher than both thresholds are used to derive the calibrated landslide susceptibility computational map. The map is drawn considering the values of a multivariate computational susceptibility index, $I_{STCU}$, which is assigned to each TCU according to the following formula:

$$I_{STCU} = \sum_i W_{ik}$$  \hspace{1cm} (5)

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.

The resulting calibrated computational map is finally evaluated by means of receiver operating characteristic, ROC, curves (Metz, 1978;...
Swets, 1988), which are plotted in the sensitivity versus \((1 - \text{specificity})\) space. In particular, the parameter used to define the success of the calibration is the area under curve, AUC, whose value needs to be higher than a specified threshold.

### 2.2.2. Model validation

The first step of the methodology ends with the validation of the computational map. To this aim, two distinct methods are herein employed for the two analyses conducted at different scales. Different validation methods are needed to properly consider the different datasets used to define the dependent variable in the two cases.

Model validation at 1:25,000 scale considers the same set of relevant independent variables arising from the statistical analysis and consists in repeating model calibration a given number of times within different test areas, defined as subsets of the test area employed in model calibration. In particular, the test area is herein randomly sampled 10 times, each time considering a number of TCUs equal to one tenth of the total number of TCUs. Validation is attained if the average values of the weights computed for each class of each variable are close to the values assumed by the same weights in the calibration phase.

Model validation at 1:5000 scale is developed by comparing the calibrated computational map, which employs a dependent variable defined using a given inventory of shallow landslides, with a different dependent variable defined using records of shallow landslide which occurred, in the same area, at later times. In particular, the comparison is carried out by computing a model true positive rate, \(\text{TPR}_{\text{model}}\), defined as follows:

\[
\text{TPR}_{\text{model}} = \frac{\text{TCUs}_{\text{landslides (new inventory)}}(\{\text{ISTCU} > 0\})}{\text{TCUs}_{\text{landslides (new inventory)}}}
\]

where: \(\text{TCUs}_{\text{landslides (new inventory)}}\) are the TCUs with landslides according to the latter inventory; \(\text{ISTCU} > 0\) are the TCUs characterised by positive values of the computational susceptibility index.

Validation is attained if the value of \(\text{TPR}_{\text{model}}\) is higher than a specified threshold. For the case study considered herein, the inventory employed for calibration refers to shallow landslides recorded during the year 2010, at medium scale, and the winter of 2009, at large scale; while the inventory employed for validation purposes at large scale refers to 2010 landslide occurrences.

### 2.2.3. Zoning algorithm

The distinction between terrain computational units (TCUs) and terrain zoning units (TZUs) introduces the following principle: 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). Indeed, the latter could be the result of a meaningful manipulation of the computational map, such as the aggregation of multiple computational terrain units into a single zoning unit (Calvello et al., 2013). Fig. 2 shows a schematic view of the procedure used to define, at both scales of analysis, the TZUs employed within the landslide susceptibility zoning maps. The TZUs are defined following two approaches: i) aggregating multiple TCUs into a larger TZU; ii) employing focal statistic techniques to get TZUs having the same dimensions of the TCUs yet containing information related to a larger area around them. In both cases, the number of TCUs belonging to the area of influence of the TZUs may be varied considering different characteristic dimensions of the TZU, herein indicated with the letters \(L_k\) and \(D_k\), respectively for the first and second approach. In both cases, the zoning susceptibility index, \(\text{ISTZU}\), is assigned to each TZU according to the following formula:

\[
\text{ISTZU} = \frac{\sum_{k=1}^{N} \text{ISTCU}_{k}}{N}
\]

where: \(\text{ISTCU}_{k}\) is the computational susceptibility index of k-th TCU belonging to the area of influence of the TZU; \(N\) is the number of TCUs belonging to the area of influence of the TZU.

The resulting zoning maps, whose number depends from the number of characteristic dimensions considered in the analyses, are comparatively evaluated employing ROC curves. The optimal zoning map may be considered the one that maximises the area under curve, AUC, of the ROC curves.

Fig. 8. Comparison between the weights computed at the end of calibration and the ten sets of weights computed for validation purposes, for each class of the four relevant independent variables of the statistical analysis at medium scale (V1, V2, V4, V6).
2.3. Test areas and dataset

The test areas are located in southern Italy, in the province of Catanzaro of the Calabria region (Fig. 3). The territory analysed at medium scale (1:25,000) extends for 136 km², it includes the lowermost part of the basins formed by the Corace and the La Fiumarella rivers, and it is bordered by the Sila horst to the north and by the Ionian sea to the south. At large scale (1:5000), the analysis is performed on two hydrological sub-catchments of the area analysed at medium scale, covering approximately 8 km², located on the left bank of the Corace river. The geomorphological data used to apply the procedure described in the previous section are derived from two digital elevation models (DEM) at different spatial resolutions, with grid cell sizes respectively equal to 25 × 25 m² at medium scale and 5 × 5 m² at large scale. The other datasets used for the analyses are reported in Figs. 4 and 5.

At medium scale, the geo-structural map and the landslide inventory derive from maps provided by Cascini et al. (2015), integrated with Google Earth optical satellite images interpretation (Guzzetti et al., 2012; Borrelli et al., 2015) and field investigations. Regarding the geology, the area is mainly characterised by: Pliocene light blue-grey silty clays partially affected by intercalations of sands and silts; alternating layers of Pliocene sands and sandstone; Pleistocene sands, gravels, and brown and red-brown conglomerates (Perri et al., 2014; Cascini et al., 2015). Fig. 4a also shows the presence of two different fault systems, NW–SE and NE–SW oriented (Van Dijk and Okkes, 1991; Tansi et al., 2006; Cascini et al., 2015). Combining the geological and structural features of the area, four morpho-structures can be identified (Cascini et al., 2015). These structures are indicated in the figure by means of two-digit IDs, the first digit referring to the geological period of the uppermost formation (1 = Lower Pliocene, 2 = Lower Pleistocene, 3 = Middle...
Pleistocene), the second digit referring to the uplift rate (increasing from 1 to 4). The landslide inventory (Fig. 4b) reports the location of about 1300 shallow landslides which occurred in 2010, whose area range from 20 m² to about 2000 m².

At large scale, the geological map (Fig. 5a) 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 already identified at medium scale (Ciurleo, 2012; Cascini et al., 2015). At this scale, two landslide inventories are available (Fig. 5b), respectively referring to landslides recorded in 2009 and 2010. The 2010 inventory reports: the source area of the landslides; the propagation zones; retrogressive deformations, such as tension cracks or minor landslides. The phenomena inventoried in 2009 and 2010, all of them classified as shallow earth slides or earth slides–earth flows (Varnes, 1978), are 118 and 429, respectively. 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. All the phenomena involve weathered clayey rocks characterised by variable thickness gradually increasing from the top towards the foot of the slopes (Fig. 5c), 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. The weathered rock thickness map was built following the procedure proposed by Ciurleo (2012).

3. Analyses and results

3.1. Medium scale

The variables employed within the statistical model implemented at medium scale (1:25,000) over the test area, which extends for about 136 km², have been expressed in raster format using 217,093 square grid cells as terrain computational units (TCUs), whose single size is equal to 25 × 25 m². The dichotomous dependent variable, derived from an inventory of shallow landslides which occurred in 2010, reports 1300 phenomena which cover 4030 TCUs of the test area. The independent variables used in the analysis (Fig. 6, Table 1) are the following seven: elevation zone (V1); slope gradient (V2); slope aspect (V3); slope curvature (V4); distance from river network (V5); geological unit (V6); morpho-structural sector (V7). All the numerical variables (V1 to V5) have been classified according to a quantile criterion employing eight classes. The categorical variables (V6, V7) have been divided, following the classification of the geological and structural features reported in the employed thematic maps, in eight and four classes, respectively.

Tables 2 and 3 report the values of the statistics used to select the independent variables which are deemed to be, following the methodology described in Section 2, relevant for the statistical analysis. Table 2 shows the values of the statistical weights computed, using Eq. (1), for each class of each independent variable Vi. The following main comments arise from the values reported in the table. The overall maximum weight is attributed to class 4 of variable V7 (W74 = 0.97), which corresponds to the morpho-structure identified as sector 3.1. High values of weights are computed for a number of classes for variables V1, V2 and V4 (W16 = 0.54, W17 = 0.56, W28 = 0.57, W29 = 0.56). Out of the eight classes of variable V6, only one geological unit, which is the class corresponding to Pliocene light blue-grey silty clays, assumes a positive weight value. Few classes of variables V1 and V6 are characterised by weight values lower than 1.00, which indicate a strong correlation between the territory classified within those classes and the absence of shallow landslides. Concerning the latter comment, it is worth highlighting that the lowest reported weight value (1.00) is not computed but imposed whenever the argument of the logarithm used in Eq. (1) is equal to zero. Indeed, the weight in a given class is set equal to the closest negative integer inferior to the minimum computed weight for all classes of all variables (−1.62) every time shallow landslides are not inventoried in that class. The independent variables defined as relevant for the analysis (V1, V2, V4, V6) are reported in Table 3, which also shows the values of the two indexes employed to assess the bivariate correlations, between each independent variable and the dependent one, in terms of: bivariate success index, \( \beta_i \) (Eq. (2)), a measure of the variable’s contribution to the success of the analysis; bivariate standard deviation index of the normalized weights, \( \sigma_i \) (Eq. (3)), a measure of the discriminant capability of the variable’s classification. As already explained in the previous section, only the variables for which the two indexes assume values higher than two specified thresholds are defined as relevant. The threshold for \( \beta_i \) is herein assumed equal to 1.7, value which corresponds to a AUC value equal to 0.7 (boundary between poor and fair accuracy according to Fressard et al., 2014) when the corresponding ROC curve is drawn assuming TPR equal to one. The threshold for \( \sigma_i \) is herein assumed equal to 0.4, value for which, using a discretization in 8-quantiles, half the classes show a density of events equal to 1.7 and the remaining events are evenly distributed among the remaining classes. Table 3 also reports, for each variable, the number of grid cells included in each term of the 2 × 2 contingency table (TP, FN, FP, TN) and the values of the two statistics needed to compute the bivariate success index (TPR, FPR).

Fig. 10. Receiver operating characteristic curves for the six landslide susceptibility zoning maps at medium scale reported in Fig. 9. (a) ROC curves obtained by aggregation; (b) ROC curves obtained by focal statistics.
Fig. 11. Variables employed in the statistical analysis at large scale. Independent variables: (a) elevation zones, V1; (b) slope gradient, V2; (c) slope aspect, V3; (d) slope curvature, V4; (e) distance rivers, V5; (f) distance from faults, V6; (g) geology, V7; (h) weathered rock thickness, V8. Dependent variable: (i) landslide inventories, years 2009 and 2010. Legend for (g): 1. Holocene alluvial deposits; 2. Holocene colluvial; 3. Holocene slope debris; 4. Pliocene light blue-grey silty clays; 5. Pleistocene sandstone; 6. Plio-Pleistocene sand and clay. Legend for (i): 1. landslides from 2009 inventory; 2. landslide source areas from 2010 inventory; 3. landslide propagation zones from 2010 inventory; 4. areas affected by retrogressive deformations from 2010 inventory.

Table 4
Classification of the independent variables employed in the statistical analysis at large scale.

<table>
<thead>
<tr>
<th>Class</th>
<th>V1 Elevation zone (m)</th>
<th>V2 Slope gradient (°)</th>
<th>V2 Slope aspect (°)</th>
<th>V4 Slope curvature (m⁻¹)</th>
<th>V5 Distance from rivers (m)</th>
<th>V6 Distance from faults (m)</th>
<th>V7 Geological unit (–)</th>
<th>V8 Weathered thickness (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>28.37 to 49.26</td>
<td>0 to 1.26</td>
<td>–1.00 to 105.18</td>
<td>–6.27 to –0.41</td>
<td>0 to 12.91</td>
<td>0 to 64.71</td>
<td>Holocene alluvial</td>
<td>0 to 0.4</td>
</tr>
<tr>
<td>2</td>
<td>49.27 to 70.15</td>
<td>1.27 to 3.53</td>
<td>105.19 to 139.15</td>
<td>–0.40 to –0.17</td>
<td>12.93 to 33.58</td>
<td>64.72 to 129.42</td>
<td>Holocene colluvial</td>
<td>0.5 to 0.9</td>
</tr>
<tr>
<td>3</td>
<td>70.16 to 87.24</td>
<td>3.54 to 7.31</td>
<td>139.16 to 171.71</td>
<td>–0.16 to –0.11</td>
<td>33.59 to 54.24</td>
<td>129.43 to 194.13</td>
<td>Holocene slope debris</td>
<td>1.0 to 1.4</td>
</tr>
<tr>
<td>4</td>
<td>87.25 to 106.23</td>
<td>7.32 to 11.34</td>
<td>171.72 to 204.27</td>
<td>–0.10 to –0.05</td>
<td>54.25 to 77.49</td>
<td>194.14 to 264.23</td>
<td>Pliocene silty clays</td>
<td>1.5 to 1.9</td>
</tr>
<tr>
<td>5</td>
<td>106.24 to 128.07</td>
<td>11.35 to 15.87</td>
<td>204.28 to 234.07</td>
<td>–0.04 to –0.08</td>
<td>77.50 to 105.91</td>
<td>264.24 to 345.12</td>
<td>Pleistocene sandstone</td>
<td>2.0 to 2.9</td>
</tr>
<tr>
<td>6</td>
<td>128.08 to 154.66</td>
<td>15.88 to 20.16</td>
<td>234.01 to 266.56</td>
<td>0.08 to 0.26</td>
<td>105.92 to 149.82</td>
<td>345.12 to 442.19</td>
<td>Plio-Pleistocene sand and clay</td>
<td>3.0 to 3.9</td>
</tr>
<tr>
<td>7</td>
<td>154.67 to 185.59</td>
<td>20.17 to 24.69</td>
<td>266.57 to 300.54</td>
<td>0.27 to 0.62</td>
<td>149.63 to 232.46</td>
<td>442.19 to 603.96</td>
<td>4.0 to 4.9</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>186.00 to 270.50</td>
<td>24.70 to 64.25</td>
<td>300.55 to 360.00</td>
<td>0.63 to 9.14</td>
<td>232.49 to 658.68</td>
<td>603.97 to 1375.09</td>
<td>≥5.00</td>
<td></td>
</tr>
</tbody>
</table>
Fig. 7 shows the calibrated landslide susceptibility computational map derived using the four variables identified as relevant. The three susceptibility descriptors used in this map are defined on the basis of the values assumed by the multivariate computational susceptibility index, \( IS_{TCU} \), as follows: low susceptibility, for \( IS_{TCU} \leq 0 \); medium susceptibility, for \( 0 \leq IS_{TCU} < 0.5 \); high susceptibility, for \( IS_{TCU} > 0.5 \). The results indicate that about 27% of the test area is characterised by low susceptibility (i.e. \( ISTCU \leq 0.5 \)); high susceptibility, for \( ISTCU > 0.5 \). The success of the analysis is testified by the high value assumed by the area under curve (AUC equal to 88.4%) of the ROC curve plotted in the sensitivity versus (1 – specificity) space.

The first step of the methodology ends with the validation of the computational map. At this scale, model validation requires repeating model calibration a given number of times within different subsets of the test area. To this aim, the test area has been randomly sampled 10 times, each time considering a number of TCUs equal to one tenth of the total number of TCUs. Fig. 8 shows the comparison between the ten values of the weights computed for each class of the four relevant independents variable (\( V1, V2, V4, V6 \)) in the ten subsets of the test area and the values assumed by the same weights at the end of calibration. The figure shows a satisfactory agreement between the two sets of data. Indeed, the absolute value of the difference between the originally calibrated weights and the average values of the weights computed for each class of each variable in each random sample (see average lines in the figure) is always lower than 0.5 (see red lines and whiskers in the figure).

To produce the landslide map for zonings purposes, two types of terrain zoning units (TZUs) have been tested and compared: TZUs defined aggregating multiple TCUs; TZUs defined employing focal statistic techniques. For each type of TZU, three characteristic dimensions, herein indicated with the letters \( L_k \) and \( D_k \) respectively for the first and second type of units (see Fig. 2), have been considered: 8, 16 and 32. The resulting landslide susceptibility zoning maps are thus six (Fig. 9). The maps may be comparatively evaluated by computing, like in model calibration, the AUC of the ROC curves (Fig. 10). A pairwise comparison between maps resulting from the two different types of TZUs and equal characteristic dimensions always designate focal statistic as the method yielding the best results. Among the three maps produced considering TZUs defined by focal statistic, the optimal landslide susceptibility zoning map for the test area may be considered the one characterised by a value of \( D_k \) equal to 16 TCUs (Fig. 9e).

### 3.2. Large scale

The test area analysed at large scale (1:5000) covers approximately 8 km² within the area used for the analysis at medium scale. All the variables employed in the statistical model have been expressed in raster format using square grid cells, whose size is equal to 5 x 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 two landslide inventories reporting 188 phenomena which occurred in 2009 and 429 phenomena which occurred in 2010. The TCUs affected by landslides in the two cases are 6632 and 17,473, respectively for the years 2009 and 2010. The independent variables used in the analysis (Fig. 11, Table 4) are the following: elevation zone (\( V1 \)); slope gradient (\( V2 \)); slope aspect (\( V3 \)); slope curvature (\( V4 \)); distance from river network (\( V5 \)); distance from faults (\( V6 \)); geological unit (\( V7 \)); thickness of weathered rock (\( V8 \)). Six of these variables (\( V1, V5, V7 \)) have been also used, albeit with a different spatial resolution, for the analysis at medium scale; the remaining two variables (\( V6, V8 \)) are derived from thematic information only available at this scale. Like in the previous analysis, all the numerical variables (\( V1 \) to \( V6 \)) have been classified according to a quantile criterion employing eight classes. The categorical variables (\( V7, V8 \)) have been divided, following the classification reported in the employed thematic maps, in six and eight classes, respectively.

Model calibration is performed considering the dependent variable derived from the 2009 landslide inventory. The values of the statistics used to select the relevant independent variables of the analysis are reported in Tables 5 and 6. The main comments to the values reported in Table 5 are the following: high values of weights are computed for a number of classes for variables \( V1, V2, V4 \) and \( V8 \) (\( W_{18} = 0.66, W_{28} = 0.75, W_{45} = 0.58, W_{58} = 0.50 \)); out of the eight classes of variable \( V6 \), only one geological unit, which is the class corresponding to Pliocene light blue-grey silty clays, assumes a weight value higher than 0.01 (\( W_{16} = 0.35 \)); many classes of variables \( V1, V2 \) and \( V7 \) are characterised by weight values lower than 1.00, at times equal to 0.00 (imposed when landslides are not inventoried in that class), which indicate a strong correlation between the territory classified within those classes and the absence of shallow landslides. The independent variables defined as relevant for the analysis (\( V1, V2, V4, V7, V8 \)) are reported in Table 6, which also shows, for each variable: the number of grid cells included in each term of the 2 x 2 contingency table (\( TP, FN, FP, TN \)); the values of the two statistics needed to compute the bivariate success index (TPR, FPR); the bivariate success index (\( \beta \)); the bivariate standard deviation index of the normalized weights.

### Table 5

<table>
<thead>
<tr>
<th>Weights</th>
<th>( V1 )</th>
<th>( V2 )</th>
<th>( V3 )</th>
<th>( V4 )</th>
<th>( V5 )</th>
<th>( V6 )</th>
<th>( V7 )</th>
<th>( V8 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( W_{11} )</td>
<td>−3.00</td>
<td>−2.05</td>
<td>−0.02</td>
<td>0.58</td>
<td>0.40</td>
<td>0.35</td>
<td>0.30</td>
<td>0.04</td>
</tr>
<tr>
<td>( W_{12} )</td>
<td>−3.00</td>
<td>−1.87</td>
<td>0.14</td>
<td>0.25</td>
<td>0.17</td>
<td>0.01</td>
<td>−3.00</td>
<td>0.50</td>
</tr>
<tr>
<td>( W_{13} )</td>
<td>−3.00</td>
<td>−1.02</td>
<td>−0.03</td>
<td>−0.21</td>
<td>−0.06</td>
<td>0.01</td>
<td>−0.34</td>
<td>0.17</td>
</tr>
<tr>
<td>( W_{14} )</td>
<td>−3.00</td>
<td>−0.82</td>
<td>0.05</td>
<td>−0.54</td>
<td>0.00</td>
<td>−0.12</td>
<td>0.23</td>
<td>0.07</td>
</tr>
<tr>
<td>( W_{1s} )</td>
<td>−1.42</td>
<td>−0.40</td>
<td>0.13</td>
<td>−0.50</td>
<td>−0.25</td>
<td>−0.08</td>
<td>0.25</td>
<td>−0.44</td>
</tr>
<tr>
<td>( W_{1f} )</td>
<td>0.02</td>
<td>−0.01</td>
<td>0.01</td>
<td>−0.09</td>
<td>−0.24</td>
<td>−0.15</td>
<td>0.05</td>
<td>−0.04</td>
</tr>
<tr>
<td>( W_{1g} )</td>
<td>0.37</td>
<td>0.35</td>
<td>0.08</td>
<td>0.74</td>
<td>0.07</td>
<td>0.41</td>
<td>0.09</td>
<td>−3.00</td>
</tr>
<tr>
<td>( W_{1h} )</td>
<td>0.66</td>
<td>0.75</td>
<td>−0.46</td>
<td>−0.02</td>
<td>−0.41</td>
<td>0.34</td>
<td>−3.00</td>
<td></td>
</tr>
</tbody>
</table>

### Table 6

<table>
<thead>
<tr>
<th>Variables</th>
<th>( TN )</th>
<th>( TP )</th>
<th>( FN )</th>
<th>( FP )</th>
<th>( TPR )</th>
<th>( FPR )</th>
<th>( \beta )</th>
<th>( \sigma )</th>
<th>Relevant</th>
</tr>
</thead>
<tbody>
<tr>
<td>( V1 )</td>
<td>195,749</td>
<td>6601</td>
<td>31</td>
<td>113,921</td>
<td>99.5%</td>
<td>38.6%</td>
<td>2.71</td>
<td>1.66</td>
<td>Yes</td>
</tr>
<tr>
<td>( V2 )</td>
<td>246,708</td>
<td>5171</td>
<td>1461</td>
<td>62,962</td>
<td>78.0%</td>
<td>50.3%</td>
<td>1.24</td>
<td>0.20</td>
<td>Yes</td>
</tr>
<tr>
<td>( V3 )</td>
<td>153,118</td>
<td>4156</td>
<td>2476</td>
<td>156,552</td>
<td>62.7%</td>
<td>50.6%</td>
<td>3.83</td>
<td>1.00</td>
<td>Yes</td>
</tr>
<tr>
<td>( V4 )</td>
<td>216,717</td>
<td>4220</td>
<td>2412</td>
<td>92,953</td>
<td>63.6%</td>
<td>30.0%</td>
<td>2.12</td>
<td>0.42</td>
<td>Yes</td>
</tr>
<tr>
<td>( V5 )</td>
<td>231,367</td>
<td>3605</td>
<td>3027</td>
<td>78,303</td>
<td>54.6%</td>
<td>25.3%</td>
<td>2.15</td>
<td>0.31</td>
<td>No</td>
</tr>
<tr>
<td>( V6 )</td>
<td>192,056</td>
<td>3700</td>
<td>2932</td>
<td>117,614</td>
<td>55.6%</td>
<td>38.0%</td>
<td>1.72</td>
<td>0.20</td>
<td>No</td>
</tr>
<tr>
<td>( V7 )</td>
<td>148,993</td>
<td>5916</td>
<td>716</td>
<td>160,677</td>
<td>89.2%</td>
<td>51.9%</td>
<td>1.72</td>
<td>1.19</td>
<td>Yes</td>
</tr>
<tr>
<td>( V8 )</td>
<td>153,789</td>
<td>6251</td>
<td>381</td>
<td>155,881</td>
<td>94.3%</td>
<td>50.3%</td>
<td>1.87</td>
<td>2.19</td>
<td>Yes</td>
</tr>
</tbody>
</table>
(\(\sigma_i\)). As already explained, the relevant variables are the ones for which the two indexes assume values higher than two specified thresholds, herein assumed equal to 1.7 for \(\beta_i\) and 0.4 for \(\sigma_i\). Fig. 12 shows the results of the analysis in terms of calibrated landslide susceptibility computational map. The three susceptibility descriptors used in this map are defined on the basis of the values assumed by the multivariate computational susceptibility index, ISTCU, as follows: low susceptibility, for ISTCU \(\leq 0.0\); medium susceptibility, for \(0 < \text{ISTCU} \leq 1.0\); high susceptibility, for \(\text{ISTCU} > 1.0\). The results indicate that about 29\% of the test area is characterised by medium or high susceptibility (i.e. ISTCU \(\geq 0.0\)). The success of the analysis is testified by the high value assumed by the area under curve (AUC equal to 89.7\%) of the ROC curve plotted in the sensitivity versus \((1 - \text{specificity})\) space.

Model validation at this scale is performed by comparing the calibrated computational map, defined using the 2009 landslide inventory of shallow landslides, with a dependent variable defined using the 2010 landslide inventory (Fig. 13). In particular, validation is carried out by computing a model true positive rate, TPR\(_{\text{model}}\) (Eq. (6)), and checking that its value is higher than a specified threshold value, herein assumed equal to 80\%. Using the definitions of accuracy provided by Fressard et al. (2014) for the AUC of a ROC curve, the assumed threshold is representative of the boundary between a “fair level” of forecasting ability and a “good level” of forecasting ability. The results of the analysis performed herein yield a value of TPR\(_{\text{model}}\) equal to 94\% indicating an “excellent level” of forecasting ability.

To produce the landslide map for zoning purposes, two types of terrain zoning units (TZUs) with three characteristic dimensions—respectively equal to 8, 16 and 32 TCUs—have been tested and compared. The resulting six landslide susceptibility zoning maps (Fig. 14) are comparatively evaluated by computing, like in model calibration, the AUC of the ROC curves (Fig. 15). A pairwise comparison between maps resulting from the two different types of TZUs and equal characteristic dimensions always designates focal statistic as the method yielding the best results; among them, the optimal landslide susceptibility zoning map for the test area may be considered the one characterised by a value of D\(_k\) equal to 16 TCUs (Fig. 14e).

4. Discussion and concluding remarks

The proposed methodology has been applied, within a test area in southern Italy, at medium and large scale in order to evaluate both the applicability of the procedure and the consistency of the results obtained for the same phenomena in the same geo-environmental context at two different scales of analysis.

The success of the analyses at both scales is proved by the very high values attained by the two statistical indicators used to the purpose (i.e. true positive rate and AUC values of the ROC curves). The comparison between the models calibrated at different scales also highlights a high level of consistency between the two analyses in relation to the independent variables identified as the most relevant predisposing factors of shallow landsliding in the area. Indeed, in both analyses the following four variables were selected for landslide susceptibility assessment: elevation zone, slope gradient, slope curvature and geology. In addition to those, the analysis at large scale also used a fifth variable, only available at this scale, to explicitly consider the important role played by the weathered rock thickness. Validation of the calibrated models was performed using a different procedure for each scale of analysis, due to the different temporal characteristics of the datasets used to define the dependent variable in the two cases. Independently of the adopted
procedure, the outcomes of this stage underline adequate model calibration in both cases.

In relation to the terrain units used for the discretization of the zoning map derived from the two computational maps, two approaches were employed and compared. The first approach aggregates multiple terrain computational units (TCU) into a larger terrain zoning unit (TZU). The second approach uses focal statistic techniques to define TZUs having the same dimensions of the TCUs yet containing information related to a larger area around them. The focal statistics approach gave better results at both scales, with an optimal value of the characteristic dimension of the area of influence equal to 16 TCUs. This dimension is coherent with the minimum dimension of the TZUs suggested, in relation to the scale of zoning, by Calvello et al. (2013).

A comparison of the optimal landslide susceptibility zoning maps at the two different scales is carried out for the test area used at the larger scale, which covers about 8 km² (Fig. 16). The territory identified as susceptible within this area decreases moving from medium to large scale, with values respectively equal to 3.2 km² to 2.6 km². This result may be associated to i) the different informative resolution of the variables adopted at the two scales, and ii) the use of the weathered rock thickness as an additional relevant statistical variable for the analysis at large scale.

As a final remark, it is worth stating that the characteristics of the landslide susceptibility zoning methodology herein proposed makes its application generalizable also in relation to other types of landslides and other geo-environmental contexts. Clearly, the results of the statistical analysis are always strongly dependent on quantity and quality of the information provided in relation to the relevant landslide predisposing factors over the study area. Therefore, in any case, an exhaustive understanding of the main physical and mechanical characteristics of the considered phenomena must precede the application of the proposed statistical methodology if one wants that the resulting landslide zoning maps is significant and useful for land use planning.

Acknowledgements

The study has been partially supported by the Project of National Relevance PRIN 2010-2011 (CUP D41J12000460001) “Landslide risk mitigation through sustainable countermeasures”, funded by the Italian Ministry of Education (MIUR).
Fig. 15. Receiver operating characteristic curves for the six landslide susceptibility zoning maps at large scale reported in Fig. 14. (a) ROC curves obtained by aggregation; (b) ROC curves obtained by focal statistics.

Fig. 16. Comparison between the optimal landslide susceptibility zoning maps resulting, over the test area analysed at both scales, from the analyses at: (a) 1:25,000 scale; (b) 1:5000 scale.


