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Artificial Neural Networks applied to landslide susceptibility assessment

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Abstract

Landslide hazard mapping is often performed through the identification and analysis of hillslope instability factors, usually managed as thematic data within geographic information systems (GIS). In heuristic approaches, these factors are rated by the attribution of scores based on the assumed role played by each of them in controlling the development of a sliding process. Other more refined methods, based on the principle that the present and the past are keys to the future, have also been developed, thus allowing less subjective analyses in which landslide susceptibility is assessed by statistical relationships between past landslide events and hillslope instability factors. The objective of this research is to define a method with the ability to forecast landslide susceptibility through the application of Artificial Neural Networks (ANNs). The Riomaggiore catchment, a subwatershed of the Reno River basin located in the Northern Apennines (Italy), was chosen as an ideal test site, as it is representative of many of the geomorphological settings within this region.

In the present application, two different ANNs, used in classification problems, were set up and applied: one belonging to the category of Multi-Layered Perceptron (MLP) and the other to the Probabilistic Neural Network (PNN) family. The hillslope factors that have been taken into account in the analysis were the following: (a) lithology, (b) slope angle, (c), profile curvature, (d) land cover and (e) upslope contributing area. These factors have been classified on nominal scales, and their intersection allowed 3342 homogeneous domains (Unique Condition Unit, UCU) to be singled out, which correspond to the terrain units utilized in this analysis. The model vector used to train the ANNs is a subset of that derived from the production of Unique Condition Units and consists of 3342 records organized in input and output variable vectors. In particular, the hillslope factors, once classified on nominal scales as binary numbers, represent the 19 input variables, while the presence/absence of a landslide in a given terrain unit is assumed to be the output variable. The comparison between the most up-to-date landslide inventory of the Riomaggiore catchment and the hazardous areas, as predicted by the ANNs, showed satisfactory results (with a slight preference for the MLP). For this reason, this is an encouraging preliminary approach towards a systematic introduction of ANN-based statistical methods in landslide hazard assessment and mapping.
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Keywords: Landslide hazard; Landslide susceptibility; Artificial Neural Network; Geographic Information System (GIS); Northern Apennines

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1. Introduction

Landslide hazard assessment represents one the most important tasks for earth scientists involved in the more general process of landslide risk assessment. It is generally based on the well-known and widely applied rule that the "present and the past are keys to the future". For this reason, most landslide hazard analyses take into account a reliable and up-to-date landslide inventory that represents the fundamental tool for the identification of the role played by hillslope instability factors in predisposing and triggering landslides. To map areas characterized by different susceptibility levels, currently available methods differentiate on the basis of how hillslope instability factors are managed. Depending on the different purposes, data availability and scale of the landslide, hazard assessment project, direct and indirect mapping techniques can be implemented (Hansen, 1984). Heuristic approaches principally based on the field interpretation of landforms by an experienced geomorphologist belong to the first category, while statistical and deterministic analyses are generally aimed to "model" the relationships that associate the presence of a landslide to the physical terrain attributes responsible for its occurrence. For this reason, they can be considered as indirect mapping techniques.

The aim of this research is to define a method with the ability to forecast landslide susceptibility through the application of Artificial Neural Networks (ANNs), a kind of indirect mapping technique, which allows "black box models" to be implemented, similar to several other statistical approaches (Carrara et al., 1991, 1995).

Recently, ANNs have been used for various scientific and engineering applications (Emami et al., 1998; Caparrini et al., 1996; Casagli and Ermini, 2001) essentially because they allow the modelling of a process, which starts from the database containing the variables that describe that particular process. They have already been applied to the study of landslides in particular, with reference to the indirect determination of the triggering parameters (Aleotti et al., 1996; Mayoraz et al., 1996) and also to landslide susceptibility mapping, with physical terrain factors (Lee et al., 2001; Fernàndez-Steeger et al., 2002). Despite these efforts, the specific setup and application of a mapping-oriented method of landslide-hazard assessment based on ANNs has never been attempted. This paper presents the results of the application of two different Artificial Neural Networks, both developed by the Trajan 6.0 Professional-Neural Network Simulator (Trajan Software, 2001), to landslide susceptibility assessment in the Riomaggiore River basin (Fig. 1), a subwatershed of the Reno river basin, located in the Northern Apennines (Italy).

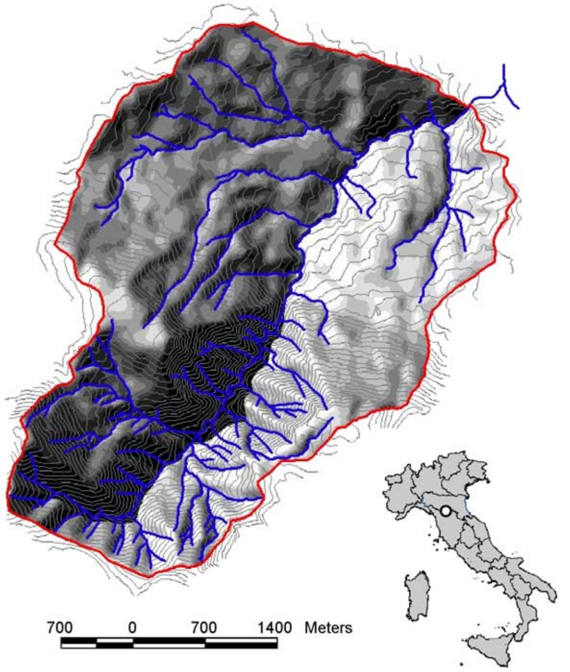

Fig. 1. Riomaggiore River catchment, the test site for the application of an Artificial Neural Network to landslide susceptibility assessment.

2. Geological settings

The Riomaggiore catchment was chosen as the test site for a wider project, which will take into account the entire upper portion of the Reno River catchment. The interest in this basin, approximately 6×5 km wide, is mainly derived from its representativeness of both geomorphological and geological settings of the landslide processes that are typical of this part of the Apennines. Very different physical characteristics are all enclosed in a relatively small area of 17 km^2, which is considered as an optimal size for performing tests on landslide hazard analysis. From a climatic point of view, this part of the Apennine chain receives a mean annual rainfall of about 2800 mm, mainly concentrated during the end of the Autumn.

The study area is located in the Northern sector of the Apennine mountains (Italy), close to the main water divide, which separates Tuscany from Emilia Romagna (Fig. 1). The region is characterized by strong spatial variations in drainage density that are correlated with bedrock geology, relief and slope processes (Tucker et al., 2001). In this region, the Apennine chain is made up mainly of arenaceous and calcareous turbidite sequences and highly deformed argillaceous units of sedimentary and tectonic origin belonging to the Ligurian Formations (Abbate and Sagri, 1970; Kliegfield, 1979; Treves, 1984). These units accreted during the Tertiary in a thrust system with a NE trend (Merla, 1952; Sestini, 1970; Società Geologica Italiana, 1992). Since the late Tortonian, this thrust system was affected by a phase of extensional tectonics, which migrated progressively from SW toward NE. In the SW sector of the chain, this latter phase produced a horst and graben structure filled with Neogene and Quaternary marine and fluvio-lacustrine sediments.

From a geological point of view, it can be roughly, equally subdivided between regular well-stratified turbidite sequences (belonging to the Sestola-Vidiciatico Unit and the Monte Cervarola sandstones) and the highly deformed mélange-like shaly rocks of the basal complexes of Ligurian Formations (Bettelli and Panini, 1987, 1991; Bartolini et al., 1982).

The Northern Apennines have been subjected to an intense and nearly continuous uplift since the Pliocene and continue to be tectonically active (Bartolini et al., 1982). Several authors (Boccaletti et al., 1985; Bertotti et al., 1997) agree in affirming that, during the middle Pleistocene, the southwestern sector was progressively uplifted above sea level and subjected to intense erosion, particularly within the uplands along the Apenninian divide.

3. Landslides

The Northern Apennines may be considered a relatively homogeneous area from the viewpoint of its general geological and landslide characteristics. The rapid tectonic uplift that took place starting during the Pleistocene, coupled with the prevalence of erodible lithologies, is responsible for the formation of steep slopes, which are very prone to instability processes. According to the Cruden and Varnes (1996) classification, most of the landslides can be classified as rotational–traslational movements associated with earth slides–earth flows. They primarily affect pelitic formations, often highly deformed, that widely outcrop in this mountain chain. Slope failures can also take place in closely jointed and altered arenaceous–calcareous turbidite sequences of Cretaceous age, as in the cases of San Benedetto Val di Sambro (Casagli et al., 1995) and Corniglio landslides (Martelli, 1916, Clerici and Perego, 2000), whereas in the Tertiary turbidite formations (such as the Marnoso Arenacea Formation), translational slides prevail, occurring along planar surfaces generally corresponding to bedding planes. Most of these landslides are reactivations of preexisting movements initially activated under different climatic and geomorphological conditions. Starting from the available data on radiocarbon dating (Bertolini et al., 2004; Bertolini and Tellini, in press), it can be hypothesized that the sliding activity in the Northern Apennines took place largely during the late Pleistocene and the early Holocene. The spatial distribution of slope movements in the Apennines area is controlled primarily by the lithological and structural characteristics of the various outcropping formations and, secondarily, by the high relief steep slopes (with maximum elevations of about 2200 m). The Riomaggiore catchment is typical of the area, where landslides often join together to form huge displaced masses that occupy large portions of the slopes.

The first step in the application of an Artificial Neural Network to landslide susceptibility assessment is represented by the landslide inventory, which has a fundamental importance for the training and the testing of the models. The landslide map of the Emilia Romagna Region administration (surveyed in the years 1996–1998) completely covers the Riomaggiore catchment area, representing a good reference for the activity of present and past slope movements. The integration of this archive was essentially carried out by means of aerial-photointerpretation at a 1:10,000 scale, coupled with an intensive field survey aimed at the validation of the results. Photointerpretation was

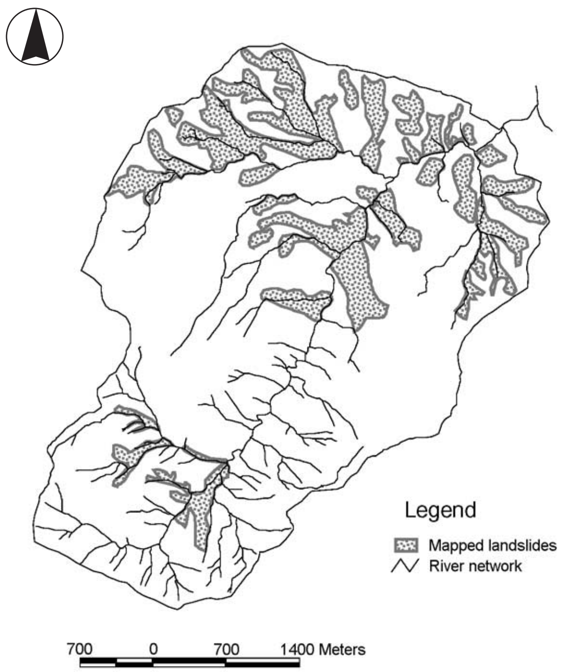

Fig. 2. Landslide inventory map. The recognition and mapping have been carried out by means of aerial photographs, whereas the degree of activity has been assessed by a subsequent geomorphological field survey. However, the time of activation for the different landslides is still not available.

based on stereoscopic aerial photographs of the Emilia Romagna Regional administration. This activity produced an inventory of 34 landslides located mainly in the Northern portion of the catchment (Fig. 2) and covering an area of 2.9 km^2, which corresponds to 16% of the Riomaggiore basin. The spatial distribution of the landslides closely reflects the different geotechnical properties of the outcropping lithologies. Landslides cover as much as 40% of the northern region of the study area, occupied by highly deformed mélange-like shaly rocks of basal complexes belonging to the Ligurian formations, while they are less frequent in the southern region, where geological formations belong to the turbidite sequences of the Sestola-Vidiciatico Unit.

4. Landslide susceptibility assessment

Landslide susceptibility assessment is a process directed to establish the likelihood that a landslide will occur in a given area on the basis of suitable physical terrain factors (Sorriso Valvo, 2002). With respect to the more general concept of absolute landslide hazard assessment, landslide susceptibility (or relative hazard) assessment considers only relative hazard in space, with no reference to time (Aleotti and Chowdhury, 1999). Depending on the difficulties in assessing the temporal probability of a landslide event, landslide hazard analyses often correspond to the production of landslide susceptibility maps that show how the territory is prone to landsliding starting from the physical terrain attributes.

5. Conventional methods

Conventional well-developed methods commonly assess landslide susceptibility by means of different approaches that, according to Soeters and Van Westen, (1996) and Aleotti and Chowdhury (1999), can be classified into four broad categories:

(a) landslide inventories;
(b) heuristic methods;
(c) statistical analyses;
(d) deterministic approaches.

For details on the application of these different procedures, see Carrara and Guzzetti (1995), Canuti and Casagli (1996), Soeters and Van Westen, (1996), Aleotti and Chowdhury (1999) and Sorriso Valvo (2002).

Landslide inventories and heuristic approaches essentially rely on the production of landslide hazard maps investigated and controlled by the earth scientist responsible for the analysis. The main limitations with this technique occur with the high subjectivity associated with the empirical ranking of the landslide preparatory factors taken into account in the analysis.

Deterministic approaches consist of slope stability analyses generally aimed at evaluating a safety factor. Their correct application requires detailed geotechnical and hydrological data and the correct knowledge of the failure mechanisms affecting the investigated slopes. This information is not easily acquired on wide areas, and, at present, deterministic methods can only be applied to small areas, at the single slope scale.

Complete statistical methods are preferred by academic and research institutions because they allow a better comprehension of the relationships between landslides and preparatory factors and guarantee lower subjectivity levels with respect to heuristic approaches. The conceptual approach of multivariate statistical methods is very close to those used by ANNs, and for this reason, they will be briefly commented upon.

Commonly, the first phase of the application of a statistical approach consists of the production of a reliable landslide inventory and the definition of the most suitable terrain units. Landslide preparatory factors are transformed into thematic vector layers and stored in a geographic information system (GIS). The subsequent data management is performed through quantitative map combinations, and the final susceptibility assessment is completed on the basis of mapping units (terrain units), whose definition is essentially a function of the survey scale and of the model utilized for the hazard mapping (Carrara et al., 1995).

In the first pioneering studies (Carrara et al., 1978), the land units were squares with sides of varying dimensions (up to 200 m), following grid based criteria, while subsequently, they have been defined taking into account vector based criteria and morphometric considerations (Carrara et al., 1991, 1995). In several applications, the terrain units agree with the concept of a Unique Condition Unit (UCU) that results from the subdivision of the territory into homogeneous terrain units with respect to the physical factors controlling landslide occurrence. Today, the increasing computational efficiency of personal computers makes it possible for the automatic recognition of UCU over large areas. This operation is usually performed by GIS overlay mapping techniques, using the landslide factors thematic layers as input data sets.

In statistical approaches, the model inputs are constituted by the factors that control the triggering of a landslide. These can be either continuous (numerical) or discrete (nominal) variables. Methods from the international literature differentiate on the basis of how the coding of nominal variables into a numerical scale is performed (Aleotti and Chowdhury, 1999). The degree of likelihood of the presence/absence of a landslide in each terrain unit constitutes the model output, and the matrix resulting from the combination of preparatory factors with the landslide inventory is analysed using multiple regression (Bernknopf et al., 1988; Jade and Sarkar, 1993; Wieczorek et al., 1996) or discriminant analysis (Carrara, 1983; Carrara et al., 1991; Chung et al., 1995; Baeza and Corominas, 1996). The final product is a statistical function that allows the totaling of a score for each terrain unit, expressing the probability of finding a landslide (Carrara, 1983; Carrara et al., 1995). Statistical approaches are more easily applied to geomorphological contexts characterized by a unique type of mass movement, while the management of different kinds of mass movement requires the development of a set of functions, each one directed to the susceptibility assessment of a single type. A disadvantage connected with the application of these techniques is that the systematic collection and analysis of landslide preparatory factors is usually a time-consuming and complex process (Aleotti and Chowdhury, 1999). An even more important problem is related to the assumptions that should be taken into account in setting up a model on a rigorous statistical basis. Such assumptions are only partially satisfied when discrete nominal variables are involved in the statistics, thus making the application of rigorous methods very difficult (Sorriso Valvo, 2002). For example, parametrical statistics require that the sample distribution of a given variable utilized in a model is normal. This assumption does not always fit well the properties of factors controlling landslide susceptibility. These difficulties can be, at least partially, overcome by the application of Artificial Neural Networks.

6. Landslide susceptibility by Artificial Neural Networks

Many Artificial Neural Networks have a lot to do with statistical methods. In the application to landslide susceptibility of Multilayered Perceptron (MLP) and Probabilistic Neural Network (PNN), both techniques can be classified as “black box models”, and furthermore, several ANNs have been developed on a statistical basis (Bishop, 1995; Patterson, 1996). For this reason, it is quite difficult to find a widely accepted definition that classifies the differences between ANNs and statistical methods. As affirmed by Perus and Krajinc (1996), “the most important thing is that ANNs allow a different view of problems which cannot be solved by (exact) statistical methods due to their theoretical limitations".

The most common feature of several ANNs is that they are based on a self-organizing structure that resembles the biological neural system of mammalian brains. Most models are composed by simple and highly interrelated processing units (neurons) that are in permanent connection with each other. Generally, neurons are located in different layers, and ANNs differentiate on the basis of the number of layers and the training procedures. Connections between processing units are physically represented by weights, and each neuron has a rule for summing the input weights and a rule for calculating an output value. The model is completed by transfer functions that allows communication between layers and the production of an output neuron.

The application of an Artificial Neural Network starts by identifying the kind of problem that is going to be modelled. In general, ANNs are applied to classification or regression problems. Typical classification problems are credit assignment (is a person a good or bad credit risk) and signature recognition (forgery, true), while in regression problems, the objective is to predict the value of a usually continuous variable (e.g., tomorrow's stock market price). The susceptibility of the territory to landsliding can be seen as a classification problem for most applications. In this way, the ANN outputs can be considered as a sort of degree of membership of each terrain unit to the class "landslide". The Trajan Network simulator (Trajan Software, 2001) is able to set up different types of ANNs available for classification problems.

7. Application to the Riomaggiore catchment

7.1. Development of ANNs

The first phase of the application of an ANN is represented by the training phase, which differentiates as a function of the type of network. In the present application, the best results have been obtained by networks belonging to the categories of the Multilayer Perceptions (MLP) and Probabilistic Neural Networks (PNN; Bishop, 1995).

MLP is perhaps the most popular and well-used type of ANN. The processing units are arranged in a layered feed-forward topology. In its basic form, MLP consists of two layers (input/output), and its complexity increases by the addition of hidden layers. Each processing unit performs a biased weighted sum of its inputs, and if the totalled score is sufficient, it activates through a transfer function to produce an output. The training phase represents the inner core of the application of an ANN, and the aim is to set the network weights and thresholds of activation in such an order to minimize the errors between the observed and computed outputs. For this reason, the ANN must be trained with an amount of information that constitutes a sort of "experience" broadly resembling those of mammal brains.

Training an ANN with the aim of investigating natural processes usually corresponds to feeding the ANN with a series of observations large enough to describe the inner variance of the investigated process. Variables describing the process, once organized on the basis of input and observed outputs, have to be utilized for training the network. This process basically corresponds to fitting the ANN to the available data set. Once fed by a database of case histories, the ANN weights and thresholds of activation are automatically adjusted by specific algorithms. The MLP supports the backpropagation algorithm (for details, see Bishop, 1995), one of the best known and utilized worldwide. The results of the training phase are usually represented by error functions (such as the sum squared error or cross entropy error functions), which give a measure of how the network fits the training set of the observed data. As a general rule, the MLP training phase is aimed at representing the multidimensional nature of the investigated process. Each data set record can be considered as a vector whose number of dimensions corresponds to the number N of variables taken into account in the data set itself. Network complexity usually increases with the increasing number of variables and, consequently, the number of weights and hidden layers. This usually leads to a lowering of the MLP error estimations. If a network fits well with the database utilized for its training, it does not mean that it will be able to correctly model the investigated process because its role is not to fit the observed data but to model a process by generalizing the learned experience to other cases not represented in the training database. The so-called "problem of overfitting or overlearning" has been carefully taken into account in the present analysis and reduced to a minimum by utilizing the tools present in the Trajan NN Simulator (Trajan Software, 2001). These tools are essentially based on the comparison between the trends of the training error and the selection error (carried out on the selection set, which is a set of records not utilized in the training phase). As the ANN training progresses, the training error naturally drops, and the selection error drops as well. The ANN overlearning starts when the selection error stops dropping or starts rising. The Trajan NN Simulator is, by default, configured to stop automatically at this moment.

PNNs differentiate from MLPs because there is an absence of a backpropagation algorithm. These ANNs are characterized by a very easy training phase that correspond to loading the original data set (model vector) directly in the network. Therefore, in this case, the model vector itself physically represents the "so-called experience" of the ANN to be used in the prediction phase. As in the case of the MLPs, it actually corresponds to a database of case histories, a matrix of values matching the different variables (m_{NL}) that describe the investigated physical phenomenon (Table 1).

In classification problems, a useful interpretation of the network outputs can be done in terms of class membership probability. In this case, the ANN learns how to carry out an estimation of the probability density function (pdf). The estimation of the pdf from the data has a long history in statistical analysis (for a review, see Parzen, 1962). Conventional statistics can, given a known model, compute the chances of a certain outcome (e.g., the probability of obtaining a head on a tossed coin is ½). PNNs are based on the Kernel approach of estimating the pdf (Bishop, 1995; Speckt, 1990). In the Kernel-based approximation, a series of Gaussian bell-shaped probability functions are associated with each available case, and their sum is used to estimate the pdf of the overall model vector.

Table 1
Model vector of an ANN

Mv_1	=	m_{11}	m_{12}	...	$m_{1\mathrm{L}}$
Mv_2	=	m_{21}	m_{22}	...	$m_{2\mathrm{L}}$
...		...			...
...		...			...
Mv_{N}	=	$m_{\mathrm{N}1}$	$m_{\mathrm{N}2}$	...	m_{NL}

A PNN, in its basic form, presents three layers: input, radial and output layer. The radial units are directly copied from the training data. A Gaussian bell-shaped function is centered around each training case, and there is an output unit per class that simply adds up the responses of the units belonging to their own class. Probabilistic neural networks are usually trained with the help of a smoothing factor or "penalty coefficient" (Perus and Krajinc, 1996), corresponding to the radial deviation of the Gaussian functions. The smoothing factor directly controls the capability of the network to generalize or to be close to the model. The outputs of PNNs can be considered as probabilistic estimations of a degree of membership to a class.

8. Training phase

The training phase was executed on a subset of the records (corresponding to 1/3 of the entire database) randomly selected from the whole set of model vectors. As previously mentioned, the model inputs represent those variables chosen to describe the susceptibility of the territory to landslides and the degree of membership to the class presence/absence of a landslide is selected as the output variable.

The parameters utilized in the analysis (lithology, land cover, slope angle, profile curvature and upslope contributing area) are classic variables for controlling landslide hazard (for a review, see Soeters and Van Westen, 1996; Carrara and Guzzetti, 1995). They are either nominal or numerical variables. In this study, according to similar approaches adopted in multivariate statistics (Chung et al., 1995; Kojima et al., 1998), it was decided to manage each variable as a string of binary numbers, after reclassification. This choice was preferred to avoid the introduction of different kinds of variables in the same analysis. For this reason, the nominal and numerical variables were subdivided into classes (Table 2), defined on the basis of how they were considered to intrinsically influence landslide mechanisms. A brief description of the main characteristics and the reclassification scheme adopted for each different parameter follows:

Lithology: the study area is characterised mainly by the presence of regularly stratified flysch formations in the southern part of the basin, which are

Table 2
Hillslope instability factors implemented for the landslide susceptibility modelling by the ANNs

Variable	Utilized classes
Lithology	•Flysch, calcareous sandstones; Intermediate Units, marls and partly tectonized limestones; Basal complexes
Land Cover	•Rangeland •Woods •Cultivated land •Grassland
Slope angle (°)	•0–6.5 •6.5–13 •13–26 •26–40 •40–90
Curvature	•Concave •Gently convex •Convex •Very convex
Up-slope contributing area (m^2)	•0–4.000 •4.000–10.000 •>10.000

abruptly interrupted to the north by a main thrust zone, giving way to argillaceous, chaotically arranged units belonging to Basal complexes (Abbate and Sagri, 1970). Geological formations outcropping in this area have been grouped into three lithological classes (Fig. 3) on the basis of a qualitative assessment of their geotechnical properties (Casagli and Catani, 1998; Table 2). Formations belonging to the first class are the Porretta Formation and the Cervarola sandstones, both resulting from the alternation of sandstones and shales and classifiable as indurated rocks characterized by a fragile behaviour, while the second class contains the marly member of the Sestola-Vidiciatico Unit (Bettelli and Panini, 1987), and the third includes the basal complexes of the Sestola-Vidiciatico Unit, composed of shales characterized by a ductile behaviour.

Land cover: land cover is mainly dominated by various types of woods, rangeland, grassland and cultivated land (Fig. 4). According to empirical observations, historical data on past landslides and a literature review, the various land covers have been grouped into four main classes, which are assumed to play a different role in controlling landslide location.

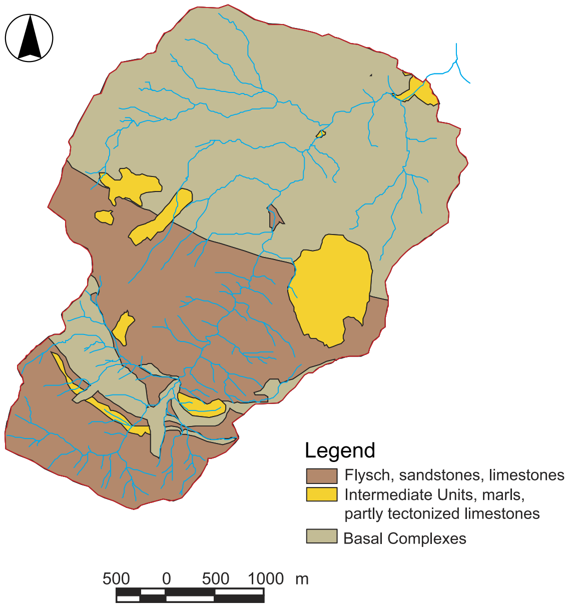

Fig. 3. Lithological map obtained by the reclassification of the 1:10,000 geological map on the basis of the mechanical characteristics of the outcropping formations.

Slope angle: the digital elevation model utilized in this work is a high-resolution DEM with a cell size of 5 m interpolated using an ArcINFO (© ESRI)

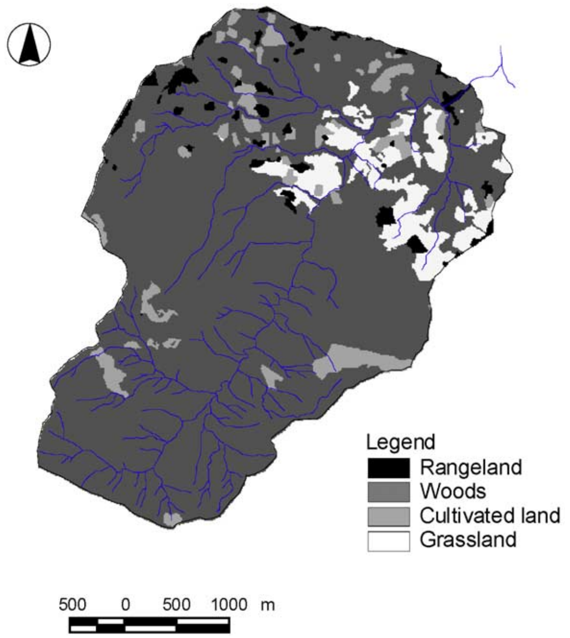

Fig. 4. Land cover map reclassified from the original 1:10,000 scale land use map.

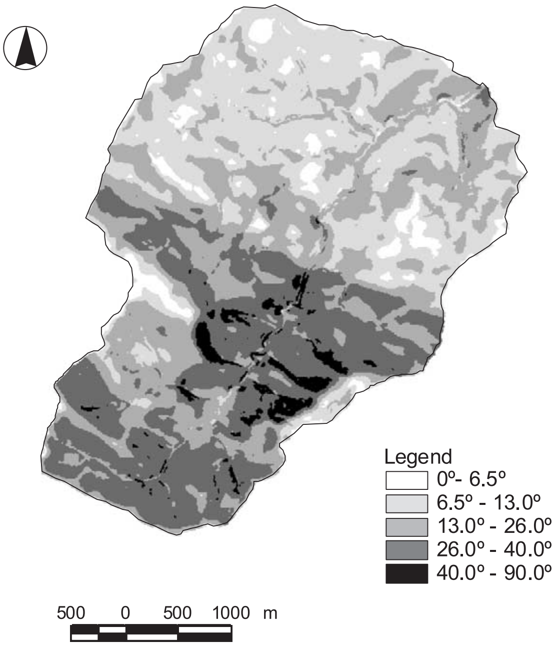

Fig. 5. Reclassified slope angle map (see text for details).

topogrid code from an original topographic survey of 1:5000. Contour line data have been integrated with a large number of ground-surveyed elevation points and by drainage enforcement; slope angle was extracted by a classical steepest descent algorithm suitable for discrete grids. Their classes were assigned with particular regard to the shear resistance parameters that are typical of landslides occurring in this area. The majority of mass movements in this region are reactivations of rotational earth slides initially activated in the Holocene, under different climatic settings, considered to be periglacial (Bertolini et al., 2004). In a review of landslides reactivated in the northern Apennines in the period 1994–1996, Bertolini and Pellegrini (2001) give the results of geotechnical laboratory tests on formations in which the landslides originated. Most formations are characterized by typical residual friction angles placed in the interval between 8° and 15° (in one case, only a minimum of 5° was reached), with a maximum peak friction angle ranging between 22° and 25°. Starting from these general considerations, boundaries of slope angle classes (Table 2) were attributed with the aim of paying particular attention to gentle slopes (usually in landslide hazard analysis, they are considered in a unique class from 0° up to 15°). Low relief hillslopes are the most represented in the northern area (Fig. 5), and, at the same time, they are prone to landslide reactivation due to the poor geotechnical properties of the outcropping lithologies.

Curvature: profile curvature is the second parameter completely derived from the DEM. It was extracted using suitably accurate numerical methods (Roering et al., 1999; Fig. 6). Usually, curvature maps give important information on landslide recognition because the most important topographic modification induced by a rotational landslide is generally represented by the formation of concave features in the crown and detachment zone, whereas convex features prevail in the middle–lower part and at the toe. Moreover, in terms of landslide susceptibility assessment, curvature influences how the superficial drainage takes place along the hillslopes (Kirkby, 1971; Dunne, 1980). For this reason, profile curvature was reclassified into four classes (Table 2), on the basis of its frequency distribution, to discriminate among valley/hollows, gently convex hillslopes,

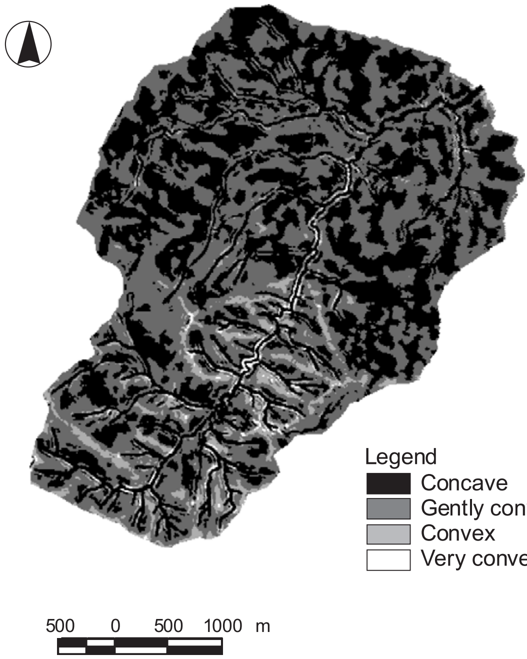

Fig. 6. Reclassified profile curvature map (see text for details).

convex portions of slopes probably representing landslide deposits and very convex, linear features, in which most of the cases were attributed to fluvial terraces or erosional scarps.

Upslope contributing area: upslope contributing area represents the most important hydrological factor selected for this analysis (Fig. 7). In particular, as widely recognized (Kirkby, 1971), it controls the water flow at a point, influencing how soil saturates, with particular reference to landsliding processes. For well-known problems of the classical D8 algorithm for the direction of flow, the upslope contributing area has been calculated by a computer code developed by Martello et al. (2000), based on the fractioning of flow proposed by Freeman (1991).

The definition of variables and classes dictates the form and position of the mapping units to be considered in the analysis, which correspond to the concept of Unique Condition Units, produced by the intersection of the hillslope factors, all ranked in nominal scales. This operation carried out by GIS raster overlay operators singles out 12,970 homogeneous spatial domains containing locally unique combinations of hillslope factors. As a function of the resolution of the base maps (1: 10,000), polygons with an area of less than 625 m^2 were considered as negligible and discarded from the data set as too small for being significant in expressing the susceptibility of the territory to landsliding. This procedure meant disregarding the 74% of the whole number of UCUs, which, however, represent only 7% of the basin area. Moreover, those polygons are mainly located along the valley bottoms, thus having little to do with sliding processes. For all these reasons, it can be assumed that no valuable information to the analysis was lost.

Fig. 8. Results of the subdivision of the Riomaggiore catchment in UCUs.

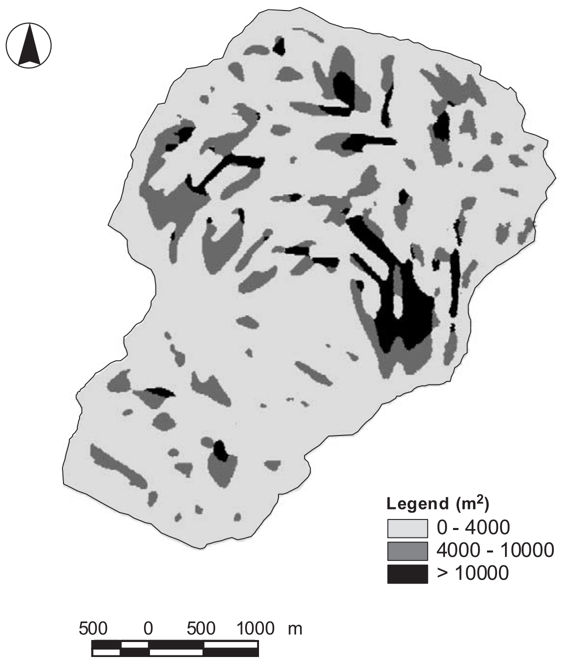

Fig. 7. Reclassified contributing area map (see text for details).

The final data set is made up of 3342 UCUs (Fig. 8), ranging in size between 625 and 118,665 m^2. The high variability of UCUs size can represent a real problem in the analysis because area cannot be managed as a landslide factor, but UCUs with very different areas reasonably must have a different weight in the model construction. To avoid this kind of conceptual limitation, each UCU was represented in the NN model by a number of identical model vectors, as resulting from the normalization of its area

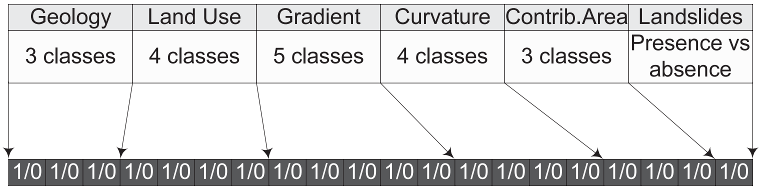

Fig. 9. Schematic representation of the binary string approach used to generate the 20-digit input vector, starting from the five classified hillslope factors.

on the basis of the minimum UCU area (625 m^2). For instance, an UCU of 1875 m^2 was transformed in three vectors all with the same "string" of variable values. The final model vector matrix utilized for feeding the NN was constituted of 22,438 records, each one represented by a vector that actually consists of two partial vectors: the input variable vector and the output variable vector. The first partial vector (input) is composed by 19 values corresponding to the 19 hillslope class factors listed in Table 2 (the so-called "predefined" dimensions of the natural system). Landslide factors have been organized as binary variables, and for this reason, the input partial vector is physically represented by a binary string composed of 19 positions, each resulting from 1/0 binary switches as a function of the presence/absence of a class of hillslope instability factors in a given UCU (Fig. 9). This same kind of approach was used by Chung et al. (1995) in a multivariate statistical analysis for similar purposes. The output partial vector contains information on the presence/absence of landslides, where 1 means the presence and 0 means the absence of a landslide.

After the training phase, the vectors have been computed in the prediction module of the neural network for every polygon of the study area. The output values represent the relative degree of membership of a polygon to the class of landslide, and they can be managed in this form or reclassified and mapped back to the geographic representation.

9. Results

Table 3 summarizes the results obtained by the application of the two neural networks (MLP and PNN) to the landslide susceptibility assessment in the Riomaggiore river basin. The network predictions are, in both cases, quite poor if considered in absolute terms, with a slightly better performance by the MLP, but fairly good when suitably reclassified. It should be noted that, for reasons of simplicity and lack of data concerning the state of activity of many landslides, the training output vector expresses only the state of presence/absence of a mass movement and not its degree of likelihood, as recommended in the preceding sections. Conversely, the ANN produces real values reflecting how close a mapped landslide is to the state of being active. The estimation error (Table 3) is therefore computed on the sole basis of the binary value given in the training set, which suffers the aforementioned approximations. This point can be better explained with reference to the way the ANN answers questions. Fig. 10 shows the results of the frequency analysis carried out for the two predictions. In both cases, they show bimodal trends. Values relative to mapped landslide areas are reproduced in grey. The first peak in the bimodal distribution, the one with lower output scores, can be associated with areas classified by the ANN as having a low susceptibility to landslide occurrence, whereas the second peak can be related to the polygons classified as having high susceptibility. It is interesting to note that the MLP net performs better than the PNN does and that a number of locations having high output values have been mapped as being unaffected by mass movements in the inventory. This may be due either to model overestimation errors or to possible cases of existent landslides, which have not been correctly recognized by the aerial photographs. The advantage

Table 3
Results gathered by the application of the Artificial Neural Networks (ANNs)

Network	Network structure	Standard error
PNN	19:19–1672–2:1	0.19
MLP	16:16–8–1	0.14

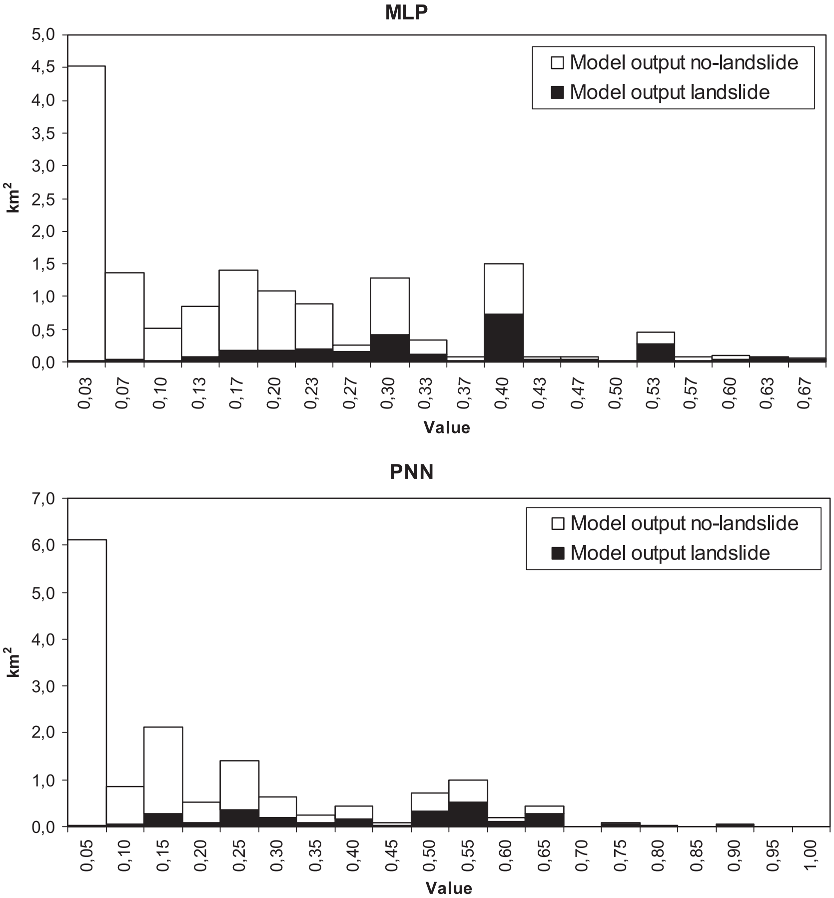

Fig. 10. Frequency analysis of the two model outputs; the distribution of model output values within the mapped landslide is superimposed in grey.

of the MLP model over the PNN is even more understandable when rating the cumulative frequency distributions (Fig. 11). The form of the distributions, especially those relative to the subsets within the mapped landslide areas (Fig. 11), suggests the possible class thresholds for classifying the landslide susceptibility in the area. In particular, in the case of the Riomaggiore basin, the threshold values can be placed in correspondence with the "points of inflection" of the mapped landslide cumulative curves. From Fig. 11, the MLP has the advantage of having less landslide data in the low-output range and a sharper boundary between the peaks of the bimodal distribution. In particular, the MLP correctly classifies 73% of the mapped landslides within the two highest classes of the susceptibility ranking (high and very high), whereas the PNN network exhibits a slightly poorer performance, assigning to the same classes 68% of the surveyed landslides.

It is clear, however, that in general, the results will depend on the choice of the optimal thresholds: More conservative thresholds would result in a smaller number of negative errors (landslides not recognized) at the expense of a higher rate of positive errors (safe areas classified as hazardous). This conservative approach should be used in territorial planning or in preliminary phases of risk analysis, in which the focus must be concentrated on predicting possible hazards and revealing the location of key areas. Conversely, a less conservative approach, based on higher thresholds in the output values, would reduce positive errors while increasing possible negative errors.

Figs. 12 and 13 show the geographic representation of the network predictions carried out on the basis of

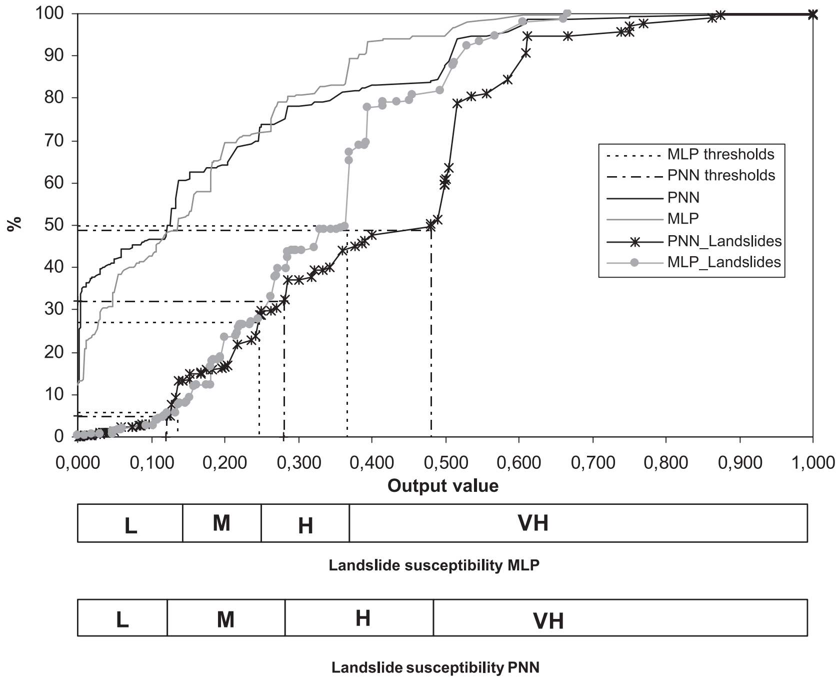

Fig. 11. Cumulative distributions of the ANN outputs for the two models as a whole and for the subsets relative to the mapped landslide areas. The highlighted thresholds have been located in correspondence to "points of inflexion" in the landslide-subset curves and have been utilized for the subsequent landslide susceptibility mapping (Figs. 12 and 13). L: low susceptibility; M: medium susceptibility; H: high susceptibility; VH: very high susceptibility.

four different susceptibility levels using the optimal thresholds for MLP and PNN networks, respectively, as deduced from Fig. 11. A marked result of both networks is the ability to classify the areas most prone to landslide initiations, with particular reference to the northwestern portion of the basin, in which polygons with higher output scores are concentrated. Interestingly, both ANNs are able to adequately classify areas free of landslides, assigning them to very low susceptibility values. In this case, output values are also consistent if considered in absolute terms.

10. Conclusions

In general, it can be affirmed that both ANNs correctly understand the structure of the data utilized for the training with reference to the understanding of the relationships that relate landslides to terrain factors. Geographic representations of the model predictions show satisfactory results for both networks. This consideration emerges from the comparison between the landslide inventory map (Fig. 2) and the landslide susceptibility maps resulting from plotting the network predictions (Figs. 12 and 13). Theoretically, the only rigorous way to validate this model for landslide susceptibility assessment would be to adopt the concept of "wait and see", because the model is not based on general rules but directly on the particular model vector (the "experience") of the Riomaggiore catchment. As in most models carried out by statistical approaches, a qualitative validation of how ANNs perform in the landslide susceptibility mapping can be made by comparing the areas predicted as more unstable with the landslide inventory map. Based on this approach, the MLP seems to offer slightly better performances because, in general, it recognizes and reproduces the shape of the landslides affecting the Riomaggiore basin. In some cases, it also appears to foresee new or missed sliding areas, as in the case of the southeastern sector of the basin, where very few inventoried landslide polygons are located but where the ANN reveals a possible underestimation of the

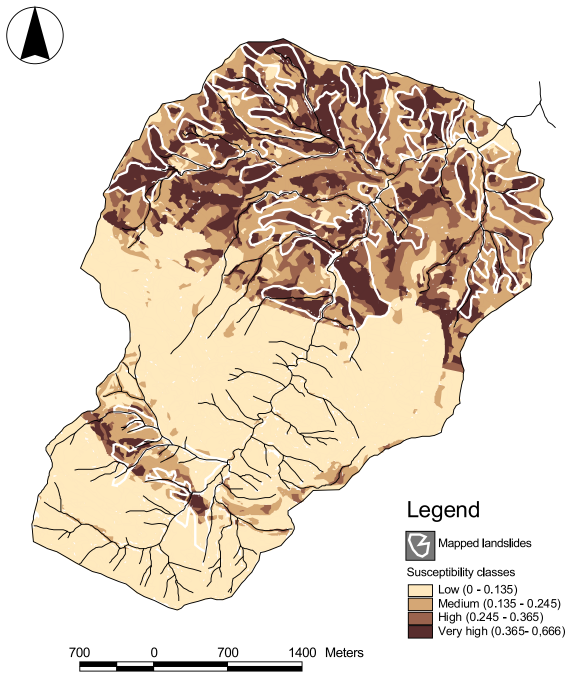

Fig. 12. Results of the landslide susceptibility assessment performed by the MLP, using the thresholds highlighted in Fig. 11.

hazard during the field survey. Estimation errors can be due to the following causes:

1. Problems in the network construction
2. Wrong or insufficient variables
3. Noisy data

In our analysis, point 1 can be excluded because about 100 different ANNs produced by the Trajan NN Simulator were tested, and from this group, only the best performers for the following analyses were selected. Concerning point 2, the choice of the variables in the ANN was compiled on the basis of a very large and globally acknowledged literature review: slope angle, land cover and lithology are all variables widely known for forming the basis of a landslide susceptibility assessment, while curvature and drainage area were selected on the basis of the specific knowledge of the test site (Bianchi and Catani, 2002) and are considered to be important factors in influencing the presence and the state of activity of the landslides in the Riomaggiore catchment area.

It can be concluded that most of the inefficiency of the network predictions is related to the noise that characterizes data with reference to both input (particularly lithology and land cover) and output variables. The output value, in particular, could be affected by two different kinds of noise: the first, which is relevant also to input variables, is essentially connected to survey mistakes. For example, errors might have been made during the geomorphological survey of landslides, which could lead to a misleading classification of landslide-free areas. An important consideration (especially within the Riomaggiore catchment where landslides are essentially reactivations of past events) is that areas classified as landslides in the survey are less affected by estimation error than those classified as landslide-free. In the first case, the geomorphologist recognizes the characteristic features of the movement (a "positive" data), while in the second case, the same features can be obliterated and are not easily interpreted.

A second type of mistake could be related to the classification of sliding areas. As already noted, it was preferred to train the ANNs with a single output

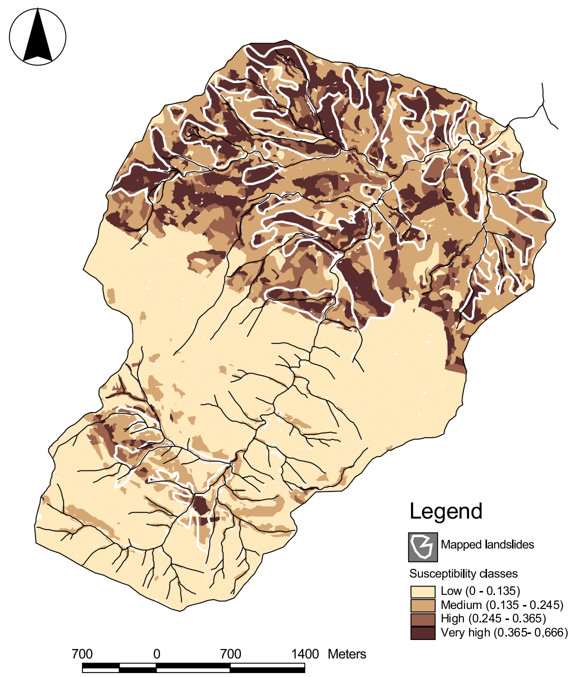

Fig. 13. Results of the landslide susceptibility assessment performed by the PNN, using the thresholds highlighted in Fig. 11.

variable (0/1) to avoid any subjective interpretation of the state of activity.

Improvements to the model could be obtained by analyzing the state of activity of the landslides and setting the different output values to the observed degree of activity, e.g., by using fuzzy set variables.

The ANNs trained in the Riomaggiore catchment, although not suitable for exportation to very different geomorphological settings, could be usefully applied in a large part of the Northern Apennines, in which geological and geomorphological conditions are very similar to those of the test site. The high percentage of the landslide inventory that has been correctly recognized by the two ANNs is comparable with the same figures relative to other prediction and classification methods (Carrara and Guzzetti, 1995). For this reason, this work can be seen as an encouraging preliminary approach towards a systematic introduction of ANN-based statistical methods in landslide hazard assessment and mapping.

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