6. LANDSLIDE SUSCEPTIBLITY ZONING

The process of categorizing …
involves an act of invention.

(Bruner, Goodnow and Austin
A Study of Thinking, 1956)

In the literature, confusion exists between the terms landslide "susceptibility" and landslide "hazard". Often, the terms are used as synonymous despite the two words expressing different concepts. Landslide susceptibility is the likelihood of a landslide occurring in an area on the basis of local terrain conditions (Brabb, 1984). It is the degree to which a terrain can be affected by slope movements, i.e., an estimate of "where" landslides are likely to occur. Susceptibility does not consider the temporal probability of failure (i.e., when or how frequently landslides occur), nor the magnitude of the expected landslide (i.e., how large or destructive the failure will be) (Committee on the Review of the National Landslide Hazards Mitigation Strategy, 2004). In mathematical language, landslide susceptibility is the probability of spatial occurrence of slope failures, given a set of geo-environmental conditions. This is called "landslide analysis" by Vandine *et al*. (2004). Landslide hazard is the probability that a landslide of a given magnitude will occur in a given period and in a given area. Besides predicting "where" a slope failure will occur, landslide hazard forecasts "when" or "how frequently" it will occur, and "how large" it will be (Guzzetti *et al*., 2005a). Landslide hazard is more difficult to obtain than landslide susceptibility, as susceptibility is a component (the spatial component) of the hazard. More generally, landslide susceptibility consists in the assessment of what has happened in the past, and landslide hazard evaluation consists in the prediction of what will happen in the future.

In this Chapter, I discuss landslide susceptibility zoning, whereas landslide hazard modelling will be dealt with in § 7. Here, I review the methods proposed to ascertain landslide susceptibility, including an analysis of the types of mapping units most commonly adopted, and of the relationships between the selected mapping units and the adopted susceptibility methods. I then examine a probabilistic model for landslide susceptibility, including problems and difficulties in its application, and I present an example of a landslide susceptibility model for the Upper Tiber River basin, an area that extends for about 4100 km^2 in central Italy. Lastly, I discuss the problem of the verification of the performances of a landslide susceptibility model, including examples for the Collazzone area, in central Umbria.

In the following, I will often refer to the literature on landslide hazard, including some of my own work (e.g., Guzzetti *et al*., 1999a). This is because of two reasons: (i) due to the mentioned confusion between susceptibility and hazard, literature on landslide hazard often discusses methods and techniques to obtain landslide susceptibility (and not landslide hazard);

and (ii) some of the arguments (e.g., selection of the mapping unit of reference, statistical modelling, and validation techniques) are common to both susceptibility and hazard modelling.

6.1. Background

Over the past decades, government, environmental and research organizations worldwide have invested resources in the attempt to assess landslide susceptibility (or hazard), and to produce maps portraying its spatial distribution (landslide susceptibility or hazard zonation). Inspection of the literature reveals that a few reviews of the concepts, principles, techniques and methodologies for landslide susceptibility and hazard evaluation have been proposed (Cotecchia, 1978b; Humam and Radulescu, 1978; Carrara, 1983; Brabb, 1984; Crozier, 1986; Hansen, 1984a; Varnes and IAEG Commission on Landslides and other Mass-Movements, 1984; Crozier, 1986; Einstein, 1988; Hartlen and Viberg, 1988; Mulder, 1991; van Westen, 1993, 1994; Soeters and van Westen, 1996; van Westen *et al.*, 1997; Aleotti and Chowdhury, 1999; Chung and Fabbri, 1999; Guzzetti *et al.*, 1999a; Crozier and Glade, 2005; Glade and Crozier, 2005b; Glade *et al.*, 2005). Comparatively, little work has been done on the systematic comparison of different techniques to determine landslide susceptibility, outlining advantages and limitations of the proposed methods (Carrara *et al.*, 1992, 1995; van Westen, 1993; Pistocchi *et al.*, 2002; Gorsevski *et al.*, 2003; Lee *et al.*, 2004; Süzen and Doyuran, 2004a; Crozier and Glade, 2005; Glade *et al.*, 2005), or to the critical discussion of the basic principles and the underlying assumptions of landslide susceptibility/hazard zonation (Varnes and IAEG Commission on Landslides and other Mass-Movements, 1984; Carrara *et al.*, 1995; Hutchinson, 1995; Soeters and van Westen, 1996; van Westen *et al.*, 1997; Aleotti and Chowdhury, 1999; Guzzetti *et al.*, 1999; Committee on the Review of the National Landslide Hazards Mitigation Strategy, 2004; Crozier and Glade, 2005). Recently, Glade and Crozier (2005b) have published a review of landslide susceptibility (and hazard) models at the catchment, regional and national scale, published in the period from 1977 to 2004.

The majority of papers discuss specific attempts at the evaluation of landslide susceptibility in limited areas. Only a few authors report on long-term projects on the evaluation of slope instability conditions, and the related hazards and risk, over large regions. Notable examples are represented by the work carried out in San Mateo County, California, by the U.S. Geological Survey (Nilsen and Brabb, 1977; Brabb *et al.*, 1978; Mark, 1992; Brabb, 1995); by the proposal made by the French *Bureau des Recherché Géologiques et Minières* for a geomorphologically based evaluation of landslide hazard (Humbert, 1976, 1977; Antoine, 1977; Landry, 1979; Porcher and Guiloppe, 1979; Delaunay, 1981; Godefroy and Humbert, 1983; Leroi, 1996); and by the work carried out in Hong Kong by the Geotechnical Engineering Office (Brand, 1988; Brand *et al.*, 1982; Burnett *et al.*, 1985; Hansen *et al.*, 1995; Ng *et al.*, 2003) and other investigators (Dai and Lee, 1999, 2001, 2002, 2003; Dai *et al.*, 2002; Zhou *et al.*, 2002; 2003; Chen and Lee, 2003, 2004; Chau *et al.*, 2003, 2004).

Italy has a long tradition of landslide mapping (Almagià, 1907, 1910; Govi, 1976; Bosi, 1978; Carrara, 1978; Cotecchia, 1978b), and efforts to produce a detailed national geomorphological inventory are under way (Amanti, 2000; Amanti *et al.*, 2001). Several regional governments have already produced geomorphological inventory maps at 1:25,000 or 1:10,000 scale. Despite these significant mapping efforts, attempts at producing susceptibility and hazard maps by the application of statistical techniques are mostly limited to academic exercises in pilot areas (Carrara, 1983; Carrara *et al.*, 1991, 1995, 2003; Guzzetti *et al.*, 1999; Ardizzone *et* *al.*, 2002; Clerici *et al.*, 2002; Donati and Turrini, 2002; Sorriso-Valvo, 2005; Guzzetti *et al.*, 2005a,d). The same occurs for the application of physically based models for determining the susceptibility of shallow landslides (Borga *et al.*, 1998, 2002a, 2002b; Crosta and Dal Negro, 2003; Crosta and Frattini, 2003) and of rock falls (Guzzetti *et al.*, 2004b). With this respect, the experiment conducted in the Upper Tiber River basin to produce a susceptibility map for a large area (~ 4100 km^2) represents an important exception (Cardinali *et al.*, 2001; 2002b). I will discuss the results of this experiment in § 6.4.

6.2. Landslide susceptibility methods

Several different methods and techniques for evaluating landslide susceptibility have been proposed and tested. However, no general agreement exists either on the methods for or on the scope of producing susceptibility maps (Brabb, 1984; Varnes and IAEG Commission on Landslides and other Mass-Movements, 1984; Carrara, 1989; Nieto, 1989; Carrara *et al.*, 1991a, 1997; Soeters and van Westen, 1996; van Westen *et al.*, 1997; Aleotti and Chowdhury, 1999; Guzzetti *et al.*, 1999a, Committee on the Review of the National Landslide Hazards Mitigation Strategy, 2004; Crozier and Glade, 2005; Glade and Crozier, 2005b). Operational and conceptual differences include: (i) the general underlying assumptions; (ii) the type of mapping unit selected for the investigation; and (iii) the techniques and tools favoured for the analysis and the susceptibility assessment.

6.2.1. Assumptions

Despite conflicting views among experts, all the proposed methods are based upon a few, widely accepted assumptions (Varnes and IAEG Commission on Landslides and other Mass-Movements, 1984; Carrara *et al.*, 1991a; Hutchinson and Chandler, 1991; Hutchinson, 1995; Turner and Schuster, 1996; Guzzetti *et al.*, 1999a). These are the same assumptions which lay at the base of landslide mapping (see § 2.1), namely:

(a) Slope failures leave discernible features that can be recognized, classified and mapped in the field or through remote sensing, chiefly stereoscopic aerial photographs (Rib and Liang, 1978; Varnes, 1978; Hansen, 1984; Hutchinson, 1988; Cruden and Varnes, 1996; Dikau *et al.*, 1996; Griffiths, 1999).

(b) Landslides are controlled by mechanical laws that can be determined empirically, statistically or in deterministic fashion. Conditions that cause landslides (instability factors), or directly or indirectly linked to slope failures, can be collected and used to build predictive models of landslide occurrence (Crozier, 1986; Hutchinson, 1988; Dietrich *et al.*, 1995).

(c) For landslides, the past and present are keys to the future (Varnes and IAEG Commission on Landslides and other Mass-Movements, 1984; Carrara *et al.*, 1991a; Hutchinson, 1995). The principle implies that future slope failures will be more likely to occur under the conditions which led to past and present instability. Hence, the understanding of past failures is essential in the assessment of landslide hazard (Varnes and IAEG Commission on Landslides and other Mass-Movements, 1984; Carrara *et al.,* 1991a, 1995; Hutchinson, 1995; Guzzetti *et al.,* 1999a).

In addition, the following assumption also applies:

(d) Landslide occurrence, in space or time, can be inferred from heuristic investigations, computed through the analysis of environmental information or inferred from physical models. Therefore, a territory can be zoned into susceptibility (or hazard) classes ranked according to different probabilities (Carrara *et al.,* 1995; Soeters and van Westen, 1996; Aleotti and Chowdhury, 1999; Guzzetti *et al.*, 1999a).

Ideally, evaluation of landslide susceptibility and its mapping should derive from all of these assumptions. Failure to comply with them will limit the applicability of any susceptibility assessment, regardless of the methodology used for the investigation. Unfortunately, as it will become clear later, satisfactory application of these principles proves difficult, both operationally and conceptually (Carrara *et al.,* 1995, 1999; Guzzetti *et al.*, 1999a).

6.2.2. Mapping units

Evaluation of the likelihood of a landslide occurring in an area on the basis of local terrain conditions requires the preliminary selection of a suitable terrain mapping unit (TMU). The term refers to a portion of the land surface which contains a set of ground conditions that differ from the adjacent units across definable boundaries (Hansen, 1984; Carrara *et al*., 1995; van Westen *et al*., 1997; Luckman *et al*., 1999). At the scale of the analysis, a mapping unit represents a domain that maximises internal homogeneity and between-units heterogeneity. Soil scientists have challenged the concept of TMU as land subdivisions separated by distinct (“crisp”) boundaries, suggesting that soil and landform variations are more continuous than discrete (Odeh *et al.*, 1992), and calling for a continuous approach to landform classification (Burrough and McDonnell, 1998; Burrough *et al*., 2001a; Gorsevski *et al*., 2003). Based on the concept of a distinct, clearly definable TMU, various methods have been proposed to partition the landscape for landslide susceptibility assessment and mapping (Meijerink, 1988; Carrara *et al*., 1995; Soeters and van Westen, 1996; Guzzetti *et al*., 1999a). All methods fall into one of the following six groups: (i) grid cells, (ii) terrain units, (iii) unique condition units, (iv) slope units, (v) geo-hydrological units, (vi) topographic units, and (vii) political or administrative units.

Grid cells divide the territory into regular areas (“cells”) of pre-defined size, which become the mapping unit of reference (e.g., Carrara, 1983; Bernknopf *et al.*, 1988; Pike, 1988; Mark, 1992; van Westen, 1993, 1994; Mark and Ellen, 1995; Chung and Fabbri, 1999; Dymond *et al*., 1999; Clerici *et al*., 2002; Lee and Min, 2002; Remondo *et al.*, 2003a, 2003b; Chau *et al.*, 2004; Lee, 2004; Lee *et al*., 2002, 2004; Ayalew and Yamagishi, 2005; Lan *et al*., 2005; Moreiras, 2005). Grid cells are preferred by raster-based GIS users. For this reason, most commonly cells are squares but rectangular, triangular or hexagonal subdivisions (Di Gregorio *et al*., 1999a,b) are possible. Each grid cell is assigned a value for each factor (e.g., morphological, geological, of land-use, etc.) taken into consideration. Alternatively, a stack of raster layers, each mapping a single instability factor, is prepared. The main conceptual limitation of grid cells refers to the representation of continuous geological and morphological forms in discrete form, and the representation of linear and area features (such as geological boundaries, landslide deposits, lithological units) using cells of predefined shape and size. Advancements in computer technology (e.g., size of available memory and processing speed) have largely (but not completely) overcome this limitation, allowing for grid cells of very small size that can capture more faithfully the terrain characteristics.

Terrain units are traditionally favoured by field geomorphologists. They are based on the observation that in natural environments the interrelations between materials, forms and processes result in boundaries which reflect geomorphological and geological differences. Terrain units are the basis for the land-system classification approach which has found application in many land resources investigations (Cooke and Doornkamp, 1974; Speight, 1977; Verstappen, 1983; Burnett *et al.*, 1985; Meijerink, 1988; Hansen *et al.*, 1995, van Westen *et al.*, 1997; Ng *et al*., 2003; Fannin *et al*., 2005). The main limit of terrain units lies in their subjectivity. It is difficulty to establish clearly defined rules to unambiguously delineate the boundaries between the different terrain units, and even more difficult to apply them consistently. For susceptibility studies, it is difficult to infer the degree of landslide propensity based solely on geomorphological forms and processes, and to derive from this information an objective subdivision of the territory.

First introduced to investigate mineral resources, unique condition units (UCU) (Bonham-Carter *et al.*, 1989; Bonham-Carter, 1994; Carrara *et al.*, 1995; Chung *et al.*, 1995; van Westen *et al.*, 1997; Chung and Fabbri, 1999) imply the classification of each factor controlling or conditioning slope instability into a few significant classes which are stored into a single map, or layer. By sequentially overlying all the layers, homogeneous domains (unique conditions) are singled out whose number, size and nature depend on the criteria used in classifying the input factors. Unique condition units are particularly suited for vector-based representations of the geographical information (Carrara *et al.*, 1995). However, they are largely adopted also by users of raster-based GIS systems (Bonham-Carter, 1994; Chung *et al.*, 1995), because of their straightforward implementation and ease of use (Carrara *et al.*, 1995; 1999). Conceptual problems with UCU include the fact that, for practical purposes, layers showing continuous thematic information (e.g., elevation, terrain slope, aspect, soil thickness) must be classified using a small number of classes. Selection of the classes is seldom based on local knowledge of the physical processes controlling landslides. Fabbri *et al*. (2003) investigated the problem, and found selection of the number of classes used to categorize continuous thematic layers not particularly significant for their data sets. Also, the number of classes and the class limits may affect the statistical analysis. In a vector-based GIS system, overlay of several thematic layers, or of layers containing many small polygons, easily results in a very large number (hundreds of thousands) of mapping units, making it difficult (or at least impracticable) to analyze the results (Carrara *et al*., 1995). Intersections of layers affected by minor digitization errors (e.g., mismatch between a landslide boundary and the river network) may results in a small UCU whose geomorphological significance is difficult to interpret. A small polygon or a single grid cell may reflect unique (exclusive) environmental conditions important to determine landslide susceptibility, or it may be the result of cartographic or mapping errors, irrelevant to landslide susceptibility.

Slope units partition the territory into hydrological regions bounded by drainage and divide lines (Carrara, 1988; Carrara *et al.*, 1991; 1995; Guzzetti *et al*., 1999a). They can be identified manually from accurate topographic maps. As an alternative, specific software was developed to automatically delineate slope units from high-quality DTMs, eventually aided by simplified versions of the drainage network (e.g., Carrara, 1988; Hutchinson, 1989; Fairfield and Laymarie, 1991). The computerized method is preferred for its speed and efficiency, and because it guarantees an objective, reproducible subdivision of terrain. Hydrological and morphometric parameters (and their statistics) can be computed for each slope unit, and used in susceptibility analyses. Significantly, hydrological and morphometric parameters obtained for individual slope units do not reflect “spot” values (like in grid cells). Instead, they refer to the entire terrain subdivision, providing more reliable and geomorphological meaningful results. Since landslides occur on slopes, and slope units represent slopes, this type of subdivision is – at least in principle – particularly suited to investigate landslide susceptibility. Depending on the type of instability to be investigated (e.g., deep seated vs. shallow slides or complex slides vs. debris flows), the mapping unit may correspond either to an individual slope unit (a sub-basin) or to the combination of two (or more) slope units representing a small catchment. Limitations of slope units include: (i) the difficulty in their preparation, which requires resources, including specialized software; (ii) the difficulty in tailoring the size of the slope units to the known distribution of landslides; (iii) a certain lack of representativeness of slope units for small shallow landslides; and (iv) the fact that hydrological boundaries (drainage and divide lines) may not correspond to geomorphological or land use subdivisions important for determining landslide susceptibility.

The latter problem is partially solved by adopting a subdivision based on geo-hydrological units. Geo-hydrological units are obtained by further partitioning the slope units based on the main lithological types cropping out in a region and considered important to separate dissimilar susceptibility conditions within the same slope (Ardizzone *et al.*, 2000; Cardinali *et al.*, 2002b). This can be easily obtained in a GIS by intersecting the slope units subdivision with a simplified lithological map. A geo-hydrological subdivision retains all the information typical of a division based solely on drainage and divides lines (i.e., the morphological and hydrological factors), and limits the problem of having in the same slope unit two or more rock types with distinctly different landslide propensity (e.g., stable hard rocks underlined by unstable weak sediments). One can imagine extending the concept of geo-hydrological units by further subdividing them based on main land use types, e.g., forested vs. non forested terrain. This further subdivision may prove useful where landslides are principally controlled by the type of land cover.

Topographic units are vector-based subdivisions obtained by partitioning a catchment, or a single slope, into stream tube elements of irregular size and shape. The upper and lower boundaries of a stream tube are defined by adjacent contours, and the lateral boundaries are delineated by flow lines orthogonal to contours (O'Loughlin, 1986; Moore *et al.*, 1988; Moore and Grayson, 1991). Thus, topographic units are a particular subdivision of slope units. For each stream tube, local morphometric and hydrological variables are computed, including the cumulative drainage area of all up-slope elements. Due to their surface and sub-surface hydrological significance, topographic units are most suited to model the behaviour of shallow landslides, coupling slope instability and infiltration models. Topographic units appear less adapt to model large, deep-seated slides. Limitations of topographic units parallel those of the hydrologically-based units (i.e., slope units and geo-hydrological units), and include: (i) the difficulty in their preparation, which requires specialized software; (ii) the difficulty in tailoring their size to the known distribution of landslides or to local topographic conditions; and (iii) the fact that surface hydrological boundaries may not correspond to sub-surface morphological and hydrological conditions important for the initiation of shallow landslides.

When investigating very large areas, such an entire region or a nation, political, administrative or demographic units can be adopted (e.g., census zones, municipalities, districts, provinces) (Guzzetti *et al.*, 2003a). Most commonly, these geographical units do not reflect morphological, hydrological, or lithological boundaries. This is undoubtedly a limitation for landslide susceptibility studies. However, clear linkage between a geographical mapping unit and political or administrative offices and/or responsibilities makes the subdivision appealing to politicians and decision makers, particularly at the regional and the national scale. Administrative units are suited to analyze and synthesize information stored in archive inventories (Guzzetti and Tonelli, 2004).

Selection of an appropriate mapping unit depends on a number of factors, including: (i) the type of landslide phenomena to be studied, (ii) the scale of the investigation, (iii) the available resources, (iv) the quality, resolution, scale and type of the thematic information required, and (v) the availability of the adequate information management and analysis tools. Each technique for partitioning the territory has advantages and limitations that can be enhanced or reduced choosing the appropriate susceptibility evaluation method (Carrara *et al.*, 1995; Guzzetti *et al.*, 1999a).

6.2.3. Methods

Review of the literature (Varnes and IAEG Commission on Landslides and other Mass-Movements, 1984; Carrara *et al.*, 1995; Hutchinson, 1995; Soeters and van Westen, 1996; van Westen *et al*., 1997; Aleotti and Chowdhury, 1999; Guzzetti *et al*., 1999a; Gorsevski *et al*., 2003; Committee on the Review of the National Landslide Hazards Mitigation Strategy, 2004, and reference therein) reveals that methods for ranking slope instability factors and assigning different susceptibility levels can be: (i) qualitative or quantitative, and (ii) direct or indirect. Qualitative methods are subjective, ascertain susceptibility heuristically, and portray susceptibility levels using descriptive (qualitative) terms. Quantitative methods produce numerical estimates, i.e., probabilities of the occurrence of landslide phenomena in any susceptibility zone. Only quantitative methods are suited for the quantitative evaluation of landslide hazard (see § 7).

A direct method consists in the (direct) geomorphological mapping of landslide susceptibility, in the field, from the aerial photographs (Verstappen, 1983) or from satellite images (Nossin, 1989). Most commonly (but not necessarily), it is associated with the production of a landslide inventory map. Indirect methods for landslide susceptibility assessment are essentially stepwise. They require: (i) the recognition and mapping of landslides over a target region or a subset of it (i.e., the training area), which is obtained by preparing a landslide inventory map, (ii) the identification and mapping of the physical factors which are directly or indirectly correlated with slope instability (the instability factors, or independent variables), (iii) an estimate of the relative contribution of the instability factors in generating slope failures, (iv) the classification of the land surface into domains of different levels of susceptibility, and (v) the assessment of the model performance.

The most common approaches proposed in the literature can be grouped into five main categories (Carrara *et al.*, 1992, 1995; van Westen, 1993; Hutchinson, 1995; Soeters and van Westen, 1996; van Westen *et al.*, 1997; Aleotti and Chowdhudry, 1999; Guzzetti *et al.*, 1999a; Committee on the Review of the National Landslide Hazards Mitigation Strategy, 2004), namely: (i) direct geomorphological mapping, (ii) analysis of landslide inventories, (iii) heuristic or index based methods, (iv) statistical methods, including neural networks and expert systems, and (v) process based, conceptual models (Table 6.1). This classification of susceptibility methods is “fuzzy”. Approaches blend one in to the other, and authors are not always clear in describing the method they have used to ascertain landslide susceptibility, including the similarities or the differences with other published methods. Van Westen *et al*. (1997) provide detailed schemes for the applications of some of the susceptibility methods in a GIS environment.

Table 6.1 – Characteristics of landslide susceptibility methods proposed in the literature.

	DIRECT	*INDIRECT*	*QUALITATIVE*	*QUANTITATIVE*
GEOMORPHOLOGICAL MAPPING	✓		✓	
HEURISTIC (INDEX-BASED)		✓	✓	
ANALYSIS OF INVENTORIES		✓		✓
STATISTICAL MODELLING		✓		✓
PROCESS BASED (CONCEPTUAL)		✓		✓

6.2.3.1. Geomorphological mapping

Geomorphological mapping of landslide susceptibility is a direct or semi-direct, qualitative method that relies on the ability of the investigator to recognize actual and potential slope failures, including their evolution and possible consequences (Humbert, 1977; Godefroy and Humbert, 1983; Kienholz *et al.*, 1983, 1984; Bosi *et al.*, 1985; Zimmerman *et al.*, 1986; Seeley and West, 1990; Pachauri and Pant, 1992; Hansen *et al.*, 1995; Pachauri *et al*., 1998; Nossin, 1999; Pasuto and Soldati, 1999; Ng *et al*., 2002; Cardinali *et al*., 2002a; D'Amato *et al*., 2003; Pallàs *et al*., 2004; Ayenew and Barbieri, 2005; Reichenbach *et al*., 2005). When carried out by experts, geomorphological mapping is a form of expert judgement. If pursued by well trained investigators, knowledgeable of the slope instability phenomena in the study area, the method can provide very reliable results. However, the method is subjective, difficult to formalize, and not fully adequate for quantitative assessments of landslide hazard (see § 7). Recently, a method to quantify geomorphological susceptibility mapping for qualitative landslide hazards and risk assessments has been proposed and tested by Cardinali *et al*. (2002a) and Reichenbach *et al*. (2005). In principle, the latter method could be programmed into an expert system, providing quantitative estimates of landslide susceptibility, hazard and risk.

6.2.3.2. Analysis of inventories

The analysis of landslide inventories attempts to predict future patterns of instability directly from the past distribution of landslide deposits. This can be accomplished by preparing landslide density maps, i.e., maps showing the percent of area covered by landslide deposits or the number of landslide events over a region (Campbell, 1973; Wright and Nilsen, 1974; Wright *et al.*, 1974; Pomeroy, 1978, 1979; DeGraff, 1985; DeGraff and Canuti, 1988; Guzzetti *et al.*, 1994; Bulut *et al*., 2000; Parise and Jibson, 2000; Chau *et al*., 2003; Moreiras, 2004). As explained in § 3.1, different types of landslide density maps can be prepared, depending on the type of mapping unit and the filtering techniques used to determine the density. The method is indirect, and the result is quantitative. If properly normalized (e.g., by the total amount of the mapped landslide area), a density map may provide frequency estimates suitable for landslide hazard mapping. However, due to uncertainties and errors associated with landslide inventories and to the complexity of landslide phenomena (§ 1.1), estimates of the probability of spatial occurrence of slope failures based solely on landslide density (i.e., not considering the geo-environmental factors leading to slope instability) may be misleading or incorrect (Ardizzone *et al.*, 2002; Galli *et al*., 2005).

6.2.3.3. Heuristic zoning

An index based approach is based on a priori knowledge, i.e., on the assumption that all the causes and instability factors of landsliding in the area under investigation are known. It is an indirect (or semi-direct), mostly qualitative method whose reliability depends on how well and how much the investigator understands the geomorphological processes acting upon the terrain. Instability factors are classified, ranked and weighted according to their assumed or expected importance in causing mass movements. Based on this information, heuristic, subjective decision rules are established to define possibly unstable areas and to zone landslide susceptibility accordingly (Nilsen and Brabb, 1977; Amadesi and Vianello, 1978; Hollingsworth and Kovacs, 1981; Neeley and Rice, 1990; Montgomery *et al.*, 1991; Pachauri and Pant, 1992; Mejıa-Navarro *et al.*, 1994; Sarkar *et al.*, 1995; McClelland *et al.*, 1997 Pachauri *et al.*, 1998; Nagarajan *et al.*, 2000; Lee *et al.*, 2002; He *et al.*, 2003; Liu *et al.*, 2004; Moreiras, 2005). Ideally, rules used to rank, weigh and combine the instability factors should be based on detailed knowledge of the physical processes controlling landslides. In practice, this is rarely done, and ranking and weighing procedures are based (solely) on the experience of the investigator, a procedure that introduces subjectivity. van Westen *et al.* (1997) argued that subjectivity is not necessarily bad, particularly if it is based on the opinion of an expert. Nonetheless, subjectivity adds to the uncertainty of the model. To limit this problem, the expected importance of each instability factor can be obtained "objectively" by investigating the relative abundance of landslides (Pachauri *et al.*, 1998; He *et al.*, 2003) or from regression analysis (Nagarajan *et al.*, 2000). This process has also limitations, the most severe of which consists in not considering the complex interactions between the multiple factors controlling slope instability. As an example, slope and lithology are often considered separately, whereas in Nature it is their complex interaction that controls the position and abundance of landslides. The results of index based models are shown using qualitative levels of landslide susceptibility. For this reason they are also not well suited for quantitative assessments of landslide hazard (see § 6). Since they are based on generally simple rules, index-based approaches are suited to be implemented in computer expert systems (Al-Homoud and Masanat, 1998; Al-Homoud and Al-Masri, 1999; Pistocchi *et al.*, 2002).

6.2.3.4. Statistical methods

Statistical models to determine spatial landslide instability are constructed to describe the functional relationships between instability factors and the past and present distribution of slope failures (Carrara, 1983). The approach is indirect and provides quantitative results suitable to the quantitative assessment of landslide hazard. The simplest statistical methods are based on the determination of the relative abundance (proportion, percentage, frequency, incidence) of landslides in the classes in which thematic layers showing the geographical distribution of stability/instability factors are ranked. Different approaches have been proposed, including: a general instability index (Carrara *et al.*, 1978; 1982), a landslide susceptibility/hazard index (Sarkar *et al.*, 1995; van Westen, 1997; Parise and Jibson, 2000; Rautela and Lakhera, 2000; Lee *et al.*, 2002; Carrasco *et al.*, 2003; Lee, 2004; Saha *et al.*, 2005), a frequency index (Parise and Jibson, 2000), and a surface percentage index (Uromeihy and Mahdvifar, 2000). These indexes measure, directly or in a weighted form, the relative or absolute abundance of landslide area or number in different terrain categories. This information is then used by the investigator to establish susceptibility levels.

More advanced methods employ a variety of classification techniques that can be broadly ordered based on the adopted "philosophical" classification approach, including (Michie *et al.*, 1994): (i) classical (*frequentist* or *Fisherian*) statistical techniques, (ii) modern (*subjectivist* or Bayesian) statistical methods, (iii) fuzzy logic systems, (iv) neural networks, and (v) expert systems.

Many investigators have adopted a classical "frequentist" approach to establish the spatial probability of landslide occurrence, and have applied a variety of statistical classification techniques including: (i) bivariate analysis (Kobashi and Suzuki, 1988; van Westen 1993; Naranjo *et al.*, 1994; Süzen and Doyuran, 2004a, 2004b; Ayalew and Yamagishi, 2005); (ii) multiple regression analysis (Carrara, 1983), (iii) discriminant analysis (Reger, 1979; Carrara, 1983, 1992; Carrara *et al.*, 1982; 1991, 1992, 1995, 2003; Guzzetti *et al.*, 1999a, 2005a,d; Nagarajan *et al*., 2000; Baeza and Corominas, 2001; Ardizzone *et al*., 2002; Cardinali *et al*., 2002b; Santacana *et al*., 2003), and (iv) logistic regression analysis (Mark, 1992; Carrara *et al.*, 1992; Mark and Ellen, 1995; Atckinson and Massari, 1998; Rowbotham and Dudycha, 1998; Dai *et al*., 2001; Dai and Lee, 2002, 2003; Olhmacher and Davis, 2003; Lee, 2004; Süzen and Doyuran, 2004a; Ayalew and Yamagishi, 2005; Pinter and Dean Vestal, 2005). When many factors are available, to reduce the number of variables and to limit their interdependence, principal component analysis (PCA) is an option (Carrara *et al.*, 1995; Baeza and Corominas, 2001).

As can be seen from the listed references, discriminant analysis and logistic regression are the two most popular techniques. Discriminant Analysis (DA) was introduced by Fisher (1936), and is used to classify samples into alternative groups on the basis of a set of measurements (Michie *et al.*, 1994; Brown, 1998; SPSS, 2004). More precisely, the goal of DA is to classify cases into one of several mutually exclusive groups based on their values for a set of predictor variables. The grouping variable must be categorical and the predictor variables must be interval or dichotomous (SPSS, 2004, p. 515). For landslide susceptibility assessment, most commonly two groups are established, namely: (i) mapping units free of landslides (G_0, stable slopes), and (ii) mapping units having landslides (G_1, unstable slopes). The assumption is made that the two groups are distinct, and that a mapping unit r pertains only to one group, i.e., if $r \in G_0$, then $r \notin G_1$. In the context of landslide susceptibility, the scope of DA is to determine the group membership of a mapping unit by finding a linear combination (or curvilinear combination in the case of quadratic DA (Michie *et al.*, 1994)) of the environmental variables which maximizes the differences between the populations of stable and unstable slopes. The goal is to establish a model to sort the mapping units into their appropriate groups with minimal error. To obtain this, consider a set of m variables $v_1, v_2, \ldots, v_m$ for each mapping unit, r, by means of which it is desired to discriminate the region between the groups of stable (G_0) and unstable (G_1) slopes, and let Z be a linear combination of the input variables, such as

$$Z = \beta_1 v_1(r) + \beta_2 v_2(r) + \ldots + \beta_m v_m(r) \tag{6.1}$$

For DA, the task is to determine the βs of equation 6.1 by means of some criterion that will enable Z to serve as an index for differentiating between members of the two groups. If only one independent variable is available (e.g., the mapping unit mean slope) equation 6.1 reduces to $Z = \beta_1 v_1(r)$, which is the equation of a line separating mapping units based solely on terrain gradient. If two environmental variables are available (e.g., slope and its standard deviation), equation 6.1 reduces to $Z = \beta_1 v_1(r) + \beta_2 v_2(r)$, which represents a plane in three dimensions that separates (discriminates) mapping units given the mean and the standard deviation of the slope. Similarly, if m independent variables are used, equation 6.1 represents a hyper plane, a multi-dimensional surface that discriminates the mapping units into alternative groups of stable or unstable slopes.

In DA, the linear discriminant function Z transforms the original sets of measurements into a single discriminant score, which represents the sample position along a line defined by the same discriminant function. To measure how far apart the two groups are along this line, different "distances" can be used, e.g., Euclidean, diagonal or Mahalonobis distances (Michie *et al.*, 1994; Gorsevski *et al.*, 2003). Most commonly, the Mahalonobis distance D_M is used:

$$D_M = \frac{(Z_0 - Z_1)^2}{V_Z} \tag{6.2}$$

where, Z_0 and Z_1 are the means of the stable and unstable groups, respectively, and V_z is the pooled sample variance. A larger value of D_M indicates that it is easy to discriminate between the two groups. Posterior probabilities are then used to express the likelihood of a sample (a mapping unit) belonging to one group or the other, i.e. $P[r \in G_0] = 1\text{-}P[r \in G_1]$ (Brown, 1998). Thus, when probabilities are derived from a DA, they represent the likelihood of a mapping unit pertaining to one of the two groups established a priori. The relative contribution of each environmental factor (of each independent variable) to the discriminating function can be evaluated by studying the standardized discriminant function coefficients (SDFC). This is particularly useful because it allows the investigator to determine if the model is geomorphologically sound.

Logistic Regression Analysis (LRA) was introduced by Cox (1958) and is used to investigate a binary response from a set of measurements (Michie *et al.*, 1994; Brown, 1998; SPSS, 2004). The technique, which regresses a dichotomous dependent variable on a set of independent explanatory variables that can be interval, dichotomous or categorical (i.e., polychotomous) (SPSS, 2004, p. 859), is widely used in the medical field, or to predict success or failure of a process based on a set of measurements. Instead of using a linear relationship between the independent variables and the response, a curvilinear model relationship is used. In landslide susceptibility investigation, the response is the presence/absence of landslides in each mapping unit, and the independent variables are the set of *m* environmental factors $v_1, v_2, \ldots, v_m$ available for each mapping unit, *r*. Since the response of the analysis must be binary, two alternative groups are established: (i) mapping units free of landslides (G_0, stable slopes), and (ii) mapping units having landslides (G_1, unstable slopes). In LRA, the relationship between the occurrence of landslides in a mapping unit and its dependency on the set of environmental variables is expressed as:

$$S = \frac{1}{(1 + e^{-\Psi})} \quad 0 \le S \le 1 \tag{6.3}$$

where, S is the (Bernoulli) probability that a mapping unit pertains to the stable (G_0) or the unstable (G_1) group. S varies from 0 to 1 on an s-shaped ("logistic") curve. In equation 6.3, Ψ is the *logit*, i.e., the natural logarithm of the odds, $log\left(\frac{p}{1-p}\right)$, which is linearly related with the independent variables:

$$\Psi = log\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 v_1(r) + \beta_2 v_2(r) + \ldots + \beta_m v_m(r) + \varepsilon \tag{6.4}$$

where, $\beta_0, \beta_1, \ldots \beta_m$ are the unknown parameters of the logistic regression model, $v_0(r), v_1(r), \ldots v_m(r)$ are the independent variables in each mapping unit and ε is the error associated with the curvilinear approximation of the model. LRA involves fitting equation 6.4 to the data, and then expressing the probability of the presence/absence of landslides in each mapping unit using equation 6.3. The relative contribution of each mapping unit to the logistic function can be obtained. Inspection of this information is useful to determine the geomorphological reliability of the model.

In the literature, discussion exists on the advantages and the limitations of LRA over DA (Michie *et al.*, 1994; Brown, 1998). A cited advantage of LRA lies in the possibility of using together different types of variables, including continuous, binary and categorical variables. The latter variables are abundant in geology and geomorphology (Carrara *et al.*, 1992). Most commonly in LRA, categorical variables are replaced by various types of contrast variables (SPSS, 2004, p. 863-5). In general, it is assumed that DA is more powerful in the presence of multivariate normality of the data; conversely, LRA is more suited to analyse datasets lacking multivariate normality, or datasets for which multivariate normality is not apparent. When data are multivariate normal, DA requires less data to achieve the same precision as LRA (Brown, 1998). Both methods require near equal number of samples in the groups, and equal variance-covariance matrices of the groups. Deviance from equality may have severe consequences for both methods. Finally, DA is less computationally intensive than LRA. The latter may not be a problem with modern personal computers, given the size of the datasets commonly used in landslide susceptibility assessments (Carrara *et al.*, 1999).

In recent years, many investigators have experimented with methods that exploit, more or less rigorously, Bayes' theorem for conditional probability. In this framework, conditional probability is a statement of the chance of a hypothesis being true or false given a piece of evidence (Gorsevski *et al.*, 2003). Bayesian probabilistic modelling is suited for example for solving problems of decision-making under uncertainties. Given the uncertainty associated with landslide phenomena and their relationships with the landscape, the method appears suited for landslide susceptibility assessment (Chung and Fabbri, 1999; Gorsevski *et al.*, 2003).

Bayes' theorem can be written as:

$$P(A \mid B) = \frac{P(B \mid A) \times P(A)}{P(B)} \tag{6.5}$$

which means that the probability of an hypothesis on some event A occurring conditioned by the fact that event B has occurred, P(A|B), is equal to the probability of event B occurring given that event A has occurred, P(B|A), multiplied by the probability of event A occurring, P(A), and divided by the probability of event B occurring, P(B). In equation 6.5, P(A) is the "prior probability", i.e., a reasonable hypothesis on the probability of event A, P(B) is the "posterior probability", i.e., the probability of B given all possible hypotheses on A, and P(B|A) is the "likelihood", i.e., the conditional probability of A given B. In an ideal Bayesian analysis, the prior probability has a weak effect on the posterior probability, as most of the information comes from the likelihood.

When applied to landslide susceptibility assessment, Bayes' theorem is used to determine the probability that a region will develop slope failures given the local environmental conditions. Following Chung and Fabbri (1999):

$$P\left(A_L \mid \{v_0(r), v_1(r), \ldots, v_m(r)\}\right) = \left[\frac{P(\{v_0(r), v_1(r), \ldots, v_m(r)\} \mid A_L) \times P(A_L)}{P\left(v_0(r), v_1(r), \ldots, v_m(r)\right)}\right] \tag{6.6}$$

where, A_L denotes that a landslide of area A will occur in a mapping unit r for which $v_0(r)$, $v_1(r)$, ... $v_m(r)$ independent environmental conditions are known. It is further assumed that the combination of environmental conditions is unique to the mapping unit r.

Equation 6.6 indicates that the probability that a mapping unit r in the study area will be affected by a landslide is equal to the probability of a landslide in the study area, $P(A_L)$, multiplied by the probability of a specific (unique) combination of environmental factors given the presence of a landslide, divided by the probability of the same combination of environmental factors in the entire study area. A straightforward assumption is to obtain the three probabilities in the right hand side of equation 6.6 in a GIS from the corresponding spatial densities. This can be obtained as follows: (i) for $P(A_L)$, by dividing the total landslide area (A_L) in the study area by the area of the mapping unit, (ii) for $P\left(v_0(r), v_1(r), \ldots, v_m(r)\right)$, by dividing the total area of the unique condition unit by the extent of the study area, and (iii) for $P(\{v_0(r), v_1(r), \ldots, v_m(r)\} \mid A_L)$, by computing the percentage of landslide area in the study area characterized by the total area of the considered unique environmental setting.

Similar approaches have been proposed by several investigators, including: weight of evidence methods (Bonham-Carter, 1991; Lee *et al*., 2002a, 2002b; Wu *et al*., 2004), weighting factors (Çevik and Topal, 2003), weighted linear combination of instability factors (Ayalew *et al*., 2004), landside nominal risk factor (Gupta and Joshi, 1990; Saha *et al*., 2005), likelihood ratio (Chung and Fabbri, 2003, 2005; Fabbri *et al*., 2003; Lee, 2004), certainty factors (Binaghi *et al*., 1998), information value (van Westen, 1997; Lin and Tung, 2004; Saha *et al*., 2005), and modified Bayesian estimation (Chung and Fabbri, 1999). Understanding the differences between the proposed approaches is not always simple, the main differences being the rigor of the approach (e.g., Chung and Fabbri, 1999) and the method used to estimate the prior probability of landslide occurrence. An advantage of Bayesian probabilistic modelling is the possibility of incorporating uncertainty into the susceptibility model, and to explicitly consider expert knowledge, which often exists for the investigated area (Chung and Fabbri, 1999). Use of expert knowledge is more difficult (but not impossible) when adopting classical statistical classification methods.

A few landslide investigators have attempted to apply fuzzy sets to landslide susceptibility zonation (Juang, 1992; Binaghi *et al*., 1998; Uromeihy and Mahdavifar, 2000; Ercanoglu and Gokceoglu, 2002; 2004; Pistocchi *et al*., 2002; Gorsevski *et al*., 2003; Saboya *et al*., 2005). Fuzzy set theory was introduced by Zadeh (1975, 1978) as an extension of ordinary set theory. In ordinary set theory an element belongs (or does not belong) to a set, i.e., it allows only 0 or 1 values as possible membership degrees. In fuzzy set theory, membership degree can take any value from 0 and 1, i.e., a fuzzy set contains elements that have varying degrees of membership. When applied to landslide susceptibility, for each class of an environmental variable (e.g., for each slope category) a membership degree is established between the presence/absence of landslides and the parameter class (e.g., the presence of landslides in the 10-20 degree slope category). Various methods can be used to establish this relationship, whose "strength" is the degree of membership. A fuzzy set is then constructed for each environmental variable, which expresses the landslide susceptibility for each of the considered classes (e.g., landslide susceptibility in each slope category). Fuzzy sets for different environmental factors are then combined using rules of various complexities (Ercanoglu and Gokceoglu, 2002) to obtain an estimate of landslide susceptibility.

Expert knowledge approaches applied to landslide susceptibility assessment include artificial neural networks and expert systems. Artificial neural networks are computational frameworks capable of simulating – albeit in a crude fashion – the behaviour of the human brain in solving a complex problem (Michie *et al.*, 1994). Conceptually, the advantage of neural networks over other classification methods consists in the fact that they are independent of the distribution of the data, although artificial neural networks are calibrated to the data and the calibration defines the functionality of the network. Also, neural networks require less data for training than other statistical methods (Lee *et al.*, 2004). Most commonly, back propagation learning algorithms are adopted. These are made by multiple layers of "neurons" (i.e., individual processing nodes), including an input and an output layer and one or more hidden layers. A neural network takes the input information and "learns" how to predict the output by establishing and adjusting weights between neurons on the same or on different layers, in response to errors between predicted and known output values. At each neuron, adjustment occurs through weighting summations and non linear functions. At the end of the training phase, the neural network should be able to predict the output values (e.g., landslide susceptibility) given a set of inputs (e.g., the environmental factors). The main limitation of artificial neural networks lays in the fact that is very difficult – if not impossible – to know why they work for any given set of data and for any given calibration set. This restrains the possibility of using findings obtained with a neural network prepared for an area to a neighbouring area. Also, the role, functionality and significance of the weights and of the non-linear calibration functions are difficult to interpret. Artificial neural networks have been applied to landslide susceptibility mapping by, e.g., Arora *et al*. (2004), Lee *et al*. (2003a, 2003b, 2004), Ermini *et al*. (2005), Ferentinou and Sakellariou, (2005), Gómez *et al*. (2005) and Wang *et al.* (2005).

Expert systems are computer programs capable of exploiting complex information to make decisions based on a set of rules. Decisions taken by expert systems include categorization, i.e., selection between alternatives (Michie *et al.*, 1994). Rules used in expert systems can be established a priori, or defined by the same system that "learns" from errors. In principle, index based landslide susceptibility methods (for which "slope instability rules" are known) are suited for the implementation in an expert system framework (Guzzetti *et al*., 1999a). Particularly interesting is the possibility of establishing rules to cope with "special cases", or individual instability conditions that cannot be captured by, e.g., statistical or physically based models. Inspection of the literature indicates that only a few authors have attempted to implement rule-based expert systems for landslide susceptibility zonation (Al-Homoud and Masanat, 1998; Al-Homoud and Al-Masri, 1999; Pistocchi *et al*., 2001). This is probably because the effort is not justified by the result obtained. An expert system is mostly suited when decisions (e.g. categorization) have to be taken repeatedly. This is usually not the case for landslide susceptibility assessments. When a susceptibility model is prepared and validated, it can be used for years without the need for any further processing.

Following the widespread availability of GIS technology and of user friendly statistical packages, statistical models have become the method favoured by many investigators to determine landslide susceptibility. However, review of the most recent literature – which is abundant (Uromeihy and Mahdavifar, 2000; Dai *et al*., 2001; Dai and Lee, 2003; Olhmacher and Davis, 2003; Ercanoglu and Gokceoglu, 2002; 2004; Çevik and Topal, 2003; Gorsevski *et al*., 2003; Lee, 2004; Lee *et al*. 2003a; 2003b; 2004; Santacana *et al*., 2003; Wu *et al*., 2004;

Ayalew *et al*., 2004) – reveals that many investigators are interested chiefly in applying different statistical methods, and much less concerned in: (i) collecting detailed, high quality information related to slope failures, (ii) identifying new environmental parameters useful to the assessment of landslide susceptibility, (iii) validating quantitatively the model results, (iv) explaining the geomorphological aspects of terrain zoning for landslide susceptibility assessment, or (v) in the examination of the socio-economical implications of the susceptibility models. This is rather unfortunate because it leads investigators to focus on the tool (a classification technique) rather than on the target (an optimal landslide susceptibility assessment). Also disappointing is the fact that in the copious literature on landslide susceptibility assessment very few attempts to quantitatively compare susceptibility models prepared by different methods, critically evaluating their advantages and limitations, are available (Carrara *et al.*, 1992; 1995; Chung and Fabbri, 1999; Pistocchi *et al*., 2002; Lee, 2004; Süzen and Doyuran, 2004a).

6.2.3.5. Process based models

Process based (deterministic or physically based) models for the assessment of landslide susceptibility rely upon the understanding of the physical laws controlling slope instability. In general, due to lack of information or poor understanding of the physical laws controlling landslide initiation and development, only simplified, "conceptual" models are considered. These models are indirect and provide quantitative results, which may or may not be suited for quantitative landslide hazard assessment depending on the types of output. Review of the literature reveals that process based models are developed mostly to study a particular type of landslide (e.g., shallow soil slips, debris flows, or rock falls), or to investigate the effect of a specific trigger, i.e., an intense rainfall period or an earthquake.

When applied to the prediction of shallow rainfall-induced landslides, process based models attempt to extend spatially the simplified stability models widely adopted in geotechnical engineering. These models calculate the stability of a slope using parameters such as normal stress, angle of internal friction, cohesion, pore water pressure, seismic acceleration, external weights, etc. Most commonly, computation results in a factor of safety, i.e., an index expressing the ratio between the local stabilizing and driving forces. Values of the index greater than 1.0 indicate stability of the slope, and values less than 1.0 identify unstable conditions. A safety factor of exactly 1.0 indicates the meta-stable condition produced by equivalence of the stabilizing and driving forces. When applied over large areas, local stability conditions are generally evaluated by means of a static stability model, such as the well known ''infinite slope model'', where the local equilibrium along a potential slip surface is considered. For simplicity, the slip surface is assumed planar, at a fixed depth, and most commonly parallel to the topographic surface, and some assumed value of pore fluid pressure is selected. More advanced models include seepage from neighbouring areas. Other models couple the infinite slope stability model with more or less complex rainfall infiltration models (Ward *et al*., 1981, 1982; Okimura and Kawatani, 1987; Benda and Zhang, 1990; Dunne, 1991; Hammond *et al*., 1992; van Ash *et al*., 1999; Montgomery and Dietrich, 1994; Dietrich *et al.*, 1995; Terlien *et al.*, 1995, Dymond *et al*., 1999; Gritzner *et al*., 2001; Borga *et al.*, 2002a; Crosta and Frattini, 2003; Crosta and Dal Negro, 2003; D'Odorico and Fagherazzi, 2003; Lan *et al*., 2005). Most commonly, distributed models for the stability of slopes are based on a raster representation of the landscape and exploit GIS-raster technology, including map algebra, to implement the models, which generally relay heavily on a digital representation of the terrain (i.e., a DTM). Alternative approaches are based on topographic units and stream tube elements, which are hydrological, vector based representations of the terrain. Some of the most advanced distributed models for the stability of slopes and the forecast of shallow landslides take as input the surface and sub-surface information on lithological, hydrological and geo-mechanical conditions, including the depth of the shear surface and of the water table at the beginning of the simulation, and a measured or inferred rainfall pattern (in space and time). These models run in incremental time steps and estimate the location and the time of the expected slope failures. With this respect, the results of such models are superior to a simple susceptibility assessment.

Specific, physically based models were developed for predicting the effects of seismic shaking on the stability of slopes over large areas, or to explain the known distribution of seismically induced landslides (Jibson *et al*., 1998; Miles and Ho, 1999; Luzi, 2000; Luzi and Pergalani, 2000; Jibson and Jibson, 2001; Lin and Tung, 2004; Paléz *et al*., 2005). Some of the most reliable approaches extend the Newmark method designed for estimating the stability of dams or embankments subject to seismic shaking to the stability of individual slopes (Newmark, 1965; Wieczorek *et al*., 1985; Wilson, 1993). When applied to large regions, these models are based on a grid partitioning of the terrain. Potential landslides are considered as rigid bodies subject to seismic acceleration, ascertained from measured or synthetic accelerographs. For each grid cell, the cumulative displacement of the rigid block subject to seismic acceleration is computed. If an established threshold is exceeded, a grid cell becomes unstable and a landslide occurs. Displacement thresholds depend on the type of landslide, and are decided largely based on the experience of the investigators. Rock falls require a smaller displacement to fail than large, deep-seated slides. Groundwater conditions can also be considered.

Physically based models to simulate rock fall processes were developed by van Dijke and van Westen (1990) and by Guzzetti *et al.* (2002a). The latter model uses a DTM and spatially distributed information on the location of the source areas of rock falls, and of the energy lost at impact points and where boulders are rolling, to simulate in three dimensions rock fall phenomena for areas ranging from a few thousands of square meters to several hundreds of square kilometres (Guzzetti *et al*., 2002a, 2003b). Results of the model include: (i) the extent and location of the areas potentially subject to rock falls, and (ii) estimates of the maximum velocity and of the maximum distance to the ground of the falling rocks. This information can be combined to obtain quantitative estimates of landslide hazards (Crosta and Agliardi, 2004; Guzzetti *et al*., 2004b).

6.2.4. Susceptibility methods and mapping units

Susceptibility methods and mapping units are conceptually and operationally interrelated (Carrara *et al.*, 1995). Table 6.2 summarizes the main correlations. In direct susceptibility mapping, the geomorphological unit of reference is implicitly defined by the interpreter who maps the portions of the territory that are subject to different geomorphological hazards (Hansen, 1984). In all other cases (i.e., grid-based modelling, unique condition units, slope-units, geo-hydrological units, topographic units), the mapping unit is explicitly defined by the operator before the investigation begins. In general, grid cells are preferred for heuristic (Pike, 1988; Mejıa-Navarro *et al.*, 1994), statistical (Carrara, 1983; van Westen, 1994; Chung and Fabbri, 1999; Lee and Min, 2002; Remondo *et al.*, 2003; Pinter and Dean Vestal, 2005) and process based or simulation (Mark, 1992; Terlien *et al.*, 1995, Di Gregorio *et al.*, 1999a, 1999b; Dymond *et al.*, 1999; Guzzetti *et al.*, 2002a; Crosta and Frattini, 2003) modelling.

Unique condition units have been applied to both heuristic (van Westen, 1993) and statistical methods (Carrara *et al.*, 1995; Chung *et al.*, 1995; Chung and Fabbri, 1999; Guzzetti *et al.*, 1999a; Ercanoglu and Gokceoglu, 2004; Lee *et al*., 2004). Slope units and geo-hydrological units have been used in statistical models (Carrara *et al.*, 1991; 1995; Guzzetti *et al.*, 1999; Ardizzone *et al.*, 2002; Cardinali *et al.*, 2002b), whereas topographic units have been used in physically based models (Montgomery and Dietrich, 1994). Municipalities were used by Guzzetti *et al.* (2004) to evaluate landslide and flood hazard in Italy. Census zones were used by Guzzetti *et al.* (2003a) to evaluate the number and percent of the population subject to landslide risk in the Perugia Municipality, in Umbria.

Table 6.2 – Relationships between mapping units and methods for landslide susceptibility assessment.

	DIRECT MAPPING	ANALYSIS OF INVENTORIES	INDEX BASED	STATISTICAL	PHYSICALLY BASED
Grid cell		✓		✓	✓
Terrain unit	✓				
Unique condition unit			✓	✓	
Slope unit		✓		✓	
Geo-hydrological unit				✓	
Topographic unit					✓
Geographical unit		✓		✓	

6.3. Probabilistic model for landslide susceptibility

As explained at the beginning of this chapter (§ 6.1), landslide susceptibility is the probability of geographical occurrence of slope failures. It is the probability that any given region will be affected by landslides, given a set of environmental conditions. In an important paper, Chung and Fabbri (1999) proposed a probabilistic model for landslide susceptibility. They considered the following (here slightly modified) propositions:

F: "a given region will be affected by landslides" (6.7)

and

L: "a given region has been affected by landslides". (6.8)

These authors then proposed that landslide susceptibility, *S* (which they called landslide hazard) in a region *r* is expressed as the following joint conditional probability:

$$S = P[F|v_1(r), v_2(r), \ldots, v_m(r)] \tag{6.9}$$

where $v_0(r), v_1(r), \ldots v_m(r)$ are the *m* conditionally independent environmental variables, given the condition expressed by *F*.

Chung and Fabbri (1999) investigated five methods to estimate the joint conditional probability in equation 6.9, including: (i) direct estimation, (ii) Bayesian estimation, (iii) regression modelling, (iv) modified Bayesian estimation, and (v) modified regression modelling.

In their simplest model, the probability of future landslides in a region is given by the past distribution of landslides in the same region, or $P[F|v_1(r), v_2(r), \ldots, v_m(r)] = [L|v_1(r), v_2(r), \ldots, v_m(r)]$. However, these authors showed that this simple estimator performed poorly when it comes to estimating future landslides in their study area. In their second model, Bayesian estimation (equations 6.5 and 6.6) was used to determine *S* based on the prior probability of landslide occurrence, and on bivariate conditional probability functions, which were obtained from the known distribution of past landslides (i.e., using proposition *L*, equation 6.8). In their third model the probability of future landslides was obtained through multivariate regression. The conditional joint probability that a region *r* will be affected by a landslide was regressed against the bivariate conditional probabilities that a landslide will occur given a thematic environmental variable. Again, not knowing beforehand the distribution of future landslides, the bivariate conditional probabilities between landsliding and each of the available environmental factors were obtained from the known distribution of (past) landslides. In their fourth and fifth models, Chung and Fabbri (1999) proposed to modify the estimates obtained through Bayesian reasoning and multivariate regression modelling based on some kind of expert knowledge, which was available to them. This was obtained by using modified bivariate conditional probability functions obtained from experts instead of the bivariate conditional probability functions obtained in a GIS from the past distribution of landslides. Experts may or may not have used (or known) the past distribution of landslides to establish their estimates.

A similar probabilistic model to ascertain landslide susceptibility is now proposed. Adopting proposition *F*, "a given region will be affected by landslides" (6.7), and knowing *m* environmental factors $v_1, v_2, \ldots, v_m$ which are related to slope instability in the region, landslide susceptibility is

$$S = P\ [F \text{ is true, given } \{ \text{ morphology, lithology, structure, land use, etc. } \}] \qquad (6.10)$$

The statement is a rephrase of equation 6.9, where *S* is the conditional probability that a region *r* will be affected by future landslides given a set of *m* independent environmental variables $v_1, v_2, \ldots, v_m$ in the same region. As before, the problem with this proposition is that the future distribution of landslides is unknown to the investigator. At the beginning of a landslide susceptibility assessment, only past landslides in a region are known (e.g., through landslide mapping). Hence, terrain classification can be made only on the basis of the known distribution of past slope failures. Adopting proposition *L*, one can write the counterpart of equation 6.10 for the past distribution of landslides. This becomes

$$D = P\ [L \text{ is true, given } \{ \text{ morphology, lithology, structure, land use, etc. } \}] \qquad (6.11)$$

or

$$D = P[L|v_1(r), v_2(r), \ldots, v_m(r)] \qquad (6.12)$$

where *D* is now the conditional probability that the region *r* was affected by landslides given the same set of known independent environmental variables, $v_1, v_2, \ldots, v_m$.

In § 6.2.3 it was shown that the spatial probability of known (past) landslides can be estimated using a variety of classical statistical techniques. Using DA or LRA, the probability assigned to any given region (i.e., to each terrain mapping unit) is the probability that the region pertains to one of two mutually exclusive groups, namely: (i) the group of mapping units having landslides, G_1, or (ii) the group of mapping units free of landslides, G_0, given the set of independent environmental variables used in the analysis. A straightforward deduction is to assume $S = D$, and $S = P[r \in G_0] = 1 - P[r \in G_1]$, or

$$P\ [F \mid v_1(p), v_2(p), \ldots, v_m(p)] = P\ [L \mid v_1(p), v_2(p), \ldots, v_m(p)] \tag{6.13}$$

In other words, if a region pertains to the group of terrain units having known (i.e., past) landslides because of the local environmental setting, it is likely that the same region will experience slope failures again in the future (even if we don't know when). Equally, if a region pertains to the group of terrain units free of (known) past landslides, it is unlikely that the same region will experience mass movements in the future.

6.3.1. Discussion

The proposed probabilistic models for landslide susceptibility can predict the spatial occurrence of future landslides under the general assumption that in any given area slope failures will occur in the future under the same circumstances and because of the same conditions that caused them in the past. This is a geomorphological rephrase of the well-known postulate "the past is the key to the future" (§ 6.2.1). However, it is not certain that the postulate applies to landslides. New, first-time failures occur under conditions of peak resistance (friction and cohesion), whereas reactivations occur under intermediate or residual conditions. It is well know that terrain gradient is an important factor for the occurrence of landslides. An obvious effect of a slope failure is to change the morphology of the terrain where the failure occurs. In addition, when a landslide moves it may change the hydrological conditions of the slope. It is also well known that landslides can change their type of movement and velocity with time. Lastly, landslide occurrence and abundance are a function of environmental conditions that vary with time at different rates. Some of the environmental variables are affected by human actions (e.g., land use, deforestation, irrigation, etc.), which are also highly changeable. As a consequence of these complications, each landslide occurs in a distinct environmental context, which may have been different from the past and that might be different in the future (Guzzetti *et al.*, 1999a).

Despite these limitations, it is reasonable to assume that the postulate holds "statistically", i.e., that in the investigated area future landslides will occur in general under the same circumstances and because of the same conditions that triggered them in the past. This means accepting the equality expressed by equation 6.13. When a landslide susceptibility assessment is attempted in any given area, this equality has to be shown correct. Alternatively, limits for the equality have to be identified. This can be done explicitly or implicitly. An explicit demonstration of the equality may come from the analysis of multi-temporal inventory maps or from archive inventories. If the type and abundance of landslides does not change significantly in the study area with time, then the assumption can be made that the equality holds, and that the spatial probability of future slope failures (S) can be obtained from the spatial probability of past landslides (D).

An implicit demonstration may come from geomorphological inference. If in an area only rainfall induced landslides are expected, and the distribution of past rainfall induced landslides is known in detail, the latter can be used to predict the former. However, the distribution of past rainfall induced landslides may not predict accurately landslides triggered by earthquakes or snowmelt in the same region. It should be understood that in many areas the past distribution of known landslides is the result of different triggers, including intense or prolonged rainfall periods, earthquakes and snowmelt events, and that most commonly, a geomorphological inventory does not distinguish the triggers of the landslides. This limits our ability to test the equality in equation 6.13. In order to apply the probabilistic models one has to further assume that our knowledge of the distribution of past failures is reasonably accurate and complete, i.e., that the landslide inventory is reliable (§ 6.2.1). All these simplifications are needed to make the problem tractable, and should always be considered when interpreting and using the results of a susceptibility model.

6.4. Landslide susceptibility in the Upper Tiber River basin

In this section, I present and discuss the results of a landslide susceptibility model prepared for the Upper Tiber River basin. The model exploits all the available geographical information on landslides and on the thematic environmental factors presented in § 2.3, and relies on the probability model of landslide susceptibility discussed in § 6.3.

To obtain landslide susceptibility the basin – which extends for 4098 km^2 – was first subdivided into ~ 16,000 slope units (§ 6.2.2). For each slope unit, a set of morphometric and hydrological parameters useful to explain the spatial distribution of landslides were then obtained from the available DTM (e.g., Carrara *et al.*, 1991, 1995). Tests were made to calibrate the size of the slope units with the dimension of the landslides. Due to the large extent of the basin, calibration was not straightforward and required several iterations. To limit the unrealistic condition of landslides falling in two or more slope units, slope units corresponding to first order channels were selected relatively large (i.e., ~ 20 hectares). Next, the slope units were further subdivided based upon the main rock types cropping out in the basin (§ 2.3). This allowed splitting the slope units characterized by two (or more) rock types, corresponding to different morphological settings and landslide types and abundances, in distinct mapping units. In the end, the procedure subdivided the Upper Tiber River basin into more than 28,600 geo-hydrological units (§ 6.2.2), which became the mapping unit of reference for the statistical assessment of the landslide susceptibility.

Using GIS technology, a large set of geo-environmental variables (139 variables) derived from the available thematic maps was assigned to each mapping unit. The data set contained: (i) two variables showing the percentage of deep seated and shallow landslide area, (ii) 17 morphometric variables, describing the slope unit and its drainage line (e.g., area, slope, aspect, stream order, contributing area, etc.), obtained from the DTM, (iii) 21 litho-technical variables, obtained by grouping, based upon the relative abundance of hard vs. weak rocks, the 35 lithological types cropping out in the basin, (iv) five geological structure variables describing dip of bedding, obtained from the information on the bedding attitude, (v) six variables describing the interaction between the bedding attitude and slope aspect, and (vi) ten variables describing land use. To these primary variables, obtained directly from existing thematic maps, were added 45 variables obtained through the combination of primary variables or geographical operations. Of the added variables, 8 refer to the morphology of the slope, 31 to the interaction between lithology and bedding attitude, and 6 to the interaction between bedding attitude and land use.

Since in the Upper Tiber River basin most of the shallow landslides are spatially associated with deep-seated failures (i.e., landslide persistence is high, § 4.4), only one model that included both type of movements was prepared. Using as dependent variable the presence/absence of landslide deposits in each mapping unit, a linear discriminant function weighted on the mapping unit area was developed. Of the 139 independent input variables (i.e., not considering the variables describing the percentage of landslide area), 41 entered into the discriminant model (Table 6.3). Of these variables, 12 refer to lithology, 9 to bedding attitude and its interactions with the local slope, 11 are morphometric, 2 describe microclimatological conditions, and 7 describe land use or its interaction with lithology.

Table 6.3 – Upper Tiber River basin. Variables selected by a stepwise linear discriminant function as the best predictors of the occurrence of landslides in the 28,600 geo-hydrological mapping units in which the basin was partitioned. Most important standardized discriminant function coefficients (SDFC) are shown in bold. Negative or positive sign of the coefficients indicates variables contributing toward stability (green) or instability (red), respectively. Variables grouped in five thematic sets. Within each set, variables listed according to the value of the SDFC, from low (stability) to high (instability) values. For lithology, numbers in parenthesis refer to codes listed in the "Photo-Geological and Landslide Inventory Map of the Upper Tiber River Basin, Italy" of Cardinali *et al*. (2001).

	VARIABLE DESCRIPTION		*SDFC*
Lithology	Coarse to fine grained alluvial and fan deposits (2, 2b, 3)	CPOAF	**-.470**
	Well-bedded limestone (31, 33, 34, 36)	CCALS	**-.245**
	Thick and massive sandstone (22)	CTTM	-.042
	Thick and massive sandstone and calcarenite (14, 15)	CTUM	.020
	Stratified pelitic layers, minor arenaceous levels (19)	CTTP	.040
	Massive peridotite, gabbros and basalt (28, 29)	CLIM	.060
	Calcareous, marly and clayey turbidites (26)	CLIPL	.062
	Clay with chaotic structure (25)	CTTC	.063
	Argillite and siltstone locally with chaotic structure (27)	CLIC	.116
	Chaotic mixture of clay and exotic rock elements (12)	CTUC	.192
	Fine-grained lake and fluvial deposits (6, 7)	CPOSA	.195
	Very old (ancient) landslides	PALEO	**.259**
Bedding and structure	Massive structure	MASS	-.067
	Bedding dipping less than 5°	I0_5	.024
	Bedding dipping away the slope free face	FRA_P	.037
	Interaction between fluvial-lake deposits and bedding attitude	CPOREG	.054
	Interaction between the Liguria Complex and bedding attitude	CLIFRA	.059
	Bedding dipping between 15° and 35°	I15_35	.060
	Interaction between siltstone and sandstone and bedding attitude	CTUPLTRA	.069
	Interaction between Umbria Terrigenous Complex and bedding attitude	CTUTRA	.135
	Interaction between Tuscan Terrigenous Complex and bedding attitude	CTTTRA	.148
Morphology	Terrain-unit mean slope angle squared	SLO_ANG2	**-.772**
	Standard deviation of terrain-unit slope angle	ANG_STD	**-.245**
	Index of terrain-unit micro-relief	R	-.138
	Convex-concave profile down slope	COV_COC	-.072
	Standard deviation of terrain-unit length	LEN_STD	-.056
	Concave profile down slope	CONV	.021
	Concave-convex profile down slope	COC_COV	.029
	Standard deviation of terrain-unit elevation	ELV_STD	.041
	Terrain unit mean elevation	ELV_M	.128
	Terrain-unit area	SLO_ARE	**.296**
	Terrain-unit mean slope angle	SLO_ANG	**.962**
Aspect	Terrain-unit aspect facing S-SW	TR3	-.045
	Terrain-unit aspect facing N-NE	TR1	.067
Land use	Interaction between forested area and Carbonate Complex	CCABO	-.193
	Urban area	AE	.047
	Area free of vegetation cover	AN	.051
	Olive groves and vineyards	CACOLPV	.072
	Forested area	BO	.156
	Pasture	PA	**.203**
	Cultivated area	SASS	**.224**

In Table 6.3, the standardized discriminant function coefficients (SDFC) show the relative importance of each variable as a predictor of slope instability. Variables with large coefficients (in absolute value) are strongly associated with the presence/absence of landslides. The sign of the coefficient tells if the variable is positively or negatively correlated to the stability of the mapping unit. As an example, the outcrop in a mapping unit of chaotic clay and silty rocks (CLIC), lake and fluvial silt and clay (CPOSA), flysch deposits dipping parallel to the slope (CTUTRA, CTTTRA) or toward the slope free face (CLIFRA), favours the probability of occurrence of landslides. To the contrary, well bedded limestone (CCALS) or massive sandstone (CTTM) cropping out in a mapping unit are in favour of its stability.

A peculiar case arises for the slope of the mapping unit that exhibits a curvilinear relationship with landslide occurrence. Landslide frequency increases with slope gradient to a threshold, above which the landslide density decreases (in Table 6.3 compare SLO_ANG and SLO_ANG2). This is a typical condition in the central Apennines, and elsewhere (Iwahashi *et al.*, 2003). The abundance (area) of landslides, and in particular of deep seated slides and slide-earth flows, increases with increasing terrain gradient up to a maximum value, where landslide area is most abundant, and then it decreases rapidly with increasing slope. Reasons for this behaviour are found in the relationship between lithology, strength of the rocks, and slope instability.

Figure 6.1 shows a reduced version and an enlargement of a portion of the obtained landslide susceptibility map for the Upper Tiber River basin (a digital version of the susceptibility map and of the maps showing the digital information used to construct the model is available at http://maps.irpi.cnr.it/website/tevere/tevere_start.htm). In the map, landslide susceptibility is shown in seven classes, from very low (dark green) where landslides are not expected, to very high (red) where abundant landslides are expected (see also Table 6.5). The enlargement shows the good matching between the predicted susceptibility class and the presence or absence of landslides in each mapping unit.

A quantitative comparison between the discriminant model and the landslide inventory map (Table 6.4) reveals that the statistical model explains correctly the occurrence of landslides in 76.3% of the mapping units in the basin. For the remaining 23.7% of the mapping units, the model provides a prediction in contrast with the geomorphological inventory map. The efficiency of the model can be measured by the number of mapping units correctly classified by the model. Four cases are possible (Table 6.4): (i) mapping units predicted as stable and without landslides (green), (ii) mapping units predicted as unstable and with landslides (red), (iii) mapping units predicted as unstable but without landslides, and (iv) mapping units predicted as stable but with landslides. Mapping units pertaining to the first class (green, case i) are areas characterized by a geo-environmental setting prone to the stability of the slope, and where the geomorphologist has not observed landslide features. These areas should be considered stable. Mapping units pertaining to the second class (red, case ii) are characterized by geo-environmental factors prone to slope instability, and where the geomorphologist has identified one or several landslides. These areas should be considered unstable. Mapping units pertaining to the third and fourth classes (grey) are cases erroneously attributed by the model, where a disagreement exists between the geomorphological inventory map and the model prediction. In the first case (iii) landslides were not identified by the interpreter because of mapping errors or because landslide features were cancelled by erosion or human action. In these areas additional field investigations are needed to establish the presence/absence of landslides and to determine the actual susceptibility conditions. The second case (iv) refers to landslides occurred due to factors not included in the model, or due to errors in the input thematic data (Carrara *et al.*, 1992, 1995; Ardizzone *et al.*, 2002). Also for this class detailed investigations are required to evaluate the landslide susceptibility.

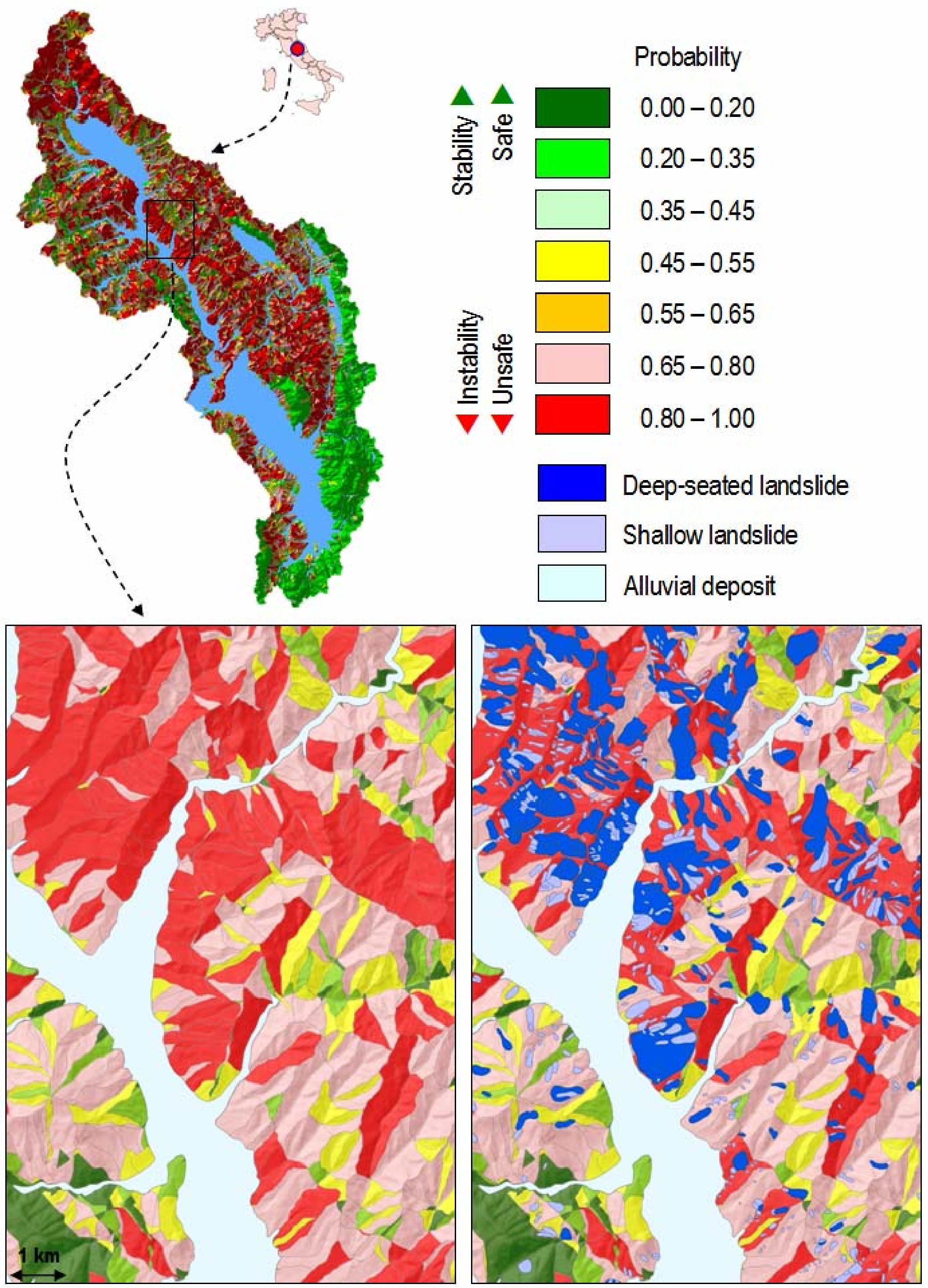

Figure 6.1 – Upper Tiber River basin. Maps showing spatial probability of landslide occurrence, in seven classes, from very low (dark green) where landslides are not expected, to very high (red) where landslides are expected to be abundant. See also Table 6.5. Lower maps are enlargements of the susceptibility map, without (left) and with (right) landslides.

Table 6.4 – Upper Tiber River basin. Comparison between mapping units classified as stable or unstable by the statistical model and the mapping units free of and containing landslides in the geomorphological inventory map. The overall correct classification is equal to 76.3%.

			PREDICTED GROUPS (MODEL)	
			GROUP 0 STABLE MAPPING UNITS	GROUP 1 UNSTABLE MAPPING UNITS
ACTUAL GROUPS (INVENTORY)	GROUP 0	MAPPING UNITS FREE OF LANDSLIDES IN INVENTORY MAP	69.4 % (case i)	30.6 % (case iii)
	GROUP 1	MAPPING UNITS CONTAINING LANDSLIDES IN INVENTORY MAP	14.7 % (case iv)	85.3 % (case ii)

Overall percentage of mapping units correctly classified equal to 76.3%.

Table 6.5 lists correlations between: (i) the seven probability classes of landslide susceptibility, (ii) the extent and percentage of terrain in each susceptibility class, (iii) the extent and percentage of landslide area in each class, and (iv) the percentage of terrain unit having landslides in each susceptibility class. It should be noted that the class in the probability range 0.45-0.55 (yellow in Figure 6.1 and in Table 6.5) shows unclassified mapping units. These mapping units are not areas where susceptibility is "intermediate". Instead, for these units the statistical model, based on the available environmental thematic information, was not capable of clearly deciding if the terrain was stable or unstable. Hence, the mapping units are ranked as of uncertain susceptibility, and they require further investigation or additional thematic data to be classified.

Table 6.5 – Upper Tiber River basin. Probability classes of landslide susceptibility, extent and percentage of mapping units, extent and percent of landslide area, and percentage of mapping unit having landslides, in each susceptibility class. Colours refer to susceptibility classes shown in Figure 6.1.

	PROBABILITY CLASS	EXTENT OF MAPPING UNIT		EXTENT OF LANDSLIDE AREA		MAPPING UNIT HAVING LANDSLIDES
	%	km^2	%	km^2	%	%
↑ INCREASING STABILITY	< 20	1246.81	30.43	10.33	2.48	0.83
	20 – 35	287.45	7.01	10.88	2.61	3.78
	35 – 45	171.82	4.19	12.59	3.02	7.33
UNCLASSIFIED	45 – 55	219.98	5.37	16.39	3.94	7.45
↓ INCREASING INSTABILITY	55 – 65	337.15	8.23	31.23	7.52	9.26
	65 – 80	845.66	20.64	112.48	27.02	13.30
	80 – 100	988.94	24.13	222.31	53.41	22.48

6.4.1. Discussion

I now discuss the problems encountered in the production of the susceptibility model for the Upper Tiber River basin, and I examine the validity of the assumptions under which the susceptibility model holds, which largely condition its applicability. The discussion is based upon the results of the Upper Tiber River basin susceptibility mapping experiment, but some of the conclusions are general and applicable to other areas, in Italy and elsewhere.

The two principal assumptions of the proposed landslide susceptibility model are: (i) that landslides will occur in the future under the same circumstances and because of the same factors that produced them in the past (§ 6.2.1), and (ii) that landslide abundance is controlled by – and can be inferred from – the local known geo-environmental conditions.

The first assumption requires that the landslide predisposing factors (the geological and environmental conditions) "remain the same in the future" in order to cause similar slope failures. But, for how long in the future must conditions not change? The statistical model does not indicate a temporal validity for thee susceptibility forecast. This is common for susceptibility maps. Landslide susceptibility assessments do not incorporate the time component of a landslide hazard assessment (which is why they are called susceptibility models), and quite often do not even provide a temporal framework for the validity of the prediction, limiting their applicability (§ 9.3), and reducing the possibility of establishing if (or two what extent) the main assumptions hold in the investigated area. A solution is to establish the validity of the susceptibility model based on: (i) external information on landslides (e.g., an archive inventory of slope failures, or quantitative information on landslide age, etc.), (ii) the expected validity of the susceptibility map for any practical application (e.g., the time frame of a building code or land use regulation to which the susceptibility map is expected to contribute), or (iii) the engineering lifetime of structures and infrastructure that can be affected by landslides (e.g., from tens to few hundreds of years).

When the expected temporal validity of the susceptibility model is established, the problem becomes that of investigating the possibility that the predisposing factors will change in the considered period, affecting landslide susceptibility. Assuming a validity of the model between 50 and 100 years (which is reasonable for the Upper Tiber River basin), it is safe to imagine that geological factors (including lithology, structure and seismicity) will not change significantly in such a short geological time. In the established period, morphological changes can occur due to stream erosion, landslides and human actions, but extensive modifications are not reasonably probable. Inspection of Table 6.3, which lists the variables entered into the statistical model, shows that the majority (34 out of 41) of thematic variables are not expected to change significantly in the considered period. Accordingly, landslide susceptibility is not expected to change in the period. However, if significant geological and morphological changes should occur, the model should be abandoned, or at least revaluated.

Further inspection of Table 6.3 reveals the presence of seven variables describing land use types that entered into the susceptibility model, some with high SDFC. These variables may change significantly in the considered period. Changes in land use, including logging, are known to affect landslide frequency and abundance (Guthrie, 2002; Glade, 2003). Qualitative estimates of land use change in Umbria indicate a reduction of about 20-25% of the forest coverage since 1950, in favour of cultivated and abandoned land. In the same period, agricultural practices have changed, largely aided by powerful mechanical equipments. Cardinali *et al.* (2000), investigating recent snowmelt induced landslides in Central Umbria (§ 3.3.3.2), suggested that areas recently deforested for agricultural purposes are more prone to landslides. If land use changes significantly in the basin, landslide susceptibility will change accordingly. Important is the fact that the obtained susceptibility model does not incorporate variables describing land use changes (e.g., variable showing areas previously covered by forest that were cleared, and as a result suffered landslides). New variables showing areas of land use change should be introduced in the model to describe the possible initiation of landslides.

In the Upper Tiber River basin, landslides are mostly rainfall induced and snowmelt induced. Rainfall is correlated with elevation, and the mean elevation of the mapping unit is considered in the model. Snowmelt is controlled by elevation and slope exposure, two variables also included in the model. Despite, meteorological factors are not explicitly included into the susceptibility model (as in any other model of this type). Changes in the frequency or intensity of the driving mechanisms will not affect (at least not in the considered period) susceptibility, but it may affect the rate of occurrence of landslide events.

Lastly, the susceptibility model aims at describing the known distribution of landslides, i.e., the available landslide inventory map. If the landslide inventory is erroneous or incomplete, the susceptibility model will be negatively affected. Determining the degree to which lack of information in the landslide inventory affects the susceptibility model is no trivial task. Minor, non-systematic errors in the inventory will not affect the model significantly. To the opposite, if the statistical model is robust it will compensate for the lack of landslide information in the inventory. Systematic inconsistencies in mapping the landslides will affect severely the susceptibility model. The model was constructed to forecast the probability of spatial distribution of shallow and deep-seated slides and slide earth flows (the most common type of mass movements in the Upper Tiber River basin). Other types of landslides, including debris flows shown in the "Photo-Geological and Landslide Inventory Map of the Upper Tiber River Basin, Italy" (Cardinali *et al.*, 2001), are not considered by the model.

6.5. Verification of a landslide susceptibility forecast

A forecast should always be verified (Jollifee and Stephenson, 2004). Models for landslide susceptibility are forecasts of the spatial occurrence of landslides, and their performance should be tested. Unfortunately, this is rarely done. Inspection of the literature reveals that only recently have authors started to publish susceptibility models together with their quantitative verifications (Chung and Fabbri, 1999; Zinck *et al*., 2001; Lee *et al*., 2002, 2003; Chung and Fabbri, 2003; Remondo *et al*., 2003a; Santacana *et al*., 2003; Lee, 2004; Chung and Fabbri, 2005; Guzzetti *et al*., 2005a,d; Moreiras, 2005). In recent papers, Chung and Fabbri (2003, 2005) and Fabbri *et al*. (2003) have defined the problems (and the misunderstandings) associated with the verification/validation of statistical models for the assessment of multivariate landslide susceptibility. Their indications are applicable to susceptibility assessments prepared using all types of methods.

In general, a susceptibility assessment (i.e., a prediction of landslide spatial occurrence) should be tested: (i) against the information used to prepare the forecast, and (ii) against the future, when it finally happens. The former is a way of investigating the "goodness of fit" of the susceptibility model. The second aims at testing the ability of the model to actually predict future landslides. In general it is easier to obtain higher levels of model fit than to achieve similar levels of prediction performance. However, the latter is more important for practical purposes. A decision maker willing to include landslide susceptibility in a land use or building code is more interested in the performance of the susceptibility model with time (i.e., the aptitude of the model to predict future landslides) and less in how well the same model fits the known distribution of past slope failures. A susceptibility model can also be tested outside the area where it was prepared. This involves testing the exportability of the model to neighbouring areas.

The goodness of fit of index based models can be ascertained by counting and comparing the percentage of landslide area in each susceptibility classes. A higher susceptibility class is expected to contain a larger percentage of landslide (unstable) area than a lower susceptibility class. For statistical models, measures of goodness of fit are obtained by preparing contingency tables showing the number of cases correctly classified and by comparing them against the cases that were misclassified by the model. Since two different types of errors can occur (i.e., mapping units free of landslides classified as unstable (error type 1); and mapping units having landslides which are classified as stable (error type 2), models can be calibrated to reduce one type of error (usually error type 2), depending on the user requirements (Carrara *et al*., 1995; 1999). Alternatively, a graph showing the model success rates can be prepared (Chung and Fabbri, 1999; 2005; Guzzetti *et al*., 2005a,d). The graph shows the percentage of the study area (in the x-axis) against the cumulative distribution function of landslide area in each predicted susceptibility class (y-axis). A straight diagonal line starting from the origin of the graph represents a model with a very low degree of success. Rapid deviation of the success rate curve from the diagonal line indicates a model with a higher performance. These graphs can also be used to test heuristic models and process based susceptibility models. For the latter, an a priori decision has to be made whether a given stability condition is considered representing a landslide or not. As an example, if a distributed model of shallow slope stability computes the factor of safety at each grid cells, all the cells with a value of the factor of safety equal or less than 1.0 can be considered as having a landslide, and tested against the inventory of past landslides.

Testing a model prediction against the future is more tricky task, as (in theory) it involves waiting for the future to happen. For many practical applications, including landslide susceptibility assessments, one has not the luxury to wait for the future to materialize and the prediction to self validate. To the opposite, one needs to have a measure of the model ability to predict the future before the model is used. To reach this goal several strategies can be adopted, all of which involve exploiting some sort of temporal information on landslide occurrence (Chung and Fabbri, 1999; 2003; Guzzetti *et al*., 2005a,d). Where an event landslide inventory map is available, the map can be easily compared in a GIS with a susceptibility model prepared with any of the discussed methods. Contingency tables and prediction rate curves can be prepared to evaluate the model performance. Prediction rate curves are similar to success rate curves, the difference being that the former are prepared using the new landslides, i.e., the landslides which have occurred after the model was prepared (Chung and Fabbri, 1999). Statistical models are more flexible. Where landslides for at least two periods are available (e.g., from the interpretation of aerial photographs of different dates), one can establish susceptibility levels using only slope failures which occurred before a selected date, i.e., the “past” landslides, and then test the result against the distribution of the landslides occurred after that date, i.e., the “future” landslides (Chung and Fabbri, 1999). Where a multi-temporal inventory map is available, the process can be repeated several times, studying the temporal variation of the model capability to predict future landslides (Guzzetti *et al*., 2005a).

Testing the exportability of a susceptibility model is also a difficult task. In principle, a sound susceptibility model developed for a representative area (the training area) should be capable of predicting landslide susceptibility in other areas, provided the environmental conditions which lead to slope instability don't change significantly. In practice, the usefulness of the approach is very limited for most, if not all, the proposed susceptibility methods. For the geomorphological approach, application to neighbouring or distant area is meaningless. Being a direct method, landslide susceptibility has to be assessed independently for each new area. The only advantage being that the experience made in one area may help the investigator in compiling the susceptibility assessment in the new area. All indirect methods are based on the collection and use of a (often large) set of environmental factors related to slope instability, including the distribution of past and present slope failures (i.e., the landslide inventory). When this information is available, it is more convenient to exploit it to prepare a more general model, rather than to attempt to apply a model constructed using a geographical sub-set of the thematic information. However, the geographical operation can be useful to test the spatial robustness of a model. This can be achieved in different ways. One technique consists in first preparing a susceptibility model for the entire study area, i.e., using the total number of mapping units, and then to prepare a number of different susceptibility models using randomly selected sub-sets of mapping units (Carrara *et al.*, 1991b). Comparison of the model performances provides indication on the robustness of the original model, and may help identifying problems with specific areas and/or peculiar environmental conditions. A slightly different approach consists in splitting the total number of mapping units in two sub-sets, a training set and a target set. A susceptibility model is prepared using the information of the training set, and it is then applied against the mapping units that represent the validation set (Chung and Fabbri, 2003). A still different approach consists in subdividing the study area beforehand into two sub-areas. A susceptibility model is constructed using the information available for one of the two areas, and then an attempt is made to apply (or test) the result in the neighbouring area. The method, which in principle appears appealing, quite easily results in practical problems that limit its application. If a new rock type or land use class are present in the target area but were not present in the training area, if the abundance of landslides differs in the two areas, or if the combination of the environmental factors changes in the new area, the exportability of the constructed model may become impossible, or geomorphologically meaningless.

6.5.1. An example of the verification of a landslide susceptibility model

For the Collazzone area (§ 2.4), the availability of a multi-temporal landslide inventory map, of information on recent landslide events, and on detailed thematic data, allows for a good opportunity to prepare a landslide susceptibility model and to verify it, using different techniques.

6.5.1.1. Susceptibility model for shallow landslides in the Collazzone area

A susceptibility model for shallow landslides in the Collazzone area was prepared adopting the same statistical classification method (i.e., discriminant analysis), a similar terrain subdivision (i.e., slope units), and a similar set of environmental thematic data used to obtain the landslide susceptibility model for the Upper Tiber River Basin (§ 6.4). To ascertain landslide susceptibility, the study area was first partitioned into 894 slope units, starting from a 10 m × 10 m DTM. As the dependent variable for the statistical analysis, the presence or absence of shallow landslides in the 894 slope units was used. The distribution of landslides was obtained from a revised version of the multi-temporal landslide inventory map available for the study area (§ 3.3.4.1). The landslide map used for the statistical analysis shows 1759 shallow slope failures, covering 5.77 km^2, 7.32% of the study area (Figure 6.2.A).

A set of 46 independent thematic variables were used in the statistical analysis, including morphological, hydrological, lithological, structural, bedding attitude, and land-use information. A step-wise discriminant function selected 16 (out of 46) variables as the best predictors of the presence (or absence) of landslides in the 894 slope units in which the study area was partitioned. In Table 6.6, the standardized discriminant function coefficients (SDFC) show the relative importance of the 16 variable as a predictor of slope instability. Variables with large coefficients (in absolute value) are strongly associated with the presence or the absence of landslides. The sign of the coefficient tells if the variable is positively or negatively correlated to instability of the mapping units.

Table 6.6 – Variables selected by a stepwise discriminant function as the best predictors of landslide occurrence in the Collazzone area. Variables with large standard discriminant function coefficients (SDFC), in absolute value, are shown in bold.

Variable description	*Variable*	*SDFC*
Slope unit mean terrain gradient	SLO_ANG	**-0.398**
Slope unit elevation standard deviation	ELV_STD	**-0.370**
Slope unit length	SLO_LEN	**-0.287**
Slope unit terrain gradient (upper portion)	ANGLE3	**-0.282**
Cultivated area	SS	**-0.276**
Bedding dipping out of the slope	FRA	**-0.241**
Convex slope (down slope profile)	CONV	-0.135
Travertine	TRAVERTI	0.105
Slope unit facing S-SE	TR2	0.133
Slope unit drainage channel order	ORDER	0.140
Alluvial deposit	ALLUVIO	0.144
Gravel	GHIAIA	0.179
Slope unit terrain gradient standard deviation	ANG_STD	**0.219**
Marl	MARNE	**0.285**
Down and across slope concave slope	CC	**0.303**
Limestone	CARBO	**0.833**

Inspection of Table 6.6 reveals that, based on the obtained susceptibility model, morphological variables associated with the presence of shallow landslides include mean slope angle (SLO_ANG), terrain gradient in the upper part of the slope (ANGLE3), slope length (SLO_LEN), and the standard deviation of elevation (ELV_STD). Other variables associated with unstable conditions include bedding planes dipping out of the slope free-face (FRA), and land use characterized by seasonal crops, e.g., wheat, maize, sunflower, and alfa alfa (SS). Lithological variables associated with stable conditions include the outcrop of layered limestone (CARBO), marl (MARNE), alluvial deposits (ALLUVIO), and travertine deposits (TRAVERTI). Other variables associated with the absence of landslides include down and across slope concave profile (CC), the standard deviation of slope angle (ANG_STD), and the order of the stream draining the slope unit (ORDER).

Figure 6.2.B portrays the obtained landslide susceptibility model. In the map, slope units are shown based on the probability that the unit pertains to the group of slope units containing landslides in the multi-temporal inventory map (Figure 6.2.A). If a slope unit has a high probability of containing a known landslide, the same slope unit is classified as landslide prone. Else, if a slope unit has a low probability of having known landslides, the slope unit is considered stable. Intermediate values of probability indicate the inability of the model to classify the slope unit, given the available thematic information.

6.5.1.2. Degree of model fitting

The first question to ask when a landslide susceptibility model is prepared through a statistical classification technique is "how well the model has performed in classifying the mapping units?" This involves determining the degree of model fit. A straightforward way of testing model fit consists in counting the number of cases (i.e., the mapping units) correctly classified by the model. Table 6.7 shows the results for the model shown in Figure 6.2.A.

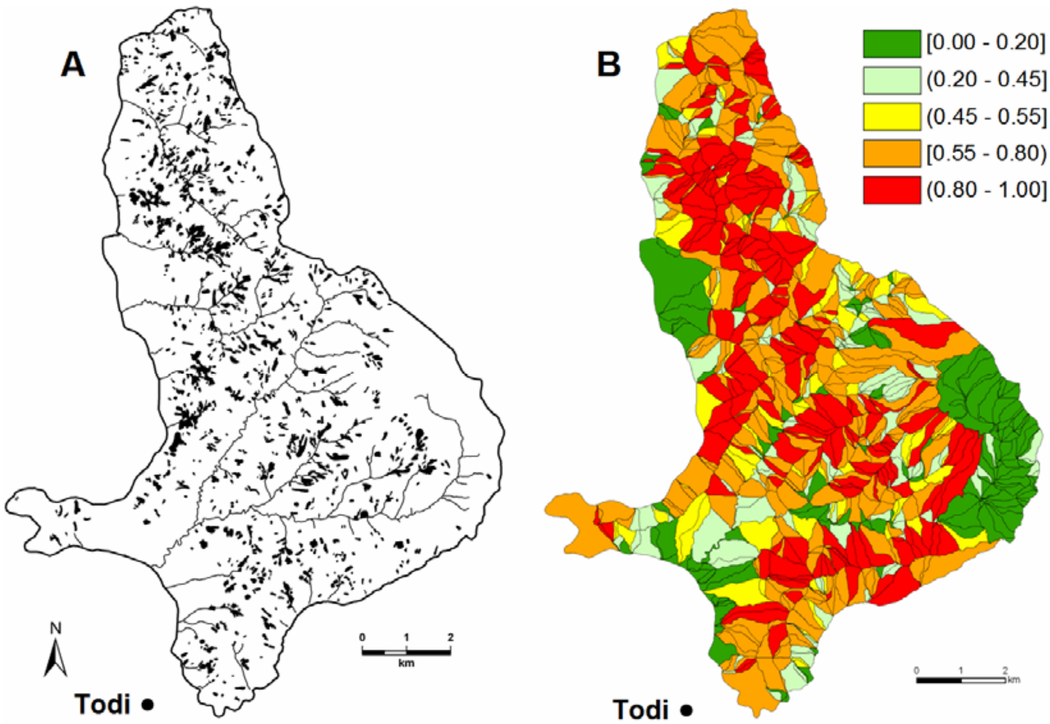

Figure 6.2 – Collazzone area. (A) Multi-temporal landslide inventory map showing shallow landslides. Map prepared through the interpretation of various sets of aerial photographs taken in the period from 1941 to 1997. Original map scale 1:10,000. (B) Map showing spatial probability of shallow landslide occurrence (landslide susceptibility). Study area subdivided into 894 slope units. Different colours indicate spatial probability in 5 classes, from low values (in green) where landslides are not expected, to high values (in red) where landslides are predicted abundant. Square bracket indicates class limit is included. Round bracket indicates class limit is not included.

The susceptibility model shown in Figure 6.2.A. correctly classifies 688 (77.0%) of the 894 slope units in which the study area was partitioned. The figure represents a measure of the "overall goodness of fit" of the model. Of the 688 correctly classified slope units, 239 were classified as "stable" and 449 were classified as "unstable" by the model. Of the 206 misclassified cases, 121 were slope units free of landslides that were classified as "unstable" by the model, and 85 were slope units that showed landslides in the inventory map and were attributed to the "stable" group by the model. The former may be the result of errors in the inventory map (e.g., unrecognized landslides, or landslides cancelled by erosion, land use changes, ploughing, or other human actions). The latter are slope units that have geological and environmental conditions typical of stable slopes, and where landslides took place owing to specific and unique conditions not accounted for by the model.

Further inspection of Table 6.7 reveals that the susceptibility model is more efficient in correctly classifying slopes that have landslides, and less efficient in classifying slopes free of slope failures. The difference can be attributed to the larger number of slope units with landslides (59.7%) in the study area.

Table 6.7 – Collazzone area. Comparison between slope units classified as stable or unstable by the statistical model (Figure 6.2.B) and slope units free of and containing landslides in the multi-temporal inventory map (Figure 6.2.A). Numbers in parenthesis show the number of slope units.

			Predicted Groups (Model)	
			Group 0 *Stable mapping units*	*Group 1* *Unstable mapping units*
Actual Groups (Inventory)	*Group 0*	*Mapping units free of landslides in inventory map*	66.4 % (239)	33.6 % (121)
	Group 1	*Mapping units containing landslides in inventory map*	15.6 % (85)	84.1 % (449)

Overall percentage of mapping units correctly classified equal to 77.0%.

An alternative way of measuring the reliability of the model – in terms of its ability to classify known landslides – consists in using Cohen's Kappa index (Cohen, 1960; Hoehelr, 1999). For the purpose, I have rearranged the data shown in contingency Table 6.7. Table 6.8 shows the proportion (observed probability) of slope units in each of the four classification classes with the marginal probabilities, obtained by summation of the probabilities along the rows and the columns. Values in parentheses represent the expected proportions on the basis of chance associations, i.e., the joint probabilities of the marginal proportions. The Kappa index (κ) is obtained as:

$$\kappa = \frac{P_C - P_E}{1 - P_C} \quad -\infty \le x \le 1 \qquad 6.14$$

where, P_C is the proportion of slope units correctly classified as stable or unstable (in our case, $P_C = 0.267 + 0.502 = 0.769$), and P_E is the proportion of slope units for which the agreement is expected by chance (in this case, $P_E = 0.146 + 0.381 = 0.527$). Thus, in this case, $\kappa = 0.513$. Landis and Kock (1997) have suggested that for $0.41 \le \kappa \le 0.60$ the strength of the agreement between the observed and the predicted values is moderate. Several other indexes can be used to measure the forecasting skill of classification. For a review see Mason (2003).

Tables 6.7 and 6.8 provide a lumped estimate of model fit, but do not provide a detailed description of the model performance of the different susceptibility classes (Chung and Fabbri, 1999, 2003). To determine this, one can conveniently compare the total area of known landslides in each susceptibility class with the percentage of area of the susceptibility class.

Table 6.8 – Comparison between the proportions of slope units classified as stable or unstable by the susceptibility model for the Collazzone area and the proportions of slope units free of and containing landslides in the multi-temporal inventory map (Figure 6.2.A). Marginal totals are obtained by summing proportions along the rows and the columns. Numbers in parenthesis represent the expected proportions on the basis of chance associations, i.e., the joint probabilities of the marginal proportions.

		Model Prediction		
		Stable mapping units	*Unstable mapping units*	*Marginal Totals*
Landslide Inventory	*Mapping units free of landslides*	0.267 (0.146)	0.135 (0.257)	0.403
	Mapping units with landslides	0.095 (0.216)	0.502 (0.381)	0.597
	Marginal Totals	0.362	0.638	1.000

κ = 0.513, moderate agreement.

Figure 6.3 shows the percentage of the study area ranked from most to least susceptible (x-axis) against the cumulative percentage of landslide area in each susceptibility class (y-axis). The most susceptible 10.0% of the study area covers 19.5% of the landslide area shown in Figure 6.2.A, and the most susceptible 50.0% of the study area covers 72.7% of the total mapped landslides. Figure 6.3 also shows that 52.3% of the mapped landslides fall in the 29.0% of the study area classified as highly susceptible (probability > 0.80), and that 87.0% of the mapped landslides fall in the 63.4% of the study area classified as susceptible or highly susceptible (probability > 0.80). Only 5.6% of the landslides shown in the multi-temporal inventory (Figure 6.2.A) are in areas classified as not, or as weakly susceptible (probability ≤ 0.45) by the model. This is in agreement with the reduced number of mapping units (85, 15.9%) having landslides and erroneously attributed to the "stable" group by the model (Table 6.7). These figures provide a quantitative measure of the ability of the susceptibility model to match (i.e., "fit") the known distribution of shallow landslides in the Collazzone area.

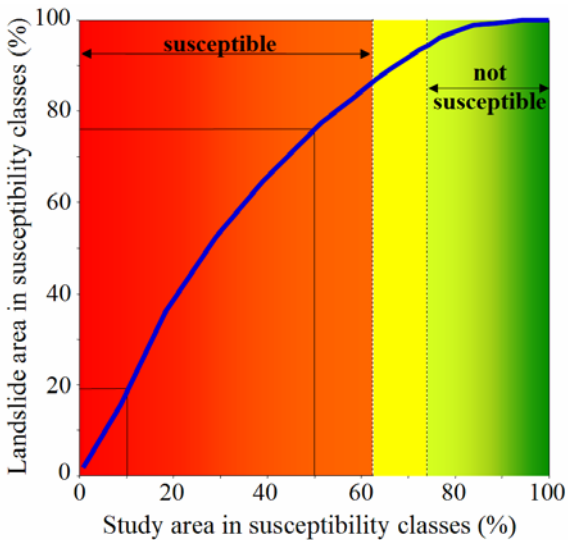

Figure 6.3 – Analysis of the fitting performance of the landslide susceptibility model prepared for the Collazzone area shown in Figure 6.2.B. x-axis, cumulative percentage of the study area in classes of probability of landslide spatial occurrence, ranked from most (left, red) to least (right, green) susceptible. y-axis, cumulative percentage of landslide area in the susceptibility classes.

6.5.1.3. Ensemble of landslide susceptibility models

To determine the reliability of the landslide susceptibility assessment shown in Figure 6.2.B, I propose an innovative method based on the preparation of an ensemble of landslide susceptibility models. The ensemble consisted of 350 different susceptibility models obtained from the same set of 46 independent thematic variables and the same multi-temporal landslide map (Figure 6.2.A), but using a different number of mapping units, from 268 (30%) to 849 (95%) slope units. To obtain this ensemble, the following strategy was adopted. First, a subset containing 30% of the slope units (268 units) was obtained by random selection from the entire set of 894 slope units. The random selection was repeated 50 times, obtaining a group of 50 different subsets, each containing 268 slope units. This collection of 50 subsets of slope units was named "group G_{30}" (i.e., 30% selected slope units). Then, the selection procedure was repeated changing the number of the selected units. In this way, collections with 45%, 55%, 65%, 75%, 85%, and 95% slope units were obtained. These collections, each listing 50 subsets of slope units, became groups G_{45} (402 units), G_{55} (491 units), G_{65} (581 units), G_{75} (670 units), G_{85} (760 units) and G_{95} (849 units). The obtained ensemble contained a total of 350 subsets of slope units, i.e., 7 groups each containing 50 subsets. Landslide susceptibility models were then prepared for each subset of the ensemble, obtaining 350 different susceptibility models, i.e., 350 different forecasts of shallow landslide susceptibility in the Collazzone area.

6.5.1.4. Role of independent thematic variables

To assess model reliability, one must first considered the role of the (46) independent thematic variables used to construct the landslide susceptibility model. For the purpose, group G_{85} can be conveniently used. This group was obtained by randomly selecting (50 times) 760 slope units, i.e., 85% of the 894 slope units. For this group, Table 6.9 lists the number and the percentage of the models that selected (or did not select) the 46 variables, and whether the variables were selected as predictors of slope stability (*S*), or of slope instability (*I*). Inspection of Table 6.9 reveals that of the 46 considered variables, 38 (82.6%) entered in at least one of the 50 models encompassing G_{85}, and 8 (17.4%) variables were never selected as predictors of landslide occurrence. Of the 38 selected variables, 15 (39.5%) were selected by 25 or more models, and 7 (18.4%) were selected by 45 or more models.

The 50 stepwise discriminant functions constructed from G_{85} selected from as few as 11 variables, to as many as 18 variables (modal value 14 variables). All the selected variables, with the exception of drainage magnitude (MAGN), were either always selected as positively (*I*, in Table 6.9) or always selected as negatively (*S*, in Table 6.9) associated with the presence of landslides. This is as an indication of the consistency of the role of the thematic variables in explaining the known distribution of landslides, which contributes to the reliability of the susceptibility model.

Inspection of Table 6.9 further indicates that more than 75% of the prepared models used the same set of ten thematic variables. These variables included: four variables describing morphology (ELV_STD, ANG_STD, SLO_LEN, SLO_ANG), three variables describing lithology (CARBO, GHIAIA, MARNE), one variable for the attitude of bedding planes (FRA), one variable describing slope aspect (TR2), and one variable describing a land use type (SS). The ten variables are also present in Table 6.6, which lists the variables entered into the susceptibility model shown in Figure 6.2.B. Comparison of Table 6.6 and Table 6.9 reveals that, with the exception of AREN (i.e., presence of sandstone), all the 16 variables selected to construct the susceptibility model shown in Figure 6.2.B are listed in Table 6.9 as the most selected variables. This is a further indication of the ability of the selected variables to explain the known distribution of landslides in the Collazzone area.

Table 6.9 – Thematic variables selected, or not selected, by 50 discriminant functions as the best predictors of shallow landslide occurrence in the Collazzone area. Group G_{85} used for the analysis. In last column, "*S*" shows variables selected as predictor of slope stability, and "*I*" shows variables selected as predictor of slope instability. Standard discriminant function coefficients (SDFC) are those listed in Table 6.6 for variables selected as best predictors of landslide occurrence by the model shown in Figure 6.2.B.

Variables		*SDFC*	*Susceptibility models* #	%	*Predictor*
Slope unit elevation standard deviation	ELV_STD	-0.370	50	100	I
Limestone	CARBO	0.833	50	100	S
Bedding dipping out of the slope	FRA	-0.241	49	98	I
Gravel	GHIAIA	0.179	47	94	S
Marls	MARNE	0.285	47	94	S
Slope unit terrain gradient standard deviation	ANG_STD	0.219	45	90	S
Slope unit length	SLO_LEN	-0.287	45	90	I
Slope unit mean terrain gradient	SLO_ANG	-0.398	41	82	I
Cultivated area	SS	-0.276	40	80	I
Slope unit facing S-SE	TR2	0.133	38	76	S
Concave profile (down slope profile)	CC	0.303	33	66	S
Slope unit drainage channel order	ORDER	0.134	30	60	S
Alluvial deposit	ALLUVIO	0.144	30	60	S
Convex profile (down slope profile)	CONV	-0.135	27	54	I
Sandstone	AREN		25	50	S
Travertine	TRAVERTI	0.105	23	46	S
Slope unit terrain gradient (upper portion)	ANGLE3	-0.282	21	42	I
Forested area	BOSCO		21	42	S
Slope unit area	SLO_ARE		13	26	I
Slope unit drainage channel length	LINK_LEN		10	20	I
Index of slope unit micro-relief (terrain roughness)	R		10	20	I
Slope unit terrain gradient (lower portion)	ANGLE1		5	10	I
Slope unit mean elevation	ELV_M		4	8	I
Concave slope profile (down slope profile)	CONC		4	8	I
Drainage channel mean slope	LNK_ANG		3	6	S
Continental deposit	CONTI		3	6	I
Sand	SABBIA		3	6	I
Slope unit drainage channel magnitude	MAGN		2	4	I/S
Urban area	URB		2	4	S
Bedding dipping into the slope	REG		2	4	S
Bedding dipping across the slope	TRA		2	4	I
Slope unit facing N-NE	TR1		2	4	I
Standard deviation of terrain unit length	LEN_STD		1	2	S
Convex-concave profile (down slope profile)	COC_COV		1	2	S
Irregular slope profile	IRR		1	2	S
Clay	ARGILLA		1	2	I
Cultivated area with trees	SA		1	2	I
Vineyards	VIG		1	2	S
Drainage basins total area upstream the slope unit	AREAT_K	Variables were never selected as predictors of landslide occurrence			
Slope unit terrain gradient (intermediate portion)	ANGLE2				
Concave-convex profile (down slope profile)	COV_COC				
Slope unit rectilinear profile	RET				
Fruits trees	FRUTT				
Pasture	PASCOLO				
Slope unit facing S-SW	TR3				
Deposit of ancient landslide	FRA_OLD				

6.5.1.5. Model sensitivity

Now that it has been established that the independent thematic variables are capable of (and consistent in) classifying the mapping units as stable or unstable slopes, I investigate the sensitivity of the susceptibility model to changes in the input data. In general, results of a robust (least sensitive) statistical model should not change significantly if the input data are changed within a reasonable range (Michie *et al*., 1994). To investigate the sensitivity of the susceptibility model to changes in the input data, I use the entire ensemble of susceptibility models, and study the variation in the overall percentage of slope units correctly classified by the 350 models. I consider three cases: (i) slope units selected by the adopted random selection procedure, and classified by the discriminant functions (selected units, i.e., “training” or “modelling” set”, Figure 6.4.A), (ii) slope units not selected by the random selection procedure, and classified by the discriminant functions constructed on the corresponding subset of selected units (non-selected units, i.e., “classification” or “validation” set, Figure 6.4.B), and (iii) all slope units, irrespective of the fact that they pertained to the selected (training) or the non-selected (classification) sets (Figure 6.4.C).

In Figure 6.4.A, the orange box plots show that an increase in the number of the selected slope units results in a decrease of the median (50th percentile) and in the variability (10th to 90th percentile range) of the model fit. This was expected. Given the large number of the available thematic variables (46), a reduced number of cases (268 mapping units for G_{30}) allows for a (apparently) better model classification (mean = 78.36% for G_{30}), at the expenses of model variability, which is large (std. dev. = 2.59% for G_{30}). Further inspection of Figure 6.4.A indicates that a reduction in the percentage of slope units correctly classified, and in the corresponding scatter in the susceptibility estimates, becomes negligible for percentages of the considered slope units exceeding 75%. Thus, susceptibility models obtained using ~ 75% or more slope units do not differ significantly – in terms of the number of correctly classified units – from the model obtained using the entire set of 894 mapping units. This is an indication of the model ability to cope with significant (up to 25%) random variation in the input data.

Figure 6.4.B provides similar results for the non-selected subsets. The overall model fit and its scatter increase with a decreasing number of non-selected units. Comparison of Figures 6.4.A and 6.4.B indicates that models prepared using the selected units result in a better classification (i.e., in a larger model classification) when compared to models obtained using the non-selected units. This was also expected. Any statistical classification provides better results on the training set, and performs less efficiently when applied to the validation set (Michie *et al*., 1994). Figure 6.4.C shows the result for the collection of the selected (training) and the non-selected (validation) subsets. The blue box plots show the cumulative effect of the slope units correctly classified in the training and in the validation sets. For this reason, the scatter around the median is reduced, particularly for proportions of slope units exceeding 75%.

6.5.1.6. Uncertainty in the susceptibility estimate of individual slope units

The adopted approach to ascertain landslide susceptibility provides a unique (single) value for the probability of spatial occurrence of the known landslides (i.e., of landslide susceptibility) for each mapping unit (e.g., Figure 6.2.B). The approach does not provide a measure of the error (i.e., the uncertainty) associated with the probability estimate. This is a limitation, which can be possibly overcome by further analysing the results contained, e.g., in group G_{85} of the obtained susceptibility models.

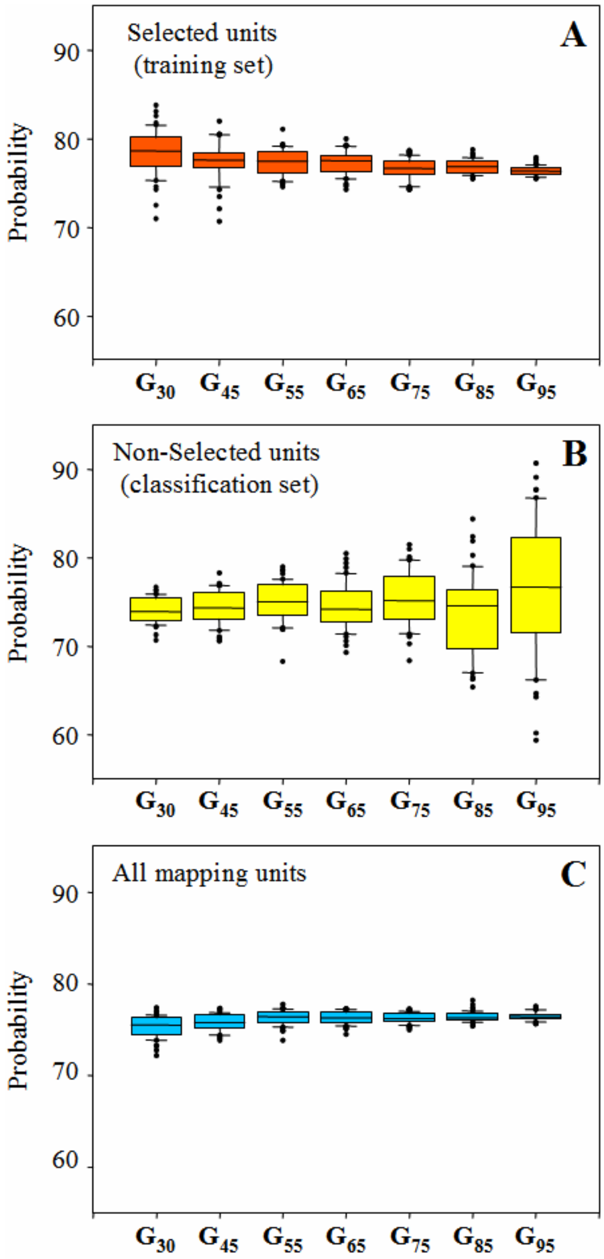

Figure 6.4 – Sensitivity analysis for the landslide susceptibility model prepared for the Collazzone area shown in Figure 6.2.B. (A) training set, i.e., slope units selected by a random selection procedure and classified by 50 discriminant functions; (B) validation set, i.e., slope units not selected by a random selection procedure and classified by 50 discriminant functions constructed on the corresponding subset of selected slope units; (C) all slope units, encompassing the selected (training) and the non-selected (validation) sets. In the box-plots, the central line shows 50th percentile (median); lower and upper limits of rectangle show 25th and 75th percentiles, respectively; lower and upper horizontal lines show10th and 90th percentiles, respectively; dots show outliers.

G_{85} lists 50 susceptibility models that resulted in 50 different estimates of the probability of spatial occurrence of landslides for the 894 slope units in which the study area was partitioned. For each slope unit, Figure 6.5.A compares the mean value of the 50 probability estimates listed in group G_{85} with the single probability estimate obtained for the model shown in Figure 6.2.B, the latter prepared using the entire set of 894 slope units. The correlation between the two estimates of landslide susceptibility is very high (r^2 = 0.9998), indicating that the two classifications are virtually identical.

Based on this result, Figure 6.5.B shows for the 894 slope units ranked from low to high values of the probability estimate of landslide spatial occurrence, 2 standard deviations (2σ) of the same probability estimate. The measure of 2σ is low (< 0.05) for slope units classified as highly susceptible (probability > 0.80) or as largely stable (probability < 0.20). The scatter in the model estimate is larger for intermediate values of the probability (i.e., between 0.40 and 0.60). This indicates that for the latter slope units, not only the model is incapable of satisfactorily classifying the terrain as stable or unstable, but also that the obtained estimate is highly changeable, and hence poorly reliable.

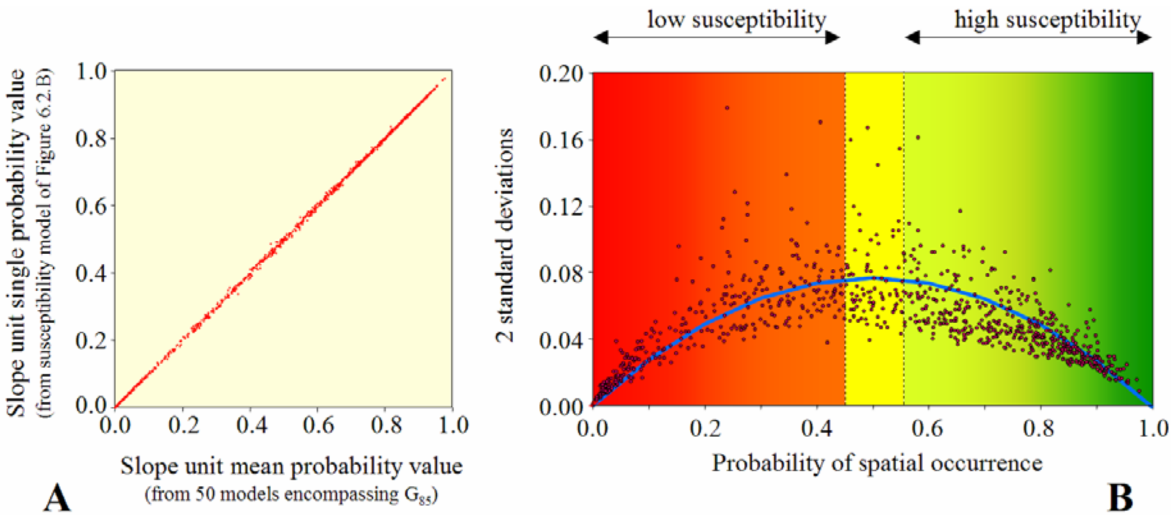

Figure 6.5 – (A) For 894 slope units in which the Collazzone area was partitioned, the graph compares the mean value of the 50 probability estimates obtained from group G_{85} (x-axis) with the single probability value obtained for the susceptibility model shown in Figure 6.2.B (y-axis). Correlation coefficient, r^2 = 0.9998. (B) Landslide susceptibility model error. For the 894 slope units in the Collazzone area, the graph shows the mean value of 50 probability estimates (x-axis) against two standard deviations (2σ) of the probability estimate (y-axis). Mean and standard deviation values obtained from group G_{85}. Along the x-axis, slope units are ranked from low (left) to high (right) spatial probability of landslide occurrence. Blue line shows estimated model error obtained by linear regression fit. Correlation coefficient, r^2 = 0.605.

The variation in the model estimate shown in Figure 6.5.B can be modelled by the following equation (blue line):

$$y = -0.309x^2 + 0.308x \quad 0 \le x \le 1 \quad (r^2 = 0.605) \qquad 6.15$$

where, x is the estimated value of the probability of pertaining to an unstable mapping unit (i.e., the landslide susceptibility estimate), and y is 2σ of the model estimate (Guzzetti *et al.*, 2005d).

The value of 2 standard deviations (2σ) of the model estimate is a proxy for the susceptibility model error. Equation (6.15) can be used to estimate quantitatively the model error for each slope unit, based on the computed probability estimate. For each slope unit, Figure 6.6 shows the error associated with the probability estimate (i.e., to landslide susceptibility), computed using equation 6.15. Figure 6.6 provides a quantitative measure of the error associated with the quantitative landslide susceptibility assessment shown in Figure 6.2.B.

To further investigate the relationship between the predicted probability of spatial landslide occurrence and its variation (error), one can rank the 894 slope units based on the mean value of the computed probability estimates obtained from group G_{85}. Figure 6.7, shows the rank of the slope unit (x-axis) against statistics of the probability estimates (y-axis). In the Figure, the thick red line shows the average value of the landslide susceptibility estimates, and the thin orange lines show $\pm 2\sigma$ of the estimate. The measure of 2 standard deviations varies with the predicted probability of spatial occurrence of landslides. The variation is small for slope units predicted as highly unstable, it increases to a maximum value towards the centre of the graph, where unclassified slope units are shown and it decreases again to small values for slope units predicted as highly stable.

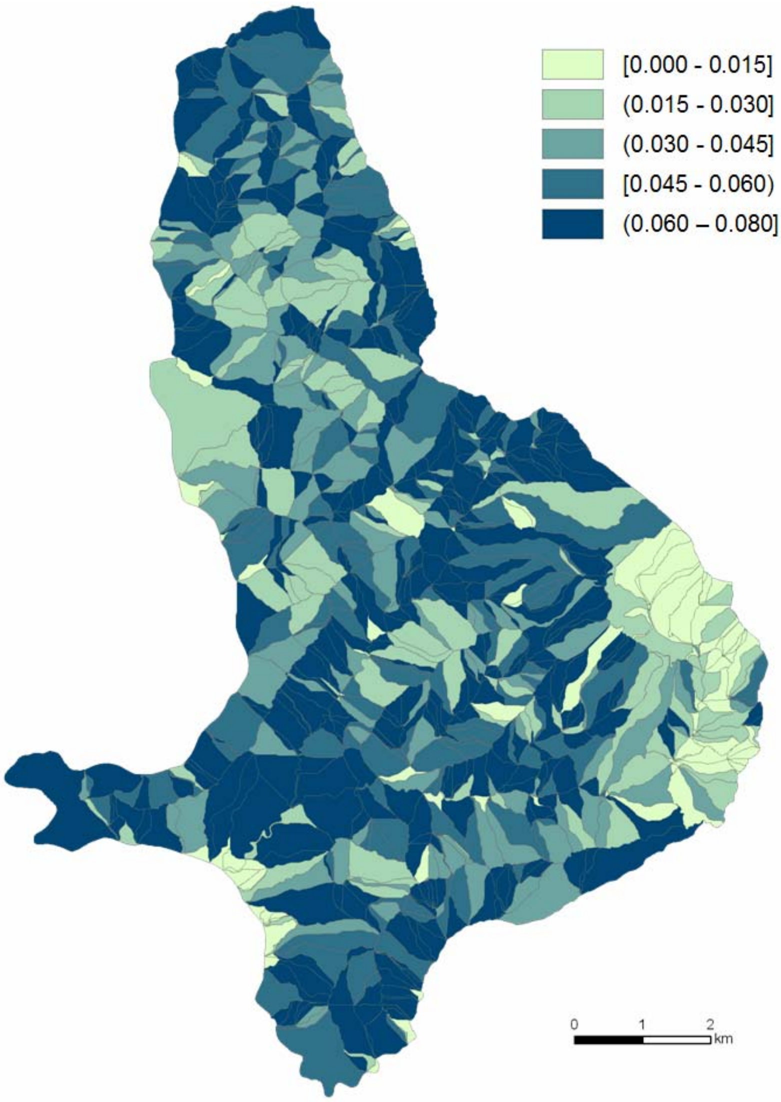

Figure 6.6 – Map showing estimated model error (2σ) for the landslide susceptibility model shown in Figure 6.2.B. Model error was computed using equation 6.15 and is shown here in 5 classes. Square bracket indicates class limit is included. Round bracket indicates class limit is not included.

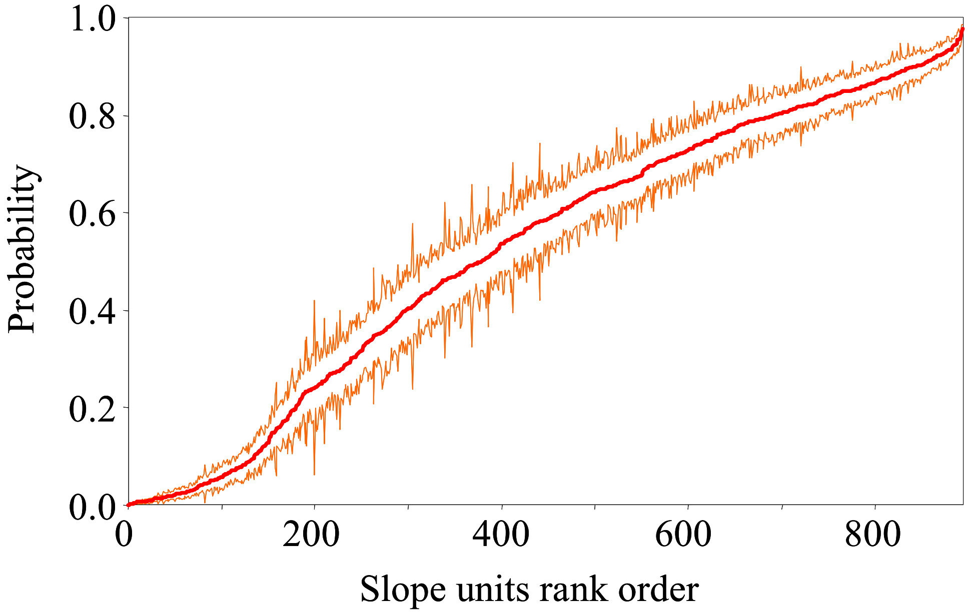

Figure 6.7 – For 894 slope units, ranked from low (left) to high (right) susceptibility values (x-axis), the graph shows the probability of the spatial occurrence of landslides (y-axis). Thick red central line shows the average value for 50 landslide susceptibility estimates. Upper and lower orange lines show ±2σ of landslide susceptibility estimate.

6.5.1.7. Analysis of the model prediction skill

The tests described in the previous sections were aimed at determining the (statistical) reliability and robustness of the susceptibility model (§ 6.5.1.2, § 6.5.1.5), and at estimating the error associated with the quantitative forecast (§ 6.5.1.6). All tests were performed using the same landslide information used to construct the susceptibility model (Figure 6.2.B), i.e., the multi-temporal landslide inventory map shown in Figure 6.2.A. A limitation of the performed tests lays in the fact that the tests do not provide insight on the ability of the susceptibility model to predict the occurrence of new or reactivated (i.e., "future") landslides, which is the primary goal of any susceptibility assessment (Chung and Fabbri, 1999, 2003; Guzzetti *et al*., 1999, 2005c,d).

To evaluate the ability of a susceptibility model to predict future landslides one must use independent landslide information (§ 6.5). For the Collazzane area, independent landslide information exists, and consists of two recent landslide event inventory maps. The first inventory shows 413 landslides triggered by rapid snowmelt in January 1997 (§ 3.3.3.2, Figure 6.8.A). In the inventory, the area of individual landslides ranges from 75 m^2 to 44,335 m^2, for a total landslide area of 0.78 km^2, 0.98% of the study area. The second event inventory shows 153 landslides triggered by heavy rainfall in the period from October to December 2004 (Figure 6.8.B). Area of the latter slope failures ranges from 51 m^2 to 47,884 m^2, for a total landslide area of 0.38 km^2, 0.49% of the study area.

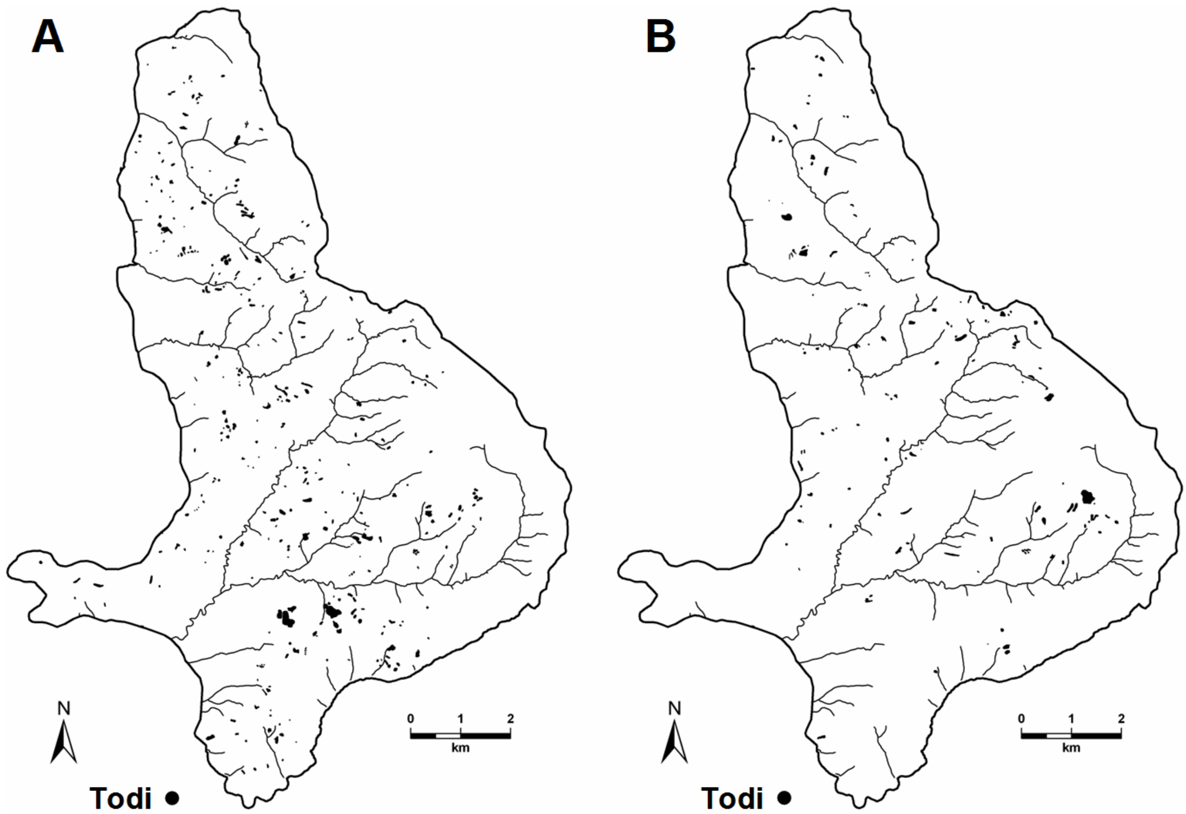

Figure 6.8 – Recent landslide event inventory maps for the Collazzone area. (A) Map showing 413 landslides triggered by rapid snowmelt in January 1997 (§ 3.3.3.2; Cardinali *et al.*, 2000; Guzzetti *et al.*, 2003). (B) Map showing 102 landslides triggered by heavy rainfall in the period from October to December 2004. Original maps at 1:10,000 scale.

In an attempt to determine the ability of the susceptibility model to predict future landslides, I now perform three tests. The first test consists in computing the proportion of the event landslide area in each susceptibility class, and in showing the results using cumulative statistics. Figure 6.9 shows the percentage of the study area, ranked from most to least susceptible (x-axis), against the cumulative percentage of the area of the triggered landslides in each susceptibility class (y-axis), for the snowmelt induced landslides in January 1997 (dark-blue dashed line), and for the rainfall induced landslides in autumn 2004 (light-blue dotted line). Inspection of Figure 6.9 reveals that the most susceptible 10.0% of the study area contains 19.5% of the snowmelt induced landslide areas (Figure 6.8.A), and 18.4% of the rainfall-induced landslide areas (Figure 6.8.B). Further, the most susceptible 50.0% of the study area contains 84.5% of the snowmelt induced landslide areas, and 73.2% of the rainfall induced landslide areas. These figures provide a quantitative estimate of the model prediction skill.

Inspection of Figure 6.9 indicates that the forecasting performance of the susceptibility model is better for the 1997 snowmelt induced landslides, and slightly poorer for the 2004 rainfall induced landslides. The difference can be attributed – at least partially – to the larger number of snowmelt induced landslides (Figure 6.8.A), a function of the different severity of the triggering events. In the study area, rapid snowmelt in January 1997 was a more severe trigger of landslides than the autumn 2004 rainfall period (Guzzetti *et al.*, 2003). Figure 6.9 shows that the prediction performance is similar (for rainfall induced landslides) or even higher (for snowmelt induced landslides) that the model fitting performance (Figure 6.3, and thin blue line in Figure 6.9). This is surprising, because the fitting performance of a landslide susceptibility model is usually higher that its prediction skill (Chung and Fabbri, 2003; Guzzetti *et al.*, 2005a,d).

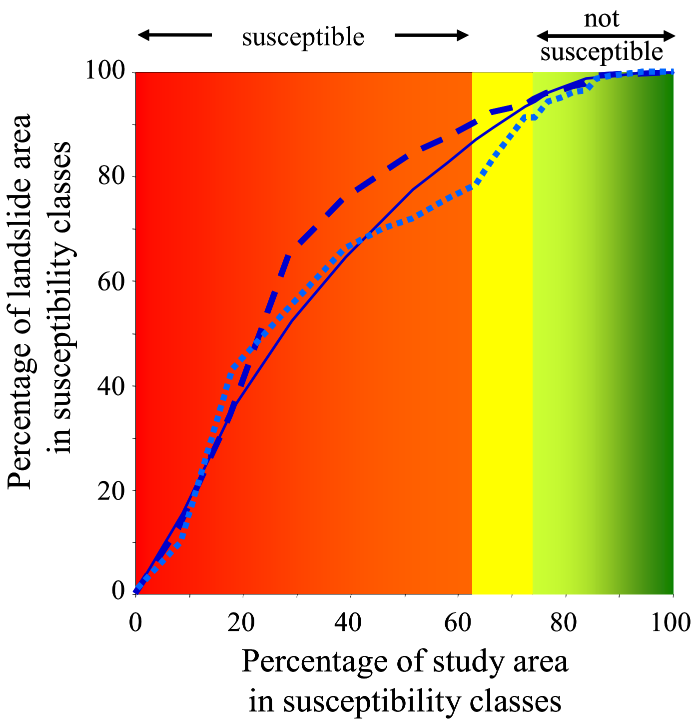

Figure 6.9 – Analysis of the prediction skill of the landslide susceptibility model prepared for the Collazzone area and shown in Figure 6.2.B. x-axis, cumulative percentage of the study area in classes of landslide spatial occurrence, ranked from most (left) to least (right) susceptible. y-axis, cumulative percentage of the events landslide area in each susceptibility class. Thick dashed dark-blue line shows landslides triggered by rapid snowmelt in January 1997 (Figure 6.8.A). Thick dotted light-blue line shows landslides triggered by heavy rainfall in autumn 2004 (Figure 6.8.B). Continuous thin line shows model fitting performance (Figure 6.3).

The remaining two tests explore further the relationship between the predicted susceptibility classes and the distribution and abundance of the triggered landslides. Figure 6.10.A shows that 65.6% of the snowmelt induced landslide areas in January 1997, and 54.7% of the rainfall induced landslide areas in autumn 2004 occurred in slope units classified as highly unstable (probability > 0.80). Further, 90.7% of the snowmelt induced landslide areas, and 88.2% of the rainfall induced landslide areas occurred in unstable or highly unstable slope units (probability > 0.55). Conversely, only 2.0% of the snowmelt induced landslide areas, and only 3.7% of the rainfall induced landslide areas where found in mapping units classified as highly stable (probability ≤ 0.20). Figure 6.10.B shows similar results, but considers the number of the triggered landslides. To obtain this statistics, the central point of each landslide polygon was identified in the GIS and the number of landslide central points in each slope unit was counted. About 57.0% of the snowmelt induced landslides, and 53.6% of the rainfall-induced landslides occurred in slope units classified as highly unstable (probability > 0.80). Conversely, only 2.2% of the snowmelt induced landslides, and only 3.3% of the rainfall induced landslides occurred in slope units classified as highly stable (probability ≤ 0.20). Figure 6.10 confirms the aptitude of the susceptibility model to predict where (i.e. in which slope unit) the snowmelt induced landslides occurred in January 1997, and where the rainfall-induced landslides occurred in autumn 2004.

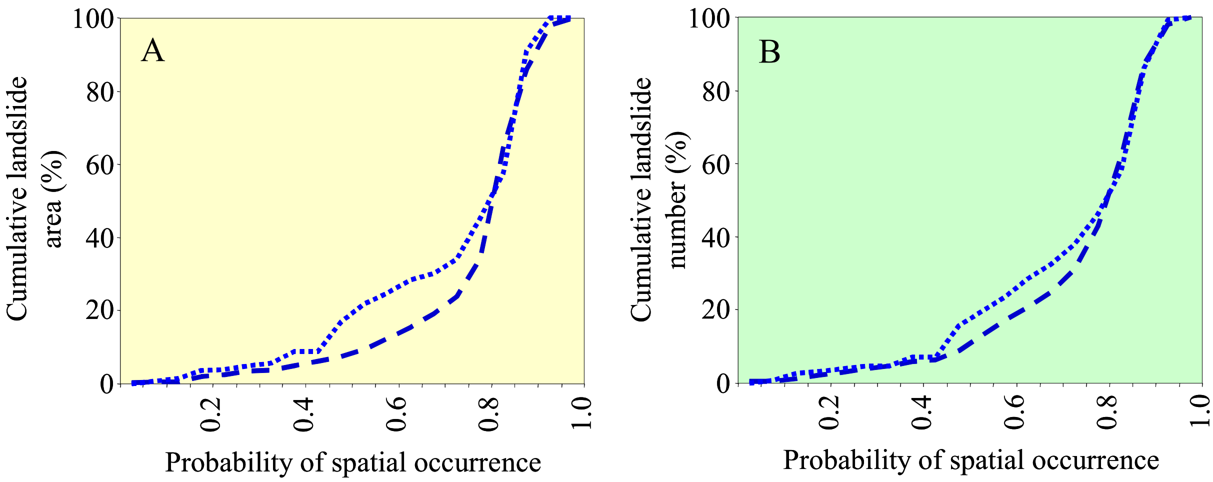

Figure 6.10 – Collazzone area. Analysis of the relationship between the predicted susceptibility classes and the distribution and abundance of the triggered landslides. (A) Cumulative statistics of triggered landslide area (y-axis) in the susceptibility classes (x-axis). (B) Cumulative statistics of the number of triggered landslides (y-axis) in the susceptibility classes (x-axis). Dashed dark-blue lines show landslides triggered by rapid snowmelt in January 1997. Dotted light-blue lines show landslides triggered by heavy rainfall in autumn 2004.

6.5.2. A framework for the validation of landslide susceptibility models

In the previous section (§ 6.5.1), I have presented a detailed example of how the quality (i.e., reliability, robustness, degree of fitting and prediction skills) of a landslide susceptibility model can be assessed quantitatively (i.e., measurably). The adopted evaluation procedure included: (i) standard methods used to evaluate the "goodness of fit" of a statistical classification (e.g., Tables 6.7 and 6.8), (ii) tests proposed in the literature to determine the degree of model fitting (Figure 6.3) and the prediction skills (Figure 6.9) of a landslide susceptibility model (Chung and Fabbi, 2003), and (iii) a scheme designed to evaluate (Figure 6.5) and to portray on a map (Figure 6.6) the error associated with the landslide susceptibility estimate obtained for each individual mapping unit.

Based on the results obtained in the Collazzone area, and aided by the scarce literature on the validation of landslide susceptibility models (Carrara *et al.*, 1992; Irigaray Fernández *et al.*, 1999; Ardizzone *et al.*, 2002; Chung and Fabbri, 1999, 2003, 2005; Fabbri *et al.*, 2003; Remondo *et al.*, 2003), I propose a general framework for establishing the quality of a landslide susceptibility assessment, including an objective scheme for ranking the quality of the assessment. A landslide susceptibility model should be tested to:

(a) Determine the degree of model fit,

(b) Establish the aptitude of the thematic information to construct the model, including an assessment of the sensitivity of the model to changes in the landslide and the thematic information used to construct the model,

(c) Determine the error associated with the probabilistic estimate obtained for each mapping unit, and

(d) Test the skill of the model prediction to forecast "future" landslides.

Determining the degree of model fit consists in establishing how well the model describes (i.e., matches) the known distribution of landslides. The task is easily performed in a GIS using the same landslide information used to construct the susceptibility model. For the purpose, contingency tables (e.g., Tables 6.4, 6.7 and 6.8), and cumulative statistics of the abundance of landslides in the susceptibility classes (e.g., Figure 6.3) can be prepared. However, for the test to be significant, the landslide information must be representative, accurate, and complete.

To evaluate the role of the thematic information in the construction of the landslide susceptibility model (e.g., Tables 6.3 and 6.6), and to evaluate the model sensitivity (e.g., Figure 6.4), one can study the list of thematic variables entered (and not entered) in a set of discriminant classification functions constructed on a sub-set of randomly selected mapping units (e.g., group G_{85}, for the Collazzone case study). In the proposed scheme, the random selection procedure accounted for the variability in the input data.

The expected error (i.e., the level of uncertainty) associated with the probabilistic susceptibility estimate obtained for each mapping unit can be determined by investigating the variability of the obtained estimate in the mapping units. For the purpose, I have assumed that two standard deviations (2σ) of the model estimate was a reasonable measure of the model uncertainty, and modelled the expected error consequently (i.e., using equation 6.14). Alternative measures of model uncertainty can be adopted.

Testing the ability of the susceptibility model to forecast new (i.e., "future") landslides can only be accomplished using landslide information not available to construct the susceptibility model (Chung and Fabbri, 2003, 2005; Guzzetti *et al*., 2005a,d). In the Collazzone area, I obtained independent landslide information from two recent event inventory maps showing new slope failures triggered by rapid snow melting and by intense rainfall. Chung and Fabbri (2003, 2005) obtained a similar result by splitting a multi-temporal inventory in two temporal subsets, i.e., a training set containing landslide occurred before an established date, and a classification set showing landslides occurred after the established date. I maintain that the scheme adopted here is superior to the scheme used by Chung and Fabbri (2003, 2005). In the first scheme, to construct the susceptibility model the entire set of available information on the past landslides is exploited, and not a temporal (i.e., limited) subset of it. As a potential drawback, the scheme is more "severe", as a much reduced number of landslides is used to ascertain the model prediction skill.

Table 6.10 lists a set of criteria for ranking and comparing the quality of landslide susceptibility assessments. Based on the listed criteria, when no information is available on the quality of a landslide susceptibility model the obtained product has the lowest possible level of quality (level 0). This level of quality should be considered unacceptable. When estimates of model fit are available, the susceptibility assessment has the least acceptable quality level (level 1). When the error associated with the predicted susceptibility estimate for each mapping unit is established, the susceptibility assessment has a higher level of quality (level

2). Lastly, when the prediction skill of the model is known, the susceptibility assessment has a still higher quality rank (level 4). The proposed scheme allows for summing the individual quality levels. As an example, a susceptibility assessment for which the fitting performance (level 1) and prediction skill (level 4) were determined is quality level 5. When, for the same susceptibility assessment, the error associated with the predicted susceptibility for each mapping unit is established (level 2), the quality level becomes 7. Adopting the proposed scheme, the landslide susceptibility model prepared for the Collazzone area has the highest quality level (i.e., level 7).

Table 6.10. Criteria and levels of quality for landslide susceptibility models and associated maps.

Description	*Level*
No information is available, or no test was performed to determine the quality and the prediction skill of the landslide susceptibility assessment.	0
Estimates of degree of model fit are available. Tests were performed using the same landslide information used to obtain the susceptibility estimate.	1
Estimates of the error associated with the predicted susceptibility value in each terrain unit are available. Tests were performed using the same landslide information used to obtain the susceptibility estimate.	2
Estimates of the model prediction performance are available. Tests were performed using independent landslide information, not used to obtain the susceptibility model.	4

The criteria listed in Table 6.10 do not guarantee as such the quality of a susceptibility estimate. To obtain this, the results of specific tests must be matched against established acceptance thresholds. Defining such thresholds is not an easy task. Based on the experience gained in numerous landslide susceptibility assessments completed in southern (Carrara, 1983), central (Carrara *et al.*, 1991; 1995; 2003; Cardinali *et al.*, 2002) and northern (Ardizzone *et al.*, 2002; Guzzetti *et al.*, 2005c) Italy, I propose a set of acceptance thresholds, and I compare the results of the performed tests to the proposed thresholds.

I consider acceptable a susceptibility model with an overall degree of model fit greater than at least 75%, and I regard a classification as very satisfactory when the overall model fit is greater that 80%. Further, I consider an extremely high value of the overall model fit (e.g., ≥ 90%) as an indication that the model matches too closely the original landslide inventory map (a case of model "over fitting"). When such case arises, the model prediction is virtually indistinct from a prediction made using solely the landslide inventory, making the model useless and unreliable. The case may arise, e.g., where the spatial distribution of landslides is "trivial" (i.e., very easy) to forecast, or where the number of mapping units is very small compared to the number of the explanatory variables (e.g., Campus *et al.*, 1999). An additional indication of the quality of the model consists in a reduced number of mapping units with landslides erroneously classified as "stable" areas by the model. The overall fit obtained for the susceptibility model prepared for the Collazzone area is 77.0% (Table 6.7), and the proportion of mapping units with landslides erroneously classified as stable areas is 9.5% (85 units).

A statistical model obtained using a reduced number of geomorphologically meaningful explanatory variables is "less expensive" and superior to a model which uses a very large number of variables. Further, use of a stable combination of variables provides for a robust model that can cope with (some) uncertainty in the input data. The discriminant function used to construct the susceptibility model for the Collazzone area shown in Figure 6.2.B selected 16 of the 46 available thematic variables (34.8%). Analysis of Table 6.9 reveals that the selected variables are consistent in classifying the slope units as stable or unstable in a large number of models. This is an indication of the robustness of the obtained model.

To appraise the fitting performance and the prediction skill of a landslide susceptibility model, Chung and Fabbri (2003) proposed comparing the proportion of landslide area in each susceptibility class (A_L) with the proportion of the susceptibility class (A_S) in the study area. For a successful classification, the "effectiveness ratio" A_L/A_S should be greater than one in the areas predicted as landslide prone by the model, and less than one in the areas predicted as stable by the model. A very effective prediction class has a ratio close to zero or very large, depending if the class predicts stability or instability. Where the effectiveness ratio is near one, the proportion of landslides in the susceptibility class is not different from the average landslide density in the study area, and the performance of the susceptibility class in determining the known ("fitting" performance) or the future ("prediction" skill) location of landslides is weak. Chung and Fabbri (2003) considered "effective" a susceptibility class with a ratio larger than at least 3 (unstable areas) or less than at most 0.2 (stable areas), and "significantly effective" a susceptibility class with a ratio larger than at least 6 or less than at most 0.1. These criteria are hard to match in complex areas where landslides are large and numerous, and where the landscape exhibits considerable geomorphological variability. For such areas, I consider "effective" a susceptibility class with a ratio larger than 1.5 or smaller than 0.5, corresponding to a 50% increase or a 50% decrease from the expected proportion of landslides in the susceptibility class.

It should be clear that all the proposed acceptance thresholds are not absolute, fixed thresholds. The proposed limits were selected heuristically, based on the experience of the investigators. The acceptance criteria need to be tested in other areas and by different investigators. Depending on the geomorphological setting and the complexity of a study area, other investigators may select different thresholds.

Lastly, I like to point out that the proposed framework for the evaluation of the quality of a landslide susceptibility model considers the most relevant sources of errors in a statistically based susceptibility assessment, but other factors resulting in errors that affect a susceptibility assessment exist. These factors include: (i) imprecision and incompleteness in the landslide information used to construct and test the susceptibility model (Carrara *et al*., 1992; Ardizzone *et al*., 2002; Galli *et al*., 2005), (ii) quality, abundance, precision and completeness of the thematic data used to obtain the susceptibility assessment (Carrara *et al*., 1992; 1999; Soeters and van Westen, 1996), (iii) characteristics and limitations of the statistical technique used to obtain the classification, including the experience of the investigator in applying the selected statistical tools (Carrara *et al*., 1992; Michie *et al*., 1994), and (iv) selection of the appropriate mapping unit (e.g., slope units, unique condition units, grid cells, etc., § 6.2.2) (Carrara *et al*., 1995; Guzzetti *et al*., 1999a). All these factors require choices from the investigator, which inevitably introduce uncertainty in the susceptibility assessment. The levels of uncertainty introduced by the listed factors should also be established.

6.6. Summary of achieved results

In this chapter, I have:

(a) Demonstrated that a large territory can be subdivided based on its propensity to generate new or reactivated landslides, using reliable and reproducible methods.

(b) Shown how to validate the performances and prediction skills of a landslide susceptibility forecasts.

(c) Proposed objective criteria for ranking and comparing the quality of landslide susceptibility forecasts.

This responds to Question # 5 posed in the Introduction (§ 1.2).