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Slope units-based flow susceptibility model: using validation tests to select controlling factors

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Abstract A susceptibility map for an area, which is representative in terms of both geologic setting and slope instability phenomena of large sectors of the Sicilian Apennines, was produced using slope units and a multiparametric univariate model. The study area, extending for approximately 90 km^2, was partitioned into 774 slope units, whose expected landslide occurrence was estimated by averaging seven susceptibility values, determined for the selected controlling factors: lithology, mean slope gradient, stream power index at the foot, mean topographic wetness index and profile curvature, slope unit length, and altitude range. Each of the recognized 490 landslides was represented by its centroid point. On the basis of conditional analysis, the susceptibility function here adopted is the density of landslides, computed for each class. Univariate susceptibility models were prepared for each of the controlling factors, and their predictive performance was estimated by *prediction rate curves* and *effectiveness ratio* applied to the susceptibility classes. This procedure allowed us to discriminate between effective and non-effective factors, so that only the former was subsequently combined in a multiparametric model, which was used to produce the final susceptibility map. The validation of this map latter enabled us to verify the reliability and predictive performance of the model. Slope unit altitude range and length, lithology and, subordinately, stream power index at the foot of the slope unit demonstrated to be the main controlling factors of landslides, while mean slope gradient, profile curvature, and topographic wetness index gave unsatisfactory results.

Keywords Landslide susceptibility · Univariate multiparametric model validation · Mapping units

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1 Introduction

Approaching the assessment of landslide susceptibility by means of geostatistical methods always poses the need to define a mapping unit, that is, the basic spatial or statistical unit for which the model is able to provide a susceptibility value. In spatial analysis, mapping units are to be intended as "a portion of land surface that contains a set of ground conditions, which differ from the adjacent units across definable boundaries" so that "a mapping unit should represent a domain that maximizes internal homogeneity and between-units heterogeneity" (Hansen 1984; Carrara et al. 1995; Guzzetti et al. 1999, 2006).

Selection of the mapping unit is actually one of the most critical steps in landslide susceptibility assessment procedures (Carrara et al. 1995, 2008; Guzzetti et al. 2006; Van Den Eckhaut et al. 2009), as it can lead to different previsional results, in terms of both prediction images and suitability of the maps for hazard mitigation and/or management use. The two most exploited types of mapping units can be referred to the following main driving criteria: morphodynamic coherence (e.g., sub-basins, slope units) and geostatistical suitability (e.g., grids, unique condition units). Selecting hydro-morphologic units maximizes the link between physical phenomenon and stochastic modeling, imposing on the spatial analysis of the conditional factors constraints such as water divides and streams, which constitute natural barriers for geomorphological processes. Hydro-morphologic units (e.g., slope units *sensu* Carrara et al. 1991) can be derived automatically or semi-automatically from a digital terrain elevation model using a GIS software.

Landslide susceptibility assessments based on conditional analysis require the overlaying of the classified layers of each instability factor in a single multivariate one, whose homogenous domains (unique condition units, UCU; Carrara et al. 1995; Chung and Fabbri 1995; Clerici et al. 2002; Conoscenti et al. 2008; Del Monte et al. 2002) can be polygons or set of cells, having morphodynamically unconstrained spatial limits: by following this approach, morphodynamic relationships between adjacent cells are neglected, since pixels or areas in a single slope could belong to several different homogeneous domains (being consequently characterized by even largely different susceptibility values).

Conversely, a problem arises in adopting hydro-morphologic units when an approach based on conditional analysis is applied. In fact, when "switching" from cells or pixels to hydro-morphologic units, the number of mapping units dramatically decreases from hundreds of thousands of cells to some hundreds slope units, each being characterized by single values for the selected controlling factors. The consequence in multivariate approaches is that a large number of under-trained classification units (correspondent to few cases or spatial units) will result, when combining all the parameters.

This paper presents the results of a research project aimed at exploring the possibility of producing susceptibility models based on the conditional analysis approach but adopting the morphodynamic spatial constraints represented by the SLope Units (SLUs). The use of a multiparametric univariate classification method is here proposed as a possible alternative to multivariate ones.

The research also explores the use of a strategy for assessing the controlling role of each single factor, based on the validation of their univariate models. To these aims, susceptibility models are prepared whose predictive performance is evaluated by means of the *effectiveness ratio* (Chung and Fabbri 2003) and of two geometric indexes of the *prediction rate curves* here proposed.

2 Materials and methods

2.1 Study area

The test area extends for about 90 km^2 and corresponds to the upper reach of the Imera river flowing from the western sector of the Madonie Mountains (the central segment of the Sicilian Apennines chain) toward the Tyrrhenian Sea (Fig. 1). The outcropping rocks mainly consist of terrigenous, carbonate, siliceous-carbonate, and siliciclastic successions (Fig. 1c), whose derived tectonic units are set to form imbricate geometric structures, as a consequence of the compressive phase that, starting from Oligocene, built up the Sicilian chain (Abate et al. 1988). Climate in the area is characterized by mean annual rainfall ranging between 700 and 750 mm, with maximum values in December–January, while almost dry conditions are experienced during the summer months.

2.2 Slope units, instability factors, and landslides

A 40-m digital elevation model (DEM) of the area (Fig. 1b) was derived by digitizing the 1:10,000 regional topographic maps. Hydrological spatial analysis carried out using GIS tools allowed us to derive from the DEM the flow direction and the flow accumulation grid layers; the latter were exploited to partition semiautomatically the investigated area in 774 SLope Units (SLUs). These are considered as morphodynamically independent and homogeneous spatial domains, made up of strictly interconnected territory cells. Each slope unit is limited by a water divide at the head and drainage lines at the foot. A threshold value of at least 16,000 m^2 extension was applied, so that the small units were merged with the adjacent larger ones.

Seven controlling factors (outcropping lithology: LTL; mean slope gradient: STP; stream power index at the foot of the SLU: SPI; mean topographic wetness index and

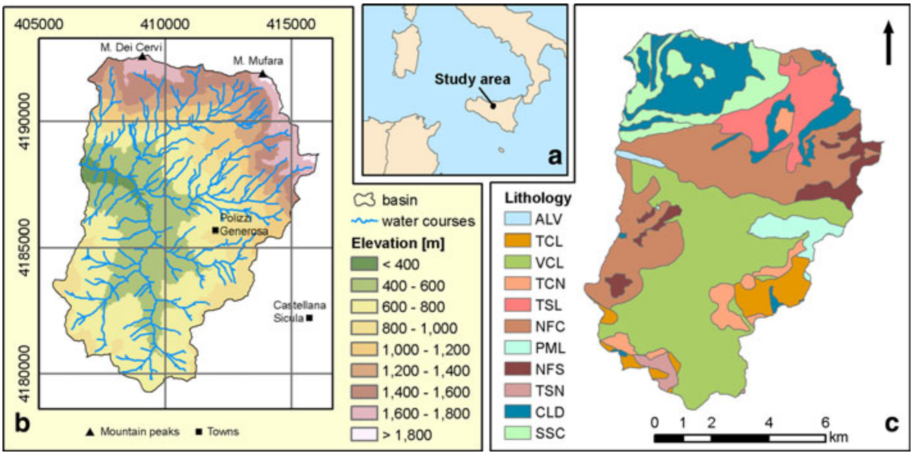


Fig. 1 Location of the test area (**a**); 40-m DEM of the area (**b**); lithology map (**c**): *ALV* Quaternary alluvial deposits; *TCL Terravecchia* Fm. clays; *VCL Varicolori* clays; *TCN Terravecchia* Fm. conglomerates; *TSL* Talus slope; *NFC* Numidian Flysch clays; *PML Polizzi* Fm. marly limestones; *NFS* Numidian Flysch sandstones; *TSN Terravecchia* Fm. sandstones; *CLD* Carbonate limestones and doloarenites; *SSC* Siliceous successions

profile curvature: TWI, PRC; slope unit length and altitude range: LNG, REN) were selected and computed for each SLU.

The way in which the morphodynamic spatial constraints of the SLUs were imposed on the susceptibility assessment procedure consisted in producing new SLU-derived factor layers by calculating zonal statistics of the source grids inside each SLU. It is not a simple reclassification of old values, and new values for each factor are generated. All the cells or pixels intersected by the same SLU will have the same factor value in the new grids.

SLU zoning is a geostatistical device to impose the morphodynamic spatial connection between each cell or pixel belonging to the same SLU. Adopting such a procedure allows us to prepare spatially distributed models in which the link between the cells is rather on geostatistical than on physical relationships.

The seven controlling factors were obtained from the lithologic map and the digital elevation model and were associated to each SLU with the following procedures: the LTL was derived intersecting the SLUs with the lithology map, considering the unique or the dominant lithologic complex; STP, TWI, and PRC were computed as the zonal mean value from the respective 40-m grid layers within each SLU; SPI was defined as the mean stream power index measured along the fluvial channel, constituting the downhill edge of the SLU; LNG and REN are, respectively, the topographic distance between the head and the foot cells and as the altitude range of the SLUs (Table 1).

Each SLU-derived factor grid layers was then reclassified in ten equal area classes, while the intersection of SLUs and the lithologic map produced six unique or dominant classes (there are five lithologies that are never dominant in a SLU). Each of the factor classes homogeneously characterizes one or more SLUs (Fig. 2).

Due to its geomorphological setting and climatic context, the study area is affected mainly by flow-type landslides, with a limited number of rotational slides, falls, and topples (Cruden and Varnes 1996). As the aim of this study is to verify methodological strategies to assess landslide susceptibility, we decided to focus the analysis selecting only the flow-type landslides, whose large number make it possible to adequately train the predictive model. We think that each of other landslide typology requires a specific selection of the controlling factors and different landslide, representation strategy and mapping unit partition.

Field surveys, carried out in October 2008, allowed us to recognize 490 flow-type landslides (Fig. 3). This type of failure involves the clayey formations to the depth of several meters (earth-flow) or, subordinately, limits the deformed volume to the surficial

Table 1 Description of the 40-m grid layers from which the seven controlling factors were derived

Factor	Source layer	Description of source parameter
LTL	Lithology map	Outcropping lithology
STP	Slope gradient	Highest first derivative of elevation
SPI	Stream power index	Calculated as ln[A*tanβ] where A and β, computed on each cell, correspond to the area of upslope drained cells and to the slope gradient, respectively
TWI	Topographic wetness index	Calculated as ln[A/tanβ], where A and β, computed on each cell, correspond to the area of upslope drained cells and to the slope gradient, respectively
PRC	Profile curvature	Second derivative of elevation, computed along the direction of the highest slope gradient
LNG	DEM	Distance between the highest and lowest cell in an SLU
REN	DEM	Difference between the highest and lowest elevation in an SLU

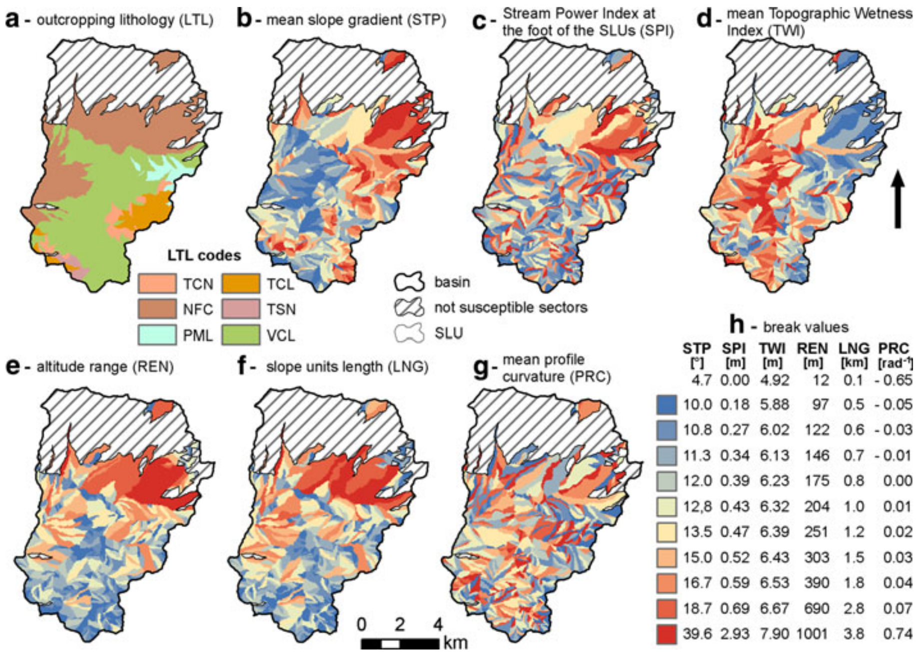


Fig. 2 Layers of the controlling factors: lithology (**a**); mean slope angle (**b**); Stream Power Index at the foot of SLU (**c**); mean Topographic Wetness Index (**d**); altitude range (**e**); slope length (**f**); mean profile curvature (**g**). The table shows break values used for the topographic factors (**h**)

deposits, such as the weathered regolitic layer or colluvium (debris-flow, soil slips). Twenty-seven earth-flows located at the foot of earth rotational slides were also included in the analysis (Fig. 3).

The landslide area covers 5.8 km^2 corresponding to 6.6% of the investigated basin. Landslides, which in Sicily are typically triggered by the winter seasonal rainfall (Agnesi et al. 1982), showed an active (116) or dormant (374) activity status in October 2008. Due to the geomorphological and geologic settings of the study area, flow landslides are completely missing in the northern sector, where calcareous, dolomitic, and quartzarenitic rocks crop out; for this reason, these areas have been excluded in the assessment procedure.

To proceed to the susceptibility assessment, each landslide was converted into a single point, selected as its centroid. The landslide centroids (LCs, Fig. 3) are fully effective in indicating the SLU conditions associated to each mapped phenomenon. In fact, according to the criteria adopted in mapping and characterizing SLUs, all the cells inside a SLU have the same factor values, and none of landslides crosses SLU limits.

2.3 Landslide susceptibility modeling and validation

To assess the landslide susceptibility of SLUs, a univariate approach was followed. The reclassified factor layers were intersected with the LC points so that landslide densities were computed for each factor class as the ratio between counts of LCs and total counts of pixels: these values, according to Bayes' theorem (Davis 1973; Carrara et al. 1995), express the conditional probability of landslide occurrence, given a factor condition. Landslide density is assumed as the susceptibility function (see also Chung and Fabbri

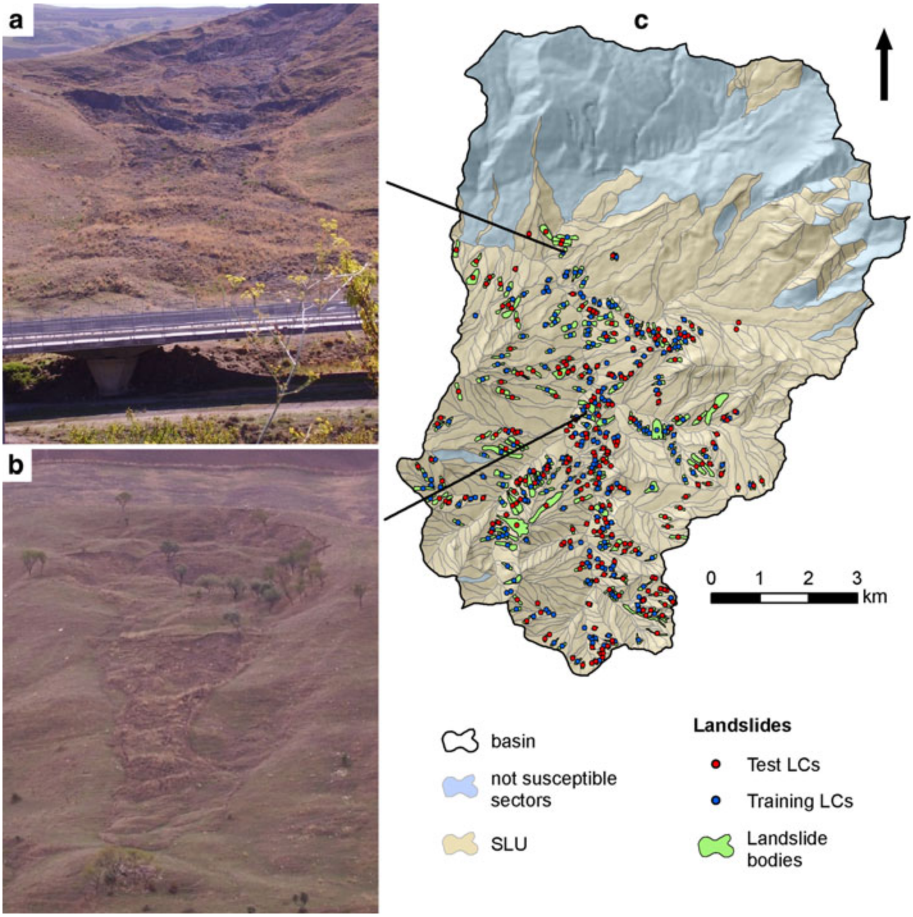


Fig. 3 **a** Examples of the flow-type landslides; **b** landslide map showing landslide bodies and centroids (LCs)

2003; Clerici et al. 2002; Conoscenti et al. 2008), so that a ranked order of landslide densities correspond to a susceptibility scale.

To estimate and compare the controlling role of the seven variables, univariate susceptibility models were prepared and validated (Remondo et al. 2003). The validation procedure exploited the *random time partition* strategy (Chung and Fabbri 2003), based on the random splitting of the landslide centroids archive into two equally populated (50% of LCs, each) subsets: LC*training* and LC*test*. The former was used to prepare a prediction image (i.e., susceptibility map) for each factor, while the latter was used as the *unknown target pattern*. *Prediction* and *success rate curves* (Chung and Fabbri 2003; Guzzetti et al. 2006; Fabbri and Chung 2008), drawn by comparing the factors prediction images with the test and training LCs, were exploited to estimate the prediction skill and the model fitting, respectively. These curves are plotted on a Cartesian diagram, interpolating points whose coordinates are given by the cumulative fraction of the total number of LCs (*Y*-axis) and by the fraction of the area predicted, cumulated from the more to the less susceptible (*X*-axis).

To evaluate quantitatively the predictive performance of the models, we proposed two geometric indexes of the *prediction rate curves*: the area between the *prediction rate curves* and the diagonal of the graph (areas above randomly predicted area, ARPA) and the tangent to the curve at the 20% of the predicted area (T20). The *effectiveness ratio* (EFR, Chung and Fabbri 2003; Guzzetti et al. 2006) is also computed to evaluate the performance of each susceptibility class.

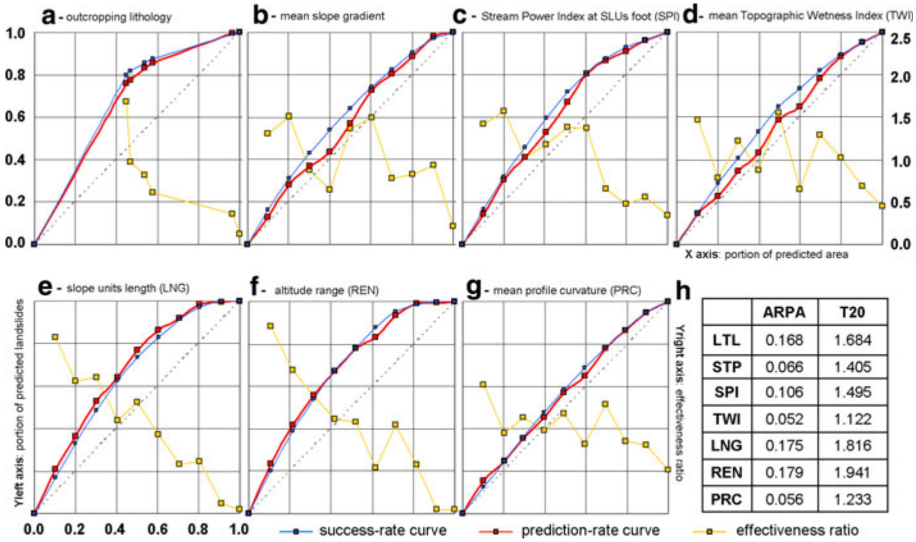
In the graph, the diagonal represents a theoretical random *prediction rate curve*, given by the same portion of landslides falling within all the susceptibility classes, no matter their susceptibility levels. For this reason, high ARPA and T20 values confirm a good predictive factor performance, indicating that the test LCs are more concentrated in the area predicted as most susceptible. In particular, T20 expresses the predictive performance of the 20% most susceptible area, while ARPA reflects the model prediction skill for the whole area and landslide data set. EFR is the ratio between the fraction of LCs accounted for each susceptibility class and the proportion of the latter in the study area. This parameter allows us to discriminate effectiveness of each susceptibility class, depending on to how far its value is from 1, which would be the same value produced by a random model, in which the fraction of observed landslides only depends on the area of each class. According to Guzzetti et al. (2006), EFR indicates an effective prediction, for each single class, when its value is at least 1.5 for more susceptible classes and at most 0.5 for less susceptible classes. Corresponding threshold values can also be derived for ARPA and T20, drawing a theoretical *prediction rate curve,* which would respect the EFR constrains, by fixing the extensions of the more and less susceptible classes at 40% of the investigated area. ARPA and T20 threshold values are obtained equal to 0.12 and 1.5, respectively. Differently from EFR, ARPA and T20 evaluate the effectiveness of the prediction for a cumulated portion (T20) or the entire (ARPA) predicted area.

3 Results

The curves derived from the validation of the univariate factor models are plotted in Fig. 4. The degree of correlation between univariate models and spatial distribution of landslides can be evaluated as satisfactory for REN and LNG (ARPA > 0.17; T20 > 1.8) and for LTL (ARPA $= 0.168$; T20 $= 1.684$); the *prediction rate curve* of LTL is heavily controlled by a single lithology (*VCL*), which actually represents nearly 50% of the most susceptible area. The SPI model is characterized by validation results (ARPA $= 0.106$; T20 $= 1.495$) that can be considered as almost satisfactory (just below the threshold values), while the *prediction rate curves* of STP (ARPA $= 0.066$; T20 $= 1.405$), TWI and PRC (ARPA < 0.07; T20 < 1.3) show unsatisfactory performances.

Similar considerations about the effectiveness of the predictor variables can be derived by analyzing the values of effectiveness ratio (represented in the right *Y*-axis in Fig. 4) and by comparing them to the threshold levels of model reliability proposed by Guzzetti et al. (2006); REN and LNG show the best EFR values as they are just above 1.5, in 20% most susceptible classes, and largely below 0.5, in 20% of the area classified as less susceptible. LTL effectiveness ratios can also be considered satisfactory, while EFR values of SPI confirm that its predictive power is very close to acceptable thresholds. On the contrary, STP-, TWI-, and PRC-derived susceptibility classes show EFR levels between 1.5 and 0.5, with the exception of the less susceptible class of the slope gradient model.

In light of the observed values of the quality indexes, the following considerations are given: slope unit altitude range and length, lithology, and stream power index at the foot of



	ARPA	T20
LTL	0.168	1.684
STP	0.066	1.405
SPI	0.106	1.495
TWI	0.052	1.122
LNG	0.175	1.816
REN	0.179	1.941
PRC	0.056	1.233

Fig. 4 Validation graphs (success and prediction rate curves; effectiveness ratio) of the single-parameter-based susceptibility models (**a**–**g**). Table showing values of curves quality indexes (**h**). For all the validation graphs: *X*-axis = portion of predicted area, *Y* left axis = portion of predicted landslides; *Y* right axis = effectiveness ratio

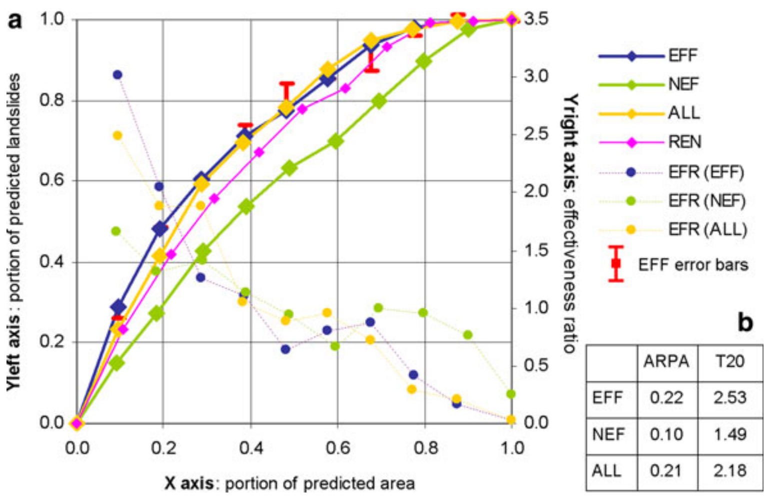
the SLUs can be considered as "effective" predictive variables, while mean slope gradient, mean topographic wetness index, and profile curvature, which showed a weak correlation with the spatial distribution of landslides in the study area, are classified as "non-effective".

Multiparametric models can be prepared by combining two or more SLU-derived factor grids and obtaining a single SLUCU (SLope Unique Condition Units) layer. A SLUCU is a unique conditions unit made up of one or more SLUs. The susceptibility of each SLUCU is here derived by averaging the LC density values from the combined factor classes.

Among the number of models that can be obtained by variously selecting and combining the controlling factors, it is worthwhile comparing those given by combining only effective (EFF) and only non-effective (NEF) predictive variables. Figure 5 allows us to compare the prediction rate curves produced by the EFF and NEF models, together with the multiparametric model produced by intersecting all factors layers (ALL = EFF + NEF); the prediction rate curve relative to the REN single factor model (Fig. 4f) is also plotted.

As expected, the EFF model shows the greatest prediction skill, testified by a very steep validation curve in the first part (T20 = 2.53), well above the diagonal (ARPA = 0.22); on the contrary, NEF confirmed the very poor predictive skill of its source parameters, as the curve is close to a random prediction rate curve, testified by a ARPA index equal to 0.1. The negative contribution of the NEF variables is projected in the ALL model, as it produces a prediction rate curve less performing than EFF (T20 = 2.18; ARPA = 0.21).

The graph in Fig. 5 also shows the error bars of the EFF model, given by the difference, computed class by class, between the number of predicted (train LCs) and occurred (test LCs) landslides, normalized to the total number of the latter: (train LCs–test LCs)/test LCs. The ratio between each bar length and the total *Y*-axis extent can be read as the percentage of over- or under-predicted events (LCs). Despite some errors arising in the middle classes,



	ARPA	T20
EFF	0.22	2.53
NEF	0.10	1.49
ALL	0.21	2.18

Fig. 5 Prediction rate curves (*solid*) and effectiveness ratio (*dotted*) for EFF, NEF, and ALL multiparametric susceptibility models, compared with the best single predictor (REN). *X*-axis = portion of predicted area, *Y* left axis = portion of predicted landslides; *Y* right axis = effectiveness ratio. The table shows curve quality indexes (ARPA and T20) values. *Error bars* of the EFF model show for each susceptibility class, differences between the number of predicted (train LCs) and occurred (test LCs) landslides, normalized to the total number of the latter: (train LCs–test LCs)/test LCs

whose susceptibility is slightly overestimated and in the medium–low susceptibility zones, that are slightly under-estimated, very small differences between predicted and occurred landslides were observed.

Considering the validation results, the EFF model, trained using all LCs, was selected to produce the susceptibility map of the studied area (Fig. 6).

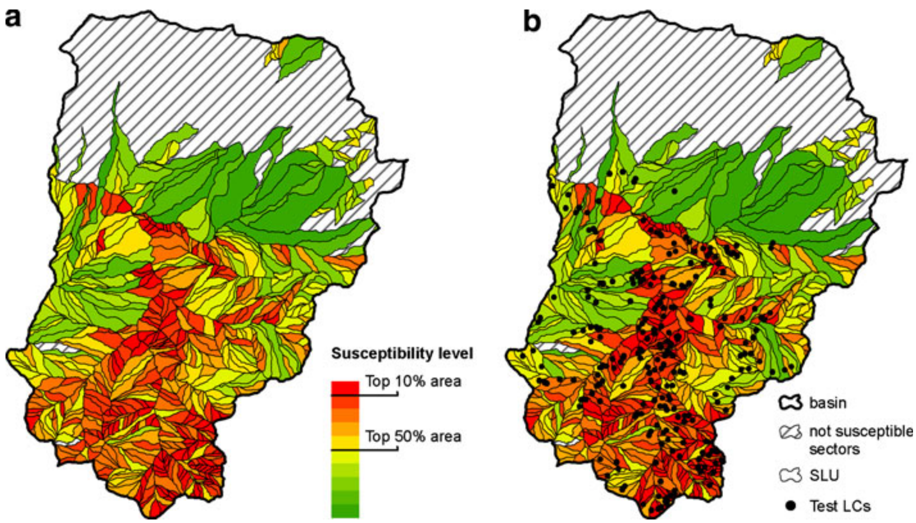


Fig. 6 Landslide susceptibility map for the best (EFF) multiparametric model (**a**). Training LCs-derived prediction image and test LCs spatial distribution (**b**)

4 Discussion and concluding remarks

The use of a morphodynamically based mapping unit in assessing landslide susceptibility by means of a conditional analysis-based geostatistical approach has proved to be effective in the test area, producing satisfactory validation results. Adopting a multiparametric univariate approach, in which the susceptibility levels are computed independently, factor by factor, and then combined to produce the susceptibility levels of Slope Unique Condition Units, allowed us to face one of the main geostatistical limitations in adopting such a mapping unit: the low number of cases (SLUs) for each combination (SLUCU) that is otherwise responsible for under-training of the predictive models.

In the Upper Imera river basin, slope unit altitude range and length, lithology and, subordinately, stream power index at the foot of the slope units demonstrated to be the main controlling factors of landslides, while mean slope gradient, profile curvature, and topographic wetness index, in spite of their expected high morphodynamic relationship with flow-type landslides activity, gave unsatisfactory results. Other simple statistics for such factors (variance and range) were checked without obtaining any improvement in the predictive skill. These results suggest the use of SLUs as a procedure, which is not totally suitable for representing the latter factors in the susceptibility models; these factors are probably much more effective in determining inside a SLU the site (the single pixel) where a landslide could initiate, but when summarized on a SLU scale, they show a loss in their predictive power.

The indexes adopted in evaluating the predictive performance of each factor proved to be useful and representative of the model performance. TAN20 expresses the skill of the model in characterizing the most unstable portion of the study area. ARPA, on the other side, gives an estimation of the cumulated effectiveness of the susceptibility models, taking into consideration the whole predicted area. These two indexes allow to estimate the overall performance of the model (EFR is the typical adopted quality index, but it refers to a single class).

Objective factors reclassification criteria (equal area and dominant outcropping lithology), together with a test procedure for selecting the factors of the model, allowed us to produce a susceptibility model whose good predictive performance has been demonstrated. Moreover, the coherence between the quality of the predictive performances of the single factors, tested by means of univariate validation tests, and their effect when included in multiparametric models, in terms of increasing or decreasing of prediction skill, demonstrate that the adopted multiparametric procedure is stable and self-consistent.

Adopting SLUs and LCs is considered a useful approach in assessing landslide susceptibility. LC representation of landslides allows us to establish stable spatial relationships with the controlling factors, not critically dependent on the exact location of the mapped landslides, as inside SLUs factors are homogeneously defined. At the same time, landslide survey is needed to correctly classify typology, activity, and morphometric features of the recognized phenomena. SLUs, on the other hand, are to be considered the fundamental mapping units for a number of reasons: factors acquire sense only if considered and recomputed within the morphodynamic units (single cell values are meaningless when considering phenomena involving portion or whole slopes); slope units are the correct spatial domains to implement a deterministic physical approach to assess the safety factor, in high susceptible cases; mitigation activities are typically planned on a slope or basin scale (a raster susceptibility representation is of no use for a territorial administration!).

However, SLUs and LCs pose a large fan of methodological problems, such as those related to the definition of their geo-environmental characteristics, in terms of statistics computed starting from raster defined informative layers, or to the need to keep low the number of classes, in order to keep the number of SLUs populating each SLUCU high. This paper intended to give a contribution to the exploration of some of these items.

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