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Landslide zoning over large areas from a sample inventory by means of scale-dependent terrain units

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ABSTRACT

A procedure is proposed to produce landslide distribution zoning maps to be considered preparatory to susceptibility, hazard and risk zoning maps, based on 1) the results from a statistical multivariate analysis of a landslide inventory, which must be available for only a portion of the territory to be zoned, and 2) the use of appropriately defined terrain mapping units. The units are divided into terrain computational units (TCUs) and terrain zoning units (TZUs), whose size is related to the scale of zoning. The procedure comprises three phases: calibration, validation and prediction. The purpose of the prediction phase is the application of a calibrated and validated statistical model in a territory, previously recognized as viable on the basis of 'a-priori applicability maps,' for which no information is available regarding the distribution of landslides or where the information provided by the landslides inventory is unreliable or heterogeneous. The proposed procedure is applied to two case studies in southern Italy for the analysis and zoning of slow-moving landslides at 1:25,000 and 1:100,000 scales, respectively. The first case study illustrates the applicability of the procedure. The aim of the second case study is to address the part of the procedure related to the evaluation of the computational maps at the end of the calibration and validation phases.

1. Introduction

The "Guidelines for Landslide Susceptibility, Hazard and Risk Zoning for Land Use Planning" (Fell et al., 2008a) define landslide zoning as the division of land into homogeneous areas or domains and their ranking according to degrees of actual or potential landslide susceptibility, hazard or risk or based on the applicability of certain hazard-related regulations. Within this process, the analysis of past events, i.e. the use of an inventory including the location, classification, volume, activity, date of occurrence and other characteristics of landslides in an area (Fell et al., 2008a), is essential to the calibration and validation of any model leading to landslide susceptibility assessment, which is the first step in the landslide risk management framework proposed by Fell et al. (2005).

The existing literature offers many definitions and interpretations of landslide susceptibility (e.g., Brabb, 1984; Soeters and Van Westen, 1996; Guzzetti et al., 1999; Dai and Lee, 2002; Remondo et al., 2003; Santacana et al., 2003; Guzzetti, 2005; Fell et al., 2008a). The most useful definitions of the term seem to be the ones proposed by Brabb (1984) and Fell et al. (2008a), as they clearly highlight the significant and relevant aspects related to landslide susceptibility zoning. Particularly, Brabb's (1984) definition stresses the forecasting nature of susceptibility maps on the basis of the following principle introduced by Varnes (1984): the past and present are keys to the future. As a consequence, the application of this concept implies that future landslides are likely to occur in the same geological, geomorphological and hydrological processes that have led to instability in the past till the present. Based on this principle, it is also apparent that the susceptibility is a feature on a territory that could be considered "homogeneous" with respect to landslide occurrences in both space and time. On the other hand, Fell et al. (2008a) highlight the need to select landslides to be considered for the creation of susceptibility maps, both in terms of size and type. Therefore, reliability, completeness and resolution must be considered when preparing and using a landslide inventory map.

When reliable and complete landslide inventories are not available for landslide zoning, two alternative approaches may be employed: (i) producing a new reliable landslide inventory over the entire area to be zoned, or (ii) producing a new landslide inventory over a portion of the area and developing a model to identify the relationship between landslides and other available thematic information; then using the model to export the results to the remaining area. Herein, following the second approach, a procedure is proposed that facilitates the production of landslide distribution zoning maps over large areas of a territory using appropriately defined terrain mapping units or TMUs (e.g., Hansen, 1984; Guzzetti, 2005), and the results of statistical multivariate analyses (e.g., Carrara, 1983; Guzzetti et al., 1999) of a landslide inventory that is available only for a portion of the territory to be zoned. The maps, which are to be considered preparatory to susceptibility, hazard and risk zoning maps, infer the expected occurrence of landslides in any part of the

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Table 1
Mapping scales for landslide inventories and susceptibility zoning in relation to landslide zoning methods, levels and purposes (modified from Fell et al., 2008a and Cascini, 2008).

Purpose	Scale		Applicability of zoning methods	Examples	Typical area
Regional zoning – information	Small	<1:100,000	Basic (applicable) Intermediate (inapplicable) Advanced (inapplicable)	Landslide inventory and susceptibility zoning to inform policy makers and the general public	>10,000 km^2
Regional zoning – information – advisory	Medium	1:100,000 to 1:25,000	Basic (applicable) Intermediate (may be applicable) Advanced (inapplicable)	Landslide inventory and susceptibility zoning for regional development; or very large scale engineering projects.	1000 to 10,000 km^2
Local zoning – information – advisory – statutory	Large	1:25,000 to 1:5000	Basic (applicable) Intermediate (applicable) Advanced (applicable)	Landslide inventory, susceptibility and hazard zoning for local areas	10 to 1000 km^2

investigated area, i.e. without leaving unclassified areas. These maps are hereafter called 'landslide distribution zoning maps' because they are used for zoning purposes and employ terrain subdivisions related to topography at the scale of the analysis, rather than to landslide spatial features.

2. Terrain units for landslide zoning maps at different scales

Reference scale is a key aspect of any landslide analysis including landslide density zoning, because the aims and objectives of such analyses and the methods used differ as a function of spatial scale. Fell et al. (2008a) indicate that landslide zoning maps should be prepared at a scale appropriate for displaying necessary information at a particular zoning level and the scale should be selected by considering the objectives of the map. Cascini (2008) observes that: (i) input data used to produce landslide zoning maps must have appropriate resolutions and quality, and (ii) the inventory used should be mapped at a larger scale than susceptibility zoning maps. Table 1 summarizes relationships among purposes, zoning methods and mapping scales for landslide inventory and susceptibility zoning. Fell et al. (2008a) and Cascini (2008) group zoning methods into three categories: 1) basic methods — heuristic and empirical procedures that process essentially topographic, geological and geomorphological data; 2) intermediate methods — procedures based on statistical analyses; and 3) advanced methods — deterministic or probabilistic procedures using hydrogeological and geotechnical data. Depending on the scale and methods to be adopted, three different purposes are defined for regional and local zoning over large areas, i.e. information, advisory and statutory. Table 1 also provides typical examples of zoning as a function of the scale of analysis.

All zoning is based on the discretization of a territory into map units. As Hansen (1984) defines, a TMU is a portion of land surface that contains a set of ground conditions that differ from the adjacent units across definable boundaries. At the analysis scale, a TMU represents a domain that maximizes internal homogeneity and between-units heterogeneity (Guzzetti, 2005). Several methods have been proposed in the literature for the identification of map units for landslide analyses (e.g., Meijerink, 1988; Carrara et al., 1995; Soeters and van Westen, 1996; Guzzetti et al., 1999). Choosing the most appropriate mapping unit depends on a number of factors, including the type of landslide phenomena to be studied; the scale of the investigation; the quality, resolution, scale and type of the thematic information required; and the availability of adequate information management and analysis tools.

According to the previously discussed issues, it is evident that the selection of an appropriate terrain subdivision, which must be defined by considering both the scale of the analysis and landslide types, is mandatory for the reliability of any landslide zoning procedure. There are two aspects related to landslide analyses that make this choice relevant: computation and zoning. To address this issue, a distinction is proposed 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). Indeed, at a given scale, a map classifying the portions of a territory that result from the discretization of the spatial model used within a landslide analysis of that territory, i.e. a computational map, does not necessarily need to be equal to the discretization of the territory appropriate for a landslide map for zoning purposes at that scale, i.e. a zoning map. The latter, for instance, could be the useful result of a manipulation of the computational results, such as the aggregation of multiple computational terrain units into a single zoning unit.

A very important issue, when dealing with such units, is the definition of their appropriate size, which must be related to the scale of analysis. The minimum area of terrain units for computational purposes at a given scale (minimum area of TCUs) is smaller than the minimum area of terrain units for zoning purposes at that scale (minimum area of TZUs), because the minimum area of a TCU is related to the 'spatial resolution' of the map, i.e. the measure of the smallest area identifiable on the map as a discrete separate unit, whereas the minimum area of a TZU is related to the desired 'informative resolution' of the zoning. For instance, when a regular square grid is used, such as for raster files in a GIS environment, a commonly used dimension of cell size is 1/1000 of the scale factor, such that the area covered by each elementary pixel increases as the scale of analysis decreases whereas, regardless of the scale, the size of each square cell on paper is always 1×1 mm. This criterion is surely adequate for defining terrain units for computational purposes (TCUs); however, it is inappropriate for a zoning map at that scale because the dimensions of the terrain units (TZUs) would be too small for zoning purposes.

Table 2
Suggested dimensions of the terrain zoning units (TZUs) at different scales.

Reference scale	Elementary pixel dimension		Minimum and maximum TZU dimensions	
	Side length (m)	Area (m^2)	Number of elementary pixels	Area (km^2)
1:X	X 10^{-3}	$X^2\ 10^{-6}$	16–1600	16 X^2–1600 X^2
1:250,000	250	62,500	16–1600	1–100
1:100,000	100	10,000	16–1600	0.16–16
1:25,000	25	625	16–1600	0.01–1
1:5000	5	25	16–1600	0.004–0.4

A size criterion is herein proposed to be used when defining the landslide zoning units at a given scale. The dimensions of the suggested TZUs at different scales are presented in Table 2. The suggested minimum dimension of the TZU is set to 16 elementary pixels corresponding to, regardless of scale, an area of 16 mm^2 on paper. This proposal is consistent with the criteria defined to represent the landslides in the Italian national landslide inventory produced by the IFFI Project (APAT, 2007) and the commentary on the international guidelines for landslide susceptibility, hazard and risk zoning for land use planning (Fell et al., 2008b), in which the authors state "Different information can be mapped depending on the scale. For example: (a) Inventory scale 1:50,000 to 1:100,000 for regional zoning. The minimum area covered by an inventoried landslide is 4 ha. Smaller landslides may be represented by a dot… (b) Landslide inventory at scale 1:10,000 to 1:25,000 for local zoning. The minimum area covered by an inventoried and mapped landslide is 1600 m^2. Smaller landslides are represented by a dot." The maximum dimension of the TZU is suggested to differ from its minimum dimension by two orders of magnitude, i.e. the maximum suggested dimension of the TZU is set to 1600 elementary pixels corresponding to, regardless of scale, an area of 16 cm^2 on paper. This criterion was conceived according to easiness and appropriateness. Regarding easiness, an 'order of magnitude' concept was employed. Two orders of magnitude in area correspond to one order of magnitude in length. A well know example in the landslide literature that employs this concept is the seven-class velocity classification of landslide movements by Cruden and Varnes (1996) whose boundaries always differ by two orders of magnitude. Regarding appropriateness, in addition to the two examples shown in Fig. 1, which respectively refer to 1:250,000 and 1:25,000 scales, the authors believe that 16 cm^2 on paper is also an appropriate upper boundary at very small scales. For instance, a region with an area of 10,000 km^2 would plot in a 1:2,500,000 scale, i.e. a commonly used national scale, as a polygon with an area of 16 cm^2.

Fig. 1 shows two examples of territory zoning using TZUs whose sizes are appropriate, according to the criteria defined above, for the scale of zoning. Fig. 1a refers to an area of about 2000 km^2, specifically the territory of a province in southern Italy (Benevento) to be zoned at 1:250,000 scale, and employs TZUs obtained using the administrative limits of the municipalities. Fig. 1b refers to an area of 120 km^2, specifically the territory of a river basin in southern Italy (Tammarecchia) to be zoned at 1:25,000 scale, and employs TZUs obtained using hydro-geological units. The two graphs on the right side of Fig. 1 show the area of the TZUs on the vertical axis (in logarithmic scale) and the corresponding TZUs on the horizontal axis, ordered according to their increasing size. In Fig. 1a, each bar represents one municipality and in Fig. 1b, each bar represents a hydro-geological unit. These examples indicate that the TZU dimensions vary greatly in both analyses. However, the vast majority of the areas (95% in Fig. 1a and 89% in Fig. 1b) fall within the previously-defined limits, which are drawn with red horizontal lines in the two graphs.

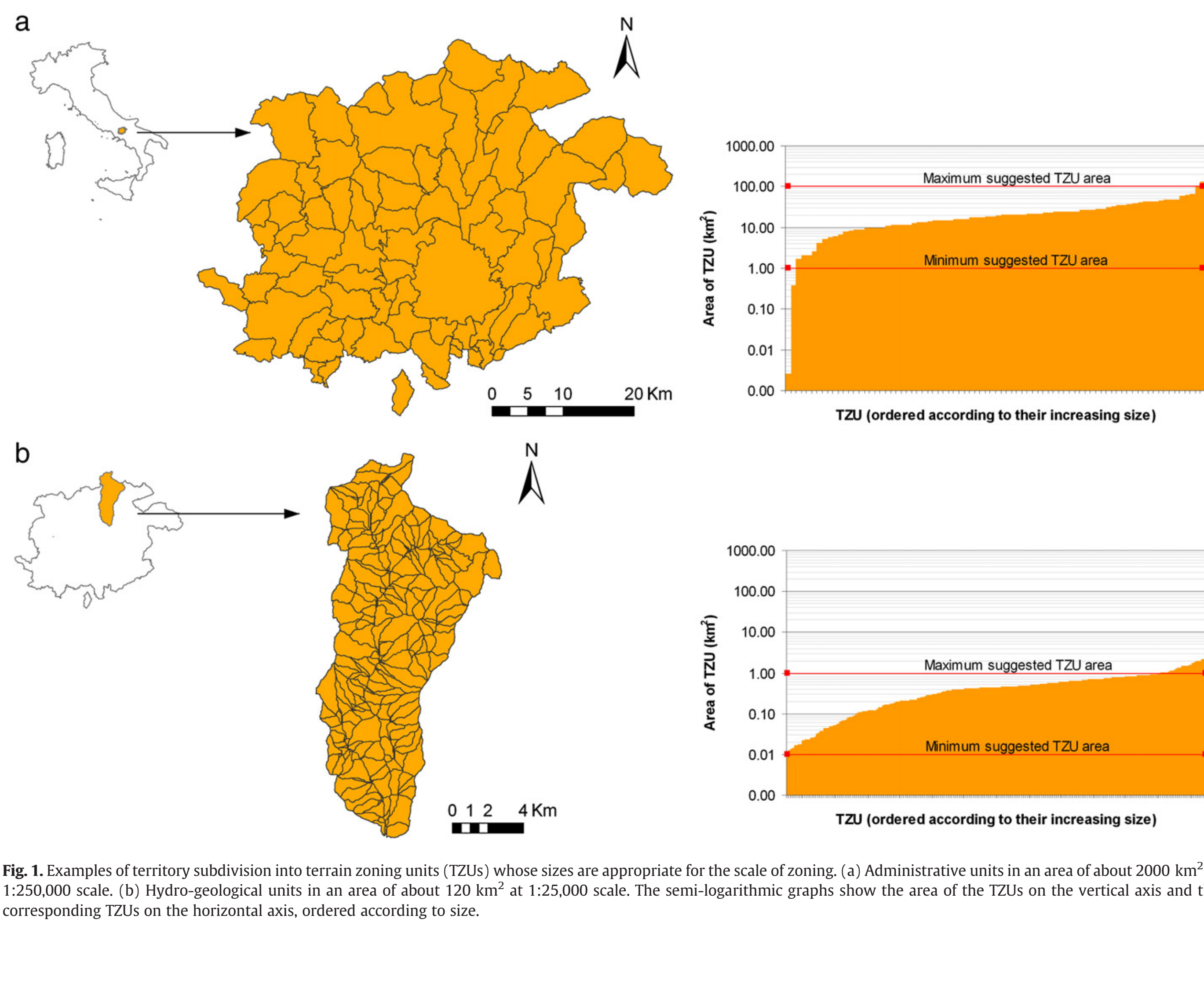

Fig. 1. Examples of territory subdivision into terrain zoning units (TZUs) whose sizes are appropriate for the scale of zoning. (a) Administrative units in an area of about 2000 km^2 at 1:250,000 scale. (b) Hydro-geological units in an area of about 120 km^2 at 1:25,000 scale. The semi-logarithmic graphs show the area of the TZUs on the vertical axis and the corresponding TZUs on the horizontal axis, ordered according to size.

3. Landslide distribution zoning maps from the statistical analysis of sample inventories

Numerous studies evaluated landslide susceptibility over large areas by means of quantitative methods, i.e. data driven statistical analyses (e.g., Carrara, 1983; Guzzetti et al., 1999; van Westen, 2004). In the majority of them, susceptibility zoning maps were generated by a model relating known landslide occurrences to relevant thematic layers by exploiting the principle that "the past and present are keys to the future" (Varnes, 1984), thus employing the statistical concept whereby the density of an event equals the probability that the same event will occur, i.e. landslide susceptibility equals landslide density. This is often an appropriate assumption, such as when a susceptibility analysis deals with the first failures of fast-moving phenomena (e.g., triggering areas of shallow landslides, debris flows or rock falls) and employs one of more landslide event maps created using well-defined triggering factors (e.g., exceptional rainfall events or earthquakes). However, this is not always true. For instance, if the aim of the susceptibility analysis is the possible reactivation of existing slow-moving landslides, such as deep-seated rotational and translational slides and earth flows (Varnes, 1978; Cruden and Varnes, 1996), then a reliable susceptibility model must consider, in addition to the presence of past landslides in the territory to be zoned, some objective information regarding the past and current state of activity for the phenomena. Nevertheless, in such cases a statistical correlation between existing landslides and relevant geomorphological predisposing factors may also be useful as a preliminary step towards this aim and the related hazard and risk analyses.

Based on these considerations and on the previously defined terrain zoning units, a procedure is proposed for landslide zoning over large areas from a landslide inventory available for a portion of the territory to be zoned. The final products of the proposed procedure are called 'landslide distribution zoning maps' and are considered cartographic products that lie between landslide inventory maps and susceptibility zoning maps. These landslide distribution zoning maps are based on a model that relates landslide density to the information provided by both significant thematic maps and a landslide inventory that should only be available for a portion of a geo-environmentally homogeneous territory. This approach allows for: (i) the definition of a clear relationship between input factors and landsliding features based on an objective interpretation of the geological/geomorphological criteria that produced the landslide inventory; and (ii) the possibility of using the relationship for landslide zoning over a territory, homogeneous with respect to the territory used to calibrate and validate the model, for which no information on the distribution of landslides is available or in areas where the information provided by the landslides inventory is unreliable or heterogeneous. The resultant maps should not be considered landslide inventories because they are maps for zoning purposes that employ TZUs related to the scale of the analysis and not to the spatial features of landslides.

A flow chart of the proposed procedure is presented in Fig. 2. The landslide analysis comprises three phases: calibration, validation and prediction. It is based on a statistical model that uses the information provided by an event map derived from a landslide inventory, and a series of relevant independent variables derived from thematic maps to create a landslide zoning or distribution map adequate to the zoning scale. For this aim, any statistical methodology that is able to identify and weight a number of significant independent variables based on the information provided by a dependent variable related to landslide occurrences is appropriate. Examples of the statistical methodologies commonly used for this purpose in landslide susceptibility and hazard studies are: discriminant analysis (e.g., Baeza and Corominas, 2001; Guzzetti et al., 2005; Frattini et al., 2008; Rossi et al., 2010), logistic regression (e.g., Ayalew and Yamagishi, 2005; Chau and Chan, 2005; Van Den Eeckhaut et al., 2006; Bai et al., 2010; Mancini et al., 2010; Atkinson and Massari, 2011), likelihood ratios (e.g., Chung, 2006; Lee et al., 2007; Dewitte et al., 2010), artificial neural networks (e.g., Ermini et al., 2005; Melchiorre et al., 2008; Nefeslioglu et al., 2008). The proposed procedure does not endorse any specific methodology, but rather prescribes the relationships between the statistical model and all of the other analysis elements, i.e. thematic maps, landslide inventories and terrain computational and zoning units.

The first phase of the analysis, calibration, begins with: the collection of input data, i.e. territorial thematic maps and a landslide inventory map to be analyzed; the choice of TCUs and TZUs for calculation and zoning, respectively; and the definition of a statistical methodology. Then, independent variables and an event map to be used in the statistical model are derived from the thematic and landslide inventory maps, respectively, based on numerical algorithms that consider the characteristics of the statistical model and the features of the input data. For example, qualitative thematic variables may need to be transformed into quantitative variables; dimensionless variables may be necessary; and only a subset of the landslide inventory may be useful as an event map. In the first part of the statistical analysis, the event map is used to derive the values of model parameters (e.g., indexes or weights of the independent variables). In the second part, the values are used to derive a computational landslide distribution map. This map is then used to evaluate the results of the analysis by comparing them to the event map. If the agreement between the two sets of data is satisfactory by means of success indexes, ROC curves and contingency tables, then the analysis moves to the next step. Otherwise, the correct application of the statistical model must be verified to evaluate the need to acquire and use other relevant thematic information that may be correlated with landslide occurrences and/or to examine the reliability of the input data. The reliability can be assessed in different ways, such as developing new studies in sample areas or comparing the data with other sources of information that may be only partially available in the area to be zoned, and thus could not be used in the multivariate analysis. The final step of this phase is the preparation of a landslide distribution zoning map, derived from an appropriate transformation algorithm of the computational map within the TZUs.

During the validation phase, the model is applied to a different territory to verify that the significant independent variables and the calibrated values of the model parameters are consistent with the model assumptions. For this aim, the territory chosen for validation purposes must be similar to the territory used to calibrate the model with a comparable geo-environmental setting and affected by a similar type of landslides. Similarly to the previous phase, the model first leads to a computational landslide map of the territory, then to a landslide zoning map as a function of the chosen TZUs. Like before, the first map is used to verify the results of the analysis by comparing it with the event map. If the agreement between the two sets of data is satisfactory, the analysis moves to the next phase; otherwise, the model must be reassessed and recalibrated using, for example, different combinations of calibration and validation areas. At the end of this stage, such assessments may be necessary if incoherent results arise.

The final phase of the analysis is the prediction phase, in which the calibrated and validated model is applied to a territory for which no information regarding the distribution of landslides is available, or in areas where the information provided by the landslides inventory is unreliable or heterogeneous. The prediction area is chosen using maps, hereafter called 'a-priori applicability maps,' which show the portions of the territory to which it

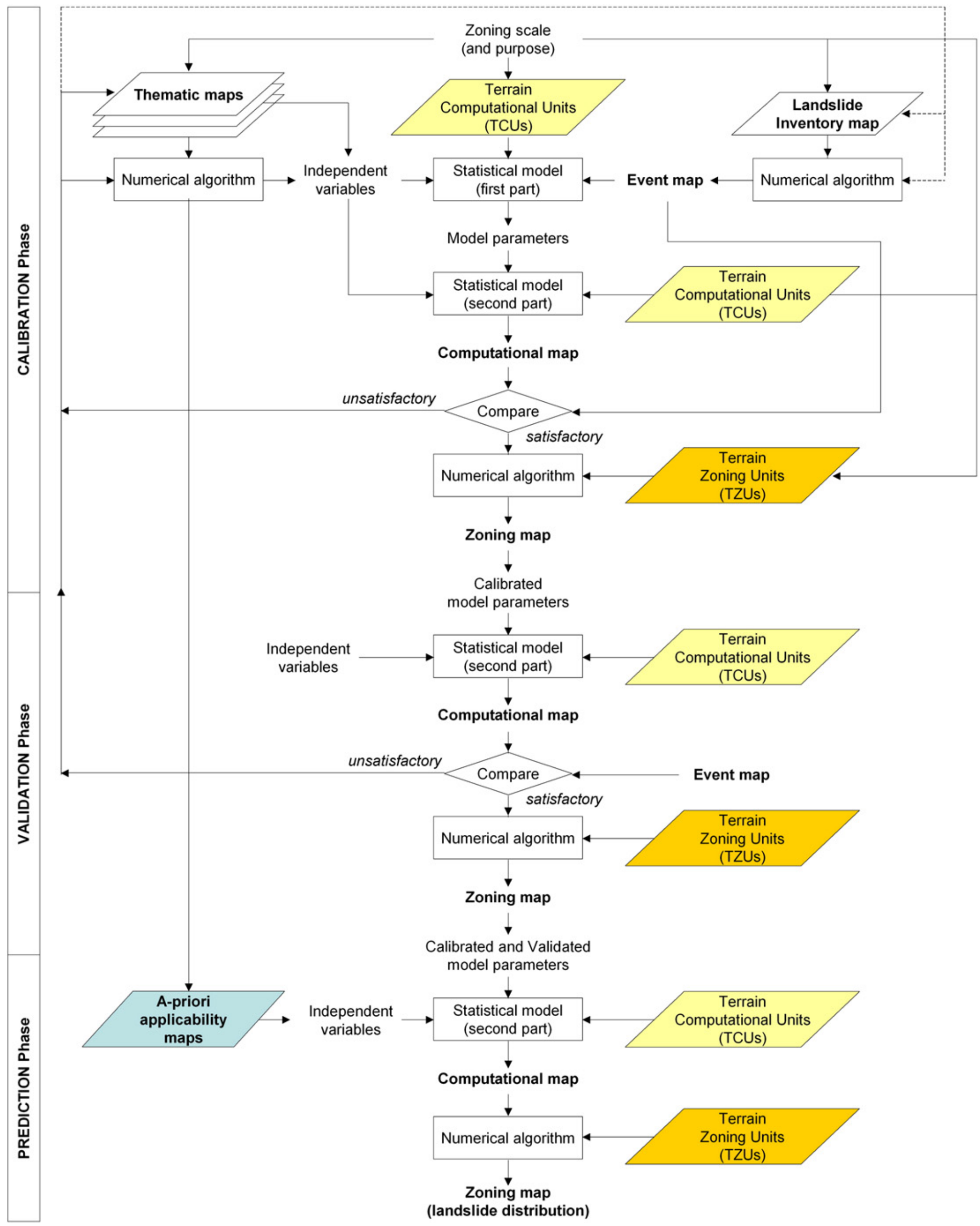

Fig. 2. Flow chart of the procedure for landslide zoning over a large area from a landslide inventory available for a portion of the territory to be zoned. Maps are in bold. Highlighted in the flowchart are TCUs (yellow), TZUs (orange) and the a-priori applicability maps (light blue).

would be possible to apply the calibrated model. Indeed, in addition to the availability of all of the thematic variables used in the model, a further constraint for the prediction is related to the absence, within the prediction area, of classes of variables that have not been exploited by the model during the calibration phase. Each significant thematic variable used in the model leads to one a-priori applicability map, which identifies the areas where the model parameters have been computed. For instance, if 'lithology' is among the independent variables used in the analysis, any portion of the territory with a lithology that does not occur in the calibration area cannot be included. The prediction area, where the calibrated model can be used, is derived from the intersection of all of the a-priori applicability maps. The final result of the analysis is a landslide distribution zoning map of the territory computed using a number of significant input variables, i.e. relevant territorial thematic maps, and employing TZUs that are appropriate for the scale of the analysis.

The main advantage of employing the proposed procedure is the production of landslide distribution zoning maps without the need for a landslide inventory that covers the whole territory to be zoned. During the first and second phase of the procedure, as an important by-product of the analysis, the reliability and homogeneity of the landslide inventory, which is used as the 'event map' within the statistical model, may also be ascertained.

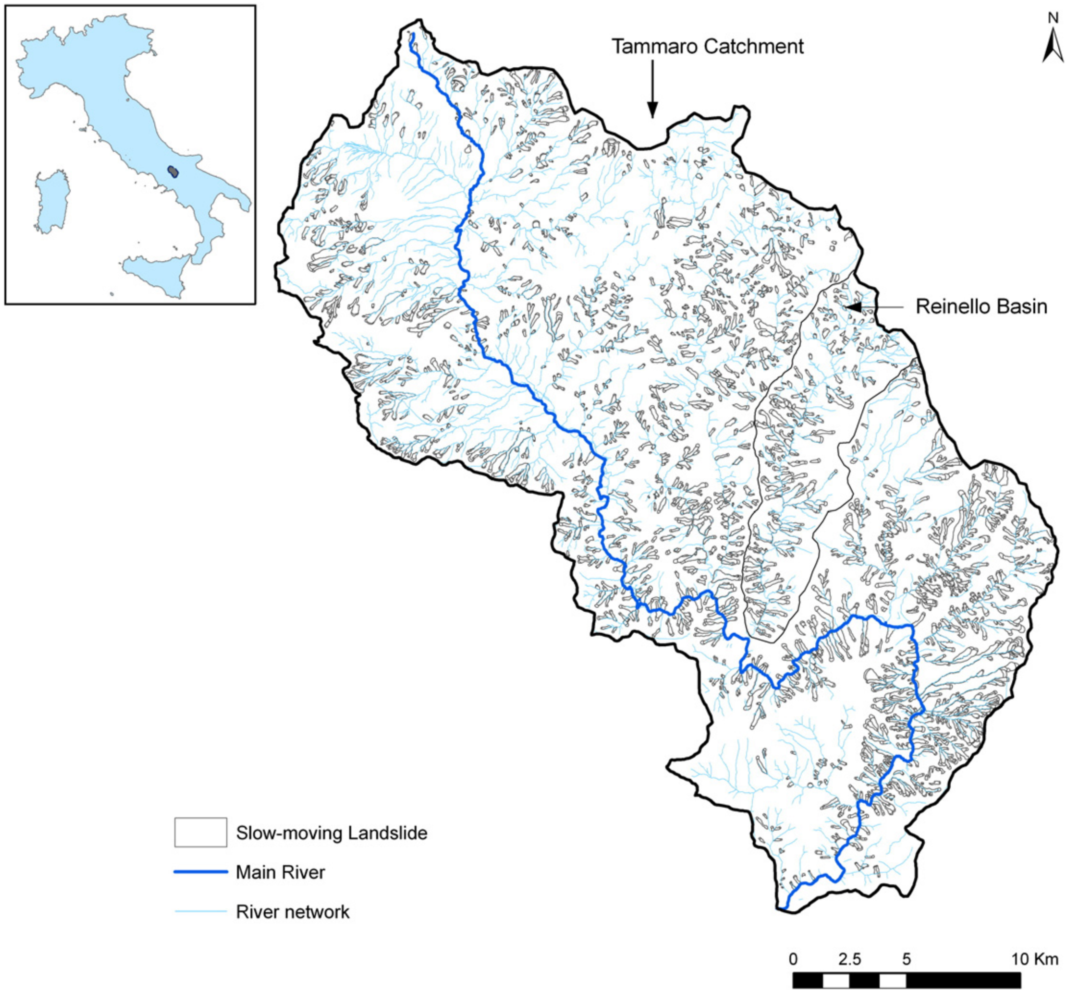

Fig. 3. Study area: the Tammaro catchment in southern Italy.

4. A case study at 1:25,000 scale

The analysis at 1:25,000 scale was performed with reference to a study area of about 670 km^2 (Fig. 3), which is the catchment of the Tammaro River, located in the Campania region of southern Italy. The landslide inventory within this area (APAT, 2007) indicates a large number of slow-moving landslides that affect more than 16% of the territory. The multivariate statistical analysis highlights the applicability of the proposed procedure for zoning the area with respect to slow-moving landslides classified as either rotational, translational slides or earth flows (Varnes, 1978).

The first two phases of the procedure, i.e. model calibration and validation, were applied to a 60 km^2 sub-catchment of the study area, specifically the Reinello River basin. Regarding the prediction phase, the model was applied to another portion of the Tammaro River basin chosen based on a-priori applicability maps. Although the usual aim of the prediction phase is the application of the model to a territory for which no information on the distribution of landslides is available, in this case study prediction is made for an area where a landslide inventory is present to evaluate the success of the prediction.

Fig. 4a shows the slow-moving landslides mapped within the territory of the Reinello River basin. The TZUs used in the analysis are hydro-geological units defined according to an algorithm (Fig. 4b) that considers both the drainage network and the geology of the area to define the homogenous units within the territory. In particular, these hydro-geological units were defined by intersecting slope terrain units, i.e. the intersection between the networks of drainage lines and ridges derived from a 25×25 m DEM and the seven classes of lithological thematic maps in the area (Fig. 4c). The subdivision of the territory according to the considered TZUs (Fig. 4d) is consistent with the size criterion proposed in Table 2. The TCUs are 25×25 m square cells derived from a 1:25,000 topographic map with 25-m spaced contour lines.

The statistical method used for this case study is discriminant analysis (e.g., Carrara, 1983; Baeza and Corominas, 2001; Ardizzone et al., 2002). This methodology is based on the evaluation, for each TCU, of a score that is used to discriminate between two groups of terrain units: landslide-affected and landslide-free areas. To avoid the bias of the obtained function, the discriminant analysis requires population sets with a similar number of individuals (Dillon and Goldstein, 1986). The total number of TCUs in the study area is about 90,000. The TCUs affected by landslides are about 18,000. Thus, only a subset of the TCUs within the landslide-free area was used during the calibration and validation phases. The two groups of terrain units were defined by taking both the total number of TCUs affected by slow-moving landslides and the same number of randomly chosen TCUs within the landslide-free area, and randomly splitting them in half. The discriminant score, or *DS*, was computed as a linear weighted combination of variables according to the following formula:

$$DS = A_1X_1 + A_2X_2 + A_3X_3 + \ldots + A_nX_n, \quad (1)$$

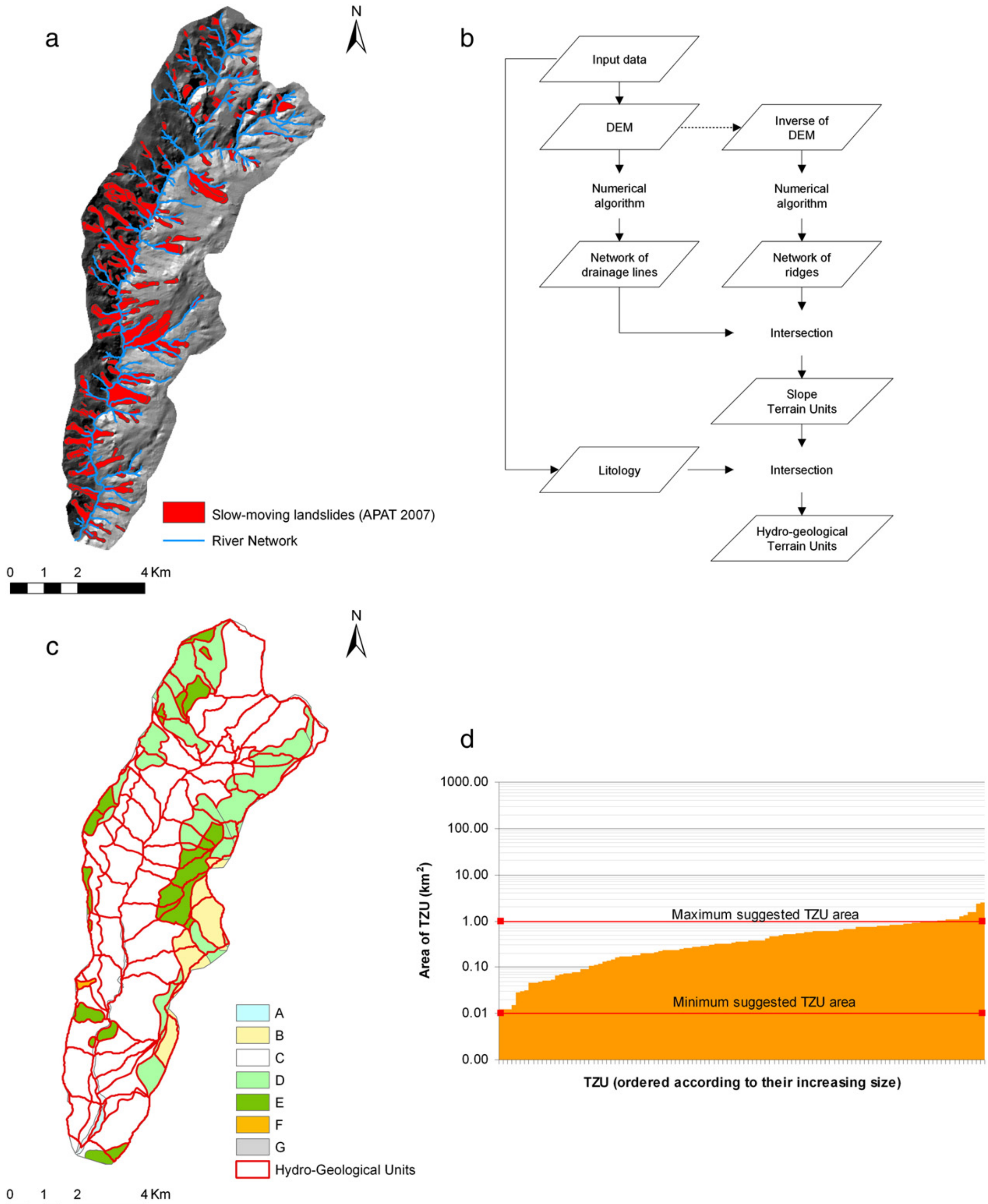

Fig. 4. Model calibration and validation in the Reinello basin. (a) Landslide inventory. (b) Procedure used to define hydro-geological TZUs. (c) Territory subdivision based on the TZUs. (d) Distribution of the TZU area and suggested limits for the minimum and maximum dimensions at 1:25,000 scale as proposed in Table 2. Legend for lithology in (c): A = alluvial deposits; B = pyroclastic soils; B = arenite sandstones, gray-green clays; D = turbidites, marl, red and green clays; E = rudites, sandstone, marl, red clays; F = turbidites, argillites; and G = gray-green and red marly clays and argillites.

where n = number of thematic variables considered in the analysis, X_i = value assumed by the i-th thematic variable (as shown later in Eq. (3), this is normalized and dimensionless), and A_i = weight of the i-th thematic variable.

Fig. 5 illustrates the eight thematic maps considered in the analysis of the case study: lithology (*GEO*), slope (*SLOPE*), distance from the river network (*DIST*), global curvature (*CURV*), profile curvature (*PROFILE*), plan curvature (*PLAN*), flow accumulation (*F_ACC*) and

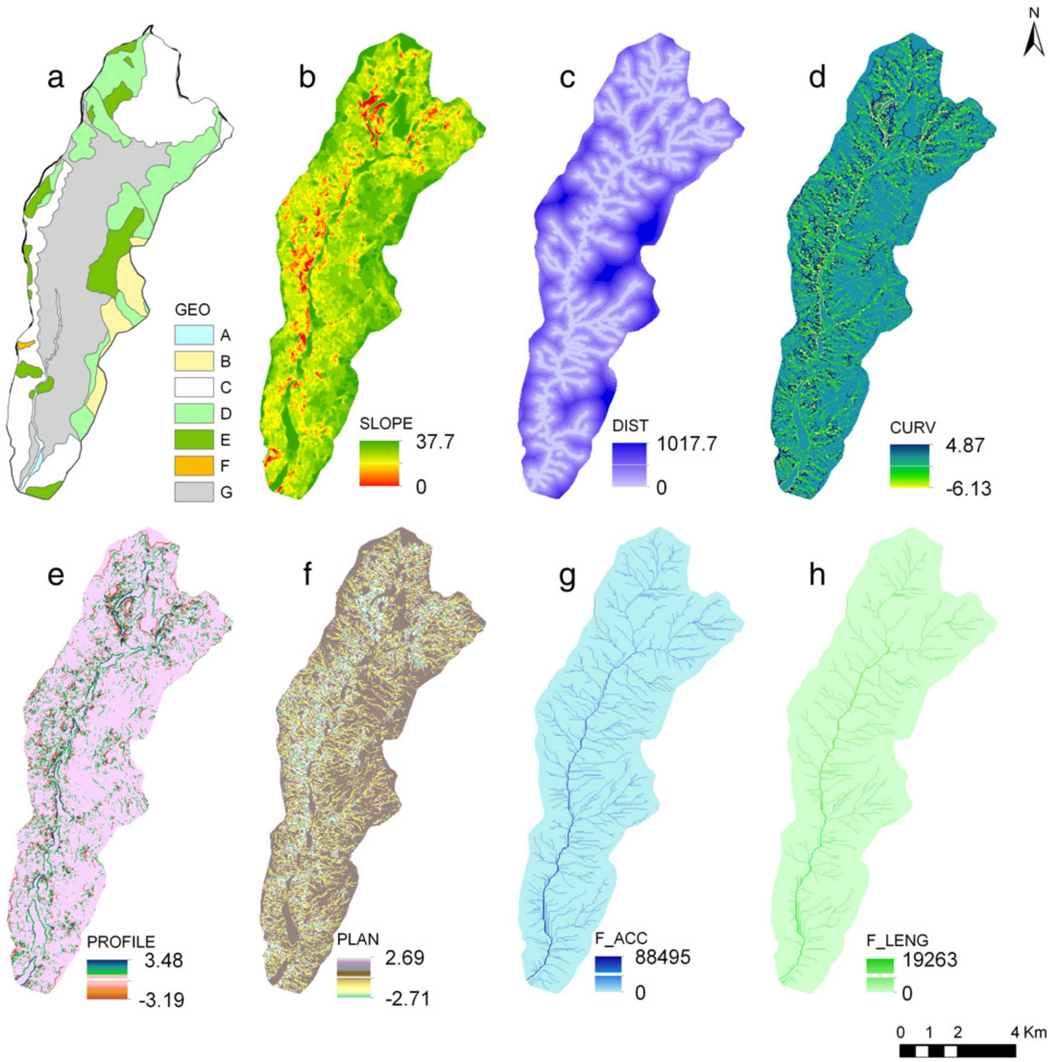

Fig. 5. Thematic maps employed in the analysis: lithology (*GEO*), slope (*SLOPE*), distance from the river network (*DIST*), global curvature (*CURV*), profile curvature (*PROFILE*), plan curvature (*PLAN*), flow accumulation (*F_ACC*) and flow length (*F_LENG*). Legend for lithology in (a): A = alluvial deposits; B = pyroclastic soils; C = arenite sandstones, gray-green clays; D = turbidites, marl, red and green clays; E = rudites, sandstone, marl, red clays; F = turbidites, argillites; and G = gray-green and red marly clays and argillites.

flow length (*F_LENG*). Before the discriminant analysis, a procedure in five steps was conducted to define the expression and number of appropriate independent and uncorrelated input variables, starting with the eight thematic variables considered.

In the first step, the qualitative thematic variables (e.g., *GEO*) were transformed into quantitative variables by considering the relative presence of landslides within each *j*-th thematic class of the qualitative variable. The following expression was used for this purpose:

$$x_i = \left[\frac{\frac{Area_j(L)}{Area_j}}{\frac{Area\_tot(L)}{Area\_tot}}\right], \tag{2}$$

where x_i = the *i*-th quantitative variable, $Area_j(L)$ = area of landslides within the *j*-th class of the original variable, $Area_j$ = area of the *j*-th class of the original variable, $Area\_tot(L)$ = total area of landslides, and $Area\_tot$ = total area.

In the second step, all of the quantitative variables that do not show a monotonic trend with respect to the landslide density (e.g., *SLOPE*) were transformed by dividing the range of values into a finite number of classes and then assigning to each class the landslide index defined in Eq. (2). This transformation defines a new variable that can be profitably used within a discriminant analysis, whose mathematical formulation only allows a linear correlation between any given variable and the landslide density.

In the third step, the values of the thematic variables were normalized into dimensionless numbers ranging from zero to one:

$$X_i = \frac{(x_i - x_{iMIN})}{(x_{iMAX} - x_{iMIN})}, \tag{3}$$

where X_i = the *i*-th normalized variable, x_i = value assumed by the *i*-th quantitative variable, x_{iMIN} = minimum value assumed by the *i*-th variable in the study area and x_{iMAX} = maximum value assumed by the *i*-th variable in the study area. This normalization defines a set of homogeneous variables whose values can be directly compared.

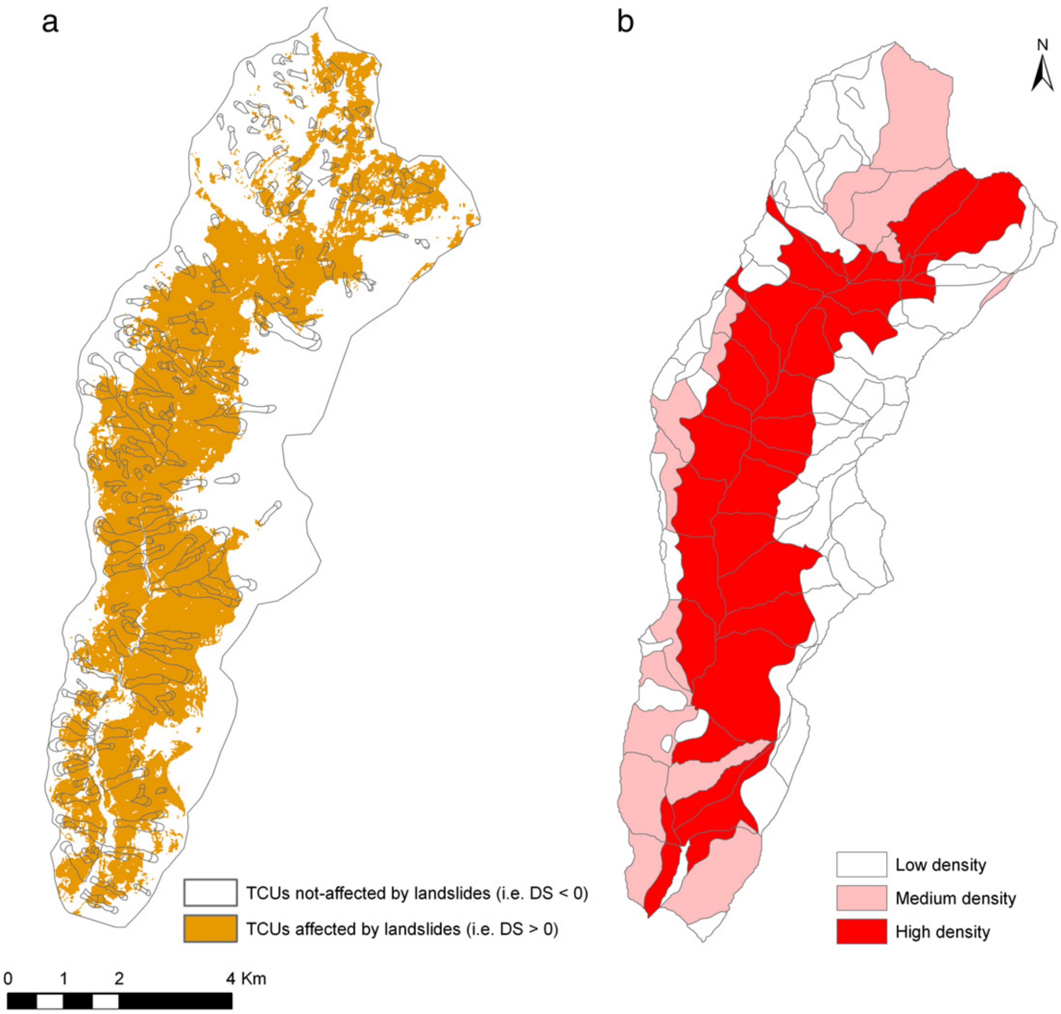

Fig. 6. Results of the calibration and validation phases for the Reinello basin. (a) TCUs affected by landslides, i.e. $DS>0$. (b) Final zoning map of the analysis, with three landslide density classes defined by considering the percentage of landslide-affected TCUs within each TZU.

Finally, the fourth and fifth steps identify which variables of the analysis to consider as independent and significant. Regarding the independence, the correlation matrix and the principal component analysis (PCA) were used. The results revealed high correlations among the three variables of curvature, X_{PLAN}, X_{CURV} and $X_{PROFILE}$, and between X_{F_ACC} and X_{F_LENG}. Regarding the significance, T- and one-way tests were used and the results showed that all independent variables are significant.

Table 3
2×2 contingency tables, calculated with reference to the computational map, within the territory of the Reinello basin: (a) calibration phase; and (b) validation phase.

(a) Calibration phase		Landslide inventory	
		Affected	Not affected
Model	Affected ($DS\geq 0$)	69.3%	41.7%
	Not affected ($DS<0$)	30.7%	58.3%

(b) Validation phase		Landslide inventory	
		Affected	Not affected
Model	Affected ($DS\geq 0$)	69.1%	40.9%
	Not affected ($DS<0$)	30.9%	59.1%

Considering the above results, five input variables, X_{GEO}, X_{SLOPE}, X_{DIST}, X_{PLAN} and X_{F_ACC}, were used for the discriminant analysis through a step-wise technique. The analysis determined the weights

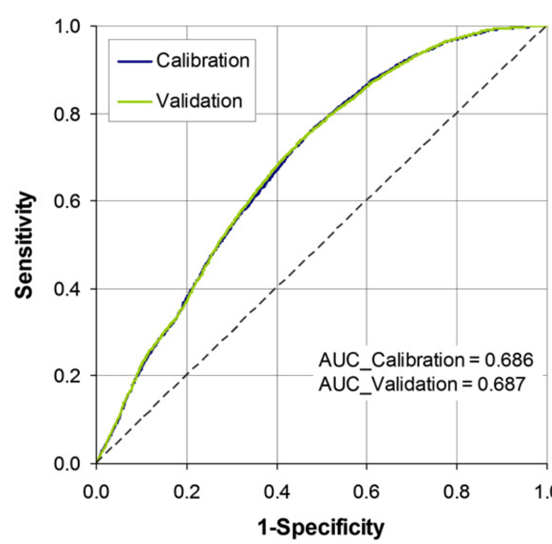

Fig. 7. Receiver operating characteristic (ROC) curves for the Reinello basin at the calibration and validation phases.

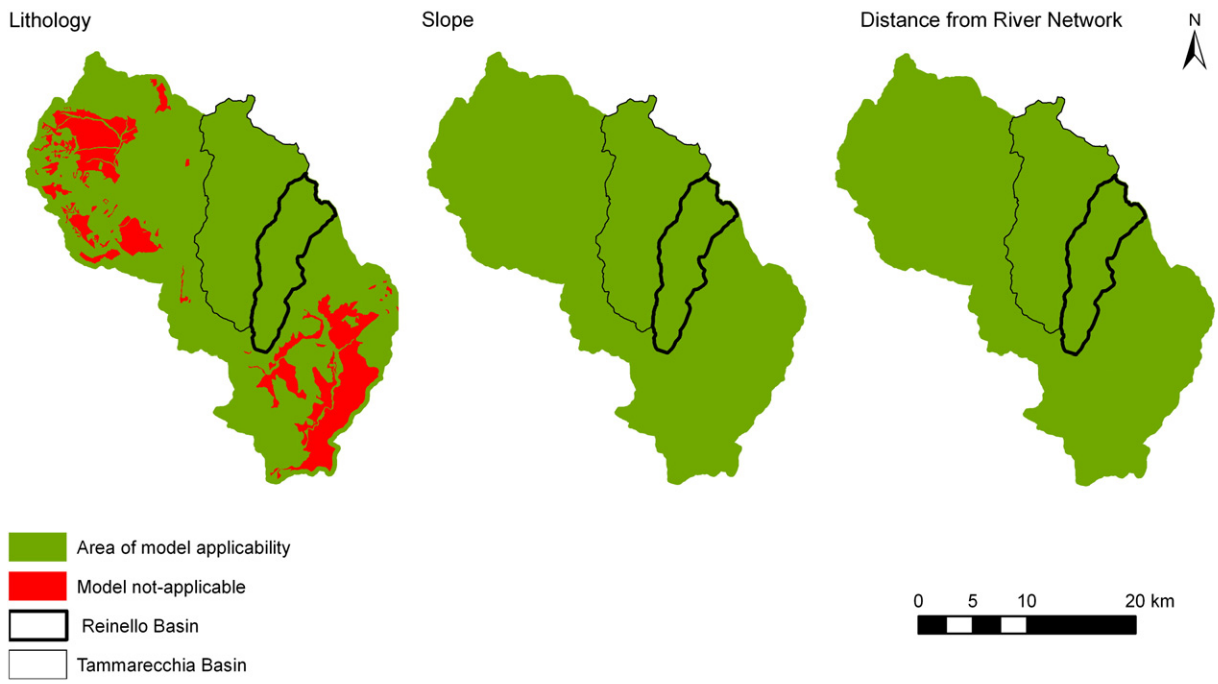

Fig. 8. Tammaro catchment: a-priori applicability maps for the three variables used to calibrate and validate the model in the Reinello basin.

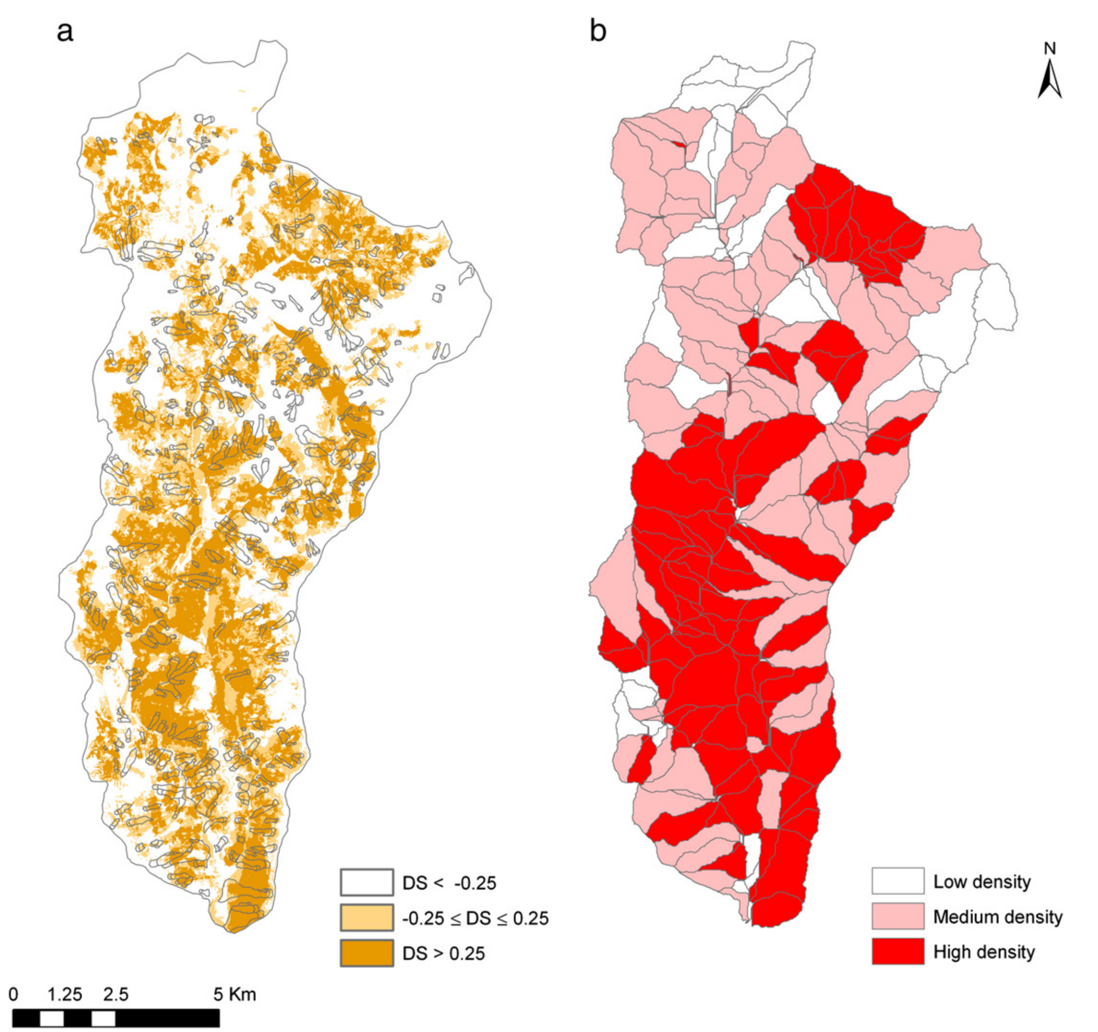

Fig. 9. Assessment results for the Tammarecchia basin. (a) Computational map of the prediction phase, drawn employing three discriminant score classes: $DS < -0.25$, $-0.25 \leq DS \leq 0.25$ and $DS > 0.25$. (b) Final zoning map of the analysis, with three landslide density classes according to the percentage of TCUs within each TZU.

Table 4
3×2 contingency tables, calculated with reference to the computational map, for the prediction phase within the territory of the Tammarecchia basin.

Prediction phase		Landslide inventory	
		Affected	Not affected
Model	Affected ($DS \geq 0.25$)	43.0%	26.7%
	($-0.25 \leq DS < 0.25$)	25.0%	22.0%
	Not affected ($DS < -0.25$)	32.0%	51.3%

and the most effective combination of variables. The obtained function considers three of the five variables:

$$DS = -1.96 + 2.03X_{GEO} + 1.52X_{SLOPE} - 2.34X_{DIST}. \quad (4)$$

Eq. (4) was used to produce the landslide distribution map (Fig. 6a). The average number of TCUs within each TZU is about 300. The landslide density of each TZU was assigned based on the percentage of landslide-affected TCUs. A TCU was considered landslide-affected if its discriminant score, as computed by Eq. (4), was positive. The final landslide distribution zoning map is presented in Fig. 6b, in which the following three landslide density classes are considered: (i) low density if the percentage of landslide-affected TCUs within the TZU is <30%; (ii) medium density if the percentage is between 30% and 60%; and (iii) high density if the percentage is >60%.

The success of this analysis was assessed using both 2×2 contingency tables and receiver operating characteristic (ROC) curves (Swets, 1988). The terms of the contingency tables, which may assume values between zero and one, are able to quantify the fit between the model and the landslide inventory. The higher the ratio of the terrain units defined as landslide-affected based on the model to those according to the inventory, which is generally called 'sensitivity', the better the model fit. Likewise, a good model fit is also shown by a high ratio of the terrain units defined as landslide-free based on the model to those according to the inventory, which is generally called 'specificity'. The contingency table for both the calibration and validation phases (Table 3) shows that the sensitivities in the two cases are 69.3% and 69.1% respectively, and the specificities are 58.3% and 59.1%. The ROC curves plot the sensitivity versus (1 − specificity) (Fig. 7). The areas under curve (*AUC*) for the calibration and validation phases are 68.6% and 68.7%, respectively, which are consistent with the contingency tables.

For the final prediction phase, the applicability of the model depends upon the availability of all thematic variables used in the model and the absence of classes of variables that have not been exploited during the calibration phase. To address this issue, the a-priori applicability maps were used, one for each significant thematic variable used, to identify the areas where the calibrated model is applicable or inapplicable. The a-priori applicability maps for the Tammaro catchment are shown in Fig. 8 with reference to the three variables: lithology (*GEO*), slope (*SLOPE*) and the distance from the river network (*DIST*). The maps clearly show that some portions of the catchment are not suitable for prediction areas due to the absence of lithological classes. Therefore, the Tammarecchia River basin (120 km^2) was chosen for the prediction phase of the analysis.

The results of the prediction phase are reported in the computational map of the discriminant analysis (Fig. 9a) and the landslide density zoning map based on hydro-geological TZUs (Fig. 9b). In the computational map, two classes indicate landslide-affected ($DS > 0.25$) and landslide-free ($DS < -0.25$) TCUs, and a third intermediate class ($-0.25 \leq DS \leq 0.25$) takes the uncertainty of the modeling results into account. The success of the analysis was also assessed using a 3×2 contingency table (Table 4), which indicates that the intermediate class accounts for about one-fourth of the TCUs affected by landslides. The number of units within the latter class is considered when the percentage of landslide-affected TCUs for each TZU is computed (Fig. 9b). Like before, the landslide density classes in the final zoning map are three: (i) low density, if the percentage of landslide-affected TCUs within the TZU is <30%; (ii) medium density, between 30% and 60%, and (iii) high density, >60%.

5. Case study at 1:100,000 scale

This section describes a landslide analysis at 1:100,000 scale for the Campania Region in southern Italy (Fig. 10). This example addresses the evaluation of the computational maps at the end of the calibration and validation phases. The effectiveness of the employed statistical model and the reliability of the landslide inventory were evaluated as a function of the chosen calibration area.

The Campania Region covers an area of approximately 13,600 km^2, of which 19% is flatland, mostly alluvial plains along the coast, and the remaining 81% comprises the hills and mountains of the Apennines Chain. The complex structural–geological characteristics of this territory and the presence of intense volcanic activity have made this area highly susceptible to different types of landslides. We used the Italian Landslide Inventory IFFI (APAT, 2007), which includes 23,430 landslides in the region, mapped as a point feature, PIFF, at the summit of the crown of each landslide. Each PIFF is associated with a specific landslide type.

Like the 1:25,000 case study, the analysis only took account of slow-moving landslides: rotational/translational slides or earth flows. Such slow-moving landslides represent more than 60% of all landslides in the region. We used the SRTM (Shuttle Radar Topographic Mission) DEM with a resolution of 3 arc sec (approximately 95 m). Fig. 10a shows the digital terrain model of the Campania region and the location of the slow-moving landslides. The region was divided into four zones based on the distribution of the main river basins (Fig. 10b). The analysis was performed using 95×95 m square cells as TCUs. For the TZUs of the landslide density map, geo-administrative units indicated by the intersection between the municipal boundaries and the main lithological complexes (Di Nocera and Matano, 2011) were used (Fig. 11a) to consider both administrative responsibilities and the effects of geology. Fig. 11b reveals that based on the previously proposed criterion (see Table 2), the size of the geo-administrative units is appropriate for the analysis at 1:100,000 scale.

We applied the information value method (e.g., Yin and Yan, 1988), which is based on the evaluation of relative landslide density ($IRLD_i$) whose value was computed for every TCU and then summed to compute the global index of landslide density (*ILD*):

$$IRLD_i = \ln W_i = \ln\left(\frac{Densclas_i}{Densmap}\right) = \ln\left[\frac{\frac{Numf_i}{Area_i}}{\frac{Numf_{tot}}{Area_{tot}}}\right] \quad (5)$$

$$ILD = \sum\nolimits_i ILRD_i \quad (6)$$

where $Densclas_i$ is the density of landslides in the i-th class, *Densmap* is the density of landslides in the entire study area, $Numf_i$ is the number of landslides in the i-th class, $Numf_{tot}$ is the total number of landslides, $Area_i$ is the area of the i-th class and $Area_{tot}$ is the total area (Note: when $Densclas_i$ is zero, the value of $IRLD_i$ is assumed to be −5, because of the logarithm in Eq. (5)).

Regarding the choice of variables to introduce in the analysis, the two thematic maps of slope and lithology were employed (Fig. 12). Slope was derived from the DEM using ArcGIS (Fig. 12a). The continuous slope values were divided into 13 classes with a constant interval of 5°. Lithology was derived from a regional geological map (Di

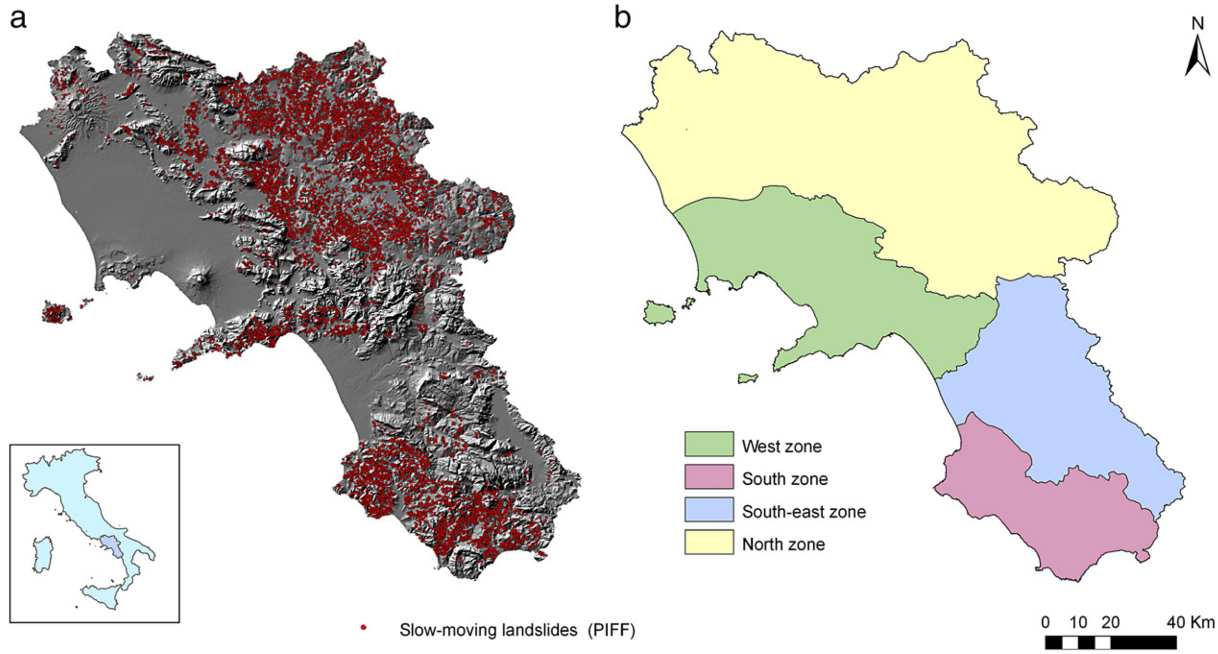

Fig. 10. Maps of the Campania region. (a) Location of the slow-moving landslides in point features or PIFF (APAT, 2007). A landslide is mapped with a PIFF at the summit of each landslide crown. (b) Zones for landslide analysis.

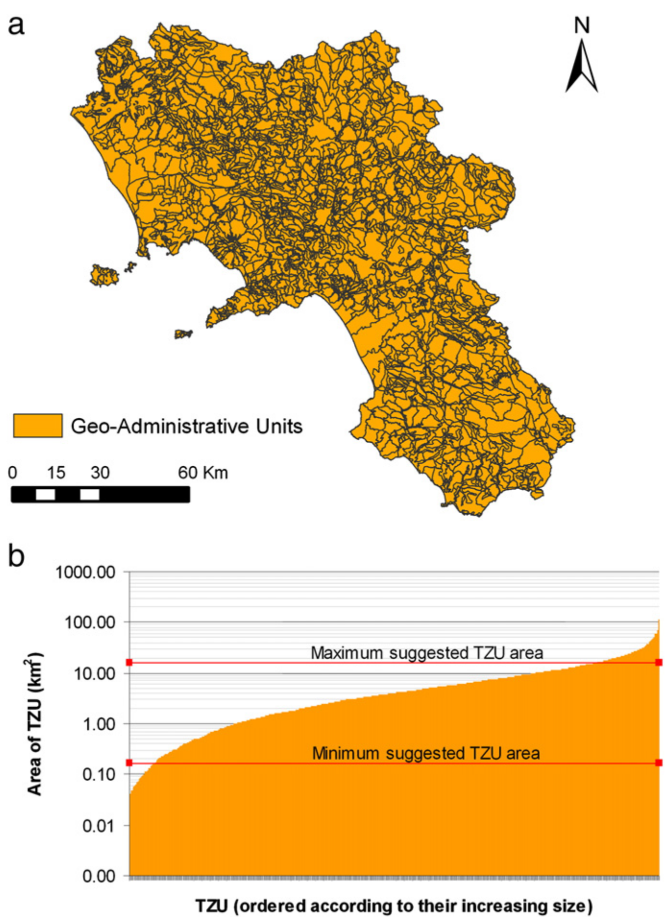

Fig. 11. TZUs used for the analysis. (a) Geo-administrative units from the intersection between the municipal boundaries and the main lithological complexes of the Campania Region. (b) Distribution of the TZU areas and suggested limits for the minimum and maximum dimensions at 1:100,000 scale as proposed in Table 3.

Nocera and Matano, 2004) with 13 main lithological complexes (Fig. 12b).

The statistical analysis followed the procedure described in Fig. 2. First, the model was calibrated four times considering each of the four zones of the Campania region (Fig. 10). The results of the analyses (Fig. 13 and Table 5). indicate that the calibrated model fits well to the slow-moving landslide events, in all four calibration areas. However, the combination of the four maps cannot be considered as a consistent map for the Campania region because the final values of *ILD* were computed from *IRLD* with different values for the four areas (Fig. 14).

The a-priori applicability maps relative to the variable lithology (Fig. 15) indicate that the only model that can be used for the whole of the Campania region is the one calibrated in the northern zone. Therefore, the values of *ILD* in the zone were used to produce the computational map shown in Fig. 16a, for which the other three zones were considered as validation areas. The reliability of the model was assessed, as in the previous phase, by evaluating the resulting sensitivity values in these areas (Table 6). The results are satisfactory for two of the three validation zones. Indeed, although the sensitivity values for the south-east and southern zones (67.6% and 78.5%, respectively) are comparable to the values when these zones were used as calibration areas (69.8% and 81.6%, respectively), the sensitivity value for the western zone (19.6%) is extremely low although it was 88.1% when the zone was used as a calibration area.

Given these results and following the procedure described in Fig. 2, we conducted a critical heuristic examination of the database used for the landslide inventory. This evaluation, which also included a comparison with other databases of events compiled by regional authorities, indicated that most phenomena mapped by the Italian Landslide Inventory IFFI (APAT, 2007) as earth flows along the Amalfi coast (part of the western zone where the majority of the landslides are mapped) are fast-moving debris flows or debris slides. These findings are consistent with the results of the bivariate statistical analysis (Fig. 14), which shows opposite signs of *IRLD* values for many classes of the two variables (e.g., slope classes from No. 5 to No. 9 and lithology class No. 2) between the western zone and the other three zones. Further details on this issue are reported in Mastroianni (2010).

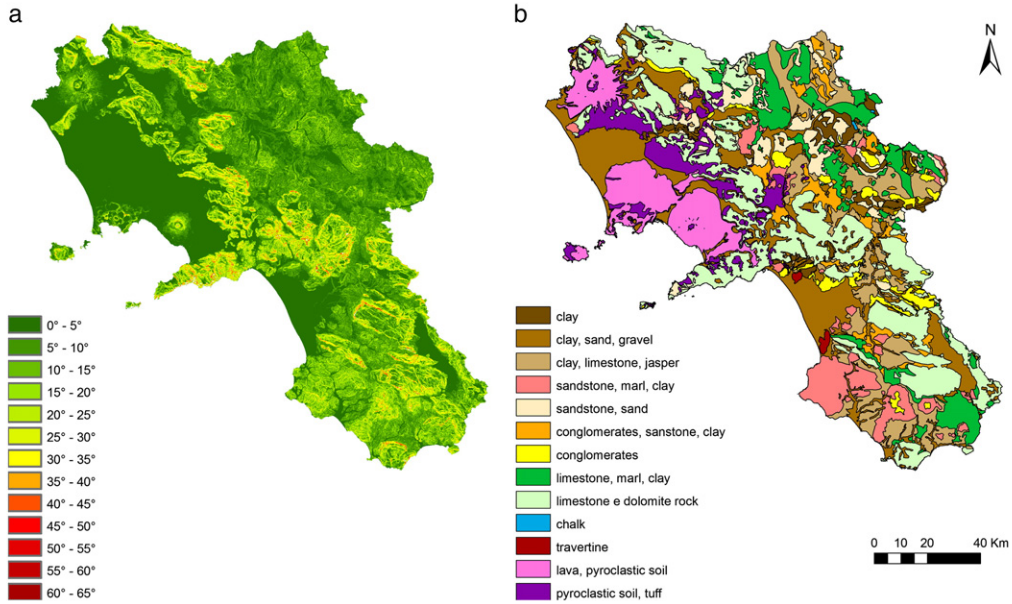

Fig. 12. Thematic maps employed in the analysis. (a) Slope divided into 13 classes with a constant interval of 5°. (b) Main lithological complexes of the Campania Region (Di Nocera and Matano, 2011).

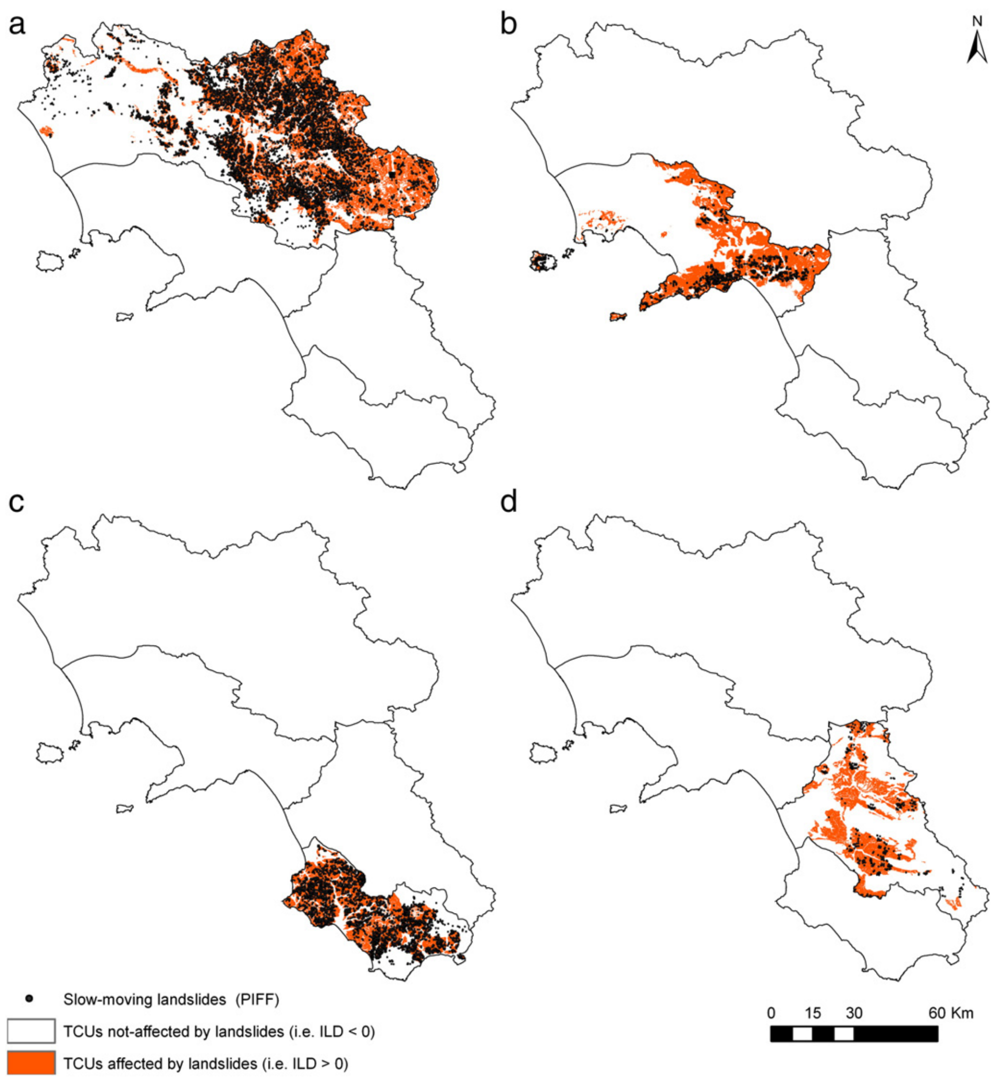

Fig. 13. Slow-moving landslides and computational maps of the model calibrated in the (a) northern, (b) western, (c) southern and (d) south-eastern zones. Landslides are mapped with a PIFF, located at the summit of each landslide crown.

Table 5
Sensitivity values of the statistical model, independently calibrated in the four zones of the Campania Region shown in Fig. 10.

Zone	No. of TCUs with landslides	No. of TCUs with $ILD \geq 0$	Sensitivity
Northern zone	9276	7196	77.6%
Western zone	1438	1267	88.1%
Southern zone	420	293	69.8%
South-eastern zone	3288	2682	81.6%
Campania region	14,422	11,438	79.3%

The final landslide distribution map is presented in Fig. 16b, with reference to the entire region. A TCU is considered landslide-affected if its global *ILD* is positive. Like the previous case study, the map was drawn by considering the percentage of landslide-affected TCUs within each TZU. The following three landslide density classes were considered: (i) low density if the percentage of landslide-affected TCUs within the TZU is less than 30%; (ii) medium density if the percentage is between 30% and 60%; and (iii) high density if the percentage is higher than 60%.

6. Discussion and conclusions

The two case studies at different scales were used to illustrate the applicability and the key components of a novel procedure which employs statistical methods to produce distribution zoning maps over large areas without using a landslide inventory for the whole territory. The maps are called 'landslide distribution zoning maps', not 'landslides inventories', because they are for terrain subdivision related to the topography at the scale of the analysis, not to the spatial features of landslides. These zoning maps should be considered as an intermediate cartographic product between a landslide inventory and a landslide susceptibility map and they can be profitably used for zoning landslide susceptibility and hazard if combined with landslide activity data from other sources (e.g., SAR Interferometry and multiple LIDAR mapping). The proposed methodology introduces a series of innovative concepts: the distinction between terrain computational units (TCUs) and terrain zoning units (TZUs); a work flow of three sequential phases – calibration, validation and prediction – to produce landslide distribution zoning maps for a territory where information on landslide distribution is unreliable or incomplete; and the introduction of a-priori applicability maps to identify areas where the calibrated and validated model is applicable.

When geo-statistical analyses are developed for zoning purposes, terrain units suitable for a geostatistical model (TCUs) are not necessarily suitable for the discretization of the zoning map derived from that model (TZUs); therefore the two units must be treated separately. This distinction between the two units and the new taxonomy reflect the fact that multivariate statistical analyses of landslides for assessing susceptibility, hazard or risk often provide maps that are not adequate for zoning. The distinction highlights the idea that at a given scale, the area of a TCU is related to the spatial resolution of the map, whereas the area of a TZU is related to the desired informative resolution of the zoning.

The sequence of operations proposed to produce a landslide zoning map over a large area is based on the information from thematic maps and a landslide inventory for a portion of the study area. Landslide distribution can be inferred for areas where landslides are not mapped. This capability is significant for landslide zoning in developing countries, where accurate landslide inventories are often unavailable. In such cases, an accurate landslide inventory for

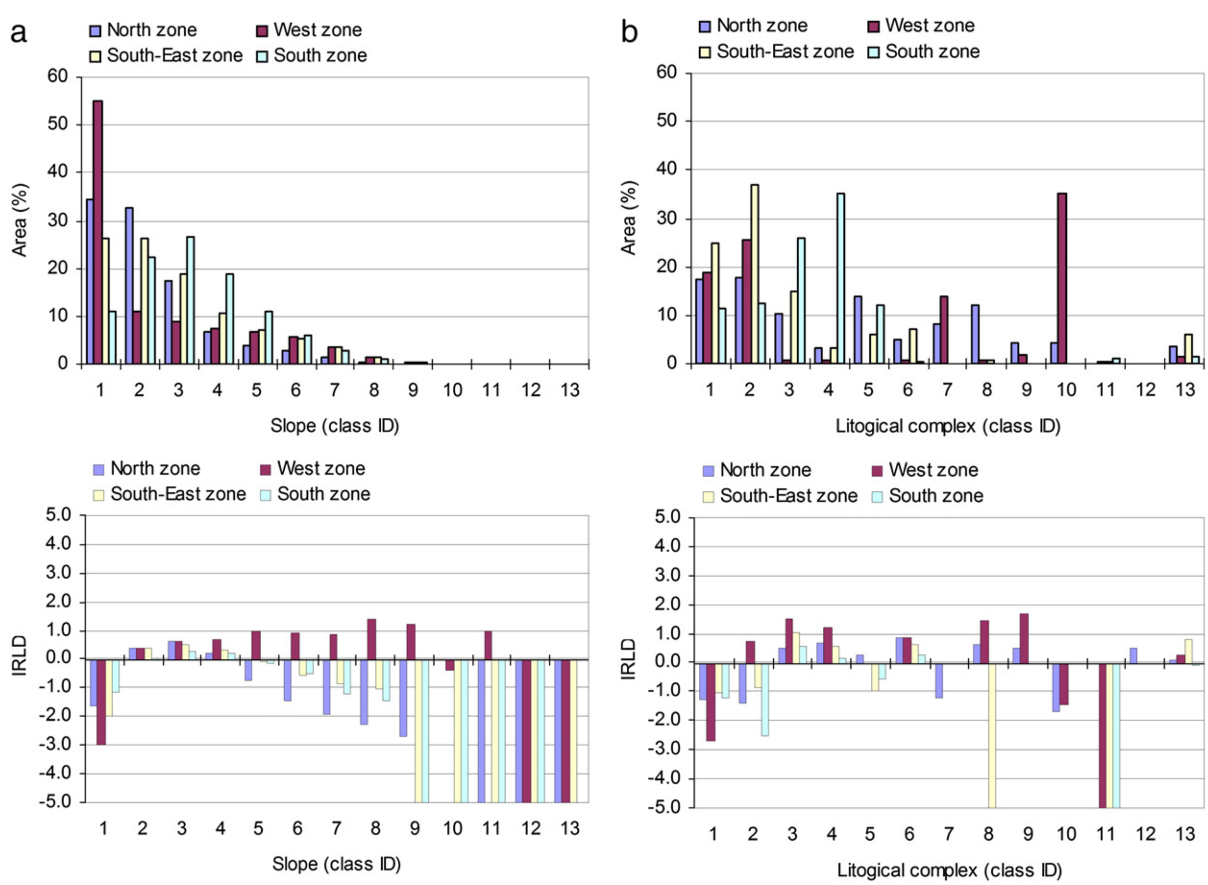

Fig. 14. Area and IRLD values for the two thematic variables of the analysis: (a) slope and (b) lithological complex.

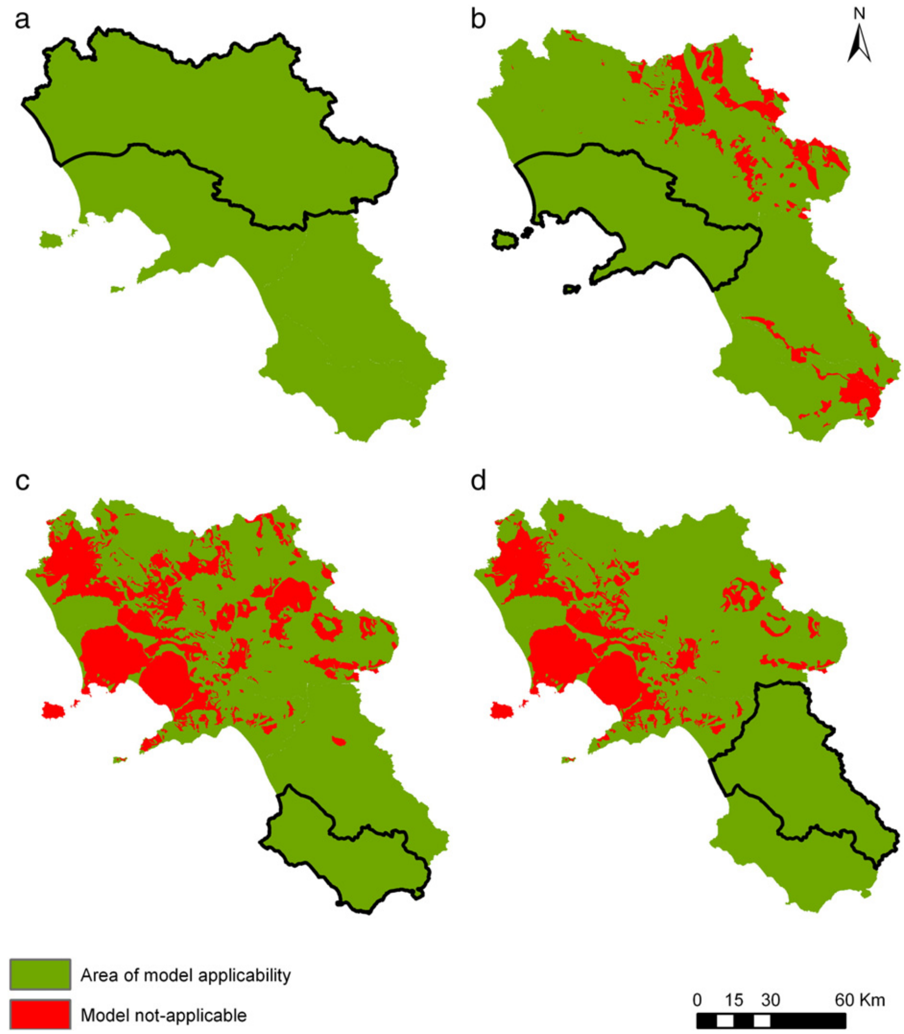

Fig. 15. A-priori applicability maps for the Campania region relative to variable lithology when the model is calibrated in the (a) northern, (b) western, (c) southern and (d) south-eastern zones.

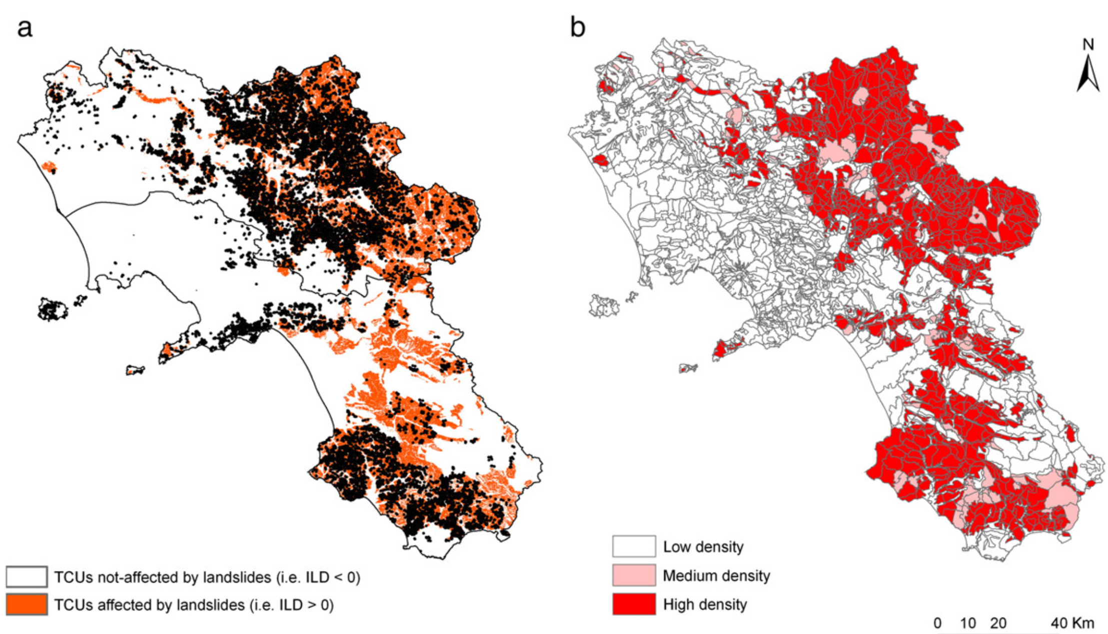

Fig. 16. Final computational and zoning maps. (a) Slow moving landslides and landslide-affected TCUs, i.e. *ILD* > 0, in the northern zone (training area) and the western, southern and south-east zones (target areas). (b) Final zoning map of the analysis with three landslide density classes according to the percentage of landslide-affected TCUs within each TZU.

Table 6
Sensitivity values of the statistical model, calibrated in the northern zone and validated in the other three zones of the Campania Region shown in Fig. 10.

Zone	Phase	No. of TCUs with $ILD \geq 0$	Sensitivity
Northern zone	Calibration	7196	77.6%
Western zone	Validation	282	19.6%
Southern zone	Validation	284	67.6%
South-eastern zone	Validation	2582	78.5%

relatively small areas can be used to calibrate and validate a model by objectively interpreting geological/geomorphological criteria. As the first case study at 1:25.000 scale indicates, the choice and significance of the calibration and validation area may be related, via a-priori applicability maps, to the homogeneity of the geo-environment and landsliding characteristics, and to the availability of the thematic variables used for statistical modeling in the prediction area. As shown in the second case study at 1:100.000 scale, the assessment of the reliability and internal homogeneity of a landslide inventory for a large area is also important. Indeed, the proposed methodology requires a critical examination of an inventory when statistical assessment indicates that the analysis has provided unsatisfactory results and the computed values of the model parameters for the calibration and validation areas are very different. The proposed approach could be further enhanced if it is coupled with data from other sources such as surface landslide movements derived from remote sensing (e.g., DinSAR).

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