The Susceptibility Map for Landslides with Shallow Initiation in the Emilia Romagna Region (Italy)

Mauro Generali and Marco Pizziolo

Abstract

The Emilia Romagna Region (RER) is probably one of the most landslide susceptible regions of the world, with ~24 % of the mountain sector covered by landslide accumulations. The regularly updated 1:10,000 Landslides Inventory Map (LIM), managed by the Regional Geological Survey, counts more than 70,000 landslides. Nowadays most land-use planning is based on LIM but this has several intrinsic shortcomings, mainly due to its scale and forecast significativity. This paper presents the methods we used to compile a detailed susceptibility map for the whole RER Apennines.

The triggering mechanism of the most common landslides phenomena in RER, disregarding of the subsequent evolution, is characterized by a first movements that may be described as "shallow phenomena" involving the upper part of the landslides (depletion areas). For this reasons we developed a model for the areas "outside" the LIM mapped landslides aimed to identify the triggering areas for future landslides. For this statistical analysis we used Bivariate Logistic Regression methods. As our aim was to predict triggering phenomena, we calibrated the model on the depletion areas, selected using a semi-automatic GIS procedure. The resulting map can be used for LIM verification and updating and adds it a forecast connotation useful for land use planning; nevertheless it has to be used by experienced users, for this purpose the model advantage and shortcomings will be discussed.

Keywords

Emilia Romagna Apennine • Landslide initiation • Susceptibility • Logistic regression

Introduction

Italy is probably one of the most landslide prone areas of the world (landslides cover ~7 % of entire country) and the Emilia Romagna Region (RER) is one of the most affected regions in Italy (APAT 2007). Like many other Italian regions, nowadays RER has a 1:10,000 Landslide Inventory Map (LIM), which represents the fundamental state-of-the-art knowledge of regional landslides. At present LIM counts more then 70,000 landslide in an area of ~11,000 km^2. It is constantly updated by aerial photo analyses and new field event reports, and it also contains information on historical events (Glade 2001).

The LIM is an irreplaceable document for land use planners, especially because in RER the majority of new landslide events involve the reactivation of past movements. Nonetheless, LIM has intrinsic predictive limitations. On the issue of landslide spatial forecast at regional scale, in the past several attempts have been made in RER to define landslide susceptibility (Bertolini et al. 2002). These are outdated products, however, because they are based on old LIM versions, simple methodologies and usable for "situational overview" (scale up to 1:25,000); they are currently

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insufficient for detailed (district to municipality) land use planning. More detailed works have been carried out by several authors but they are territorially restricted and methodologically inhomogeneous so they can neither be merged together, nor extrapolated to the neighbouring areas. With this work we try to fill this gap in spatial prediction through detailed analysis, which is extended to the whole region, focused on the most common landslide type and able to cover the whole RER Apennines. The homogeneous coverage of the ~11,000 km^2 and the analysis detail (usable up to 1:5,000 scale) make these maps a useful contribution to the "local scale" land use planning processes and to hazard and risk mitigation policies for the entire region.

Regional Setting

The Emilia Romagna Region (RER) straddles the northern and central belt of Italy. About half of the >22,000 km^2 of the region and in particular the southern part, is characterized by hilly and mountainous areas, with altitudes ranging from just tens of metres to 2,163 m a.s.l.

The geology differs significantly between the Emilia Apennines (central and western side), and the Romagna Apennines (eastern side): the former is almost completely characterized by sedimentary (and mostly weak) rocks, often formed by Cretaceous-Paleogenic structurally complex clay and clay shale or tectonized alternances (flysch) (Ligurian Units), surmounted by Eocene-Miocene marine deposits (Epiligurian Units), while the latter is dominated by the Oligo-Miocene Flysch deposits (Marly-Sandstone Formation); both are delimited in their frontal side by Plio-Pleistocene marine and transitional deposits (Fig. 1).

The RER Apennines mean Landslide Index (area covered by landslides / total area) is ~24 % but in some municipalities it reaches or exceeds 50 %. Most of the landslides are characterized by slow to extremely slow movement, mainly constituted by slides, earth-flows and complex landslides. They rarely threaten human life directly but often affect property, infrastructure, rivers and landscapes, causing severe damages and high risk levels. The main predisposing factor is the weakness of the bedrock and hillslopes materials, while the main triggering factor is precipitation.

Amongst the predisposal factors, especially for small and medium events, we must not underestimate the great importance of the area's recent history: in recent centuries Man has greatly modified the natural environment, first of all with widespread timber harvesting and conversion to agriculture and later with the construction of many villages, towns and infrastructures. In the past few decades most of the farms and fields have been abandoned and forests have reclaimed many hill slopes, but the resident population has continued to grow nonetheless: at 1/1/2007 the hilly and mountainous areas of the RER had a population of 1,342,149 people, 31.78 % of the whole RER, amounting to an increase of 5 % over 10 years, who are particularly concentrated in hills and larger villages. Nowadays there are >145,000 buildings and > 8,100 km of roads located directly on landslide accumulations or in a meaningful bound but they are certainly underestimated.

Materials and Methods

In this chapter we present the LIM data and the typical landslide processes that we deal with; these are the background for the conceptual framework delineation. We'll then present the identification and/or creation of the data we'll further use in the statistical analysis.

Landslides Inventory Map

Over three decades, RER's Geological Survey (SGSS) has progressively developed an historical LIM which, derived originally from detailed (1:5,000–1:10,000) field surveys in '80 and '90, has been updated with periodical and extensive correction, integration and validation by further field check and multi-temporal aerial photo interpretation. The LIM used in this work dates back to 2006 and counts 70,037 landslide polygons, classified according to type of movement and state of activity. In this map approximately 54.7 % of the landslides (corresponding to ~28 % of the total landslide area) are classified as active[1] and the remaining 45.3 % as dormant; landslides classified as stabilized are negligible.

LIM is one of the main product used by the land use planners due to the Apennine singularity: >80 % of the landslides events with area >5,000 m^2 see a total or partial reactivation of a mapped landslide; but the landslides inventory map has also several shortcomings:

1. Mapping subjectivity, unavoidable in every individual survey and intellectual work, can be reduced but not eliminated;
2. It's lacking in small landslides, especially dormant, due to the difficult reconnaissance and their progressively masking, especially in cultivated slopes;
3. It doesn't give any information about the "out of landslide" areas;
4. It represent a "snapshot" of the moment then:

[1] The State of activity definition doesn't correspond to that used by Varnes (1978), WP/WLI (1993) or Cruden and Varnes (1996), but assume as active a landslide that has shown activity in the last ~30 years.

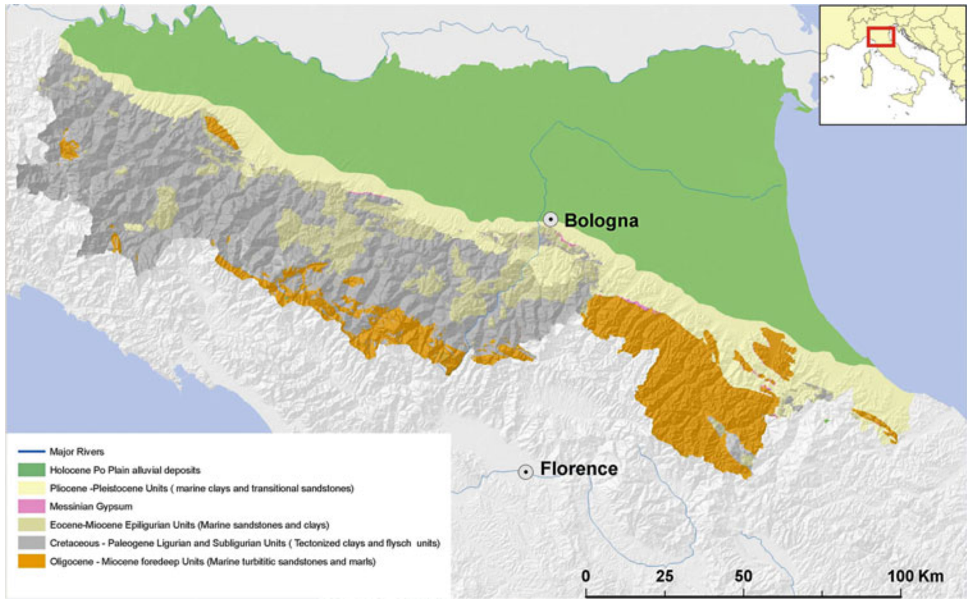


Fig. 1 Structural-Geological Map of the Emilia Romagna Apennines (from Cerrina Feroni et al. 2002)

- It's subject to a pretty fast ageing (mainly regarding the activity state), then it requires a constant updating;
- It doesn't contain forecast information and doesn't provide suggestions on the future landslides evolution.

For these reasons, purely LIM-based land-use planning is still too "risky" and a forecast contribution is generally desirable. Actually, across most of the RER territory, planning is still based on the landslide activity state classification, a characteristic very difficult to assess objectively and subject to suddenly changes that can lead to contradictions like that shown in the example of Fig. 2.

As land use planning in RER underestimates this kind of behaviour, the resulting planning maps overestimate the hazard in recently activated areas and underestimate the risk in many dormant landslides areas. For this reason we believe land-use planning, at every scale, should approach this issue with a less observational and more forecast-oriented approach. Our issue has been to produce a map with the following requirements: (1) coverage of the whole Emilia Romagna Apennines (~11,000 km^2); (2) high detailed resolution, such as can be used up to scale 1:5,000; (3) focused on forecasting the most frequent type of landslide; (4) ability to predict both the areas most prone to landslides outside of mapped landslides and to evaluate the mapped landslide reactivation likelihood; (5) ability to evolve towards relative hazard and specific risk assessment.

Type of Landslide Movement

In RER, most phenomena can be classified as earth-slides, earth-flows and complex landslide. Their triggering phase usually involves the retrogression of pre-existing depletion areas (originating past movements) and the onset of a small first slide movement (Figs. 3 and 4[1]).

The subsequent phase, through an "undrained loading" mechanism (Hutchinson and Bhandari 1971; Hutchinson 1988), sees the partial or total reactivation of the landslide accumulation which is the result of previous reactivations (Figs. 3 and 4[2, 3]).

We should note that even big landslide accumulations can be reactivated by a small retrogression movement (Fig. 3), so it is very important to try to locate even small potential sources of such movements.

Most of the landslides present this kind of evolution and can thus be treated in the same way as regards forecasting their triggering phase, so these are the type of landslides selected and used for the statistical model.

Analysis Methods

Many different methods for assessing landslide susceptibility have been proposed and compared in literature (Carrara 1983; Hutchinson 1995; Aleotti and Chowdury 1999; Chung and Fabbri 1999; Guzzetti et al. 1999; Crosta et al. 2001; Wang et al. 2005; Chung 2006; van Westen et al. 2006). Among these, physically-based and statistical models are the most widely used (e.g., Guzzetti et al. 1999; Dai et al. 2002). The former require detailed geotechnical and hydro-geological data to reproduce the physical processes (white-box models), whereas the latter rely only on comparison with past landslides (black-box models), and are more suitable for modelling susceptibility to landslides in large areas where such knowledge is lacking (Van Den Eeckhaut et al. 2006). Due to the vastness and heterogeneity of the study area,

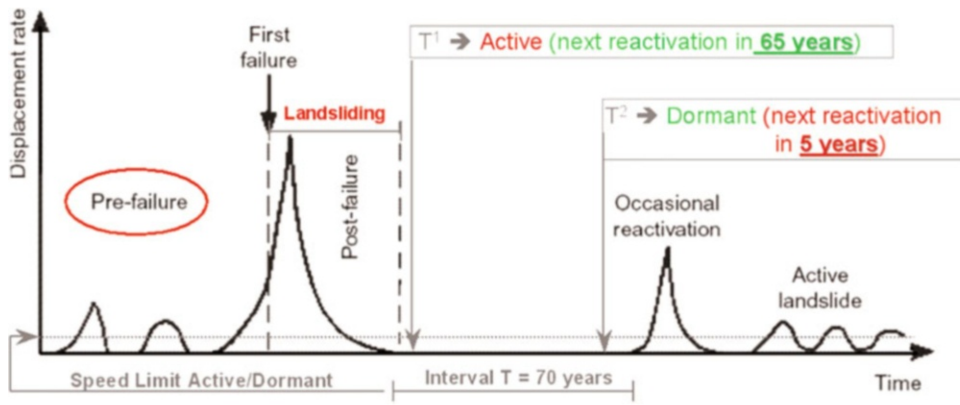


Fig. 2 A classic landslide temporal behaviour (modified from Leroueil et al. 1996). The image shows that in a quite long reactivation period perspective, a landslide mapped as dormant may be more hazardous than one classified as active

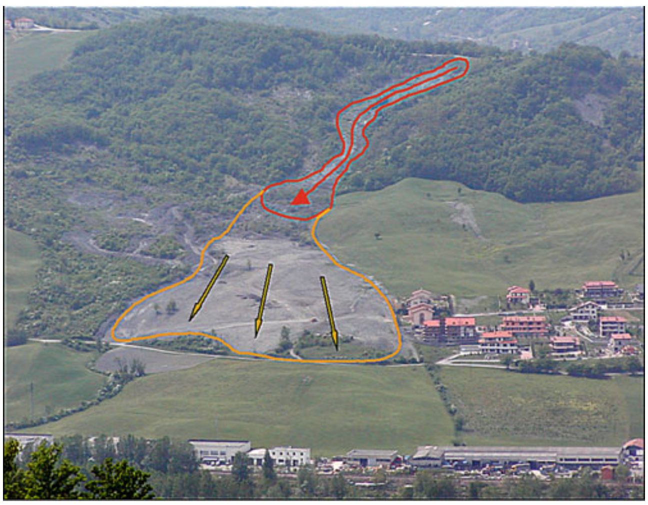


Fig. 3 An example of "undrained loading" reactivation: the Spazzavento Landslide (Bologna Province) of January 2002: the shallow earth-flow (*red boundary*) triggered a dormant landslide of ~20 m thickness (*orange boundary*)

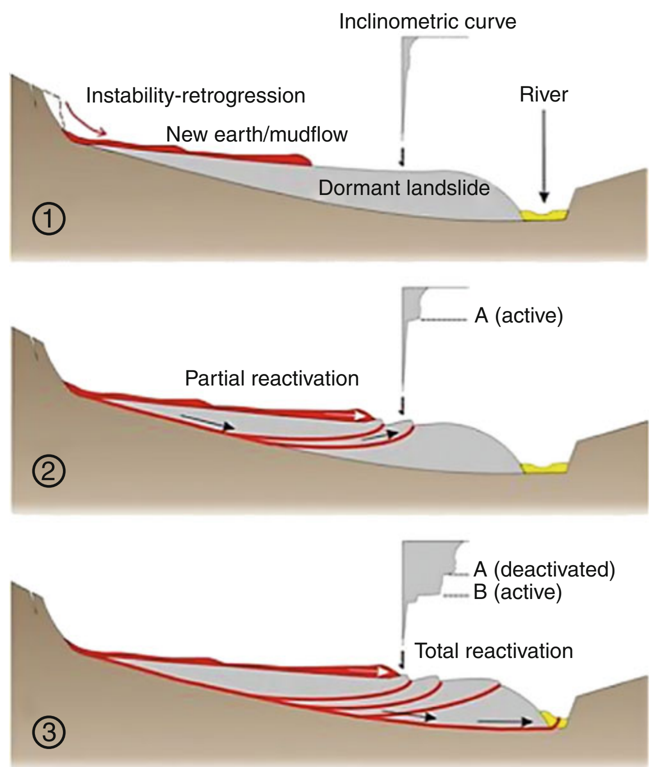


Fig. 4 Schema of the "undrained loading" reactivation mechanism (from Bertolini e Pizziolo 2008). A retrogression of the depletion area, involving a relatively low amount of material, may partially or totally reactivate a dormant landslide with a volume of 2–3 order magnitude higher then the first reactivation movement

we chose the latter method and, in particular, a multivariate regression method.

The conceptual model for all statistical models is that "the past (and present) landslide locations are the key to the future" (Carrara et al. 1995; Zêzere 2002). More specifically, locations susceptible to landslides will be selected because of their similarity in environmental characteristics to those of landslides already mapped in the study area. This basic assumption is one of the greatest limitations because climatic conditions or land use may change, hence the past is not strictly an indicator for the future. Chung and Fabbri (2003b) found some other weak points in statistical modelling practices that can be summarized as follows: (1) Simplification of inputs and categorization of continuous data layers cause the loss of much of the original significance of the data; (2) Assumptions in predictive models are unavoidable but rarely they are discussed in detail by the authors; (3) In any prediction, the methods used to make prediction are of no scientific value unless the validity of the prediction results is measured. In the follows we describe how we tried to overcome these problems.

Conceptual Framework

The conceptual model of every statistical methodology is approximately the same (Carrara et al. 1995; Guzzetti et al. 1999; Van Den Eeckhaut et al. 2006): (1) Identification of unstable zones in the study area; (2) Mapping of environmental factors which are supposed to be correlated with slope instability; (3) Estimation of the relative contribution of these factors in generating slope-failures; (4) Application of the model and classification of every land unit into domains of different susceptibility levels.

Despite this homogeneity, the results of different frameworks (not just statistical procedures), may differ greatly. According to several authors (van Den Eeckhaut et al. 2009; Rossi et al. 2010; Suzen and Doyuran 2003), backed up by our own tests (section "Multivariate Versus Monovariate Approach"), differences between various statistical methods do not lead to particularly substantial differences in the final map; the real differences come from other matters, namely: (a) the type, amount and quality of the input data; (b) the conceptual framework: model assumptions and construction.

Since the statistical models rely on the assumption that the past is the key of the future (black-box model), the amount and quality of past data bear the greatest importance. Literature abounds with works that discuss statistical questions but show models calibrated on just a few tens or, at best, few hundreds of landslides. Statistical models require "statistical stability", especially when using categorical (dummy) variables; that is why an appropriately large and high quality dataset is the most important starting point.

As to conceptual framework, in literature two different approaches are used to identify "unstable areas": the first specifies landslide accumulation as instability evidence (Carrara et al. 1990; Cardinali et al. 2002; Ayalew and Yamagishi 2005; Lee et al. 2008; Wang et al. 2007); the second uses the depletion areas as unstable zones (Suzen and Doyuran 2003; Van Den Eeckhaut et al. 2006). The two approaches are substantially different: the former focuses on products, the latter on processes. Considering that every statistical regression will find the conditions more likely similar to those used in the calibration phase, even with the same original dataset, the results of the two approaches will differ greatly: the model calibrated on landslide accumulations will likely find other "existing" landslide accumulations while the model calibrated on depletion areas is focused to highlight conditions that can lead to new landslide phenomena. In the study area context we believe the first approach to be quite useless because, aside from being landforms, "landslides" are, first and foremost, a process (landsliding) and landslide accumulations are merely the final result of a process generated elsewhere. Furthermore, if the landslide inventory map on which the model is based is presumed to be essentially complete, it is virtually useless to try to find many other landslide bodies, especially in the absence of any connection between shapes and processes.

Land Unit

Since we wanted to use the depletion zones as unstable areas, and the former are usually much smaller than the produced accumulation, despite the wide area to model (~11,000 km^2), we had to use a high detail land unit for statistical analysis: the 10 × 10 m cells of the DEM derived from the 1:5,000 Regional Technical Maps (CTR), in turn derived from the 1973–1976 1:13,000 aerial photographs. A wider unit (like elementary slopes, UCU – Unique Condition Unit, etc.), could not locate small but important local morphologies; we must indeed bear in mind that many morphometric parameters derived from DEM use a kernel of 3 × 3 cells, so the 10 × 10 m DEM is generally representative of the morphology in a 30 × 30 m area.

Choice of Regression Model

When one decide to approach the landsliding forecast using a statistical approach, he/she wants to solve the following problem: he/she knows the sites where the landslide exists (and where not) and wants to determine why the phenomenon could be found just in those locations and not elsewhere. Once one understand which are the main predisposal factors and how each of them influence the phenomenon, he/she wants to apply this "new knowledge" to outguess the locations where the same phenomena are most likely to occur again. This is the ideal field of application of Binomial Logistic Regression (LogR) which, in this context, can be used to predict the probability that a phenomenon will occur at an unsampled location.

In landslide forecasting, LogR has become popular quite recently (e.g., Carrara et al. 1995; Atkinson and Massari 1998; Begueria and Lorente 1999; Gorsevski et al. 2000; Lee and Min 2001; Dai and Lee 2002; Dai and Lee 2003; Ohlmacher and Davis 2003; Vanacker et al. 2003; Ayalew and Yamagishi 2005; Lee 2005; Akgün and Fikri 2007; Van Den Eeckhaut et al. 2006; Wang et al. 2007; Bai et al. 2008a, b; Rossi et al. 2010), because of its many advantage.

Like all other statistical regression methods, logistic regression requires the independent variables to be statistically independent (Hosmer and Lemeshow 1989). Apart from this, its requirements are much less restrictive than other statistical models (like Discriminant Analysis or OLS), regarding the independent (predictor) variables characteristics: (a) they may be either numerical or categorical (in this case represented by dummy variables); (b) they need not be normally distributed; (c) it does not assume homoscedasticity.

Chung and Fabbri (2003a) highlighted that discretization procedures may lead to the loss of significativity of variables. Furthermore the analysis results may appreciably vary according to different class subdivisions. The possibility in LogR of using both categorical and continuous variables, avoids the necessity of converting continuous variables into discrete (categorical) maps.

A further great advantage of LogR is also that predicted values can be directly interpreted as probability because they are constrained to fall into an interval between 0 and 1. Goodness-of-fit tests such as the likelihood ratio test are available as indicators of model appropriateness.

In LogR landslide presence/absence will be the dichotomous dependent variable (Y): 1 = presence; 0 = absence of landslide. Its presence will be influenced by the existence, in the same location, of (Xi) independent variables (where i = 1, 2, ….. n, are the different predictor variables). The role of the LogR model is to quantify the influence of the Xi variables in order to: (1) evaluate the relative contribution of each variable in helping us understand the process; (2) combine all the influences to obtain the odds of every other area unit to be a landslide prone area.

Logistic regression applies "maximum likelihood estimation" method, after transforming the dependent into a "logit variable" (the natural log of the odds of the dependent occurring or not – (2)). In this way, logistic regression estimates the odds of a certain event occurring. Note that logistic regression calculates changes in the log odds of the dependent, not changes in the dependent itself as OLS (Ordinary Least Square) regression does. The logistic response function can be written as:

$$P_{(Y=1)} = \hat{P} = \frac{1}{1+e^{-z}} \tag{1}$$

where P is the probability of occurrence of a landslide (Y = 1). The (1) can be linearized with the Logit transformation to obtain the Log odds:

$$z = Log\frac{\hat{P}}{\left(1-\hat{P}\right)} \tag{2}$$

where (z) is linearly related with the independent variables:

$$z = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots. + \beta_n X_n \tag{3}$$

Where β_0 is the model intercept and the β_i are the coefficients for the independent variables X_i (i = 1, 2, … n) estimated by maximum likelihood.

As z varies between $-\infty$ and $+\infty$, the probability varies from 0 to 1 on an S-shaped curve (Suzen and Doyuran 2003).

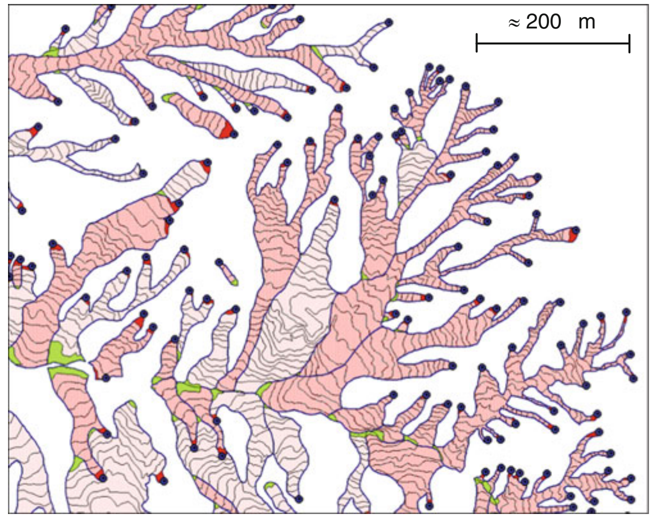


Fig. 5 Identification of unstable areas (*blue dots*) on the LIM polygons

Identification of Unstable Areas

Since the RER LIM derives from the geological map, it only maps landslide accumulations, not their depletion areas. Furthermore, many landslides have a multi-lobed shape, characterized by several branches merging into a single accumulation "GIS-polygon" but each one with its own distinct depletion zone. Mapping all the depletion areas of the >70,000 landslides by aerial photo-interpretation would have been a useful but enormous effort which was not feasible at the time. To solve this issue in the SGSS we wrote a series of GIS procedures (language Avenue for ArcView 3.x) that allowed us to obtain the higher elevation point of each branch of each landslide polygon (Fig. 5). These points usually fall within the depletion area, so the cells corresponding to each of these points have been assumed to be statistically representative of the correspondent landslide initiation conditions.

This procedure gave us further advantages:

1. The possibility to obtain a great number of unstable points in a relatively objective way;
2. The capability to don't lose information and to take the most advantage from the landslide inventory map (if we simply used only the upper point for each landslide polygon we'd have lost many useful information).

After an appropriate semiautomatic cleaning of misplaced points, we got 112,050 unstable points that became the 1's (presence of landslides) in the logistic regression model.

Identification of Stable Points

Despite its popularity, logistic regression may cause some problems if the total area affected by landslides is much smaller than the total study area. Indeed LogR sharply underestimates probabilities if the number of 1's (presence) in the population is dozens to thousands of times smaller than the number of 0's (absence), (King and Zeng 2001). According to the same authors, the number of non-landslide points should be from equal to five times greater than the number of landslide points. In actual fact in our map, the number of triggering points identified as described in section "Identification of Unstable Areas", is three orders of magnitude lower than the total number of cells of the area. To overcome such a problem, the strategy is to randomly sample on the map a numerical suitable set of "probably stable points". The reason of the random sample is to ensure a distribution of points statistically proportional to the overall presence of each value for each variable, thus to significantly compare the relative presence for landslide and non-landslide points. For this issue, prior to seed random stable points on the map, we had to find the portion of slopes most likely stable through progressive exclusion of non suitable areas. We proceeded as follows: (1) identification of the limit between the Po valley and intravallive plains and the hillslopes, based on geological and morphological evaluations; (2) from the remaining hillslopes, exclusion of some "probably unstable areas"; such areas were set, by experience, as a 30 m buffer around the mapped landslides; in this way we have probably excluded most landslide depletion areas and those areas surrounding the accumulations, often affected by stress detension and retrogression instability phenomena.

At the end of this cleaning operation, we randomly sampled about 140,000 "probably stable points" which will be the "0's" of the LogR model, each of which has been associated with the corresponding set of independent variable values.

Independent Variables

The general consensus is that any independent variable must be: (1) operational (having a certain degree of affinity with the dependent variable); (2) complete (be fairly represented all over the study area); (3) non-uniform (varying spatially); (4) measurable (can be expressed by any of the different types of measuring scales); (5) non-redundant (its effect should not account for double consequences in the final result) (Ayalew and Yamagishi 2005). Variables preparation/generation is therefore an important phase of the modelling process, which has to strike a balance between significativity and spatialization feasibility.

Independent variables maps may be classified in several ways according to their origin as: i. field survey based, ii. DEM based and iii. Remote Sensing based, or according to the data type as: continuous or categorical. Field survey based maps are very time and money consuming ones but they are often fundamental for a landslide model (e.g. geological maps and its derivates). Remote Sensing Based maps are recently on the increase but in landslide models are not widely adopted yet. Finally in the last decade, DEM and digital terrain analysis provided a great contribution to morphometry and hydrology applications and nowadays dozens of variables may be generated from DEM quickly and cost-effectively (Moore et al. 1991; Gallant and Wilson 2000).

In this work we decided to use two field based derived variable maps (lithotechnical and land use maps), and to test a series of DEM-derived continuous maps.

Lithotechnical Map

Based on RER Geological Map (scale 1:10,000), a lithotechnical map was elaborated following these steps: (1) conversion of the >500 geological units into lithological units; (2) GIS-intersection of the lithology with the geo-structural paleo-domain (which strongly influences the diagenesis degree and the structural characteristic of the rock mass); (3) further amalgamation of the still many classes to achieve the more suitable number of 16 lithotechnical classes.

Land-Use Map

The wide use of land-use maps in almost every susceptibility analysis witnesses the importance always given to this parameter. Notwithstanding we agree with those authors that recognized problems in the use of land use maps as predictor variables when applied to landslide susceptibility models (Van Den Eeckhaut et al. 2006). Indeed many ancient or dormant landslides last activated decades or centuries years ago, when the land use (and climate) was very different from the current day. In the RER Apennines, in the last few centuries there has been widespread timber harvesting and agricultural development, more recently followed by a progressive and important abandonment of farming. In these conditions land use tends to be more a dependent variable rather than a causal one and it must be used with awareness. Trying to overcome its limitation, in this work we used the oldest release of the Land Use Map (24 classes), derived by 1976 aerial photo, in order to better represent the pre-landslide condition, at least for recent landslides.

DEM-Derived Maps

Starting from the 10x10m DEM we computed about 30 parameters. For several parameters, we also used different software and algorithms. With ArcGIS® we used the unique standard methods, based on the algorithm of ESRI, "Neighbourhood Method" (Srinivasan and Engel 1991), for basic geomorphometry and "D8" (O'Callaghan and Mark 1984) for basic hydrology. To test more advanced algorithms, we used the software SAGA-GIS (Conrad

2006) and algorithms like that of Zevenbergen and Thorne (1987) for basic geomorphometry and "D∞" (Tarboton 1997), for basic hydrology.

Despite of the large number of geo-morphometric parameters (Gallant and Wilson 2000), in literature we didn't find one able to describe the small scale terrain undulations (hummocky) that characterize areas like landslide accumulations, colluviums deposits, etc., affected by high tension stress/strain and, in general, recognisable as very landslide prone areas in field surveys.

To highlight this distinguishing morphology we had to devise a new parameter, conceptually similar to the Topographic Position Index (TPI) and Slope Position Index (SlPI) (Weiss 2001; Jenness 2006), which we called: Local Roughness Index (LRI) (Fig. 6).

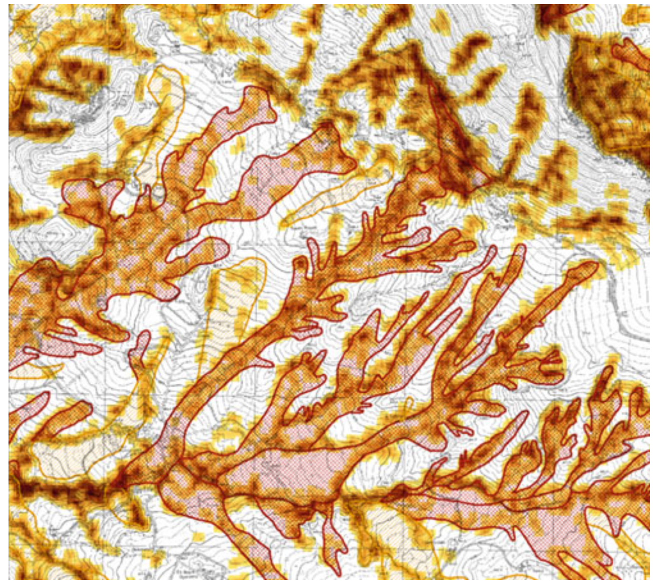


Fig. 6 Comparison between the "Local Roughness Index" (LRI) Map (*yellow to brown raster pixels*) and the LIM (polygons with cross hatch). It's noticeable the good agreement between the DEM-derived parameter and the Landslide Inventory Map

Preliminary Analysis of the Independents

At each point, 1's and 0's of the dataset, the corresponding value of all the variables (continuous and categorical), was extracted, producing the database for model calibration; then, each parameter was subject to several preliminary analyses to decide whether or not it should be included in the multivariate model.

Two different kinds of preliminary analysis were performed on the "candidate" predictor variables: (1) a collinearity matrix analysis between each combination of two variables and (2) a univariate test of association of each independent with the dependent, through a Bayesian analysis.

Independents Correlation

As with other statistical regression methods, logistic regression is sensitive to collinearity among the independent variables (Hosmer and Lemeshow 1989). Many of the independents, even if appreciably correlated with the dependent, should not be used at the same time in a multivariate model. Violating this conditional independence (CI) can severely bias the simulated maps by over- or underestimating landslide probabilities (Thierya et al. 2007). Thus we tested collinearity among all the variables and decided to exclude those with $R^2 \geq 0.5$ and use wisely those with $0.3 < R^2 < 0.5$.

Bayesian Test of Association

A bivariate test of association through the application of the Bayes theorem has been performed between the occurrence of each independent candidate and that of landslides (1's) and non landslide (0's) points. The Bayes Theorem is expressed by (4).

$$P(F|Xi) = \frac{P(Xi|F) \cdot P(F)}{P(Xi)} \quad (4)$$

where: $P(F(\mid Xi)$ is the "conditional probability" or "posterior probability", of occurrence of a landslide F, once given the presence of the analysed independent Xi and is constrained between 0 and 1. $P(Xi \mid F)$ is the conditional probability of Xi given F, also called "plausibility function"; $P(F)$ is the "prior probability", in the sense that it does not take into account any information about Xi; $P(Xi)$ is the "marginal probability" of Xi and acts as a normalizing constant. The application of (4) leads to graphics like those of Fig. 7. Figure 7 shows that landslide probability does not change significantly with variations in Aspect, whereas an increase in Slope generates a rapid increase in probability, reaching a maximum for about 20°, tending to lower, stabilize and rise again for high slope values (even if it shows an unstable behaviour).

Based on these observations, we can say, for instance, that Slope is an important causal factor and must be used in the LogR model while Aspect contribution is negligible and may be discarded. Graphs like Fig. 7 have been prepared for all variables, taken singularly or in "interference" with lithotechnic; the latter because we presumed the influence of many parameters varies depending on lithotechnical classes and disregarding this issue may lead to an excessive smoothing of the effect of the factors themselves. Figure 8 shows that this is an effective problem and should be considered in the final model.

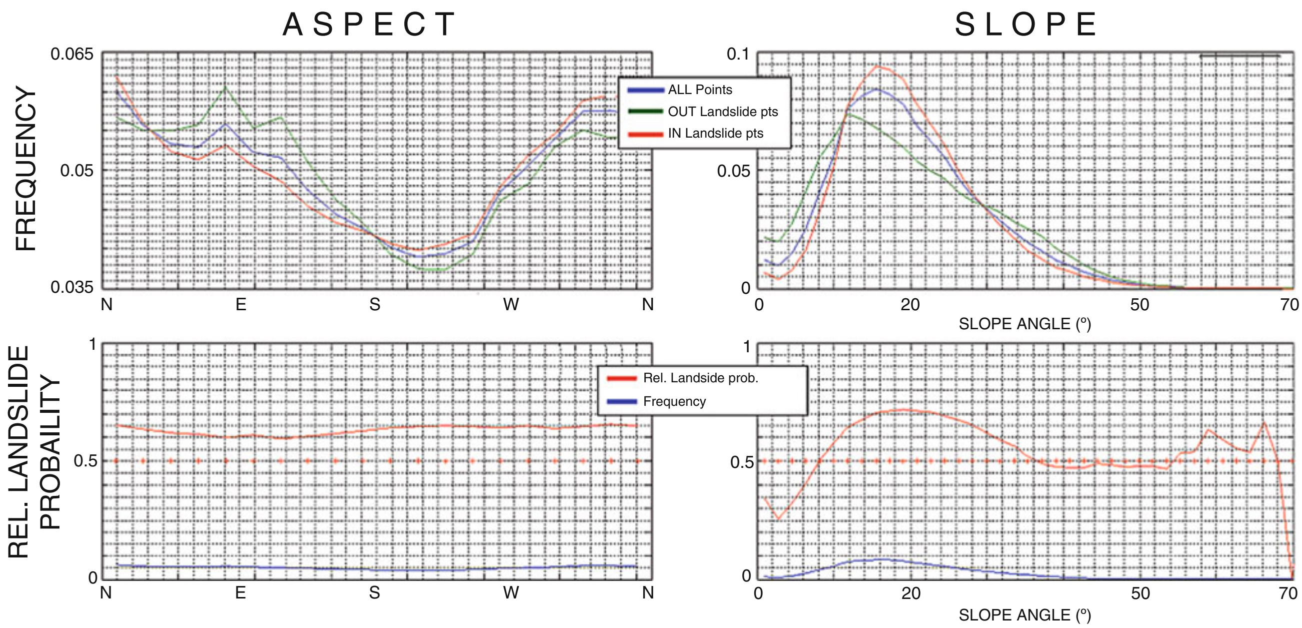


Fig. 7 Frequency distributions of 1's, 0's and total points and the "posterior landslide probability" calculated with (4). The graphs show the different effects of two independents variable on the conditional probability (or relative landslide probability), to have a landslide varying the value of the variable themselves

Logistic Regression Models (Calibration and Validation)

Like every statistical models, landslide prediction models have no scientific value unless the validity of the results is measured (Chung et al. 2002; Chung and Fabbri 2003a, 2005). Given that the "wait and see" validation is not feasible, as is usually done we randomly subdivided the dataset: 80 % of the dataset points were used for calibration and the remaining 20 % for validation. The apportionment of 80/20 has been chosen to maintain a good amount of data for the calibration phase, still leaving enough data for a comprehensible validation.

To test the "goodness of fit" of the model to the calibration data, we used the −2 Log Likelihood (−2LL) while to validate the model prediction performance we used the ROC (Receiver Operating Characteristic) (Swets 1988). ROC curves plot the proportion of false positives against the true positives at each level of the criterion and are an easy numerical and visual approach which compares a Boolean map of "reality" (presence or absence of landslides), with the probability map. The ROC area is the integral of the curve: a value of 0.5 corresponds to a random prediction while 1 equals a perfect model. The closer the result is to 1, the better the prediction performance we obtain.

Even with the same dataset (dependent and independents variables) and the same statistic method (LogR), the results can still be different, depending on the way the variables are combined together. Based on issues discussed before, we chose to test first of all single variable models, then multivariate models, increasing the number of the variables independently onset in the regression, and lastly, complex models with "interference" between variables, such as lithotechnic and slope (Fig. 8); this way we further guide the model, trying to get the best performance from the model itself. Table 1 shows the increase of performance of the different models calibrated on all landslides (irrespective of the activity state), starting from the easiest to the more complex ones.

The last model, that gave us the best prediction performance (0.78), comprises 2 categorical (Lithotechnic and Land-use) and eight continuous DEM derived variables [Elevation, Slope[2], Convergence Index Aspect (CI), Topographic Position Index (TPI), Local Roughness Index (LRI), Topographic Wetness Index (TWI)[3] , annual mean Solar Radiation (SR) and Drainage Density (DD)], and has the following formulation:

[2] We used the Zevenbergen and Thorne (1987) algorithm that performs better then others on sharp slope changes.

[3] For the flow accumulation we used the D∞ algorithm (Tarboton 1997), that performs much better then D8 to identify the accumulation/dispersion of water flow along the hillslopes.

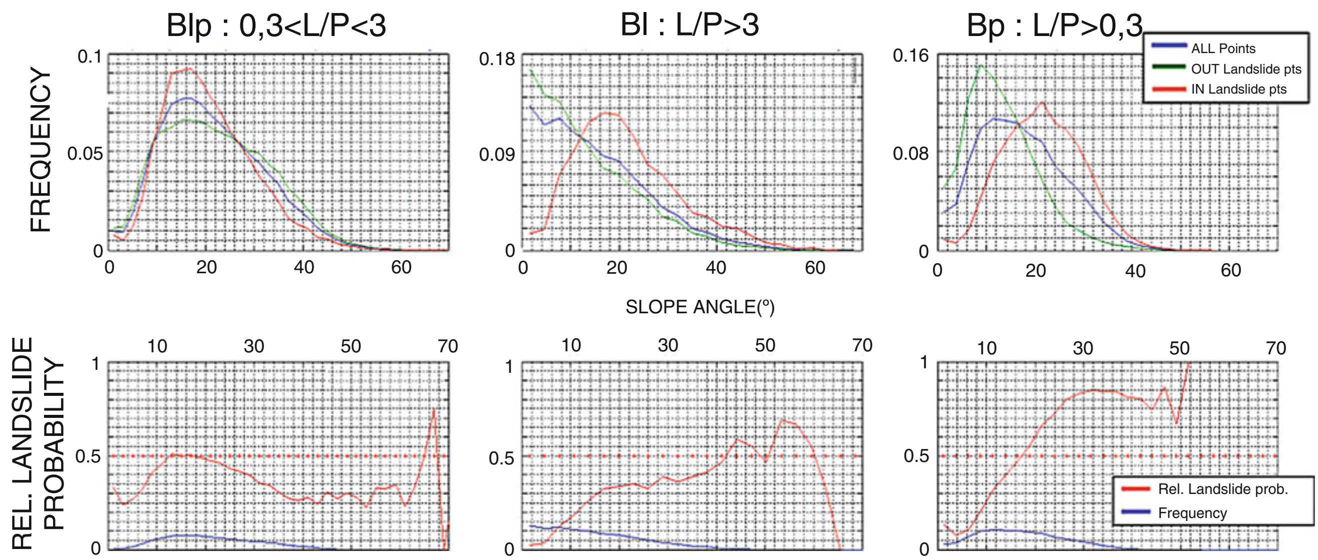


Fig. 8 These graphs are similar to those *right* of Fig. 7 but branched for different lithology (Flysch formations with different Arenitic/Pelitic ratio). We can note how the effect of slope on instability varies significantly on different lithotechnical classes and suggest the use of a multivariate model with "interference" between variables

$$Logit(\hat{P}) = Z = \beta_0 + \sum\sum \beta_{ij} X_i \cdot LIT_j + \sum\sum \beta_{ij} X_i \cdot USE_j \quad (5)$$

where Xi are the continuous variables, $LITj$ are the lithotechnical classes, $USEj$ are the land-use classes and the β are the parameters given by the LogR model for the best calibration fitting; in particular β_0 is the model intercept and β_{ij} are the regression parameters given to the variables combination.

The term "susceptibility" by definition is time-independent (Guzzetti et al. 1999), so that a susceptibility map would foresee the landslide prone areas at "indefinite time". With this assumption, a landslide susceptibility map should be calibrated on all LIM landslides, regardless of their last activation or present activity state. Unfortunately, using all landslides may produce several "side effects":

1. The land-use "independent" variable on ancient landslides is probably more a landslide dependent variable than one affecting them (section ". Land-Use Map");
2. Morphology can slowly evolve due to weathering, erosion, etc. and the depletion area morphology of an ancient landslide may be totally remodelled, especially in a territory like RER Apennines which, over the last few centuries, has undergone important human changes;
3. Reconnaissance of old and ancient landslides may be difficult, so landslide mapping may be much less accurate than for recent or active landslides.

Each of these issues can negatively influence susceptibility map reliability. To overcome all of these problems, we might consider calibrating the model only on landslides mapped as active; this way we can:

1. Be more confident about the reliability of the independent variables significance;
2. We further introduce a sort of "temporal information" which, even if it does not lead to a really definable "hazard map", it gives some more useful information at a time scale compatible with long term land-use planning.

After the modelling described above, we tested the model of (5) only on the 38,178 active landslides and the ROC area lunged up from 0.78 to 0.85. Figure 9 shows that the red line represents much better results: it says that, at a certain level of territory stated as unstable (specificity), the model can locate many more landslide areas (sensitivity); in opposite, to predict a certain amount of landslides (Y), it produces fewer "false alarms"(X). For this performance and for the advantages described above, we decided to adopt this latter model as the final susceptibility model.

Table 1 Index of the models tested and relative improvement in fit (decrease in − 2LL) and prediction performance (ROC area)

Dependent variables		−2LL	ROC area	
Costant		312137.35	0.500	
Slope		310447.42	0.574	Single variable
Convergence index aspect		307924.03	0.610	
Topographic wetness index		310215.97	0.534	
Drainage density		311982.11	0.495	
Solar radiation		312024.55	0.505	
Local roughness index		310295.37	0.562	
Topographic position index		312044.96	0.515	
Lithomap		292630.20	0.659	
Land cover		300084.88	0.635	
Climate		305367.60	0.593	
Slope position index		307445.30	0.554	
Slope		285515.60	0.691	Two summed variables
Convergence index aspect	add lithomap	288682.80	0.681	
Topographic wetness index	add lithomap	289122.20	0.673	
Drainage density	add lithomap	292629.30	0.662	
Solar radiation	add lithomap	292605.20	0.659	
Local roughness index	add lithomap	288889.30	0.678	
Land use	add lithomap	285285.50	0.688	
Slope		281285.02	0.703	Two variables with interference
Convergence index aspect	interference with lithomap	307533.01	0.612	
Topographic wetness index	interference with lithomap	292501.79	0.663	
Drainage density	interference with lithomap	294854.76	0.656	
Solar radiation	interference with lithomap	293446.81	0.657	
Local roughness index	interference with lithomap	302688.37	0.609	
Topographic position index	interference with lithomap	309827.62	0.554	
Sum of all the factors stand alone		268332.60	0.747	Complex models
Sum of all the factors stand alone + all the factors with interference with lithomap		260578.34	0.763	
Sum of all the factors with interference with lithomap + all the factors with interference with land use		253929.30	0.780	

Figure 10 shows the differences in the susceptibility frequency distributions calculated for points "outside landslide boundaries" (0's) and "landslide points" (1's). We can note a significant difference between the two groups, nevertheless there are many 0's with high and 1's with low susceptibility. The former is probably because either they are not recognized as landslides or simply have a high level of landslide susceptibility; the latter are more difficult to explain but the reasons may be as follows:

1. They belong to old landslides, probably stabilized or with the original morphology strongly modified;
2. The triggering phase has been affected by local factors not accounted for in the model (like human interference, structural issues, etc.);
3. Because for LIM cartography limits and automation of the points selection, they wrongly fall within stable areas.

Figure 11 breaks down the 1's distribution of Fig. 13 into active and dormant landslide points. Here we can appreciate the greatest significance of active points with respect to the dormant ones (we must, in any case, bear in mind that the model has been calibrated only on active landslides, so this result for dormant landslides was to be expected).

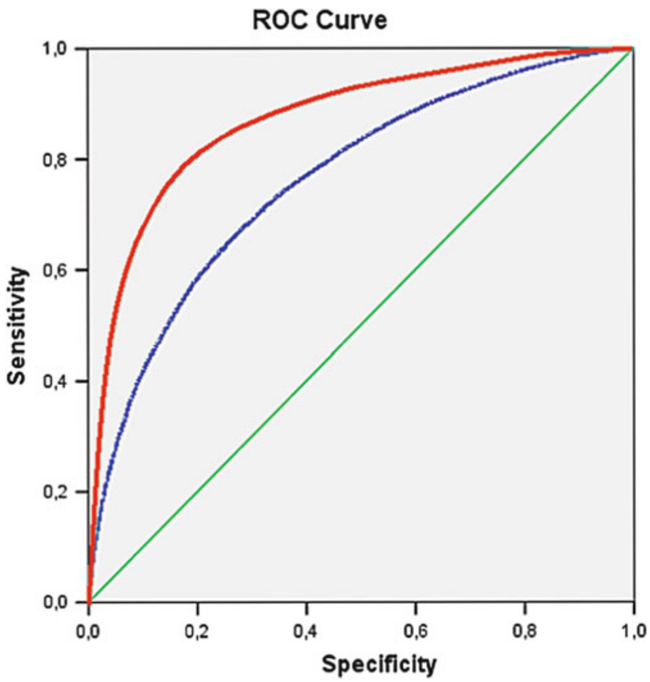


Fig. 9 ROC curves. – the *green* line represents a random forecast (only the intercept is included in the model – area = 0.5). The *blue* line represents the performance of the model calibrated on all landslides (0.78) while the *red* one the model calibrated only on active landslides (0.85)

Multivariate Versus Monovariate Approach

We compared the LogR method with a monovariate approach: the Frequency Ratio model. In this last, every independent variable is categorized and the frequency of observed unstable points is evaluated for each class of each regressor. The final susceptivity index (SI) is obtained by summing the frequency of the regressors values (divided by the variables number).

The comparison shows that considering simpler combination of independent variables, the monovariate approach is even better than the multivariate one, but increasing the complexity (adding more regressors and interactions), the gain of the multivariate approach is higher (Fig. 12).

Results

Combining in ArcGIS the coefficients obtained by LogR with the (5) and performing the inverse transformation of (1), we obtained the map of P which represents the "landsliding susceptibility" of the whole RER Apennine (Fig. 13). The pixel value ranges from 0 to 1 and can be considered as the probability for each cell to be the source of a landslide.

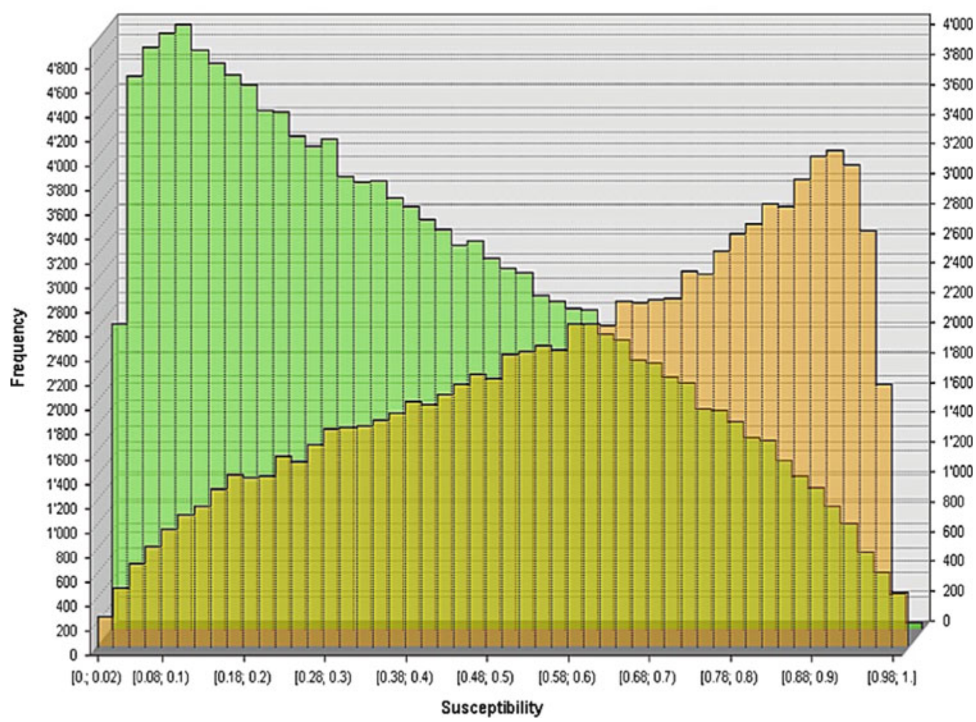
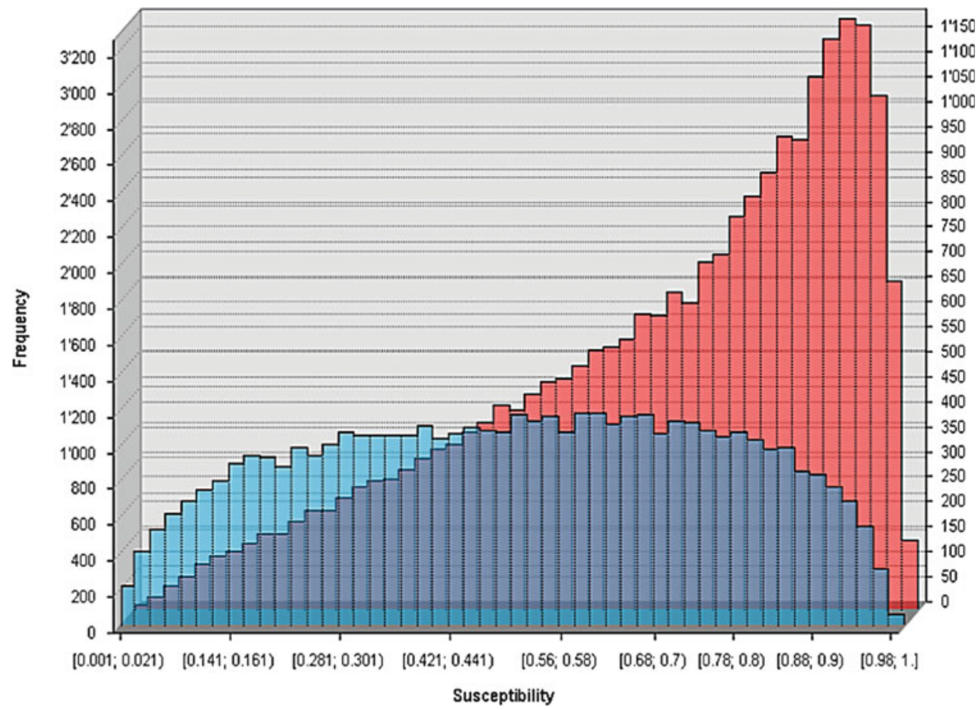


Fig. 10 Comparison between the frequency distributions of susceptibility calculated by the model of (5) for 0's (*green* – mean = 0.37) and 1's without distinction between active and dormant landslides (*orange* – mean = 0.61)

Fig. 11 Comparison of the frequency distribution of susceptibility calculated by the last model for dormant (*blue* – mean = 0.50) and active (*red* – mean = 0.68) landslides



COMPLEXITY

Mod.	LogR	Freq. Ratio
1	0.573 ± 0.004	0.623 ± 0.004
2	0.696 ± 0.004	0.709 ± 0.004
3	0.708 ± 0.004	0.725 ± 0.004
4	0.759 ± 0.004	0.755 ± 0.004
5	0.769 ± 0.004	0.743 ± 0.004
6	0.773 ± 0.004	0.747 ± 0.004

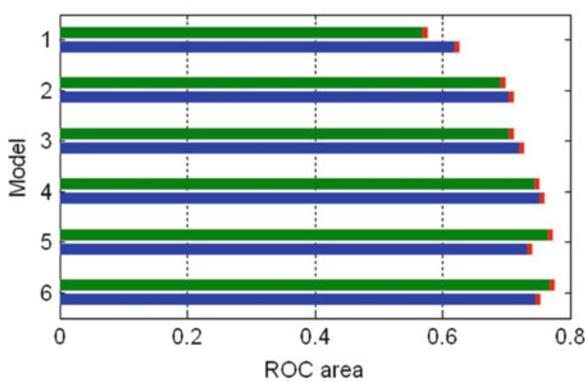


Fig. 12 Comparison of model performance: LogR (*green bars*) verus Frequency Ratio (*blue bars*) models

The resolution in the above image of Fig. 13 doesn't do justice to the product detail but shows the overall area and the lithological guided pattern of susceptibility (compare Figs. 1 and 13). Below there are two subsequent enlargements. In the lower right enlargement the LIM has been overlaid in order to compare the details of the resultant map with the depletion areas of the mapped landslides and their tendency to retrogressive and widening evolutions; note how, in the same lithotechnical class, susceptibility varies rapidly and greatly, concentrating on medium and steep slopes and slightly concave areas. Interpreting the map, in any case, it is crucial to bear in mind that it aims to identify the triggering areas and not the further evolution (runout) of displaced material; for this reason the "green areas" on mapped landslides, particularly if morphologically depressed, must not be presumed to be "stable areas" but areas less prone to be affected by a local landslide activation.

Discussion and Conclusions

RER Apennine is affected by a huge number of landslides which results in a mean landslide index of ~24 %. The absence of a susceptibility map covering the entire RER area with a high detail level and the heterogeneity of the area, led us to develop and apply a statistical method based on the singularity of the territory.

In this work we have tried to emphasize how the appropriateness of modellization relies not so much on statistical method choice, as on:

1. The amount and quality of the LIM input data;
2. The appropriateness of preliminary choices, that can be called the "conceptual framework", to fit the specificity of the target landslide.

In particular, we aimed to predict the areas more likely to generate new landslide events or actual landslide backward

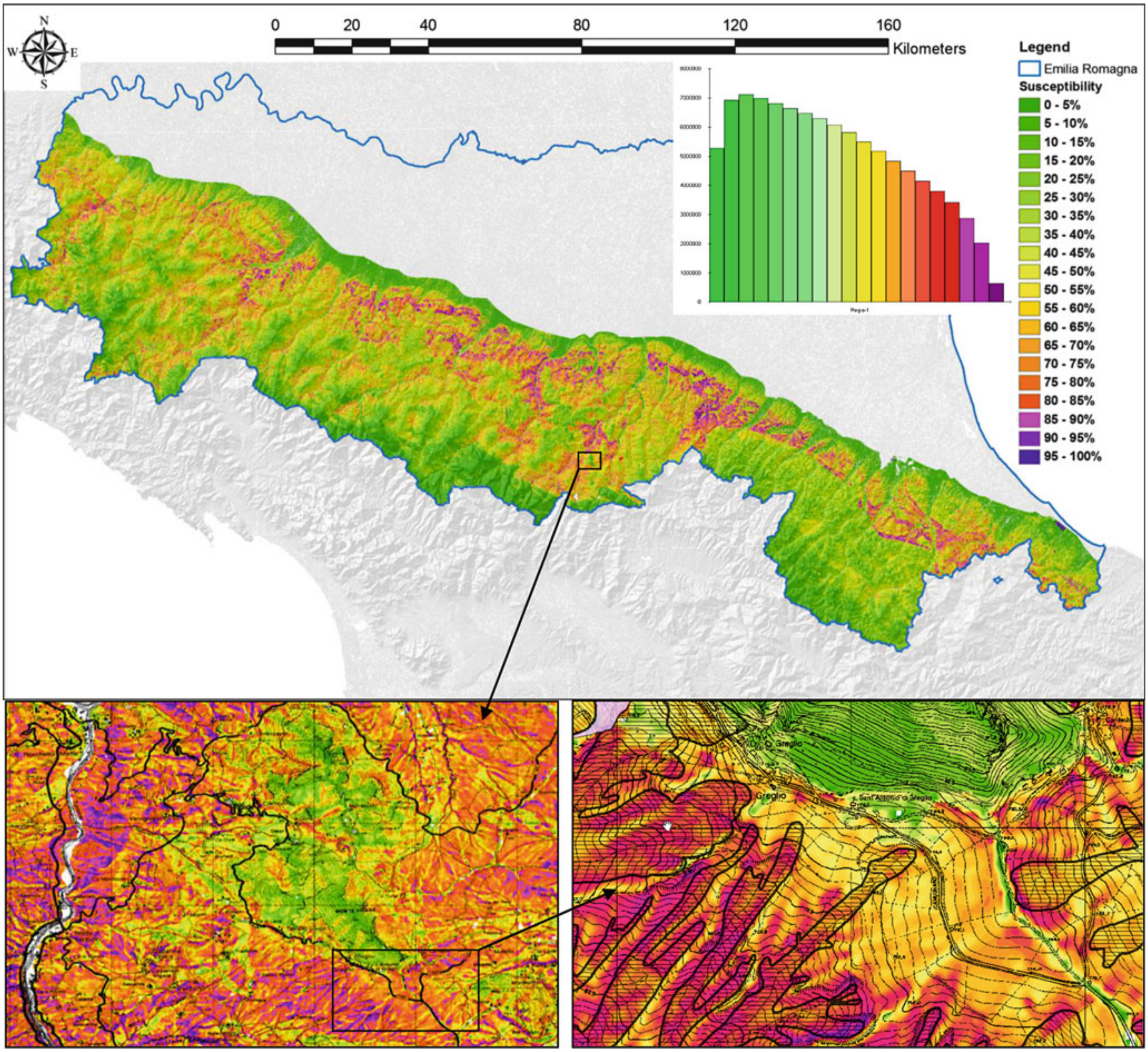


Fig. 13 Susceptibility map of the whole RER Apennine (above: 28,650 × 14,459 10 × 10 m cell map – 113,840,217 actually calculated – mean susceptibility = 0.41; σ = 0.25). The histogram shows the frequency distribution of the susceptibility all over the area. Below two progressive enlargements of the resulting map. On the *lower right* the susceptibility map with the LIM overlaid (*black striped hatch polygons*)

evolution. With the used approach it's been possible to focus the modellization on the starting processes (landsliding), correlated with the triggering area conditions, instead of on the effects (landslides accumulations). We believe that this approach is generally preferable and the result is in any case helpful in identifying the landslides (usually small), not reported in the LIM or improving it's polygons quality (Fig. 13).

Despite of the detailed scale of the input map that it requires, by means of the 10 × 10 m DEM we can develop high resolution maps for detailed field applications; furthermore, unlike a small scale product, which does not allow zooming in for further detail, such a detailed map can be generalized in many ways to be used for smaller scale applications.

On the other hand, as every other kind of model, unavoidable assumptions and simplifications lead to shortcomings and limitations that should be always highlighted by modellers and properly understood by final users. Table 2 briefly summarizes the main assumptions and simplifications of our choices and the shortcomings which each of these produces.

Table 2 Report of the main model shortcomings

Model feature	Shortcomings
Retrogressive triggering model	It cannot predict landslides triggered by slope undercut or for block reactivation of part of the landslide accumulation
Small base unit (cells 10 × 10m)	With this cell dimension the morphometric parameters are often significant for an area just a few dozen linear metres wide, so we cannot foresee landslides which, in the triggering area, present dimensions of many dozens or hundreds of metres[a]
Model with high morphological and no structural components	We cannot foresee landslides which are strongly influenced by structural tectonics, bedrock- strata/ hillslope relationship (like for rock-slides), particular hydro-geological circulations (like permeability contrast, faults circulations, etc.)[a]
Model calibrated on slides, flows and complex landslides	We cannot foresee different types of movements (rockfalls, topples, lateral spreadings, DGPV, etc.)
Model designed to predict the triggering areas	There are no hints about the magnitude of possible landslides, nor about their downslope evolution (runout) or retrogression upslope; It is landscape knowledge that must address an ostensible evolution scenario. Particular attention may be paid in assuming as stable many areas which, for instance because of their low slope, may be classified at low susceptibility: they actually may be landslide accumulations, then the susceptibility map has always to be used in conjunction with LIM

[a]Anyway those kind of landslides would be hardly ascribed to the group of shallow landslides

Some of the issues depicted in Table 2 can be overcome with different (but potentially complementary) approaches and modellizations. It'll be nonetheless easy in a GIS environment to develop different models for different landslide specificity and overlay or merge someway the different results. For instance a further development and application of the presented model we've worked on to overcome the lack of landslide evolution forecast (runoff area), partially uses the output of the presented model to predict the mapped landslides reactivation likelihood.

The mapped landslide reactivation likelihood model will be published in a further paper.

Joining a detailed and updated LIM with the forecast information given by these kind of models (even if black box type), may results in a virtuous growing of knowledge and, hopefully, a better land use planning.

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