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**STATISTICAL MODELS FOR LANDSLIDE
SUSCEPTIBILITY ASSESSMENT:
METHODOLOGICAL ISSUES AND GUIDELINES
FOR MEDITERRANEAN CONTEXT**

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SUSCEPTIBILITY ASSESSMENT: METHODOLOGICAL
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CONTENTS

Acknowledgments	I
Resumen	II
1 INTRODUCTION	
1.1 The problem	1
1.2 Basic Concepts	4
1.2.1 Landslides and soil protection	6
1.2.2 Landslide emergency in Italy	7
1.3 Aims and scientific contribution	10
2 LANDSLIDES	
2.1 General concepts	12
2.2 Landslides and their classification	14
2.2.1 Types of movement	16
2.2.1.1 Front landslides	17
2.2.1.2 Slope landslides	21
2.3 Landslide inventories	38
2.3.1 Historical analysis of maps, archives and publications	40
2.3.2 Photo-interpretation of aerial and satellite images	41
2.3.3 Field-survey : geomorphological mapping	42
2.3.4 Remote sensing analysis with open-source softwares	42
2.4 Materials and methods used for producing the landslides archive in the studies areas	45
2.5 Multi-temporal landslides inventory	46
3 LANDSLIDE SUSCEPTIBILITY	
3.1 Basic theoretical coincepts	49
3.2 Methods for susceptibility assessment	52
3.3 Some geomorphological considerations	60
3.4 Model building procedures	61
3.4.1 Mapping unit	61

3.4.2	Variable selection	66
3.4.3	Scalability	68
4	METHODOLOGICAL ASPECTS IN MODEL BUILDING TECHNIQUES	
4.1	General concepts	72
4.2	Statistic approach	72
4.3	Landslide inventory	73
4.4	The diagnostic area	74
4.5	Factors selection	77
4.6	Mapping units	79
4.7	Model validation and exportation	80
5	APPLICATIONS AND EXPERIMENTAL TESTS	
5.1	Test 1a: The Tumarrano river basin: Exporting a Google Earth™ aided earth flow susceptibility model he Tumarrano river basin	84
5.1.1	Geological and climatic framework	84
5.1.2	Landslides	88
5.1.3	Selected controlling factors	90
5.1.4	Model building and validation techniques	98
5.1.5	Discussion and concluding remarks	104
Test 1b:	The Tumarrano river basin: Forward logistic regression for earth flow landslide susceptibility assessment	108
5.1.6	Landslides	110
5.1.7	Model building strategy	113
5.1.8	Controlling factors and independent variables	115
5.1.9	Diagnostic areas	119
5.1.10	Model suite	120
5.1.11	Validation	121
5.1.12	Model fitting	123

5.2	Test 2: The Beiro river basin: Geological and climatic framework	150
5.1.1	Landslides	129
5.1.2	Model building	133
5.1.3	Factors selection procedures	134
5.1.4	Multivariate models	140
5.1.5	Susceptibility modeling and validation	144
5.1.6	Discussion and concluding remarks	125
5.3	Test: The Imera basin: Geological and climatic framework	150
5.3.1	Slope units, instability factors and landslides	152
5.3.2	Susceptibility modeling and validation	157
5.3.3	Results	159
5.3.4	Discussion and concluding remarks	162
6	CHAPTER VI. DISCUSSION AND CONCLUDING REMARKS	165
6.1	Discussion and concluding remarks	182
6.2	Discussion and recommendations for future implementation of multi-scale susceptibility assessment approaches in Sicily: the SUFRA project	160
6.2.1	Breakdown of activities	184
6.2.2	Definition of the control factors	185
6.3	SUFRA₂₅₀ (TIER₁_SICILIA609)	185
6.4	TASK SUFRA₅₀ (TIER₂_SICILIA609)	186
6.5	SUFRA_{10/25} (TIER₃_SICILIA609)	187
6.6	SUFRAMON	188
	CONCLUSIONES Y CONSIDERACIONES FINALES	189
	LIST OF FIGURES	215
	LIST OF TABLES	221
	REFERENCES	222

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RESUMEN

La población mundial, que cuenta dos mil millones de habitantes alrededor del año 1950, ha crecido a un ritmo casi exponencial en las décadas siguientes hasta 4 mil millones y 5,3 en 1990 (Naciones Unidas - Departamento de Asuntos Económicos y Sociales, 2010). Sin duda un gran aumento tanto en términos absolutos cuanto relativos. Según las estimaciones de las Naciones Unidas, la población mundial se estima que alcanzará los ocho millones y medio de 2025. Estas tasas de crecimiento se producen, obviamente, tanto en Europa, donde la población ha crecido de 550 millones en 1950 a 750 millones en 2010, y en Italia, donde en el período 1861 a 2008 hubo un aumento de la población de 22 millones de habitantes a casi 60 millones (fuente: ISTAT, 2010). La población ha crecido, sin embargo, a tasas más altas en los países en desarrollo, con una tendencia a la constante en los países industrializados en las últimas décadas. Dicha población mundial intenso tiene consecuencias directas sobre el territorio urbano, mientras que lleva a una extensión de las actuales áreas urbanas menores y pequeñas ciudades. Todo esto, cada vez más, dar lugar a problemas de gestión y uso del suelo, produciendo un crecimiento del componente de la vulnerabilidad en la ecuación de riesgo. Crecimiento de la población no justifica un aumento de las condiciones hidrogeológicas de la inestabilidad. Si es así, ya que la población se ha convertido en firme en los últimos años, al menos en la mayoría de los países industrializados, no hay que hacer frente a riesgos cada vez mayor. En cambio, el modelo de desarrollo económico, basado principalmente en redes e infraestructuras, así como los asentamientos, por supuesto, produce un doble efecto: un aumento de los activos expuestos a la amenaza, una presión sobre el territorio, capaz de hacer la activación de los fenómenos peligrosos más frecuentes.

Los fenómenos naturales también tienen un impacto en el marco socio-económico, ya que son responsables de la pérdida de bienes y servicios y, en ocasiones, una pérdida en términos de vidas humanas. En tal situación, la vulnerabilidad de la zona está relacionado con el desarrollo de su sistema de infraestructura social, civil y urbano.

Este concepto se expresa claramente en la declaración "Los desastres ocurren cuando los riesgos se encuentran con la vulnerabilidad" (Wisner et al., 2004). Esto nos lleva a considerar los desastres naturales como los **fenómenos sociales reales**.

Cuando se habla de riesgo geomorfológicos y de políticas ambientales, uno de los pioneros es, sin duda, Earl E. Brabb, que ya en 1991 en un artículo titulado "El problema de movimientos de ladera del mundo", sostuvo que los deslizamientos son un problema mundial que causa cientos de muertes y miles de millones de dólares de daño cada año en todo el mundo. Los problemas geomorfológicos son y serán un tema importante y un requisito fundamental del conocimiento para la política de toma de decisiones. A pesar de 20 años han pasado desde que el trabajo Brabb, la situación no parece haber cambiado. No son aún insuficientes los procedimientos de todo el mundo aunque sólo sea compartida que permite evaluar la calidad y precisión de un inventario de deslizamientos o la forma de clasificar en términos de susceptibilidad a los deslizamientos de un área y para evaluar cuantitativa y cualitativamente el rendimiento predictivo.

Las imágenes y escenas de devastación, destrucción y muerte que ocurren cada año, hacen que el problema de los riesgos geomorfológicos es un problema social. ¿Quién es el responsable? Seguimos construyendo, incluso en lugares que no son adecuados para la construcción. Tenemos que admitir por lo menos una doble responsabilidad. Si bien es cierto que los acontecimientos que causan un derrumbe apenas son "previsibles", por el contrario sí podemos identificar y predecir donde estos fenómenos se producen con mayor capacidad destructiva, produciendo más daños y reducir al mínimo la vulnerabilidad. Por lo tanto, si no es posible evitar, ya que no es posible predecir, la palabra clave debe ser "*la prevención*".

Cada vez deslizamientos de tierra u otros eventos con características destructivas y letales, que a menudo se supone y se define como "impredicible", nos ofrece con el escenario de las víctimas, los heridos y desaparecidos, el público se estremece y recuerda la vulnerabilidad de los bienes de la comunidad y direcciona la discusión sobre el tema de prevención de los desastres naturales o por lo menos tratar de minimizar las consecuencias trágicas que lo acompañan. La ola emocional que sigue a la fase de emergencia se produce entre las llamadas a "*enrollar las mangas*" a una "cultura de prevención" que "nunca vuelva a suceder", e induce a los legisladores y los técnicos para

intervenir con una variedad de medidas urgentes de mitigación y obras y de intervención inmediata, tal vez proponiendo también las regulaciones y leyes dirigidas a "evitar otro desastre similar".

Hoy Saponara, ayer Génova, el día antes Giampileri y San Fratello y así sucesivamente durante décadas: Salerno (1954) con 318 víctimas, 250 heridos y sin hogar cerca de 5.500, y el Longarone y el desastre de Vajont (1963) con cerca de 2.000 muertes de Agrigento, (1966), Valtellina (1987) 53 muertes y 4.000 millones de liras de los daños, el deslizamiento de tierra en el Val di Stava de julio de 1985 (269 muertos), las corrientes rápidas del 5 de mayo de 1998 y Sarno y Quindici y otras áreas de la región Campania, con 153 muertes, Maierato (2010), son algunos de los eventos más importantes que lleva a más de 4.000 las muertes causadas por movimientos gravitativos en medio siglo, un promedio de 4 muertes por mes, además de un daño económico incalculable. Pero cada día hay una lista de los deslizamientos de tierra, carreteras y puentes bajando, a pesar de que pasa desapercibido. A falta de una cultura de prevención y un aumento de la cultura de emergencia en su lugar. Y la protección civil se ve ahora como la única ancla de salvación y la asistencia de los municipios y la población involucrada.

Italia es un País que se desmorona debido a la negligencia del hombre y a la falta de prevención. Hay 5,596 sobre 8,101 municipios en riesgo hidrogeológico, el 84% de los centros de población se define en riesgo. Esto sin duda demuestra que las construcciones se construyeron cuando no se podía. De estos municipios, 1.700 (alrededor del 21%) están en riesgo de deslizamientos, 1.285 (casi el 16%) en riesgo de inundación y 2.596 (32%) se encuentran en una combinación de deslizamientos de tierra y riesgo de inundación. El área total clasificada como de alto riesgo asciende a 36.551 km² (7,1% del total nacional) dividido en km² de áreas de deslizamientos de tierra y 7.791 km² de áreas inundadas 13.760. Estas cifras ponen de relieve la inestabilidad hidrogeológica con el que cada región debe enfrentar, tarde o temprano, contra la cual el flujo de millones de euros, a menudo sólo le prometió, no servirá de mucho para la estabilización y obras de medida de seguridad. El informe de Legambiente revela que los municipios son la punta de lanza de una evidente debilidad de nuestro territorio.

No hay una única manera de preparar los mapas de susceptibilidad, como lo demuestra la enorme cantidad de artículos científicos producidos incluso durante la última década, y lo mismo es cierto en cuanto a la zonificación de los peligros y los riesgos involucrados, todavía sigue siendo un problema sin resolver en gran medida (Carrara et al., 2009). La contribución de este trabajo las siguientes fases de un estudio con el fin de definir la estructura de la sensibilidad, los riesgos y peligros de un área:

1. Construcción de la base de datos: en este trabajo las diferentes técnicas y métodos de detección de deslizamiento de tierra y delimitación se comparan directamente (trabajo de campo) e indirectamente (fotografías aéreas, software de visualización remota del territorio) y su posterior despliegue en un sistema GIS.
2. Elección y definición de la escala de análisis: De hecho, uno de los problemas más actuales de la proposición se relaciona con los métodos de evaluación de susceptibilidad a escala múltiple.
3. Unidades cartográficas: las diferentes unidades se utilizan para la cartografía y zonificación del territorio, cuya previsión de resultados se comparan con el fin de ser capaces de identificar las unidades de la asignación básica más adecuada para la planificación y para fines de defensa civil, teniendo en cuenta la exactitud científica de que la modelo debe soportar.
4. Elección de los factores control: en el trabajo, es la posibilidad de identificar el conjunto más probable de los factores que se consideran relacionados directamente o indirectamente a la inestabilidad de la ladera. Se proponen procedimientos de prueba y seleccionar el conjunto de posibles factores de control, así como la construcción de modelos específicos para cada tipo de deslizamientos.
5. Construcción de modelos: como para la construcción de un modelo geoestadístico, las soluciones se comparan diferentes y el modelo de presentación de los mismos resultados y la objetividad que se elija, teniendo en cuenta que las necesidades de una implementación más bajo en términos de costo y tiempo.
6. Validación: los modelos están sujetos a diferentes técnicas de validación, que luego se comparan entre ellos.

- 7 Exportación espacial de un modelo de susceptibilidad: este es un ensayo para definir y validar los términos de susceptibilidad a los deslizamientos de una amplia zona en los gustos de cientos o miles de kilómetros cuadrados, en base a los estudios de detalle de algunos sectores que lo representan.

Al igual que muchos otros autores, con el propósito de este trabajo es hacer una contribución a la comunidad científica, tratando de ofrecer una modesta contribución en la solución de algunos problemas en este campo a través de experimentos y modelos realizados en una variedad de contextos y comparar los resultados entre ellos.

En este sentido, unas pruebas se llevaron a cabo en algunas áreas, previamente seleccionadas, será probado y verificado el resultado de algunos de los procedimientos en los años de investigación doctoral. A continuación, un resumen de los resultados vendrán de estas pruebas experimentales

TEST 1a: TUMMARRANO river basin: Model Exportation

En el marco de un estudio de la susceptibilidad de deslizamientos regional en el sur de Sicilia, una prueba se ha realizado en la cuenca del río Tumarrano (unos 80 km²) tiene como objetivo caracterizar las condiciones de su susceptibilidad movimientos de ladera mediante la exportación de un modelo, definido y entrenado en el interior un número limitado (unos 20 km²) representativas del sector ("el área de origen"). Además, la posibilidad de explotar software de Google Earth y el banco de datos de fotos para producir imágenes de los archivos deslizamiento de tierra ha sido comprobado. El modelo de susceptibilidad se define, de acuerdo con un enfoque multifactorial basadas en el análisis condicional, con unidades únicas condiciones (UCUs), los cuales fueron obtenidos mediante la combinación de cuatro factores seleccionados control: litología afloramiento, la pendiente, la curvatura del plan y el índice de humedad topográfica. La capacidad de predicción del modelo de exportación, formado con 206 deslizamientos de tierra, se compara con la estimada para toda el área estudiada, mediante el uso de un archivo completo de deslizamiento de tierra (703 deslizamientos de tierra), para ver hasta qué punto el mayor tiempo/dinero necesario se tienen en cuenta los costos para.

TEST 1b. Tummarrano river basin: modelo de susceptibilidad basado en la Forward logistic regression

La regresión logística con pasos hacia adelante, nos ha permitido obtener un modelo de susceptibilidad por los flujos de tierra en la cuenca del río Tumarrano, que se definió mediante el modelado de las relaciones estadísticas entre un archivo de eventos 760 y un conjunto de 20 variables predictoras. Para cada movimiento del inventario, un punto de identificación de deslizamientos (LIP) se produce de forma automática, como corresponde al punto más alto a lo largo de la frontera de los polígonos de deslizamientos de tierra. Los modelos equilibrados (760 estable/760 inestable) se presentaron a adelante el procedimiento de regresión logística. Una estrategia de construcción del modelo se aplicó para ampliar la zona considerada en la preparación del modelo y para comprobar la sensibilidad de los modelos de regresión con respecto a los lugares específicos de las células se considera estable. Un conjunto de dieciséis modelos se preparó de forma aleatoria extraer los subconjuntos diferentes células estables. Los modelos fueron sometidos a regresión logística y validados. Los resultados mostraron que las tasas de error satisfactoria y estable (0,236 en promedio, con una desviación estándar de 0,007) y AUC (0.839, para la formación, y 0.817, para conjuntos de datos de prueba). Como en relación a los predictores, la pendiente en el barrio de las células y la curvatura topográfica de gran perfil y plan local-fueron seleccionados de forma sistemática. Litología arcillosa afloramiento, drenajes midslope, crestas locales y midslope y los accidentes geográficos cañones eran también muy frecuentes (de 8 a 15 veces) en los modelos de la selección hacia adelante. La estrategia de construcción del modelo nos ha permitido producir un modelo de flujo de tierra realizando la susceptibilidad, cuyo modelo de ajuste, la predicción de la habilidad y solidez se estimaron sobre la base de los procedimientos de validación.

Test 2. Imera river basin: modelo de susceptibilidad por flujo de tierra basado en las unidades de ladera.

Un mapa de susceptibilidad de un área, que es representativa en términos de marco geológico y los fenómenos de inestabilidad de ladera de grandes sectores de los Apeninos de Sicilia, fue producida usando unidades de ladera y un modelo

multiparamétrico univariado. La zona de estudio, que se extiende por aproximadamente 90 km², fue dividida en 774 unidades de la pendiente, cuya ocurrencia esperada avalancha se estimó un promedio de siete valores de vulnerabilidad, determinado para el control de los factores seleccionados: litología, pendiente media del gradiente, SPI en el pie, el índice de humedad topográfica y la curvatura del perfil, y el rango de altitud. Cada uno de los reconocidos 490 deslizamientos de tierra estuvo representada por su punto de centro de gravedad. Sobre la base de análisis condicional, la función de la susceptibilidad aquí adoptada es la densidad, calculado para cada clase. Modelos univariante fueron preparados para cada uno de los factores que controlan, y su rendimiento predictivo se estimó por curvas de tipos de predicción y la relación de efectividad aplicada a la categorías de vulnerabilidad. Este procedimiento nos permitió discriminar entre factores efectivos y no efectivos, de modo que sólo la primera se combinó posteriormente en un modelo multiparamétrico, que fue utilizada para producir el mapa de susceptibilidad final. la validación de este último mapa nos permite comprobar el rendimiento y la fiabilidad de la predicción modelo. Los principales factores reguladores resultaron: la litología y, subordinadamente, el SPI a el pies de la unidad, y también el gradiente medio de la pendiente, la curvatura del perfil, y el índice de humedad topográfica dieron resultados satisfactorios.

CHAPTER I. INTRODUCTION

*“man can't prevent everything,
but he is able to predict with good accuracy many things”*

1 INTRODUCTION

1.1 The problem

1.2 Basic concepts

1.2.1 Landslides and soil protection

1.2.2 Landslide emergency in Italy

1.3 Aims and scientific contribution

1.1 The problem

The World population, which counted two billion inhabitants around 1950, has grown at an almost exponential rate in the following decades up to four billion in 1980 and 5,3 in 1990 (United Nations – Department of Economic and Social Affairs, 2010). Definitely a high increase both in absolute and relative terms. According to estimates by the United Nations, the World population is estimated to reach eight billion and a half around 2025 (Chart 1.1), and then it will become steady around ten billion in 2050 because of the expected decline in fertility. These growing rates occur, obviously, both in Europe, where population has grown from 550 million in 1950 to 750 million in 2010, and in Italy, where in the period from 1861 to 2008 there was a surge in population from 22 million inhabitants to almost 60 million, (source: ISTAT, 2010). The population has grown, however, at higher rates in developing Countries (Fig. 1.1), with a tendency to become steady in industrialized Countries in the last decades. Such an intense world population has direct consequences on urban territory while leading to a spread of current minor urban areas and small towns. All this will, increasingly, result in management and land

use problems, producing a growth of the vulnerability component in the risk equation. Population growth alone does not justify an increase of hydro-geological conditions of instability. If so, since the population has become steady in recent years, at least in most industrialized countries, we should not face increasing risks. Instead, the economic development model, largely based on networks and infrastructures, as well as settlements of course, produces a double effect: an increase of assets exposed to threat; a stress on the territory, able to make the activation of hazardous phenomena more frequently. It is however true that recent disasters with great loss of lives (i.e., Sarno Giampileri, Aulla, Genova and Saponara) are actually the results of the response (letting nature take its course) to the changes in territorial asset occurred after the war. Another cause may be found in environmental changes: when the stress regime in a region changes (such as extraordinary rainfall intensity), the response is obviously new for both sides/slopes and the population. The WWF notes that from 1956 to 2001, urbanized areas in Italy have increased by 500 times and it is estimated that from 1990 to 2005 we have transformed 3,5 million hectares of land.

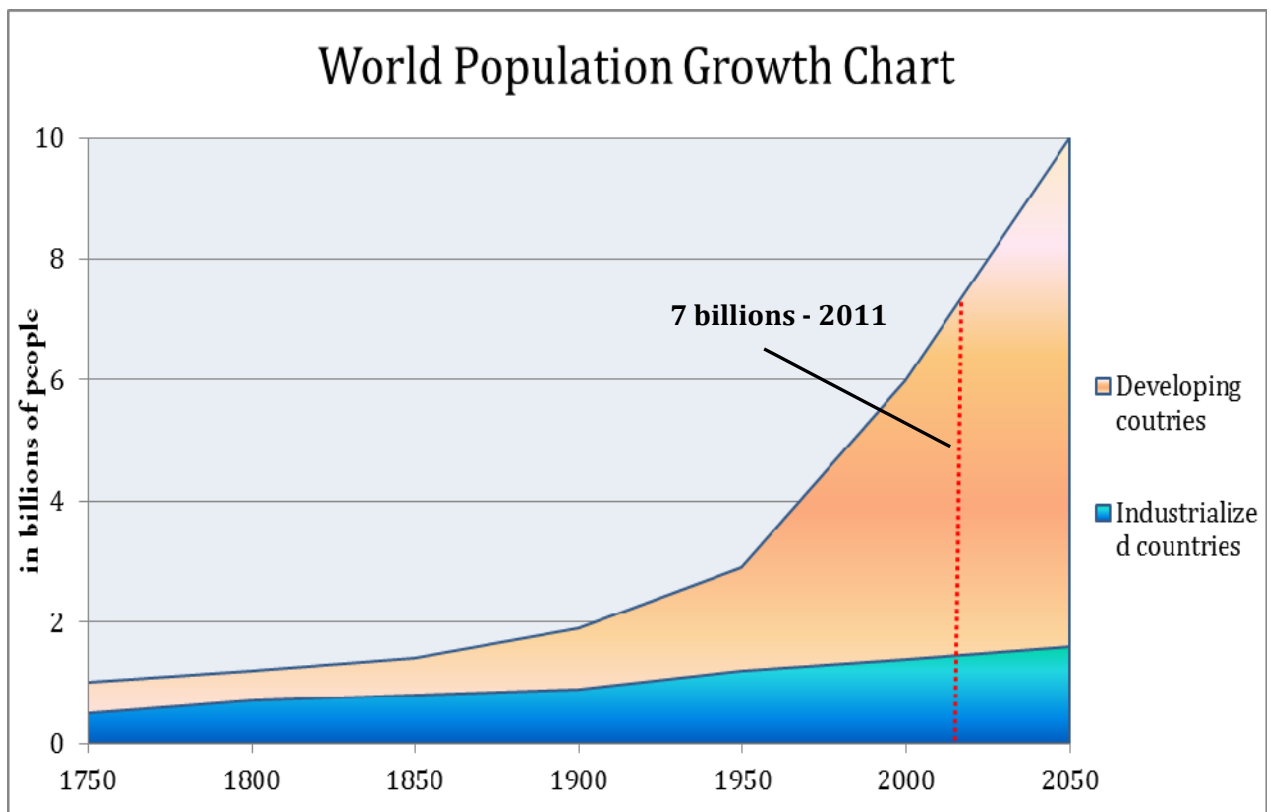


Fig. 1.1 - World Population Growth Chart. United Nations - Department of Economic and Social Affairs, 2010

The problem of interaction between humans and the natural environment is a very complex and diversified issue, not often approached in a systematic way, also because of the severe limitations of sources to be invested on research on a medium and long-term, for a better and effective knowledge of the environment, primarily on measures aimed at reducing risk (Plattner, 2005).

Natural phenomena also have an impact within the social-economic framework as they are responsible for the loss of goods and services, and sometimes, a loss in terms of lives. In such a situation, the vulnerability of the area is related to the development of its social, civil, and urban infrastructural system.

This concept is well expressed in the statement "disasters occur when hazards meet vulnerability" (Wisner et al., 2004). *This leads us to consider natural disasters as real social phenomena.* This condition is strongly valid especially with regard to landslides (Brabb and Harrod, 1989; Brabb, 1991).

Since economic problems common to all countries do not allow either to invest in research projects on a medium and long-term or the stabilization of structures or areas on a large-scale, a new philosophy of environmental policy opens up for all active political and administrative subjects that should govern the use and exploitation of the territory. For this reason, the scientific community is engaged in a continuous search for methods and techniques to estimate the degree of real and potential instability, using the minimum amount of equipment and possible economic resources.

Usually there is a substantial difficulty in identifying the most reliable procedures, that allow to approach this matter in a non-traditional manner based on modeling and investigative techniques built on the exchange of experiences between experts and conducting studies and experiments on all continents, and showing different strategies and possible technical combinations depending on the type and/or the number and complexity of the investigation, producing susceptibility, hazard and risk maps, used as the basis for decision-making processes in land management. In this framework, further efforts are needed in trying to make the different methods more objective and shared by all in order to be simple and reproducible, and most of all in transferring the knowledge gained in laws that underpin territorial planning, building regulations, and in civil defense plans (Guzzetti, 2006). When discussing about landslides and environmental policies, one of the pioneers is undoubtedly Earl E. Brabb, who already in 1991 in a paper entitled "The World Landslide Problem", sustained that landslides are a worldwide

problem that cause hundreds of deaths and billions of dollars of damage every year all over the world. The same added that these losses can be reduced if the problem is identified and acknowledged in time, but many countries are simply equipped with maps showing where landslides produced problems in the past and they have even less susceptibility maps that could allow policy makers control land use. Landslides, adds Brabb, are generally more predictable and controllable than other natural events of catastrophic nature such as earthquakes, volcanic eruptions and storms, but despite this, few countries have taken advantage of this knowledge to reduce landslide hazard. Geomorphological problems are and will be an important issue and a fundamental requirement of knowledge for the politics of decision-making. Although 20 years have gone by since Brabb's work, the situation does not seem to have changed. There are still insufficient globally shared procedures even just allowing to assess the quality and accuracy of a landslide inventory or how to classify in terms of landslide susceptibility of an area and to evaluate quantitatively and qualitatively predictive performance.

1.2 Basic concepts

One of the most obvious effects of rapid territory development in the past decades is the increasing impact that natural disasters have on man and his activities. Institutions are therefore committed to investing their resources in both the implementation of structural interventions to mitigate the risk as well as implementation of early warning systems and defining guidelines for land management; the latter activities allow, in fact, to avoid or minimize damage to persons and property, produced by natural phenomena, without necessarily investing in expensive resources and long structural interventions. The term "risk" is used in relation to the various components of the social and territorial fabric, as an expression of the expected consequences in the assets as a result of this disastrous phenomenon of assigned intensity at a given time interval. Within the guidelines for the preparation of prevention and management plans in terms of geological risk of the Sicilian Civil Protection Service (Regional Hydro-geological and Environmental Risks department), the term Hydro-geological Risk means the effect on different parts of the territory led by natural disasters such as landslides (geomorphological risk) and floods (hydraulic risks) triggered by events related to climate and its changes.

Two main components contribute to the definition of risk: territorial hazard (geomorphological and hydraulic) and vulnerability. The latter depends on both the physical resistance of structures or assets exposed to the threat and the so-called vulnerability of social organization, which is linked, in fact, to the capacity of disaster prevention and management that a community has developed prior to the same disaster.

The propensity of a territory to be affected by new landslides, the degree of hazard or risk that characterizes it, are usually expressed with the help of a map in which the area is divided into different zones according to the different values that qualify it. In this mapping, the territory is *zoned* or divided into homogeneous zones or user-defined fields/areas, whose ranking is defined according to their real or potential degree of landslide hazard (Varnes, 1984). Over the decades, many research groups and national and international commissions have tried to provide precise definitions, trying to reduce the existing confusion of terms in the management of natural hazards. In this section, some basic concepts are expressed as well as the terminology that will be used in the thesis below.

Landslide events that develop in a given area involve a large number of environmental variables, to determine undoubted difficulties in identifying a suitable action of management, control and planning. In order to do so, understanding the problem without having a clear conceptual framework and method to be used may not be sufficient. The "forecast" of the phenomena and therefore the modeling phase is always required to designated public administration bodies and territorial control, carried out by the creation of digital simulation models which become crucial at the time when decisions must be taken/made. The creation of maps indicating the different vocation planning of an area, based for example on landslide hazard maps, not only allows you to compose the scene of the incident consequences of a given failure, but also to react under emergency, if magnitude, area, and associated potential damage are known.

Planning is a subject which studies and regulates the processes of local governance and to evaluate the resulting dynamics of evolution and development. The principles guiding the choice of planning require development policies coherent with the principles of environmental protection and sustainability in an effort to control the

excessive human presence, able to transform irreversibly natural systems and preserve the quality of life for future generations.

Information, territorial knowledge and assessment of its natural predisposition and vulnerability are the basis of planning. These forms of knowledge and the use and application of the best technologies available to facilitate information processing and optimization of procedures for evaluation and zoning of the territory, will yield the best design solutions to achieve the desired objectives.

Planning is aimed to government land use and management of spatial information, and is achieved by *regulating* the area according to different uses, which should be awarded taking into account the natural predispositions.

Planning activities can affect a large portion of territory, in other words include a supra-municipal area or one that does not match with administrative boundaries (e.g. Provincial Territorial Coordination Plan, Hydro-geological Plan) or urban (e.g. General Regulation Plan). The geological, geomorphological, hydro-geological and seismic component should be placed at the base of the strategic development of the territory. In national legislation, water management is understood both as a natural resource but also as an element of risk, and has been regulated at the watershed level since the nineties (national framework law 183/89 on soil protection). This allow us to overcome divisions and inconsistencies produced by the adoption of targeted areas having only administrative boundaries that, therefore, do not take into account natural dynamics.

The zoning of landslide hazard area is considered the most effective level of knowledge for territorial planning and territorial governance purposes. A map showing portions of an area classified as "hazardous" is of great importance due to the fact that these areas are subject to limitations and constraints that also affect the usability or simply the economic value.

1.2.1 Landslides and soil protection

The images and scenes of devastation, destruction and death that occur every year, make the problem of geomorphological risks a social problem. What is accountable here? The frequency and intensity of the precipitation with which they occur? The

fragility of the natural environment? Or should we answer man and his complex world of economic development and social responsibility? We continue to build, including in places that are not suitable for construction. We must admit at least a double responsibility. Although it is true that the events that trigger landslides are scarcely "predictable", on the other hand we can certainly identify and predict where these phenomena will occur with greater destructive capacity, producing more damage while minimizing the vulnerability. So, if it is not possible to avoid, as it is not possible to predict, the key word should be "prevention".

Each time landslides or other events with destructive and lethal characteristics, which are often supposed and defined as "unpredictable", offers us with the scenario of the victims, the wounded and missing, the public is shaken and remembers the vulnerability of community assets and addresses the discussing on the issue of prevention of natural disasters or at least trying to minimize the tragic consequences that accompany it. The emotional wave that follows the emergency phase occurs between calls to "roll up the sleeves" to a "culture of prevention" to "never to happen again", and induces the legislators and the technicians to intervene with a variety of urgent measures and mitigation works and of immediate intervention, perhaps proposing also regulations and laws aimed at "*preventing another similar disaster.*"

1.2.2 Landslide emergency in Italy

Today Saponara, yesterday Genova, the day before Giampileri and San Fratello and so on for decades: Salerno (1954) with 318 victims, 250 injured and about 5,500 homeless, and the Longarone and the Vajont disaster (1963) with nearly 2.000 deaths, Agrigento (1966), Valtellina (1987) 53 deaths and 4.000 billion lire of damage, the landslide in the Val di Stava of July 1985 (269 deaths), the rapid flows of May 5, 1998 and Sarno and Quindici and other areas of the Campania region with 153 deaths, Maierato (2010), are some of the major events leading to more than 4000 the deaths caused by landslides in half a century, an average of about 4 deaths per month in addition to an incalculable economic damage. But every day there is a list of landslides, roads and bridges going down, even though it goes unnoticed. A lack of a prevention culture and a surge of emergency culture instead. And the Civil Protection is now seen as the only anchor of salvation and assistance by the municipalities and the population involved.

Italy is a country that crumbles due to man's negligence, overindulgence and lack of prevention. This is the dramatic picture emerging from a study updated in December 2010, by Legambiente, the Ministry of the Environment and the National Civil Protection Department which led to the identification, enumeration and classification of Italian municipalities according to different levels of subjection to hydro-geologic risk. There are 5,596 out of 8,101 municipalities at hydrogeological risk. Although only 12% of the country is at hydrogeological risk, 84% of populated centers is defined at risk. This certainly shows that constructions were built when you were not supposed to. Of these municipalities, about 1,700 (about 21%) are at landslide risk, 1,285 (almost 16%) at flood risk and 2,596 (32%) are at a mix of landslide and flood risk. The total area classified as high risk amounts to 36,551 km² (7.1% of national total) divided into 13,760 km² of landslides areas and 7,791 km² of flooded areas. These numbers demonstrate a hydro-geological instability with which each region must face sooner or later, against which the flow of millions of euros, often only promised, will not do much for the stabilization and safety measure works. The Legambiente report reveals that the municipalities are the spearhead of **an obvious weakness of our territory**.

The region having the largest number of instability is Piemonte (1046), Sardinia, instead, is the region with the fewest (42) only because census data are not updated; Calabria, Umbria and Valle d'Aosta (which is also the most virtuous region for hydrogeological prevention works) are the regions with the highest percentage of municipalities classified at risk (100%), followed by Marche (99%) and Tuscany (98%), Sardinia is the one with a lower percentage (11%) (Tab 1.1).

Region	Municipalities at risk from landslides	Municipalities at risk from flood	Municipalities at risk from landslides and flood	% Municipalities at risk
Calabria	57	2	350	100%
Umbria	40	1	51	100%
Valle d'Aosta	11	0	63	100%
Marche	125	1	117	99%
Toscana	15	31	234	98%
Lazio	234	3	129	97%
Basilicata	56	2	65	94%
Emilia Romagna	10	128	164	89%
Molise	41	1	79	89%
Piemonte	138	303	605	87%
Campania	193	67	214	86%
Liguria	30	55	103	80%
Sicilia	200	23	49	70%
Friuli Venezia Giulia	68	58	11	63%
Lombardia	231	435	248	59%
Abruzzo	103	20	55	58%
Trentino Alto Adige	59	8	44	33%
Veneto	41	108	12	28%
Puglia	44	1	3	19%
Sardegna	4	38	0	11%
TOTAL	1700	1285	2596	73% (mean)

Tab. 1.1 – Report on the status of the areas at geomorphological risk in Italy (Legambiente, 2010).

Italy, besides having a territory particularly prone to heavily collapse, has a highly populated territory with a density of 189 inhabitants per km², much higher than France (114 inhabitants/km²) and Spain (89 inhabitants/km²), in Lombardy and Campania respectively, the density changes to 379 and 420 inhabitants per km². As clear from the **Report on landslides in Italy** (National Geological Survey, 2007), commissioned by the ISPRA (National Institute for Environmental Protection and Research), in the last 50 years almost 500 thousand landslides have been recognized and recorded for an area of about 20 thousand km², corresponding to 6.6% of the entire national territory. These data should be updated. As indicated by the last study conducted by the Ministry of the Environment (2010), 9.8% of the national area is to be

ranked highly hydro-geological critical and 6.633 municipalities are involved, representing 81.9 percent of the national territory. This value, according to a report EURISPES (Report Italy, 2010) is "largely underestimated", therefore agreeing that "a reliable estimate is made up of about 2 million phenomena and consequently the percentage of the Italian territory subject to ongoing phenomena is more than 20%." The Ministry of Environment, through the work for the realization of development plans undertaken by the hydrogeological Basin Authority, estimated a funding requirement of almost 40 billion euros to hydro-geologically secure the entire country, and 4.1 billion for more urgent works. Undoubtedly, the amounts are considerably high, but it is enough to consider that almost 21 billion euros were spent just to stanch the damages by hydro-geological disasters occurred in the decade 1994-2004.

1.3 Aims and scientific contribution

There is no single way to prepare susceptibility maps, as evidenced by the enormous amount of scientific papers produced even during the last decade, and the same is true as for the zoning of the hazard and risk involved, still remaining a largely unsolved problem (Carrara et al., 2009). The contribution of this paper the following phases of a study in order to define the susceptibility structure, hazard and risk of an area.

- 1 *Construction of the landslide database:* in this work different techniques and methods of landslide detection and delimitation are compared, directly (field work) and indirectly (aerial photographs, remote viewing software of the territory) and their subsequent deployment in a GIS system.
- 2 *Choice and definition of the analysis scale:* the problem of scale models of susceptibility is approached. In fact, one of the most actual problems of the proposition is related to approaches to multi-scale susceptibility evaluation.
- 3 *Mapping units:* different units are used for mapping and zoning of the territory, whose foresight results are compared in order to be able to identify the basic mapping units most suitable for planning and for civil defense purposes, taking into account the scientific accuracy that the model must bear.
- 4 *Choice of controlling factors:* during the work, it is the possible to identify the most probable set of factors considered to be directly or indirectly related to the instability of the slope. Procedures for testing and selecting the set of

possible controlling factors are proposed as well as the construction of specific models for each type of landslide.

- 5 *Model building*: as for the construction of a geo-statistical model, different solutions are compared and the model presenting the same results and objectivity is chosen, considering it needs a lower implementation in terms of cost and time.
- 6 *Validation*: models are subject to different validation techniques, which are then compared to each other.
- 7 *Spatial exporting of a landslide susceptibility model*: this is a trial to define and validate the terms of landslide susceptibility for a wide area in the likes of hundreds or thousands of square kilometers, based on studies of some fields that represent it.

Having clear that the result of this type of study is intended to provide maps that can be used by planners in a useful manner, these must be characterized by an immediacy in understanding even by non-experts and they must also be easy to read and interpret. Therefore, these methods should be as simple as possible, for example, susceptibility levels must be clearly expressed not only in quantitative but also in descriptive terms (Clerici et al., 2010).

Like many other authors, the purpose of this work is to make a contribution to the scientific community by trying to offer a modest contribution in solving some problems in this field through experiments and modeling carried out in a range of contexts and comparing the results between them.

CHAPTER II. LANDSLIDES

2 LANDSLIDES

2.1 General concepts

2.2 Landslides and their classification

2.2.1 Types of movement

2.2.1.1 Front landslides

2.2.1.2 Slope landslides

2.3 Landslide inventories

2.3.1 Historical analysis of maps, archives and publications

2.3.2 Photo-interpretation of aerial and satellite images

2.3.3 Field-survey: geomorphological mapping

2.3.4 Remote sensing analysis with open-source softwares

2.4 Materials and methods used for producing the landslide archives in the studied areas

2.5 Multi-temporal landslide inventory

2.1 General concepts

Considering the phenomena able to determine the hydrogeological risk conditions and, more generally, the transformation of the landscape, landslides certainly occupy an important role and can be treated as a single type of instability phenomena strictly falling within the class of landslide phenomena, which are characterized by the fundamental role exerted by gravity force in determining the triggering, propagation and arrest mode, and as mixed phenomena *sensu* Castiglioni (1979), in which water not only plays the role of controlling factor (predisposing - trigger) but, through the run-off phenomenon, of the real agent. This concerns rapid flow landslides. The correct

interpretation of the slope phenomena, is a component in the process of building susceptibility models, in which the correct geomorphological reading of the area investigated, as well as the morphodynamics of the phenomena taking place, plays a central role, capable of determining the reliability of the model.

The landslide recognition and classification phase is, in fact, far more critical than the analysis regression and susceptibility model validation. At the same time, a proper selection of factors derives only from a correct interpretation of the preparatory and triggering mechanisms of the phenomena recognized. Whether the aim is to define the status of existing landslides of an area or the propensity to instability of a slope, or make the zoning of a region according to the hazard and/or landslide risk, a fundamental step is the correct identification and classification of forms of instability that occurred, in other words, the construction of a landslide inventory for the area investigated. Today, there are many techniques that can be used to identify the shapes produced by landslides that hit an area, but none of these can be considered conclusive and, by itself, sufficient for the realization of the inventory. In fact, more often, different detection techniques and analysis are combined in order to build the "best" inventory of possible landslides of a specific area and highlight the real state of existing landslides.

For the evaluation of the more suitable technique for the construction of the inventory of instability forms, we mainly considered: i) the objective for which the research is finalized, but, also, ii) the extension of the study area iii) the scale of the maps and aerial photos used as a cartographic base, as well as iii) the publications and the historical information accessible and useful to rebuild the picture of landslides and events that have generated the triggering or reactivation (Malamud et al., 2004).

Depending on the scale of investigation, for example, the final susceptibility map can also be the combined representation of the various types of landslides analyzed without any distinction of types, but on a large scale, it is more appropriate to proceed with the separate differentiated analysis of individual types of landslides to consider the resulting product as a suitable forecasting tool (Chacòn et al., 2006).

A first fundamental choice is linked to the type of classification to be adopted. On one hand, it is obvious to the geomorphologist that it is impossible to bring together different types of motion in a single class, then attempting to justify the distribution of the phenomena with a set of common factors; on the other hand, it's not even useful to imagine the production, for the same area, of a number of models or susceptibility maps equal to the number of the phenomena classes, using the classification systems usually adopted in applied geomorphology. It is therefore necessary to develop a classification system that is both simplified and coherent in morphodynamic and stochastic terms, grouping in the same class phenomena that are controlled by the same set of factors. On the other hand, the geomorphological criteria on which this kind of simplification can change depend on the geomorphological conditions of the specific application area. Therefore, it is necessary to identify useful patterns in the definition of generalized protocols.

2.2 Landslides and their classification

Landslides are natural events in the evolution of an area. They represent a problem and become a danger/hazard when they interact with man and man-made environment. A simple definition of a landslide (Cruden, 1991) describes this phenomenon as "a movement of earth, rock or debris down a slope. "The material involved may be limited to the eluvio-colluvial layer, typically 0.5-3 m (coverage landslides) or involve deeper volumes affecting the rock in place (substrate landslides). It is therefore a phenomenon of rock or debris volume deformation, which emerges in at least one of the surfaces that surround it. The way in which the deformation occurs in different forms depends on the morphodynamics phase that taken into account (posting - spreading - crash) and on the hydrological and geomorphological conditions.

It is therefore possible to define classification systems based on kinematics distinctions (movement type) or related to the type of material involved. As noted by Guzzetti (2006), there is a conceptual ambiguity on the landslides arising from the use of the same term, landslide, referring both to the deposit of landslide (displacement volume)

and the movement of material along a slope or a pre-existing landslide body (Bosi, 1978; Cruden, 1991), in addition to a general confusion that originates from the variable and complex nature of the phenomenon itself (Chacòn et al., 2006), due to profoundly different morphological characteristics, behaviour, state of activity and its evolution.

There are numerous international publications that have been involved at different stages in the problem identification, classification and mapping of landslides which, to date, are available and have been consulted in the preparation of this memorandum: (Varnes, 1978; Hansen, 1984; Carrara et al., 1985; WP/WLI, 1993a, b; Cruden and Varnes, 1996; Dikau et al., 1996; Soeter and Van Westen, 1996; Guzzetti et al., 2000; Amanti et al., 2001). One of the most commonly classifications used today is undoubtedly that of Cruden and Varnes (1996), whose scheme (Fig. 2.1) includes three types of material that make up the slope, before the opening movement/triggering (Carrara et al., 1985), (rock, soil and debris), distinguished on the basis of some geotechnical properties (cohesion, in particular, grain-size and clay content).

From a litotecnic point of view, the following must be understood: i) **rock**, an aggregate of natural mineral grains bound together by high and permanent cohesive forces, even after prolonged stirring in water; for ii) **debris**, an aggregate nature of grains, mainly

TYPE OF MOVEMENT		TYPE OF MATERIAL		
		BEDROCK	ENGINEERING SOILS	
			Predominantly coarse	Predominantly fine
FALLS		Rock fall	Debris fall	Earth fall
TOPPLES		Rock topple	Debris topple	Earth topple
SLIDES	ROTATIONAL	Rock slide	Debris slide	Earth slide
	TRANSLATIONAL			
LATERAL SPREADS		Rock spread	Debris spread	Earth spread
FLOWS		Rock flow (deep creep)	Debris flow (soil creep)	Earth flow
COMPLEX		Combination of two or more principal types of movement		

Fig. 2.1 – Schematic classification of landslides (Cruden and Varnes, 1996)

consisting of elements with a diameter greater than 2 mm, unconnected or maybe disrupted by modest solicitations or shaking in water, for iii) **soil**, an aggregate of grains, consisting primarily of elements less than 2 mm. Certainly the description of a landslide can be developed also by giving information about the status, distribution and style of activity and speed of movement. The classification consists of seven main classes: Falls, Topples, Translational slides, Rotational slides, Lateral spreads, Flows and Complex movements, the latter arising from the simultaneous and combined action of more than one mechanism. The authors distinguish between the flows, translational and rotational types, and among the flows, faster from slower ones (Varnes, 1978; Hutchinson, 1988; WP/WLI, 1990; Cruden, 1991; Cruden and Varnes, 1996).

Cruden and Varnes (1996) consider the term "complex landslides" too general and misleading. In nature, in fact, complex landslides are more the rule than the exception. To avoid this, where possible, the landslides have been identified with a pair of terms thus resulting in composed landslides of: one, indicating the first movement (or the place at higher altitude, where the movements were simultaneous) and the other related to the second movement.

2.1.1 Types of movement

The definition of the type of movement is the most important and common criterion to classification schemes found in literature (Varnes, 1978; Vallaro, 1992; Amanti et al., 1992, 1996; Carrara et al., 1985; Cruden and Varnes, 1996; USGS, 2004). For purely applicative reasons, a typological distinction is made between scarp landslides (crashes, rollovers, expanding) and the slope landslides (sliding, flows). During the exposure of the classification of different types of movement used in this thesis, some of the instabilities recognized and recorded in the areas under study are presented.

2.2.1.1 Front landslides

FALLS: Falls are abrupt, downward movements of rock or earth, or both, that detach from steep slopes or cliffs. The falling material usually strikes the lower slope at angles lower than the angle of fall, causing bouncing. The falling mass may break on impact, may begin rolling on steeper slopes, and may continue until the terrain flattens (Figs. 2.2; 2.3).

The materials move when reaching ground level, if the morphology of the slope allows it, and may continue the movement leaping and bouncing along the slope. The initial detaching, by falling to the ground and subsequently impacting it, can cause an intense crushing of the material involved in a number of elements of widely varying sizes. The material accumulated at the base of the slopes, if morphologically possible, may be involved in subsequent gravitational movements or even, to

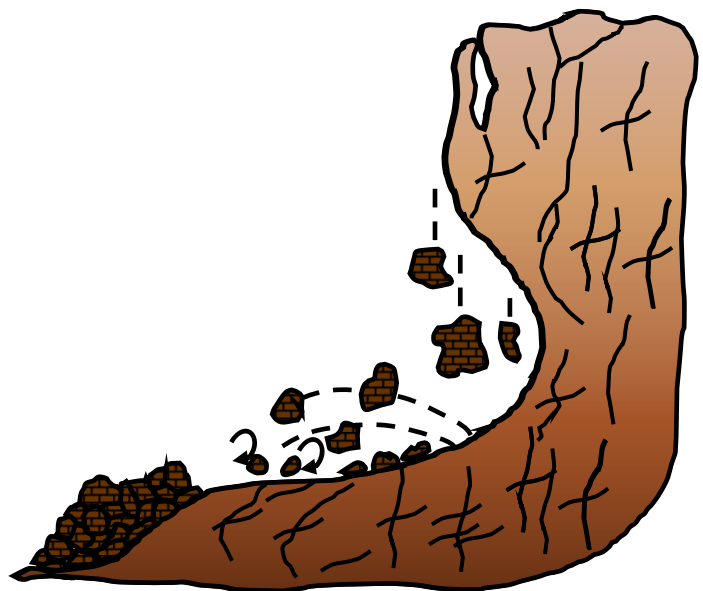


Fig. 2.2 – Schematic model of a rock fall movement (modified after Vallario, 1992)

roll or bounce, able to go through considerable distances. As a result of exceptional weather events, landslides can create fast debris flows.

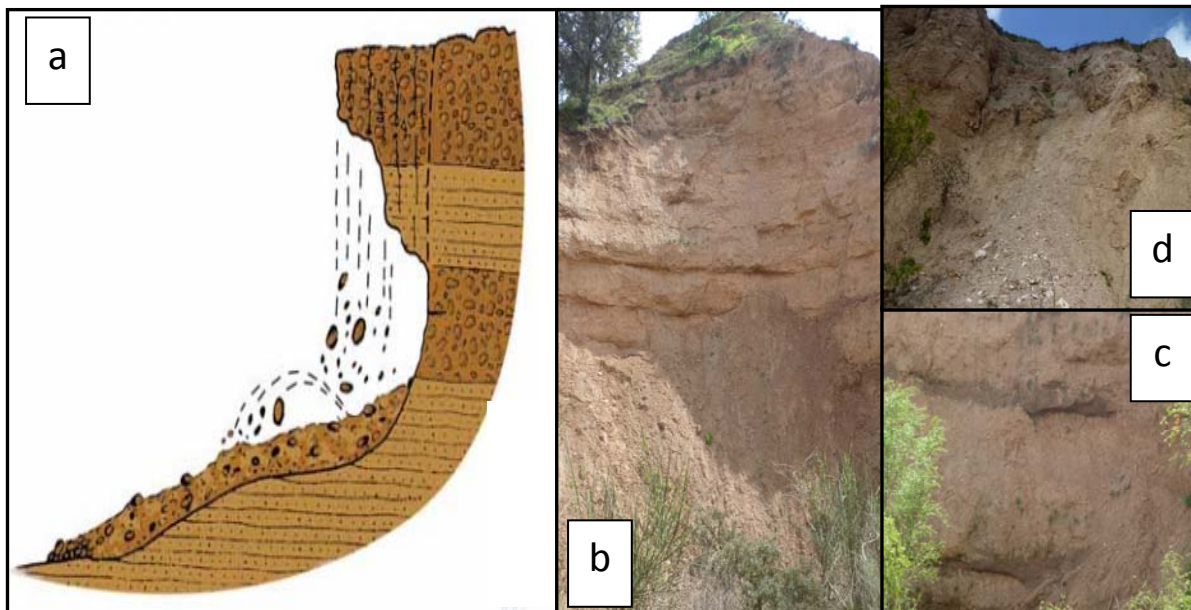


Fig. 2.3 - Schematic model of fall in the over-consolidated soil stratification and present varying degrees of cohesion. The elements, can stop in the impact or be involved in movements for the next bounce or roll (b, c, d) falls in over-consolidated soil Beiro River Basin (Spain).

TOPPLES: A topple (Fig. 2.4) is recognized as the forward rotation out of a slope of a mass of soil or rock around a point or axis below the center of gravity of the displaced mass. Toppling is sometimes driven by gravity exerted by the weight of material upslope from the displaced mass. Sometimes toppling is due to water or ice in cracks in the mass. Topples can consist of rock debris (coarse material), or earth materials (fine-grained material).

The predisposing and triggering causes of these phenomena are similar to those already given for the phenomena of falls, but stand only for the geometry of some families of discontinuities, which must be either sub-vertical and sub-horizontal. The fractures in the upper areas can be filled with rubble or gaping. The speed of a reversal are extremely variable, from very slow to extremely fast, if evolution is in a landslide collapse.

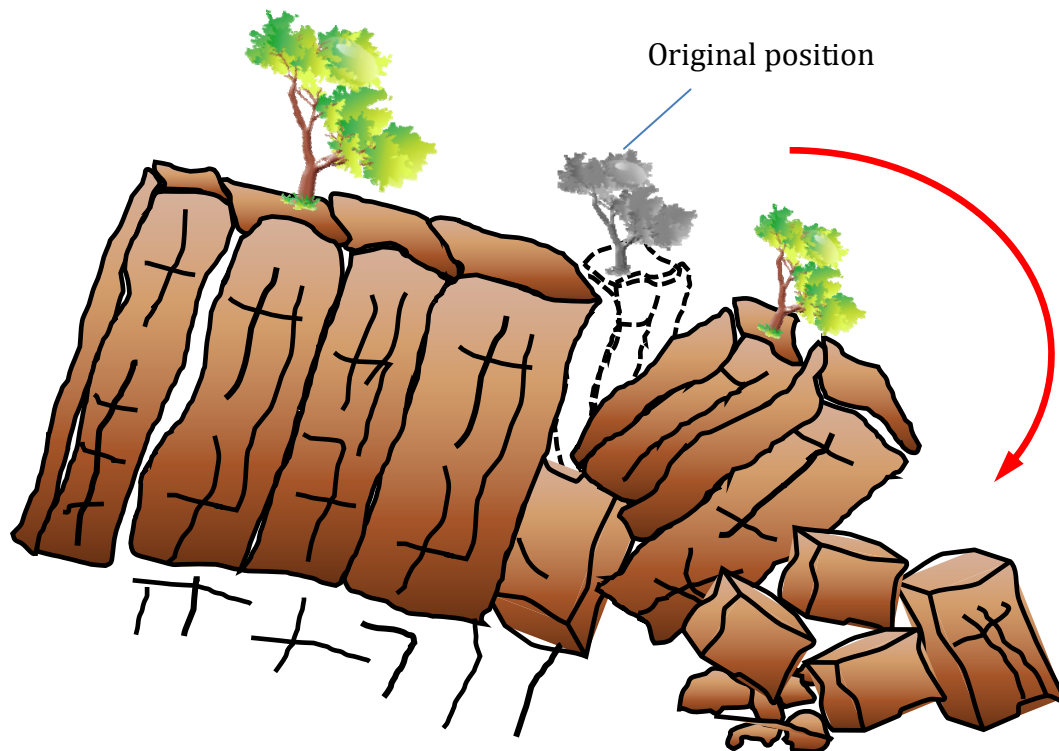


Fig. 2.4 - Schematic model of a topple coherent material intensely fractured (modified after Varnes, 1978).

LATERAL SPREADS: An extension of a cohesive soil or rock mass combined with the general subsidence of the fractured mass of cohesive material into softer underlying material. Spreads may result from liquefaction or flow (and extrusion) of the softer underlying material. Types of blocks include spreads, liquefaction spreads, or lateral spreads. Lateral spreads usually occur on very gentle slopes or essentially flat terrain, especially where a stronger upper layer of rock or soil undergoes extension and moves above underlying softer and weaker layers. Such failures are commonly accompanied by some general subsidence into the underlying weaker units. In rock spreads, solid ground extends and fractures, pulling away slowly from stable ground and moving over the weaker layer without necessarily forming a recognizable surface of rupture. The softer, weaker unit may, under certain conditions, squeeze upward into fractures that divide the extending layer into blocks. In earth spreads, the upper stable layer extends along a weaker underlying unit that has flowed following liquefaction or

plastic deformation. If the weaker unit is relatively thick, the overriding fractured blocks may subside into it, translate, rotate, disintegrate, liquefy, or even flow.

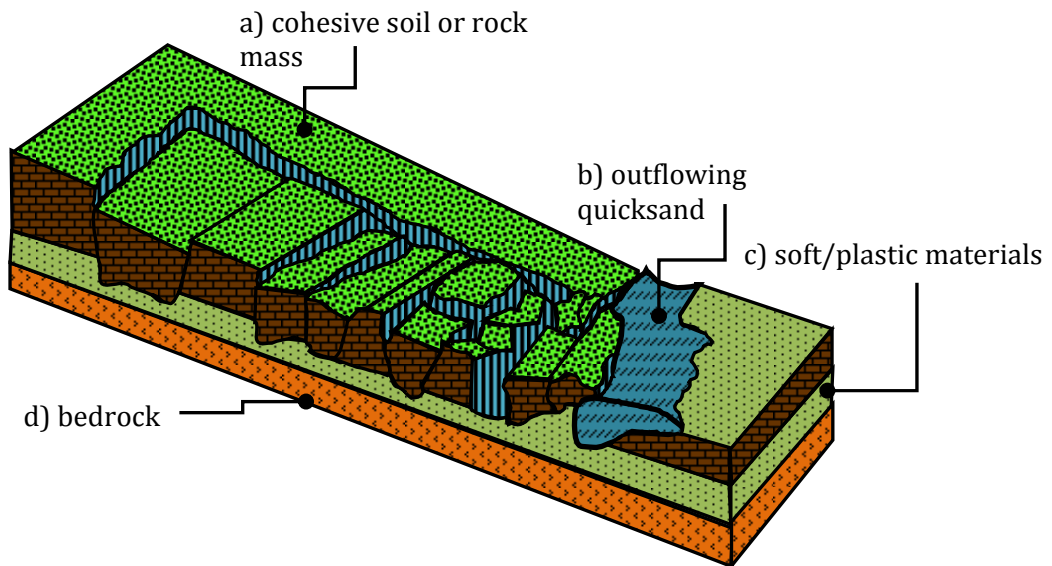


Fig. 2.5 - Schematic model of a lateral spreading. A cohesive soil or rock mass (a) lays on soft materials (c) confined by the underlining bedrock (d), producing the outflowing of soft materials (b).



Fig. 2.6 - Photograph of lateral spread damage to a roadway caused by liquefiable layer underlies road surface.

2.1.1.1 Slope landslides

SLIDES: A slide is a downslope movement of a soil or rock mass occurring on surfaces of rupture or on relatively thin zones of intense shear strain. Movement does not initially occur simultaneously over the whole of what eventually becomes the surface of rupture; the volume of displacing material enlarges from an area of local failure.

Rotational slide: A landslide on which the surface of rupture is curved upward (spoon-shaped) and the slide movement is more or less rotational about an axis that is parallel to the contour of the slope. The displaced mass may, under certain circumstances, move as a relatively coherent mass along the rupture surface with little internal deformation. The head of the displaced material may move almost vertically downward, and the upper surface of the displaced material may tilt backwards toward the scarp. If the slide is rotational and has several parallel curved planes of movement, it is called a slump. (Fig. 2.7).

The moving mass, frequently, breaks down into several blocks, rotating in different directions, both upstream and downstream, which sometimes may remain relatively intact internally, without suffering chaoticization. The landslide mobilized beyond the nail of the rupture surface, overlapping the original underlying soil surface delimiting the foot of the landslide, which may also be interested in consecutive or successive/following movements, for example in case there are lithotypes involved in the sliding with mechanical response predominantly of pseudo-coherent type, it can be recorded as an evolution of the movement in a slow flow. Even the rotational flows can occur in rocks, debris and in the lands.

Speed movement can vary by several orders of magnitude, from a few centimeters per year to several meters per second. According to Varnes (1958) the rotational slides in rock can move at speeds ranging from a few centimeters per year, to several meters per month, while those that occur in soils and land, generally of small size, can reach speeds more than 3 m/sec. Geomorphological elements allowing to recognize a rotational slide, are the presence of longitudinal and/or transversal cracks due to compressional and

extensional movements, a landslide slope particularly evident and the presence of counterslope areas indicating the tilting of the occurred landslide (Fig. 2.8).

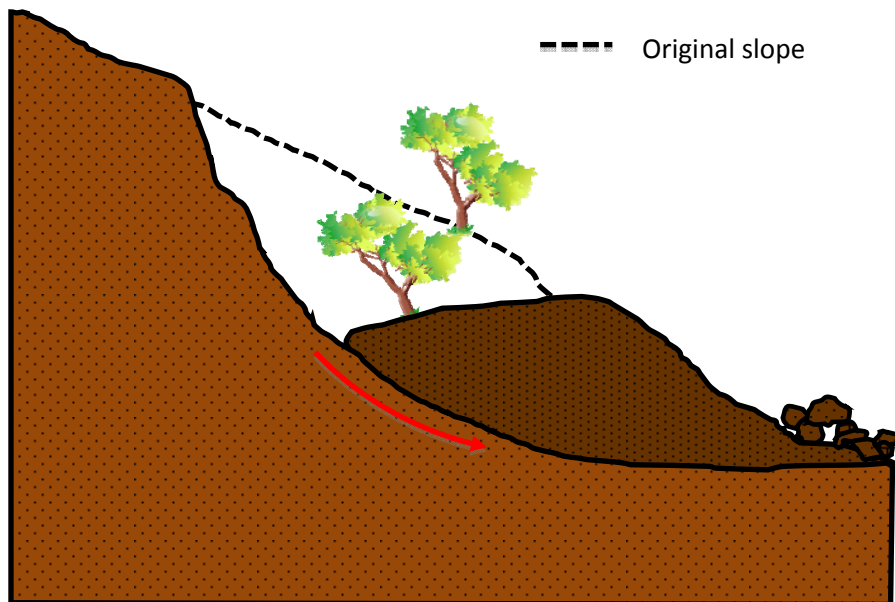


Fig. 2.7 - A typical rotational rock slump occurs when the underlying rock fails due to earthquake movement or a build up of water pressure. A large area of hillside drops down and sideways, leaving behind a sheer exposed wall of earth and rock material ('headscarp').

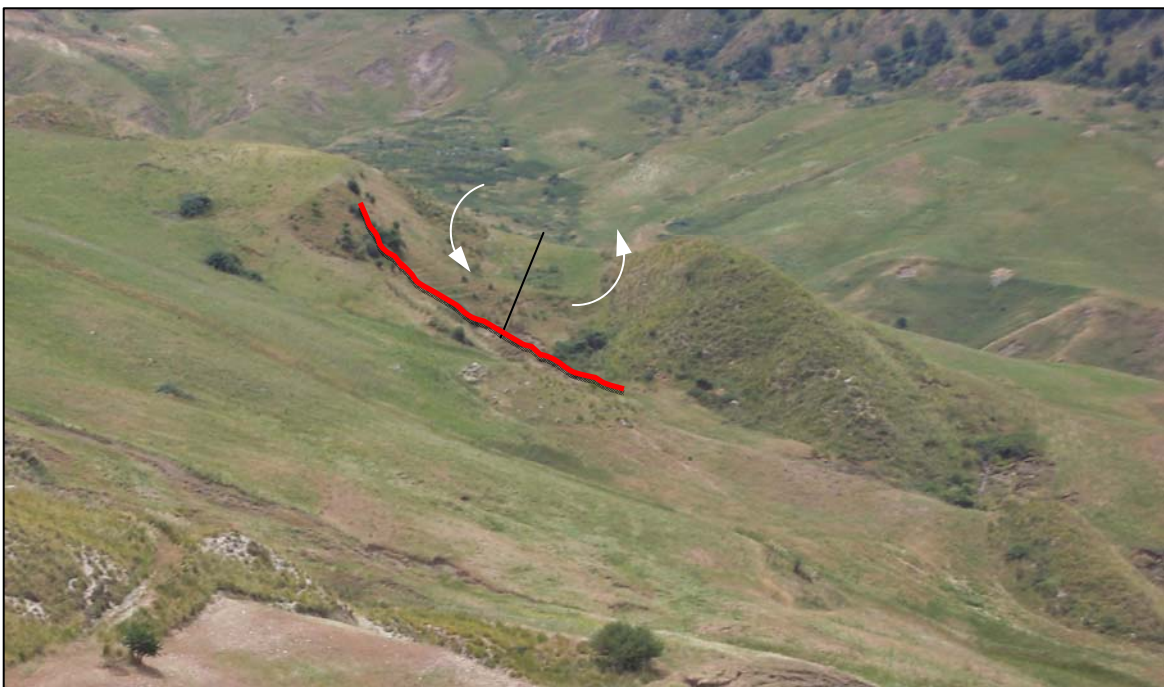


Fig. 2.8 – Rotational component in a landslide. In a sub-basin of the river Platani.

Translational slide: The mass in a translational landslide moves out, or down and outward, along a relatively planar surface with little rotational movement or backward tilting. This type of slide may progress over considerable distances if the surface of rupture is sufficiently inclined, in contrast to rotational slides, which tend to restore the slide equilibrium. The material in the slide may range from loose, unconsolidated soils to extensive slabs of rock, or both. Translational slides commonly fail along geologic discontinuities such as faults, joints, bedding surfaces, or the contact between rock and soil. In northern environments the slide may also move along the permafrost layer (Figs. 2.9; 2.10; 2.11). The dislocated mass can be completely unstructured and disjointed, and remain relatively integrate or broken down into multiple chunks, which can conserve their internal structure.

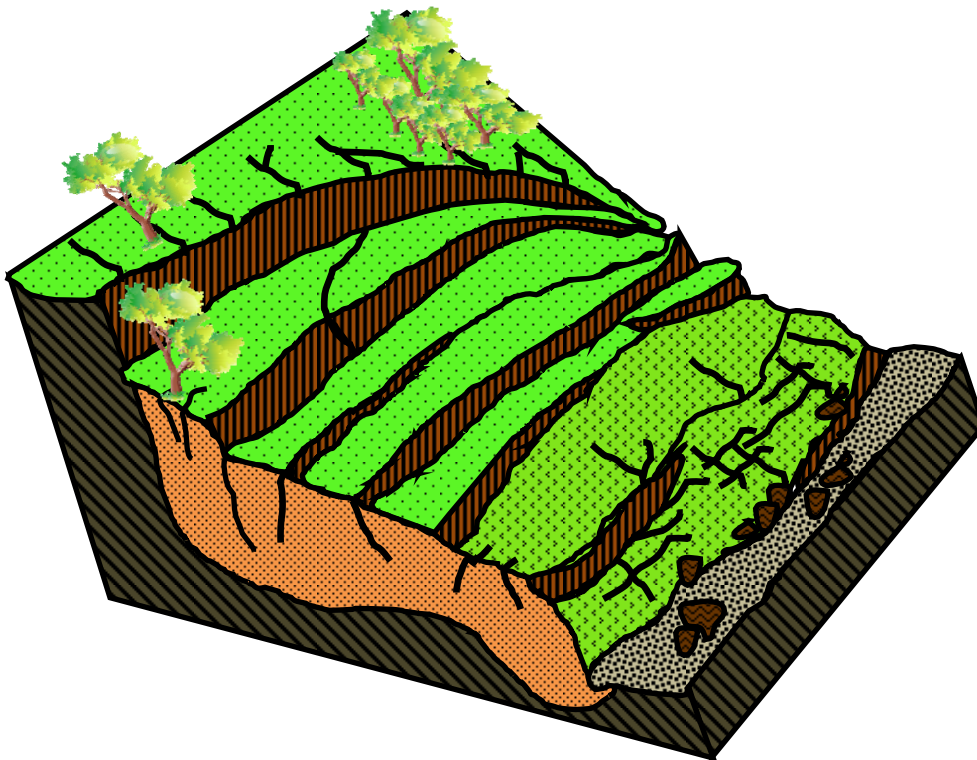


Fig. 2.9 – Geomorphological elements and kinematics of the translational slide, Cartuja-Granada (Spain).

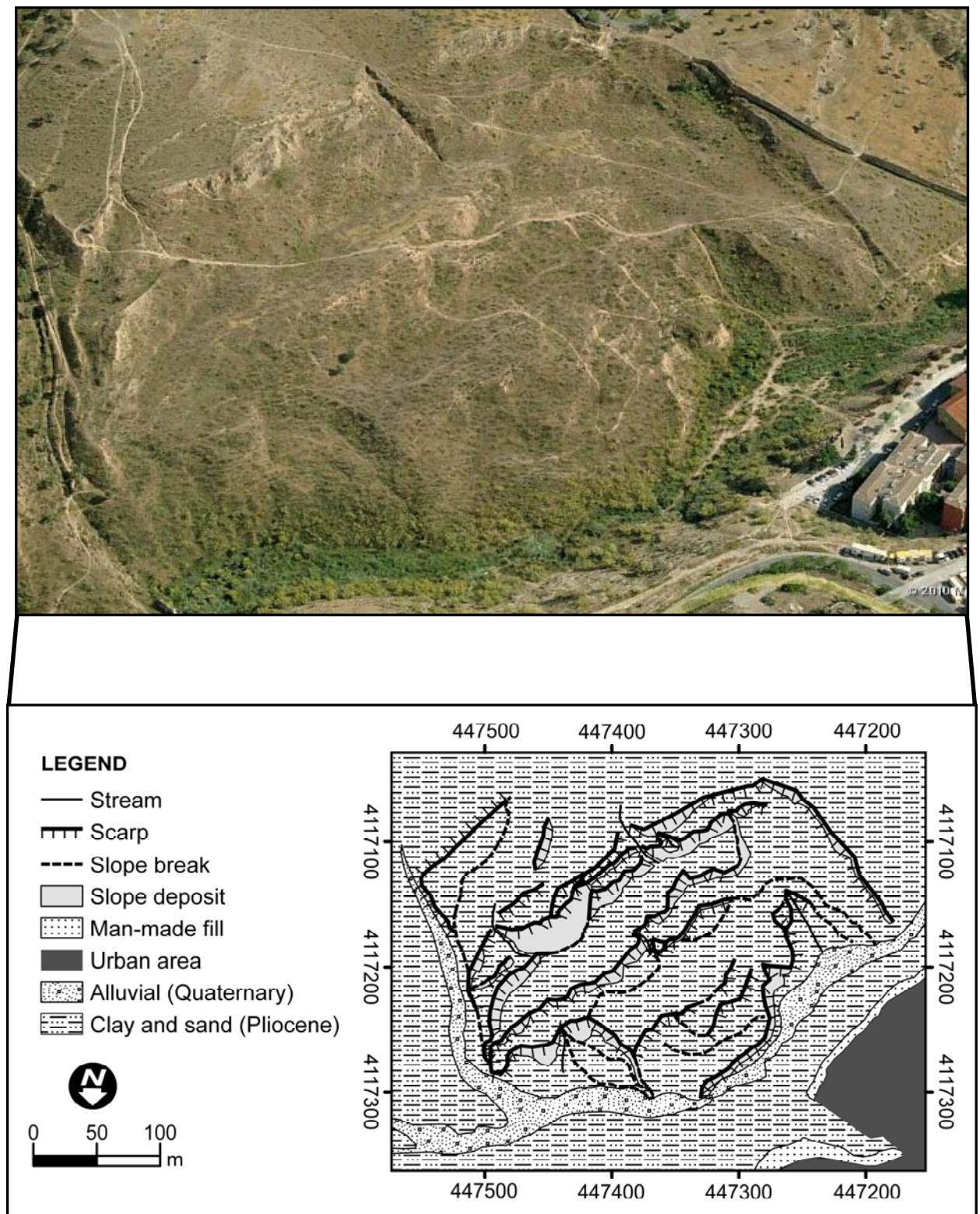


Fig. 2.10 – Geomorphological elements and kinematics of translational slide Cartuja-Granada (Spain)
From Chacòn et al., 2012).

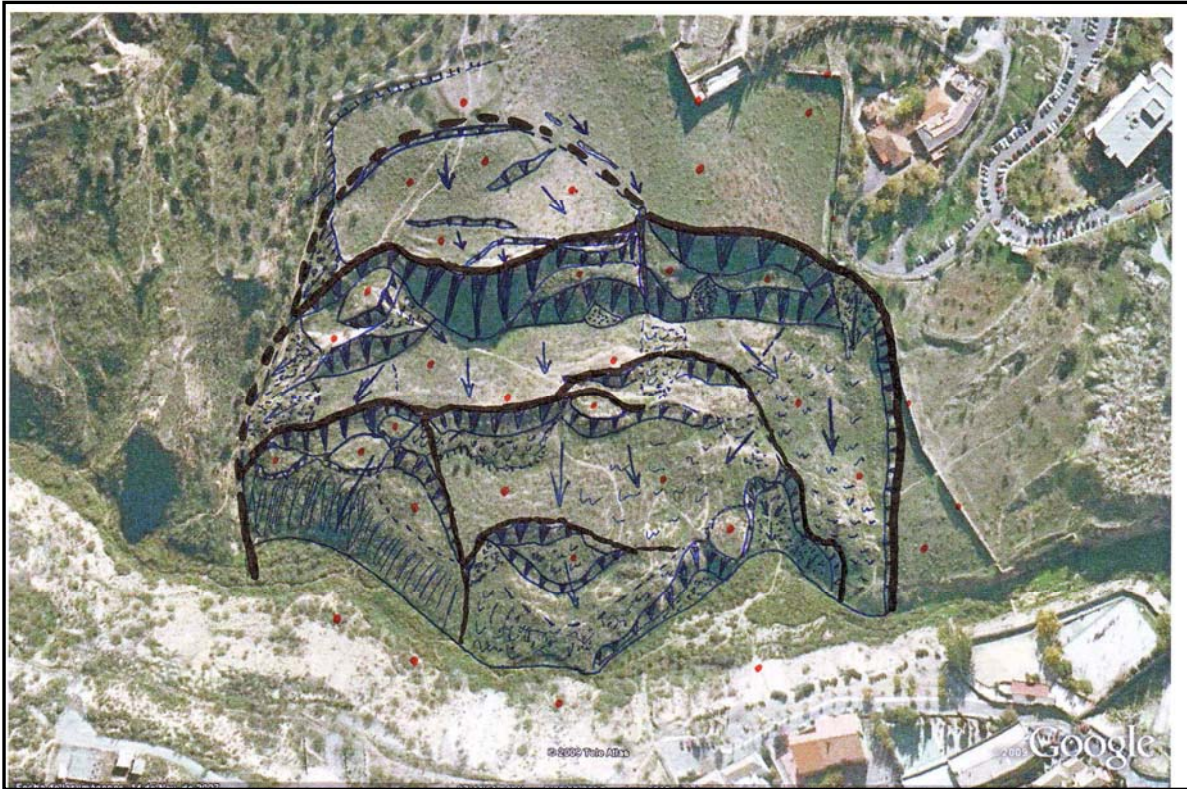
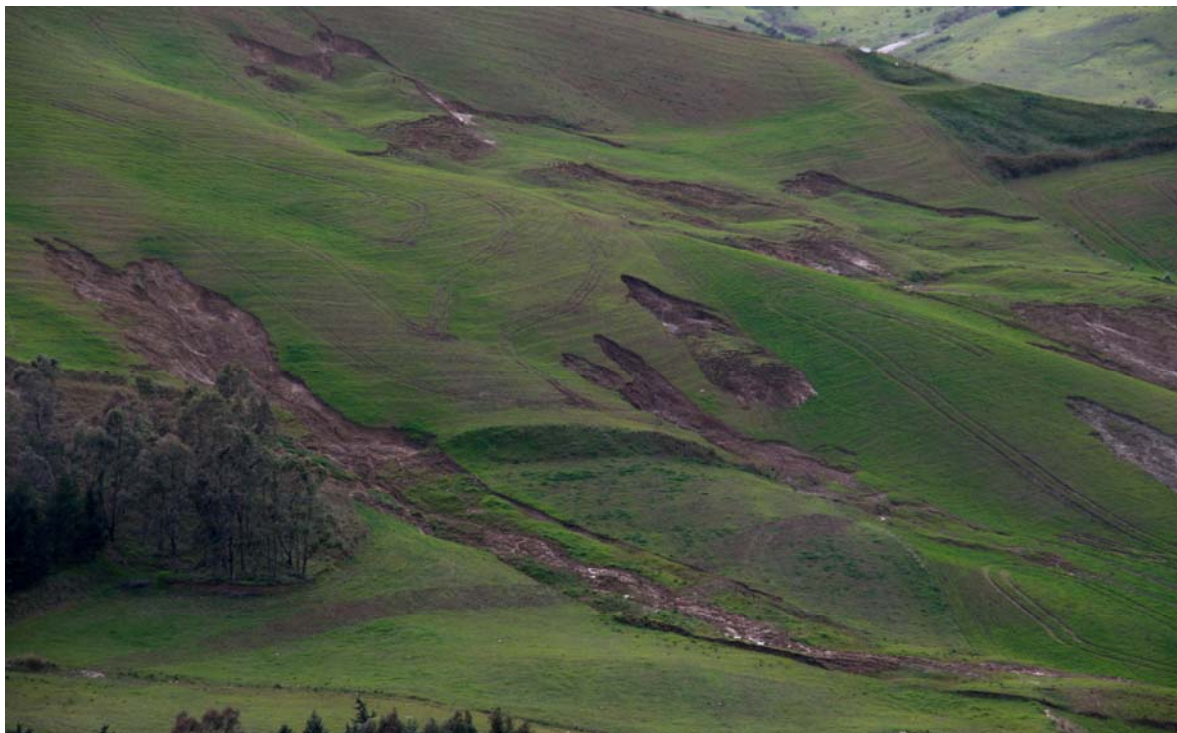


Fig. 2.11 – Kinematics reconstruction of the translational slide, Cartuja-Granada (Spain).

FLOWS: For the types of landslides, described in previous paragraphs, the movement is essentially moving a mass from its initial position, in which the internal deformation of the material moved doesn't necessarily occur. The motion may be in free fall, resulting in a rotation of the mass (rotational slide) or simply slipping down the slope (translational slide). A flow is a spatially continuous movement in which the surfaces of shear are short-lived, closely spaced, and usually not preserved. The component velocities in the displacing mass of a flow resemble those in a viscous liquid. Often, there is a gradation of change from slides to flows, depending on the water content, mobility, and evolution of the movement (Fig. 2.12).



Fig. 2.12 - Examples of surface flow landslides identified and counted in Tumarrano river basin during field-survey in April 2009.



The speed of movement, as well as the gradient of the slope, depends on water content. Since the individual elements that make up the mass move independently, the typical behavior for avalanches is flow of a viscous fluid at different rates for various spatial regions of the landslide. In fact, speeds are greater at the center and surface portions of the mass, while much lower along the edges and in contact with the ground level because friction is greater in these portions. The solid material that feeds a flow consists of clusters of elements of various origins and nature: deposits, alluvial sediments, layers of alteration, plant material, inert products of erosion, etc. (Fig. 2.13; Fig 2.15). For this reason, the grain size of material involved in the flows may vary (Fig.2.14). Varnes (1978) distinguishes according to the fraction and size of the transported material **debris flows** (20%-80% of fragments > 2 mm), **earth flows** (> 80% of particles < 2 mm), **mud flows** if the silt-clay component predominates.

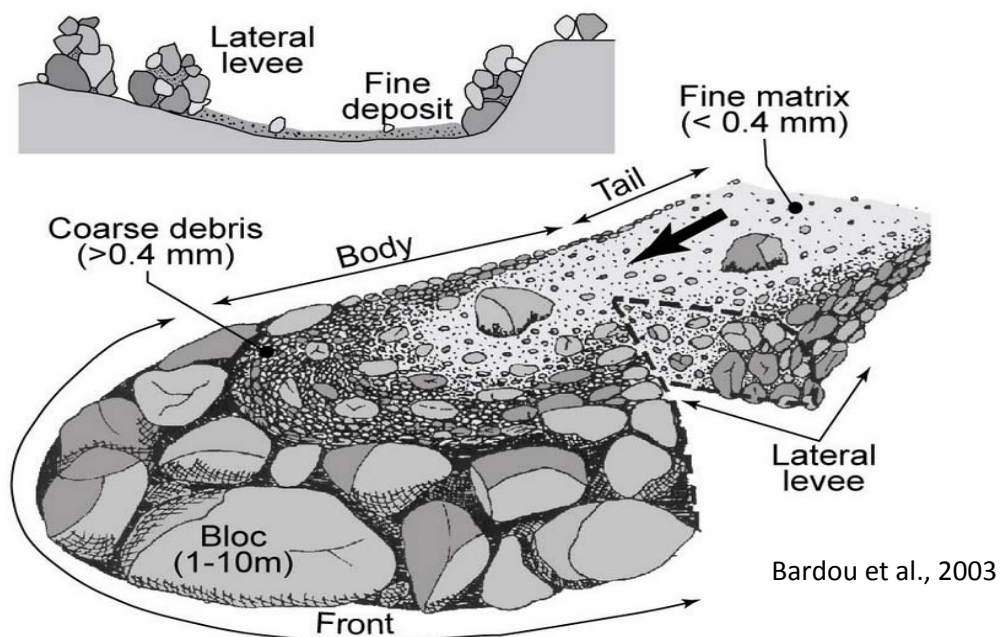


Fig. 2.13 - Scheme of detritic material incorporated in a debris flow

The presence of debris and soil that can be saturated by a fairly rapid intake of large amounts of water in the outcrop area, combined with a high pending of the slope, is a condition that causes the triggering of a movement like flow. A flow of debris in

movement has a high erosive capacity; in fact, it can greatly increase its volume by incorporating, on its way, large quantities of material: large stone blocks, whole tree trunks, artefacts, etc. The debris flows have a huge destructive power that depends on the distance travelled by the material, the speed of the unstable mass, the quantity and size of the debris transported.



Fig. 2.14 - Representation of detritic material incorporated in a debris flow.

From a morphological point of view a debris flow can be conventionally divided into three zones: the initiation area or triggering, represented by high-gradient/pending from an area where the phenomenon has its origin, ii) the flow or transport area, often an existing furrow erosion, in which the debris flow propagates, enriched with new material as digging the bottom and the sides; the accumulation area, which is the storage area generally located at the foot of the slope. The storage area, often recognized as a fan that opens on the lower slope below ground and larger items that accumulate on its surface and the front edge (Fig. 2.16).

Cruden and Varnes (1996), divide the debris flows into: channelled (channelized flows)

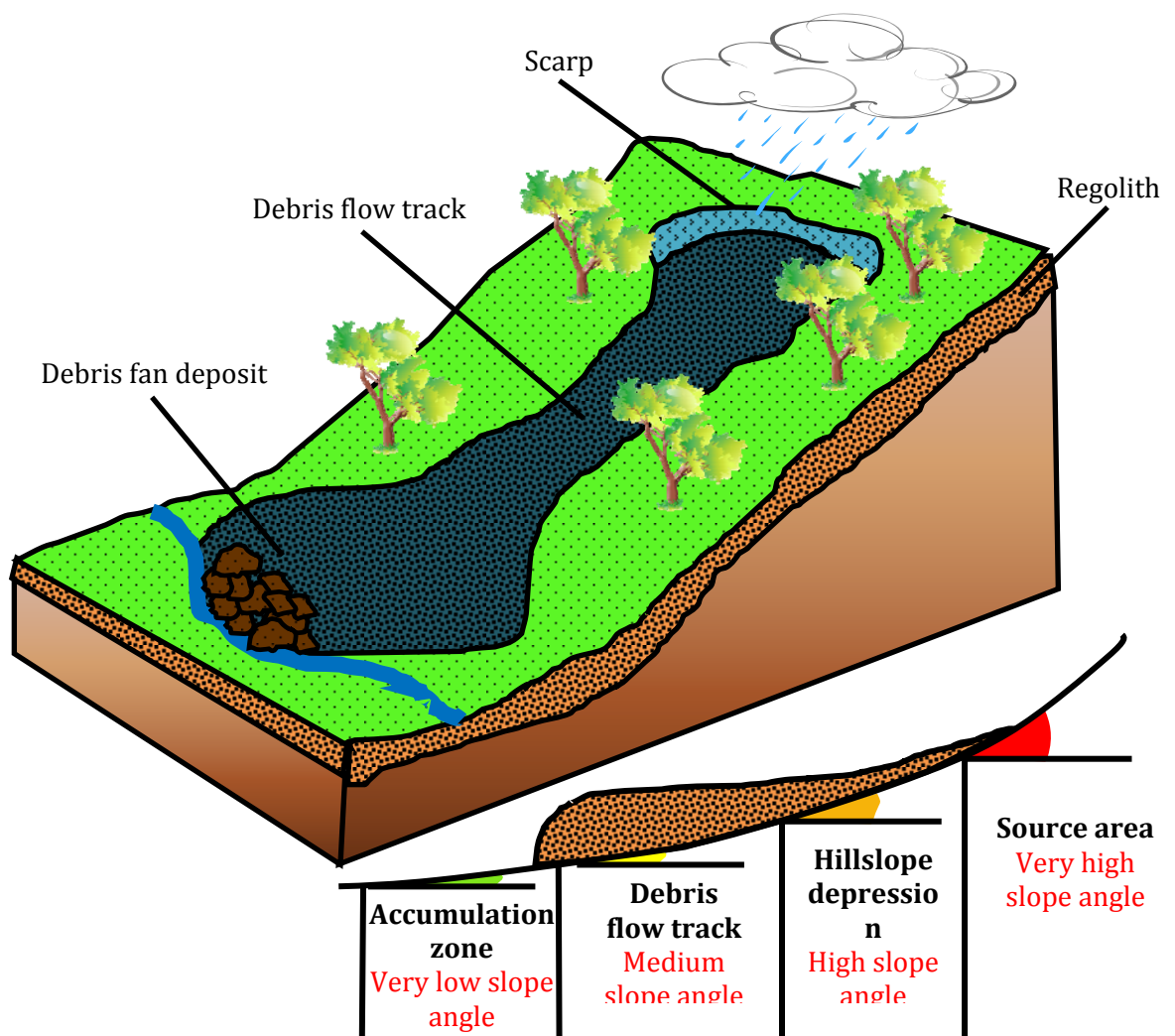


Fig. 2.15 - Different parts of a debris flow movement.

and non-channelled (open-slope flows), the difference between the two types can be seen especially in the flow area, because the “open-slope” flows spread in a less concentrated way on the slope, creating also a very large transit area. Then, depending on the morphology of the area, water availability and the size of the elements that constitute it, the debris flow can be deposited at the foot of the slope, often obstructing the course of a river becoming a dam or natural embankment, or it may continue to slide turning into a channelized debris flow.

Debris flows are triggered usually after a rain of high intensity and they represent a class of "one-shot" movements. For this reason, challenging and complex in hazard and risk associated studies are complicated.

The term "rapid flow" (rapid flow) is used to represent the complexity of the kinematics of a series of landslides, which has several different types of motion/movement that characterize the different phases and, therefore, portions of the slope in which these phenomena are produced. Whatever the specific dynamics through which it generates instability and makes the initial/triggering movement, the prevailing characteristics of the analyzed phenomena lie in the fact that the downstream propagation mode of the

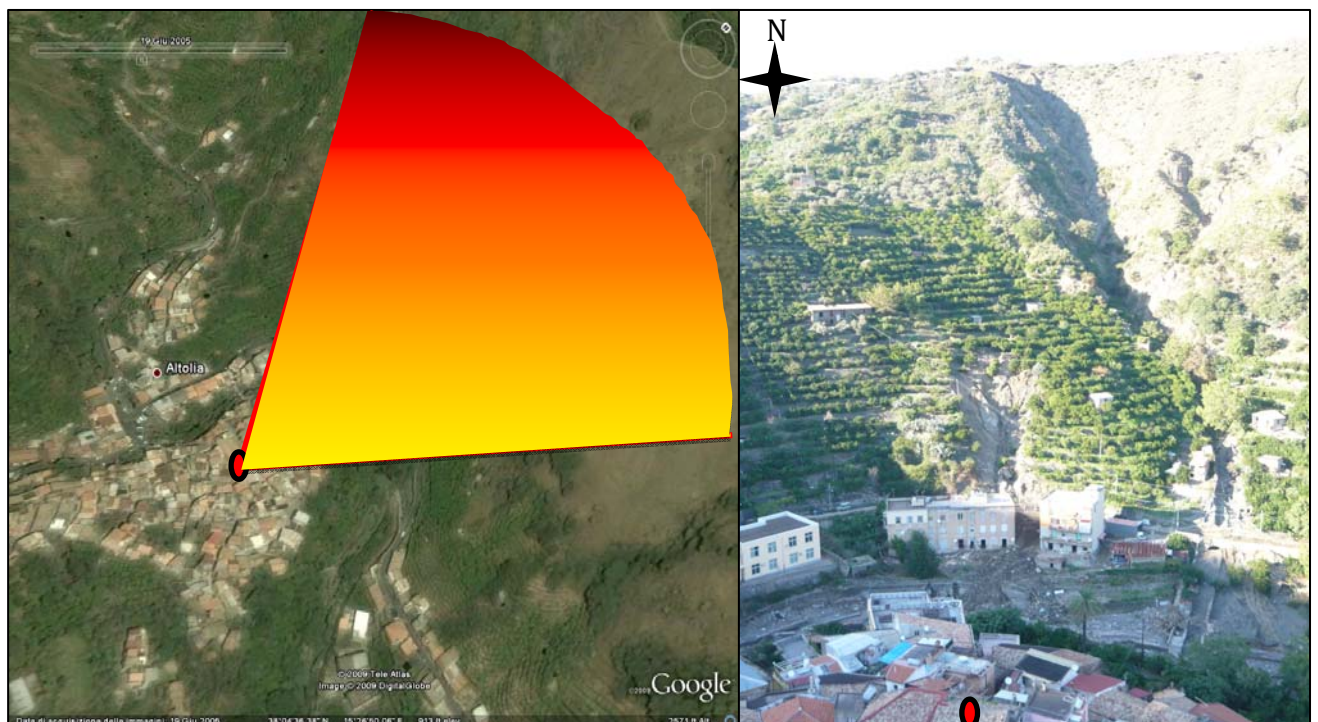


Fig. 2.16 – First in October 2009. View of some of rapid debris flows that triggered on the slopes and then channeled into the river below in full for the heavy rains. The material is then set in motion is propagated downstream with increasing speed, increasing its volume.

phenomenon are very similar and are better represented in terms of geomorphological features such as rapid flow of debris various in size.

With regard to the initial movement that causes the activation, based on the morphometric characteristics of the crown and the supplying area of deformed volumes, triggers for *flows* and triggers for *slides* are recognized, without excluding the case of mixed mechanisms (*flow slides*). The way in which the movement takes place generally depends on the initial water content, the morphometric characteristics of the slope and the structural conditions (thickness and geometry) that the hydrological/geomorphological system, cover/bed rock presents. The triggers for flows



Fig. 2.17 – Overview of a slope affected by the rapid development of multiple debris flows coalesced, triggered during flood event that hit the town of Altolia (Me) in 2009. The material in question coincides with the layer of loose material. These materials are often placed on very steep slopes and in poor stability, in association with intense weather events, dangerous flows of feed with a high destructive power.

are determined by the detachment of a mass of debris in conditions of high or complete water saturation. Under these conditions, due to the increase of mobilized resistance, there is the sudden collapse of resistance available along a fringe, usually shallow (Fig. 2.18a). In general, flow type movements (*slide*) are triggered when the depth is limited to a few tens of centimeters (a frequent condition at the head on the slopes), a surface of regular discontinuity and parallel plane



Fig. 2.18 – Examples of rapid flows of debris flow (a) and debris slides (b).

to the topographic surface (Fig. 2.18b). In these conditions, the detachment is modelled with a translational sliding breaking, which can follow an intermediate evolution for *flow slide*, linked to the remodelling that the mass of debris and mobilized water undergoes, of impact on the movement plane, or better, directly to the *rapid flow* phenomenon.

In the case of flow phenomena, in the initial failure mechanism, the generalized loss of cohesion of the medium prevails, which makes the whole mobilized mass able to move like a viscous fluid on the surface of the slope.

Regarding the mechanisms of initiation/triggering, there are three fundamental modes of initiation: a) increase of the mobilized resistance and collapse of the resistance available; b) lateral undermining or to the foot; c) *piping*.

The collapse of the resistance available is made at a surface or fringe of rupture, which has a longitudinally concave morphology, characterized by the presence of a main stream of rupture, which is a reference axis for the efforts related to the cover load and, in parallel director of a hypodermic runoff water booster. In this case, parallel or throttled landslides are formed (with hourglass symmetry), with arched crowns and

rotation centers located along the "axis of rupture" (Fig. 2.19). However, when the geometry of the rupture surface is controlled by a separation plan between the cover and the bedrock, then there is slide activation and the development of triangular or trapezoidal symmetries in landslides.

A linked trigger instead of the interaction of multiple phenomena, in which the onset of the trigger activation forms a chain of one or more other phenomena, can be to the



Fig. 2.19 - Activation for loss of cohesion (a), undercutting (b) and *piping* (c).

incision to the foot or side of a slope unit, operated by the propagation of a fast flow. A similar action could be carried out by a stream or watershed line along which there is a hyper-concentrated flow (Fig. 2.19b).

The high water content is responsible for deformation, in which the constituent elements of the mass involved are nearly free to move around each other. The modest initial thickness and the deformed high volume flow determine an increased topography control towards the kinematics of the phenomenon (Fig. 2.20). In some cases, when the movement is triggered under conditions of reduced saturation, a phenomenon more similar to a visco-plastic deformation can be observed, in case the role of topographic control is lower (Fig. 2.20).

The shape of the crown may be a diagnostic morphometric element indicating an trigger type. (Fig. 2.20 a, b), although straight crowns can be observed (Fig. 2.20 c, d) as a result of a clear control exercised by the topography and in particular by the presence of the upstream sector of sub-horizontal surfaces of crowns, which play an important role in accumulating and channeling large volumes of water inside the cover. A slide type of initial movement is a possible match to open crowns (Fig. 2.20), which often follow the transport areas of nearly uniform width (ribbon landslides). In contrast, arched crowns are associated with flows movement types, at least in the initial section.



Fig. 2.20 – Examples of flows triggered by rapid flow with arched crown (a, b) or straight (c, d)

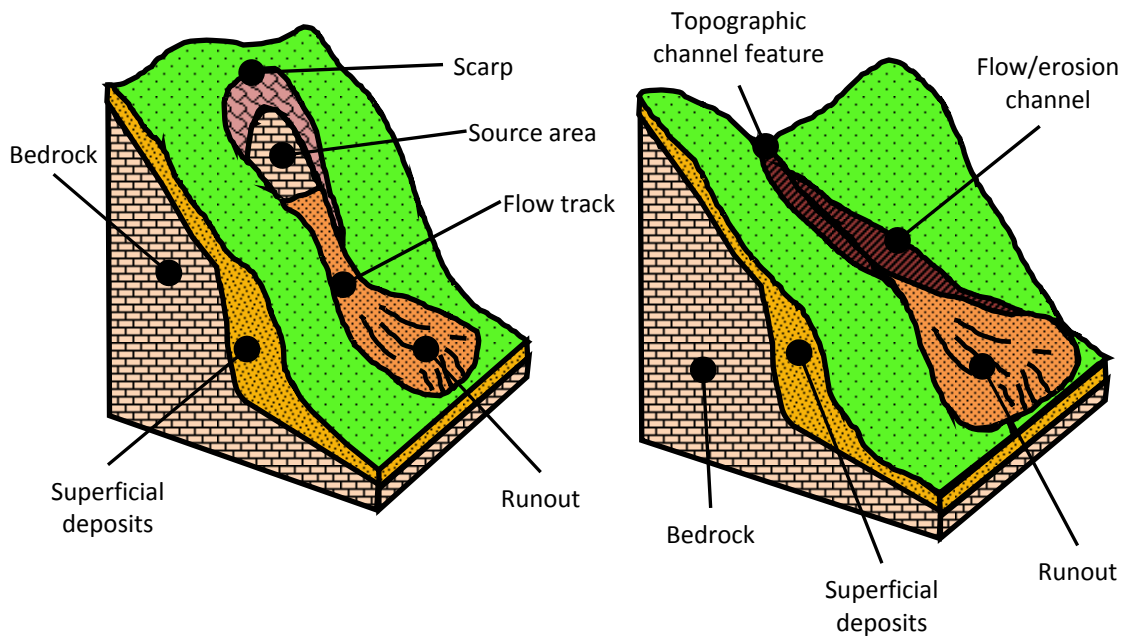


Fig. 2.21 (top) - flows with crown of debris avalanches associated with rectilinear flow and geometry box-activation (a, b) Landslides of the slope (c, c ') and channelized landslides (d, d'). Figure 2.22 (bottom)-Hillslope (a) and channelised (b) debris flow.



Fig. 2.22 - Individual landslides (a) multiple parallel (b) multiple confluent (c) and multiple convergent (d, e).

As previously mentioned, there are several classifications in the international literature that can be used to identify and index the instability of an area. A widely used classification is shown below in figure 2.23.

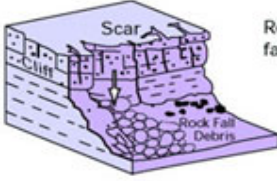
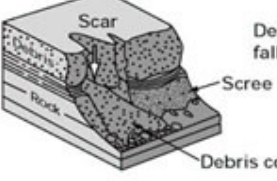
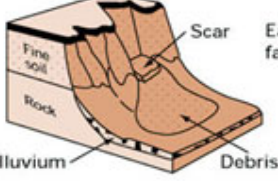
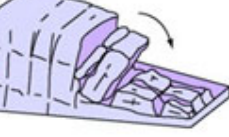
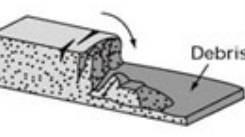
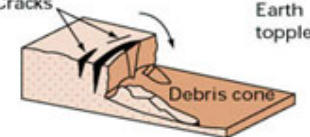
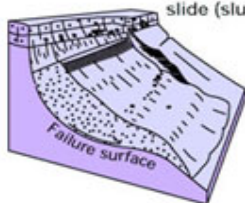
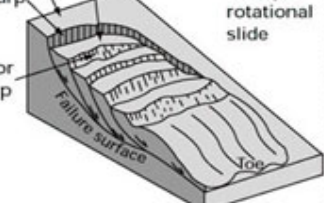
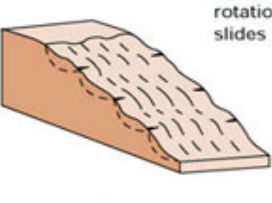
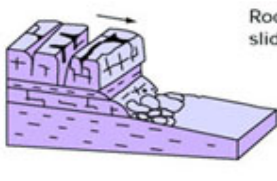

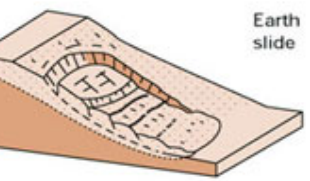
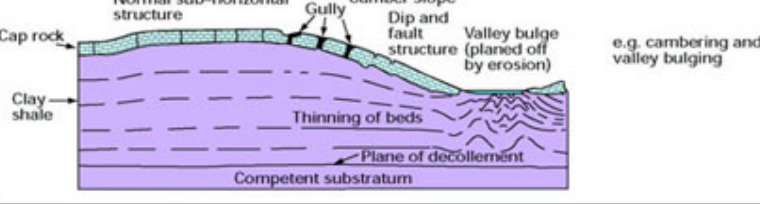
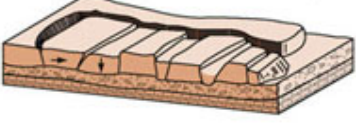
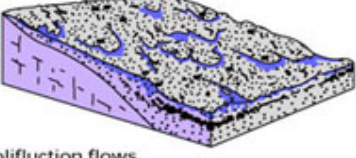
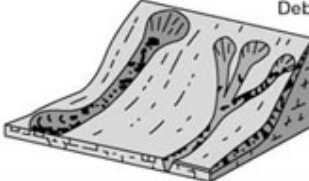

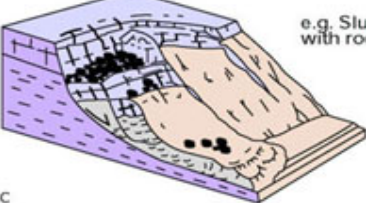
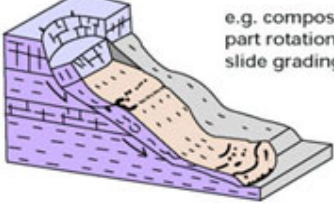
Material		ROCK	DEBRIS	EARTH
Movement type				
FALLS		 <p>Rock fall</p>	 <p>Debris fall Scree Debris cone</p>	 <p>Earth fall Scar Fine soil Rock Colluvium Debris cone</p>
	TOPPLES	 <p>Rock topple</p>	 <p>Debris topple Debris cone</p>	 <p>Earth topple Cracks Debris cone</p>
SLIDES	Rotational	 <p>Single rotational slide (slump) Failure surface</p>	 <p>Multiple rotational slide Crown Scarp Head Scarp Minor Scarp Failure surface Toe</p>	 <p>Successive rotational slides</p>
	Translational (Planar)	 <p>Rock slide</p>	 <p>Debris slide</p>	 <p>Earth slide</p>
SPREADS	 <p>Cap rock Normal sub-horizontal structure Clay shale Thinning of beds Plane of decollement Competent substratum Gully Camber slope Dip and fault structure Valley bulge (planed off by erosion) e.g. cambering and valley bulging</p>			 <p>Earth spread</p>
FLOWS	 <p>Solifluction flows (Periglacial debris flows)</p>	 <p>Debris flow</p>	 <p>Earth flow (mud flow)</p>	
COMPLEX	 <p>e.g. Slump-earthflow with rockfall debris</p>		 <p>e.g. composite, non-circular part rotational/part translational slide grading to earthflow at toe</p>	

Fig. 2.23 – Classification type of landslide (Modified after Varnes, 1978 and DoE, 1990).

2.3 Landslide inventories

The construction of the inventory of landslides that occurred along the slopes is a fundamental and essential condition for the application of statistical models designed to estimate the probability that new activations may be of interest to areas not previously investigated. The recognition of landslides is carried out through the identification of morphological changes on the soil that the gravitational events generate and leave after having exhausted their motion/movement, which are classified and mapped. Depending on the different types, different geomorphological indicators are sought to demonstrate the occurrence of a landslide according to the principle that similar landslides in their manifestation on the soil will leave such evidence of their passage. The morphological indicators help an expert geomorphologist also to obtain information about the status of the activity, on kinematics, time of activation, and also the volume of the masses involved. The interpretative contribution by a technician in the recognition of landslides implies a certain degree of subjectivity of the archives made that can lead to an error of the estimate of the susceptibility and to the lower reproducibility of the model.

An inventory of landslides commonly represents the sum of all the events that occurred in an area. Alterations to the slope profile that testify the occurrence of a landslide tend, over time, to be less evident because of erosion, new landslides, human activities, vegetation, making the limit "in landslide/not in landslide" difficult to detect with the passing of time. Generally, "newer" phenomena generated as a result of recent heavy rainfall or earthquakes, are more easily identifiable and interpretable from the most remote ones, in which diagnostic elements begin to dissolve. Normally, when the investigation takes place in order to map the landslides that have been activated shortly before the acquisition of images of a given area, the geomorphologist has definitely an advantage in recognizing the boundaries of the mass dislocated, because they are much more recognizable because of the colour contrast significantly present, especially in the case of small surface movements activated along the slope of such flows and scrolling of the covering material. Contrary to the neo-activation of landslides, the recognition and classification of older and deeper movements is more difficult because the boundaries

between mobilized slope mass and stable slope have no sharp boundaries but are characterized instead by a gradual transition.

Usually, the methodology used for identification and inventory of landslides, has always been i) geomorphological mapping carried out with direct field surveys. This is generally associated to ii) photo-interpretation of aerial and satellite images along with the iii) photo analysis and historical archives have provided in the past the main support for the construction and implementation of landslide archive. More recently, there are new technologies iv) remote analysis of satellite photographs of the territory that leverage the open-source programs such as Google Earth™, Bing Maps 3D, etc. (Conoscenti et al., 2009, Costanzo et al. 2011a), or based on v) analysis and processing of data acquired by radar, the interpretation of spectral images at high resolution (Guzzetti et al., 1999).

The accuracy and reliability of an inventory of landslides, is directly dependent on the quality of information sources (Guzzetti et al., 1994; Ibsen and Brunsden, 1996; Glade, 1998, 2001; Cruden, 1997; Glade, 200). After the recognition phase of the landslide perimeter, the information obtained must be transferred to a GIS environment to be treated statistically with calculations for susceptibility evaluation. This is therefore necessary in a phase of digitization of the instability forms and it is certainly not an easy task, actually prone to error (Malamud, 2004). During this phase, the geomorphologist should be able to position the recognized instability forms, on the digital cartography in a GIS environment, helping with the natural elements (hydrography, topography, vegetation, etc.) and man-made elements (buildings, various infrastructures, etc..) in the territory. The error depends on the work scale. For example, even an error of 1 mm, in placing the confines of a landslide on a 1:25000 map, corresponds to an inaccuracy of 25 meters above ground level; this appears to be more significant for small to medium-sized landslides. The accuracy and detail of the inventory is directly subject to the work scale. In fact, working on small scales, for regional studies (> 1:1 million), the inventories can be simplified by providing an overview of the degree of landslides in a region. For larger-scale studies (1:5000 - 1:25.000) we can obtain a more precise distinction, for instance the scroll area of the accumulation zone and the escarpment, which represent

practical information to gain a deeper understanding of the essential movement for landslide hazard studies.

2.3.1 Historical analysis of maps, archives and publications

A key step in the realization of the inventory of landslides is undoubtedly the census and the collection of existing and accessible data spread between the various bodies involved in land management (municipalities, provinces, river basin authorities, regions, government agencies, ministries, Universities, etc.). Of course there are several sources and the information available is not always complete and also redundant in some cases, making it unusable. If, on one hand, today we have proper information available at research institutions and land management, in the form of substantial and increasingly detailed databases with respect to geological, climatic, soil and topography (DEM), often in digital format already and geo-referenced, nonetheless a strong problem arises for the databases related to the slope failures. Several experiments have been conducted in this area: S.C.A.I. (Study of Unstable towns), the A.V.I. project (Inhabited Vulnerable Italian), the I.F.F.I. Project (Italian Landslides Inventory) and the establishment of regional Basin Authority which, however, typically provide a degree of reliability, precision and, above all, the temporal consistency of the archive that suggests as necessary for forecasting purposes, to conduct further specific surveys (remote and on the surface) for areas of interest. These sources generally have incomplete coverage and usually are limited to those areas in which the movement has produced some damage, or have some significance in terms of social infrastructure (Ibsen and Brunsden, 1996). In this sense, it is necessary to balance the need to build sufficiently reliable landslide archives as well as chronologically consistent with the high cost of time and money invested, resulting from the implementation of systematic surveys on the surface.

2.3.2 Photo interpretation of aerial and satellite images

The Earth's surface can be observed from above, and this allows us to appreciate the existing relationships between different objects and the spatial relationships between different territorial phenomena. The advantage of photo-interpretation is that of being a rapid and effective analysis method of the territory, through which it is possible to locate and characterize the areas affected by landslides with a reliable degree of accuracy.

The use of the photo-interpretation method is, without doubt, an appropriate investigation instrument, at each stage of building the landslides inventory. Photo-interpretation is the main source of data for the exploration of the territory. National and regional administrations have acquired aerial survey covers over several decades that can be easily consulted. The photo-interpretation technique of aerial and/or satellite pictures is a very complex experimental phase, mainly based on the experience and the operator's ability to identify and recognize landslides from remote images of the earth's surface. The success of this phase of analysis is directly dependent on the geometric resolution of the images and requires experience and training as well as a systematic methodology with well-defined and objective shared criteria interpretation (Speight, 1977; Malamud, 2004). The photo-geological survey was one of the techniques used to build the instability inventory of the areas under study. This type of analysis has been done through the use of heat digital aerial images at a 1:10.000 scale (flight 2008-0.25 resolution/pixel) of the survey area, with which it was possible to have a sufficient interpretation of the territory with regard to identification of landslides with a margin of error that can be considered satisfactory. The image analysis of an area gives the possibility to recognize shapes and contrasts not easily identifiable on the soil/land: in the field-survey the observation point, usually not too high, results in a narrow and deformed vision of the study area.

Enlargements of the original images are often used, because the aerial survey of the filming reaches high resolution, recording the smallest features/peculiarities of the landscape.

2.3.3 Field-survey: geomorphological mapping

In the research carried out for the realization of this thesis, the field work/survey is mainly used for the verification of suspicious disruption forms recognized during the photo-interpretation. The field survey, carried out also, when possible, by means of direct access to public areas, has confirmed the validity of photo-interpretation. This type of geomorphological mapping, allows you to see easier the main escarpments, lower slopes and secondary fracture compression, extension, exposed surfaces, and other geomorphological elements that allow an update of the state borders and the evolution movement, and collect more data on the volumes involved and other useful information for hazard estimation..

2.3.4 Remote sensing analysis with open-source software

In recent years, traditional techniques have been accompanied with more advanced techniques that exploit the potential of software used for the restitution of aerial photos (Google, BingMaps3D and others). The use of these types of applications based on a 3D-view, simplify the recognition and the direct perimeter of the landslide. In Chapter IV, Costanzo et alii (2011a) show the results of the research conducted in Sicily, aimed at verifying the possibility of determining conditions for landslide susceptibility within a sample catchment area, using the system (software database and photo-satellite images) Google Earth™ that seems to provide a medium/means of great interest within the forecast, due to the extreme speed/rapidity of access to information, flexibility of management and analysis of 3D images, to the immediate connection with the GIS systems the ability to select an area for longer periods of relief.

These programs are particularly suitable because:

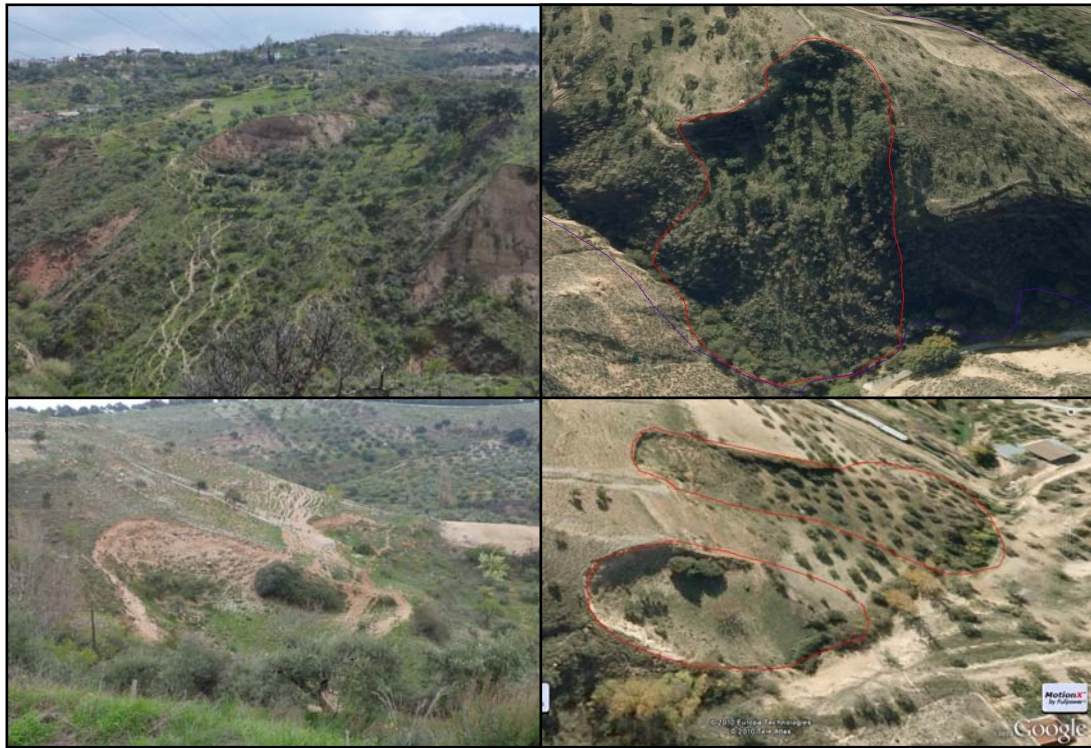
1. They are characterized, already, by air coverage with high spatial resolution images for most of the planet.
2. They allow rotating the point of view and digitizing directly during the interpretation phase of the movement shape.

3. The coverage is updated with a certain constancy and there is the possibility to capture images and therefore movements of different manifestation to build time archives.

Here (Figs. 2.24) are some examples showing that despite having used the free version of Google Earth, this has proven to be an ideal tool for locating and mapping geomorphological processes.



Figs 2.24 - Different techniques of pattern recognition, gravitational using open source software and traditional techniques; a, b) Beiro river basin; c) Platani sub-basin.



2.4 Materials and methods used for producing the landslide archives in the studied areas

The construction of landslide inventories for this research was carried out using remote sensing analysis techniques (aerial photogrammetry, systems like Google Earth™) and direct field-survey. Relying on the computerized landslide archives already available in Sicily (landslide Inventory in Italy - IFFI and Excerpt from the Basin Plan for the Hydrogeological asset - PAI), we proceeded in the study areas to a homogenization of the data structure transferring PAI data on IFFI, at least at the first level. Furthermore, using the 2007-2008 flight (analyzing both the aerial photos and orthophotos), an update and homogenization of the archive time was carried out. The classification of landslides adopted (Fig. 2.25) has been defined on a kinematic basis, distinguishing the landslide based on the estimated speed (fast and slow landslides) and the depth of the volume involved (distinguishing cover landslides from substrate landslides). A differentiation is then proposed according to the characteristics of the material involved (rock / debris / soil).

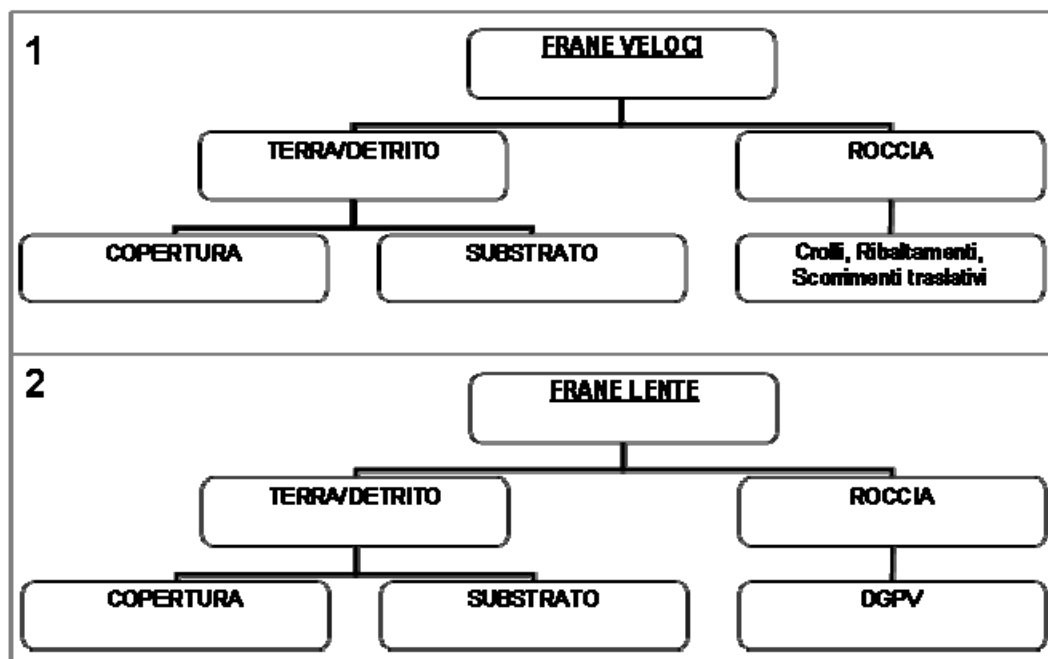


Fig. 2.25 - Diagram of the classification of landslides used for the construction of landslide inventories for the areas under study.

Surface landslides occur mainly on steep slopes along which the gradient reaches relatively high values. The landslide inventory used was structured in an alphanumeric archive, organized in census/survey tabs, and in a GIS database, structured according to the IFFI specifics (detailed level: LIP- Landslide Identification Point; polygonal level: AREA; linear level: direction).

2.5 Multi-temporal landslide inventory

One of the fundamental characteristics of a landslide inventory is in the exact determination of the time when movements took place or the chronological dating of landslides. Since the after-war, the availability of a higher number of photos or satellite coverage for the same area, of different ages and their interpretation, made it possible to recognize the instability forms to create a multi-temporal database, which are available for dating events in different detection ages (Guzzetti et al., 2005). An instability archive in which the information relating to the age of the movement is available is more complete and complex to obtain. The limited availability of aerial images related to different periods is one of the main difficulties during the implementation phase of a multi-temporal archive indeed. The "monitoring" phase represents now, and to a greater extent in the coming decades, a fundamental role in the studies that aim to estimate the hazard area and, therefore, it is essential to gain knowledge of the return times of individual landslides events or the "triggers" that originated them.

A key element for the construction of multi-temporal archives is linked to the recognition of landslides and the fact that these are actually interconnected phenomena (at least for landslides affecting adjacent slopes) and however "disturbed" by the interaction with other modelling processes such as water and river erosion. Therefore, the geomorphological analysis of an area provides a clear interpretation to only a part of the landslide (the ones triggered at a time not too long before the time of detection), while part of the morphodynamic response observed could have been obliterated by the processes and following phenomena, with the same "harmful" effects for modelling, could have been caused by landslides affecting other adjacent slopes or other

interconnected morphodynamic areas. The landslide archives now available for statistical analysis, however, are at best hypothesis of events recognized on the basis of surveys carried out in the same period: usually, the detection of aerophotogrammetric or satellite coverage. The absolute dating of each individual event reported in a map is an exceptional event and never proposed in the literature on the scale of larger areas (river basins), rather than restricted to individual slopes. Thus, building a landslide archive results, in fact, from an image of the morphodynamics responses of the slope at a certain time (A). A comparison with image coverage related to a previous period (B) would theoretically allow, by subtraction, to select events initiated in the time interval of the two mentioned.

However, this does not solve the problem of the possible interaction between different phenomena. So we could seek the causes of an event recognized in B in the physical-environmental characteristics of the mapping unit in which we have recognized the event, when instead the event was caused by an event that took place between period A and period B, which, because of subsequent erosion (i.e. runoff), leaves no traces in B. In this sense, diachronic landslides are certainly a type of phenomenon extremely difficult to treat. They are, in fact, phenomena (typically, in Sicily, rotational sliding and lateral expansions) persisting over several periods of observation, presenting various degrees of evolution that often never reach an exhaustion stage. For this reason, self-induction effects must be taken into account.

The need to consider triggering as a constant actually requires some specifications. If we defined a susceptibility model based on the landslide archive dated period A, and through this we want to predict the distribution of landslides of the following period C, we should assume that the morphodynamic response observed in A has been produced by a meteorological and/or climatic stress equal to the period active between A and B. Any difference between the two triggering phenomena would produce false prediction errors. This effect must be taken into account in the validation phase, when you switch to the model calibration phase. This effect is typical when the triggers responsible for the landslide scenario used for the definition of the model are of seismically induced type. Any landslide distribution that occurred at a later date but before the return time

of the earthquake magnitude will be less severe and the model seems to overestimate the susceptibility.

Only in one case each detected event can actually be dated: these are the events triggered by stress of extraordinary intensity (earthquakes and floods of exceptional magnitude). In this case, it is typical to observe a response of slopes with simultaneous activations in the tens per square kilometer (a recent example in the Giampilieri or Sarno cases). However, in this case, another applicable limit of the method is presented. In fact, these events tend to saturate the slope responses, producing very high number of activations, leaving little control to the site susceptibility. Even the least susceptible areas are activated with the same frequency as the most susceptible. It has an answer in this case dominated by the morphodynamic source. Under normal conditions there is still a co-dominated response (source-asset) for which the susceptibility patterns work more reliably.

Of the aspects described above, it is necessary to take into account in the implementation of some purely geomorphological decisions: detection technique and phenomena classification; choice of detection periods; choice of the diagnostic area; validation techniques.

3 LANDSLIDE SUSCEPTIBILITY

- 3.1 Basic theoretical concepts**
- 3.2 Methods for susceptibility assessment**
- 3.3 Some geomorphological considerations**
- 3.4 Model building procedures**
 - 3.4.1 Mapping units
 - 3.4.2 Variable selection
 - 3.4.3 Scalability

3.1 Basic theoretical concepts

International literature refers to *landslide susceptibility* (Brabb, 1984; Soeters and van Westen, 1996), as the spatial probability to meet gravitational instability conditions within an area (hereinafter referred to as *mapping unit*), based on its physical-environmental conditions. A landslide susceptibility map allows therefore, depending on the spatial variability of the physical-environmental features of the classified area (typically a slope, a catchment or an administrative territorial unit), to differentiate the units in which the same is divided, according to a higher or lower degree of landslide susceptibility; it describes the distribution of the spatial (geographic) probability associated with the occurrence of a landslide.

To each landslide event, a magnitude of released energy can be associated, corresponding to the mechanical energy produced when mobilizing. The *magnitude* of a landslide can be kinematically represented as the half product of the mass involved in deformation by the square of the strain rate. Landslide hazard is thus defined as the combination or product of magnitude and probability of occurrence (typically expressed in terms of return times) associated to a possible landslide event. Each mapping unit, in

which the studied territory is partitioned, can be classified in terms of landslide hazard referring to a specific (volume and kinematics) landslide event. From this point of view, a mapping unit can be characterized by a number of hazard values, each associated to a specific expected failure phenomenon. On the other hand, the variability of landslide types compatible with a specific part of the territory is usually strongly simplified, as it is controlled by its geological asset i.s. (geomorphological and hydrological). Nevertheless, the complete assessment of spatial-temporal occurrence of a landslide event must include different types of prediction (Hartlén and Viberg, 1988): prediction of *where* a landslide can occur (spatial prevision); prediction of *when* a landslide can verify in a given spatial context (prediction time); prediction of the *type* of landslide (prediction type); prediction of the *size* (areal and/or volumetric) and of a landslide *speed* or *energy*; prediction of the *spreading distance*, retrogression limits or lateral expansion (evolution prediction).

The probability issue is definitely hard to determine. Unlike seismic and volcanic activity indeed, there are no historical records available on landslide events, except for extremely limited experimental areas. This circumstance prevents the use of a classical statistical approach in order to determine the return time of a projected phenomenon. This is why we need to resort to an indirect solution: once the phenomena are identified, on the basis of heuristic or deterministic morphodynamic models they are put in relation with their triggering factors (typically meteorological or seismic events); a temporal statistic performed on the latter, which exploits a wide availability of historical records, finally allows to estimate time recurrence for triggering.

Landslide activity, because of its associated magnitude, is a clear threat to the territory, facilities and people involved. From this point of view, each part of the territory is characterised by a landslide *vulnerability* value. Generally, it depends on the territorial level of exposure to the threat, determined by the socio-economic value of the assets as well as by their resistance to the solicitation expected. Here engineering considerations regarding the quality and sustainability of buildings are involved, as well as all elements defining the so-called vulnerability of the social organisation. The latter is related to prevention (planning) and reaction (civil protection) skill of a given community. All the studies aimed at assessing landslide hazard involve activities aimed at eliminating this

form of vulnerability: the so-called mitigation actions, which can work both on hazard and vulnerability.

In light of the above-mentioned considerations, vulnerability assessment must consider as many multiple threats in any part of the territory as the characteristics and types of landslides.

The hazard and vulnerability assessment allows to obtain an estimate of landslide *risk* (specifically the hydro-geological risk assessment). The risk corresponds, by fact, to a probability of having damage. In fact, the hazard expresses the possibility of an event of a given magnitude, while vulnerability expresses the amount of damage associated to a hypothetical event, depending on the degree and resistance (or protection) value of the territory.

When estimating the risk, we do not simply multiply hazard by vulnerability, since the latter varies with the former; therefore, it is more appropriate to define the risk in terms of combination of hazard and vulnerability, which can be analytically expressed in form of an integral. Within the landslide risk, applied geomorphology can offer useful and reliable approaches in order to determine its hazard, offering quantitative and objective approaches for variable-scale studies.

3.2 Methods for susceptibility assessment

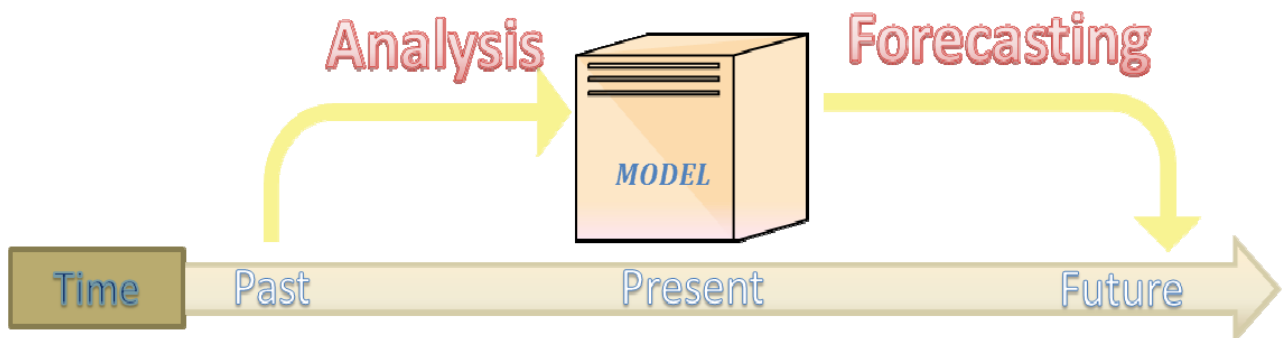


Fig. 3.1 – Schematic flow of a model

The concept of landslide susceptibility is different from the one of hazard, but it is also of great utility on studies of landslide risk. The evaluation of landslide susceptibility depends on the physical-environmental characteristics of the classified area and can be investigated and represented by predictive models. These models represent a simplified reproduction of the real world or a part of it.

A predictive model must be able to represent the response to climatic or seismic stresses of a natural system, which is described by its geo-environmental characteristics; the response consists in the spatial distribution of new landslides or in the so-called prediction image. The effectiveness of the model can therefore be measured by comparing the final expected results (the susceptibility map) with the effective result which are observed empirically (the new-landslide map).

The use of models is essential when one needs to study the natural environment, allowing for a simplification of the infinite natural variables as well as operating with conventional computers with acceptable processing time. The different approaches and methods used in the last decades to accomplish landslide susceptibility assessment are characterized by the modalities with which they move within this framework. The methods of evaluation have rapidly evolved depending on both the enhancement of the theoretical knowledge about landslide phenomenon, and on the increased possibility of exchange of information and interaction between different study groups, as well as on

the growth of hardware and software available for acquisition and processing of analysis data (Brabb, 1984; Carrara et al., 1995; Guzzetti et al., 1999b; Soeter et al., 1996; Irigaray C., 1999; Chacòn et al., 2006; Guzzetti et al., 2006).

A wide fan of approaches and methods is defined by the international literature. Consequently, there is a big disorganization of the techniques and of the tested models for the mapping of instability of an area or for the definition of models to be adopted. There is an ongoing tendency to deal with the problem differently at a national and regional level. In this context, many research groups collaborate to define common models in order to approach the geomorphological issue. Issues related to the geomorphological features cannot be confined to a specific region or to a particular nation. These are in fact widely present on a global scale.

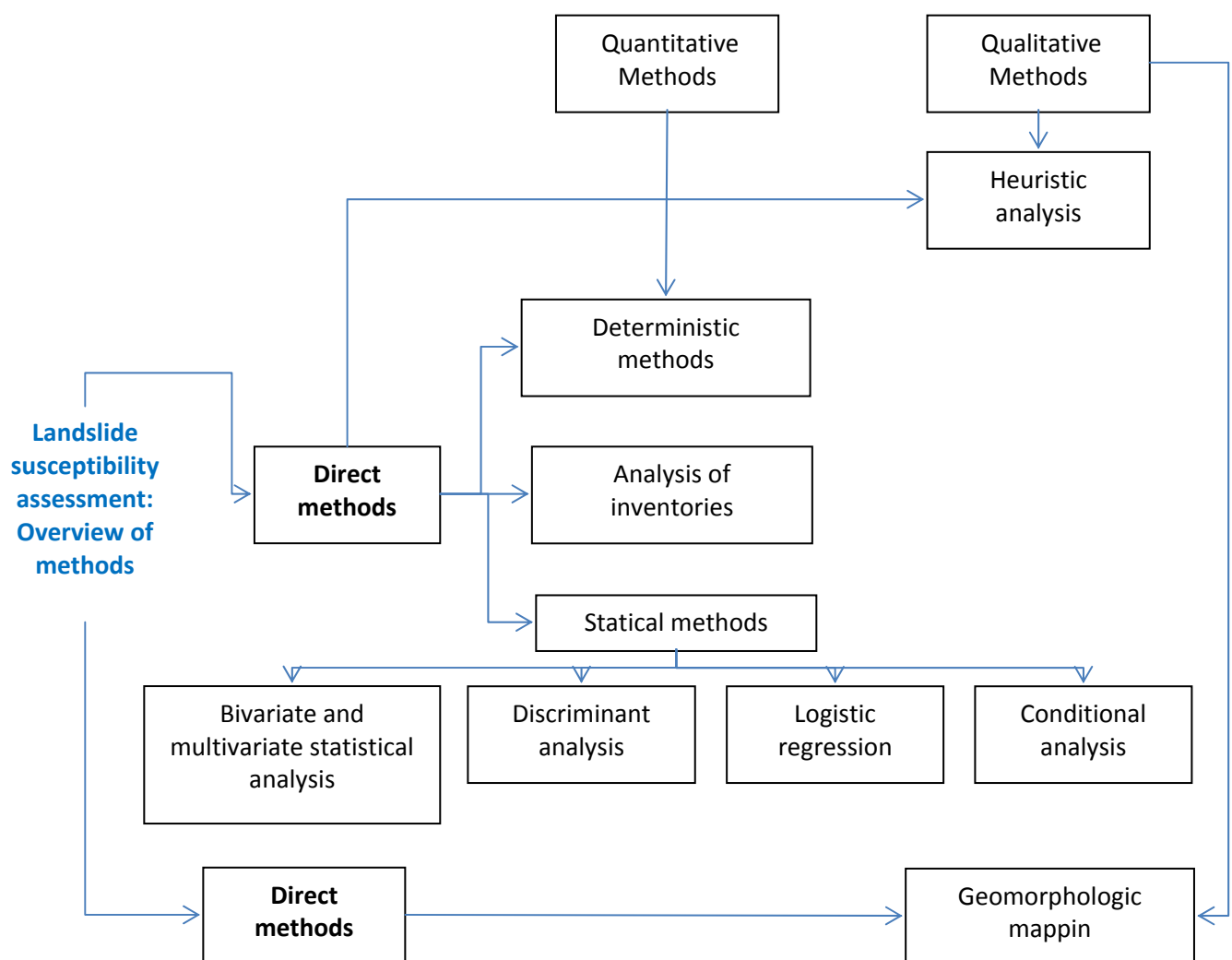


Fig. 3.2 - Schematic representation of the main methods used for the evaluation of landslide susceptibility.

If you refer to Figure 3.2, it is possible to identify some main methods or approaches to susceptibility mapping. For nearly a decade Europe has been trying to adopt common strategies for the single states, leading to discussion in the commissions of the European Parliament and European Council. The objective is to synthesize all the acquired experience and try to discipline with common approaches all the useful techniques to recognize “hazardous” geomorphological areas, trying to dictate the guidelines to estimate the degree of instability and eventual mitigation techniques for hazard and risk involved, but more generally to develop a regulatory framework of approaches and procedures aimed at soil protection. Nowadays, it is possible to classify the methods used in the literature according to some peculiar characteristics of the contemplated procedures. In fact, we can distinguish **direct and indirect methods, quantitative and qualitative methods and subjective and objective methods.**

Direct methods are based on direct land recognition or on satellite images of conditions of tendency to instability on the basis of the interpretation of morphodynamic conditions of the analyzed area. For this reason direct methods consist almost all the times in the realization of a map inventory of landslides in a systematic way reporting all forms of gravitational instability recognizable at the time of detection. From the map/inventory it is then possible to project the conditions of susceptibility on the interested slopes according to more or less simple morph-dynamic models. Similarly, geomorphological survey consists in recognizing conditions of possible slope instability, which, while not presenting recognizable signs of distress, whose geomorphic characteristics are considered predisposing factors for the phenomenon. These methods provide reliable interpretations, depending on the degree of preparation of the operator.

Indirect methods come to the definition of conditions of susceptibility by analyzing the spatial distribution of a series of geo-environmental attributes selected as predisposing factors. The relations between factors and landslides can be defined heuristically, by indexing the factors of instability in terms of their effect on the phenomenon, or they can be obtained through stochastic modeling procedures that

exploit the geostatistical relationships between the factors and at least one historical landslide (in some cases defined only on one area of entire area of study). The distinction between quantitative and qualitative methods refers to the characteristics of the scale of susceptibility that comes at the end of the procedure, which can be simply qualitative-descriptive (of categorical type) or quantitative (ordinal or continual).

The distinction between **subjective** and **objective methods** depends on spatial/temporary reproducibility. Objective methods are those that reach the same final result, regardless of who is the operator. It is obvious that all methods contain a certain degree of subjectivity (for example in the face of recognition of landslides of the past or in the choice of factors), but some procedures allow neither the justification nor the explanation of these items.

Geomorphological or analytical methods are based exclusively on direct recognition of conditions of susceptibility by the operator. They consist in the creation of a landslide map based on direct (field survey) and indirect (photo interpretation of images, remote sensing techniques, consultation of archives and previous publications) recognition. Therefore, the quality of the final map is strongly dependent on the operator's skills in building the final map and implementing an archive of slides in which more or less recent perimeter moves are properly registered (Van den Eeckhaut et al., 2009) as well as his knowledge of geology, topography and dynamics of the slopes to classify the territory in different categories in relation to the different susceptibility (DeGraff, 1985). We must consider that a certain number of landslides in a territory is difficult to identify and classify as they can be remodeled from morphological processes or covered by vegetation so that, their detection, both in direct ground control and especially through techniques of photo interpretation, results quite difficult. In this regards we cannot exclude the case in which the photography of the analyzed area belongs to different time from when some instability was activated (Van Western, 1993).

From this point of view, we are dealing with methods characterized by a strong degree of subjectivity, the bigger its size the more marked is the interpretation of possible recognized phenomenon. In this case it is a direct method, subjective and qualitative. The legend of the susceptibility paper is typically qualitative and conversational.

The analytical-geomorphological approach is based on the correct interpretation of the geomorphological conditions of the area studied, and requires as input data maps as well as geological, pedological, climatological data as a map/inventory of landslides. The latter is typically made on the basis of specific surveys on the ground and photo-interpretation. The scale and detail applicability of the method are related to the availability of adequate data input, of course, significantly influencing the times and therefore the costs.

One type of approach in some ways opposite to the geomorphological-analytical type consists of **deterministic or physically based methods**. These, in fact, are the physical and mathematical modeling of the phenomenon, according to stability models from 1D to 3D, which require input data on the physical-mechanical, hydrostatic and hydrodynamic conditions in the volume of the rock underground. It is also necessary to hypothesize the geometry (flat, circular, concave upward, etc.) and the depth of the potential rupture surfaces. Undoubtedly, indirect methods can provide objective and quantitative results (usually expressed in terms of Safety Factor). However, the costs configured by the need to parameterize the territory adequately are such that the application to the scale of even a small basin can be excluded. Moreover, the uncertainty of an incorrect definition of failure modes to consider, threaten to make the costs of application of these methods is not justified by the predictive capability of the models themselves. For this reason, the deterministic approach is typically reserved for single slopes, for which maybe it has been suggested, using other approaches, a high susceptibility or slope on which the probability of re-activation of a landslide formed in a past event (for which the geometry and depth of the failure surface can be assumed with less uncertainty) is studied. These methods are widely used when one wants to quantitatively determine the physical laws that control a specific type of landslide or the triggers factors that cause it.

All methods used in the field of regional studies adhere to the **indirect approach**. In fact, all these methods derive the degree of collapse propensity of an area indirectly, as a function of a set of geo-environmental factors also known (Campbell, 1973, Wright et al., 1974; DeGraff, 1985; Guzzetti, 1994). In this sense, the differences between the different indirect methods are related to the functions they derive from, the factors, so we can

obtain the susceptibility. **Heuristic methods** are based on indexing (usually in ordinal scale) the control factors, which are chosen according to the operator's experience. In this sense, they are highly subjective indirect methods, whose scales of susceptibility can be regarded as qualitative or semi-quantitative, of ordinal type. Heuristic methods do not require input landslides maps/inventory and wherever geo-environmental data input is already available, rapidly applicable to vast territorial extensions. The degree of susceptibility of map detail is of course influenced by geo-environmental data input.

Most approaches and methods designed to evaluate the landslide susceptibility are based on the identification and spatial characterization of a set of control factors, and the quantification of the spatial relationships existing between these and an archive of past landslides, using a principle basis: *the past and the present are the key to the future* (Varnes et al., 1984; Carrara et al., 1991; Hutchinson, 1995; Aleotti and Chowdhury, 1999; Guzzetti et al., 1999). This is the implementation of the principle of actualism, according to which the geological past can be reconstructed starting from observable phenomena in the present (Lyell, 1833). As part of the prediction of landslides, the principle predicts that the areas affected by landslides in the future, are those which have characteristics similar to the ones already registered in the past landslide (Varnes et al., 1984; Carrara et al., 1991). The higher the number of characteristics in an area compared to those areas affected by landslides in the past, the greater, therefore, will be its propensity to future instability.

When the relation between factors and landslides of the past, therefore, can be used to predict the future, a stochastic approach is used, defined as a **statistical approach**. It is, in fact, a quantitative way to parameterize the relation factors-landslides, obtained directly from nature, in other words by witnessing the phenomena used to reconstruct the past.

The archive consists of layers of factors, typically structured in a grid format, which describe the spatial distribution of the whole area of investigation and the physical environmental variables that can be correlated with the distribution of landslides. Typically, these topographical factors are derived from a Digital Elevation Model (DEM) and thought to control the landslide: slope and exposition, topographic curvature,

convergence and divergence of the flow, topographic soil moisture index, geomorphological indexes in nature; as well as factors related to geology (lithology, position, tectonization), hydrology (rainfall), pedology (type, texture, thickness, and land use), etc.

One of the reasons for which the geo-statistical methods have seen a collapse of construction costs was associated with the simultaneous development of GIS technology, as well as high capacity and performance freeware and the increasingly impressive availability of spatial data banks, even at high resolution, by the local administrations. As an example, today at the Department of Environment and Territory of the Sicilian Region it is possible to log on in webGIS to databases, which include color orthophotos from various periods.

Geo-statistical methods designed to evaluate landslide susceptibility are based not only on the principle of actualism, but as well on at least two other elements or fundamental assumptions (Varnes et al., 1984, Carrara et al., 1991, Hutchinson and Chandler, 1991, Hutchinson, 1995; Turner and Schuster, 1996, Guzzetti, 2006):

1. Landslides leave behind obvious morphological characters; most of these can be recognized, classified and mapped in both countryside through remote investigation techniques, such as aerial photographs and satellite images (Rib and Liang, 1978; Varnes, 1978; Hansen 1984; Hutchinson, 1988; Dikau et al., 1996, Costanzo et al., 2011a).
2. The mechanisms that determine the landslides are controlled by physical laws which can be empirically, statistically or deterministically determined. The conditions that cause landslides can be expressed by instability factors, directly or indirectly related to the event, and these can be collected and used to define predictive models of landslide occurrence (Dietrich et al., 1995).

For the definition of a geo-statistical susceptibility-based model, it is therefore necessary to define two input elements: a landslide inventory and a database of factors. All geo-statistical analysis procedures are carried out with the aid of GIS technology, which allows processing and treating of geo-referenced data in vector and raster. It is however necessary to establish an archive or inventory of gravitational instability forms, allowing

to reconstruct the framework of previous landslides. This information requires the creation of a "landslide mapping" in which, in fact, there are forms associated to the action of landslides that occurred in the past (i.e. deposits and scarps of landslides, landslide channels, fractures, etc.). This information is formalized and structured in both the spatial (vector format) and geomorphological component (through associated charts).

A first geostatistical method is very simple and derives from factors meaning that an **analysis of the inventory** is limited to landslides, resulting in a density function of local events and assigning cells to areas in the past characterized by a greater number of events, the higher level of susceptibility. The method obviously requires a landslide archive landslides and is limited in resolution (typically cells have the size of a minimum order of several hundred meters). The scale of susceptibility is still expressed in quantitative and objective terms.

Other methods based on a statistical approach are related to the definition of a relational function, which evaluates the correlation between the spatial distribution of geo-environmental characteristics of an area and the incidence with which it was affected by landslides in the past (Carrara, 1983; Harlen and Viberg, 1988).

Statistical methods are objective, as they combine quantitative and indirect ease of application to large areas, the scalability of the results and costs of building content, providing robust, verifiable forecast scenarios in quantitative terms. Their increasing popularity (also common heuristic methods) is primarily due to the ability to retrieve information more easily about the spatial input variables, which are the basic layers on which to build the model itself, once a time-consuming, time and economic resources and the ability to define the structure of the landslide area of medium or large size, starting from information layers that can be processed in a GIS environment. GIS applications have made it possible to treat these data in a more efficient and productive way being able to handle a large volume of data with the supplied hardware and software commonly included in research facilities.

3.3 Some geomorphological considerations

Although international literature tends to an extreme specialization in terms of stochastic models for the landslide susceptibility problem, using increasingly sophisticated regression techniques or statistical approaches based on self-learning algorithms used in robotics or neural network-type protocols, some main issues, partly due to the assumptions of this type of research, are totally geomorphological. For this reason, landslide susceptibility assessment, especially if carried out through indirect stochastic approaches, is an activity specifically pertaining to the applied geomorphologist.

The possibility to predict the spatial distribution of future landslides, by assigning to each part of the territory or mapping unit a specific probability for new failures, in light of the analysis of relationships between the morphodynamic responses observed in the past (landslide data base), its present permanent physical-environmental conditions (geological setting) and external events (earthquakes, storms, etc.), belongs to a typical geomorphological approach. Geomorphology allows us to put in relation weather conditions, geological setting, processes and forms. In particular, Applied Geomorphology investigates these relationships working on shorter time intervals, focusing on high-frequency and high-intensity morphodynamic components (i.e. meteorology and not climate).

Within the above-described procedures, we have already described some methodological (geomorphological) aspects accepted by the international scientific community and determining the current limits and, therefore, the most urgent research topics. These are mainly geomorphological issues, as they require, instead of the development of the most sophisticated statistical analysis techniques, applications and experiments relying on procedures already available, verifying and adjusting the geomorphologic criteria driving their application and exploring geomorphological-hydrological contexts generate general methodological considerations.

Differently expressing the actualism theory, which states that “the present is the key to the past”, we can also assume the principle by which: “the Past holds the key to the

future". The sources of stress which acted in the past producing the presently recognized landslides are the same which will act in the future; this also implies that new phenomena will occur under the same physical-environmental conditions which led to the past ones. Prediction is so possible in light of the circumstance that the latter can be generally considered as time-invariant.

Two geomorphological considerations must nevertheless be done. The landslide scenario which we can observe on the field at the time T_0 , cannot be considered as a homogeneous result of morphodynamic response to a given input (rainfall, earthquake, etc.). What we typically observe on the field is the cumulated slope response to cumulated input! This theoretical impossibility to consider as coeval all landslides that we recognized at a given time, is even more paradoxical if we consider that the resolution with which we are able to describe the topography of a given area is nowadays so detailed that actually every topographical variable that we would consider as independent becomes a dependent variable in the process. From this point of view, it would be necessary to have the topographical data before the landslides acknowledged. Obviously this is impossible, as activations in a given area are not contemporary, except in Sarno-like episodes (5 May 1998) or Giampileri (1 October 2009). This is a highly important limit in geo-statistic procedure, since it involves several variables (usually considered independent) taken from the topography of classified areas, variables through which we try to indirectly model the system forcing agents (forcing agents on rupture horizons).

3.4 Model building procedures

3.4.1 Mapping Unit

Regardless of the geo-statistical model chosen to estimate the degree of susceptibility of an area, a fundamental step in model building is the selection of an adequate base-mapping unit, which represents homogeneous territorial domains, on which statistical calculations are made. This choice represents an important step in the realization of the model. In fact, the choice of a mapping unit rather than another drives considerably, as the initial step, the statistical approach used and consequently the representation of the

final product (hazard or susceptibility map). From a scientific perspective, the territorial units are characterized by homogeneity in terms of the dynamics within them, being formed by a precise combination of geo-environmental conditions that can separate them, with well-marked limits from the adjacent (Hansen, 1984). In a theoretical mapping, a unit of a portion of territory maximizes both the homogeneity inside the inhomogeneity of the external morphodynamics (Hansen, 1984, Carrara et al., 1995; Guzzetti et al., 1999, 2006). The mapping unit of is topologically the smallest component (structure or shape and size) for which we can aim to define a degree of susceptibility. The main mapping units currently used in the literature of geo-statistical analysis are essentially two types: **cells and topographic units** (Guzzetti et al., 1999; Carrara et al., 1995; Rotigliano et al., 2011). The first are strongly influenced by the raster structure of most geo-environmental data in nature used in the analysis, although structures can be used with cells of different size than the source data. The topographic units are defined on the basis of morphodynamic, corresponding to basins, sub-basins, hydro-morphological units or slope units. Even in this case, the challenge for the scientific community is linked to the need to maximize the morphodynamic link between mapping units and impact (i.e. degree of interconnection between adjacent units) while maintaining the need to find objective solutions defined according to quantitative protocols and regardless of the operator's choices. The choice of a mapping unit is a fundamental step in the evaluation procedure. Cell-type mapping units, obtained by dividing into squared cells the area analyzed, are increasingly being used. This choice, which was initially suggested by the better computer handling of the raster structure, is now used, since the resolution of topographic data has reached values that can actually make it possible to represent conditions almost on time.

On the other hand, the recovery of a geomorphological approach suggests that the phenomenon we want to model is rather the result of the characteristics wider around the side of a few centimeters side cell! The shape and extent of this diagnosis depend on the kinematic characteristics of the phenomenon and the spatial mode of the factors controlling it. At the same time, a morphodynamic analysis of landslides makes it immediately clear that the conditions of susceptibility of a cell area are certainly characteristics of the control factors that, but also, at times, especially, by the terms of susceptibility of the cells morphodynamically connected to it. It would be necessary to

move to distributed models, for which three approaches can be followed: deterministic, using physical-mathematical modeling; stochastic, introducing susceptibility functions that spatialize or regionalize the values of adjacent cells; geomorphological, defining mapping units on morphodynamics. The use of mapping units defined on hydro-morphological characteristics allows to consider this problem by adopting simple and manageable solutions during statistical processing.

It is necessary to proceed with defining the criteria of selecting mapping units that allow to return the distribution size of the phenomenon, but at the same time meet the criteria of objectivity and handling information. The choice of mapping unit must also take into account the return scale of susceptibility maps and the use of the same that are programmed to do so. All these considerations naturally push towards the adoption of geomorphological defined units including all portions of the territory between them morphodynamically related: the slope units (Carrara et al., 1995, Van Den Eeckhaut et al., 2009, Rotigliano et al., 2011b).

Topographic or hydro-morphologic units



Figura 3.3 - An example of division of territory into morphodinamical slope units.

This category of mapping units includes all those portions of territory consisting of territorial units interconnected under a hydrological profile. The hydro-morphological

units limited by lines of the watershed ridge at the top and at the bottom, represent a partition of the territory according to hydrologically connected neighborhoods. Although it is possible to divide the territory into hydro-morphological units through manual procedures, it is preferable to use spatial analysis procedures based on objective and quantitative algorithms, choosing from the many GIS packages provided. In a territory, we can manually recognize broken lines representing the separation gradient of a portion of land and the adjacent; these are the watershed lines between a slope and another. Quite recently, several procedures were tested to detect and track automatically or semi-automatically hydro-morphological mapping units using specific software that creates the hydrographic network and watershed lines starting from high resolution ground elevation models (Carrara et al., 1991; Xie et al., 2004; Guzzetti et al., 1999).

Automated procedures undoubtedly allow to invest less time for the realization of the slope unit bringing down the possible analysis costs. The automation of the procedure gives objectivity and reproducibility to the final product so, but in particular parts of the territory (flat areas or areas with a strong downward) it may result in interpretation errors by defining the slope units that the operator's experience can definitely avoid. The operator's intervention and interpretation capability remove the required objectivity from the final product, an essential feature of the geo-statistical approach methods, hence they may affect a large part of the final product's quality.

During the analysis process, the mapping units identified should be "*characterized*", in other words it is necessary to classify each mapping unit according to the statistical distribution of their internal hydrological, topographical and morphological attributes. This task, depending on the purpose of susceptibility analysis, the type of mapping used and the scale of the investigation, is carried out by analyzing the statistical distribution of geo-environmental parameters within each territorial unit. The use of slope units also allows to ignore or minimize the effect of greatly altered relationships produced by the geostatistical problem of interdependence between adjacent cells (these are all included in one unit), caused by landslides, interacting on the same slope, and the cause and effect relation between landslides and topography (since the topographical features can be set at a much greater extension unit (the slope) than the surround affected by the

phenomenon (landslide area). At the same time, the use of mapping units defined on the basis of hydro-morphological allows to face the scalability problem of susceptibility models. In fact, one of the most discussed problems is related to the approaches to the evaluation of multi-scale susceptibility.

The literature proposes, even as uniform protocols for the European Union, multi-scale assessment approaches, involving the variation of the protocols used, depending on the extent of the investigated area and the scale map or forecast images that must be produced. Typically, these are protocols that reasonably provide for the adoption of low resolution criteria, based on heuristic approaches, for small-scale studies, and stochastic approaches for large-scale studies. Similarly, the adoption of large cells is used in the former (in the order of tens of kilometers) mapping units, while in the latter is preferred for the adoption of cells (equal to hundreds of metres) or hydro-morphological units. The result of this approach is, however, that the classification of the territory obtained is not nested, meaning that the same piece of territory can vary its level of susceptibility depending on the estimated image scale observed.

Regular cell-grid mapping units

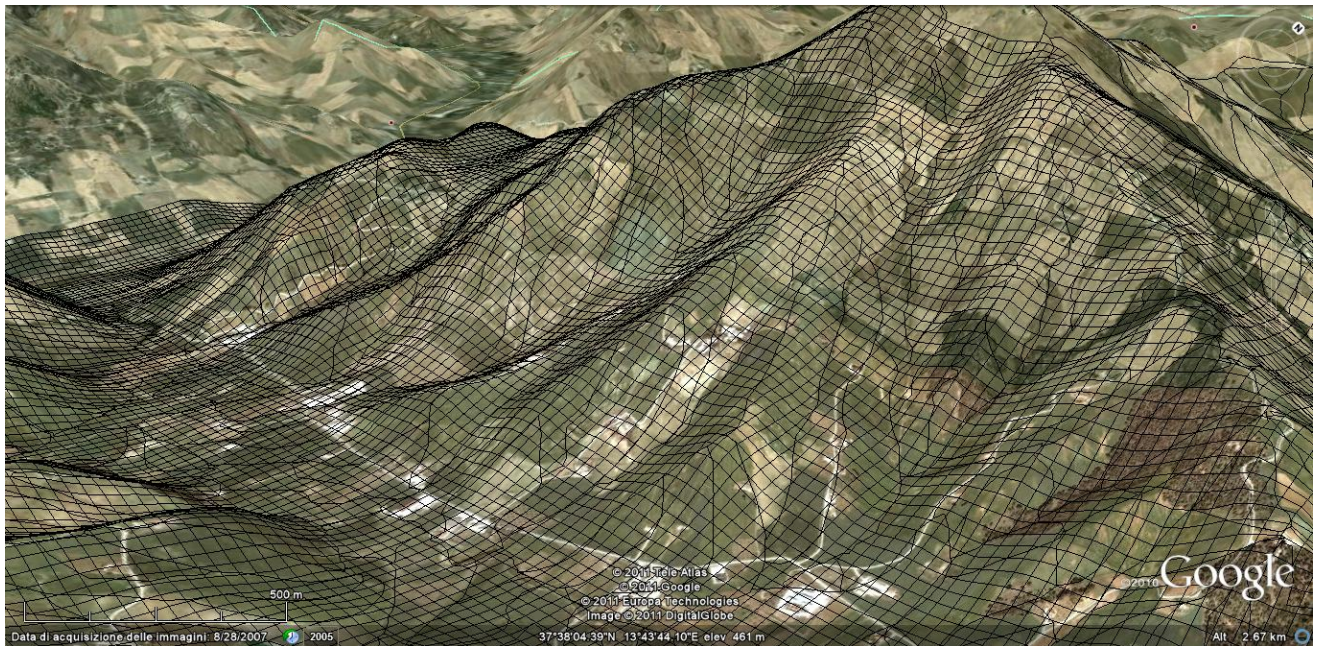


Fig. 3.4 - an example of division of territory into square grid cells

Many geo-environmental variables describing the morphological and hydrological characteristics of an area come from a Digital Elevation Model (DEM) of the study area.

The DEM format is commonly represented as a predefined square-shaped grid. Consequently, the basic mapping unit in statistical analysis corresponds to the DEM grid. Each cell is characterized by a single value, which represents the value of the environment variable for that portion of area. The area, the number and combination of factors in the cells are strongly dependent on the factors used. Also this specific type of mapping unit is characterized by a degree of subjectivity resulting from the intervention of the operator during the choice of factors and possible reclassification in the ranges or classes. Unlike the grid-cell units, the slope units often include multiple cells of a grid and the limits of the grid do not coincide with the natural limits of a slope unit.

Therefore, the value taken by the entire slope unit will be assigned and analyzed even in relation to the hydrological dynamics and continuity that the cells have along the slope. In the cell-based statistical calculation unit, each unit provides a mapping value of the environment variable that represents a timely and independent manner, thus it is not morphodynamically connected to and dependent by the adjacent cells. This consideration is of particular significance and importance in the susceptibility evaluation procedure. Paradoxically, we could have the case in which a cell has a high susceptibility and/or hazard value, while the adjacent cells are marked by low value, which does not happen using the hydro-morphological units particularly suitable to produce maps for zoning purposes.

3.4.2 Variable selection

It can be stated that one of the key points to determine the susceptibility conditions of an area with multivariate statistical techniques, is the selection of an appropriate number of factors that can justify the spatial distribution of past and future forms of instability. In fact, many of these techniques give an estimate of the importance of each factor in relation to the others, or its specific contribution in generating a particular type of landslide in the area investigated. Many of these techniques order, by hierarchizing it, the contribution of each factor in determining the landslide-specificity of an area by identifying the minimum and maximum number of factors needed, beyond which the performance variation of the model can be defined as insignificant or even negative. Given the availability of a number of geo-environmental parameters, their quantity can

be reduced in order to avoid interdependence phenomena, by using many updated identified and tested techniques: the principal analysis component (PCA), analysis of the correlation coefficients or co-gradation, cluster analysis etc.. (Baeza and Corominas; 2001; Fernandez et al., 2003; Carrara et al. 2005; Chacòn et al., 2006; Jiménez-Perálvarez et al., 2009).

Generally, there are two reasons that guide us in choosing the smallest possible number of geo-environmental variables, for the construction of the forecasting model, which allow the realization of what, is called the "best model" for a specific area capable of providing an acceptable performance forecast (Costanzo et al., 2011b). On the one hand, achieving or obtaining each parameter mean a considerable disburse of time and money, on the other a large number of environmental variables results in a large number of possible combinations characterizing, in an excessively specific manner, each of the territorial units chosen as the basis for statistical analysis. A high number of combinations brings along a progressive decrease in the distribution of each combination class. The consequence is an unexpected decrease in the performance of the susceptibility model caused by the inclusion of variables, which are well related to a small number of cells, but poorly correlated to the global distribution of the remaining part and thus affecting the choice of the most predictive variables. Even the selection of factors is an essential step in assessment procedures of landslide susceptibility, in which the nature of geomorphological criteria take priority weight.

Depending on the type of landslides, a maximum parsimony criterion in the number of factors used is necessary indeed to identify a first set of control factors that can be justified on the basis of morphodynamic models defined as heuristic at a first approximation, the distribution of the observed phenomena. Then we can use regression techniques that highlight the effective role played by each of the geo-environmental variables considered. However, it is also common practice as well as and recommendations in the manuals of applied statistics, to maintain certain diagnostic value of variables (i.e. slope) even when with regression procedures in steps, we have greatly reduced the influence. A type of approach for certain ways opposite to the analytical-geomorphological is the one made of deterministic or physically-based methods.

3.4.3 Scalability

One of the first aspects to face in planning stages of a research that aims to define the set of susceptibility conditions of an area is to establish the scale of work at which to perform the analysis. Studies of applied geomorphological characteristics can be made at different scales. As I previously stated, the geo-statistical approach is the only one applicable for areas of studies of thousands of square kilometers, given the availability of time and economic resources. The scale of the variables available taken into account strongly influences the scale of work, but also the investigative approach used. For example, in order to analyze the slope scale and the presence of high resolution and quality of data available, as well as timely, empirical methods are preferred over geo-statistical models, which are instead particularly suitable for analysis at the basin scale and/or regional level. High detailed maps are, in fact, more appropriate mostly to produce zoning hazard and risk maps at an individual side/slope.

For areas in the hundreds of square km, the most frequently used scales are 1:10.000 - 1:25.000, which are a great compromise between the minimum detail required for the production of susceptibility and hazard maps especially in perspective of spatial planning and territorial defense, and the problem of data management, including the resolution and the availability of the factor maps necessary for analysis. Obviously, the increasing resolution of the factor maps used in the analysis makes the analysis more laborious as it requires greater capacity in terms of performance even of the software and the hardware used. As a result of these considerations, the choice of the scale at which to perform the analysis must be properly considered in relation to: 1) the purpose for which the analysis is performed, 2) the availability of economic resources and/or data input; 3) timing requirements. The importance of facing the problem of choice of the investigation scale is especially true when it comes to geodynamic processes. These are so complex that often it is necessary to model the characteristics of a specific portion of territory. There is an undoubted difficulty in creating a model that more faithfully represents the system, which cannot be comprehended with a model that retains the characteristics of only a part of the system or limiting the attention to individual subsystems. This does not allow to highlight the dynamics leading to the generation of non-local phenomena which, however, derive from interrelations on a local scale.

In the latest research and applications made during the last decade, the problem of multi-scale analysis has been faced using different approaches that agree in trying to identify and define the intervals at which to perform scalar analysis, especially in relation to purposes of research, considering geomorphological features such as local events with regional and national consequences (Günther et al., 2007). In Europe, the experts of member Countries more advanced in research aimed at studying geomorphological issues, have concentrated their activities in a research program headed by the European Commission: Joint Research Center (JRC) in Brussels. The assignment of this center is to provide scientific and technical support to design, development, implementation and monitoring of EU policies, acting as a reference center of science and technology for the EU countries. The Group has also developed preliminary models for the evaluation of landslide susceptibility on a European scale (Chart 3.1), identifying and using an approach at three different *levels*, each of which is called "*Tier*" for which common approaches are identified, eventually using data available while carrying out three different scales of analysis for susceptibility calculation (Hervàs et al. 2007; Eckelmann et al., 2006; Günther et al., 2007; Reichenbach et al., 2007)

MAP	Tier 1 (1:1.000.000)		Tier 2 (1:250.000)		Tier 3a (1:25.000)	Tier 3b (1:10.000)
	Methodological Approach	Heuristic, " <i>weighted factors</i> "		Probabilistic, bivariate or multivariate quantitative		Probabilistic, bivariate or multivariate quantitative
Landslide inventory scale	1:200.000		1:50.000		1:10.000	1:10.000-1:2.000
Landslide inventory representation	Points	Polygons	Points	Polygons	Polygons	Polygons
Average size of landslides	1 – 5 ha	> 5 Ha	500 – 2.500m ²	> 2.500 m ²	> 100 m ²	any

Table 3.1 - The three main scales of analysis proposed by JRC guidelines (Hervas and others, 2007)

For the first level (Tier 1), 1:1,000,000 scale, the standard approach is heuristic, which shows it is easier to evaluate qualitatively and actionable areas with regard to the

predisposition to instability, especially for those areas for which data related to the preparatory and triggering factors is available, but the inventory of landslides that occurred in the past is absent or severely scarce (Guzzetti et al., 1999, Guzzetti, 2006). Landslide areas must have considerable areal extension (1-5 hectares) and can be represented with either points or polygons without any typological distinction. For this scale of analysis is fundamental a set of variables and geo-environmental trigger factors accessible and common throughout Europe (Eckelmann, 2006). The susceptibility map represents the resulting distribution of the areas into three levels: high, medium and low (or zero), according to different propensity to instability. Maps of susceptibility testing were also made to test the procedure for Europe (Panagos et al., 2006), for Italy (Reichenbach et al., 2007; Pasuto et al., 2007), for Germany (Günther et al., 2007) and similar rules for certain areas of England (Hobbs, 2007), Greece (Poyiadji, 2007), Spain (Chacon, 2007), France (Malè et al. 2007).

The second level of analysis (Tier 2), scale 1:250.000, is designed primarily to define the structure of the susceptibility of areas for which the mapping unit is represented by small watersheds or municipal areas. This methodological approach is essentially of geo-statistical nature, being mainly a quantitative analysis. For this level the predisposing factors that may be used in the analysis and collected at national level (DEM 10x10 m; land use scale 1:100.000; major tectonic events associated with the seismicity of the Quaternary) are shown. The inventory of landslides, of 1:10.000-1:25.000 scale when the forms are represented as polygons, and 1:100.000 to 1:200.000 in case it is represented in the form of PIFF (ID Point of the landslide Phenomenon), using the classification by Varnes (1978). Potential ignition sources, the average distribution of daily rainfall and data for local seismic acceleration are added to the predisposing characteristics. The performance level is then quantified in predictive terms by validating the model with an archive of landslide events, where available.

These first two levels of analysis have been validated, respectively Tier 1 (Günther et al., 2007) and Tier 2 (Reichenbach et al., 2007). The methodological approach and the steps that have been identified to the level called Tier 3, which was previously divided into two sublevels, are still under implementation and subsequent validation

1. Tier 3a: 1:25.000 scale for which the approach identified is probabilistic and multivariate statistical;
2. Tier 3b: scale 1:10.000 for which we need some geotechnical information on which to test a physically based approach.

In this thesis the landslide susceptibility was estimated both at regional scale and identifying smaller areas (test area), at scales of basin or sub-basin, through the use of statistical models only.

- 4.1 General concept**
- 4.2 Statistical approach**
- 4.3 Landslide inventory**
- 4.4 The diagnostic area**
- 4.5 Factors selection**
- 4.6 Mapping units**
- 4.7 Model validation and exportation**

4.1 General Concept

In the subject of landslide susceptibility assessment, in light of the issues which were above described (Chapter III) some methodological questions are nowadays taking basic position. Especially different stages in the model building procedures illustrate the limitations of range-optimization that the research adept is urged to deal with.

As already discussed, an operational sequence to build a landslide susceptibility model, passes through several steps, of which each can impropriate a different strategy. In some cases it is about autonomous interventions, in terms of modifying the strategy for model building in one of its stages without altering the other operation phases. In other cases some determinations can be reflected in more than one stadium of the model construction process.

4.2 Statistical approach

One of the first decisions to deal with in the range of model definition is well-connected to the stochastic characteristics of landslide phenomena and hence to its statistic

modeling type. Accordingly a clear delimitation is attached to the binary or multiple nature (discrete or continuous) of the assessed susceptibility ranks that provide a proper discrimination. In the case of a binary classification, the vulnerability model operates as distinction between zones or units mapped stable or unstable. Regarding multiple categorization, however, the classification determines mapping units on an ordinal or ratio scale showing a graduated conception of susceptibility.

The binarization of the stability-conditions and the basics of the approaches by Fisherian or frequentist statistical techniques among linear discriminant analyses or logistic regression (although, with appropriate action, these techniques can be used for multiple classifications). The application of a scaled susceptibility-classification is strongly connected to the appliance of a classification based on conditional analysis.

There have been two susceptibility model testing operations in the basin of the Tumarrano torrent (Chapter V) concerning flow events: One is utilizing conditional analysis (Costanzo et al., 2011a – Chapter V) while the other is using logistic regression analysis (Costanzo et al., 2011b – Chapter V).

4.3 Landslide inventory

Research departments and landscape management offices offer complete more and more detailed databases of geological, climatic, pedologic and topographic factors (DEM-derived), often already digitized and georeferenced. On the other hand, a severe problem is connected to the slope failure databases. Various experience have been accomplished in this operational range (project AVI, SCAI, IFFI and PAI). A typical grade of reliability, precision and furthermore temporal homogeneity of the archive was demonstrated that actually suggests the essentiality of the realization of targeted surveys (remotely sensed or by field work) in the study area, especially for forecasting purposes. In this sense, it is necessary to align the need for preparing landslide archives sufficiently reliable and chronologically uniform to the rising costs and expenditure of time that is associated with the realization of field-data collection.

In my thesis will present the results of a few tests (Tumarrano, Imera and Beiro basins) accomplished in Sicily and Andalusia aligned to verify the possibility to determine the landslide-susceptibility conditions inside an hydrographic sample basin, utilizing Google Earth™ (software and database of satellite images); that seems, in fact, to carry out a highly interesting contribution in the field of forecast section due to the rapid availability of information, the versatility of management and analysis of the 3D images, the immediate access to a GIS and the possibility to choose different superficial evolutions stages for a single area.

4.4 The diagnostic area

The diagnostic area is the area morphodynamics related to a previous landslide event that allows "to read" of its preparatory and environment-physical causal conditions, to understand the previous causative conditions (Rotigliano et al. 201b - chapter V). The diagnostic area does not necessarily coincide with a type of gravitative instability landform and it could also correspond to an area of zonal statistics in relation to the layer of independent variables or factors.

In a large number of scientific works related to the assessment of landslide susceptibility, the diagnostic area corresponds to the deposition zone or to the union of the depletion zone and accumulation area (in the following: landslide area). But recently, the problem of the diagnostic areas has been analyzed more critically, tending to more accurate solutions in terms of morphodynamic and accordingly to provide a satisfying predictive efficiency. On the other hand, one has to keep in mind that actually a susceptibility map provides a spatial distribution of likelihood that that type of diagnostic area comes again into observation!

In the field of doctoral research activity, a study has been carried out to evaluate landslide susceptibility in the Tumarrano river basin (Chapter V), which compares models that are obtained by using different diagnostic areas, according to Rotigliano (201b).

The basic idea was to compare the predictive performances models based on rupture zone or landslide area, exploiting the same set of instability factors.

In the Tumarrano river basin (Fig. 4.1), it has been pointed out for earth-flow landslides how the rupture areas (in general susceptibility maps and validation curves) provide a

more predictive efficiency, highlighted by the largest part under the produced prediction rate curve. Despite the limits of the utilized type of diagnostic area difficulties associated to the survey of these forms arise. In particular, the rupture area of slope failure is hard to be extracted and, therefore, with a high degree of subjectivity. These limits even increase if you take into consideration the possibility of remote geomorphological analysis to create a landslide archive. From this point of view, concerning objectivity and automaticity, the definition of the diagnostic area can allow, assuming that the prediction-model results will be satisfying, not only a saving of time in the process but above all a saving in terms of reliability and objectivity of the model.

As part of this research, a procedure has been defined to automatically generate possible diagnostic areas out of a landslide inventory. Using 3D analysis tools it is indeed possible to determine the highest elevation point in the landslide body. That corresponds to the LIP (Landslide Identification Point, Costanzo et al., 201b). Limiting the significant diagnosis in the point (more the cell) located at the highest elevation point, certainly builds a strong morphodynamic simplification, particularly more severe the larger the spatial resolution of the discrete variable data sets becomes. At the same time, the LIP usually corresponds to points situated along the perimeter of the area affected by landslides, the section of highest elevation points and so in central position in relation to the crown of the landslide.

Another refinement regarding the LIP is linked to the spatial generalization of its position, obtainable by realizing a buffer-area around the LIP, hereinafter referred to as BLIP (Buffered-LIP), a surrounding area of significance, expressed by mean conditions, in the depletion zone around the inner part of the examination area. A final improvement of the process can be gained by eliminating the buffered part of back-falling into the interior of the landslide, which, although not highly striking, is afflicted by the morphodynamical limitations described above. Those investigated areas were marked as CLIPBLIP (Clipped-BLIP). Of course, in all these kind of automatically defined procedures of research areas failures and errors may occur, mostly connected to the geomorphological criteria of the feature definition (the LIP may show back-falling along the flank instead along the head part) or due to the poor resolution of the applied DEM. However, these errors usually are limited and do not have the ability to derange the final

model. In the case of susceptibility valuation of landslides in the Beiro river basin (Chapter V), among the adopted diagnostic areas were sections of rupture zones or source areas of landslides (Fernández, 2003), in order to recognize the triggering conditions for each type of movement (Fig. 4.2).

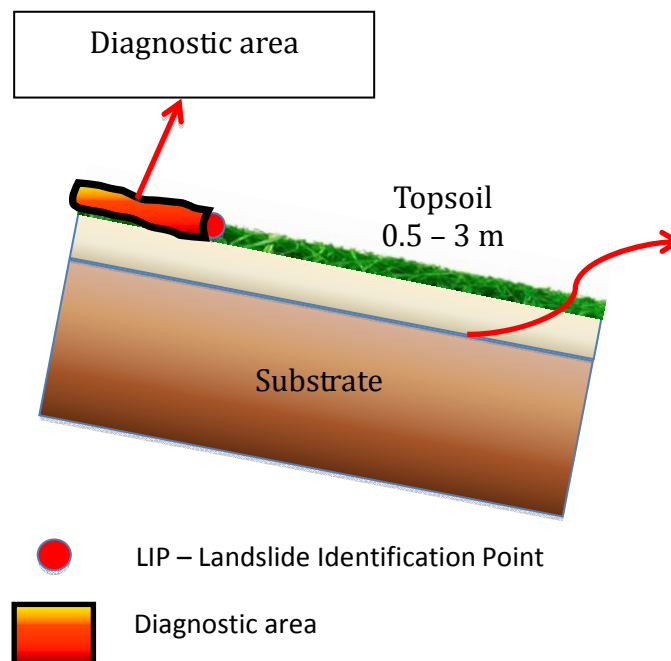


Fig. 4.1 – Representation of the areas identified as a diagnostic area of statistical computing. a) Debris flow in the basin of the stream Tumarrano (Ag).

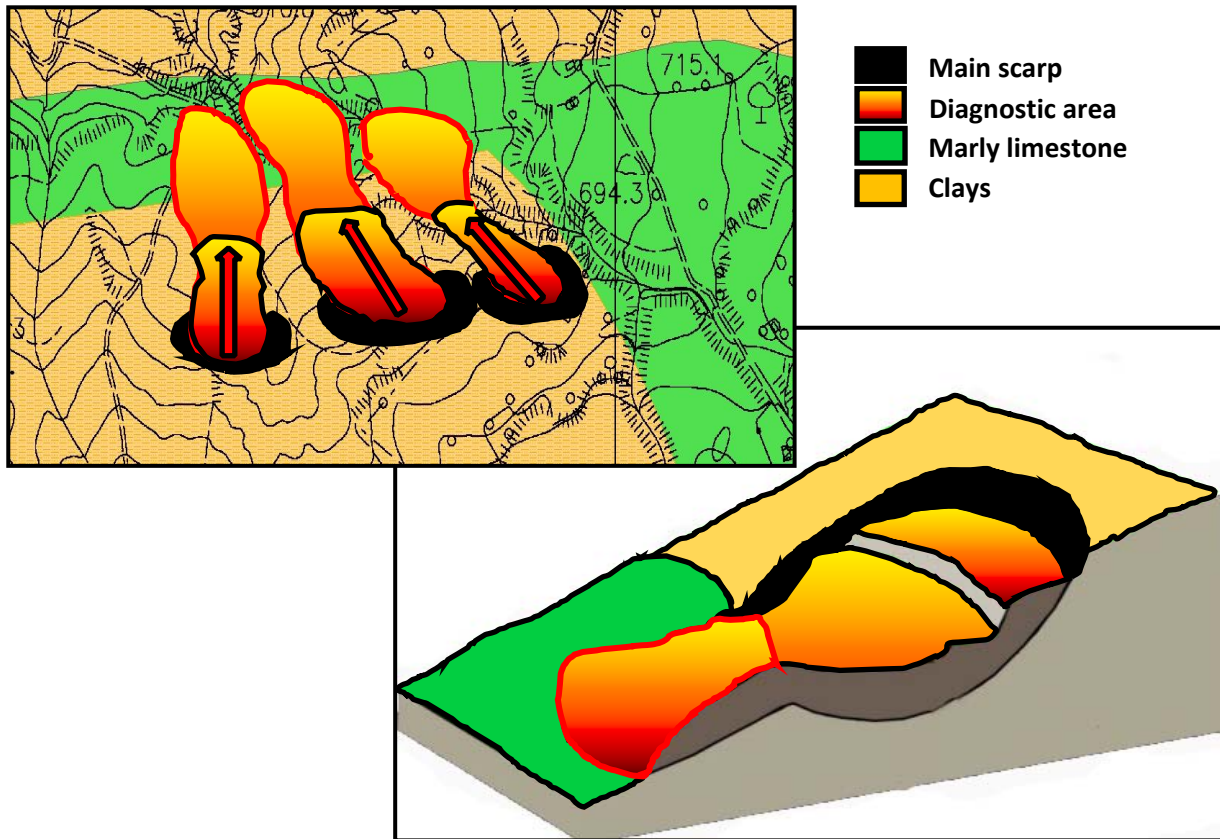


Fig. 4.2 - If only the Orange unit is affected by the slope rupture, the green unit is considered as not susceptible! Only the rupture surface should be considered as the diagnostic area for the susceptibility assessment and large and middle-scale mapping.

4.5 Factors selection

One of the key points in the evaluation of landslide susceptibility using multivariate statistical models is the selection of control factors (predictive variables). In fact, it is generally accepted that the greater the number of control factors the better the prediction performance. Two basic considerations control the need to keep the number of predictive variables as low as possible once an acceptable prevision performance was achieved. On the one side, each information-layer from which the spatial distribution of a possible control factor could be derived, often takes time and causes expenses. On the other side, if multivariate classification techniques are used, the increase of the numbers of factors is

responsible for a larger number of combinations or unique condition units (UCU), with a consequent diminishing of the number of cases (cell counts) for which each specific condition is observed and classified. Furthermore, the reduction of cell count, in general, is not random but depends on the spatial correlation between the factors. That could produce an unexpected decrease in prevision efficiency of a susceptibility model.

Procedures and criteria are necessary for the *a priori* decision whether to include or eliminate one factor in the definition of the multivariate models among the possible approaches. The statistical analysis of the contingency tables spatially produced by the crossing between factors and landslides allows the calculation of correlation or association indices to control the decision (Fernández et al., 2003; Chacón et al., 2006; Irigaray et al., 2007; Jiménez-Perálvarez et al., 2009). Statistical parametric and non-parametric methods are widely applied to derive correlation, association and co-gradation indices expressing the strength and significance with which an explanatory variable explains the issue of stability or instability conditions of a slope. But to adequately define the factor selection, valuations are also achieved by predictive performance, whether for each single variable or multivariate models.

The large diffusion of geological data already implemented in GIS-datasets and the availability of more and more accurate digital elevation models, together with the implementation of automated hydrological and topographical analysis tools nowadays offer the operator a more or less unlimited number of independent variables that express the control factors (this includes the fact that it is possible to define multiple classification modes for one and the same attribute). However, a well-fitting forecasting model should be defined on the base of the most efficient criteria since the general stability or robustness of the predictive images decreases as the number of model parameters taken into consideration increases. So, once all the parameters significantly correlated to the phenomena are included in the model, if by one side, no 'damage' is theoretically to be associated with the addition of uncorrelated parameters, in practice however, an increase in the model instability and a decrease in its predictive performance is seen (see Chapter III and V).

First of all, it is possible to utilize some simple statistical analysis tools to analyze association, co-gradation and correlation between control parameters and landslides. However, this type of verification is limited by a univariate dimension of relations rather not able to express the quality of the 'net'-correlation of the model construction and validation process. From this point of view it seems more appropriate to proceed to a parameter input analysis in terms of forecasting rather than correlation, taking into account the spatial relations between parameters and landslides, including the effect connected to partition in training and test fields, essential for the validation.

4.6 Mapping units

The studies and research focused on validation of landslide susceptibility in a determined area and realized by following a statistical approach always pose the need to define mapping units, i.e. the spatial or statistical basis entity for which the model is able to provide a value of susceptibility. In spatial analysis, the mapping units are intended as 'a section of earth's surface that contains a series of ground conditions which differ from the adjacent unity by settable limitations' in sense of 'an entity of mapping that should illustrate a subject area that maximizes the internal homogeneity and the heterogeneity between the units (Hansen, 1984; Carrara et al., 1995; Guzzetti et al., 1999, 2006).

The selection of the most appropriate mapping units for the research goals is actually one of the most crucial parts in the preparation of the landslide susceptibility models (Carrara et al., 1995, 2008; Guzzetti et al., 2006; Van Den Eeckhaut et al., 2009). This may lead to different predictive results in terms of forecasting and suitability of the hazard maps regarding to land mitigation and/or land management. The two types of mapping units commonly used can be related to the following principles: Morphodynamic coherence (i.e. sub-basin, slope-units) and geostatistical requirements (i.e. grids, unique condition units). Choosing hydro-morphological units, the association between physical phenomena and stochastic modeling is maximized by imposing orders in spatial analysis regarding parameters like watershed line and waterways, which demonstrate natural barriers in the geomorphological processes. The hydro-morphological units (i.e. slope-units, Carrara et al., 1991) can be derived automatically or semi-automatically by a digital elevation-model of the area implemented in GIS.

Valuation of landslide vulnerability based on conditional analysis requires a classification layer overlapping of every instability factor in each multivariate layer, characterized by homogeneous domains (Unique Conditions Units, UCU: Carrara et al., 1995; Chung and Fabbri, 1995; Clerici et al., 2002; Conoscenti et al., 2008; Del Monte et al., 2002) that can be polygons or a cell cluster showing spatially unlimited morphodynamic constraints. Following this approach, the morphodynamic relations between adjacent cells are disregarded, due to the fact that the pixel or sections in a single slope may be part of another homogeneous domain (and so being characterized by largely different vulnerability values).

In contrast, once an approach based on conditional analysis is applied, a problem in the application of hydro-morphological units may occur. Coming from cell or pixel of hydro-morphological units, the number of mapping-units decreases drastically from hundreds of thousands to a few hundreds of slope-units, each of which is characterized by single values of the chosen control factors.

The results of the research accomplished in the test area of the Imera river sub-basin, aim to examine the possibility to create a susceptibility model based on conditional analysis applying slope-units devices (SLU).

4.8 Model validation and exportation

All validation techniques are based on the availability of a certain amount of landslides (landslide test) that are exclusively used to test the model and have not been utilized for its construction. This landslide *testing* should therefore be accomplished temporally or spatially different from the landslide training used for the construction of the model. Unfortunately that happens quite rarely and in fact it is usual in all countries to not provide an accurate and continuative landslide monitoring system that would allow the creation of a homogeneous, spatially and temporally arranged archive with the hereafter ability to verify the prediction models created by previous landslide events. This difficulty is a consequence of: i) the objective complexity due to realization of a monitoring system on wide scale, ii) the unquestionable complex of geomorphological interpretation problems among landslide phenomena, but overall the non fully-developed authorities (local, municipal authorities) and also because the landslide events often occur in regions

of only little common interest, usually covering areas of low environmental vulnerability, and hence lacking in trigger documentation and recording.

Definitely the chronicle insufficiency of sources of a medium- or long-term predictive planning strategy should be added to all those elements, although recent studies pointed out that possible savings are immense by implementing preventive measures in relation to mitigation and restoration measures that are activated following the occurrence of a disaster. The validation procedures consist of the construction of susceptibility model using available datasets of a determined area that is utilized as training section to verify the efficiency of the model in a application area (test area).

Based on the same principle which is exploited in the validation procedures, it is possible to prepare susceptibility model by working only a representative sector of the whole investigated area, which is then characterized by exporting this *source model*. The exportability of the source model from a training area is a process that needs to be controlled carefully to provide the scientific precision of the validation. In the *training* phase, the model is tested according to the precise distribution of the geo-environmental variables. The selection of the area, in which the model is transferred has to be reasonable with respect to the training area and needs to be characterized by comparable geo-environmental conditions. In fact, it can be confirmed, that a model, trained for certain slope or exposure intervals and then applied in the implementation area underlies changing variables and hence the model is not well defined, providing imprecise validations. Another limitation for the model transferability could be represented by a substantial quantitative or qualitative unbalance of the slope failures on which the model is trained. As a matter of fact, a certain number of typological events are essential to maintain the statistical significance of the sample characterization.

A technique which is widely used in literature to determine two sub-domains as homogeneous as possible is a random partition from a homogeneous domain. The partition techniques allow the division of an area (spatial partition) or a landslide sample (temporal partition) in two subgroups using an automatic process that provides randomness and objectivity. The partition technique provides the possibility to gain a

study area or a landslide sample which can be exploited as an application area to test the model (Chung and Fabbri, 2003; 2005). Consequently, the validation process allows to evaluate the degree of correspondence between the different susceptibility classes of the classified area and the distribution of landslides, to understand and assess the role of the environmental variables in the model.

Maps, related to the geological, topographic and climatic conditions as well as land use and landslide inventory are often available, however, either their spatial resolution lacks due to large scale or their extension is limited due to more detailed map content. But often, the public administration needs to define the landslide susceptibility conditions for entire hydrographic basins or even on regional scale of thousands of square kilometers what would blow the budget of investigation. Evaluation studies of landslide susceptibility are usually based on limited sectors that contain highly detailed information. Within the research that is presented in this chapter (see Tumarrano test), a strategy will be set and attempted done to focus on cost-optimization of investigations to validate landslide susceptibility. In terms of landslide susceptibility, it will be verified if it is possible to characterize the interior conditions of hydrographic basins and areas of larger extend reaching up to hundreds of square kilometers, based on a study of geo-environmental conditions and on the implementation of a landslide inventory on one or more representative sections in the research area. That is carried out by transforming the susceptibility values calculated for each mapping unit in the *source area* to an area of similar geo-environmental conditions (*export area*); the robustness and performance of the model is then evaluated on the basis of the comparison of the prediction images that have been produced as well as the spatial distribution of the landslide archive over the entire export area.

CHAPTER V. APPLICATIONS AND EXPERIMENTAL TESTS

5 APPLICATIONS AND EXPERIMENTAL TESTS

5.1 Test 1a: The Tumarrano river basin: Exporting a Google Earth™ aided earth flow susceptibility model

- 5.1.1 Geological and climatic framework
- 5.1.2 Landslides
- 5.1.3 Selected controlling factors
- 5.1.4 Model building and validation techniques
- 5.1.5 Discussion and concluding remarks

Test 1b: The Tumarrano river basin: Forward logistic regression for earth flow landslide susceptibility assessment

- 5.1.6 Landslides
- 5.1.7 Model building strategy
- 5.1.8 Controlling factors and independent variables
- 5.1.9 Diagnostic areas
- 5.1.10 Model suite
- 5.1.11 Validation
- 5.1.12 Model fitting

5.2 Test 2: The Beiro river basin: Geological and climatic framework

- 5.2.1 Landslides
- 5.2.2 Model building
- 5.2.3 Factors selection procedures
- 5.2.4 Multivariate models
- 5.2.5 Susceptibility modeling and validation
- 5.2.6 Discussion and concluding remarks

5.3 Test: 3 The Imera basin: Geological and climatic framework

- 5.3.1 Slope units, instability factors and landslides
- 5.3.2 Susceptibility modeling and validation
- 5.3.3 Results
- 5.3.4 Discussion and concluding remarks

5 Application and Experimental Tests

As part of the research were therefore made application of the test areas, aimed at developing some of these issues and that will be presented in this chapter.

5.1 Test 1. The Tumarrano river basin

5.1.1 Geological and climatic framework

The test site is a catchment in central-southern Sicily, called the Torrente Tumarrano basin that extends for approximately 80 km² (Fig. 5.1).

For the reconstruction of the sedimentary series outcropping of land area in question have been used, in addition to the direct detection of the campaign, paleontological-stratigraphic study of the microfauna present in the rock samples collected during the field-survey.

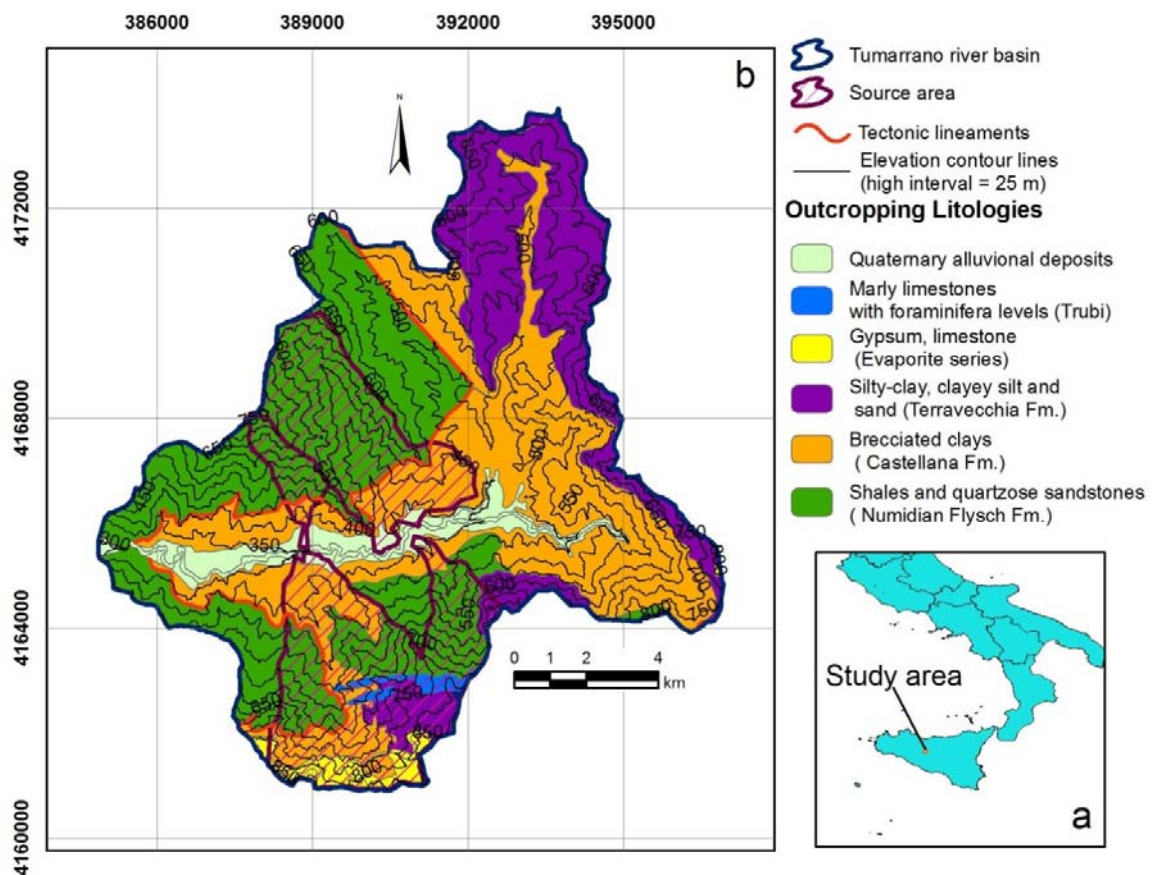



Fig. 5.1- Location and geological map of the study area.

Overall we can say that the survey work and investigations made it possible to define a sufficiently clear framework relating to that aspect of the slopes stratigraphic, lithological and structural. The study of samples collected provides a wealth of information that is relevant importance in the creation of a map of the lithological outcrops. The analysis has served to Micro-paleontological and bio-stratigraphic identification of the units to which the samples report. In this case, have been taken No. 9 in the samples distributed thoughtfully Tumarrano. In this case, have been taken No. 9 in the samples distributed thoughtfully Tumarrano. The exact location of the samples was measured using a GPS receiver that allowed the subsequent location of the samples prepared in the geological map for the area. The geographic coordinates of each sample are shown in Table 5.1:

	Sample	Latitude	longitude	Results
	0	37.5923°	13.7493°	Sterile
	1/a	37.5931°	13.7447°	Sterile
	1/b	37.5931°	13.7447°	Tortonian low
	3	37.6012°	13.7358°	Serravallian
	5	37.6007°	13.7516°	Zanclean (MPL1)
	6	37.641°	13.7444°	Sterile (quartz)
	Spa/1	37.6462°	13.7652°	Sterile
	Spa/2	37.6462°	13.7652°	Sterile
	7	37.6643°	13.7792°	Tortonian
	8	37.6779°	13.7876°	Serravallian
	10	37.6619°	13.7716°	Oligocene

Tab. 5.1 - Location and sample results.

The results obtained have allowed to verify the information derived from the field-survey, confirm the bibliographic information available and, where necessary, refine the limits of the lithologies outcropping in the area. The geological setting is marked by tectonic contacts between brittle (limestones and quartzarenites) and ductile (clays and silty clays) lithologic complexes, in the north-western sector; elsewhere, smoothed long slopes, where clays and marls outcrop, characterize the landscape. Along the slope, deposits from Tortonian to Holocene in age outcrop. The oldest are sand-clays and marl-clays from Tortonian "Terravecchia" Fm. To these follow selenitic and laminitic gypsum gradually passing to gypsarenites of the Messinian "Gessoso-Solfifera" Fm. The

youngest deposits (Holocene in age) outcrop at the top of the slope and are colluvial deposits made up by clays, marly-clays and silts, accumulated on gypsum in a continental environment (Fig. 5.1b). The lithologies can be referred to the following lithostratigraphic terms Numidian Flysch, (Upper Oligocene - Lower Miocene), widely present in the basin, predominantly quartzarenitic sandstones and interbedded mudstones originating from the deformation of Imerese units; Stratigraphically below the terrains consist mainly of brownish brecciated clays with included lithoid of varying age, size and nature, with chaotic aspect and characterized by abrupt changes in thickness corresponding to the terms of the Fm. Castellana clay (Serravallian) (Fig. 5.2a), resulting from the deformation of the Sicilidi Units; follow the terrigenous deposits belonging to Fm. Terravecchia (Tortonian), which appear mainly in the northern portion, in the form of a yellowish sandy-arenaceous complex, separated by very



Fig. 5.2a - Detail of an outcrop of the Serravallian-Tortonian clays (equivalent Castellana Fm.).

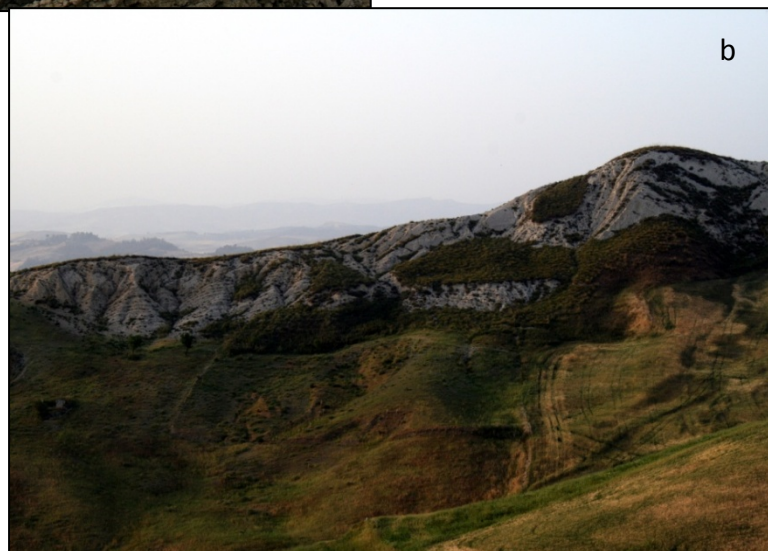


Fig 5.2b – Trubi Fm. Outcrop in a Tumarrano basin.

compact marly levels. Above Fm. Terravecchia, in the extreme southern sector of the basin, are the Messinian evaporate deposits represented by “Calcari di base formation” large blocks discontinuous, poorly stratified, vacuolar and intensely fractured, sometimes occurs in greyish-white limestone benches with parallel lamination. The limestone base cannot be dated with certainty as the combination wildlife is virtually absent in thick banks, yellowish-white decametric thickness (Fig. 5.3).

The evaporitic sequence is closed, at discordance from Fm. Trubi (Lower Pliocene.) Sealing the underlying sequences (Fig. 5.2b). In succession, there are also deposits and Holocene alluvial deposits in current and recent, emerging mostly in areas adjacent to the bed of the stream Tumarrano. The area has suffered intense and prolonged tectonic phases, which led to dislocations and thrust from the late Miocene. In particular: the land of the Numidian Flysch, overthrust present with reports on the latest land (Fm. Castellana, Fm. Terravecchia). Another tectonic event in the basin is represented by a normal fault that displaces the soil with a prevailing direction NNW-SSE and ENE-WSW.



Fig 5.3 - Calcareous levels in the south sector of the Basin Tumarrano.

The study area is a representative forest ecosystem of an internal hilly clayey landscape of central broken by small valleys that represent elements of a developed catchment, river with elements from 1 to 5 order. The climate is characterized as Mediterranean (CSA) with cool to cold, wet winters and warm to hot, dry summers. Climatic data from 1965 to 2003 show a mean annual air temperature of 16.7 °C and a mean annual rainfall of 577 mm. The soils are mainly (80%) exploited for agricultural use (wheat), and second portion of the North-West, appear to be strongly covered by dense vegetation of tall trees represented by *Eucalyptus camaldulensis*, *E. occidentalis* and *Pinus halepensis*. Only a small portion of the basin (less than 5%) are devoted to pasture.

5.1.2 Landslides

One of the main goals of this research was to verify the suitability of Google Earth to produce the landslide archives needed for assessing the landslide susceptibility. Two images have been analysed, one dated at 29/06/2006 (DigitalGlobe catalogue Id = 10100100050DDD01) and one dated at 28/08/2007 (DigitalGlobe catalogue Id = 10100100071CDC04), whose standards of pixel resolution are 46–60 cm

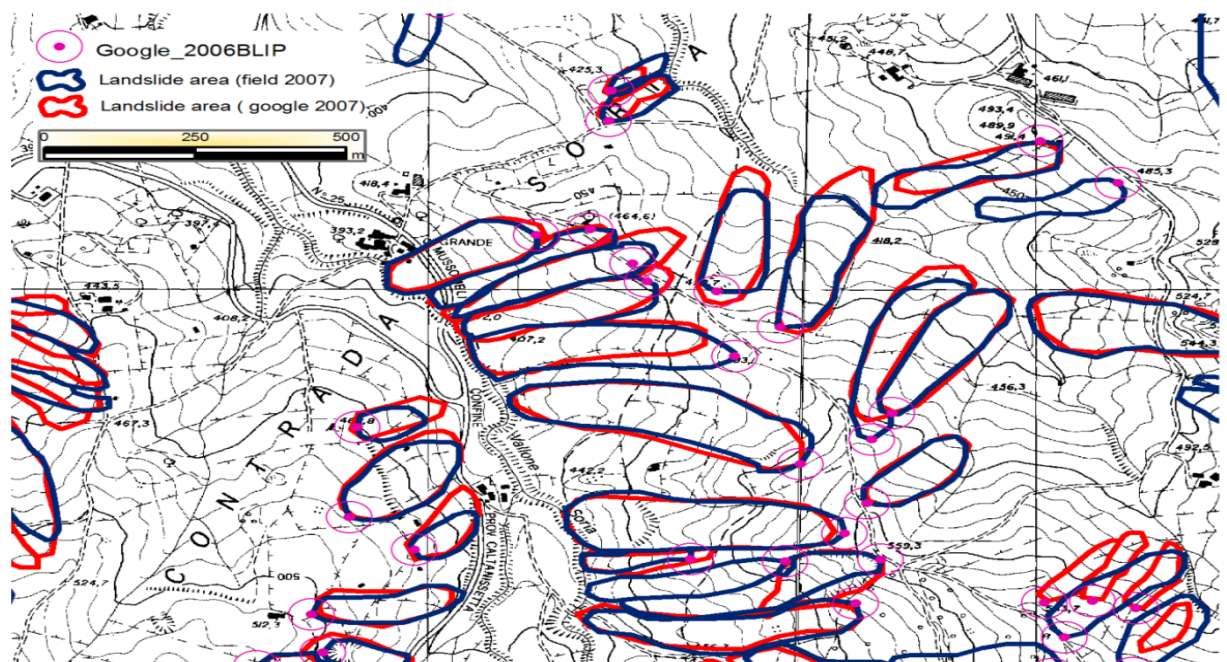


Fig. 5.4 - Excerpt of the landslide inventory maps for comparison, between the 2007 landslide archives obtained from field survey (in blue) and Google Earth™ remote analysis (in red). 2006BLIPs are also showed as purple circles.

(http://www.digitalglobe.com/index.php/48/Products?product_id=2). To verify the reliability of the landslide archives prepared at a scale of 1:10,000 by exploiting Google Earth™ (hereafter simply shortened as “Google”), a test was conducted in the source area: two archives, consisting of vector layers, representing the earth-flow landslide areas, were produced by (i) a field survey carried out in 2007 (295 landslides) and (ii) a Google recognition on 2007 images (282 landslides). By comparing the two landslide maps (Fig. 5.4), a large fit is observed, showing in a large number of cases (65% of landslides) only slight differences in the landslide boundaries.

The landslide classification here adopted is the one after Cruden and Varnes (1996). A Google landslide archive was produced from images taken in 2006 (Figs. 5.5) for the whole basin, by mapping polygons enclosing the landslide areas of 703 earth-flow landslides (206, in the source area and 497, in the target area). According to this archive, the total landslide area is 8%. For each of the two landslide Google archives (2006 and, limited to the source area, 2007), the highest point along the crown of each landslide was selected, and a buffer of 30 m was applied. In this way, circles centred on the

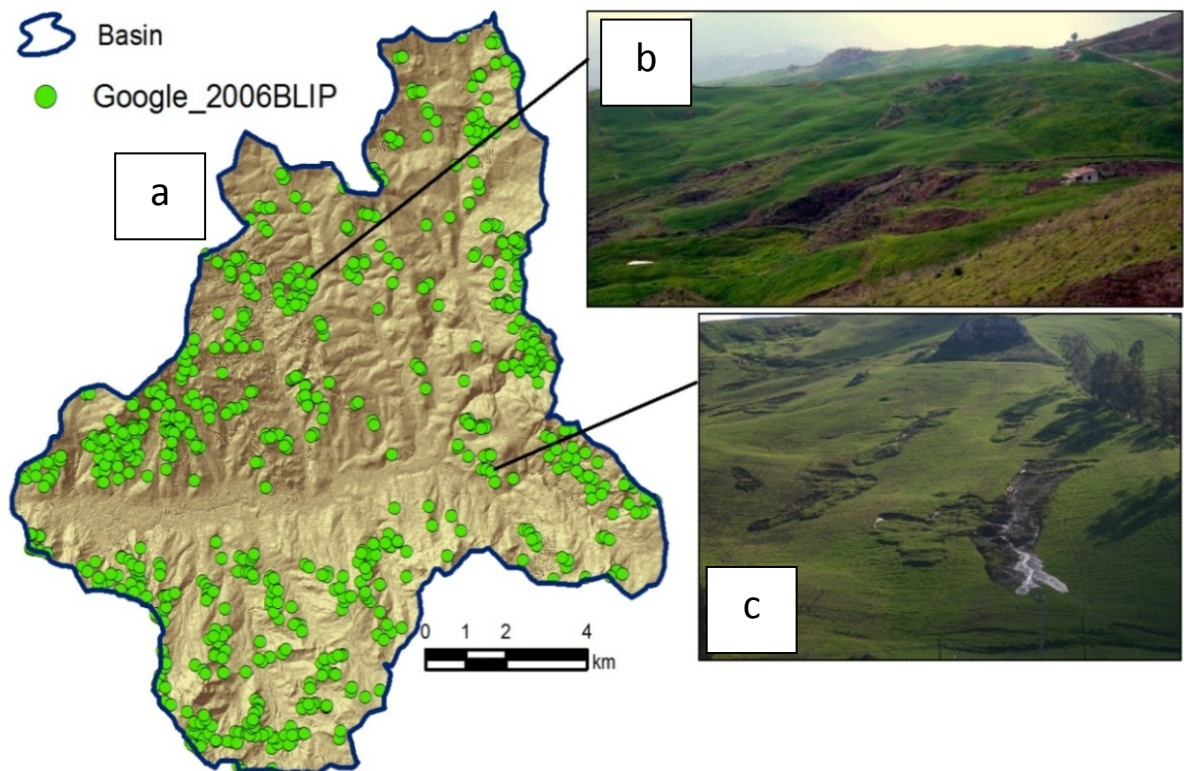


Fig. 5.5 – Spatial distribution of buffered landslide identification points (BLIPs), obtained for the Tumarrano river basin by Google Earth™ remote analysis on 2006 images (a); field examples (b, c).

depletion zones of the landslides were delimited and stored to produce the archives of the buffered landslide identification points (BLIP), here used as diagnostic areas.

According to the strategy adopted in the present research, the following data sets were prepared: Google_2006BLIP, derived from the landslides mapped in the whole Tumarrano river basin from 2006 images; Google_2007BLIP, derived from the landslides mapped in the source area from 2007 images; and Field_2007BLIP, derived from landslides field mapped in the source area in 2007.

Google Earth has made it possible to recognize and to survey a greater number of landslides compared to those of PAI (Piano di Assetto Idrogeologico) prepared by the Sicilian region, and to detail more precisely the movements previously identified (Fig. 5.6).

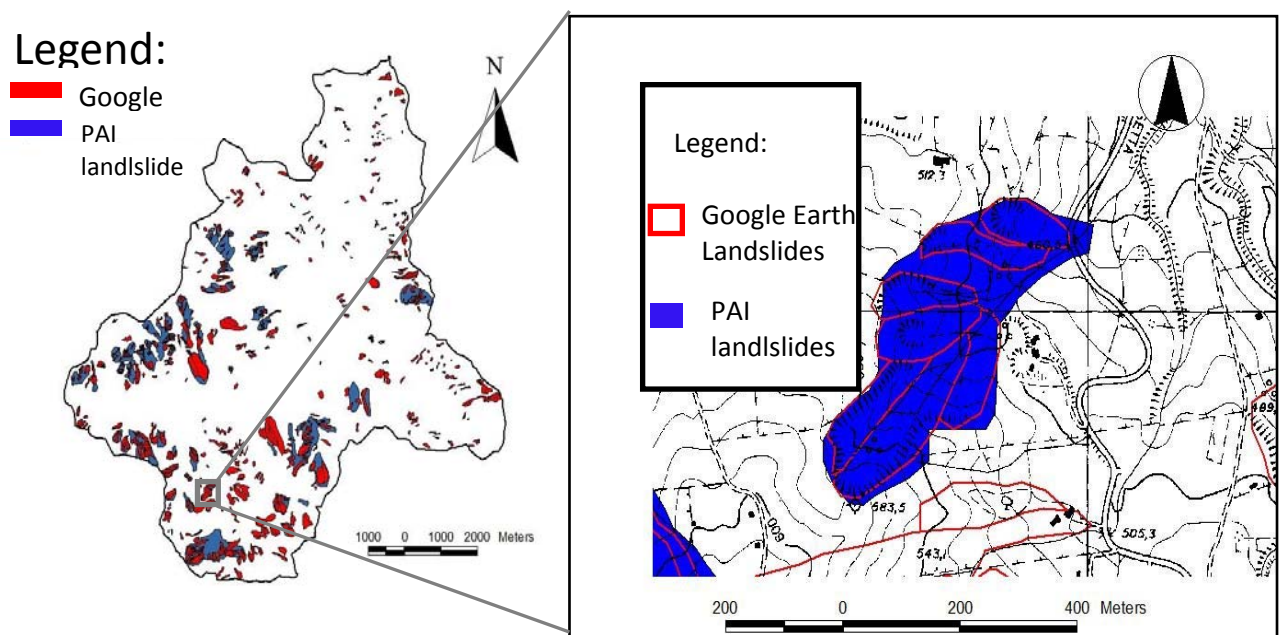


Fig. 5.6 - Excerpt of the landslide inventory maps for comparison, between the landslide archives obtained from PAI database (in blue) and Google Earth™ remote analysis (in red).

5.1.3 Selected controlling factors

The following geoenvironmental controlling factors were heuristically selected, in the light of the analysed landslide typology: (i) steepness (SLO), as it indirectly determines

the geometry of possible failure surfaces; (ii) topographic plan curvature (CUR), as it links each mapped cell to a more general topographic condition, such as convergence or divergence of stresses (Ohlmacher 2007); (iii) topographic wetness index (TWI), which express the potential water saturation degree of soils and/or shallow rocks (Wilson and Gallant 2000), since loss of cohesion is a typical triggering mechanism for earth flows; (iv) outcropping lithologic complex (LIT), expressing the mechanical properties of the outcropping rocks, which obviously heavily control the dynamic response of slopes.

The first three parameters were computed from a 10-m DEM, using the 3D-Analyst extension and the Topocrop and Demat scripts for Arcview GIS (Environmental Systems Research Institute-ESRI), according to Wilson and Gallant (2000). The DEM was acquired from the Sicilian Regional Council of Territory and Environment, which is derived from a LIDAR (light detection and ranging) coverage available for the entire Sicilian territory, having a resolution of 0.25 m and an altimetric precision of 0.1–0.2 m. The DEM was preprocessed to blur irregularities such as sinks.

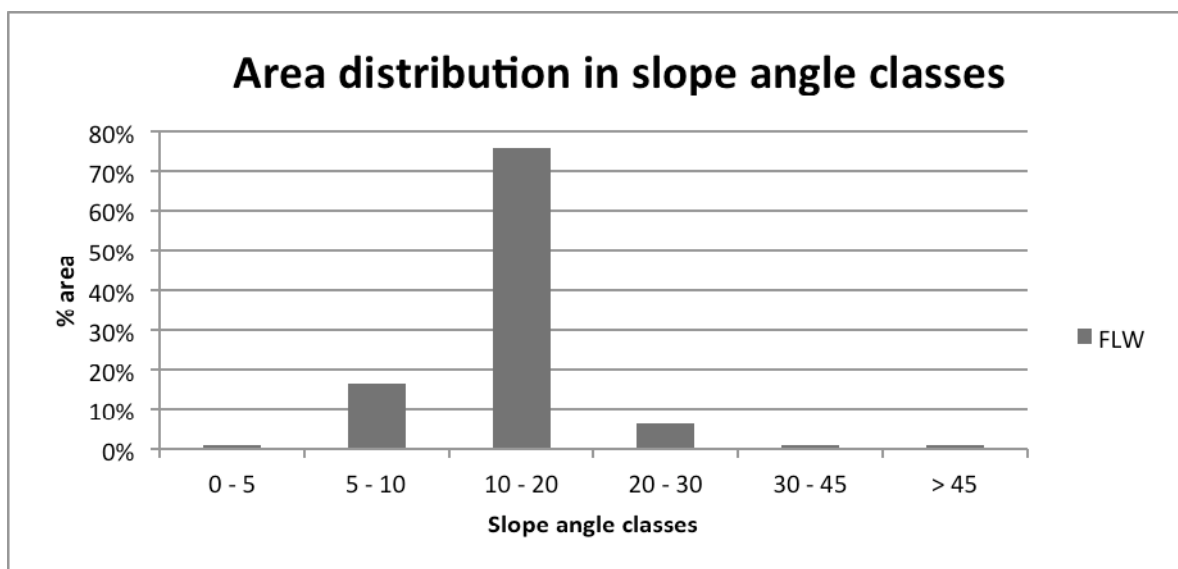


Fig. 5.7 - Frequency distribution of areas based on slope classes. It can be seen as the dominant class is the one with values ranging from 10° to 20°.

The SLO parameter is the most widely used in literature for the evaluation of landslide susceptibility: in fact, this is indirectly related to the inclination of the possible plans or horizons of rupture and, therefore, is usually correlated with landslide distribution (Figs. 5.7; 5.8). The layer of the slope is expressed in GRID format and has been reclassified in a heuristic based on the following ranges: 0° - 5° , 5° - 10° , 10° - 20° , 20° - 30° , 30° - 45° and $>45^{\circ}$.

The parameter TWI (Topographic Wetness Index), expressed on the basis of the topography condition of the slope, which control the geometry of the runoff, the amount of water that can infiltrate and saturate the rock outcropping, thus differentiating the cells in which the slope is divided, depending on the degree of humidity or saturation potential. The presence of water directly affects the stability of the land, because on one hand it increases the weight of volume, on the other, significantly change the resistance of land available to conduct pseudo-coherent.

The calculation of the TWI is realized in an automated way from the DEM (Wilson and Gallant, 2000) using the relation:

$$TWI = \ln (Ca/\tan\beta),$$

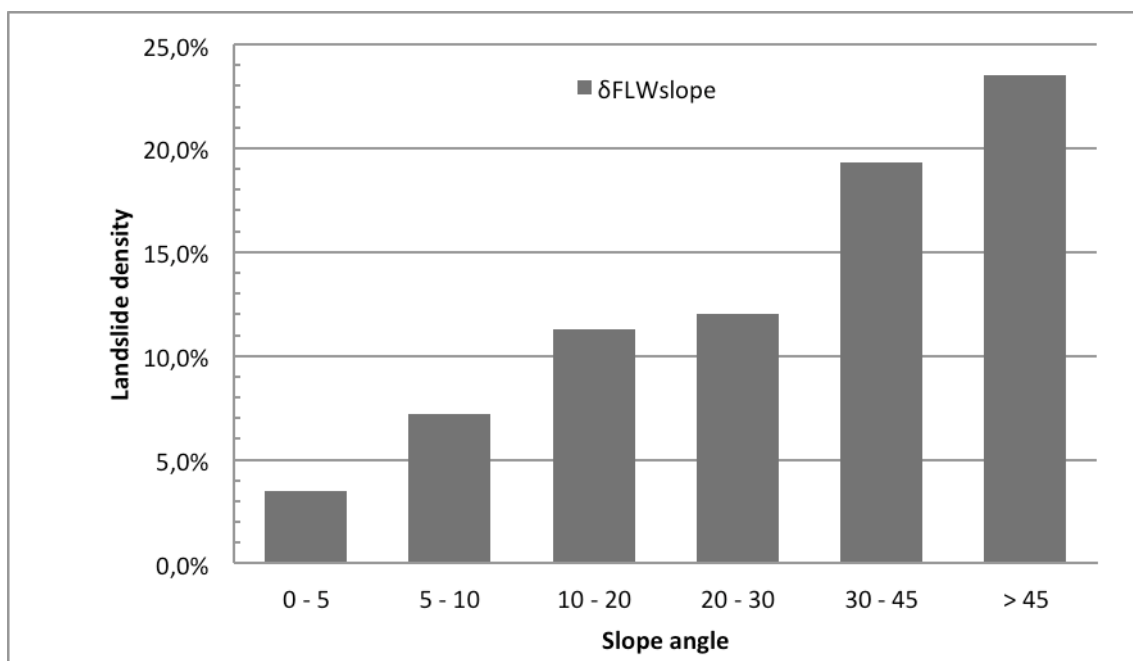


Fig. 5.8 - Frequency distribution of landslide density for each class of slope.

where C_a , indicates the contributing area of each cell, and β indicates the angle of slope of the cell. The TWI has been re-classified such as CUR factor in standard deviations (Fig. 5.12). The performance of the TWI is naturally marked by the presence of surface drainage lines, which have at their disposal extensive areas of power and at the same time, have more modest values of slope, the greater is their hierarchical order. Nevertheless, the variations of the parameter of interest here are those which characterize the slopes where low values may be observed in the medium - low to medium - high.

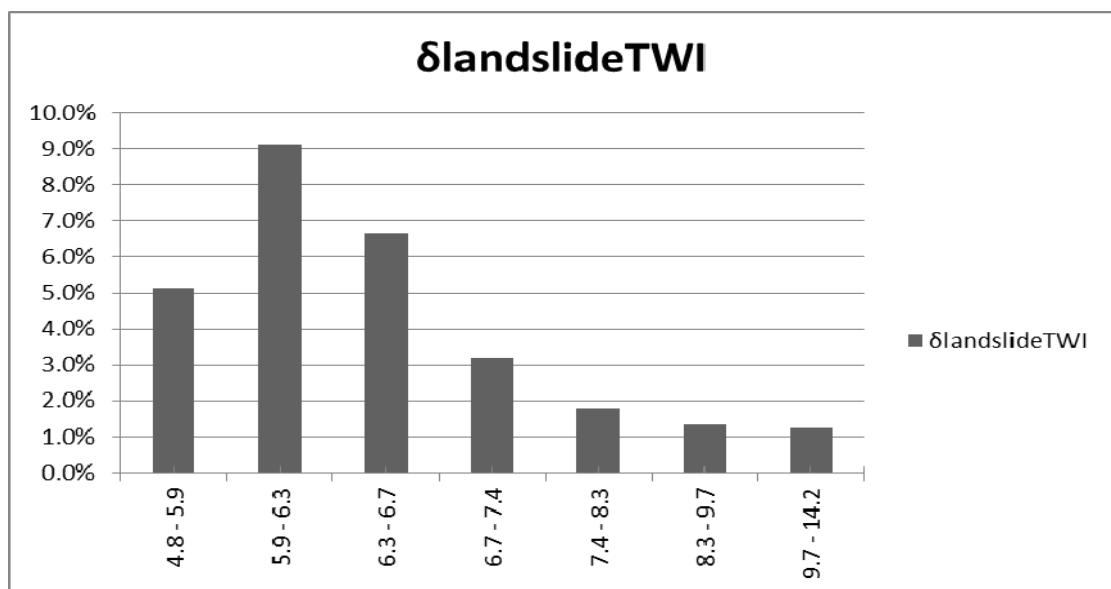


Fig. 5.9 - Frequency distribution of landslide density for each class of TWI.

The Fig. 5.9 shows that, the areas with highest density of landslides are those who are at low values of TWI, this probably due to the fact that the lowest values of TWI and we find them in areas topographically higher and then characterized by higher slopes, which can lead to more landslides, as noted in the analysis between landslides and the slope factor. It is known that at the base of the elaborate modeling of natural phenomena that occur on the surface topography. The slope of the curves in fact represent the deviation of the gradient vector per unit length (in radians) along particular curves drawn on the surface in question. The CUR parameter (Fig. 5.10), calculated as the slope of the derivative exposure, allowed to discriminate sides concave

and convex planes. The ratio was calculated using finite differences to a report that produces negative values, the convex portions, and positive values to the traits of concave side. This is a parameter widely used in literature (Wilson and Gallant, 2000; Ohlmacher, 2007), because it allows conditions to characterize the susceptibility of a slope at a point, depending on the topography, analyzed in a more general scale. The histogram presented indicates a homogeneous distribution of landslides in areas both concave and convex time, while a strong decrease in density, for those classes of planar curvature values close to zero, i.e., those flat areas. The result obtained with the univariate analysis according to which to find the density by a factor of landslide control CURVPLAN will equal:

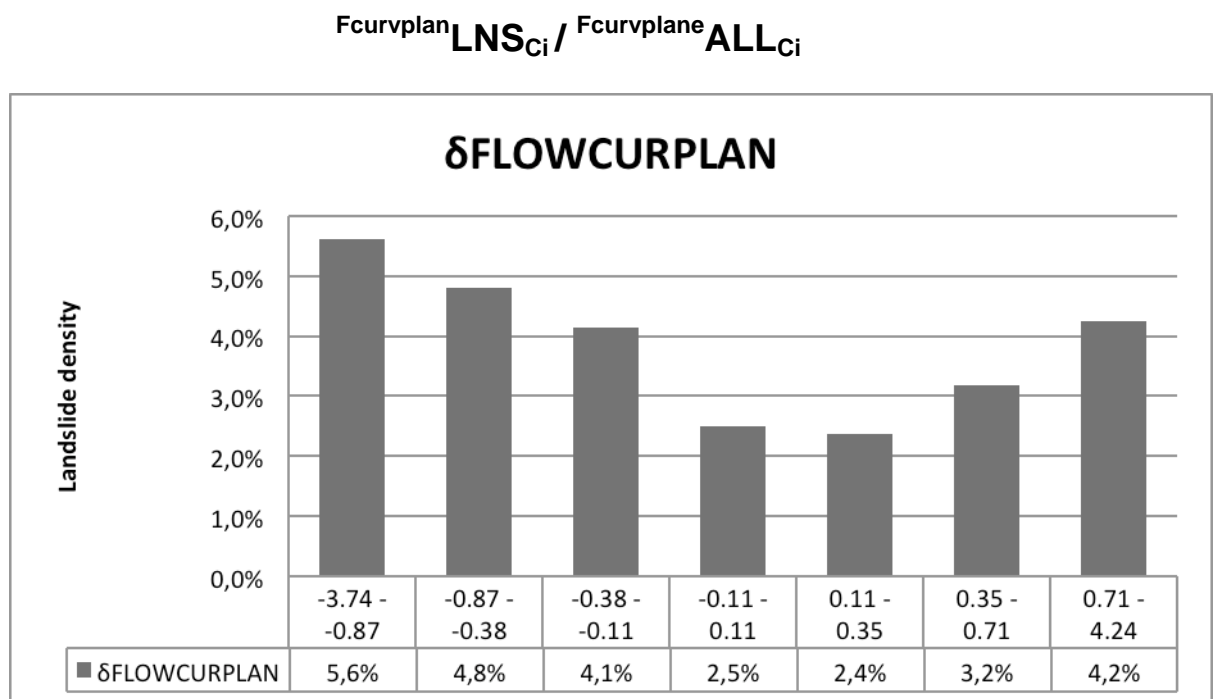


Fig. 5.10 - Frequency distribution of landslide density for each class of CURPLAN

As for the characterization of the outcropping lithology is produced using the bibliography for the area (Giunta et al., 1979, Monaco et al., 2000), with a detailed geological survey was carried out in a complex amalgamation litho-technical, depending on the geo-mechanical response or expected behavior. In this way, it was possible to reduce significantly the number of classes, simplifying and strengthens geostatistical analysis. I'm so identified the following 4 classes: pseudo-coherent, incoherent, semi-coherent, consistent. The outcropping lithologic complexes were derived by grouping lithologies recognized from geological maps drawn on a 1:10.000 scale prepared on the basis of available data (Giunta et al., 1979; Monaco et al., 2000) and detailed field and remote surveys (Figs. 5.11; 5.12).

Outcropping lithologies	Slope angle classes (°)					
	0-5	5-10	10-20	20-30	30-45	>45
Clays	3%	27%	66%	4%	0%	0%
Sands	7%	41%	47%	5%	0%	0%
Clays and brecciated clays	9%	35%	54%	2%	0%	0%
Quartz-arenite	2%	13%	61%	22%	3%	0%
Alluvial deposits	72%	19%	8%	0%	0%	0%
Limestone	4%	16%	62%	18%	0%	0%
Marly limestones	2%	37%	48%	13%	0%	0%
Sand-gypsum	8%	41%	46%	5%	0%	0%

Fig. 5.11 - Frequency distribution of the density of landslides for different classes of lithological outcrops.

A larger number of controlling factors could have been used but, the main task of the research was to verify the reliability of the proposed assessment strategy rather than to gain the best predictive model; consequently, a more simple and parsimonious model was preferred. Besides, using a limited number of widely adopted (e.g. Conoscenti et al., 2008; Irigaray et al., 2007; Ohlmacher, 2007; Remondo et al., 2003; Clerici et al., 2010) controlling factors allows us to avoid the generation of a huge number of poorly diffused UCUs, which would weaken the conditional analysis. The four-factor GRID layers were finally combined in a single UCU layer. Figure 5.12 shows the spatial distribution of the four controlling parameters, while Table 5.2 shows the characteristics of the most

diffused UCUs in the target and in the source areas. Only 525 of the 1,176 possible UCUs values occurred; this is largely due to the mutual dependence between factors. The UCU layer defined for the whole basin was also split in a UCU_source and a UCU_target layers, by clipping it inside and outside the limits of the source area, respectively. The two UCU layers can be considered equivalent, as the same UCUs representing 80% of the source area accounts for 77% of the target area.

From Figure 5.13 we observe that the class is made up of predominantly litotecnic class is pseudocoherent behavior. They are part of this class all the terms in which there is

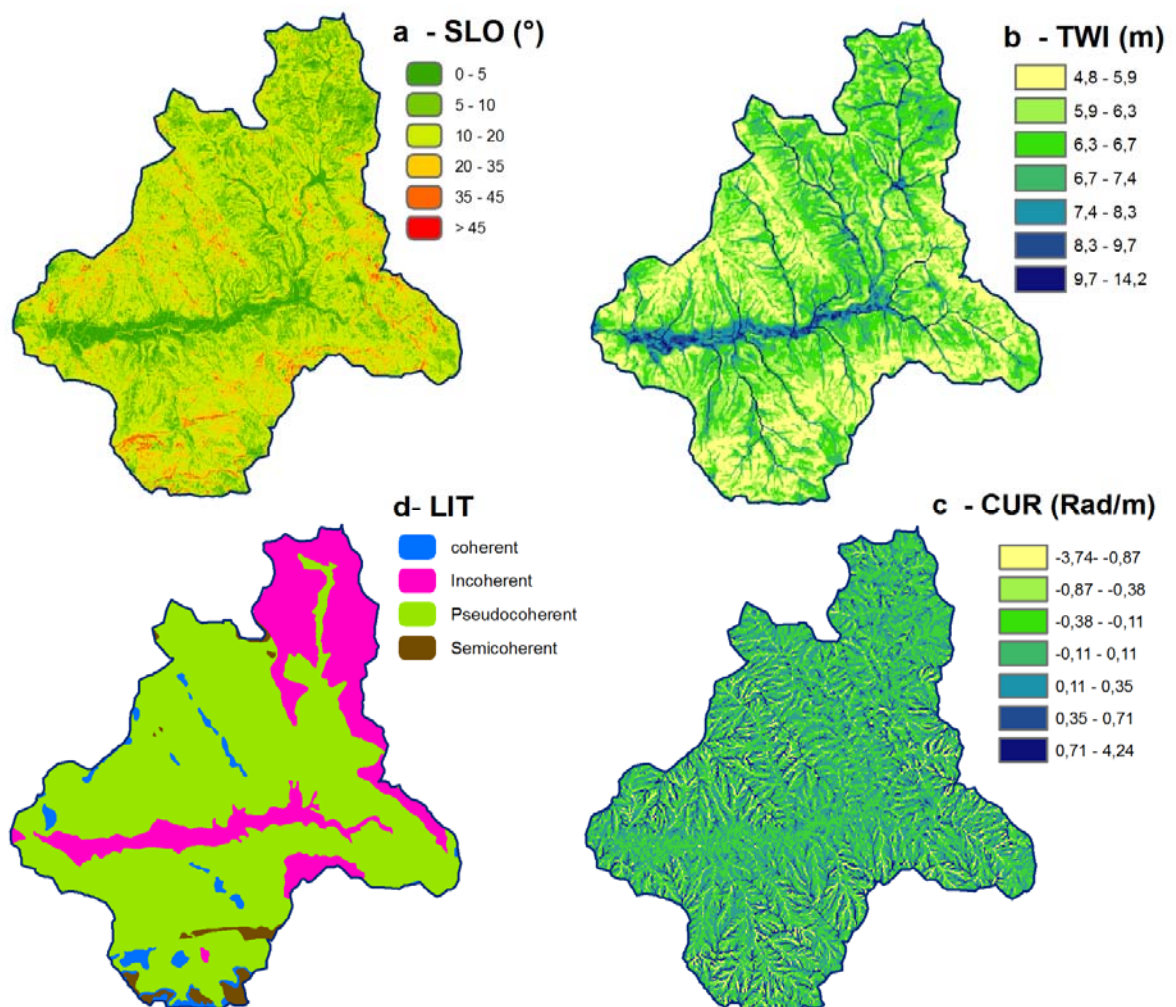


Fig. 5.12 - Spatial distribution of the four selected controlling factors.

clay abundant clays: Fm. Castellana, the Fm. Terravecchia and Numidian Flysch. For these units, the characteristic feature of the mechanical behavior is the extreme variability of cohesion and shear strength as a function of water content. At the

coherent terms for prospective lithological base made from limestone and quartz-arenitic counters, the complex terms for prospective incoherent sand of Fm. Terravecchia and current and recent deposits, while the terms for prospective limestone-marl semicoherent of Trubi Fm.

Of course, could be used a larger number of control factors, but the main objective of this experiment was to verify that the proposed strategy is viable to get the best

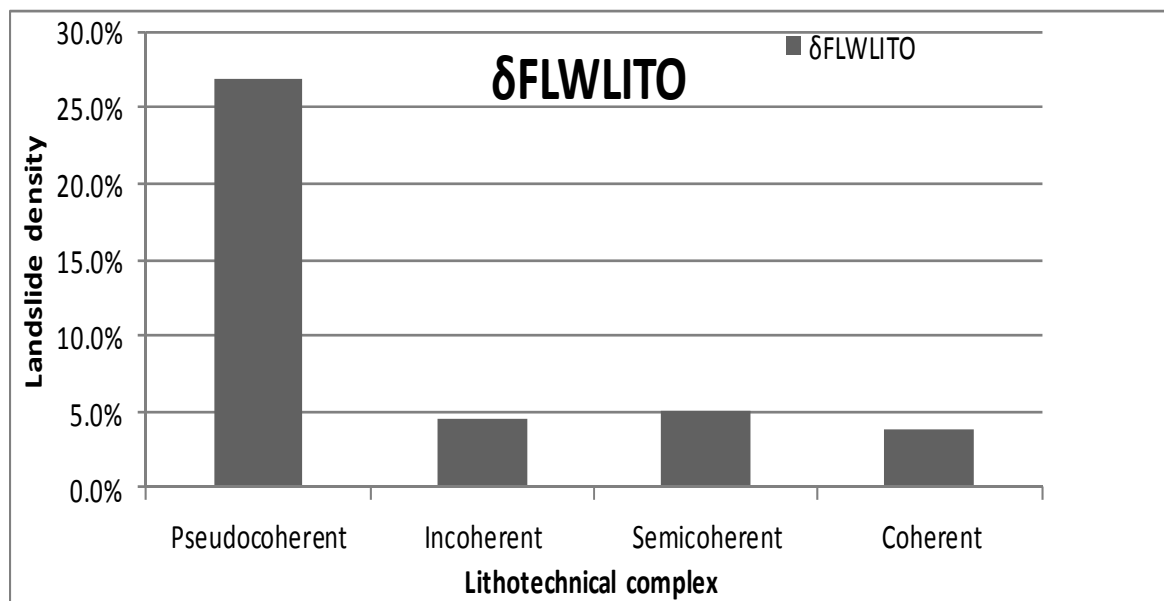


Fig. 5.13 - Frequency distribution of the density of landslides for different classes of lithologies in different behavior. Predominantly litotecnica class is pseudocoherent behavior.

predictive model, a consequence of this, it was preferred to a lower number of factors to create a more simple, robust and reliable. Also, use a relatively small number of control factors, is an approach widely used in the literature (e.g. Conoscenti et al. 2008; Irigaray et al. 2007; Ohlmacher 2007; Remondo et al. 2003; Clerici et al. 2010), and as well cannot generate an overly large number of UCUs (Unique Condition Unit) which could weaken the conditional analysis.

Once the layers defined in the grid format of the four factors, we proceeded to their combination into a single information layer, which consists of a Grid whose cells are characterized according to the type of combination of factors obtained (Carrara et al., 1995, Clerici et al. 2002; Irigaray et al., 2007). It is therefore a GRID representing the spatial distribution of units of unique conditions (UCU).

The combined representation of the physical-environmental, it effectively to conduct the analysis of susceptibility and to arrive at a characterization of the same, according to a multivariate approach that protects the predictive power of the model compared with the effects of cross correlation between same factors.

UCU	FACTORS				COUNT		CUM_COUNT%	
	SLO (°)	TWI (m)	CUR (rad/m)	LIT	TARGET	SOURCE	TARGET	SOURCE
87	5-10	5.5-6.4	0.0-1.0	PSEUDO-COHERENT	138194	46992	0,20	0,20
85	5-10	5.5-6.4	-1.0-0.0	PSEUDO-COHERENT	108601	38708	0,36	0,36
80	0-5	6.4-7.3	0.0-1.0	PSEUDO-COHERENT	59769	16892	0,45	0,44
81	0-5	6.4-7.3	-1.0-0.0	PSEUDO-COHERENT	48219	13762	0,52	0,49
109	5-10	5.5-6.4	1.0-2.0	PSEUDO-COHERENT	32508	14169	0,57	0,56
3	5-10	5.5-6.4	0.0-1.0	INCHOERENT	29139	662	0,61	0,56
2	0-5	6.4-7.3	0.0-1.0	INCHOERENT	24074	799	0,65	0,56
108	5-10	5.5-6.4	-2.0--1.0	PSEUDO-COHERENT	23436	10221	0,68	0,60
4	0-5	6.4-7.3	-1.0-0.0	INCHOERENT	22406	665	0,71	0,61
92	0-5	5.5-6.4	0.0-1.0	PSEUDO-COHERENT	11416	3492	0,73	0,62
107	0-5	7.3-8.1	-1.0-0.0	PSEUDO-COHERENT	9976	2372	0,74	0,63
94	10-20	4.7-5.5	0.0-1.0	PSEUDO-COHERENT	9190	4428	0,76	0,65
119	5-10	6.4-7.3	-1.0-0.0	PSEUDO-COHERENT	8712	3129	0,77	0,66
38	0-5	7.3-8.1	0.0-1.0	PSEUDO-COHERENT	7847	1801	0,78	0,67
101	10-20	4.7-5.5	-1.0-0.0	PSEUDO-COHERENT	7652	3636	0,79	0,69
89	0-5	6.4-7.3	1.0-2.0	PSEUDO-COHERENT	7418	2535	0,80	0,70
128	5-10	6.4-7.3	-2.0--1.0	PSEUDO-COHERENT	5823	2352	0,81	0,71
117	5-10	5.5-6.4	2.0-2.9	PSEUDO-COHERENT	5601	2820	0,82	0,72
106	10-20	5.5-6.4	-1.0-0.0	PSEUDO-COHERENT	5417	2526	0,83	0,73
113	0-5	6.4-7.3	-2.0--1.0	PSEUDO-COHERENT	5044	1793	0,84	0,74
98	10-20	5.5-6.4	0.0-1.0	PSEUDO-COHERENT	4941	2279	0,84	0,75
97	0-5	5.5-6.4	-1.0-0.0	PSEUDO-COHERENT	4911	1534	0,85	0,76
96	10-20	4.7-5.5	1.0-2.0	PSEUDO-COHERENT	4731	2428	0,86	0,77
118	5-10	5.5-6.4	-2.9--2.0	PSEUDO-COHERENT	3931	1988	0,86	0,77
249	5-10	5.5-6.4	-1.0-0.0	COHERENT	3715	1851	0,87	0,78
250	5-10	5.5-6.4	0.0-1.0	COHERENT	3663	1891	0,87	0,79
8	5-10	5.5-6.4	-2.0--1.0	INCHOERENT	3655	153	0,88	0,79
103	0-5	9.0-15.5	-1.0-0.0	PSEUDO-COHERENT	3614	931	0,88	0,79
110	0-5	8.1-9.0	-1.0-0.0	PSEUDO-COHERENT	3548	884	0,89	0,80
123	10-20	4.7-5.5	-2.0--1.0	PSEUDO-COHERENT	3160	1660	0,89	0,81
155	5-10	5.5-6.4	0.0-1.0	SEMI-COHERENT	2702	2134	0,90	0,81
158	5-10	5.5-6.4	-1.0-0.0	SEMI-COHERENT	2661	2102	0,90	0,82

Tab. 5.2 - Most diffused UCUs in the source and in the target areas

The combination of four factors in each UCU, has produced a very large number of homogeneous domains (525 classes of combinations), but much less than the total number of 1176 possible combinations, that fact is a confirmation of mutual dependence between factors and, therefore, the need to address the problem using a multivariate

approach. Table 5.2 lists the most common features of UCU in the basin, with a frequency of at least 500 cells (0.8 km²).

The table shows as most diffused UCUs are all characterized by argillaceous lithologies and then to conduct pseudo-coherent, almost falling in the class of slope values from 10° to 20°. The UCU layer defined for the whole basin was also split in a UCU_source and a UCU_target layers, by clipping it inside and outside the limits of the source area, respectively. The two UCU layers can be considered equivalent, as the same UCUs representing 80% of the source area accounts for 77% of the target area.

5.1.4 Model building and validation techniques

The conditional analysis (Davis, 1973, Carrara et al., 1995) is widely used in the literature (e.g. Clerici et al., 2006, 2010, Chacòn et al. 2006; Conoscenti et al., 2008, Del Monte et al., 2002; Irigaray et al., 2007; Pelvárez-Jimenez et al., 2009). According with the approach used, the value of landslide susceptibility associated with each area, depending on its physical environment, has been constructed by the spatial linking of the combined factors and information layers of landslides. Intersecting the two layers (UCUs and landslides), it is possible to calculate the density of landslide area BLIP δ , as the ratio of the portion of the landslide and the BLIP of the total area A, each i-th UCU:

$$^{BLIP}\delta_{UCU_i} = ^{BLIP}A_{UCU_i}/A_{UCU_i}.$$

From a probabilistic point of view, it shows that the density of landslide corresponds to the value of the probability of finding an area in a landslide, conditioned to a particular combination of control factors. The function $f = ^{BLIP}\delta (UCU)$ is therefore the function chosen to represent probabilistic landslide susceptibility conditions.

Regarding the validation of the susceptibility models, a widely adopted procedure that allows us to estimate both the model fitting and the prediction skill was applied, based on the analysis of success and prediction rate curves, respectively (Chung and Fabbri, 2003; Conoscenti et al. 2008; Fabbri and Chung 2008; Guzzetti et al. 2006; Irigaray et al. 2007; Van Den Eeckhaut et al. 2009). Chung and Fabbri (2003) identified in this case two possible techniques: a random distribution of the archive of landslides in two

separate files, each of which simulates a time different (random partition): This is a device that allows you to get a the set of "*training events*", with which we build the model, and a set of "test events", whose spatial distribution, we intend to play. The alternative to this method is instead based on the division of the area investigated in two areas (*spatial partition*), using axes of symmetry may be recognized (that separate limits, within the investigated area, two sectors with similar characteristics): in this case the model is built in a "*training domain*", is exported in a "*test domain*", so it is possible to compare, in the latter, the image estimate produced by the distribution of observed landslides. Conoscenti et alii (2008b) propose a validation strategy that works instead of a random distribution of cells of each of the UCU (spatial random partition), in a group training and a test numerically balanced. This approach ensures a perfect balance between the number of cells present in the training and testing area, for each value of UCU, allowing to work according to an objective space partition (as random) and perfectly symmetrical from the point of view geostatistical, which produces two sub-areas actually twins. Partitions based on random distribution of landslides or of detection of symmetry axes of the geological, are increasingly exposed to spatial variations of control factors (whether included in the model, whether they are ignored), which could limit the ability forecast domain training towards the test domain.

Each UCU is therefore assigned a value of landslide susceptibility as a function of areal density in cells found in landslide training domain (*training density*). Drawing in a scatter plot the cumulative proportion of cells in landslide training, depending on the training portion of the cells accumulated total, sorted by decreasing density of training, it is possible to evaluate the quality of the fit of the model (*model fit*), depending on the characteristics geometric curve that is obtained: the **success rate curves**. Similarly, the **prediction rate curves**, obtained by plotting the cumulative proportion of cells testing in landslide, according to the part of the cumulative total test cells, provided the criterion derived by a judge on the density of training, it is possible to evaluate the predictive ability of the model (*prediction skill*). If, in the test domain, the susceptibility of the UCU is correctly classified (i.e., if the model defined in the domain training is actually correct), then, taking into account the cumulative representation, validation curves show generally strong gradients in the initial (the percentage of landslide area in

question will be more susceptible to higher classes) and a linearly decreasing trend, as they take into account the responses of the UCU less susceptible.

In order to quantitatively compare the predictive performance of different models, three geometric indexes of the validation curves were defined: the tangent at 20% of the predicted area (T₂₀), the area between each of the two curves and the diagonal of the graph (areas above randomly predicted area, ARPA) and the area difference between success and prediction rate curves (SHIFT). Also, the effectiveness ratio (Chung and Fabbri, 2003) was computed (EFR). T₂₀ gives an estimate of the prediction skill of the 20% most susceptible area, while ARPA is an overall estimator of the prediction skill, evaluated on the 100% of the investigated area. SHIFT is a descriptor of the stability of the predicting performance when applying the susceptibility model to predict test landslides: over- and under-estimation of the predicted susceptibility (i.e. portion of predicted landslides) of a classified UCU result in a shift of the prediction rate curves below or above the success rate curves, respectively. Finally, the classic EFR is computed performance index, or For Each UCU susceptibility class, as the ratio of the predicted area between the portion and the portion of landslides accounted for. Differently from EFR, ARPA and evaluate the effectiveness of the T₂₀ prediction for cumulated portions of the classified area. By drawing on Theoretical validation curves, satisfying the threshold values for EFR ($0.5 > EFR > 1.5$) to propose by Guzzetti et al. (2006) indicated effective prediction to classes, Corresponding threshold values can be derived for ARPA Also (0.12) and T₂₀ (1.5) (Costanzo et al., 2011a).

A first susceptibility model was obtained for the source area by intersecting the Google_2006BLIP archive (206 landslides) and the UCU_source layer, so that landslide density values were computed and a susceptibility map produced (Fig. 5.14a).

This model was validated following two procedures. A pure chronological validation was applied by exploiting the Google_2007BLIP landslide archive (282 landslides), so that the prediction image of Fig. 5.14a was compared with a successive landslide distribution. Earth flows in hilly and mountainous areas of Sicily have in fact a typical time recurrence of 1 year (they are almost seasonally events; Agnesi et al. 1982). The validation curves obtained (Fig. 5.14b) draw quite satisfactory shapes ($T_{20} > 1.85$; ARPA > 1.5 ; SHIFT < 0.02) demonstrating good model fitting and prediction skill; the 20% most susceptible predicted area explains about the 40% of the landslides. In fact, it must

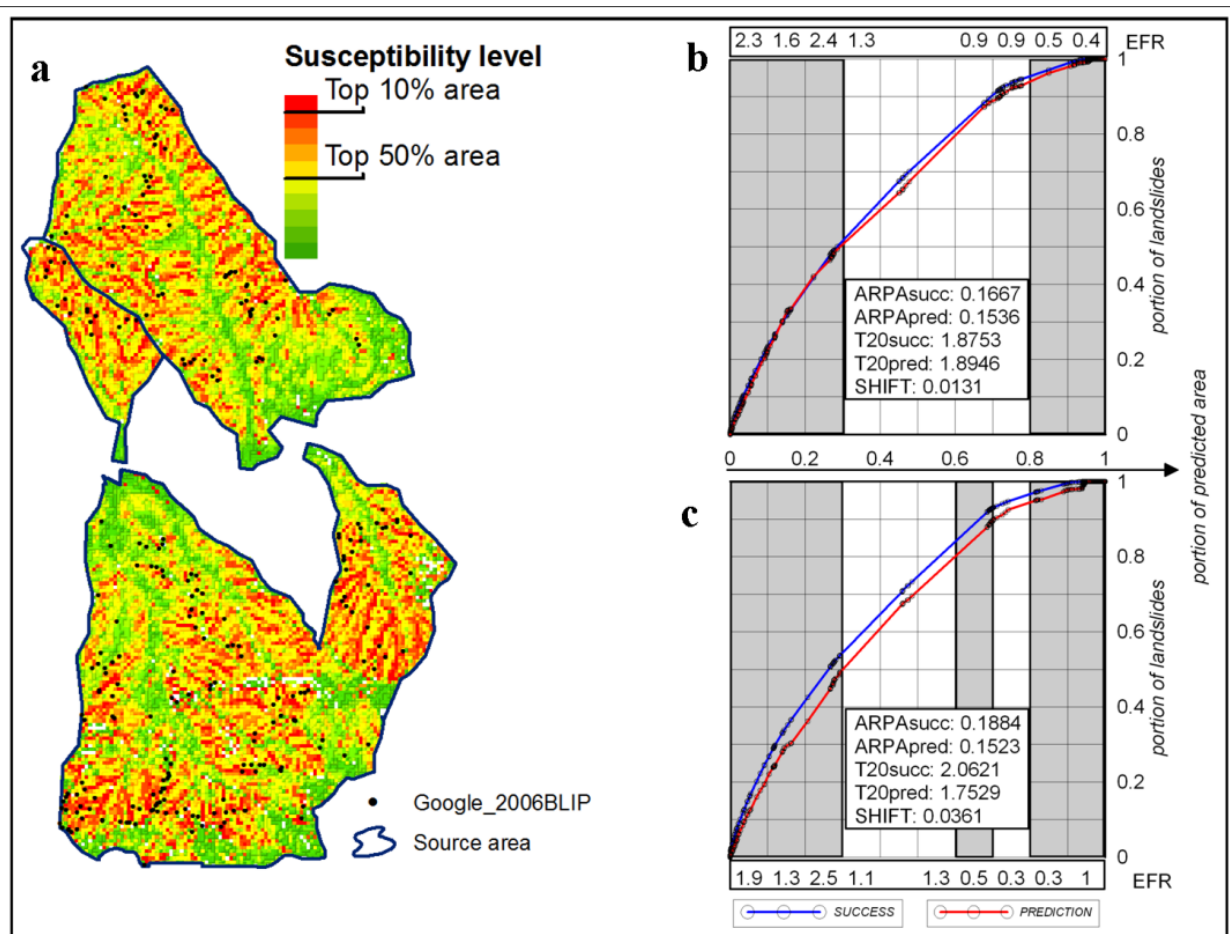


Fig. 5.14 - Susceptibility map, chrono-validation and cross-validation graphs obtained for the source area. The susceptibility map a was produced by computing the BLIPs density for each UCU using the whole Google_2006BLIP data set. In the chrono-validation graph b, the success rate curve is produced from the model trained by using the whole Google_2006BLIP data set, and the prediction rate curve results by comparing the susceptibility map with the spatial distribution of the Field_2007BLIPs. In the crossvalidation graph c, the success rate curve is produced from the model trained by using a randomly selected (50%) training subset of the Google_2006BLIP data set, and the prediction rate curve results by comparing the susceptibility map with the spatial distribution of the randomly selected test subset of the Google_2006BLIPs (the ones not selected for training the model). EFR values are also reported in both the two validation graphs.

be noticed that 37% (76) of additional landslides were recognized in 2007, so that the overlapping between the two archives can be considered as limited (no obvious strong correlation was to be a priori expected). A random partition-based validation procedure was also performed, by randomly splitting the Google_2006BLIP layer into two subsets, which are composed by an equal number of randomly singled out BLIPs. A training subset is then exploited to compute a new prediction image, and a test subset is used for validation. The validation curves (Fig. 5.14c) are also satisfactory in this case ($T_{20} > 1.75$; $ARPA > 1.5$), but showing a gap of approximately 0.25% of BLIPs between success and prediction rate curves, confirmed by a SHIFT of 0.036.

Once the model passed the validation procedures in the source area, the density values of each UCU, computed using all the 2006BLIPs, were transferred as susceptibility values to the corresponding UCUs in the target area (Fig. 5.15a). The validation of this exported model was carried out by spatially intersecting these susceptibility values with the 2006BLIPs in the target area, to produce a prediction rate curve; the latter was firstly compared with the success rate curve, obtained in the source area. The validation graph (Fig. 5.15b) confirms the high stability of the model for the 50% most susceptible area (accounting for about the 70% of landslides; $T_{20_{pred}}$ about 1.7), with a lowering of the performance, mainly corresponding to UCUs poorly diffused and trained in the source area, evidenced by a large SHIFT (0.062).

In order to compare the results that were obtained by the exportation procedure to those that would have been produced by a standard approach, a susceptibility model was defined and cross-validated by intersecting the Google_Blip2006 with the UCU_target layer. The prediction rate curve (Fig. 5.17c) obtained by cross-validating the model in the target area can be compared with that obtained by exporting the model from the source area (Fig. 5.15b).

Small differences between the two prediction curves are evidenced in the 50% most susceptible area (highlighted by larger values of EFR and T_{20}), while as was expected, a shape much more fitted on the success rate curve is drawn by the prediction curve produced by the cross-validation.

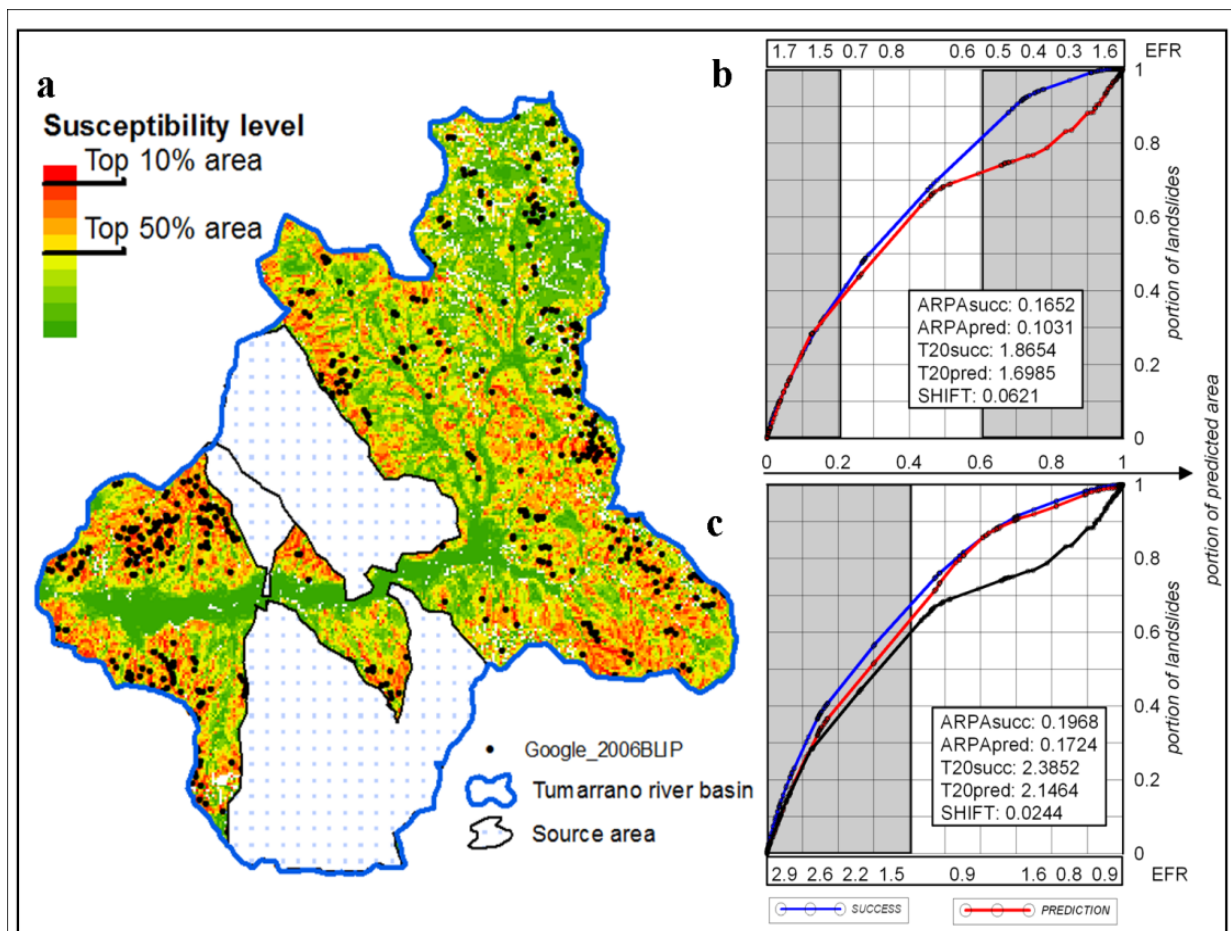


Fig. 5.15 - Susceptibility map and validation graphs obtained for the target area. The susceptibility map a was produced by extending the BLIPs density values computed for each UCU in the source area using the Google_2006BLIP data set. In the validation graph b, the success rate curve is produced by comparing the susceptibility map and the spatial distribution of the Google_2006BLIPs in the target area; the prediction rate curve results by comparing the susceptibility map with the spatial distribution of the Google_2006BLIPs in the target area. In the cross-validation graph c, the success rate curve is produced from the model trained in the whole target area, by using a randomly selected (50%) training subset of the Google_2006BLIP data set, and the prediction rate curve results by comparing the susceptibility model (whose map is not shown) with the spatial distribution of the randomly selected test subset of the Google_2006BLIPs. EFR values are also reported in both the two validation graphs.

5.1.5 Discussion and concluding remarks

The research whose results have been shown was focused on testing the possibility to approach the landslide susceptibility assessment in a large basin, by exporting models trained in limited and representative sectors. In this sense, the analysis and discussion of the data here are much more focused on variations in performance between predictive models and source models exported, rather than on their absolute quality.

The research found a good predictive model based on a small number of parameters, combined in UCUs, which has been verified through a validation in space for the whole basin and for a representative part, with time validation.

In general, the validation curves obtained have shapes according to the geometric constraints of the indicators required (Chung and Fabbri, 2003). The EFR calculated interval of 10% of the area planned for describing classes as satisfactory ($0.5 > \text{EFR} > 1.5$), we must remember that the results are far better standards EFR (Chung and Fabbri, 2003). The problems occur in the intermediate classes (about 50% of the investigated area) where the area is dominated, both as the source in the test areas, the same four UCUs very large (SLO: $0^\circ - 5^\circ$; LIT: pseudocoherent; TWI: 5.54 - 6.4; CUR -0.3 - -0.1). The validation of models of the source area showed a better overall performance when using an archive of multitemporal BLIP compared with that obtained from a random partition. This could be due to fewer BLIPs used training and test used in the latter case (50% of 206), resulting in a successful running yield curve ($T_{20} = 2.06$; $\text{ARPA} = 0.19$) responsible for the observed SHIFT (0.036), despite the morphometric indices of the yield curve prediction ($T_{20} = 1.75$, $\text{ARPA} = 0.15$). The success rate curves produced considering all the BLIPs in the source area (Fig. 5.14, blue) does not reach such a performance ($T_{20} = 1.87$; $\text{ARPA} = 0.17$), being more similar to the curve produced by cross-validation in the validation source area.

As for the exported model, all indices show a quite satisfactory prediction for the area in the first 50% of UCUs more susceptible, although we observe an inflection of the curve for the source area for areas in 68% of cases lithotypes to be inconsistent behavior, however, this loss of predictive ability of the model is limited to the classes exported less sensitive. Given the objective of the research, it is important to note that the exported model is characterized by a good predictive power for 50% UCUs, very similar to that of the model trained using the entire target area (Figure 5.15). This result is due to appropriate selection of the source. Research shows, relative to the area of study, that we can evaluate the landslide susceptibility in a field representative and export the model created in an area where we do not have equivalent information about the landslide with an effectiveness almost equivalent to that obtained using landslide created an archive for this purpose. After choosing a set of causal factors chrono-

validated (a partition of the time), the susceptibility estimated in the 'area of origin' was then exported to the destination area, demonstrating to be a good explanatory variable of its distribution landslide. In general, we should note that geological maps, topographic, climatic and land use, satisfactory resolution and reliability, are often available at very low cost, and although several projects were undertaken for the production archives landslide, they do not really are complete, not sufficiently detailed and chronologically ambiguous. This is why studies evaluating landslide susceptibility are generally focused on areas where the archives are available. Yet, when the areas under investigation spanning several thousand square kilometers, the costs of the investigation are often too high. Google Earth™ offers the possibility to realize efficiently and faster archives multi-temporal landslide, which allow us to evaluate the conditions of landslide susceptibility on a regional scale.

Test 1b: The Tumarrano river basin: Forward logistic regression for earthflow landslide susceptibility assessment

Landslide susceptibility assessment is undoubtedly one of the more addressed topics in the last decades by applied geomorphologists. Tens of papers are yearly published by international journals which attests for the great interest of the matter both for scientific and land management and civil protection aims (Aleotti & Chowdhury, 1999; Chacón & Corominas, 2003; Chacón et al., 2006; Guzzetti et al., 1999; Guzzetti et al., 2005). Among the approaches that can be followed in assessing the landslide susceptibility, the stochastic ones more and more gain importance and see increasing number of applications, particularly for basin scale studies. These are based in the definition of statistical relationships that quantitatively and objectively link the spatial distribution of past landslide events to that of a set of geo-environmental variables. Based on the assumption that new landslides will be conditioned by the same factors that cause the past ones, prediction images can be produced. Prediction images or susceptibility maps can be submitted to validation procedures, so to estimate model

fitting, prediction skill, robustness and adequacy, also if having a test (not used in training the model) events inventory.

Conditional analysis (e.g. Clerici et al., 2010; Conoscenti et al., 2008; Costanzo et al., 2012; Irigaray et al., 2007; Jiménez-Pelvárez et al., 2009, Rotigliano et al., 2011a,b), discriminant analysis (e.g. Baeza & Corominas, 2001; Carrara, 1983; Carrara et al., 2008; Guzzetti et al., 2006; Rossi et al., 2010) and logistic regression (e.g. Atkinson and Massari, 1998; Ayalev and Yamagishi, 2005; Bai et al., 2010; Can et al., 2005; Carrara et al., 2008; Dai and Lee, 2002; Davis et al., 2006; Nandi and Shakoob, 2009; Nefeslioglu et al., 2008; Ohlmacher and Davis, 2003; Van den Eckhaut et al., 2006; Van den Eckhaut et al., 2009) are the more frequently adopted statistical techniques.

Logistic regression (Hosmer and Lemeshow, 2000) has been adopted in many studies in the last two decades. The large use of this multivariate technique for landslide susceptibility modeling is mainly due to its capability to work on any type of independent variable (either ratio or interval or ordinal or nominal scale), no matter the deviance of the considered variables and residuals from a normal distribution. This allows the analyst to manage the model with a more direct and geomorphological sound approach, without needing to define normal distributed transformed variables. All the discrete independent variables are binarized and transformed in dichotomous or polychotomous variables. The dependent is defined as a dichotomous in terms of stable/unstable status of the mapping unit we want to classify.

One of the main problem concerned with using logistic regression is the requirement of balanced dataset, in which the number of stable and unstable cells would be the same. This is obviously rarely verified in real nature, so that typically together with all the unstable cells an equal number of randomly selected cells is singled out from the investigated area. The logistic regression is then run on this very limited subset, often neglecting the larger whole remaining area and assuming the regression equation as representative of it as well.

A test was carried out in a basin of central Sicily to adopt an approach for estimating possible lack in robustness of the susceptibility model due to the limited extension of the really processed area. The procedure is based on the preparation of a suite of

balanced model, each including the same unstable cells but different randomly select stable ones. The forward logistic regression techniques was then applied to derive models, whose performances and structure (type and number of predictors) were compared to estimate the robustness of the whole procedure and of the results.

5.1.6 Landslides

The landslide inventory was prepared (Costanzo et al., 2011) from a remote Google Earth™ aided recognition exploiting high resolution images of the area (Catalog ID: 1010010008265000, Date: Jun 11, 2008, Catalog ID: 10100100071CDC00, Date: Aug 28, 2007; Sensor: QBo2, Band Info: Pan_MS1;) made available at: <http://browse.digitalglobe.com/imagefinder/catalogListDisplay.do?noCache=1324202819153>. Compared to the work of Costanzo *et alii* (2011), the inventory of landslides has been implemented with a field survey were also carried out in 2009.

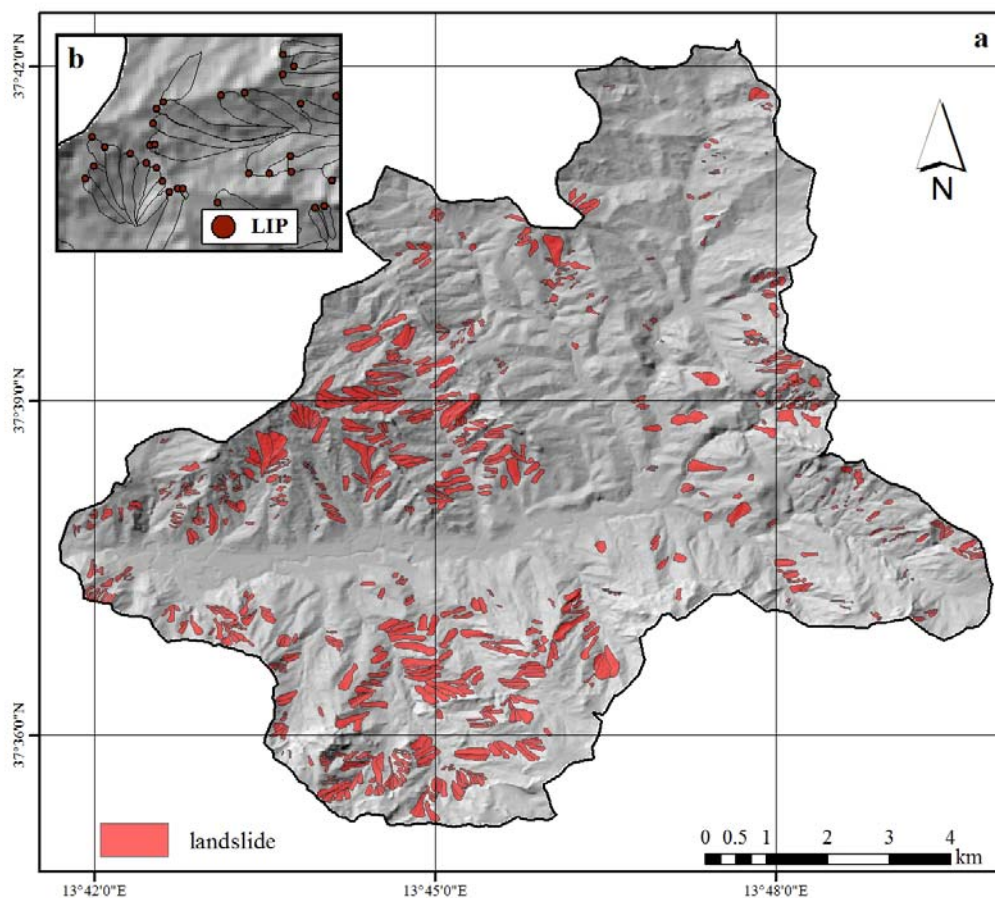


Fig. 5.16 - Earth flow landslides map (a); examples of LIPs generation (b)

The landslide archive consists of 760 earthflows (Fig. 5.16). The extension of the landslide bodies is very variable with more than 300 cases having an area less than $5,000\text{m}^2$, about 200 in the range $5,000\text{-}13,000\text{ m}^2$, and 125 in the range $13,000\text{-}26,000\text{m}^2$. Landslides involves earth or debris type materials taking the form of open slope or long runout phenomena (Fig. 5.17). As regarding to the status of activity and time recurrence, the slopes affected by landslides have typically seasonal reactivation cycles, characterized on average by a maximum of one-two years lasting dormant stages (Fig. 5.18). New activations on slopes are subordinately recognized.

Few other types of movement were recognized, which are mainly classifiable as slides or falls. These landslides are not considered in the following section as this study was focused on flow landslides; besides, the susceptibility assessment of the other types of movement would have require the selection of different set of controlling factors.



Fig. 5.17 - Field and remote (Google Earth) examples of earth flow landslides in the Tumarrano river basin.

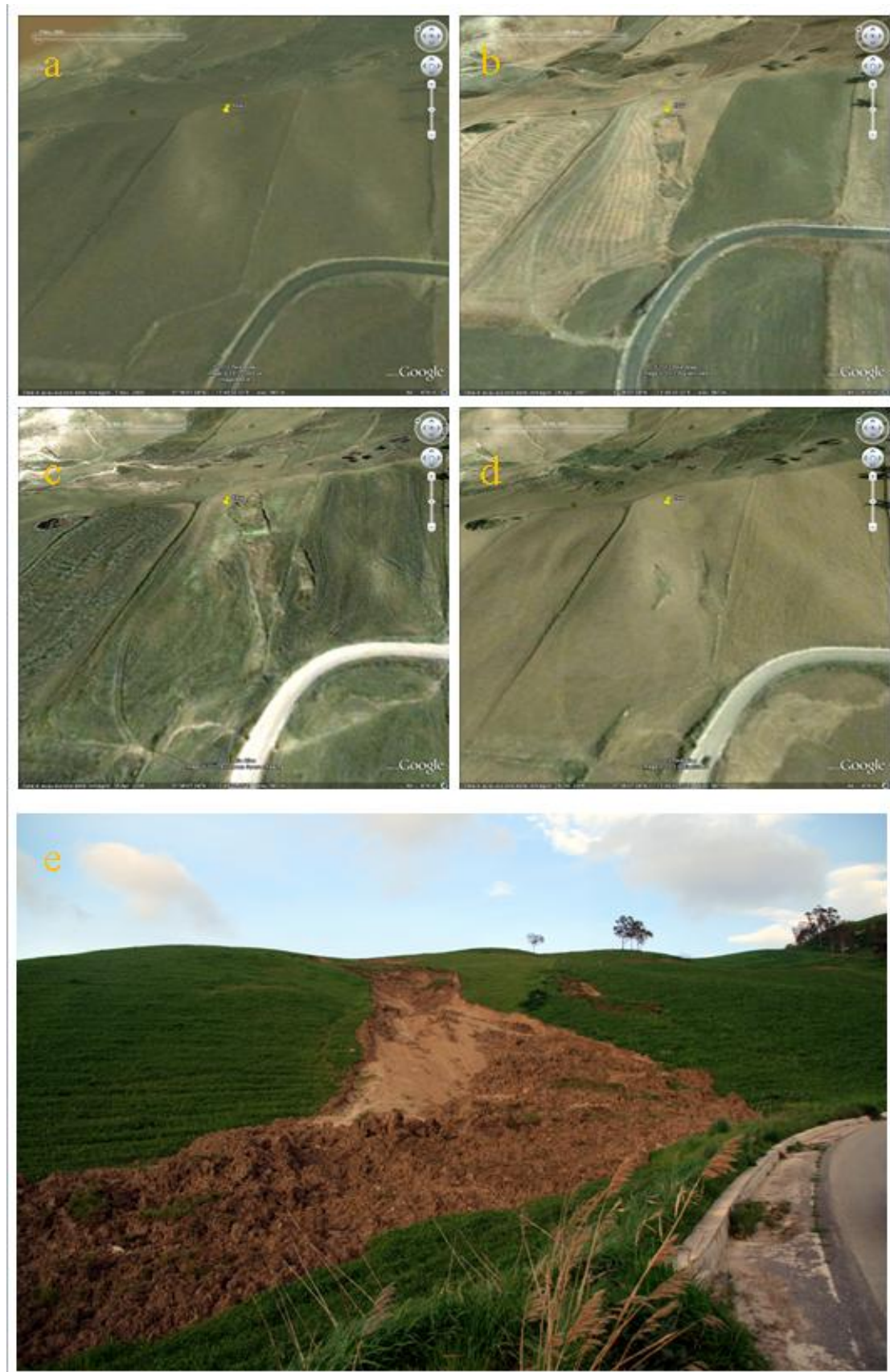


Fig. 5.18 - Example of seasonal re-activation cycles of earth flow landslides in the Tumarrano river basin: a, 2000; b, 2005; c, 2006; d, 2007; e, 2009 (from field).

5.1.7 Model building strategy

Logistic regression aims at modeling a linear relationship between the logit (or log odds) of the outcome and a set of p independent variables or covariates (Hosmer and Lemeshow, 2000):

$$g(x) = \ln[\pi(x)/(1-\pi(x))] = \alpha + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_p x_p,$$

where $\pi(x)$ is the conditional mean of the outcome (i.e. the event occurs or unstable slope conditions are found) given the condition x , α is the constant term, the x 's are the input predictor variables and the β 's are their coefficients. The fitting of the logistic regression model, which is performed by adopting maximum likelihood estimators, allows to estimate the coefficients β_p . It is so possible to predict the outcome from the input predictors and their coefficients.

As the fitting of the model is based on maximizing the value of the likelihood, comparing the likelihood itself allows to estimate the goodness of different regression models. Particularly, by multiplying by -2 the log-likelihood ratio, the negative log-likelihood ($-2LL$) statistic is obtained, which has an approximately chi-square (χ^2) distribution, so that the significance of a difference between the fitting of different models can be estimated. The $-2LL$ statistic can be exploited to compare the fitting of the model having only the constant term (all the β_p are set to 0) with the fitting of the model which includes all the considered predictors with their estimated non-null coefficients, so to verify if the increasing in the likelihood is significant; in this case at least one of the p coefficients is different from zero.

By exponentiating the β 's, odds ratios (OR) for the independent variables are derived. These are measures of association between independent and dependent and directly express how much more likely (or unlikely) it is for the outcome to be positive (unstable cell) for unit changing of the considered independent. Unit changings in case of continuous or dichotomous discrete variables are straightforward, while in case of polychotomous discrete variables are intended in relative terms with respect to a common reference group or class. No matter the type of variables, the ORs allow us to easily compare the role of unit changings of each predictors with respect to the others, as

the β 's are conditioned by the scale and classes adopted in classifying the factors. Negatively correlated variables will produce negative β 's and OR limited between 0 and 1; positively correlated variables will result in positive β 's and OR greater than 1.

At the same time, the -2LL allows to compare models obtained by considering different set of predictors, so that for example the significance of the increasing in the model fitting produced by including each landslide factor can be quantitatively assessed. Based on this approach, logistic regression can be performed following stepwise procedures, which enable to quantify the importance of each predictor and select among a large set of variables a restricted group made up only of the ones that significantly increase the performance of the multivariate model. At any step, the most important variable is the one that produces the greatest change in the log-likelihood relative of a model which does not contain it. This procedure describes the *forward selection* scheme in applying multiple logistic regression, which is the one we adopted in this study.

At step (0), the fitting of each of the p possible univariate logistic regression models $L_j^{(0)}$ is compared with the fitting of the "intercept only model" L_0 . The first entry x_{ε_1} in the model will be the j -th x variable producing the smallest p -value for the χ^2 -test on $G_j^{(0)} = -2(L_0 - L_j^{(0)})$. At step (1), the fitting for the model including the intercept and the first entry x_{ε_1} is then $L_{\varepsilon_1}^{(1)}$. $p-1$ models, each including the first entry and one of the other remaining predictors, are then prepared and their log-likelihood $L_{\varepsilon_j}^{(1)}$ estimated. Again, the one more minimizing the p -value for the log-likelihood chi-square test on $G_j^{(1)} = -2(L_{\varepsilon_1}^{(1)} - L_{\varepsilon_j}^{(1)})$ is selected as second entry in the model. The procedure follows in the same manner to the final step (m), for which including a j -th entry will result in a p -value for the log-likelihood chi-square test larger than a threshold significance values p_E (probability for entry). This threshold p_E was set in the following analysis at 0.01.

For the performing of the forward stepwise logistic regression an open source software for data mining was used (TANAGRA, Rakotomalala, 2005).

5.1.8 Controlling factors and independent variables

The first stage in model building was the production in ArcGIS of a data matrix, where each row corresponds to an individual case (i.e. a single grid cell) while columnar data show the values of the explanatory and response variables. The data matrix, whose records are the observed cases (i.e. the mapping units or, in this case, grid cell) contain at least $p+1$ fields, which correspond to the information both on the p independents and on the dependent status. Actually, the number of fields is typically larger due to the need to binarize all the discrete (nominal and ordinal scale) variables.

To perform the GIS analysis the definition of raster layers for the outcome (landslides) and all the considered predictor variables were prepared.

The selection of the controlling factors that are to be used as independent variables in the logistic regression analysis is typically driven by the following procedure: 1) testing the largest set of geo-environmental variables which could have statistically significant relationships with slope failures; 2) performing statistical tests so to exclude those variables which result as to be not significantly correlated with the dependent (with the exception of those variables which have a high diagnostic morphodynamic meaning); 3) finally, adopting the most parsimonious but performing number of independent variables. The whole sequence must obviously configure acceptable time/money costs for acquisition and processing of the spatial layers of the selected variables. In this sense a strong constrain is the set of already available variables. Moreover, the predictive performances of each considered factor or variable has to be evaluated considering both its morphodynamic diagnostic role and the resolution of the available data.

In this study we exploited a geological map which was specifically prepared for the landslide research and a soil use map, which was derived from the 1:100.000 CORINE2006 coverage based on photo-interpretation from LANDSAT 1988 and aerial photos (1:75.000 scale), made available by the Sicilian Region; as regarding to the topographic attributes, a detailed DEM (8m side-cell), which derived from a LIDAR flight, was acquired from the Sicilian Region.

No matter the scale of the source maps from which the geo-environmental attributes were derived, all the grid layers were structured with a 8m square cell; this was in fact the resolution of the more detailed source map i.e. the DEM, whose derived topographic attributes are considered of great importance. At the same time, we accept to run the risk to trash geological l.s. predictors from the forward selection procedure, because of the lower resolutions of their source maps. However, Authors were prepared to force the model for inclusion of highly diagnostic geomorphologic variables, in spite of their possibly poor estimated importance.

By processing these source data layers a set of 16 topographic and 4 geo-environmental independent variables was defined.

The DEM was processed by using GIS surface tools to derive the following primary and secondary topographic attributes: aspect, steepness, topographic wetness index, stream power index and topographic curvatures. Aspect and steepness were derived by using 3D analyst extension of Arcview. Aspect was used for further processing to produce a discrete nominal variable (see below), while the average of the steepness in a neighborhood area of one cell (SLONGB) was computed as landslide controlling factor. In this way, rather than local steepness, more general conditions were included in the model to represent the role of gravitative stresses. By using Terrain analysis tools, topographic wetness index (TWI) and stream power index (SPI) were derived. These secondary attributes typically express potential condition for infiltration and water erosion, respectively (Wilson and Gallant, 2000). As with respect to landslide modeling it is highly interesting to define the saturation of soils and stream power index on slopes (away from streams) a further processing of these variables was performed. TWISLO and SPISLO variables were also computed by dividing TWI and SPI values, respectively, for their standard deviation evaluated for a neighborhood of two cells. This new attributes ranges from minimum, along the streams, to maximum, away from streams on slopes, where both TWI and SPI values are lower but more constant. Topographic curvatures were also derived both considering a local (one cell = 8m) and a large (2 cells = 16m) curvature calculation. Eight curvature variables were so derived, by combining planar or profile and concave or convex shapes, for the two 8m and 16m curvatures: 8PLANCONC, 8PLANCONV, 8PROFCONC, 8PROFCONV, 16PLANCONC,

16PLANCONV, 16PROFCONC and 16PROFCONV were so derived. The altitude (HEIGHT) of each cell was also used as a proxy variable to represent possible rainfall or climatic variations inside the basin.

From the geological map a grid layer of the outcropping lithology (LIT) was prepared. Each of the ten outcropping lithologies was assumed as to be a specific term, according to the expected morphodynamic response. The CORINE2006 coverage was converted in a grid file of soil use (USE) by using the third level full CORINE legend. Aspect (ASP), Curvature Classification (CCL) and Landform Classification (LCL) were derived by processing the DEM with topographic analysis tools. Aspect was defined by partitioning the whole 360° range into eight 45° interval classes. Landform classification was derived by using a freeware ArcView extension tool (Jenness, 2006) which compare small and large neighborhood TPI (topographic position index) computed for each cell. The TPI values reflect the difference between the elevation of the considered cell and the average elevation in the neighborhood area. To compute the TPI the inner and the outer neighborhood areas were set to 400 and 800 m, respectively. Ten landform classes are obtained allowing us to assign the morphological conditions (position and shape) to each cell. Curvature classification was obtained by processing the DEM exploiting a terrain analysis module (Morphometry) of SAGA GIS (Olaya, 2004).

All the discrete variable were binarized before to be included in the logistic regression based model building procedure.

Tables 5.3a and 5.3b list the variables which were considered in the model building procedure.

a

Independent variables			
<i>Categorical variables: binary response [0,1]</i>			
<i>name: code</i>	<i>classes</i>	<i>variable</i>	<i>count%</i>
OUTCROPPING LITHOLOGY: LIT	clays	LIT_CLAY	28.845
	clayey and breccia clays	LIT_CLBRE	44.290
	clayey sands	LIT_CLYSN	16.457
	alluvial	LIT_ALL	5.683
	arenites	LIT_ART	1.849
	gypsum arenites	LIT_GYART	1.058
	carbonates	LIT_CARB	0.817
	marls	LIT_MARL	0.622
	arenaceous	LIT_ARN	0.247
	debris	LIT_DBR	0.132
SLOPE ASPECT: ASP	North	ASP_N	13.016
	North-East	ASP_NE	13.560
	East	ASP_E	11.175
	South-East	ASP_SE	9.624
	South	ASP_S	10.476
	South-West	ASP_SW	14.791
	West	ASP_W	14.001
	North-West	ASP_NW	13.356
CURVATURE CLASSIFICATION: CCL	Convex/Concave	CCL_CXCC	34.907
	Planar/Concave	CCL_PCC	31.795
	Concave/Convex	CCL_CCXC	17.799
	Planar/Planar	CCL_PP	15.243
	Concave/Planar	CCL_CCP	0.105
	Convex/Convex	CCL_CXCX	0.079
	Planar/Convex	CCL_PCX	0.069
	Convex/Planar	CCL_CXP	0.002
LANDFORM CLASSIFICATION: LCL	Upper Slopes, Mesas	LCL_UPPSLO	49.344
	Local Ridges/Hills in Valleys	LCL_LOCRID	9.446
	Canyons, Deeply Incised Streams	LCL_CANDEE	8.363
	Midslope Drainages, Shallow Valleys	LCL_MIDDRAIN	7.494
	Midslope Ridges, Small Hills in Plains	LCL_MIDRID	6.722
	Open Slopes	LCL_OPEN	6.445
	Plains Small	LCL_PLASMA	5.986
	U-shaped Valleys	LCL_USHAPE	5.603
	Upland Drainages, Headwaters	LCL_UPDRAIN	0.453
	Mountain Tops, High Ridges	LCL_MOUNTOP	0.144
LAN USE: USE	non irrigated arable lands	USE_211	86.786
	fruit tree and berry plantations	USE_222	0.628
	olive trees	USE_223	2.692
	pastures	USE_231	1.201
	coniferous forest	USE_312	3.875
	burnt areas	USE_334	0.594
	natural grasslands	USE_321	0.201
	sclerophyllus vegetation	USE_323	3.817
	beaches, dunes and sand plains	USE_331	0.206

b

Independent variables	
<i>Continuous variables</i>	
<i>description</i>	<i>variable</i>
Elevation	HEIGHT
Neighborhood steepness	SLOPENGB
Topographic Wetness Index	TWI
Slope-TWI	SLOPETWI
Stream Power Index	SPI
Slope_SPI	SLOPESPI
Local Profile concave curvature	8PROFCONC
Local Profile convex curvature	8PROFCONV
Local Plan convex curvature	8PLANCONV
Local Plan concave curvature	8PLANCONC
Large Profile concave curvature	16PROFCONC
Large Profile convex curvature	16PROFCONV
Large Plan convex curvature	16PLANCONV
Large Plan concave curvature	16PLANCONC

Tab. 5.3: Descriptions and codes of the independent categorical (a) and continuous (b) variables.

5.1.9 Diagnostic areas

In a binary logistic regression, the dependent or outcome to be predicted has a dichotomic behavior, morphodynamically corresponding to stable or unstable status for a so-called mapping unit. As in the present research the adopted mapping units are 8m side cells in which the area have been partitioned, the status of each of these will be characterized as stable or unstable.

Diagnostic areas are sectors spatially or morphodynamically connected to past-landslide areas so that their conditions are expected to be similar to those that had characterized before-failures the sites where failures occurred (Rotigliano et al., 2011b). Their geo-environmental conditions are statistically considered as the causative factors for landslide occurring and landslide susceptibility can be estimated in terms of similarity of the site conditions of each mapped cell. Diagnostic areas can be defined geomorphologically, as corresponding to gravitative pure landforms, or according to morphodynamic and spatial criteria, as neighborhood areas morphodynamically connected to the slopes or sites of past landslides. Typically, the most adopted diagnostic areas are selected based on landslide typology (Dikau et al. 1996): scarps, areas uphill from crowns and landslide area, for rotational slides; source areas and landslide areas, for flows. However a source of subjectivity and ambiguity arises in mapping the diagnostic areas as the ones above described.

A test is here proposed to adopt a very simple approach to automatically define the diagnostic areas (Rotigliano et al., 2011a; Costanzo et al., 2011). In this research the diagnostic area was identified in the cells coinciding with the LIP (Landslide Identification Point) of each landslide; the LIPs are generated from the DEM as the highest cells along the boundary of the polygons delimiting the landslide areas and are obviously positioned along the central sectors of the crown areas (Fig. 4). This kind of solution exploits the high morphodynamic specificity of this landslide sector, which could enable a good discrimination for prediction, but at the same time could suffer for noise due to errors in DEM or landslide boundaries mapping.

5.1.10 Model suite

Logistic regression requires for a near balanced number of positive (unstable) and negative (stable) cases in the worked dataset (Atkinson and Massari, 1998; Süzen and Doyuran, 2004; Nefeslioglu et al., 2008; Van Den Eeckhaut et al., 2009; Bai et al., 2010; Frattini et al., 2010). Particularly when using grid cell based models, positive cases are dramatically less than negatives. For this reason a typical procedure consist on randomly selecting a number of negative cases equal to the number of positives. By the other side, problems arise when reducing the portion of cells of the basin that are included in the regression analysis. The constrain given by the low number of positive is actually responsible for implementing the regression models by working only on a very small percentage of the studied area! This could reduce the robustness of the model, as the regressed logistic equation will depend on the particular set of selected stable cells. By performing more than one random extraction for balancing the positive cases, different equation could arise. By the other side, each of the models could be affected by overfitting, as it will work very well inside a cluster of the hyperspace of the p predictors, whose shape and dimension will depend on the characteristics of the really worked cells.

In order to face the problem of sizing and selecting the landslide free cells a balanced-suite approach was used.

According to this criterion, an equal number of unstable and stable cells was extracted from the dataset. Because of the very low number of positive cases (unstable cells), balanced models account only for a very poor portion of the whole studied area (1520 over 1,213,092 total cells). That would have meant to train the susceptibility model just on the 0.124% of the whole basin! To explore the effects produced by enlarging the area on which the model would have been trained, a suites of models were prepared by differently merging the set of 760 LIPs and randomly extracted subsets of stable cells.

A suite of 1520 counts models was prepared by merging the 760 unstable cells with sixteen different randomly selected subsets of 760 stable cells: all the unstable 760 LIPs were systematically included in each model, together with an equal numbers of stable cells which were randomly extracted from the set of the stable cells. It is important to note that differently from the 760 LIPs, which are systematically included, each unstable

subset was included only in one model. In this way, a total number of $[760+(760*16)]=1,920$ cells, corresponding to around the 1% of the whole investigated area, was included in the suite of models (Fig. 5.19).

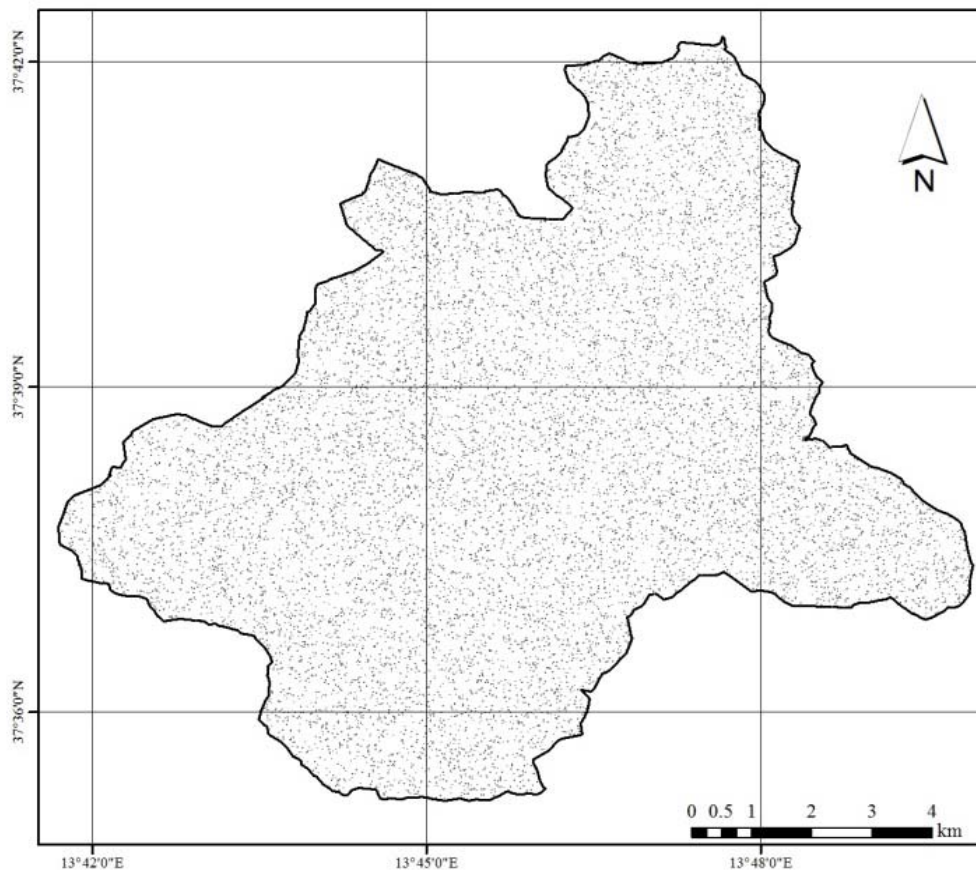


Fig. 5.19 - Spatial distribution of the randomly selected stable cells included in the model suite.

5.1.11 Validation

To estimate the performance of a susceptibility models different stages of the model building procedure are to be taken into consideration. Particularly, model fitting, prediction skill and robustness are among the main performance characteristics which must be quantitatively estimated (Carrara et al., 2003; Guzzetti et al., 2006; Frattini et al., 2010; Rossi et al., 2010).

The model fitting express the adequacy and reliability with which the model classify the known phenomena (i.e. the positive and negative cases on which the maximum likelihood method has worked in estimating the β 's coefficients). Mathematical or statistical evaluation on how well the predictors describe the known phenomena must be coherent with a geomorphologic reading of the results so to give sense to the overall relationships between landslide and factors.

Together with classical confusion matrices, other alternative methods can be adopted such as the ones quoted in Guzzetti *et alii* (2006) and Frattini *et alii* (2010). The prediction skill of the model is determined by its ability to predict the unknown stable and unstable cases. The latter can be obtained (as was done in this study) by randomly extracting a subset of cells from the initial dataset, before to proceed in regressing the model. In some other cases, available temporal or spatial partitioned landslide inventories can be exploited. Finally, the robustness of the model depends on its invariance with respect to small changes both in the input variables or in the model building procedure. The robustness of the models is typically evaluated by preparing suite or ensemble of models (e.g. Guzzetti *et al.*, 2006; Van Den Eckhaut *et al.*, 2009) obtained by randomly extracting different not overlapping subsets of the whole investigated area and comparing the regressed models, in terms of selected factors, adequacy, precision and accuracy.

Model fitting was evaluated for each model by computing the statistic $-2LL$; the smaller the negative log-likelihood the better the fit of the model. The logistic regression component of the software TANAGRA provides also the results of the model chi-square test, that allows for assessing the global significance of the regression coefficients; the significance was evaluated also individually for each independent variable incorporated in the model by means of the Wald test.

The accuracy of logistic regression in modeling landslide susceptibility of the study area was evaluated by drawing, for each model, the Receiver Operating Characteristic (ROC) curves (Goodenough *et al.*, 1974; Lasko *et al.*, 2005) and by computing the values of the Area Under the ROC Curve (AUC; Hanley and McNeil, 1982). A ROC curve plots true positive rate TP (sensitivity) against false positive rate FP (1-specificity), for all possible cut-off values; sensitivity is computed as the fraction of unstable cells that were

correctly classified as susceptible, while specificity is derived from the fraction of stable cells that were correctly classified as not-susceptible. The closer the ROC curve to the upper left corner ($AUC=1$), the higher the predictive performance of the model; a perfect discrimination between positive and negative cases produces an AUC value equal to 1, while a value close to 0.5 indicates inaccuracy in the model (Fawcett, 2006; Reineking and Schröder, 2006; Nandi and Shakoor, 2009; Akgün and Türk, 2010). In relation to the computed AUC value, Hosmer and Lemeshow (2000) classify a predictive performance as acceptable ($AUC>0.7$), excellent ($AUC>0.8$) or outstanding ($AUC>0.9$). ROC curves were drawn both for the validation (test) and calibration (training) cells, in order to evaluate the predictive performances of the models and to further investigate their fit to the training observations (model fitting); moreover, the difference between apparent accuracy (on training data) and validated accuracy (on test data) indicates the amount of overfitting (Märker et al., 2011).

Once a balanced model was prepared, a 75% random proportional splitting of the data was further applied to extract the calibration cells subset which was then used for the logistic regression. The 25% percent not used for calibration was finally exploited for validating the model and estimating its prediction skill.

The models fitting to the observed data was also evaluated by exploiting two pseudo- R_2 statistics: the McFadden R_2 and the Nagelkerke R_2 . The first is defined as $1 - (L_{MODEL}/L_{INTERCEPT})$ being confined between 0 and 1. As a rule of thumb (Mc Fadden, 1979), values between 0.2 and 0.4 attest for excellent fit. Nagelkerke R_2 is a corrected pseudo- R_2 statistics, ranging from 0 to 1 (Nagelkerke, 1991).

5.1.12 Model fitting

The model suite produces good fittings (Tab. 5.4) which are characterized by a mean error rate of 0.235 (std. dev.=0.01). The numbers of predictors singled out from the 16 repetitions is 12.7 (std. dev.=1.3). Pseudo- R_2 statistics attest for excellent fitting as well. AUC values for both the two (known and unknown LIPs) ROC curves are excellent ($AUC>0.8$) with the exception of models 6, 8 and 12, for which it is however largely acceptable ($AUC>0.75$). No evidence of overfitting is assessed, as AUC are very similar for training and test LIPs. The stability of the AUCs is higher for the training (std.

dev.=0.009) than for the test dataset (std. dev.=0.017). The confusion matrix (Tab. 5.5) attests for recall and 1-precision larger for “NO” than “YES”, with a difference of 0.0413 and 0.0195, respectively.

	MODEL SUITE																AVERAGE	STD.DEV.
	M01	M02	M03	M04	M05	M06	M07	M08	M09	M10	M11	M12	M13	M14	M15	M16		
ERROR RATE	0.2439	0.2272	0.2316	0.2395	0.2596	0.2281	0.2307	0.2228	0.2368	0.2351	0.2430	0.2325	0.2219	0.2298	0.2307	0.2439	0.2348	0.010
-2LL INTERCEPT	1572.044	1572.044	1572.044	1572.044	1572.044	1572.044	1572.044	1572.044	1572.044	1572.044	1572.044	1572.044	1572.044	1572.044	1572.044	1572.044	1572.044	0.00
-2LL MODEL	1131.535	1133.699	1172.383	1159.81	1187.809	1101.785	1138.118	1083.559	1142.463	1110.029	1149.155	1108.188	1116.559	1138.753	1152.826	1156.830	1136.47	27.43
CHLSQUARE	440.509	438.345	399.661	412.234	384.235	470.259	433.926	488.485	429.581	462.015	422.889	463.856	455.485	433.291	419.218	415.214	435.58	27.43
d.f.	15	11	15	12	13	15	12	12	12	13	10	11	14	11	15	12	12.7	1.7
P (>CHLSQUARE)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
McFADDEN'S R ²	0.2802	0.2788	0.2542	0.2622	0.2444	0.2991	0.2760	0.3107	0.2733	0.2939	0.2690	0.2951	0.2897	0.2756	0.2667	0.2641	0.2771	0.0174
NAGELKERKE'S R ²	0.4292	0.4275	0.3960	0.4064	0.3832	0.4526	0.4239	0.4667	0.4204	0.4462	0.4150	0.4476	0.4411	0.4234	0.4121	0.4088	0.4250	0.0220
AUC ROC (KNOWN LIPs)	0.841	0.840	0.834	0.831	0.820	0.852	0.838	0.853	0.837	0.850	0.832	0.844	0.847	0.842	0.835	0.829	0.839	0.009
AUC ROC (UNKNOWN LIPs)	0.824	0.830	0.825	0.841	0.828	0.792	0.826	0.789	0.811	0.820	0.805	0.785	0.817	0.834	0.822	0.828	0.817	0.017

Tab. 5.4 - Performances of the model suite: error rate, -2LL test, McFadden and Nagelkerke pseudo R², AUCs of the ROC curves.

TP	FN	FP	TN	YES	NO	TOT	ERROR RATE	RECALL		1-PRECISION		SUITE
								YES	NO	YES	NO	
422	149	129	440	571	569	1140	0.24386	0.7391	0.7733	0.2341	0.2530	M01
425	146	113	456	571	569	1140	0.22719	0.7443	0.8014	0.2100	0.2425	M02
425	146	118	451	571	569	1140	0.23158	0.7443	0.7926	0.2173	0.2446	M03
426	145	128	441	571	569	1140	0.23947	0.7461	0.7750	0.2310	0.2474	M04
420	151	145	424	571	569	1140	0.25965	0.7356	0.7452	0.2566	0.2626	M05
435	136	124	445	571	569	1140	0.22807	0.7618	0.7821	0.2218	0.2341	M06
433	138	125	444	571	569	1140	0.23070	0.7583	0.7803	0.2240	0.2371	M07
422	149	105	464	571	569	1140	0.22281	0.7391	0.8155	0.1992	0.2431	M08
420	151	119	450	571	569	1140	0.23684	0.7356	0.7909	0.2208	0.2512	M09
428	143	125	444	571	569	1140	0.23509	0.7496	0.7803	0.2260	0.2436	M10
431	140	137	432	571	569	1140	0.24298	0.7548	0.7592	0.2412	0.2448	M11
434	137	128	441	571	569	1140	0.23246	0.7601	0.7750	0.2278	0.2370	M12
431	140	113	456	571	569	1140	0.22193	0.7548	0.8014	0.2077	0.2349	M13
424	147	115	454	571	569	1140	0.22982	0.7426	0.7979	0.2134	0.2446	M14
425	146	117	452	571	569	1140	0.23070	0.7443	0.7944	0.2159	0.2441	M15
413	158	120	449	571	569	1140	0.24386	0.7233	0.7891	0.2251	0.2603	M16
425.9	145.1	122.6	446.4	571	569	1140	0.23481	0.7458	0.7846	0.2233	0.2453	MEAN
5.9	5.9	9.8	9.8	0	0	0	0.00953	0.0104	0.0173	0.0138	0.0082	STDV

Tab. 5.5: Confusion matrix for the model suite.

As regarding to the predictors (Tab. 5.6), a first group of six variables was almost systematically (more than 15/16 times) with very low mean rank order (i.e. the iteration of the forward selection procedure, in the final list of controlling factors), which is less than 8. SLOPENGB is selected as first predictor for 16 times with a positive coefficient. Sixteen times were also extracted: 16PROF curvatures and 8PLAN curvatures, with

negative and positive coefficients, respectively; the mean rank R is very low (less than 4) with the exception of 16PROFCONC whose R mean values is 7.2, even if the mode is 5. LIT_CLAYS, with a positive coefficient and a mean rank of less than 6, is selected for 15/16. A second group includes four variables which were selected less than 16 times but more than 50% (8) times: LCL_MIDDRAIN and LCL_MIDRID, with negative coefficients, LCL_LOCRID and LCL_CANDEE, with positive coefficients; high mean ranks characterize the LCL selected classes. A third group includes the nine variables which were selected for more than 4 times (25%), with middle – high rank orders (between 6 and 12): LIT_ALL, 8PROFCONV, TWI, SLOPETWI and LCL_UPPSLO, with negative coefficients, ASP_W, CCL_PP, 16PLANCONC and LCL_PLASM, with positive coefficients.

With the exception of LIT_ALL, the selected variables produced high significance (>95%) Wald tests. All the selected variables were regressed with congruent coefficients (always positive or negative, with the exception of LCL_UPPSLO) and quite constant ranks.

PREDICTORS	Coef.	Std-dev	Wald	Signif	ODDS	R	FREQ	R (MODEL SUITE)																				
								M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	M13	M14	M15	M16					
SLOPENGB	0.097	0.0293	46.5	0.0159	1.1024	1.0	16	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
16PROFCONV	-1.553	0.2125	65.1	0.0000	0.2161	2.7	16	2	4	2	2	3	2	2	4	2	2	2	2	2	5	2	5	2	5	2	5	2
8PLANCONC	1.431	0.2237	59.5	0.0000	4.2788	3.4	16	3	3	3	5	5	4	3	3	3	3	3	3	3	3	3	4	4	4	3	4	3
8PLANCONV	1.296	0.2385	48.9	0.0000	3.7601	3.6	16	4	2	4	4	4	3	4	2	4	4	4	4	4	2	5	3	4	4	3	4	4
16PROFCONC	-0.710	0.2000	25.2	0.0006	0.5009	7.2	16	10	9	6	6	10	5	5	5	7	5	5	5	10	7	15	5	5	5	5	5	5
LIT CLAYS	0.616	0.1340	17.2	0.0019	1.8665	5.9	15	6	6	5	10	2	10	6	6		6	6	6	6	6	6	2	6	6	6	6	6
LCL MIDDRAIN	1.100	0.3179	20.1	0.0001	3.1740	7.5	13	9	7	7	8		6		7	6	10		8	9	3	10	9					
LCL LOCRID	-1.237	0.3133	11.7	0.0033	0.3025	9.8	13		11		11	6	9	11	12	10	13	7	7	12	11							7
LCL CANDEE	0.888	0.2978	14.3	0.0021	2.5415	8.9	11	14	8	8	7		7		8	8	10			8								12
LCL MIDRID	-1.370	0.2558	13.7	0.0009	0.2613	8.1	8	7				11		7	9		7	8			8							8
ASP W	0.655	0.0605	10.2	0.0019	1.9288	11.0	7	11		9			14		10					11								10
16PLANCONC	0.715	0.1211	11.6	0.0018	2.0578	6.7	6		5		3			9		9		9			7		7					7
8PROFCONV	-0.391	0.1236	11.2	0.0041	0.6803	6.8	6					7	8				5				4		6		11			11
CCL (P/P)	0.566	0.0387	9.2	0.0029	1.7630	9.4	5	8											10	10		10	9					9
LITO ALL	-5.116	5.5536	5.1	0.2067	0.0584	10.6	5		10			8	15		11					9								
SLOPETWI	-0.006	0.0009	9.6	0.0033	0.9936	11.6	5					9	13					11		11	14							
TWI	-0.630	0.2678	11.5	0.0027	0.5459	10.0	4	5			12			10							13							
LCL PLASMA	1.186	0.3575	15.5	0.0013	3.4350	10.3	4			10			11				9											11
LCL UPPSLO	-0.202	0.6083	11.3	0.0013	0.9604	11.5	4			13		12		12					9									
8PROFCONC	0.424	0.0534	11.8	0.0013	1.5297	8.7	3				9			8								9						
CCL (CX/CC)	-0.550	0.0208	10.5	0.0013	0.5768	11.5	2			11			12															
SLOPESPI	-0.160	0.0582	11.8	0.0013	0.8527	12.0	2	12		12																		
HEIGHT	0.002	0.0001	8.4	0.0039	1.0021	13.0	2										12											14
LIT CLAYSAN	-0.807	0.0000	13.0	0.0003	0.4464	11.0	1									11												
ASP NE	-0.677	0.0000	8.3	0.0040	0.5082	12.0	1											12										
USE 211	0.802	0.0000	11.3	0.0008	2.2306	13.0	1																					13
USE 231	-2.355	0.0000	5.4	0.0203	0.0949	13.0	1					13																
SPI	0.428	0.0000	13.6	0.0002	1.5342	13.0	1	13																				
LCL UPPDRAIN	15.449	0.0000	0.0	0.9820	5123150	14.0	1			14																		
ASP_SW	0.539	0.0000	7.4	0.0065	1.7148	15.0	1	15																				

Tab. 5.6 - Predictors selected by the forward logistic regression of the model suite.

5.2 Test 2. The Beiro river basin

5.2.1 Geological and climatic framework

The area considered in the study (Fig. 5.20) stretches NE of the town of Granada (Andalusia, Spain), coinciding with the basin of the Beiro river (9.8 km²), which is a sub-basin of the Guadalquivir river (657 km), a Spanish river that flows through Andalusia to the Mediterranean. Despite the nearness to the sea, the climate in the area is of continental type, being characterized by marked temperature and rainfall short and long-period changes. According to the termo-pluviometric station of “Granada-Cartuja”, 720 above sea level, rainfall is mainly concentrated between October and April, while between May and September it is generally very low (particularly in July and August when it is less than 10 mm). It rarely rains and the high mountains of Sierra Nevada do not allow the sea to mitigate the climate. Temperatures in winter are often below zero while in summer they are always above 30°C. High diurnal temperature ranging is also recorded, reaching up to 15°C. According to the De Martonne aridity index (1942) the area can be classified as a semi-arid climate.

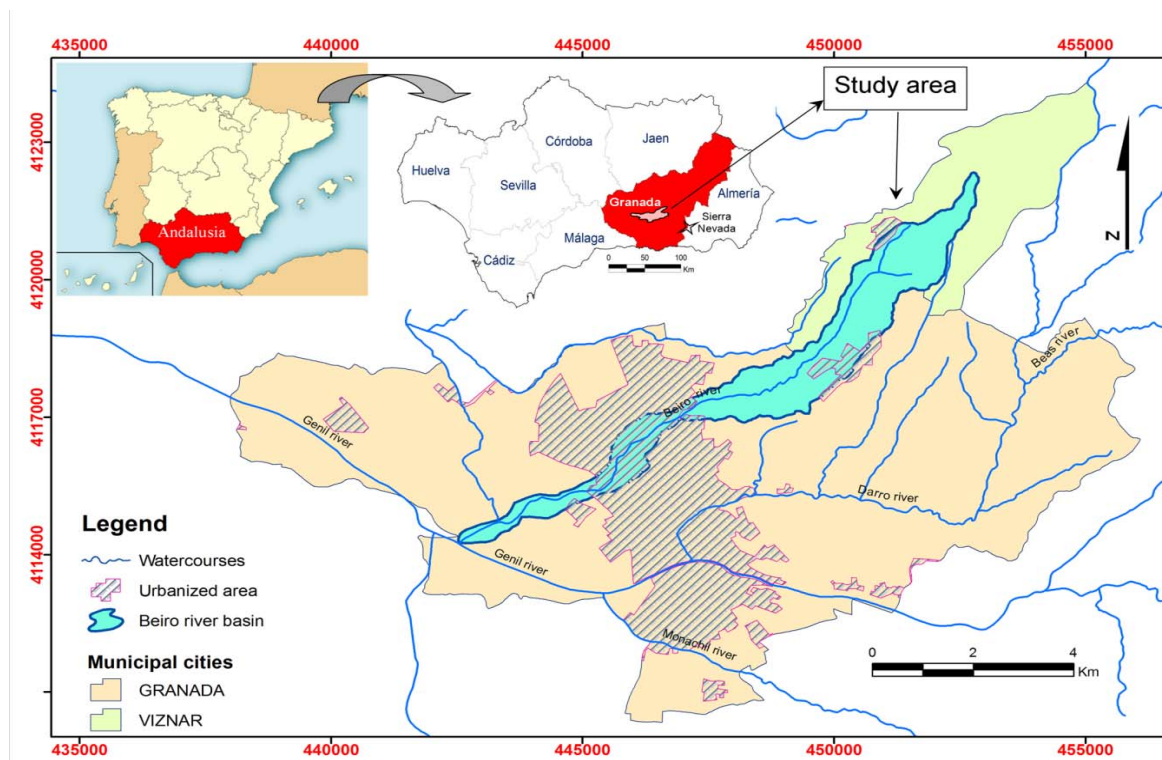


Fig. 5.20 - Geographical setting of the study zone

The geological setting of the Beiro river basin (Fig. 5.21) is characterized by terrains, which are aged from Pliocene to recent Quaternary, being tectonically limited to the North by Triassic dolomitic marbles which are very tectonized (Vera, 2004). This terrain is the only formation of the Alpujarride complex that outcrops in the study zone. This complex is followed by Pliocene deposits and incoherent Pleistocene and Quaternary post-orogenic deposits that filled deep valleys, producing the great alluvial fans. The post-orogenic deposits which outcrop in the study zone, from bottom to top, are: the terrains of the “Pinos-genil formation”, that marks the transition to continental facies (mainly Pliocenic conglomerates and, in the higher part of the sequence, sandy layers); the Cenés-Jun sequence, made of lacustrine deposits of lutite, sand, silt and gravel; the “Alhambra conglomerates” sequence made mainly of conglomerates and sand. The sequence is closed by Quaternary alluvial deposits which are the terrain on which the town is settled.

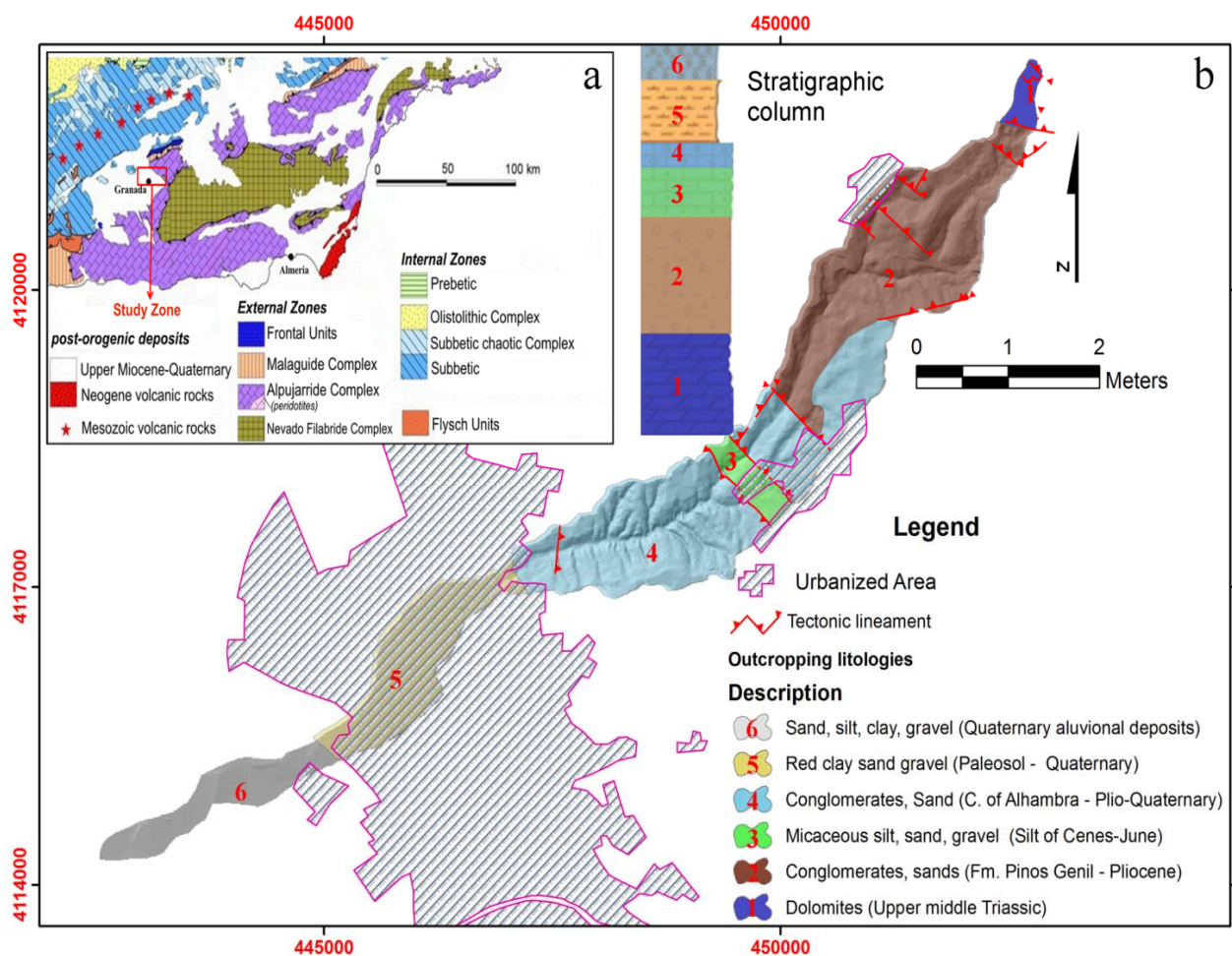


Fig. 5.21 - Geological setting of the study zone. Regional geology (a) (modified after Vera, 2004); Beiro river basin (b).

The landscape is generally marked by sub-planar areas, corresponding to a lower Pleistocene smoothing of the previous relief deeply engraved by Upper Pleistocene to Holocene stream incision, surrounded by steep reliefs. The geomorphological setting, together with the climatic conditions, is responsible for a wide diffusion of landslides, characterized by several movement typologies and variable area extensions (Chacón et al., 2006).

	Sample			
	A	B	C	D
Latitude	37.1982	37.1193	37.1203	37.1248
Longitude	3.3562	3.3529	3.3448	3.3321
Liquid Limit LL	46.47	37.41	18.23	48.82
Plastic limit LP	15.26	11.29	3.99	14.23
Plasticity index IP	31.21	26.12	14.24	34.59
Unified Soil Classification System (USCS)	GC with SP-SC	GC	GC with CL	GC with CL
GC: clayey gravel; SP: poorly-graded sand; SC: clayey sand; CL: clay				

Tab. 5.7 size classification of sampled material

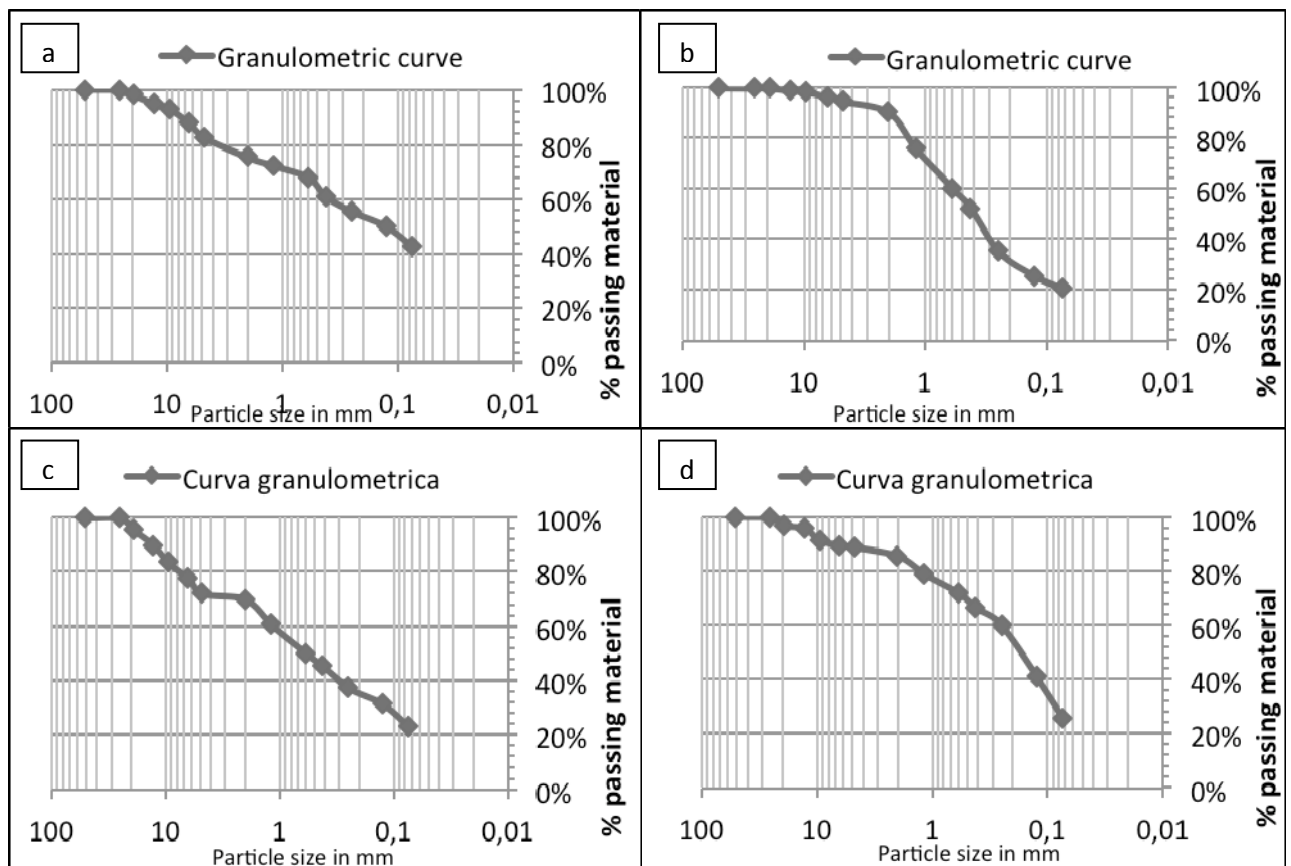


Fig. 5.22 – Granulometric curve derived from tests performed on some of the samples taken during the field-survey.

5.2.1 Landslides

For the Beiro river basin, we have produced a database of 127 slope movements (Fig. 5.24), which have been classified (Varnes 1978; Cruden and Varnes 1996, Dikau et al., 1996) as falls, translation slides, earth flows, debris flows and flow slides (Tab. 5.8). The archive, was obtained by using different recognition techniques. First, we carried out the interpretation of aerial photos in a scale of 1:33,000 taken between 1956-1957 by “Ejército del Aire de España” and European air force (also known as “*the American flight*”) and the ones taken in scale of 1:18,000 by the Geographic Minerary Institute of Spain (IGME) in 1978. Another step towards the definition of the landslide archive was a field-survey carried out in scale of 1:10,000 between March and April 2010. During the field survey, rock and soil samples were also collected and analyzed, particularly in order to distinguish between debris and earth type of material. Also, we compared the landslide archive obtained with the one derived by using open source software like Google Earth (GE) and similar (Conoscenti et al., 2009; Costanzo et al., 2011, Rotigliano et al., 2011). The latter were chosen in light of the excellent spatial resolution (DigitalGlobe Catalog ID: 1010010007D4E108, Acquisition Date: March 24, 2008; Catalog ID: 1010010004736A01, Acquisition Date: Aug 15, 2005; spatial resolution 46-60 cm per pixel) of the images, as well as because of the easy access to updated cartography and of the possibility to dynamically managing the points of view for each single slope (Fig 5.23).

The landslide survey has allowed to produce an archive consisting in:

- Falls (28 cases, 3.8% of the landslide area): these landslides mainly affect the over-consolidated silty and sandy quaternary terrains. The fall movements found in this area are usually not very extended and cover an area of about tens of square meters each. The areas interested by this kind of movements are usually the ones where the geosstructural conditions are responsible for near vertical slopes. Weathering processes, particularly high diurnal and seasonal temperature ranging, are responsible for fractures enlargement inside the rocks. The triggering factors for fall movements are the undercutting at the foot of escarpments and the intensive rainfall.

- Translational slides (1 case, 18.71% of the landslide area): a single landslide, which is locally called the Beiro's translational slide, affecting conglomeratic deposits with sandy and silty intercalations (Alhambra Formation). The extension of the movement reaches up to 70.000 m² with a main body 420 m wide and 225 m long. The movement is characterized by a diachronic activity, alternating dormant to active stage, with low or extremely low velocity (Chacón, 2008 a, b; 2010; Chacón et al., 2010).

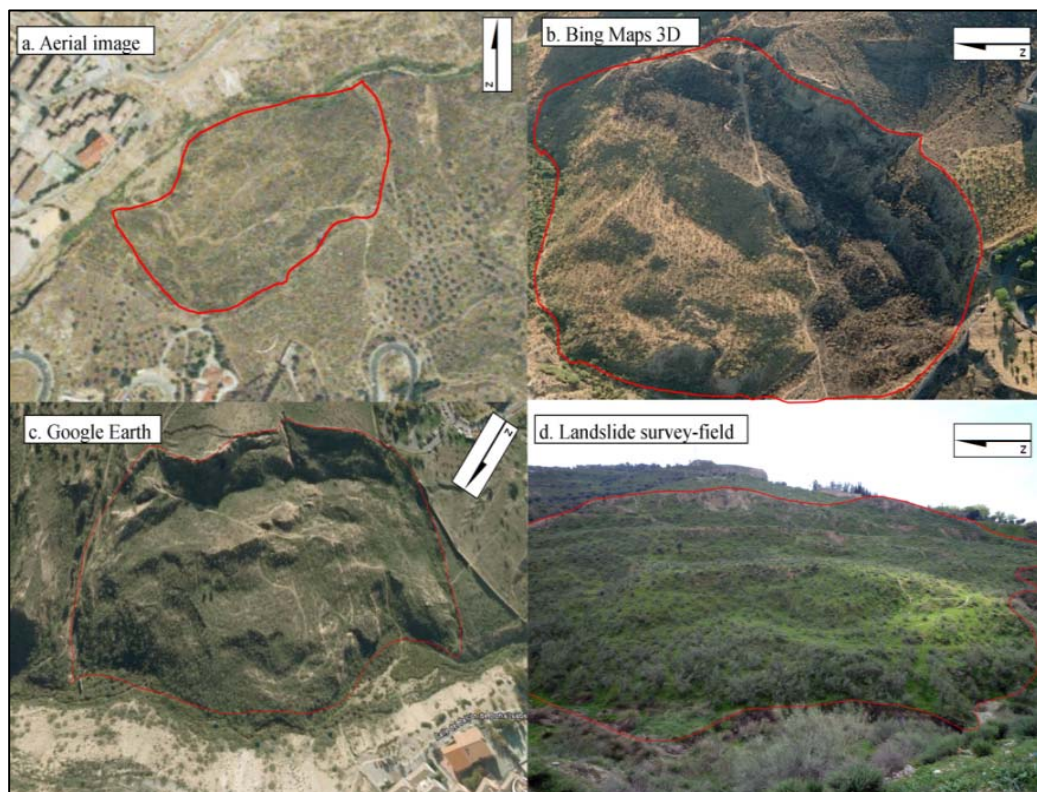


Fig. 5.23 – Beiro translational slide view by different techniques.

- Earth flows (36 cases, 54.2% of landslide area): the terrains interested by earth flows are unconsolidated sandstone and conglomerates mildly diagenized.
- Debris flows (57 cases, 12.7% of the landslide area): these are the most common slope failures in the area but they only cover 0.5% of the Beiro river basin. The debris flows involve terrains mainly consisting in surficial regolithic layers produced by intensive weathering and typically occur, triggered by rainfall, along highly steep slopes.
- Flow-slides (5 cases, 10.6% of landslide area): these landslides are complex movements that initiate with the collapsing and the flowing of saturated earth or

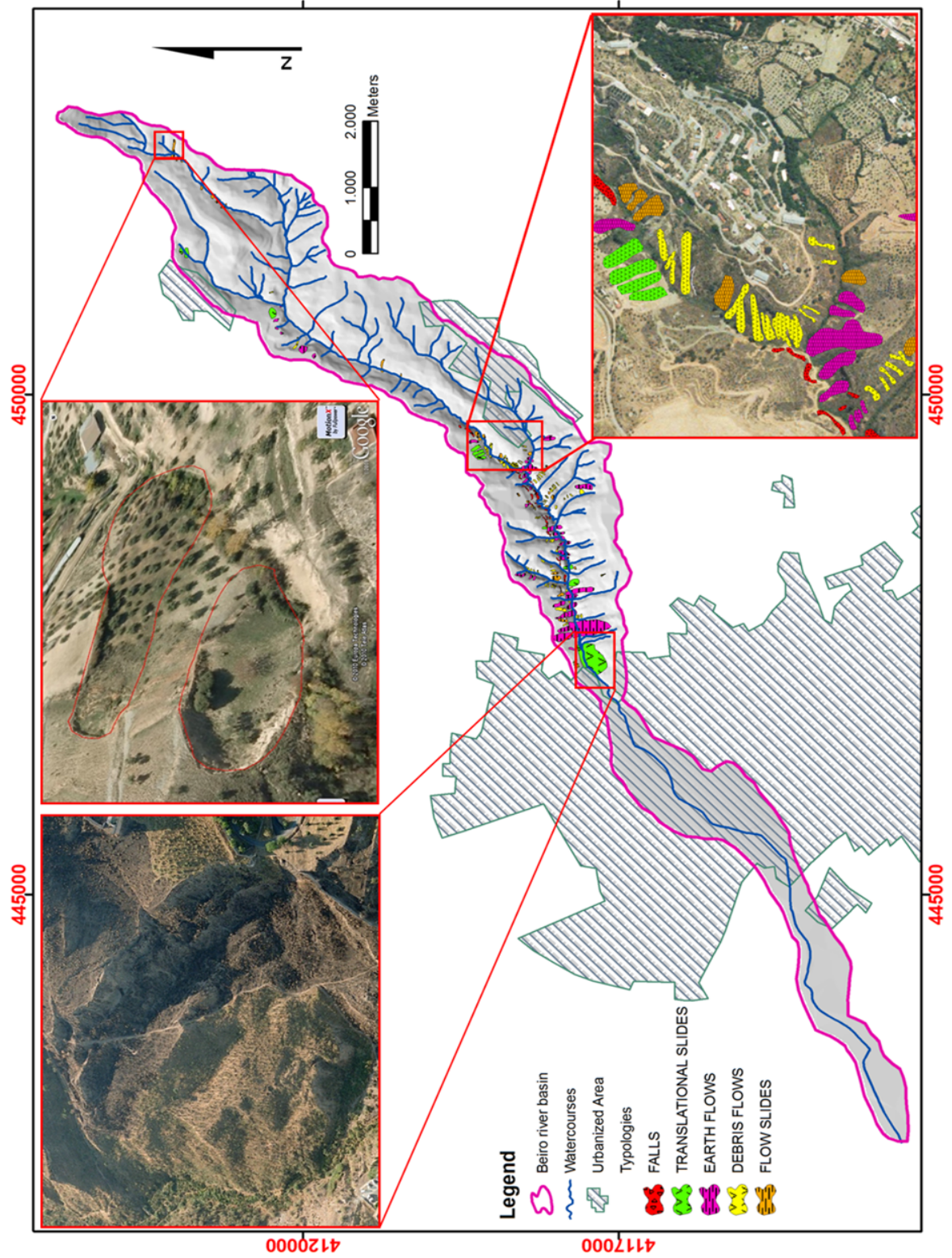
debris volumes, whose movements evolves downhill in a pure slide (Dikau et al., 1996). The terrains typically interested by flow-slides are carbonates, sandstones and conglomerates. The slip surface is not easily defined for this type of landslide.

TYPE	Cases	Area [m ²] for a single landslide				Std. Dev	Percentages		Affected lithology [% of cases]					
		max	min	mean	total		T ₁	T ₂	Al	Rcsg	SoCJ	Alh	Cs	Dol
Falls	28	1802	50	356	14249	390	3.8%	0.1%	0	0	15	75	9	0
Translational slides	1	69755	69755	69755	69755	-	18.7%	0.7%	0	0	0	100	0	0
Earth flows	36	48997	165	3668	201788	6704	54.2%	2.1%	0	0	0	60	34	0
Debris flows	57	2984	85	571	47438	526	12.7%	0.5%	0	0	13	65	21	0
Flow-slides	5	9758	434	2204	39683	2108	10.6%	0.4%	0	0	18	67	15	0
Total	127				372913		100%	3.81%			Area of Beiro river basin 9.8 km ²			

Al: Aluvional deposits. Rcsg: red clay, sand and gravel; Alh: Conglomerates of Alhambra; SoCJ: Silt of Cenes-June; Dol: dolomites; T₁: percentage in terms of landslide area; T₂: percentage in terms of total area. Std. Dev: standard deviation

Tab 5.8 - Landslide inventory, extension of landslide and lithology affected by slope ruptures.

Fig. 5.24 – Landslide inventory. Spatial distribution of landslide, obtained for the Beiro river basin by Google Earth™ remote analysis.



5.2.2 Model building

The “landslide susceptibility” function spatially expresses where, inside an investigated area, a new landslide phenomenon, characterized by its specific mass, volume and velocity (or defined by its typological features), is more likely to occur. No response is given to the “when” query and a “relative hazard” is assessed (Guzzetti et al., 2005; Guzzetti et al., 2006).

In order to define the landslide susceptibility in the Beiro river basin, a multivariate approach based on the conditional analysis and, a very similar, matrix method in a GIS environment was applied (Carrara et al., 1995; Soeters and van Westen, 1996; Guzzetti et al., 1999; Chung and Fabbri, 2003; Irigaray et al., 1999; Irigaray et al., 2007; Jiménez-Perálvarez, 2009). This approach is based on the selection of multivariate mapping units, the ones to be classified according to a susceptibility scale, and of diagnostic areas, which are derived from landslide archives and allow us to discriminate between stable and unstable conditions. The susceptibility of each mapping unit is defined as a function of its geo-environmental conditions, depending on the conditional spatial relationships between factors and past landslides.

Among the different types of mapping units, unique condition units (UCUs) are defined by combining the informative layers expressing a set of geo-environmental variables, which are selected as the landslide controlling factors. The susceptibility level of each UCU is computed as the ratio between unstable and total areas, according to (Davis, 1973; Carrara et al., 1995; Clerici et al., 2002; Conoscenti et al., 2008).

$$P(\text{landslide} | UCU^i) = \frac{P(UCU^i | \text{landslide}) \cdot P(\text{landslide})}{P(UCU^i)},$$

where probabilities can be computed in terms of ratio between counts of cells, so that

$$P(\text{unst} | UCU^i) = \frac{\left(\frac{UCU_{unst}^i}{UCU_{unst}} \right) \cdot \left(\frac{UCU_{unst}}{UCU_{ALL}} \right)}{\left(\frac{UCU^i}{UCU_{ALL}} \right)} = \left(\frac{UCU_{unst}^i}{UCU^i} \right) = \delta_{UCU^i} \text{ where the subscript } \textit{unst} \text{ replaces}$$

The GRID layer of UCUs and diagnostic unstable areas are spatially intersected, so that for each of the UCUs, the number of unstable cells can be computed. The final

susceptibility value for each UCUs is finally obtained by dividing the number of unstable and total cells. The density function (δ_{UCU^i}), which hereafter is named landslide density function, corresponds, for the cells having a UCU_i value, to the ratio between unstable (UCU_{unst}) and total counts (UCU_{ALL}) of cells. A very similar theoretical background subtends the matrix method (Irigaray et al., 2007; Jiménez-Pelvárez et al., 2009).

According to largely adopted procedures (e.g. Fernandez et al., 2003; Rotigliano et al., 2011), the area limited between the landslide crown and the toe of the failure surface has been used as the diagnostic area, as it better allows to single out physical-environmental conditions that are similar to those responsible for the past landslide activations. According to Fernández et al., (2003), we will refer to this area as “rupture zone”.

5.2.3 Factors selection procedures

Slope stability is directly connected to the types of terrain, to the presence of discontinuity surfaces, to the morphology of the slopes (slope angle, aspect, curvature, land use and hydrogeological conditions, etc.), while the triggering of new landslides, is usually connected to internal and external conditions, such as intensive rainfall or earthquakes. The triggering factors can also be anthropologically induced by deforestation, intensive erosion different uses of lands, drilling, etc. (Crozier, 1984; Hansen, 1984).

For this study we considered the following 15 controlling factors (Tab. 5.9):

- *Topographic factors*

In describing and quantifying the environmental conditions, DEM is the most important data source as it directly influences the quality of the derived factors, (Burrough, 1986). The DEM here used was derived by digitalizing the cartography (1:10,000) made by the Government of Andalusia, which was obtained from aerial photos in scale 1:20,000. The derived variables, which were tested for preparing the susceptibility models are: Slope aspect (ASPECT), which was reclassified in classes of 45°, from 0 (due north) to 360, (again due north, coming full circle) clockwise. Flat areas, having no downslope direction are given a value of -1. Slope aspect can be considered as a proxy variable for the attitude of the outcropping layered rocks. Elevation (ELEV), which was reclassified in equal classes from 650

m to 1659 m above sea level (Fernández et al., 2008), can express both topographic condition and, indirectly the role of thermo-pluviometric conditions. Illumination (ILL), ranging from 0 to 255, where 0 represents the shadowed areas and 255 the brightest, allows to differentiate cells with respect to evapo-transpiration. Plan curvature (PLAN) (Ohlmacher, 2007) and profile curvature (Dikau, 1989) were reclassified in $\frac{1}{2}$ standard deviation, from -17.2 to $+16.4 \text{ rad}^{-1}$ and from -16.5 to $+22.9 \text{ rad}^{-1}$, respectively. Topographic curvatures control the way in which both surface runoff and gravitative stresses acting on shallow failure surfaces can converge or diverge. Slope angle (SLOPE) was classified in 6 natural breaks intervals expressed in sessagesimal degrees (1. 0° - 2° ; 2. 2° - 5° ; 3. 5° - 15° ; 4. 15° - 25° ; 5. 25° - 35° ; 6. $>35^\circ$). SLO is typically considered the main controlling factor in landslide modeling. Topographic wetness index (TWI), which was reclassified in standard deviation from 4.7 m to 17.9 m (Rodhe and Seibert, 1999; Zinko et al., 2005), expresses a potential index of saturation of soils (Sharma, 2010). Topographic roughness (ROUGH) is a measure of the texture of a surface and was reclassified in 5 classes, from 1 to 1.9 by natural breaks (Hobson, 1972). It is quantified by the vertical deviations of a real surface from a linear planar shape. Topographic position index (TPI) compares the elevation of each cell in a DEM to the mean elevation of a specified neighborhood around that cell (Weiss, 2001; Zinko et al., 2005); it was reclassified in 10 natural breaks classes from -8.4 to 9.2 . TPI allows to express a quantitative way the geomorphological setting. Stream power index (SPI) is the time rate of energy expenditure and has been used as a measure of the erosive power, which can control the initiation of landslides. SPI can be calculated as: $\text{SPI} = A_s \tan \beta$, where A_s specific catchment area and $\tan \beta$ is local slope (Sharma, 2010).

- *Geological l.s. factors:*

these are derived from available maps which have been validated and detailed for this research through field checks. Lithology (LITO): is one of the most important factors because of its influence on the geo-mechanical characteristics of terrains. The various litho-stratigraphic units outcropping in the area were grouped in 6 lithological classes (1. Alluvial; 2. Calcarenes, sands, marls and limestones; 3. Calcareous marble; 4. Conglomerates, sands and limestone; 5. Phyllite, micaschist, sandstone; 6. Sand, silt, clay, gravel), which were defined on the basis of the prevailing rock composition (Clerici et al., 2006). Land use (USE), which was reclassified in six classes: 1. Bush; 2. Permanent crops; 3. Shrubland; 4. Urban areas; 5. Extractive areas; 6. River beds. Distance of tectonic lineament (DIST), which was reclassified in 3 classes: 1 (0-

200m), 2 (200-400m), 3(>400m), corresponding to the distance from the faults and thrust faults. Geomorphological units (GEOM), reclassified in: 1. karst platform; 2. Floodplain. 3. Hills; 4. Mountain chain. Edafic units (EDAF), reclassified in five classes: 1. Calcareous cambisol; 2. Regosol; 3. Lithosol; 4. Luvisol; 5. Fluvisol.

A) FALLS					B) TRANSLATIONAL SLIDES					C) EARTH FLOWS				
FACTOR	R	G-K	ARPA	SHIFT	FACTOR	R	G-K	ARPA	SHIFT	FACTOR	R	G-K	ARPA	SHIFT
ROUGH	.48	.97	.467	.00	USE	.54	-.72	-.243	.61	USE	.54	-.73	.393	-.11
USE	.47	.96	.453	.00	TWI	.44	-.63	.172	.08	SLOPE	.43	.67	.266	.03
SLOPE	.42	.95	.450	.02	SLOPE	.44	-.62	.028	-.18	LITH	.52	-.67	.350	-.02
EDAF	.28	-.68	.376	.01	DIST	.43	.55	.112	.08	ROUGH	.16	.67	.254	.01
SPI	.20	.48	.248	.05	ILL	.42	.54	.291	-.07	TWI	.36	-.67	.275	.04
TWI	.20	-.41	.177	.04	GEOM	.31	.48	-.047	.40	ELEV	.27	.67	.378	-.09
LITH	.19	-.41	.022	-.30	ROUGH	.31	.47	.083	.09	SPI	.17	.29	.084	.01
ELEV	.32	-.38	.353	.06	LITH	.40	.45	.137	.20	GEOM	.46	-.21	.324	.01
DIST	.14	-.34	.235	.04	ASPECT	.39	.44	.170	.18	DIST	.28	.25	-.141	.31
ILL	.50	-.29	.221	.14	SPI	.25	.33	.012	.02	ILL	.46	.12	.220	.06
PROF	.37	-.25	.013	.04	ELEV	.54	-.32	-.064	.50	PLAN	.45	.10	.228	.02
PLAN	.49	.15	.179	.10	EDAF	.38	.09	.037	.33	EDAF	.44	.10	.311	.04
ASPECT	.25	-.13	.451	.04	TPI	.29	-.03	.191	.05	ASPECT	.40	.06	.233	.03
TPI	.38	-.09	.368	.03	PROF	.29	-.03	.149	.04	PROF	.40	-.03	.190	.02
GEOM	.25	-.02	.276	.00	PLAN	.30	-.01	.193	.03	TPI	.41	.01	.214	.01
D) DEBRIS FLOWS					E) FLOW SLIDES					ASPECT: Aspect [sessagesimal degrees clockwise from N]; DIST: Distance of tectonic lineaments (m); EDAF: Edafic units; ELEV: Elevation [m a.s.l.]; GEOM: Geomorphological units; ILL: Illumination LITH: Lithology; PLAN: Plan Curvature [rad-1]; PROF: Profile curvature [rad-1]; SLOPE: Slope angle [sessagesimal dregrees]; TWI: Topographic Wetness Index [m]; ROUGH: Roughness; TPI: Topographic Position Index; SPI: Stream Power Index; USE: Land use. R: linear and contingency correlation coefficient; G-K: Goodman and Kruskal's gamma; ARPA: areas above randomly predicted area; SHIFT: shift between prediction and success rate curves				
FACTO R	R	G-K	ARPA	SHIFT	FACTOR	R	G-K	ARPA	SHIFT					
LITH	.54	-.92	.327	.05	ROUGH	.55	.83	.384	-.05					
SLOPE	.45	.90	.368	.03	GEOM	.49	.83	.256	.07					
ROUGH	.45	.90	.417	-.02	SLOPE	.42	.81	.494	-.15					
TPI	.43	.89	.345	.03	TWI	.41	-.80	.371	.08					
USE	.43	-.67	.343	-.10	USE	.28	-.60	.401	-.15					
TWI	.23	-.46	.450	-.10	LITH	.26	-.55	.450	-.10					
SPI	.22	.40	.168	.03	SPI	.03	.46	.150	.04					
ELEV	.34	-.28	.334	.02	ILL	.34	.27	.172	.10					
GEOM	.34	.09	.397	.01	ASPECT	.23	.24	.292	.06					
DIST	.06	.05	.005	.02	PLAN	.33	.13	.267	.05					
ASPECT	.21	.03	.238	.05	TPI	.31	.13	.251	.03					
ILL	.38	.03	.134	.09	PROF	.30	.11	.232	.04					
PLAN	.36	.03	.334	.06	DIST	.10	-.10	-.153	.22					
EDAF	.26	-.02	.249	.02	ELEV	.30	.09	.268	.03					
PROF	.32	.00	.273	.03	EDAF	.26	-.04	.083	.14					

Tab. 5.9 - Correlation between the source area of the landslide and the determining factors. Factors highlighted in gray show the best models.

Before to combine in a UCU layer the parameters, univariate geostatistical relationships between each variable and landslides were estimated (Chacòn et al., 1993; 1994), by analyzing the association coefficients of contingency tables. By cross tabulating a factor

grid layer and a landslide vector layer, is possible to derive contingency tables whose statistical correlation can be quantitatively estimated (Irigaray, 1995; Fernandez, 2001; El Hamdouni, 2001). By using statistical software packages like Unistat and IBM SPSS, the following correlation indexes were computed: Chi-square (χ^2), linear and contingency correlation coefficient (R), Pearson's index (Φ^2), Tschuprow (T) and Cramer (V) coefficients, Goodman e Kruskal's gamma (G-K) (Goodman and Kruskal, 1954; Davis, 1986).

Also, the predictive role of each single factor with respect to the assessment procedure was estimated, by validating susceptibility models based on single factor. The method requires (Chung and Fabbri, 2003) the spatial random partition of the landslide archive in a training subset, used to classify the susceptibility levels of the UCUs and to produce a prediction image, and a test subset, considered as the unknown target pattern. The prediction image is then compared with the actual spatial distribution of the test rupture zones and success and prediction rate curves are produced. Some morphometric indexes of the validation curves was finally used to estimate the performance of the models. The quality of the susceptibility models was estimated by applying a procedure based on the quantitative analysis of the shape of the success and prediction rate curves, which exploited two morphometric indexes: ARPA, areas above randomly predicted area; and SHIFT, shift between prediction and success rate curves (Rotigliano et al., 2011a,b). Since the diagonal trend attests for a not-effective prediction, a high performance produces high values of ARPA; a good fit of the model is testified by low SHIFT results. By drawing a theoretical validation curve respecting these threshold

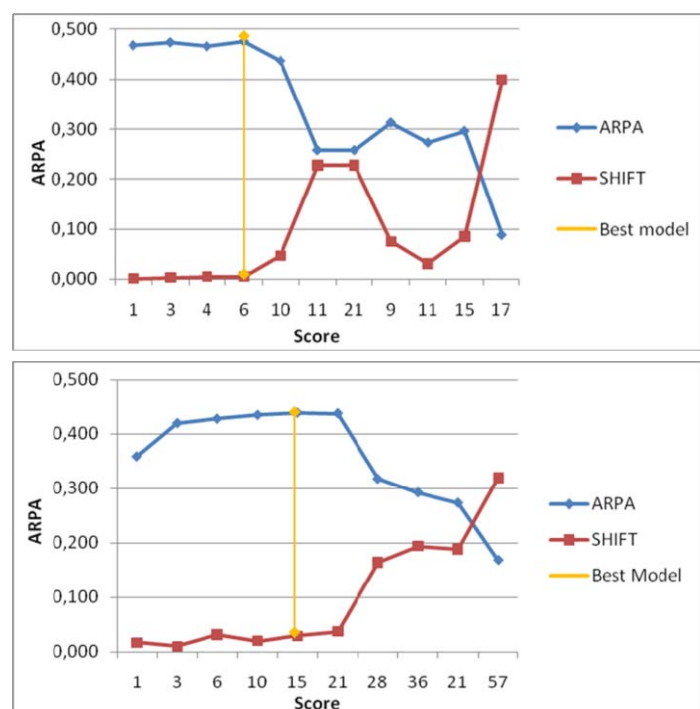


Fig. 5.25 – Correlation between ARPA and SHIFT morphometric indexes for suite models; Falls (a); Debris flows (b).

indexes of the validation curves was finally used to estimate the performance of the models. The quality of the susceptibility models was estimated by applying a procedure based on the quantitative analysis of the shape of the success and prediction rate curves, which exploited two morphometric indexes: ARPA, areas above randomly predicted area; and SHIFT, shift between prediction and success rate curves (Rotigliano et al., 2011a,b). Since the diagonal trend attests for a not-effective prediction, a high performance produces high values of ARPA; a good fit of the model is testified by low SHIFT results. By drawing a theoretical validation curve respecting these threshold

values, Rotigliano et alii (2011) indicate 0.12 as the lower limit of ARPA for an effective susceptibility model.

In light of the results of the procedure for evaluating the relevance of each factor, it was possible for each of the landslide typologies, to rank the controlling factors according to a predictivity scale.

Among the very high number of possible models which can be prepared for each landslide typology starting from the 15 factors, a suite of models is here discussed, which has been defined to the aim of highlighting the way in which the univariate performances of the single factors propagate when the latter are combined in multivariate models. Particularly starting from the single parameter best model, predictive performances were estimated both when progressively or randomly adding less performing factors. The results of the multivariate models were submitted to validation by applying both the success and prediction rate curve method and the analysis of the degree of fit (Chacón et al., 2006; Irigaray et al., 2007).

Tables 5.9a-d show the results of the analysis of the contingency tables for each landslide typology, showing the factors listed according to a decreasing order of the G-K's absolute value. G-K has ranges from -1 to +1. We chose to use the G-K gamma because, differently from χ^2 is not dependent from the size of the sample (Sheskin, 2007). When G-K is close to 1, we have high correlation (for positive values we have a direct correlation, for negative ones it is indirect or negative); instead, G-K values close to zero indicate no correlation. The predictor variables are classified as "effective" (EFF) or "not effective" (NEF) depending if the condition G-K index > 0.5 and R > 0.4 applies or not (Fernandez et al., 1996; Fernandez et al., 2003; Irigaray et al., 2007).

As regards the factors, slope angle is among the more effective instability factors for all the 5 landslide typologies, having very high G-K values (G-K>0.8) for falls, debris flows and flow slides. Roughness, land use and topographic wetness index are also among the main causative factors. Roughness has high correlation (G-K>0.8) for all the typologies, with the exception of earth flow (G-K=0.67) and translational slides, for which it does not enter among the more predictive variables. Land use is a good predictor variable for all the typologies, with the exception of flow slides, while topographic wetness index is not among the effective variables both for debris flows and falls. Among the factors

which are classified as EFF variables for only one landslide typology, geomorphologic units, for flow slides, topographic position index and lithology, for debris flows, are strongly ($G-K > 0.8$) effective. Finally, the distance from tectonic lineaments and illumination, for translational slides and elevation, for earth flows, show medium G-K values. All the other variables do not satisfy the condition and are in the following considered as not effective.

By looking at results from the “landslide typology point of view” the following results can be highlighted: falls can be explained by three EFF variable, which produces very high G-K (> 0.95) and ARPA (> 0.45) values; five EFF variable have been observed for debris flows, giving high G-K (close to 0.9, except for USE) and variably high ARPA values; four variables for flow slides produces G-K values close to 0.8, and medium-high ARPAs; medium G-K and very variably low ARPA values characterize the five explanatory variables for translational slides; the six EFF variable for earth flows, finally, are characterized both by medium G-K and ARPA values.

The relationships between G-K and ARPA can be summarized as follows. The validation of all the models prepared by using a single effective variable gives high ARPA values, well above the threshold of 0.12 (typically > 0.25). Translational slide represents an exception, since the models prepared for SLOPE and DIST do not fit the ARPA threshold limit; for this landslide typology, ARPA values quite above the 0.12 limit are among the NEF variables. Larger (> 0.3) ARPA values for NEF single parameter values are observed for falls (EDAF, ELEV, ASPECT, TPI, GEOM), earth flows (GEOM, EDAF), debris flows (TWI, ELEV, GEOM, PLAN) and flow slides (USE, LITH). Five of the latter cases are represented by factors just below the limit of the EFF factors (EDAF, for falls, GEOM, for earth flows, TWI, for debris flows, USE and LITH, for flow slides). ARPA values close or larger than 0.4 seems to be strictly related with EFF variable or, in case of NEFs, with G-K greater than 0.45, with the very surprising exceptions of GEOM, for falls and debris flows.

5.2.4 Multivariate models

According to the results of the contingency tables, for each landslide typology, the factors have been ranked from I (the best predictor) to XV (the least predictor), depending on the value of the association indexes (Tab. 5.10).

In order to verify both the correctness of the threshold values adopted in classifying the factors and the extent to which univariate correlation between each single factor and landslides propagates onto the predictive performances of multivariate models, a large set of combinations of variables has been used to prepare susceptibility models. The factors have been combined to produce a suite of UCU layers, which have been then intersected with the landslide (rupture zone) archive, to derive the susceptibility grid layer. All the prepared models have been submitted to validation procedures. Particularly prediction and success rate curves were drawn, by randomly splitting the landslide archive in a training and a test balanced subsets. For the quantitative evaluation of the validation curves, two morphometric parameters have been computed (ARPA and SHIFT).

Among the great number of models which have been evaluated, here the results for the most diffused landslide typologies (falls and debris flows), are discussed (Fig. 5.24). The two suites of models allowed to verify a strong coherence between progressively adding variables to the multivariate models and variation of ARPA. An expected score was computed for each model by adding the rankings of the combined variables (so that the lower the score the more effective the factors). When EFF variables are added to the model, large quite increasing ARPA and very small stable SHIFT are observed; the maximum ARPA value is for the best model (which includes only EFF variable). A

SUMMARY					
FACTOR	FLL	TSL	EFL	DFL	FLS
ELEV	VIII	XI	VIII	VIII	XIV
SLOPE	III	V	VI	II	III
ASPECT	XIII	IX	XIII	XI	IX
TWI	VI	II	V	I	IV
PROF	XI	XIV	XIV	XV	XII
PLAN	XII	XV	XI	XIII	X
ROUGH	I	VII	IV	III	I
TPI	XIV	XIII	XV	IX	XI
SPI	V	X	VII	VII	VII
LITH	VII	I	III	VI	VI
USE	XV	III	I	V	V
DIST	IX	IV	IX	X	XIII
GEOM	II	VI	II	IV	II
EDAF	IV	XII	XII	XIV	XV
ILL	X	VIII	X	XII	VIII

Tab. 5.10 – Summary of classification of the determining factors for each type of slope failure. FLL: falls; TSL: Translation slides; EFL: Earth flows; DFL: Debris flows; FSL: Flow slides

transition to models including NEF variables, is clearly marked by best+1 models, prepared by adding to the best models the best of the NEF variables. If another NEF variable is added or a lower score is produced, the decreasing of ARPA is very marked (46%, for debris flows, 27% for falls) and strictly coherent with the increasing of SHIFT. For models including also NEF variables, it is possible to observe a clear inverse correlation between ARPA and SHIFT.

MODEL SUITE: FALLS					
MODEL	RANKS	SCORE	COMBINED FACTORS	ARPA	SHIFT
FLL_A	I	1	ROUGH	.467	.00
FLL_B	I-II	3	ROUGH-USE	.474	.00
FLL_D	I-III	4	ROUGH-SLOPE	.466	.01
FLLBEST	I-II-III	6	ROUGH-USE-SLOPE	.476	.01
FLLBEST+1	I-II-III-IV	10	ROUGH-USE-SLOPE-EDAF	.437	.05
FLL_C	I-II-III-V	11	ROUGH-USE-SLOPE-SPI	.258	.23
FLL_G	I-II-III-XV	21	ROUGH-USE-SLO-GEOM	.258	.23
FLL_E	IV-V	9	EDAF-SPI	.313	.08
FLL_F	V-VI	11	SPI-TWI	.273	.03
FLL_H	IV-V-VI	15	EDAF-SPI-TWI	.296	.09
FLL_I	IV-VI-VII	17	EDAF-SPI-LITH	.088	.40
MODEL SUITE: DEBRIS FLOWS					
MODEL	RANKS	SCORE	COMBINED FACTORS	ARPA	SHIFT
DFL_I	I	1	LITH	.327	.02
DFL_II	I-II	3	LITH-SLOPE	.419	.01
DFL_III	I-II-III	6	LITH-SLOPE-ROUGH	.427	.03
DFL_IV	I-II-III-IV	10	LITH-SLOPE-ROUGH-TPI	.434	.02
DFLBEST	I-II-III-IV-V	15	LITH-SLOPE-ROUGH-TPI-USE	.438	.03
DFLBEST+1	I-II-III-IV-V-VI	21	LITH-SLOPE-ROUGH-TPI-USE-TWI	.437	.04
DFLBEST+2	I-II-III-IV-V-VI-VII	28	LITH-SLOPE-ROUGH-TPI-USE-TWI-SPI	.317	.16
DFLBEST+3	I-II-III-IV-V-VI-VII-VIII	36	LITH-SLOPE-ROUGH-TPI-USE-TWI-SPI-ELEV	.292	.19
DFL_III+XV	I-II-III-XV	21	LITH-SLOPE-ROUGH-PROF	.273	.19
DFLBEST+WORST	I-II-III-IV-V-XIII-XIV-XV	57	LITH-SLOPE-ROUGH-TPI-USE-PLAN-EDAF-PROF	.168	.32

Tab. 5.11 - The two suites of models allowed high coherence between the progressive addition of variables to the multivariate models and variation of ARPA;

In light of the above described results, models for two UCU layers have been prepared for each landslide typologies: best models, including only EFF variables, and best+1 models, which get also the best among the NEF variables.

Table 5.12 lists the results of the validation of the suite of susceptibility models which were prepared, whose validation graphs are showed in Fig. 5.26. All the models are largely satisfactory, with ARPA values higher than 0.35 and very limited SHIFT (<0.05), with the exception of EFLBEST+1, which is characterized by low ARPA and high SHIFT, and FSLBEST+1, which associate high ARPA to a very high SHIFT. Generally, the best models gave ARPA values greater than the ones which were produced by one of the single combined variables or, when ARPA are similar to the ones resulted from a single factor model (e.g debris flow and flow slides) a lowering of SHIFT is produced by combining EFF variables. Particularly, the susceptibility models for falls and debris flows, which are prepared by combining EFF variables characterized by high G-K and ARPA (Tabs. 5.9a, d), confirmed to have a high predictive skill; coherently, the earth flow best model shows a quite ($ARPA < 0.4$) predictive skill, in accordance to the quite good performances of the single combined variables. Surprisingly, flow slides and translational slides best models produce results opposite to the ones which were expected. TSLBEST is in fact characterized by very high performance, in spite of the medium to low G-K and ARPA values (Tab. 5.9b); on the contrary, FSLBEST gives a results that is similar to the performance of the single combined factors (Tab. 5.9e). It seems that variables add in a congruent increasing and incongruent decreasing way, for translational slides and flow slide, respectively.

Finally, as regard to the best+1 models, it must be noticed that high ARPA (>0.4) best models are less susceptible to decrease their performance when the best NEF variables are added.

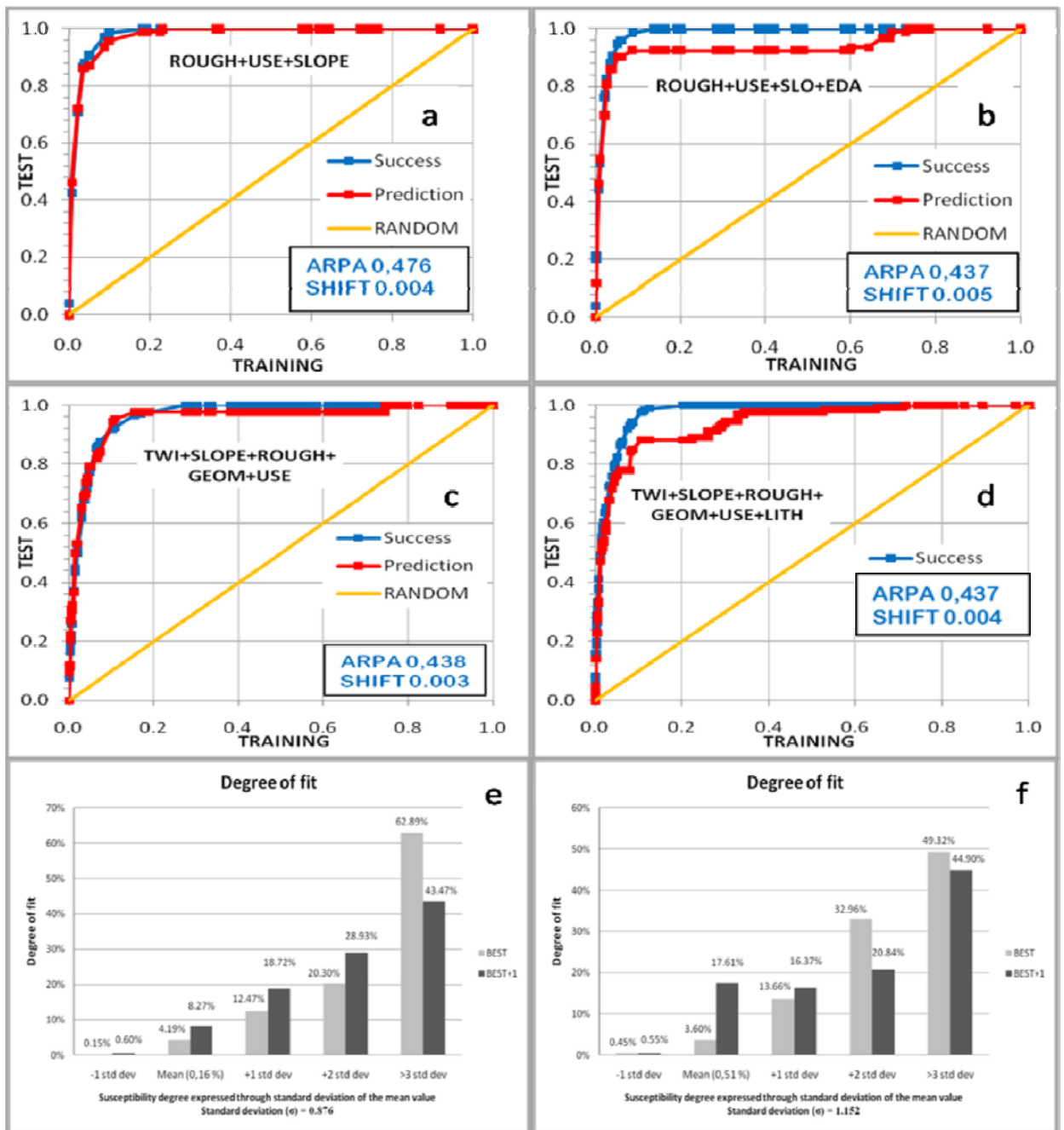


Fig. 5.26 - Comparison of best and best +1 model . With validation curves Fall best model (a); fall best+1 model (b); debris flows best model (c); debris flows best+1 model (d). Degree of fit between susceptibility range and falls (e) or debris flows (f).

5.2.5 Susceptibility maps and validation

Susceptibility maps for the five best models were prepared, in which five equal area reclassified susceptibility classes have been produced: very low, low, moderate, high and very high. The relative error between intersected target landslides by the different susceptibility classes was used to estimate the predictive skill of the maps. The degree of fit was computed for each susceptibility class (Fig. 5.27) confirming the very good predictive performances of the five susceptibility models.

Finally, a general landslide susceptibility map was produced by cumulating, for each of the five classes, the landslide area produced for the five typologies (Fig. 5.28). Also in this case, fully satisfactory predictive results have been obtained.

Susceptibility maps for the five best models were prepared, in which six classes, based on a standard deviation reclassification method (from -1 standard deviations to more than 4, with respect a mean value of 9.8% of density) were used. Adopting standard deviation criteria in depicting

landslide susceptibility is coherent with the relative meaning of the concept of

susceptibility itself: how much more likely is a new failure in a site with respect to another. The relative error between intersected target landslides by the different susceptibility classes was used to estimate the predictive skill of the maps. The degree of fit was computed for each susceptibility class confirming a very good predictive

MODEL	CODE	COMBINED FACTORS	ARPA	SHIFT
<i>FALLS_BEST</i>	FLLBEST	ROUGH-USE-SLOPE	0.476	0.00
<i>FALLS_BEST+1</i>	FLLBEST+1	BESTS+EDAF	0.437	0.05
<i>TRANSLATIONAL SLIDES_BEST</i>	TSLBEST	LITH-TWI-USE-DIST-SLOPE	0.468	0.01
<i>TRANSLATIONAL SLIDES_BEST+1</i>	TSLBEST+1	BESTS+GEOM	0.432	0.05
<i>EARTH FLOWS_BEST</i>	EFLBEST	USE-GEOM-LITH-ROUGH-TWI-SLOPE	0.392	0.00
<i>EARTH FLOWS_BEST+1</i>	EFLBEST+1	BESTS+SPI	0.299	0.11
<i>DEBRIS FLOWS_BEST</i>	DFLBEST	TWI-SLOPE-ROUGH-GEOM-USE	0.438	0.03
<i>DEBRIS FLOWS_BEST+1</i>	DFLBEST+1	BESTS+LITH	0.437	0.04
<i>FLOW SLIDES_BEST</i>	FSLBEST	ROUGH-GEOM-SLOPE-TWI	0.379	0.04
<i>FLOW SLIDES_BEST+1</i>	FSLBEST+1	BESTS+USE	0.334	0.21

Tab. 5.12 - Summary of the results of the validation of the suite of susceptibility models, for best and best+1. FLL: falls; TSL: Translation slides; EFL: Earth flows; DFL: Debris flows; FSL: Flow slides.

performance of the five susceptibility models. Finally, a general landslide susceptibility map was produced by cumulating, for each of the five classes, the landslide area produced for the five typologies. Also in this case, fully satisfactory predictive results have been obtained (Fig. 5.26a, b).

5.2.6 Discussion and concluding remarks

A procedure to select the best determining factors connected to landslide susceptibility has been defined. The method allows the determining factors to be ranked according to their expected contribution to the predictive skill of multivariable model, classifying them as “effective” or “non-effective” and the factors were ranked from I (the best predictor) to XV (the poorest predictor), depending on the value of the association indexes for each landslide typology and establish their best susceptibility model. The identification of the most determinant factors is an important step in a classification process. Statistical methods should be able to get the most parsimonious and geologically meaningful models. The exclusion of poorly related predictive variables is an advantage during the model building procedure allowing to reduce the complexity of the susceptibility model, which in turns become easier to be interpreted from a geological point of view.

Theoretically, a manual selection of the most relevant factors by an expert geomorphologist could be considered the best approach, but because the number of probable descriptors is often large, it is not always actually possible without imposing subjective choice in the model building process. Therefore, the best variables must be selected automatically. The automatic process can be used as a preliminary approach in order to filter unnecessary attributes.

Procedures of forward selection of variables have been applied for logistic regression and discriminant analysis models (e.g. Carrara et al., 2008; Van den Eckhaut et al., 2009). In the present paper a similar approach is proposed for models based on conditional analysis, which is applicable to the matrix method and unique condition units method. This methodology has been applied to the Beiro River basin in the north-eastern area of the city of Granada (Spain).

The results demonstrated that slope angle is among the more effective instability factors for all the 5 landslide typologies studied. Roughness, land use and topographic wetness index are also among the main causative factors. Roughness has high correlation in all the typologies, with the exception of earth flow, for which it is not among the predictive variables. Land use is a good predictor variable for all the typologies, with the exception of flow slides, while topographic wetness index is not among the effective variables for debris flows or falls. The lithology is not always present in the suite of the best models selected by the chosen statistical coefficients. The latter, in fact, is particularly determining for medium-large landslides, for instance earth flows, while is not of great significance for smaller landslides like falls and debris flows. This can be explained by considering that these movements affect equally the debris landslides and those over-consolidated terrains that outcrop in the area, leading to a non-significant statistic in the determining factors. Also, the geological map which was exploited does not have the necessary resolution to produce measurable spatial variations of the terrains with the same detail than the landslide archive does; the lithological terms that we had to adopt do not respond to geo-mechanical properties, as different types of rocks were grouped in single classes. Generally, (earth- and debris-) flow landslides are controlled by topographic conditions together with land use and outcropping lithology, while flow slides are completely explained by topographic continuous (slope, topographic wetness index and roughness) and nominal (geomorphologic unit) features. Topographic wetness index is an important predictor for earth flows and the first among the non-effective for debris flows. Falls are very effectively explained by just two topographic (slope and roughness) and one nominal (land use) attributes. Results for translational slides are heavy affected by the circumstance that just one case was observed.

Generally, the univariable validation method resulted coherent with simple association and co-gradation index. At the same time the score (or order of importance) for each variable, which was evaluated on a univariable basis, resulted to be coherent with the influence in the performance of the multivariable models: adding effective variable always resulted in an increasing of the model fitting.

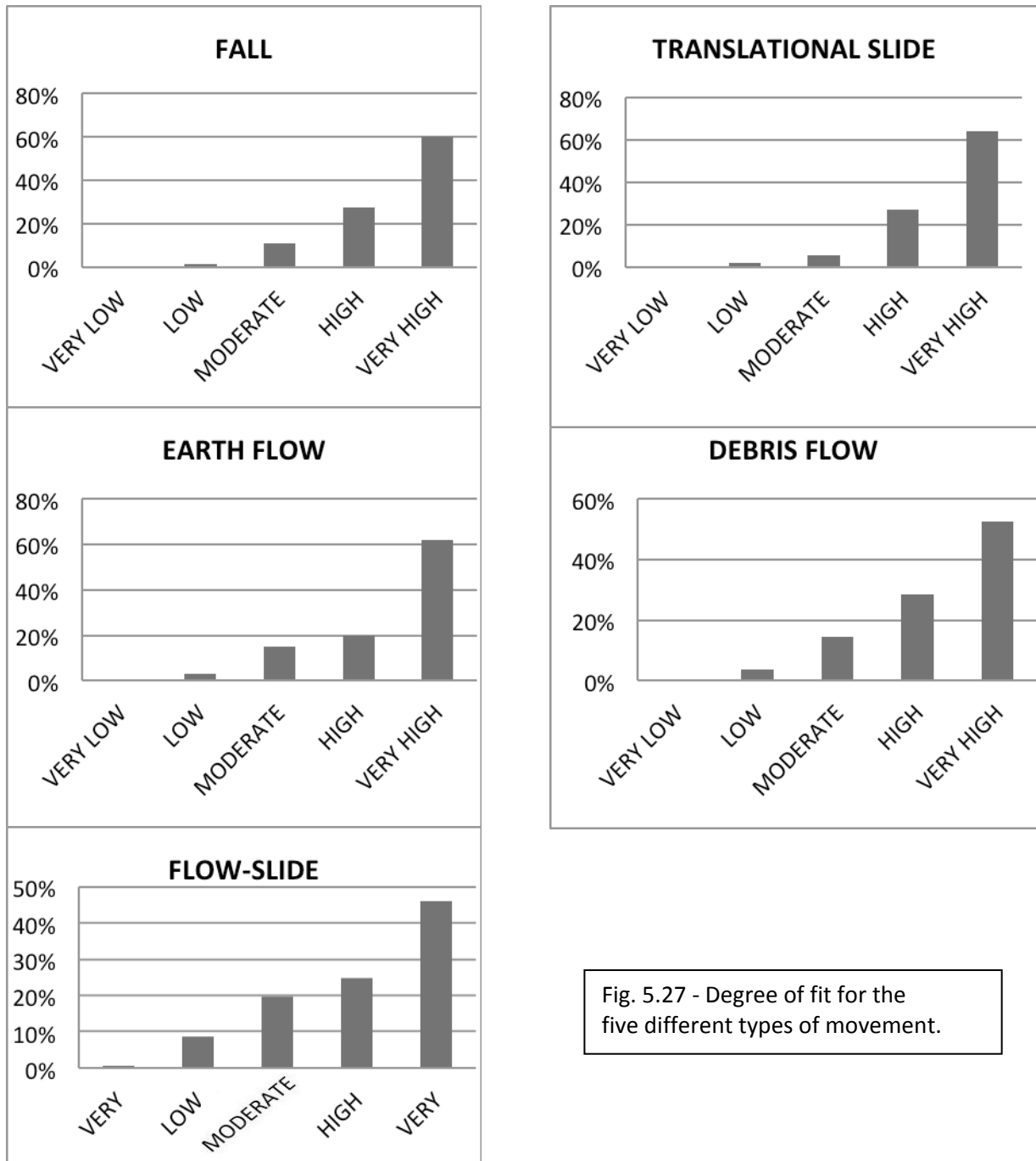


Fig. 5.27 - Degree of fit for the five different types of movement.

However, the best susceptibility maps obtained following the GIS matrix method and the proposed procedure effectively explain the spatial distribution of slope movements. These maps provide valuable information on the stability conditions of broad regions, and are essential in the planning phase to ensure that suitable corrective measures are taken. The option of organizing the controlling factors according to a statistical correlation coefficient could save both economical and time resources. This kind of statistical approach, however, requires excellent quality of the data input, regarding both the variables examined and the details and the resolution of the landslide archive, even though Google EarthTM, was of excellent help in identifying the area subject to geomorphological instabilities. The main limit is thus due to the scale of the maps available for an area, which is also the scale that the definitive map will have. The possibility of exploiting Google EarthTM images was here demonstrated on the basis of a comparison of coeval remote and field derived landslide dataset. This tool offers the opportunity to efficiently and more rapidly implement multi-temporal landslide archives, allowing us to assess the landslide susceptibility conditions on a regional scale, for very large areas (hundreds of square kilometers) for which landslide archive are typically lacking.

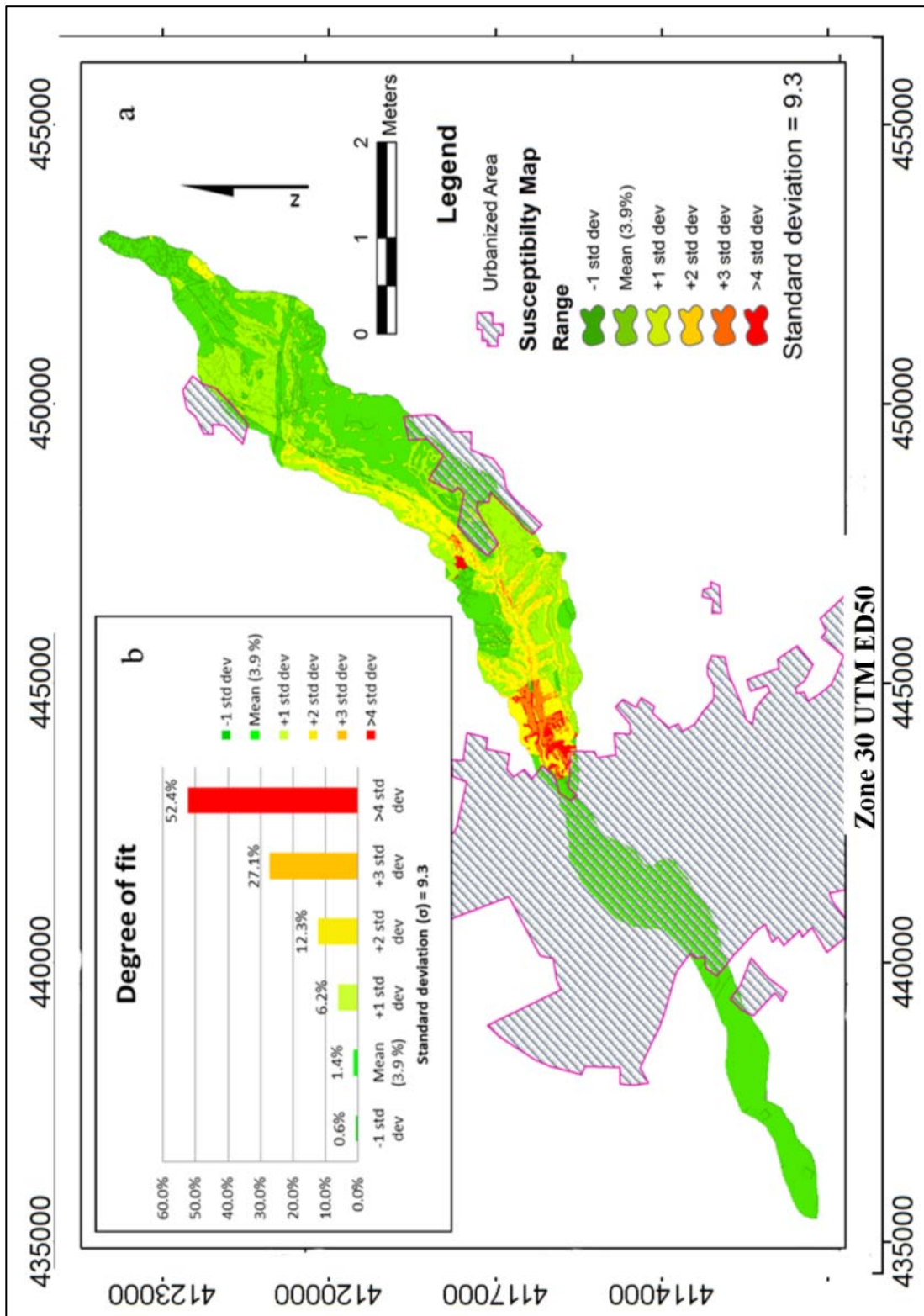


Fig. 5.28 - Landslide susceptibility map (a) and validation (b)

5.3 TEST 3: Imera sub-basin: Geological and climatic framework

The application area covers about 90 km², and corresponds to the upper portion of the Imera river, one of the main rivers of Sicily, which flows from the western sector of the Madonie to the Tyrrhenian Sea (Fig. 5.29a). In the studied area a successions of Meso-Cenozoic and Upper Tortonian–Lower Pliocene late-orogenic rocks are present (Grasso et al., 1978; Abate et al., 1988). The Meso-Cenozoic successions are made up of sandy clays and marly clays (Argille Variegate; Lower Oligocene–Upper Cretaceous) or marly calcilutites (Formazione Polizzi; Oligocene–Upper Eocene) belonging to the Sicilide Units; clay with intercalations of sandstone levels (Flysch Numidico) of the Numidian Units (Lower Miocene–Upper Oligocene); mainly carbonate rocks of the Panormide Units (Middle Oligocene–Upper Trias); alternations of shales, marls, radiolarites, and carbonates of the Imerese Units (Oligocene–Upper Trias); and alternations of marls and

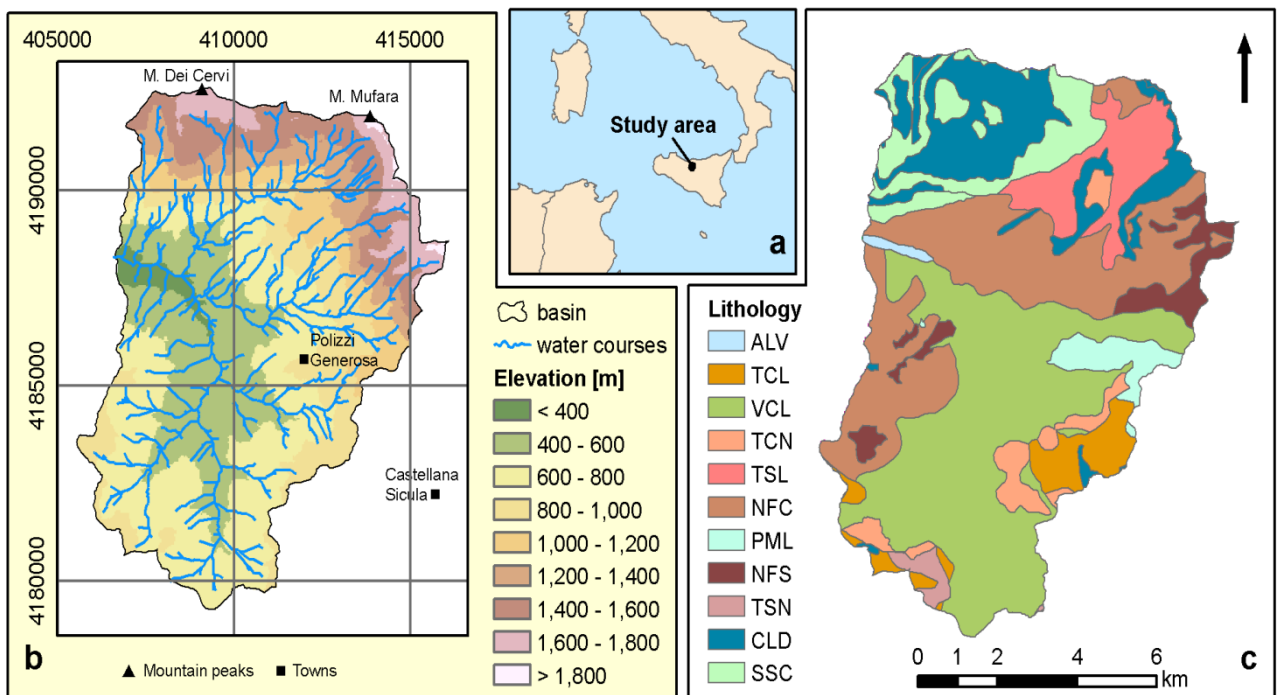
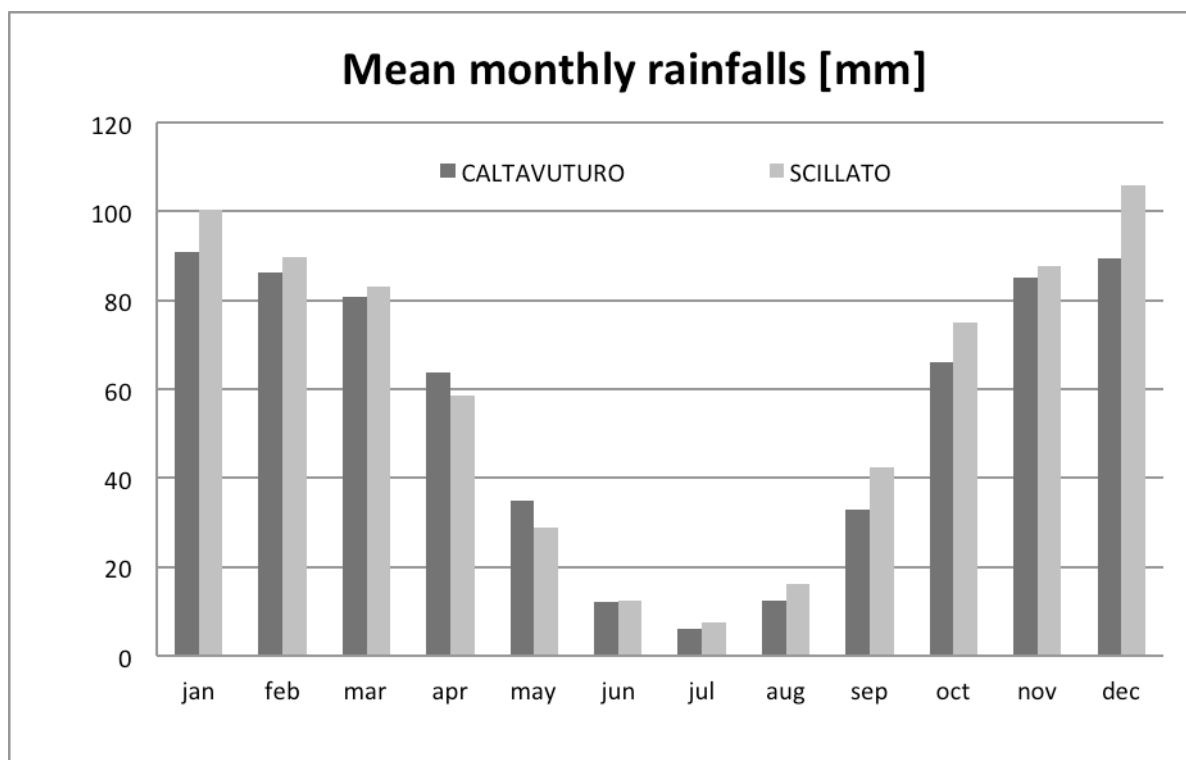


Fig. 5.29 - Location of the test area (a); 40-m DEM of the area (b); lithology map (c): ALV Quaternary alluvial deposits; TCL Terravecchia Fm. clays; VCL Varicolori clays; TCN Terravecchia Fm. conglomerates; TSL Talus slope; NFC Numidian Flysch clays; PML Polizzi Fm. marly limestones; NFS Numidian Flysch sandstones; TSN Terravecchia Fm. sandstones; CLD Carbonate limestones and doloarenites; SSC Siliceous successions.

calcilutites of the Lercara Units (Trias). The late-orogenic units are made up of fluvial-

delta (clays, sandstones, and conglomerates of the Formazione Terravecchia; Lower Messinian–Upper Tortonian). Reef and pelagic (marly calcilutites of the Trubi formation (Lower Pliocene) rocks covering the Meso-Cenozoic successions (Fig. 5.29c) Miocene overthrusts and Plio-Pleistocene fault systems are responsible for the existing tectonic setting (Catalano et al., 1996), which consists of a pile of imbricate tectonic units (thin-skinned tectonics) that have been folded and faulted. The selective erosion, thanks to the tectonic or stratigraphic superimposition of terrigenous covers on carbonate rocks,



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is responsible for a strict congruence between topographic and tectonic highs and lows (Hugonie, 1982).

The Thiessen and the isohyetal methods were applied to evaluate the basin rainfall. Were processed and analyzed monthly rainfall data recorded in the time interval between 1950 and 2003. The distribution of rainfall has been reconstructed on the basis of rainfall data in the vicinity of the persistent object of the study and managed by the Regional Office. The climate in the area is characterized by annual rainfall of between 700 and 750 mm (Figs 5.30, 5.31), are concentrated mainly in few of the winter semester

days, while summer period is characterized by almost drought conditions. The climate of this sector of Sicily represents an example of the Mediterranean type, being characterized by wet and mild winter periods and hot and dry summer times. The most common land use category is represented by arable lands, while some sporadic plots are occupied by pastures, shrublands and grasslands. The landscape is in general characterized by gentle slopes affected by severe water erosion and landslide phenomena (mainly classifiable as earth flows and rotational slides).

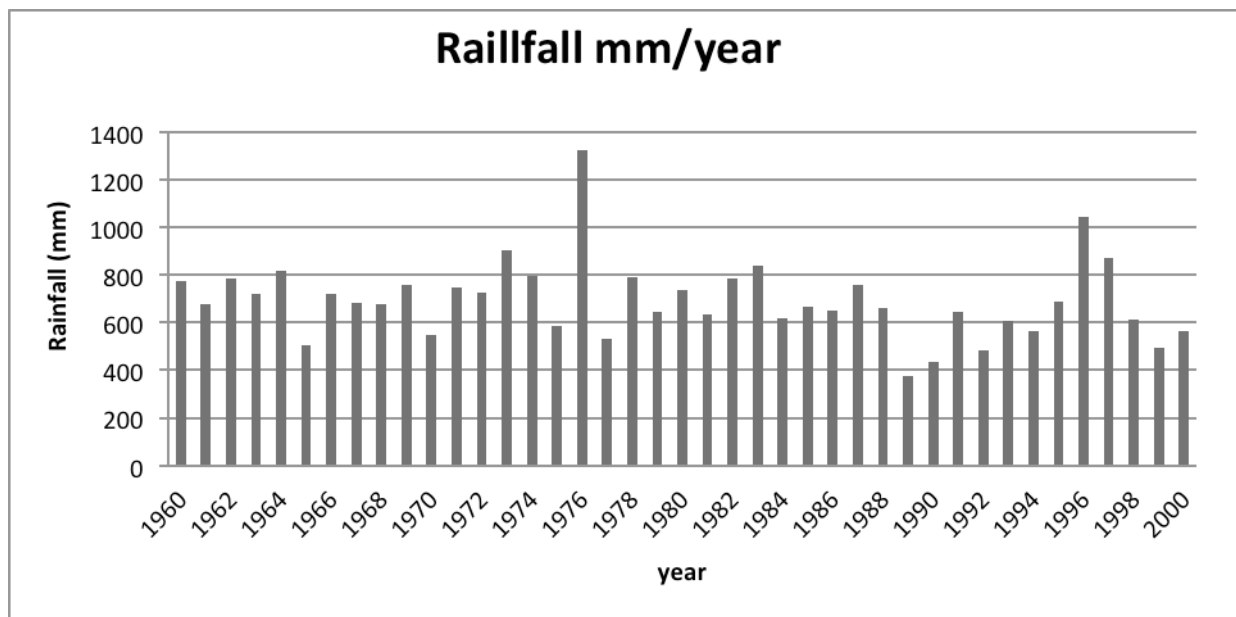


Fig. 5.31 - Mean annual rainfalls in mm/year for the basin area.

5.3.1 Slope units, instability factors and landslides

A Digital Elevation Model (DEM) with a 40m square grid cells was obtained for the area under study, digitizing topographic sections regional scale 1:10.000, (Fig. 5.29b). The spatial analysis carried out using GIS tools allowed us to derive the DEM from the Flow Direction Grid and Flow Accumulation, semi-automatically used to partition the area (Fig. 5.32) studied in 774 units of slope (SLU). Methods to partition the territory in mapping units for susceptibility analysis are mostly referable to two categories: those dividing the landscape in regular cells of the same size (cell units) and those that, in accordance with morphodynamic and hydrological criteria, separate portions of slopes that are limited by elements of the river network and by water divides (slope units). In

the present research, a procedure combining regular cells and slope units is proposed. Mapping units were derived by intersecting a regular grid of 50 m cells and a vector layer of slope units; therefore, the mapping units correspond to regular cells, where they are completely contained inside the boundaries of the slope units, while they assume an irregular shape, given by streams or water divides, where overlapped by the limits of the slope units. A threshold value of at least 16.000 m² extensions was applied, so that the small units were merged with the adjacent larger ones.

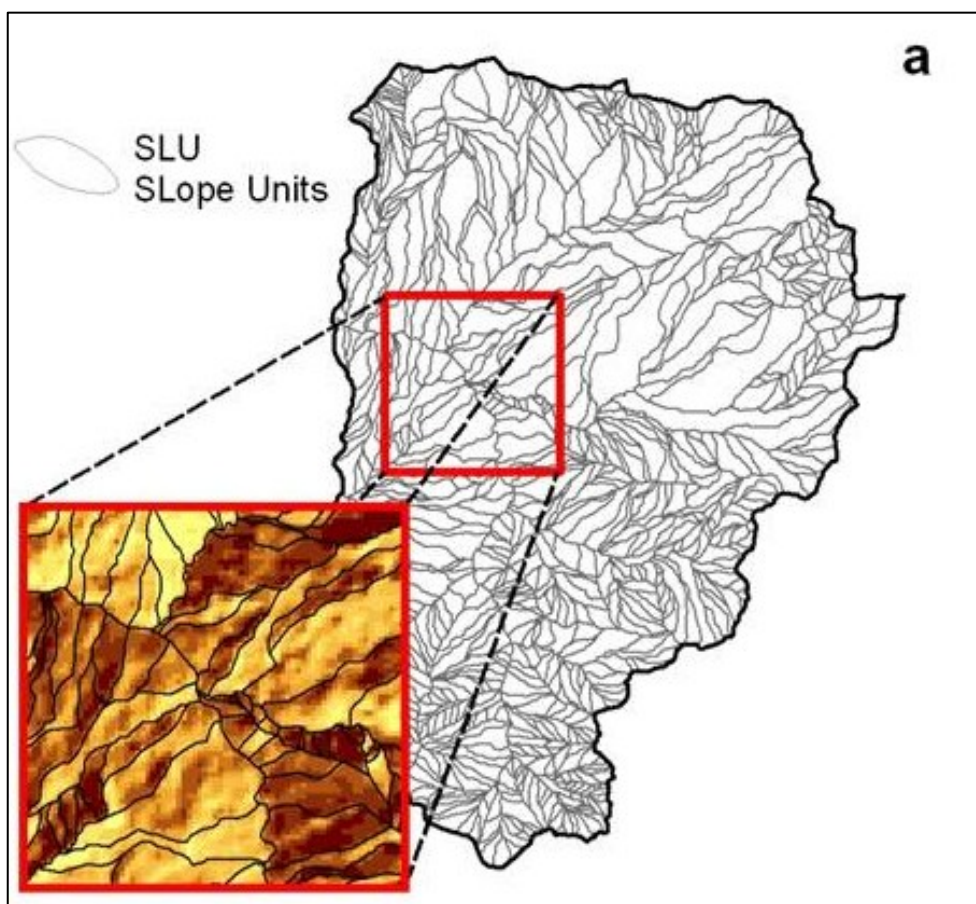


Fig. 5.32 - 774 Slope Units (SLU) Semi-automatically derived.

Seven controlling factors (outcropping lithology: LTL; mean slope gradient: STP; stream power index at the foot of the SLU: SPI; mean topographic wetness index and profile curvature: TWI, PRC; slope unit length and altitude range: LNG, REN) were selected and computed for each SLU. The way in which the morphodynamic spatial constraints of the SLUs were imposed on the susceptibility assessment procedure consisted in producing

new SLU-derived factor layers by calculating zonal statistics of the source grids inside each SLU. It is not a simple reclassification of old values, and new values for each factor are generated. All the cells or pixels intersected by the same SLU will have the same factor value in the new grids. SLU zoning is a geostatistical device to impose the morphodynamic spatial connection between each cell or pixel belonging to the same SLU.

Adopting such a procedure allows us to prepare spatially distributed models in which the link between the cells is rather on geostatistical than on physical relationships. The seven controlling factors were obtained from the lithologic map and the digital elevation model and were associated to each SLU with the following procedures: the LTL was derived intersecting the SLUs with the lithology map, considering the unique or the dominant lithologic complex; STP, TWI, and PRC were computed as the zonal mean value from the respective 40-m grid layers within each SLU; SPI was defined as the mean stream power index measured along the fluvial channel, constituting the downhill edge of the SLU; LNG and REN are, respectively, the topographic distance between the head and the foot cells and as the altitude range of the SLUs (Table 5.13).

Factor	Source layer	Description of source parameter
LTL	lithology map	outcropping lithology
STP	slope gradient	highest first derivative of elevation
SPI	stream power index	calculated as $\ln[A \cdot \tan\beta]$ where A and β , computed on each cell, correspond to the area of upslope drained cells and to the slope gradient, respectively
TWI	topographic wetness index	calculated as $\ln[A/\tan\beta]$ where A and β , computed on each cell, correspond to the area of upslope drained cells and to the slope gradient, respectively
PRC	profile curvature	second derivative of elevation, computed along the direction of the highest slope gradient
LNG	DEM	distance between the highest and lowest cell in a SLU
REN	DEM	difference between the highest and lowest elevation in a SLU

Tab 5.13 - Description of the 40 m grid layers from which the seven controlling factors were derived.

Each SLU-derived factor grid layers was then reclassified in ten equal area classes, while the intersection of SLUs and the lithologic map produced six unique or dominant

classes (there are five lithologies that are never dominant in a SLU). Each of the factor classes homogeneously characterizes one or more SLUs (Fig. 5.33).

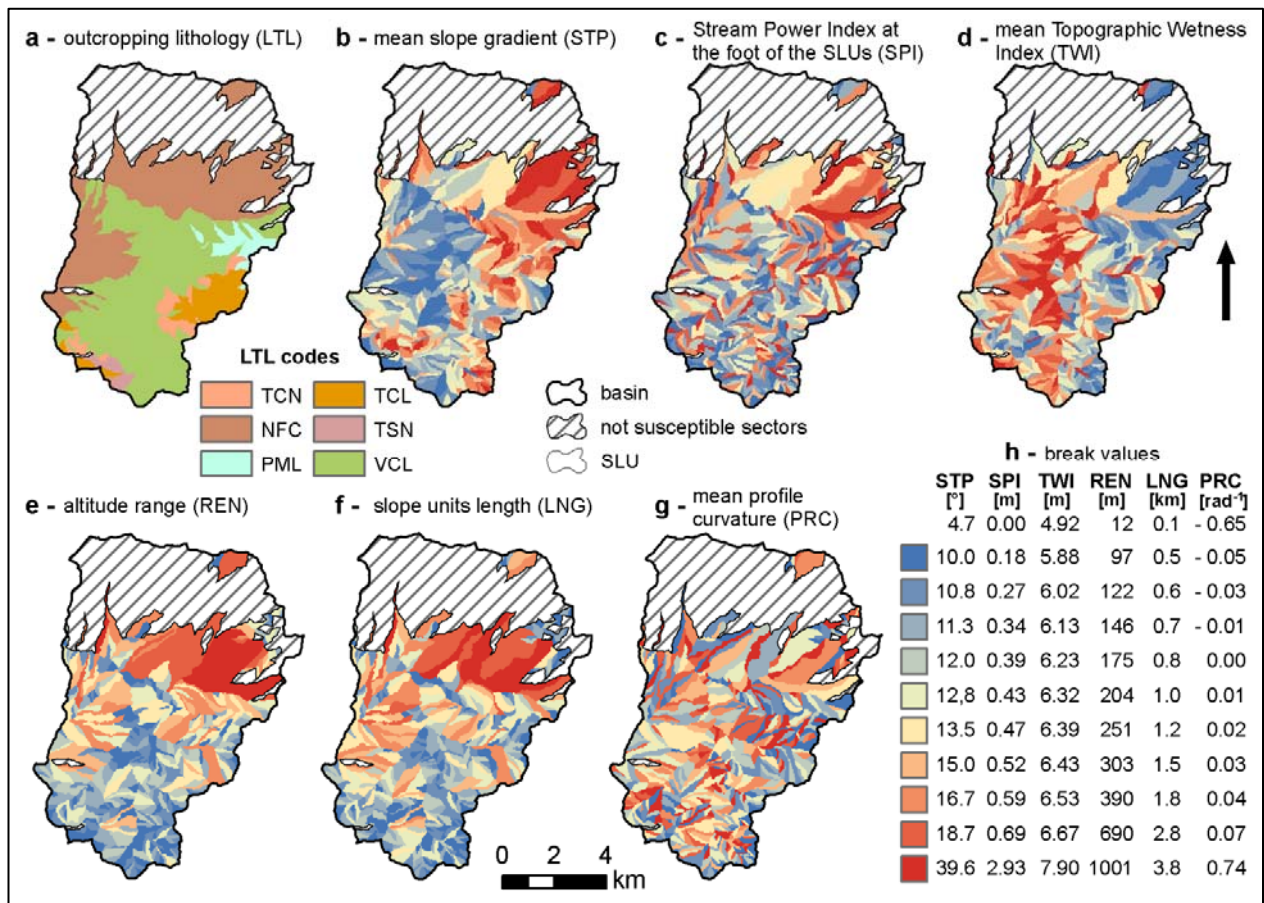


Fig. 5.33 - Layers of the controlling factors: lithology (a); mean slope angle (b); Stream Power Index at the foot of SLU (c); mean Topographic Wetness Index (d); altitude range (e); slope length (f); mean profile curvature (g). The table shows break values used for the topographic factors (h).

Due to its geomorphological setting and climatic context, the study area is affected mainly by flow-type landslides, with a limited number of rotational slides, falls, and topples (Cruden and Varnes 1996). As the aim of this study is to verify methodological strategies to assess landslide susceptibility, we decided to focus the analysis selecting only the flow-type landslides, whose large number make it possible to adequately train the predictive model. We think that each of other landslide typology requires a specific selection of the controlling factors and different landslide, representation strategy and mapping unit partition. Field surveys, carried out in October 2008, allowed us to recognize 490 flow-type landslides (Fig. 5.34). This type of failure involves the clayey formations to the depth of several meters (earth-flow) or, subordinately, limits the

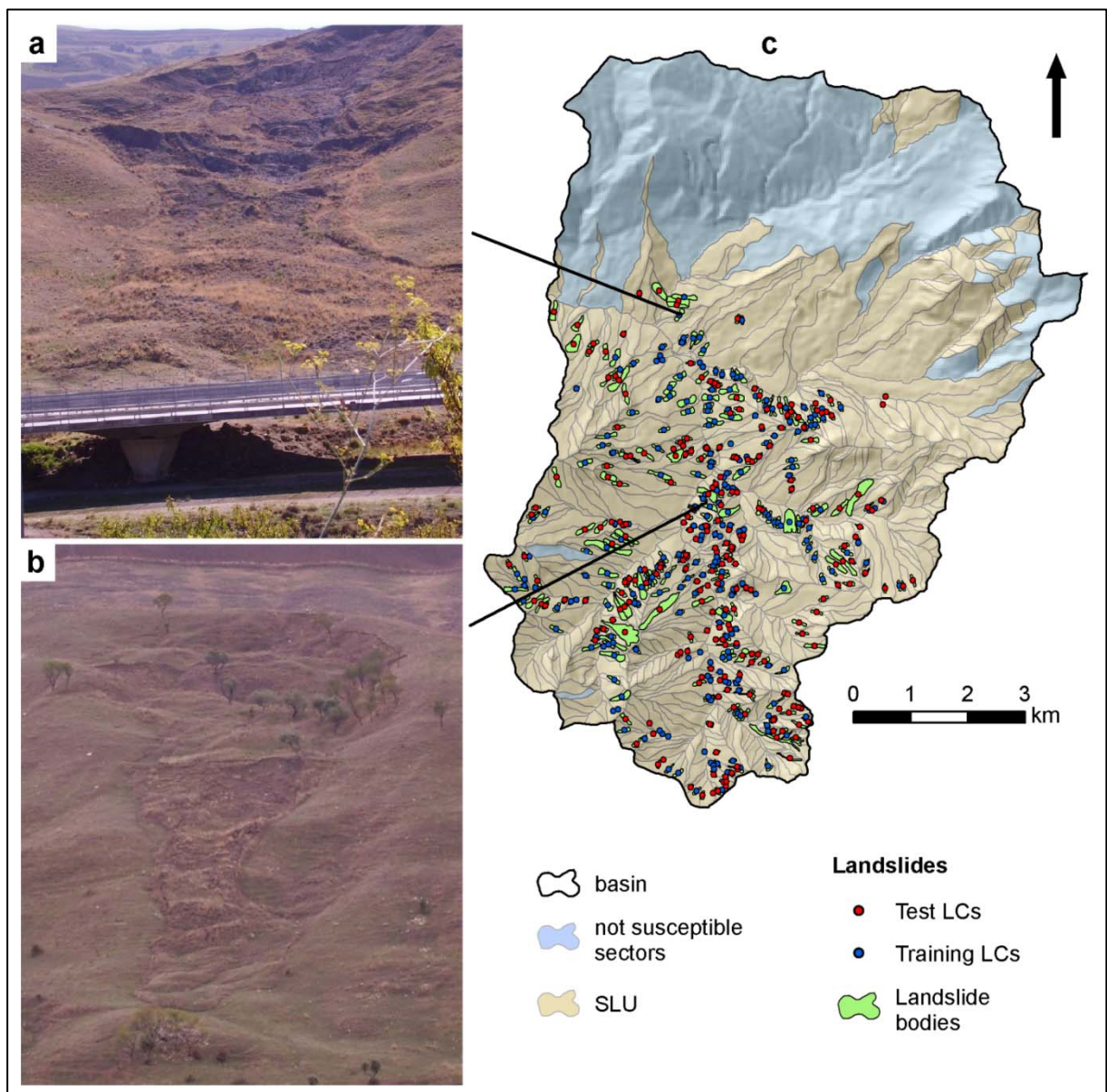


Fig. 5.34 - A Examples of the flow-type landslides; b landslide map showing landslide bodies and centroids (LCs).

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

The landslide area covers 5.8 km² corresponding to 6.6% of the investigated basin.

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

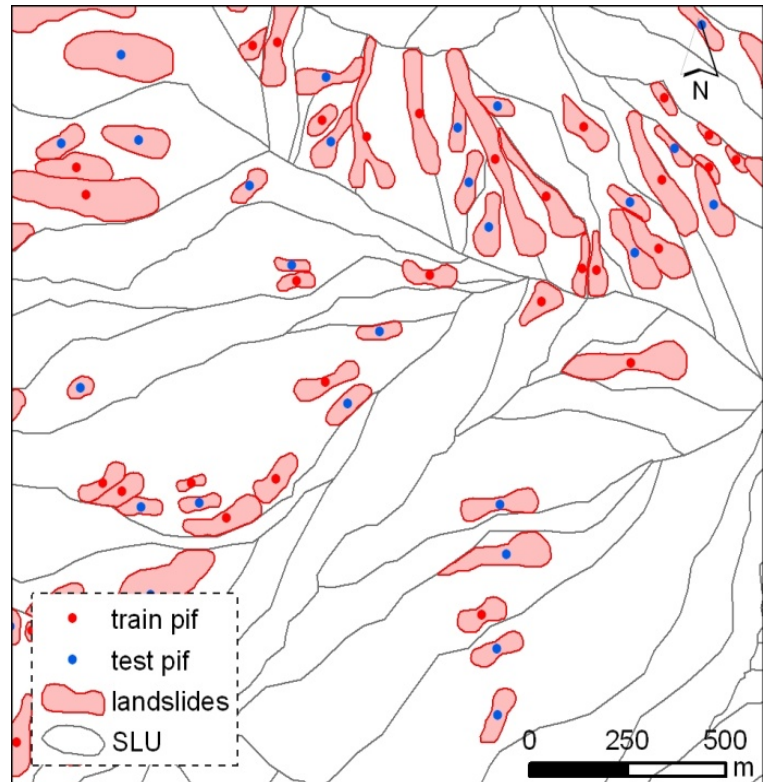


Fig. 5.35 - Landslide centroids map; b) spatial relationship between SLUs, landslides and LCs (pif) in a representative sector.

proceed to the susceptibility assessment, each landslide was converted into a single point, selected as its centroid. The landslide centroids (LCs, Fig. 5.35) are fully effective in indicating the SLU conditions associated to each mapped phenomenon. In fact, according to the criteria adopted in mapping and characterizing SLUs, all the cells inside a SLU have the same factor values, and none of landslides crosses SLU limits.

5.3.2 Susceptibility modeling and validation

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

Landslide density is assumed as the susceptibility function (see also Chung and Fabbri 2003; Clerici et al. 2002; Conoscenti et al. 2008), so that a ranked order of landslide densities correspond to a susceptibility scale. To estimate and compare the controlling role of the seven variables, univariate susceptibility models were prepared and validated (Remondo et al. 2003). The validation procedure exploited the random time partition strategy (Chung and Fabbri 2003), based on the random splitting of the landslide centroids archive into two equally populated (50% of LCs, each) subsets: LC_{training} and LC_{test}. The former was used to prepare a prediction image (i.e., susceptibility map) for each factor, while the latter was used as the unknown target pattern. Prediction and success rate curves (Chung and Fabbri 2003; Guzzetti et al. 2006; Fabbri and Chung 2008), drawn by comparing the factors prediction images with the test and training LCs, were exploited to estimate the prediction skill and the model fitting, respectively. These curves are plotted on a Cartesian diagram, interpolating points whose coordinates are given by the cumulative fraction of the total number of LCs (Y-axis) and by the fraction of the area predicted, cumulated from the more to the less susceptible (X-axis).

To evaluate quantitatively the predictive performance of the models, we proposed two geometric indexes of the prediction rate curves: the area between the prediction rate curves and the diagonal of the graph (areas above randomly predicted area, ARPA) and the tangent to the curve at the 20% of the predicted area (T₂₀). The effectiveness ratio (EFR, Chung and Fabbri 2003; Guzzetti et al. 2006) is also computed to evaluate the performance of each susceptibility class. In the graph, the diagonal represents a theoretical random prediction rate curve, given by the same portion of landslides falling within all the susceptibility classes, no matter their susceptibility levels. For this reason, high ARPA and T₂₀ values confirm a good predictive factor performance, indicating that the test LCs are more concentrated in the area predicted as most susceptible. In particular, T₂₀ expresses the predictive performance of the 20% most susceptible area, while ARPA reflects the model prediction skill for the whole area and landslide data set. EFR is the ratio between the fraction of LCs accounted for each susceptibility class and the proportion of the latter in the study area. This parameter allows us to discriminate effectiveness of each susceptibility class, depending on to how far its value is from 1, which would be the same value produced by a random model, in which the fraction of observed landslides only depends on the area of each class. According to Guzzetti et al.

(2006), EFR indicates an effective prediction, for each single class, when its value is at least 1.5 for more susceptible classes and at most 0.5 for less susceptible classes. Corresponding threshold values can also be derived for ARPA and T₂₀, drawing a theoretical prediction rate curve, which would respect the EFR constraints, by fixing the extensions of the more and less susceptible classes at 40% of the investigated area. ARPA and T₂₀ threshold values are obtained equal to 0.12 and 1.5, respectively. Differently from EFR, ARPA and T₂₀ evaluate the effectiveness of the prediction for a cumulated portion (T₂₀) or the entire (ARPA) predicted area.

5.3.4 Results

The curves derived from the validation of the univariate factor models are plotted in Fig. 5.36. The degree of correlation between univariate models and spatial distribution of landslides can be evaluated as satisfactory for REN and LNG (ARPA = 0.17; T₂ = 1.8) and for LTL (ARPA = 0.168; T₂₀ = 1.684); the prediction rate curve of LTL is heavily controlled by a single lithology (VCL), which actually represents nearly 50% of the most susceptible area. The SPI model is characterized by validation results (ARPA = 0.106; T₂₀ = 1.495) that can be considered as almost satisfactory (just below the threshold values), while the prediction rate curves of STP (ARPA = 0.066; T₂₀ = 1.405), TWI and PRC (ARPA = 0.07; T₂₀ = 1.3) show unsatisfactory performances.

Similar considerations about the effectiveness of the predictor variables can be derived by analyzing the values of effectiveness ratio (represented in the right Y-axis in Fig. 5.36) and by comparing them to the threshold levels of model reliability proposed by Guzzetti et al. (2006); REN and LNG show the best EFR values as they are just above 1.5, in 20% most susceptible classes, and largely below 0.5, in 20% of the area classified as less susceptible. LTL effectiveness ratios can also be considered satisfactory, while EFR values of SPI confirm that its predictive power is very close to acceptable thresholds. On the contrary, STP-, TWI-, and PRC-derived susceptibility classes show EFR levels between 1.5 and 0.5, with the exception of the less susceptible class of the slope gradient model. In light of the observed values of the quality indexes, the following considerations are given: slope unit altitude range and length, lithology, and stream power index at the foot of the SLUs can be considered as “effective” predictive variables, while mean slope gradient, mean topographic wetness index, and profile curvature,

which showed a weak correlation with the spatial distribution of landslides in the study area, are classified as “non-effective”. Multi-parametric models can be prepared by combining two or more SLU-derived factor grids and obtaining a single SLUCU (Slope Unique Condition Units) layer. A SLUCU is a unique conditions unit made up of one or more SLUs. The susceptibility of each SLUCU is here derived by averaging the LC density values from the combined factor classes.

Among the number of models that can be obtained by variously selecting and combining the controlling factors, it is worthwhile comparing those given by combining only effective (EFF) and only non-effective (NEF) predictive variables. Figure 5.36 allows us to compare the prediction rate curves produced by the EFF and NEF models, together with the multi-parametric model produced by intersecting all factors layers (ALL = EFF NEF); the prediction rate curve relative to the REN single factor model (Fig. 5.36f) is also plotted. As expected, the EFF model shows the greatest prediction skill, testified by a

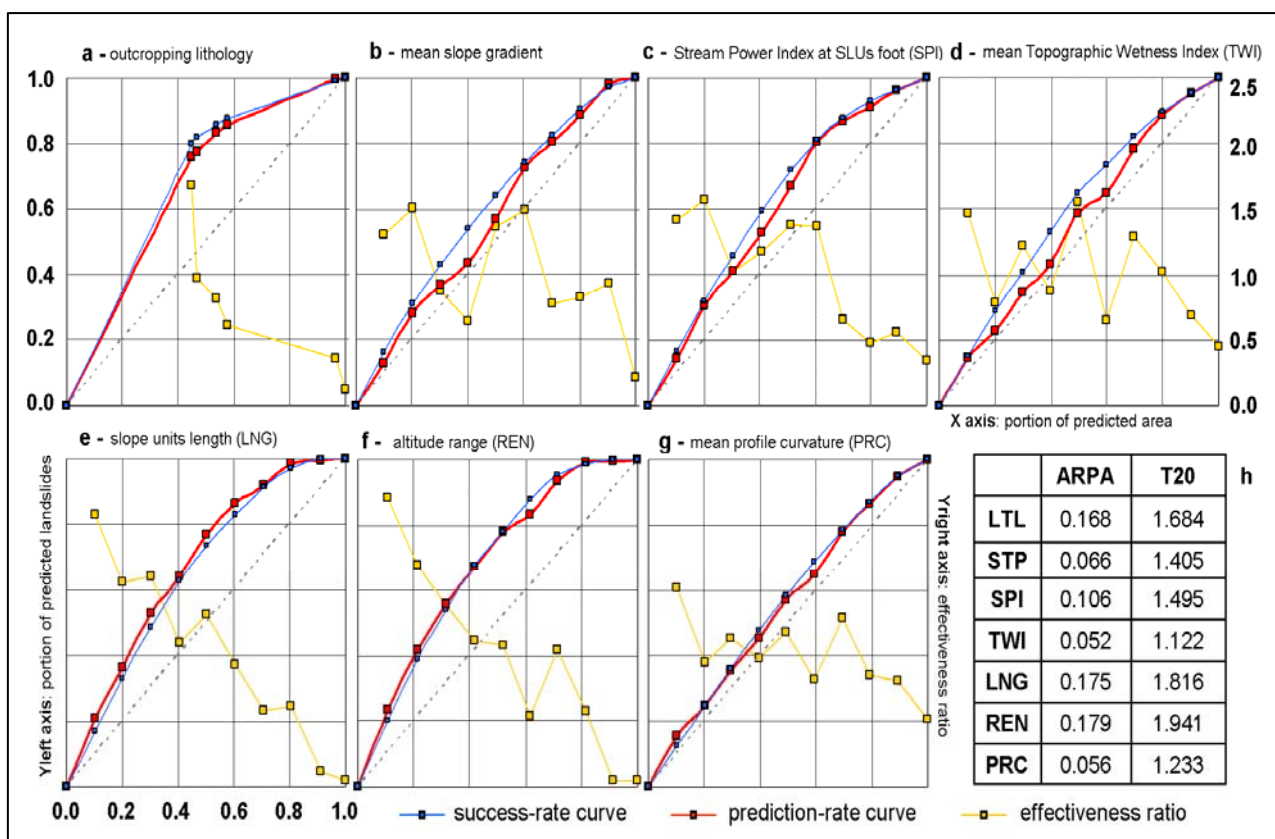


Fig. 5.36 - Validation graphs (success and prediction rate curves; effectiveness ratio) of the single-parameter based susceptibility models (a–g). Table showing values of curves quality indexes (h). For all the validation graphs: X-axis = portion of predicted area, Y left axis = portion of predicted landslides; Y right axis = effectiveness ratio.

very steep validation curve in the first part ($T_{20} = 2.53$), well above the diagonal (ARPA = 0.22); on the contrary, NEF confirmed the very poor predictive skill of its source parameters, as the curve is close to a random prediction rate curve, testified by a ARPA index equal to 0.1. The negative contribution of the NEF variables is projected in the ALL model, as it produces a prediction rate curve less performing than EFF ($T_{20} = 2.18$; ARPA = 0.21). The graph in Fig. 5.37 also shows the error bars of the EFF model, given by the difference, computed class by class, between the number of predicted (train LCs) and occurred (test LCs) landslides, normalized to the total number of the latter: (train LCs–test LCs)/test LCs. The ratio between each bar length and the total Y-axis extent can be read as the percentage of over- or under-predicted events (LCs). Despite some

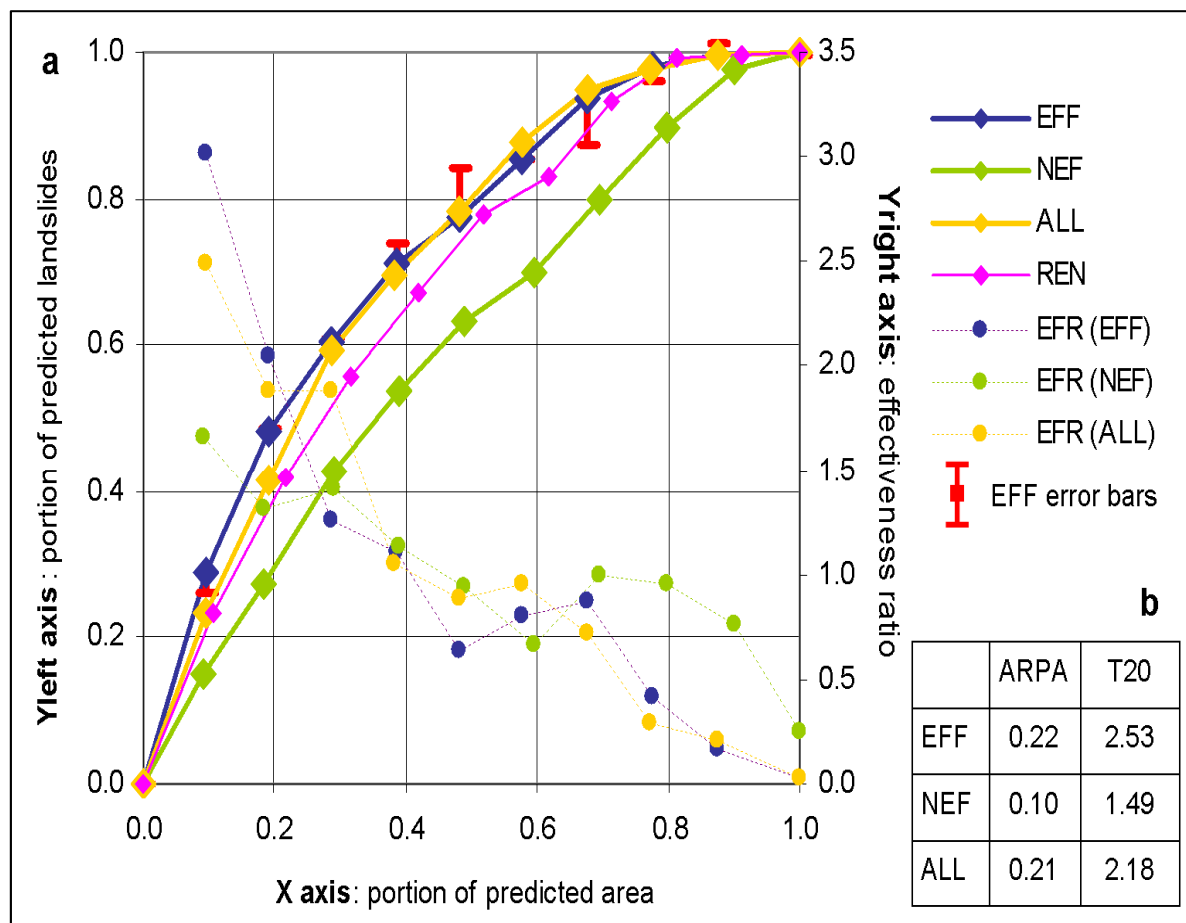


Fig. 5.37 - Prediction rate curves (solid) and effectiveness ratio (dotted) for EFF, NEF, and ALL multi-parametric susceptibility models, compared with the best single predictor (REN). X-axis = portion of predicted area, Y left axis = portion of predicted landslides; Y right axis = effectiveness ratio. The table shows curve quality indexes (ARPA and T20) values. Error bars of the EFF model show for each susceptibility class, differences between the number of predicted (train LCs) and occurred (test LCs) landslides, normalized to the total number of the latter: (train LCs–test LCs)/test LCs

errors arising in the middle classes, whose susceptibility is slightly overestimated and in the medium–low susceptibility zones, that are slightly under-estimated, very small differences between predicted and occurred landslides were observed. Considering the validation results, the EFF model, trained using all LCs, was selected to produce the susceptibility map of the studied area (Fig. 5.34).

5.3.4 Discussion and concluding remarks

The use of a morpho-dynamically based mapping unit in assessing landslide susceptibility by means of a conditional analysis-based geostatistical approach has proved to be effective in the test area, producing satisfactory validation results. Adopting a multi-parametric univariate approach, in which the susceptibility levels are computed independently, factor by factor, and then combined to produce the susceptibility levels of Slope Unique Condition Units, allowed us to face one of the main geostatistical limitations in adopting such a mapping unit: the low number of cases (SLUs) for each combination (SLUCU) that is otherwise responsible for under-training of the predictive models. In the Upper Imera river basin, slope unit altitude range and length, lithology and, subordinately, stream power index at the foot of the slope units demonstrated to be the main controlling factors of landslides, while mean slope gradient, profile curvature, and topographic wetness index, in spite of their expected high morphodynamic relationship with flow-type landslides activity, gave unsatisfactory results. Other simple statistics for such factors (variance and range) were checked without obtaining any improvement in the predictive skill. These results suggest the use of SLUs as a procedure, which is not totally suitable for representing the latter factors in the susceptibility models; these factors are probably much more effective in determining inside a SLU the site (the single pixel) where a landslide could initiate, but when summarized on a SLU scale, they show a loss in their predictive power. The indexes adopted in evaluating the predictive performance of each factor proved to be useful and representative of the model performance. TAN₂₀ expresses the skill of the model in characterizing the most unstable portion of the study area. ARPA, on the other side, gives an estimation of the cumulated effectiveness of the susceptibility models, taking into consideration the whole predicted area. These two indexes allow to estimate the overall performance of the model (EFR is the typical adopted quality index, but it refers

to a single class). Objective factors reclassification criteria (equal area and dominant outcropping lithology), together with a test procedure for selecting the factors of the model, allowed us to produce a susceptibility model whose good predictive performance has been demonstrated. Moreover, the coherence between the qualities of the predictive performances of the single factors, tested by means of univariate validation tests, and their effect when included in multi-parametric models, in terms of increasing or decreasing of prediction skill, demonstrate that the adopted multi-parametric procedure is stable and self-consistent. Adopting SLUs and LCs is considered a useful approach in assessing landslide susceptibility. LC representation of landslides allows us to establish stable spatial relationships with the controlling factors, not critically dependent on the exact location of the mapped landslides, as inside SLUs factors are homogeneously defined. At the same time, landslide survey is needed to correctly classify typology, activity, and morphometric features of the recognized phenomena. SLUs, on the other hand, are to be considered the fundamental mapping units for a number of reasons: factors acquire sense only if considered and recomputed within the morphodynamic units (single cell values are meaningless when considering phenomena involving portion

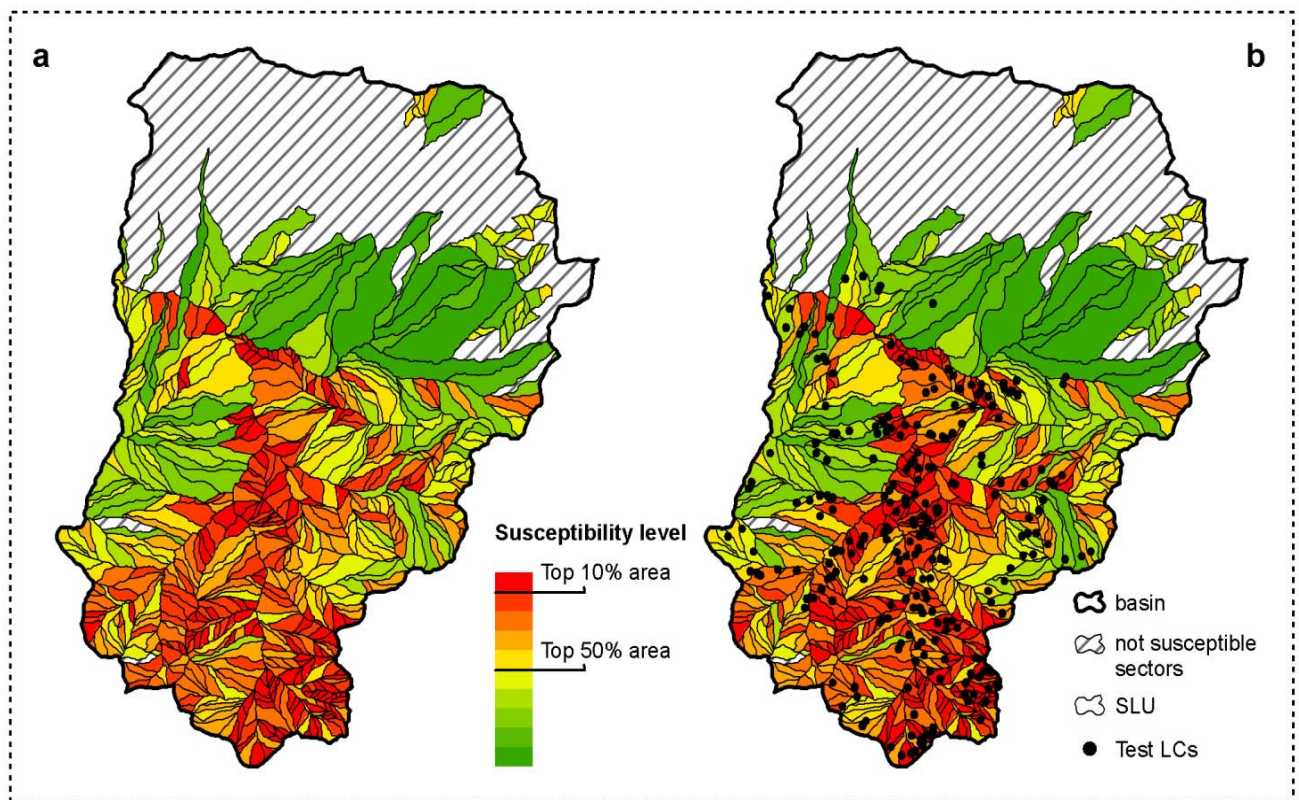


Fig. 5.38 - Landslide susceptibility map for the best (EFF) multiparametric model (a). Training LCs-derived prediction image and test LCs spatial distribution (b).

or whole slopes); slope units are the correct spatial domains to implement a deterministic physical approach to assess the safety factor, in high susceptible cases; mitigation activities are typically planned on a slope or basin scale (a raster susceptibility representation is of no use for a territorial administration!).

6.1 Discussion and concluding remarks

In the thesis presented here, some test areas were identified (Chapter V, Sections 5.1; 5.2; 5.3; 5.4) for which general information was provided on landslides, morphology asset, lithology, geostructural, climate as well that physiographic features. In these areas, concepts, methods and tools acquired during the research have been tested and verified for the recognition, mapping of landslides and testing of models for susceptibility zoning.



Fig 6.1 - Location of study areas. a) in Sicily; b) in Spain

Figure 6.1 shows the position of the three different study areas selected and Tab 6.1 summarizes the statistics of landslide areas.

	Tumarrano river basin	Beiro river basin	Imera Sub-basin
Described test	§ Cap. IV sez. 3.1	§ Cap. IV sez. 3.2	§ Cap. IV sez. 3.3
Area extend (km^2)	80	10	90
Elevation (m)	318-891	623-1552	400-1800
Lithology	Mostly sedimentary rocks	Mostly sedimentary rocks	Mostly sedimentary rocks
Climate	Mediterranean	Mediterranean Semi-Arid	Mediterranean
Landslide typology	Earth flows	Falls, Translational slide, earth flows, debris flows, flow-slides	Flow Types
Studies	Inventory of landslides, Model Exportation , validation techniques,	Inventory of landslides, selection factors, validation techniques,	Inventory of landslides, selection factors, mapping unit, validation techniques,
Number of cases	760	128	490
Landslide	4.5	0.37	0.37
Percentage in terms of total area	28.10%	3.70%	8.40%
Title of research	Exporting a Google Earth™ aided earth-flow susceptibility model:	Factor selection procedures in a Google Earth™ aided landslide susceptibility model	Slope units-based flow susceptibility model: using validation tests to select controlling factors

Tab. 6.1 - Statistics for the different study zones

The reasons underlying the choice of these areas can be summarized as follows:

1. The areas are located in geological and morphological conditions deemed as adequate for the type of studies carried out;
2. The availability and resolution of the basic data levels representing the distribution of the geo-environmental variables taken into consideration.
3. The cover images (orthophotos, Google images, 3D BingMaps etc.) necessary for the implementation of an inventory of disruptive forms.

The extension of the selected areas range from about 10 square kilometres (the basin of the Beiro river, Andalusia, Spain, § 5.3.1) up to nearly 90 km², the area corresponding to the sub-basin of North Imera (§ 5.3.4). In accordance with the objectives outlined in Chapter I, tests were carried out in the experimental area to verify the validity of some concepts matured during the PhD in Geology at DISTeM (Department of Earth and Sea Sciences) at the University of Palermo. In particular, all area applications underwent an effectiveness and reliability test for the remote observation of the Earth (Google Earth), with free wide area access. For all areas mapped by Google, along with the analysis of several aerial images, the construction of the archive was able to identify 1320 landslide areas, divided into: 28 landslides, 1229 earth flows, 1 translational slide, 57 debris flows, and 5 flow-slide type movements (of course field-surveys were carried out for all areas, at least on representative portions and problematic areas). The adequateness of this type of instrument for the construction of the archive is simply justified by the immediate savings in building time of the inventory and, even more important given the chronic lack of funds for research, the possibilities of building an archive of landslide areas basically at no cost. Although we used the free version, Google Earth, has proven to be an ideal tool for locating and mapping geomorphological processes. It allowed to complete the exploration of the territory for the digitization of landslides. The census forms can easily be analyzed, then, under any territorial Information System (ArcGIS/ArcMap-ESRI, SAGA, Global Mapper, QuantumGIS, etc.). The archive thus created is treated statistically, using existing maps (geology, topography, land use, hydrology, etc.) in order to improve knowledge on the causes and mechanisms involved in determining the forms of instability.

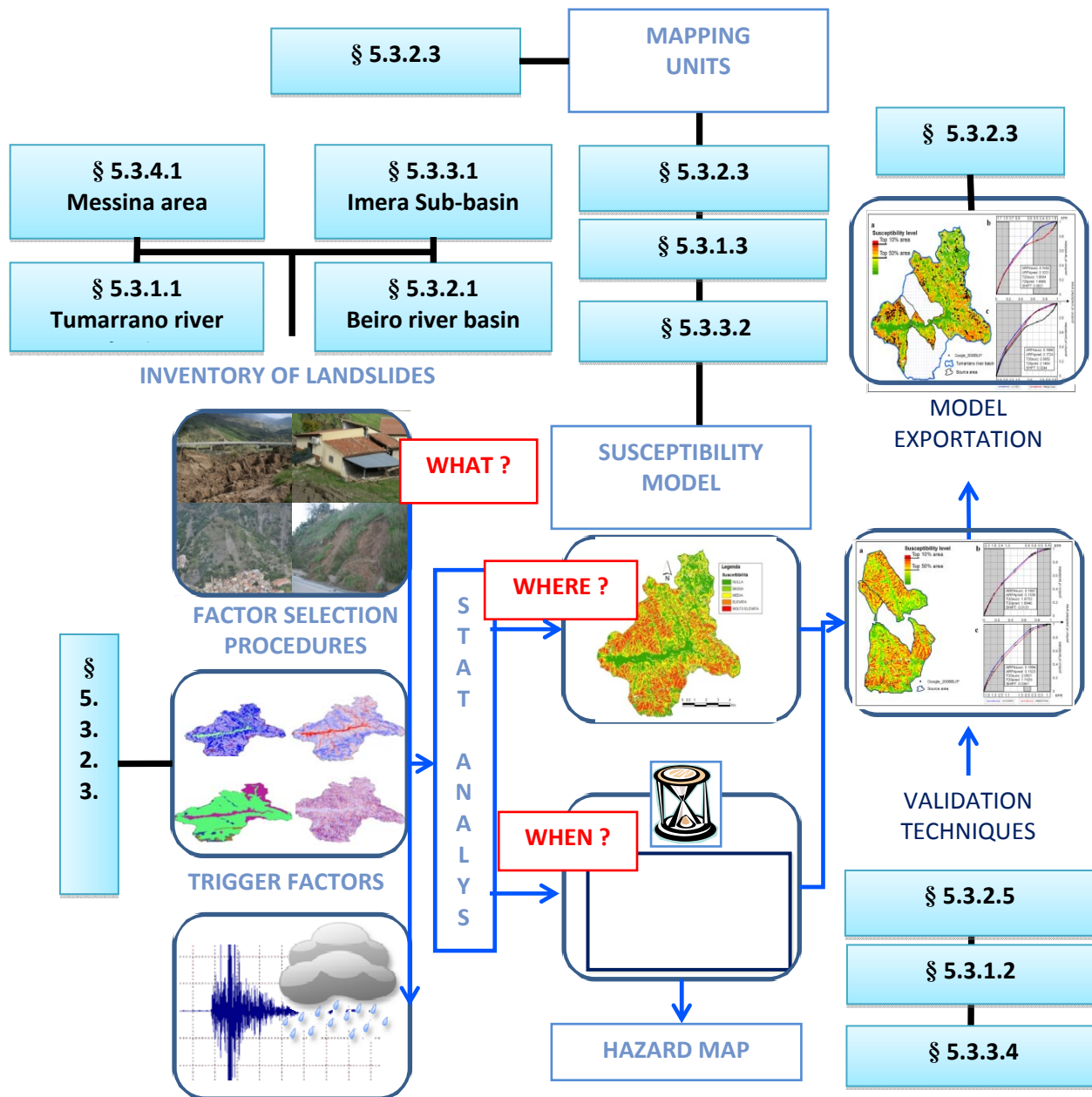


Fig. 6.2 - Flowchart of the methodology followed. For each of the steps is shown the section of Chapter 4 where we affront the problem.

For example, the inventory created for the experiment carried out in the Tumarrano basin, allowed to create a susceptibility model, which showed good predictive capability with a small number of parameters, combined with Unique Conditions Units. The model was verified through both spatial validation for the whole basin and its representative temporal part. For each landslide area mapped, an identification point

was selected (LIP: Landslide Identification Point), corresponding to the point of maximum altitude falling within the landslide, and, therefore, placed at the crown of the landslide. Around each LIP a buffer area with a radius of 30 meters was then identified. The buffer areas around the identification points (BLIP: Buffered LIP) were used as diagnostic areas. The latter must, in fact, indicate the physical-environmental conditions that produced the triggers of the observed phenomena. Intersecting the BLIP layer with any layer that expresses alleged control conditions of the phenomena, it is possible to define predicted functions corresponding to the density of the diagnostic area (of BLIP) within the class factor. This corresponds to the probability of having a new event on a given physical-environmental condition. First, we evaluated the univariate relationships that bind a single factor with the distribution of landslides. This analysis has shown that for earth flows the most important controlling factors are the emerging litotechnical complex and topographic wetness index.

While a side effect is exercised by the slope, the validation curves produced by the susceptibility model that relates to the whole basin, attest the good predictive capacity and stability of the model. As for the time validation of landslides, it provides very satisfactory results, since the two detection periods differ by a single year; this range is, in fact, sufficient for this type of movement to be reproduced in a full scenario of activations similar to the one the susceptibility map was created with.

For the Tumarrano river basin, forward logistic regression has allowed us to derive an earthflow susceptibility, which was defined by modeling the statistical relationships between an archive of 760 events and a set of 20 predictors. For each landslide of the inventory, a landslide identification point (LIP) was automatically produced as corresponding to the highest point along the boundary of the landslide polygons. Balanced models (760 stable/760 unstable) were submitted to forward logistic regression procedure. A model building strategy was applied to enlarge the area considered in preparing the model and to verify the sensitivity of the regressed models with respect to the particular locations of the considered stable cells. A suite of sixteen models was prepared by randomly extracting the different stable cells subsets. Models were submitted to forward logistic regression and validated. The results showed satisfying and stable error rates (0.236 on average, with a standard deviation of 0.007)

and AUCs (0.839, for training, and 0.817, for test datasets). As regarding to the predictors, the steepness in the neighborhood of cells and large-profile and local-plan topographic curvatures were systematically selected. Clayey outcropping lithology, midslope drainages, local and midslope ridges and canyons landforms were also very frequently (from 8 to 15 times) included in the models by the forward selection. The model building strategy allowed us to produce a performing earthflow susceptibility model, whose model fitting, prediction skill and robustness were estimated on the basis of validation procedures.

The large and widespread use of known geostatistical methods has gone through at least three decades in landslide hazard studies, but still does not eliminate some of the conceptual and operational nodes, only sporadically resulting in the enforcement by the authorities involved in studying landslide risk in Italy. The study conducted in the basin of the Tumarrano intends to offer a contribution to this field of research aimed at developing assessing methods of landslide hazard conditions, applicable on a regional scale. In this sense, a strong multiplication of costs is needed to rebuild instability archives with a good degree of resolution and more periods of observation, concerning areas with extensions in the order of thousands of square kilometers. In the work, the possibility to carry out a survey of the landslide was confirmed once again, using Google Earth™, whose results were compared with those produced by the detection of the field survey; this comparison showed no significant differences and, above all did not show unequivocally a better quality of field data (suffering from a point of view which is often too close).

The procedure adopted in building the earthflow susceptibility model allowed us to obtain sixteen performing models, whose model fitting and prediction skill resulted to be very comparable, so that the predictive models can be considered as not heavily dependent on the particular locations for the extraction of the worked unstable cells. A subset of 10 predictors (over 51) was selected at least 8 times over sixteen by the forward logistic regression procedure. A subset of 9 predictors was selected a number of times between 4 and 7. For each of the selected variables, the regression coefficients obtained from the suite of models have coherent signs and very similar values. The number of predictors selected for each model of the suite is quite similar too (12.7). It is generally

verified that the more frequently is a predictor selected, the higher the rank order (the iteration of the forward selection procedure) in the final list of controlling factors, for which it is singled out.

The main controlling factors for earthflow landslides in the study area are: topography (steepness and curvatures), outcropping lithology (clays) and landform classification (Midslope Drainages, Canyons, Local and Midslope Ridges). As expected, the probability for having unstable conditions is positively correlated with the mean steepness in the neighborhood of the cells. No matter the sign, topographic local plan curvatures and topographic large profile curvatures showed positive and negative correlations, respectively. This seems to indicate these curvatures as good predictors because they express the role of mechanic stresses (connected to the shape of the topographic surface) rather than indicating convergences/divergences of runoff. Concavities and convexities showed on average very similar positive coefficients for local plan curvature. As regarding to the large profile curvature, convexities influence (decrease) much more than concavities the odds of unstable cells.

Ridges are not the sites for unstable cells, while these are much more expected on the slopes of Midslope Drainages and canyons. This means that earthflows crowns are far downhill from the head of the slopes, where in some cases rotational slides are recognized. Westward slope aspect is a positive condition for landslides.

As expected, clayey outcropping lithology is a very important condition for determining unstable conditions. Alluvial deposits, on the contrary, seem to be stable, even if this predictor showed a very low significance in the Wald test. At the same time this relationships could be due to the fact that alluvial deposits outcrop down on valley floor, where landslides are not possible due to topographic conditions.

Surprisingly both TWI and SLOPETWI are negatively correlated with the odds of unstable cells. This could be due to the prevalence of the steepness control in landsliding (high TWI occurs on low steepness). Slope aspect and Curvature classification were involved in the models just with one class, among the more selected predictors. Soil use resulted to be almost useless in predicting unstable cells.

The strategy here adopted to build the susceptibility model seems to be adequate to apply logistic regression, which require a balanced sizing of the worked dataset, without losing the connection between the goodness of the model and its real spatial representativeness. Though about just 1% of the whole area was really included in the worked dataset, the robustness of the regressed model has been evaluated by comparing the performances of each of a suite of sixteen balanced models. The good stability of the results seems to suggest no need to increase the number of models in the suite. Automatic model building procedure could be defined, in case of higher variability to consider larger fraction of the whole area (in this case 160 models would have been requires to reach up to 10% of the area).

The problem of sizing the dataset should be never evaded when exploiting logistic regression for modeling landslide susceptibility. A number of researches optimize very sophisticated statistic procedures, without considering the real spatial representativeness of the fitted models and working on just few hundreds or thousands cells against hundreds square kilometers of mapped basins. Model suite generation together with forward selection procedure is one of the possible tool to accomplish with intrinsic limits of logistic regression.

The use of Google Earth™ can therefore be an element of fundamental importance for the future development of methods for assessing landslide hazard: both for the detection rate, which is both flexible and detailed, and for the possible immediate access and spatial overlap of controlled photo-images, to multi-temporal coverage. This step opens the possibility to carry out temporal validation of the models and to analyze the return periods of activation events, setting the bases to evaluate danger rather than landslide susceptibility. The ability to build high quality and detailed landslides inventories allows to generate more reliable susceptibility models, characterized by valuable predicting qualities.

In the realization of the landslide inventory, photo-interpretation analysis was an essential tool to perform the perimeter of the areas affected by landslides, with the aim of creating a landslide database. The advantage of photo-interpretation is to be a rapid and effective method of territorial analysis, through which you can locate and characterize, with an acceptable degree of accuracy, the areas affected by landslides. The

high resolution (15 cm in some cases!), of the areas covered available allowed us to create an archive hard to obtain with mere fieldwork, allowing to precisely defining the relations that exist between landslides. In addition, the comparison with different covers of aerial images has allowed us to minimize.

A multivariate approach was applied to assess the landslide susceptibility in the Beiro river basin, which extends for about 10 km² over the north-eastern area of the city of Granada (Spain).

According to conditional analysis, landslide susceptibility models were obtained for each of the landslide typologies by computing the density of unstable cells for unique condition units, obtained by combining some selected controlling factors. Univariate tests, using both association coefficients and validation results of single parameter susceptibility models, allowed to select among 15 geo-environmental variables only good predictor variables, which have been combined in unique conditions units.

The controlling factors adopted were derived from a Digital Elevation Model (DEM) having a square cell of 10m was, which was obtained by digitizing the maps of IGME (scale 1:10,000) and a set of available thematic maps (geologic, geomorphological, pedologic and soil use). Thematic data were integrated by field and remote checks.

As regarding to the predictor variables, slope angle and, particularly for falls, roughness resulted to be the most determinant instability factor for this area. Other determinant factors are land use and topographic wetness index. The distance from tectonic lineaments (contact) is particularly relevant for translational slides, while lithology is very important for earth flows and translational slides.

Among the approaches adopted to assess the landslide susceptibility (Carrara et al., 1995; Guzzetti et al., 1999), the ones based on the conditional analysis exploit the frequency or density of observed unstable conditions (marked by landforms produced in the past) as the susceptibility function, which is computed for the set of mapping units in which a study area is partitioned. Each unit is firstly characterized in terms of those geo-environmental conditions, which are considered to control landsliding, and classified according to the relationships between past landslides and these permanent-conditioning factors. These methods are computationally very simple and light, being easily implementable in GIS systems (e.g. Carrara et al., 1991; Clerici et al., 2006; Irigaray

et al., 2007; Conoscenti et al., 2008) and the goodness of the results is, for each mapping unit, critically dependent on the number of observed cases.

Suites of susceptibility models, each obtained by differently selecting the predictor variables, were prepared and tested in order to verify the relationships between the ranking of predictivity of the single factors and the effects produced when including each in multivariate models.

Among the association coefficient adopted, the Goodman–Kruskal coefficient resulted to be coherently with univariate validation indexes, the best in indicating the most significant controlling factors. At the same time, validation results described by degree of fit and validation curves demonstrated to be coherent in indicating the predictive performance of the models. Satisfactory results were obtained for the earth flows, falls, susceptibility models, while unsatisfactory validations were observed for translational slides, due to the low number of recognized cases, which limits the stability of the splitting procedure.

In order to verify both the adaptability and the ability to predict susceptibility models, two different procedures for validation were applied (spatial validation and adaptation degree), confirming an increasingly good predicting reliability. In some cases, (falls and debris flows) the performance of predicting models can also be considered equally good, as can be seen from the values of the morphometric indicators used (ARPA and SHIFT), reaching 0,476 in the case of falls and 0,438 for debris flows, probably because they are the most frequent and statistically representative types. As for the predictive variables, for the Beiro area, the slope, the surface roughness index and lithology are effective factors for all types of movement. Other common and decisive factors for almost all types of landslides are: land use and topographic wetness index, which indirectly represents the saturation conditions of the slope. Among the statistical coefficients capable of measuring the correlation or co-gradation degree between a dependent variable and an independent variable, the Goodman-Kruskal range was used, since it is more stable and scarcely conditioned by the magnitude of the event considered. In fact, many of the coefficients and statistical indices known in literature (Chi-square, Cramer, Schuprow, Cochran, Pearson, Kendall, Sommers, R, etc.), used to express the degree of dependence between two variables, are not adequate to statistically treat phenomena

that, as well as having a certain distribution in terms of frequency of cases, are each characterized by their occurrence within a specific area involved. We can state that each event enters with a different weight, depending on its area in the statistical calculations, in other words, all cases used to determine the degree of correlation between them are not the same as in theory.

The ability to select only the "best" variables from a set of numerous levels available, can improve the statistical procedures used to produce susceptibility models and to obtain more predictive capabilities than those of the past. The improvement is also attributed to the use of statistical techniques that make possible the use of quantitative variables as continuous data as well as higher quality and resolution themes. In this test, it could also be confirmed that the inclusion of a large number of variables may not necessarily correspond to an improvement in predictive capability: in fact, the increase in the number of variables leads to increase the number of combinations, resulting in a decrease in the number of cases (cell count) for which each specific condition is observed and "trained". In addition, the decrease in cell count, usually, is not random but depends on the spatial correlation between the factors. This could produce an unexpected loss/decrease of performance of a predictive susceptibility model. In addition, there is a risk that some variables may become redundant when used in combination with others or as a combination of some.

The problem of assessing the propensity of slope instability was also addressed during the preparation of the susceptibility model for the area coinciding with the Imera sub-basin (§ sez.5.3 Chapter V). A careful survey of gravitational phenomena (490) based mainly on field surveys and Google, made it possible to assert that the area is largely affected by gravitational morphogenesis. A susceptibility map for an area, which is representative in terms of both geologic setting and slope instability phenomena of large sectors of the Sicilian Apennines, was produced using slope units and a multi-parametric univariate model. The study area, extending for approximately 90 km², was partitioned into 774 slope units, whose expected landslide occurrence was estimated by averaging seven susceptibility values, determined for the selected controlling factors: lithology, mean slope gradient, stream power index at the foot, mean topographic wetness index and profile curvature, slope unit length, and altitude range. Its centroid

point represented each of the 490 landslides recognized. On the basis of conditional analysis, the susceptibility function here adopted is the landslide density, computed for each class. Univariate susceptibility models were prepared for each of the controlling factors, and their predictive performance was estimated by prediction rate curves and effectiveness ratio applied to the susceptibility classes. This procedure allowed us to discriminate between effective and non-effective factors, so that only the former was subsequently combined in a multi-parametric model, which was then used to produce the final susceptibility map. The validation of this map latter enabled us to verify the reliability and predictive performance of the model. Slope unit altitude range and length, lithology and, subordinately, stream power index at the foot of the slope unit proved to be the main landslide controlling factors, while mean slope gradient, profile curvature, and topographic wetness index gave unsatisfactory results.

Conversely, a problem arises in adopting hydro-morphologic units when an approach based on conditional analysis is applied. In fact, when “switching” from cells or pixels to hydro-morphologic units, the number of mapping units dramatically decreases from hundreds of thousands of cells to some hundreds slope units, each being characterized by single values for the selected controlling factors. The consequence in multivariate approaches is that a large number of under-trained classification units (corresponding to a few cases or spatial units) will result when combining all the parameters. This paper presents the results of a research project aimed at exploring the possibility of producing susceptibility models based on the conditional analysis approach but adopting the morphodynamic spatial constraints represented by the Slope Units (SLUs). The use of a multi-parametric univariate classification method is here proposed as a possible alternative to multivariate ones.

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

The use of a morpho-dynamically based mapping unit in assessing landslide susceptibility by means of a conditional analysis-based geostatistical approach, has proved to be effective in the test area, producing satisfactory validation results. Adopting a multi-parametric univariate approach, in which the susceptibility levels are computed independently, factor by factor, and then combined to produce the susceptibility levels of Slope Unique Condition Units, allowed us to face one of the main geostatistical limitations in adopting such a mapping unit: the low number of cases (SLUs) for each combination (SLUCU) that is otherwise responsible for under-training of the predictive models. In the Upper Imera river basin, slope unit altitude range and length, lithology and, subordinately, stream power index at the foot of the slope units, proved to be the main landslide controlling factors, while mean slope gradient, profile curvature, and topographic wetness index, in spite of their expected high morphodynamic relationship with flow-type landslides activity, gave unsatisfactory results. Other simple statistics for such factors (variance and range) were checked without obtaining any improvement in their predictive skill. These results suggest the use of SLUs as a procedure, which is not totally suitable for representing the latter factors in the susceptibility models; these factors are probably much more effective in determining inside a SLU the site (the single pixel) where a landslide could initiate, but when summarized on a SLU scale, they show a loss in their predictive power.

The indexes adopted in evaluating the predictive performance of each factor proved to be useful and representative of the model performance. TAN₂₀ expresses the skill of the model in characterizing the most unstable portion of the study area. ARPA, on the other side, gives an estimation of the cumulated effectiveness of the susceptibility models, taking into consideration the whole predicted area. These two indexes allow to estimate the overall performance of the model (EFR is the typical adopted quality index, but it refers to a single class). Objective factors reclassification criteria (equal area and dominant outcropping lithology), together with a test procedure for selecting the factors of the model, allowed us to produce a susceptibility model whose good predictive performance has been demonstrated. Moreover, the coherence between the quality of the predictive performances of the single factors, tested by means of univariate validation tests, and their effect when included in multi-parametric models, in terms of

increasing or decreasing of prediction skill, demonstrates that the adopted multi-parametric procedure is stable and self-consistent.

The condition of instability is found primarily on the basis of the peculiar lithological conditions. The most important predisposing factor is to be found in poor mechanical properties of emerging materials. Major active landslides are mainly referring to the triggering of first-generation surface phenomena typologically related to flows, and to reactivation processes of previous phenomena. The main triggering cause of reactivation phenomena of inactive movements is related to the erosion of the waterways producing remobilization, particularly near to the foot of accumulation (SPI at foot). The triggering factor is typically represented by rainfall that can mobilize large coverage portions of or trigger movements in formations with pseudocoherent-similarly coherent behaviour. In this research, variables acquired at different times and at reasonably contained costs were tested, so that they could be used in larger areas than the ones considered in this analysis.

The results of the model, based on the characterization of slope units, appeared encouraging, demonstrating the validity of the proposed model and also the ease of its application. The adoption of the slope unit as the basic unit of mapping and statistical computing is considered a useful approach for the evaluation of landslide susceptibility. The representation of landslides through the use of centroids allows us to establish, stable spatial relations with the control factors, not depending critically on the exact shape of the landslides mapped. These two simple but effective solutions bring some substantial improvements in the creating process of the susceptibility model. The SLUs are considered an essential mapping unit for a number of reasons:

1. The factors to consider are calculated only inside the morphodynamics unit (the values of individual cells are meaningless if one considers phenomena involving partial or whole slopes);
2. The slope units are spatially correct domains to implement a deterministic physical approach helpful in assessing the safety factor, in the most susceptible slopes;

- Mitigation activities are generally expected on slope or basin scales (a representation of the susceptibility of cells is useless for territorial administration!).



The adoption of specific elements to represent the instability leads to significant savings in terms of economic resources and time to build an inventory, which will also be characterized by a higher degree of objectivity, as it will not be not bound by the interpretive skills of the operator on the shape and evolution of the landslide. Obviously, the SLU and centroids can potentially be affected by a large number of problems such as those relating to the definition of their geo-environmental characteristics in terms of statistical calculations from available data in raster format.

The overall quality of the results of operations for the construction of a susceptibility model is directly dependent on the quality of data entered into the model (DEM, instability factors, landslides), and at present there is no conclusive and unique methodology to assess the propensity to disruption; on the contrary, there are different methods that can be used in relation with i) the analysis scale, ii) the quality and iii) the quantity of data and iv) time and financial resources.

It is important for all those dealing with planning, soil protection and civil protection to start considering the possibility of formalizing methods for the assessment of the areas subject to landslides, a much preferable option than the current status, with maps showing just the status of present landslides, without any consideration for future activations. On the other hand, more and more vehemently we feel the need for a systematic inventory of all activations that have already happened as well as be prepared for the acquisition of new methodologies for activations in the near future in order to prepare more reliable and realistic scenarios and models of slope stability.

The knowledge of the state of present landslides and the ability to predict scenarios of future instability are useful tools playing a crucial role in the choices of land use. From a careful evaluation of the literature, I have noted that all studies that aim to evaluate and quantify the propensity of slope instability are based on the concept that intends to identify and classify the factors according directly and/or indirectly to geomorphological instability. Applications created in the sample areas show that the choice of using Google Earth to build an inventory of the landslide phenomena, the statistical procedures for the selection of the most "effective" determining factors, the techniques of landslide representation, the choice of mapping unit based on hydro-morphometric units and the ability to export the model created in spatially remote areas or with different extensions, are desirable and fully compatible tools in line with policies and activities of government agencies that must deal with geomorphological problems. The susceptibility models created with the identification of areas most prone to instability assess the possibility of imposing constraints to the exploitation for purposes of soil conservation and environmental protection. A further stage to susceptibility and hazard maps is to assess the presence and value of goods dear to man. The identification of the goods exhibited (natural or anthropogenic) is used to define the degree of vulnerability of the area or areas where, in case of a landslide, we are at greater risk of loss in economic terms or, far more serious, loss of lives.

It is increasingly important that the budget at any level of government (municipal, provincial, regional or national) should include specific financial resources dedicated to soil and territory protection, even just to update the status of the landslide maps of the

territory or existing maps, by virtue of the development of infrastructures and human settlements.

The territory has always been affected by natural events and actions that are consistently more invasive and more or less profoundly affect the territory up to the extent of jeopardizing its integrity, at times reducing the possibility of using part of it or the whole for the community. Over the last century, we have witnessed an exponential urbanization process and construction practices that paid little or no attention to the preparation and peculiarities of the territory.

The absence of an environmental culture in the management of territorial transformations is manifested in the frequency of occurrence of hydrological phenomena that threaten the integrity of the territory in its various characters, and can be evaluated in the magnitude of the effects they cause on both the artifacts and the environment itself. A common practice for the urbanization of natural areas of river relevance or easily floodable, is the removal of the minor hydrographic reticule, the reduction of the hydraulic sections of rivers. Many human settlements took place in areas of well-known slope instability. Likewise, building expansions have occurred in high-risk areas.

In recent years, different methods and techniques for the assessment of landslide susceptibility and hazard risk have been proposed or tested. Most of these approaches are based on multivariate techniques that can estimate the synergic influence of different control factors, and show how approaches can provide more objective and realistic models for the representations of the conditions of landslide susceptibility. The susceptibility is an intrinsic characteristic of the slope, depending on the combination of environmental variables.

6.2 Discussion and recommendations for future implementation of multi-scale susceptibility assessment approaches in Sicily: the SUFRA project

The complete identification of possible hazardous situations depending on the hydrogeological conditions of an area can be achieved through complex methodologies, suitable to predict the occurrence in areas never interested in the past by such phenomena. However, the time limits imposed by the law to carry out the delimitation of risk areas allow, in general, to assume, as an essential element for detecting the hazard level, location and characterization of known events that occurred in the past or involve the present.

The Environment and Territory Department of the Sicilian Region, has implemented the PAI Project (Excerpt Basin Plan for Hydrogeological Asset) since 2003, producing at the Environment and Territory Department, a dedicated structure made up of several staff units, including geologists, engineers, architects and surveyors, coordinated by technicians and managers. PAI was therefore conducted on the entire Sicilian territory, with a 1:50.000 scale coverage map in which areas of different risk levels are defined. For these areas are also identified interventions aimed at the safety of the threatened infrastructures (urban centers, large infrastructures, strategic buildings, areas of significant conservation value, archaeological, historical- artistic, etc.) and for the safeguarding of people.

Among the various approaches used in the classification of the susceptibility conditions of an area, it is necessary to use methods that ensure, along with the ability to properly characterize the susceptibility conditions, an objective, quantitative, testable and extensible expression of landslide susceptibility. From this point of view, harmonized protocols of generalizable procedures are being defined on a European scale.

In particular, a levelled approach (TIERS) was recently prepared by the committee of experts set up at the JRC (Joint Research Centre) of the European Commission. This approach consists of three nested levels (from TIER₁, TIER₂ and TIER₃) with a gradually increasing resolution degree of the predicted models, and map outputs on a wider scale (Hervas et al, 2007). By varying the level, the resolution of information levels of the

factors, the specificity of mapping units, as well as the complexity of the techniques used to classify their level of susceptibility increase.

The harmonized approach to the classification of susceptibility in the TIERS procedure , while on one hand is an important safety benchmark for national and regional administrations, for which it is advisable to start a phase of first application as soon as possible, on the other hand suffers from an excessive lowering of the quality of data and, therefore, the models obtained, caused by the fact that the group of experts who developed the method had to take into account data availability on a very large number of regions. From this point of view, initial data suitable to increase significantly the TIER detail are available at the ARTA-Sicily. .

From the analysis of these considerations, a framework agreement of cooperation, called SUFRA (Landslide Susceptibility) was first proposed and then signed in 2011 with the aforesaid Department, taking its cue from these reflections, identifying a first phase of application of the method, with the realization of the TIER₁ level on a regional scale, using both the source data identified by the JRC, for a 1:500.000 scale, and data available for the Sicilian territory, for which a TIER₁ to 250,000 will be created. The susceptibility modelling will be based on heuristics.

For the realization of the TIER₂ and TIER₃ levels, the source data identified by the JRC will be used, as a reference sample area, formed in the area falling within the CARG Paper on a 1: 50,000 scale "Termini Imerese-Capo Plaia" .

The multilevel approach will ensure consistency between the scenarios produced. The susceptibility scenarios described by the maps will also be compared and homogenized with those hazards arising from the PAI, proceeding to a punctual and detailed analysis of all possible discrepancies that may result. For the area identified, the following procedure has been proposed, which can then be validated and verified, even with future activations. Following the validation phase and testing the robustness of the scientific guidelines proposed below, the skills and the experience acquired can be used as a basis for the production of susceptibility, hazard and landslide risk maps.

6.2.1 Breakdown of activities

For the areas under investigation, the ARTA-Sicily has available for research purposes, the following data:

- Topographic, geological (CARG,) and soil maps (including the acquisition of the same in the digital version)
- Aerial photos (consultation and possible acquisition of copies in digital format)
- Digital aerial data (acquisition of photograms and aerial images flight ATAO7/o8)
- DEM ATAO7/o8 (acquisition)
- IFFI landslides archive (acquisition)
- PAI landslides archive (acquisition)
- Geological and geotechnical reports filed with the ARTA-Sicily (consultation)
- Persistent Scatterers Interferometry Data
- LIDAR data

From the computerized landslide archives already available for the Sicilian territory (IFFI and PAI), it is possible to proceed in the areas of study to a homogenization of the data structure by transferring PAI data on IFFI, at least at the first level. Furthermore, using the flight 2007 (analyzing both aerial photos and aerial images) it will be possible to proceed to an update and the temporal homogenization of the archive.

The landslides inventory which will be used will be divided into an alphanumeric archive, organized in census tabs and a GIS database, structured according to IFFI specifics (detailed level: PIFF; polygonal level: AREA; linear level: direction).

In the phase of susceptibility modelling, simplified or targeted archiving mode depending on the scale and the type of predicted maps to be produced will be considered.

6.2.2 Definition of the control factors

The information layer on the following control factors will be defined, from which the predictive variables will then be obtained, used to define susceptibility models on various scales:

- Geological features
- Use and soil texture features
- Climatic features
- Seismic features
- Hydrographic features
- Litotecnica features
- Topographical features

6.3 SUFRA₂₅₀ (TIER₁_SICILIA₆₀₉)

The Sicilian territory will be divided into a squared mesh of 2.5 km side. For each cell a susceptibility level will be estimated by classifying information levels on heuristic basis relating to geology, land use, climate, hydrographic and morphometric characteristics.

To define the cell characteristics, the following source data will be used:

- Geology: Structural Model of Italy; Lithology outcropping (*Piano Cave*).
- Land use: Corinne level; Land Use map (Fierotti).
- Climate: Climatological Atlas of the Sicilian Region.
- Hydrography: hydrographic network and basin limits.
- Morphometric: DEM cell 250 (IGMI) and cell 40 (Flight Italy 2000)

The mapping unit will consist of 2.5 km squared cells, while the cut will be made up to 250000 sheets, to the limits of the main basin area or provincial boundaries.

The classification of the weight of each factor and the incidence rates for each class of each factor will be conducted on a heuristic basis, optimizing their marks, even on the basis of areas of scaling and calibration of the method, which will be used for the SCAI, AVI, IFFI and PAI or DiSTeM archives.

6.2.4 TASK SUFRA₅₀ (TIER₂_SICILIA₆₀₉)

For the area falling within sheet 609, a landslide susceptibility model will be made, which will be implemented using different mapping units: a grid cell of 500 m side, with 50 m squared grid cells, hydrographic units (first order basins), hydro-morphological units. With the use of grids, after performing the classification of the susceptibility level, we will proceed to dissolve the hydrographic units. The SUFRA₅₀ approach is a stochastic type and models will therefore be defined using different multivariate methods of classification: conditional analysis, discriminant analysis and logistic regression.

In order to define the characteristics of the mapping unit, the following source data will be used:

- Geology: Geology CARG.
- Land use: Corine2006 level.
- Climate.
- Hydrography: Index of the erosive power of the river system.
- Morphometrics: DEM cell 20 (Flight Italy 2000) and DEM cell 2 (Flight 2007/08)

To define the landslide archive, a IFFI 2007 update will be carried out (using the flight 2007 in colour on medium scale 1:20,000), starting from the available data (SCAI, AVI, IFFI, PAI, DiSTeM).

The susceptibility model will be made subject to validation, obtaining information on the adaptability, predictive ability, resolution and stability. The model will be compared with PAI maps.

The susceptibility map will be cut according to the sheet to 50,000, the municipal limits and the limits of the basin area.

6.2.5 SUFRA_{10/25} (TIER₃_SICILIA609)

From the scenario produced at SUFRA₅₀ level, with some areas of interest, such as those with high susceptibility, we will proceed to a more detailed classification which will be conducted on a stochastic, increasing the detail of the information input. The analysis scales may be 1:25000, in case of areas of interest in linear development (i.e. road axis) or 1:10000, in case of areas of interest such as basin or areas of urban interest. The SUFRA_{10/25} level aims to be the base map level on which to implement any deterministic approaches to the evaluation of landslide susceptibility, based on geotechnical modelling of the slopes.

The areas studied will be divided into slope units, which will be classified according to their physical-environmental characteristics.

To define the characteristics of the mapping unit, the following source data will be used:

- Geology: Geology CARG; litotecnic complexes (regulation plans data).
- Land use: Corine2006 level.
- Climate.
- Hydrography: Index of the erosive power of the river system.
- Morphometrics: DEM cell 2 (Flight 2007/08-derived)

Even the SUFRA_{25/10} classification is a stochastic type and will therefore be performed using different methods of multivariate classification: conditional analysis, discriminant analysis and logistic regression.

To define the landslide, archive and IFFI 2007 update will be carried out (using the flight 2007 in colour on medium scale 1:20,000), starting from the available data (SCAI, AVI, IFFI, PAI, DiSTeM).

6.2.6 SUFRAMON (SICILIA609)

The area falling within the sheet 609, will be divided into monitoring units. These correspond to the slope units and for each of these susceptibility and landslide conditions will be defined by identifying a procedure to transfer to the municipalities the start of the direct monitoring of the gravitational instability, according to a protocol involving them in conjunction with ARTA and the DiSTEM in a common project.

CONCLUSIONES Y CONSIDERACIONES FINALES

En la tesis que aquí se presenta, fueron identificados algunas zonas de prueba (Capítulo V, Secciones 5.1, 5.2, 5.3, 5.4). Y para los se proporcionaron que la información general proporcionada por deslizamientos de tierra, la morfología, la litología, el climatología i indormaciones geoestructural, así como por las características fisiográficas. En estas áreas, conceptos, métodos y herramientas adquiridas durante la investigación han sido probados y verificados por el reconocimiento, la cartografía de deslizamientos de tierra y prueba de modelos para la zonificación de la susceptibilidad.



Fig. 6.1 - Location of study areas. a) en Sicilia; b) en España

La Fig. 6.1 muestra la posición de las tres diferentes áreas de estudio y la tabla 6.1 resume las principales estadísticas de las áreas seleccionadas.

	Cuenca del río Tumarrano	Cuenca del río Beiro	Cuenca del río Imera
Sección de la tesis	§ Cap. IV sez. 3.1	§ Cap. IV sez. 3.2	§ Cap. IV sez. 3.3
Area se extienden (km^2)	80	10	90
Rango de elevación (m)	318-891	623-1552	400-1800
Litología	En mayoría rocas sedimentarias	En mayoría rocas sedimentarias	En mayoría rocas sedimentarias
Clima	Mediterráneo	Mediterráneo Semi-Arid	Mediterráneo semi-árido
tipo de deslizamiento	Flujos de tierra	Caidas, deslizamientos traslacional , flujos de tierra, flujos de derrubios, flujo-deslizamiento	Flujos de derrubios
Estudios	Archivo de los movimientos, Model Exportation, validation techniques.	Archivo de los movimientos, validation techniques.	Archivo de los movimientos, mapping units, validation techniques.
Número de casos	760	128	490
Movimientos Porcentuales en términos de superficie	4.5 28.10%	0.37 3.70%	0.37 8.40%

total

Título del Trabajo Internacional	¹ Exporting a Google Earth™ aided earth-flow susceptibility model.	Factor selection procedures in a Google Earth™ aided landslide susceptibility model	Slope units-based flow susceptibility model: using validation tests to select controlling factors
	² Forward logistic regression for earthflow landslide susceptibility assessment in the platani river basin		

Las razones de la elección de estas áreas se pueden resumir de la siguiente manera:

1. Las áreas se encuentran en condiciones geológicas y morfológicas que se consideran apropiadas para el tipo de estudios;
2. La disponibilidad y el nivel de resolución de bases de los datos que representan las distribuciones de la variables geo-ambientales tomadas en cuenta.
3. Las imágenes de cobertura (ortofotos, imágenes de Google, 3D BingMaps etc) necesarias para la ejecución de un inventario de formas disruptivas.

La extensión de las áreas seleccionadas van desde unos 10 kilómetros cuadrados (la cuenca del río Beiro, Andalucía, España, § 5.3.1) hasta casi 90 km², para el área correspondiente a la sub-cuenca del norte de Imera (§ 5.3. 4). De acuerdo con los objetivos planteados, las pruebas se llevaron a cabo en el área experimental para verificar la validez de algunos conceptos madurado durante el doctorado en Geología en la DISTeM (Departamento de Ciencias de la Tierra y Mar) en la Universidad de Palermo. En particular, todas las aplicaciones de la zona se sometió a una prueba de eficacia y fiabilidad del una programa *open-source* para la observación a distancia de la Tierra (Google Earth). Para todas las zonas cartografiadas por Google, junto con el análisis de varias imágenes aéreas, la construcción del archivo fue capaz de identificar 2383 movimientos de ladera, divididos en: 28 caídas, de 1229 flujos de tierra, un deslizamiento

traslacionales, 57 flujos de derrubios, y 5 flujo-deslizamientos. Por supuesto campo de las encuestas se llevaron a cabo en todas las áreas, al menos en porciones representativas y las áreas problemáticas).

La adecuación de este tipo de instrumento para la construcción del archivo es justificado por los ahorros inmediatos en el tiempo de construcción del inventario y, aún más importante debido a la falta crónica de fondos para la investigación, las posibilidades de construir un archivo de las áreas de deslizamientos, básicamente, sin costo alguno. Aunque hemos utilizado la versión gratuita, Google Earth™, ha demostrado ser una herramienta ideal para la localización y mapeo de procesos geomorfológicos. Que permitirá completar la exploración del territorio para la digitalización de los deslizamientos. Los formularios del censo pueden ser analizadas, entonces, bajo cualquier Sistema de Información Territorial (ArcGIS/ESRI ArcMap, SAGA, Global Mapper, QuantumGIS, etc.) El archivo así creado es tratado estadísticamente, usando los mapas existentes (geología, topografía, usos del suelo, hidrología, etc) con el fin de mejorar el conocimiento sobre las causas y los mecanismos que intervienen en la determinación de las formas de inestabilidad.

Por ejemplo, el inventario creado para el experimento llevado a cabo en la cuenca del Tumarrano, permitió crear un modelo de susceptibilidad, que mostró una buena capacidad de predicción con un pequeño número de parámetros, junto con las unidades de condiciones únicas UCU. El modelo fue verificado a través de la validación, tanto espacial para toda la cuenca y su parte temporal representante. Para cada área de deslizamiento de tierra asignada, un punto de identificación ha sido seleccionada (LIP: Punto de deslizamientos de identificación), que corresponde al punto de máxima altitud que entran en el deslizamiento de tierra, y, por tanto, colocado en la corona del deslizamiento. Alrededor de cada punto fue identificado entonces una zona de amortiguamiento con un radio de 30 metros. Las zonas de amortiguamiento alrededor de los puntos de identificación (BLIP: LIP buffer) fueron utilizados como áreas de analisis. Este último debe, de hecho, indican las condiciones físico-ambientales que producen los factores desencadenantes de los fenómenos observados. Intersección de la capa de BLIP con cualquier capa que expresa supuestas condiciones de control de los

fenómenos, es posible definir funciones predijo que corresponde a la densidad del área de diagnóstico (de BLIP) en el factor de clase. Esto corresponde a la probabilidad de tener un nuevo evento en un determinado estado físico-ambientales. En primer lugar, se evaluó la relación univariante que se unen a un único factor con la distribución de los deslizamientos de tierra. Este análisis ha demostrado que los factores más importantes que controlan los flujos de tierra son el TWI, que indirectamente representa la humedad potencial de la ladera, y los complejo litotecnico.

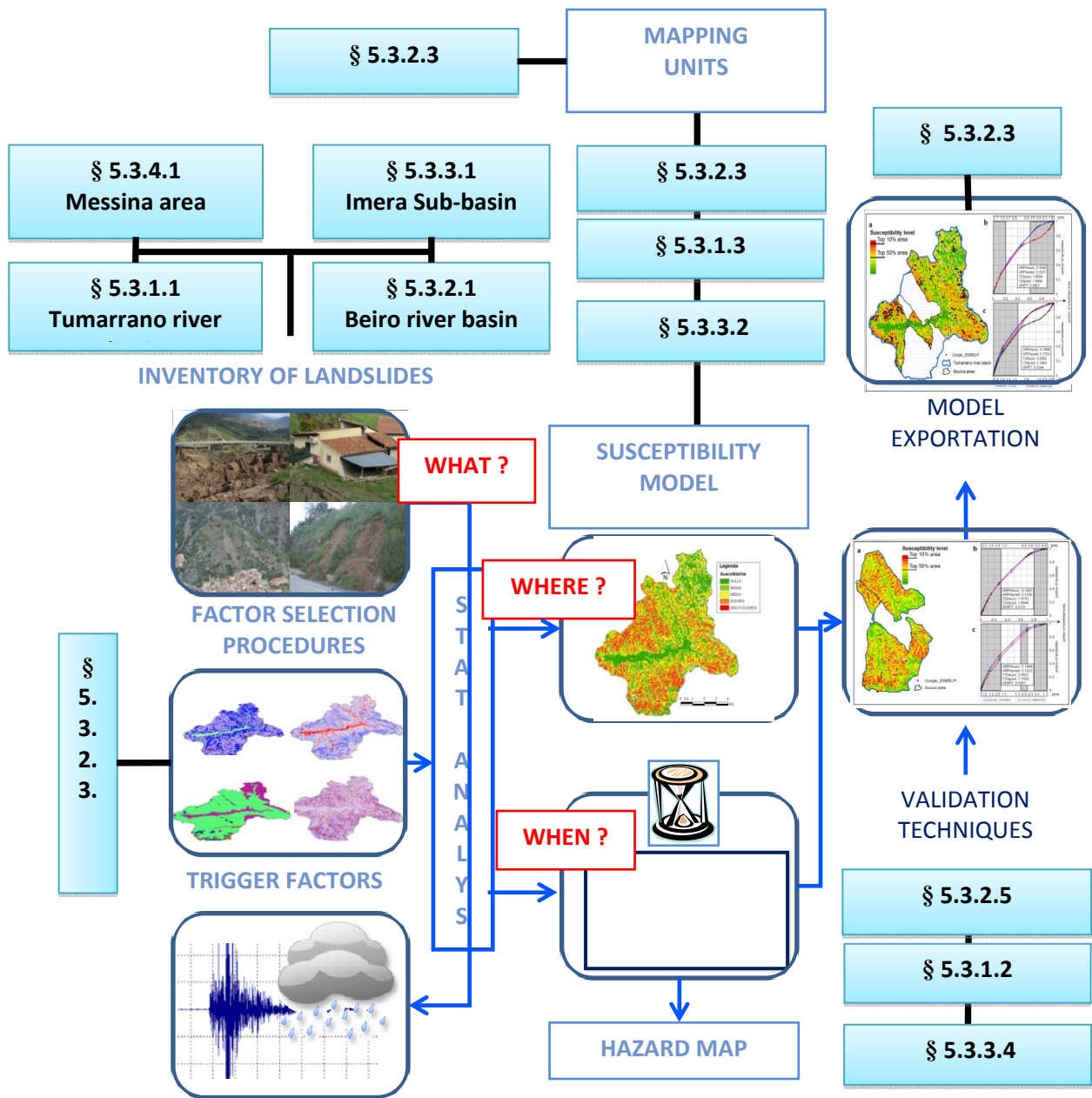


Fig. 6.2 - Diagrama de flujo de la metodología seguida. Para cada uno de los pasos que se muestra la sección del capítulo 4 en el que afrontar el problema.

Mientras que un efecto secundario es ejercido por la pendiente, las curvas de validación producidos por el modelo de susceptibilidad que se refiere a toda la cuenca, dan fe de la buena capacidad predictiva y la estabilidad del modelo. En cuanto a la validación temporal en tiempo de deslizamientos de tierra, que proporciona resultados muy satisfactorios, aunque los dos períodos de detección difieren en un solo año, este rango

es, de hecho, suficiente para este tipo de movimiento que se reproduce en un escenario lleno de activación similar a la uno el mapa de susceptibilidad fue creado.

Para la cuenca del río Tumarrano, la “*forward logistic regression*”, nos ha permitido obtener una susceptibilidad por los flujo de tierra, que fue definida por el modelado de las relaciones estadísticas entre un archivo de eventos 760 y un conjunto de 20 variables predictoras. Para cada movimiento de ladera del inventario, un punto de identificación de deslizamientos (LIP) se produce de forma automática, como corresponde al punto más alto a lo largo de la frontera de los polígonos de deslizamientos de tierra. Los modelos equilibrados (760 estable/760 inestable) se presentaron a adelante el procedimiento de regresión logística. Una estrategia de construcción del modelo se aplicó para ampliar la zona considerada en la preparación del modelo y para comprobar la sensibilidad de los modelos de regresión con respecto a los lugares específicos de las celda se considera estable. Un conjunto de dieciséis modelos se preparó de forma aleatoria extraer los subconjuntos diferentes celdas estables. Los modelos fueron sometidos a regresión logística y validados. Los resultados mostraron que las tasas de error satisfactoria y estable (0,236 en promedio, con una desviación estándar de 0,007) y AUC (0.839, para la formación, y 0.817, para conjuntos de datos de prueba). Como en relación a los predictores, la pendiente en el barrio de las celda y la curvatura topográfica de perfil y plan fueron seleccionados de forma sistemática. *Clayey outcropping lithology, midslope drainages, local and midslope ridges and canyons landforms* eran también muy frecuentes (de 8 a 15 veces) en los modelos de selección. La estrategia de construcción del modelo nos ha permitido producir un modelo de susceptibilidad por flujos de tierra realizando, cuyo modelo de ajuste, la predicción de la habilidad y solidez se estimaron sobre la base de los procedimientos de validación.

El uso generalizado de métodos geoestadísticos ha pasado por lo menos tres décadas en los estudios de susceptibilidad de deslizamientos, pero no elimina algunos de los nodos conceptuales y operativos. Sólo de forma esporádica, como resultado de la aplicación por las autoridades involucradas, en el estudio de riesgo de deslizamientos en Italia. El estudio llevado a cabo en la cuenca del río Tumarrano tiene la intención de ofrecer una contribución a este campo de investigación dedicada a desarrollar métodos de

evaluación de las condiciones de susceptibilidad de movimientos de ladera, aplicable a escala regional. En este sentido, la fuerte multiplicación de los costos de se necesita para reconstruir archivos de inestabilidad con un buen grado de los períodos de resolución y más de la observación, sobre las zonas con extensiones en el orden de miles de kilómetros cuadrados. En el trabajo, la posibilidad de llevar a cabo una encuesta del derrumbe se confirmó una vez más, a través de Google Earth™, cuyos resultados se compararon con los producidos por la detección de la encuesta de campo, esta comparación no mostraron diferencias significativas y, sobre todo lo no muestran de manera inequívoca una mejor calidad de los datos de campo (el sufrimiento desde un punto de vista que es a menudo demasiado cerca). El procedimiento adoptado en la construcción del modelo de susceptibilidad flujo de tierra nos ha permitido obtener dieciséis modelos, cuyo modelo de ajuste y la capacidad de predicción resultó ser muy similar, de modo que los modelos predictivos pueden ser considerados como no dependiente en gran medida de la ubicación en particular para la extracción de las celda inestables. Un subgrupo de 10 factores predictores (más de 51) fue seleccionado por lo menos 8 veces sobre dieciséis en el procedimiento de regresión logística. Un subconjunto de predictores (9) fue seleccionado un número de veces entre 4 y 7. Para cada una de las variables seleccionadas, los coeficientes de regresión obtenidos en el conjunto de los modelos tienen signos coherentes y valores muy similares. El número de predictores seleccionados para cada modelo de la serie es muy similar también (12,7). En general se comprobó que la mayor frecuencia es un factor de predicción seleccionado, mayor será el orden de importancia (la repetición del procedimiento de selección en la lista definitiva de los factores de control, para lo cual se destaca.

Los principales factores de control de flujo de tierra en el área de estudio son: topografía (inclinación y curvatura), afloramiento de la litología (arcillas) y el relieve de clasificación (Drenajes Midslope, cañones, colinas locales y Midslope). Como era de esperar, la probabilidad de tener condiciones de inestabilidad se correlaciona positivamente con la pendiente media en el barrio de las celdass. No importa el signo, las curvaturas topográficas plan y de perfil, mostraron correlaciones positivas y negativas, respectivamente. Esto parece indicar estas curvaturas como buenos

indicadores, ya que expresan el papel del estrés mecánico (conectado a la forma de la superficie topográfica) en lugar de indicar las convergencias/divergencias de la escorrentía. Concavidades y convexidades mostraron en promedio coeficientes positivos muy similar a la curvatura del plan local. Como en relación a la curvatura de gran dimensión, la influencia de convexidades (disminución) mucho más que concavidades las probabilidades de que las células inestables.

Como era de esperar, el afloramiento de litología arcillosa es una condición muy importante para determinar las condiciones inestables. Los depósitos aluviales, por el contrario, parecen ser estables, aunque este indicador mostró una significación muy bajo en la prueba de Wald. Sorprendentemente, tanto TWI y SLOPETWI se correlacionan negativamente con la probabilidad de que las celdas inestables. Esto podría ser debido a la prevalencia del control de la inclinación de los deslizamientos (TWI alta se produce en la pendiente baja). Aspecto pendiente y la clasificación de curvatura estuvieron involucrados en los modelos sólo con una clase, entre los predictores más seleccionados. El uso del suelo resultó ser casi inútil en la predicción de las celads inestables.

La estrategia aquí adoptadas para desarrollar el modelo de susceptibilidad parece ser adecuada para aplicar la regresión logística, que requieren un tamaño equilibrado del conjunto de datos trabajado, sin perder la conexión entre la bondad del modelo y su representatividad espacial real. A pesar de sólo el 1% de toda el área fue incluida en el conjunto de datos muy trabajado, la robustez del modelo de regresión se ha evaluado mediante la comparación de los resultados de cada una de un conjunto de dieciséis modelos. La buena estabilidad de los resultados parece que sugieren que no hay necesidad de aumentar el número de modelos en la suite. Procedimiento automático de la construcción del modelo se podría definir, en caso de una mayor variabilidad a considerar mayor fracción de toda la zona (en este caso 160 modelos habría sido necesario para llegar hasta el 10% del área). El problema de tamaño del conjunto de datos no debe ser eludida cuando la explotación de regresión logística para modelar la susceptibilidad. Una serie de investigaciones optimizan los procedimientos estadísticos muy sofisticados, sin tener en cuenta la representatividad real espacial de los modelos

equipados y trabajando en sólo unos pocos cientos o miles de celdas en contra de cientos de kilómetros cuadrados de cuencas asignada.

Un enfoque multivariante se aplicó para evaluar la susceptibilidad de los movimientos de ladera en la cuenca del río Beiro, que se extiende por cerca de 10 km² en la zona noreste de la ciudad de Granada (España). De acuerdo con el análisis condicional, los modelos de susceptibilidad fueron obtenidos para cada una de las tipologías de movimientos mediante el cálculo de la densidad de las celdas inestables para las unidades de condición única, que se obtiene mediante la combinación de algunos de los factores de control seleccionados. Pruebas univariadas, utilizando los coeficientes de asociación y de resultados de la validación de los modelos con los parámetros de susceptibilidad, permite seleccionar entre los 15 y variables geo-ambientales, solo las únicas variables predictoras buenas, que se han combinado en las unidades de condiciones únicas.

Entre las variables, el ángulo de inclinación y, sobre todo para las caídas, la aspereza resultó ser el factor mas determinante por la inestabilidad de esta zona. Otros factores determinantes son el uso del suelo y el índice de humedad topográfica. La distancia de los lineamientos tectónicos (contacto) es particularmente relevante para las deslizamientos de traslación, mientras que la litología es muy importante para los flujos de tierra y deslizamientos traslacional.

Entre los enfoques adoptados para evaluar la susceptibilidad a los movimientos de ladera (Carrara et al, 1995; Guzzetti et al, 1999), basados en el análisis condicional permiten de explotar la frecuencia o densidad de observar las condiciones inestables (marcada por formaciones producidas en el pasado) como la función de la susceptibilidad, que se calcula para el conjunto de las unidades de mapatura en el que se divide un área de estudio. Cada unidad en primer lugar se caracteriza en términos de las condiciones geo-ambientales, que se considera que controlan los movimientos, y se clasifican de acuerdo a las relaciones entre los movimientos pasado y estos factores permanentes acondicionado. Estos métodos son computacionalmente muy simple, siendo fácilmente implementable en sistemas de información geográfica (por ejemplo,

Carrara et al, 1991;. Clerici et al, 2006;. Irigaray et al, 2007;.. Conoscenti et al, 2008) y la bondad de la resultados es, por cada unidad de mapeo, depende fundamentalmente del número de casos observados.

Suites de los modelos de susceptibilidad, obtenidos de manera diferente, cuando esté preparado y probado para verificar la relación entre la clasificación de capacidad de predicción de los factores individuales y los efectos que producen cuando se incluyen en cada una de los modelos multivariados.

Entre los coeficientes estadísticos capaz de medir la correlación o co-gradación de grado entre una variable dependiente y una variable independiente, la gama de Goodman-Kruskal fue utilizado, ya que es más estable y condicionada apenas por la magnitud del fenómeno considerado. De hecho, muchos de los coeficientes e índices estadísticos conocidos en la literatura (Chi-cuadrado, Cramer, Schuprow, Cochran, Pearson, Kendall, Sommers, R, etc), que se utiliza para expresar el grado de dependencia entre dos variables, no son adecuados estadísticamente para el tratamiento de los fenómenos que, además de contar con una cierta distribución en términos de frecuencia de los casos, cada uno caracterizado por su aparición en un área específica en cuestión. Podemos afirmar que cada caso entra con un peso diferente, dependiendo de su área en los cálculos estadísticos, en otras palabras, todos los casos para determinar el grado de correlación entre ellas no son las mismas que en la teoría. El coeficiente de asociación de Goodman-Kruskal resultó ser coherente con los índices de validación univariados, el mejor en la indicación de los factores más significativos de control. Al mismo tiempo, los resultados de validación descrito por el grado de ajuste de curvas y la validación con las curvas demuestran ser coherente en la que indica el rendimiento predictivo de los modelos. Se obtuvieron resultados satisfactorios para los flujos de tierra, caídas, los modelos de susceptibilidad, mientras que la validación satisfactoria se observaron para las deslizamientos traslacionales, debido al bajo número de casos reconocidos, lo que limita la estabilidad del procedimiento.

A fin de verificar la adaptación y la capacidad de predecir los modelos de susceptibilidad, dos procedimientos distintos para la validación se aplicaron (validación

espacial y el grado de ajuste), lo que confirma una vez más la fiabilidad buena predicción. En algunos casos, (caídas y flujos de derrubio) los resultados de los modelos de predicción también se puede considerar buenos, como se puede ver a partir de los valores de los indicadores morfométricos utilizados (ARPA y SHIFT), llegando a 0.476 en el caso de caídas y de 0.438 para flujos de derrubios, probablemente porque son los tipos más frecuentes y representativos estadísticamente. En cuanto a las variables de predicción, para la zona de Beiro, la pendiente, el índice de rugosidad de la superficie y la litología son factores efectivos para todo tipo de movimiento. Otros factores comunes y decisivo para casi todos los tipos de deslizamientos de tierra son: el uso del suelo y el índice de humedad topográfica.

La posibilidad de seleccionar sólo las "mejores" variables de un conjunto de niveles disponibles numerosos, pueden mejorar los procedimientos estadísticos utilizados para producir modelos de susceptibilidad y para obtener más capacidad de predicción respecto al pasado. El mejoramiento también se atribuye a la utilización de técnicas estadísticas que hacen posible el uso de las variables cuantitativas, los datos continuos, así como una mayor calidad y resolución de temas. En esta prueba, también se pudo confirmar que la inclusión de un gran número de variables que no necesariamente corresponden a una mejora en la capacidad de predicción: de hecho, el aumento en el número de variables conduce a aumentar el número de combinaciones, lo que resulta en una disminución en el número de casos (recuento de celdas) para los que se observa cada condición específica y "entrenado". Además, la disminución en el recuento de celdas, por lo general, no es aleatoria sino que depende de la correlación espacial entre los factores. Esto podría producir una pérdida inesperada/disminución del rendimiento de un modelo predictivo de la susceptibilidad. Además, existe el riesgo de que algunas variables pueden ser redundantes cuando se utiliza en combinación con otros, o como una combinación de algunas.

El problema de la evaluación de la propensión de la inestabilidad de taludes también se abordó durante la preparación del modelo de susceptibilidad para la zona coincidiendo con sub-cuenca del río Imera (§ sez.5.3 Capítulo V). Un estudio cuidadoso de los fenómenos gravitacionales (490) basado principalmente en estudios de campo y Google,

han permitido afirmar que la zona es interesada en gran medida por la morfogénesis gravitacional. Un mapa de susceptibilidad de un área, que es representativa en términos de marco geológico y los fenómenos de inestabilidad de ladera de grandes sectores de los Apeninos de Sicilia, fue producida usando unidades de ladera y un modelo multi-paramétrico univariado. El área de estudio, que se extiende por aproximadamente 90 km², fue dividida en 774 unidades de talud, los que se espera la ocurrencia de movimientos se estimó un promedio de siete valores de vulnerabilidad, determinada por la selección de los siguientes factores de control: litología, pendiente media, SPI a los pies, TWI medio y la curvatura del perfil, longitud de la unidad y altura. Su punto centroide representa cada uno de los 490 deslizamientos de tierra reconocido. Sobre la base de análisis condicional, la función de la susceptibilidad aquí adoptada es la densidad de deslizamientos de tierra, calculado para cada clase. Modelos univariantes de susceptibilidad fueron preparados para cada uno de los factores que controlan, y su rendimiento predictivo fue estimado por las curvas de tipos de predicción y la relación de efectividad aplicado a las clases de sensibilidad. Este procedimiento nos permite discriminar entre los factores de forma eficaz y no eficaz, de modo que sólo la primera se combinó posteriormente en un modelo multi-paramétrico, que se utilizó para producir el mapa de susceptibilidad final. La validación de este último mapa nos permite comprobar el rendimiento y la fiabilidad de predicción del modelo. Unidad de la pendiente y la longitud del rango de altitud, litología y, subordinadamente, el índice de flujo de energía a los pies de la unidad de la pendiente resultó ser el deslizamiento de tierra principal de control de los factores, mientras que la pendiente media, la curvatura de perfil, y el índice de humedad topográfica dio resultados poco satisfactorios.

Por el contrario, surge un problema en la adopción de unidades hidro-morfológicas cuando se aplica un enfoque basado en el análisis condicional. De hecho, cuando se pasa desde las celdas o píxeles a las unidades hidro-morfológicas, el número de unidades de mapeo reduce drásticamente a partir de cientos de miles de celdas para algunas unidades cuesta cientos, cada uno caracterizado por valores individuales para el control de los factores seleccionados. La consecuencia de los enfoques múltiples es que un gran número de unidades de clasificación sub-entrenados (que corresponde a unos pocos

casos o unidades espaciales) dará lugar a la hora de combinar todos los parámetros. Este trabajo presenta los resultados de un proyecto de investigación destinado a estudiar la posibilidad de producir modelos de susceptibilidad basado en el enfoque del análisis condicional, pero la adopción de las limitaciones espaciales morfodinámicos representado por las unidades de talud (SLU). El uso de un método de clasificación multi-paramétrico univariado que aquí se propone como una posible alternativa a los multivariado. La investigación también analiza el uso de una estrategia para evaluar la función de control de cada factor, basado en la validación de los modelos univariantes. Para estos fines, los modelos de susceptibilidad están preparados y su rendimiento predictivo es evaluado por medio de las curvas de validación (Chung y Fabbri 2003) y dos índices geométricos de las curvas de predicción de velocidad que aquí se propone. El uso de una unidad de mapeo morfo-dinámica basándose en la evaluación de susceptibilidad a los deslizamientos por medio de un análisis basado en condicional enfoque geoestadístico, ha demostrado ser eficaz en el área de prueba, con resultados satisfactorios de validación. La adopción de un enfoque multi-paramétrico univariado, en el que los niveles de susceptibilidad se calculan de manera independiente, factor por factor, y luego se combinan para producir los niveles de susceptibilidad de las Unidades de pendiente única condición, nos ha permitido hacer frente a una de las limitaciones principales geoestadística en la adopción de dicha asignación, unidad: el bajo número de casos (SLU) para cada combinación (SLUCU) que sea responsable de menores de la formación de los modelos predictivos. En la cuenca superior del río Imera, la unidad de la pendiente y la longitud rango de altitud, litología y, subordinadamente, el índice de flujo de energía a los pies de las unidades de la pendiente, resultó ser el deslizamiento de tierra principal de control de los factores, mientras que la pendiente media, la curvatura de perfil, y la humedad topográfica índice, a pesar de su esperada alta relación morfodinámica con la actividad de flujo de tipo deslizamientos de tierra, dieron resultados satisfactorios. Otras estadísticas simples de dichos factores (varianza y rango) fueron revisados sin obtener ninguna mejora en su capacidad de predicción. Estos resultados sugieren el uso de UGO como un procedimiento, que no es totalmente adecuado para la representación de estos últimos factores en los modelos de susceptibilidad; estos factores son probablemente mucho más eficaz en la

determinación dentro de un SLU el sitio (el píxel), donde un deslizamiento de tierra podría iniciar, pero cuando se resume en una escala SLU, que muestran una pérdida en su poder predictivo.

Los índices adoptados en la evaluación del poder predictivo de cada factor a demostrado ser útil y representativo del comportamiento del modelo. TAN₂₀ expresa la habilidad del modelo para caracterizar la parte más inestable de la zona de estudio. El uso de el ARPA, en el otro lado, se obtiene una estimación de la eficacia acumulada de los modelos de susceptibilidad, teniendo en cuenta toda la zona prevista. Estos dos índices permiten estimar el rendimiento global del modelo (EFR es el típico índice de calidad aprobado, pero se refiere a una sola clase). Criterios objetivos de reclasificación factores, junto con un procedimiento de prueba para la selección de los factores del modelo, nos ha permitido elaborar un modelo predictivo de la susceptibilidad que un buen rendimiento ha demostrado. Por otra parte, la coherencia entre la calidad de las actuaciones de predicción de los factores individuales, a prueba por medio de pruebas de validación univariado, y su efecto cuando se incluye en varios modelos paramétricos, en términos de aumento o disminución de la capacidad de predicción, demuestra que el procedimiento múltiparamétrico adoptado es estable y consistente.

La condición de inestabilidad se encuentra principalmente sobre la base de las condiciones litológicas peculiar. El factor predisponente más importante es que se encuentran en propiedades mecánicas no buenas de los materiales emergentes. Grandes movimientos activos son principalmente refiriéndose a la activación de los fenómenos de la superficie de la primera generación tipológicamente relacionado con los flujos y procesos de reactivación de los fenómenos anteriores. La principal causa desencadenante de fenómenos de reactivación de los movimientos inactivos está relacionada con la erosión de los cursos de agua produciendo removilización, en particular cerca de los pies de la acumulación (SPI al pie). El factor desencadenante suele ser representado por las lluvias que pueden movilizar una gran parte de la cobertura o los movimientos de disparo en las formaciones con pseudocoherente-igualmente coherente de comportamiento. En esta investigación, las variables adquiridas en diferentes momentos y con costos razonables contenidos se pusieron a

prueba, por lo que podría ser utilizado en áreas más extensas que las consideradas en este análisis.

Los resultados del modelo, basado en la caracterización de las unidades de talud, parecían alentadores, lo que demuestra la validez del modelo propuesto, así como la facilidad de su aplicación. La adopción este tipo de unidad, como la unidad básica de la cartografía y el cálculo estadístico se considera un método útil para la evaluación de la susceptibilidad a los deslizamientos. La representación de los deslizamientos de tierra a través del uso de los centroides nos permite establecer, estabilidad de las relaciones espaciales con los factores de control, que no depende críticamente de la forma exacta de los deslizamientos de tierra asignada. Estas dos soluciones simples pero eficaces traer algunas mejoras sustanciales en el proceso de la creación del modelo de susceptibilidad. Las SLUs se consideran unidad de mapeo esencial para una serie de razones:

1. Los factores a considerar se calculan únicamente dentro de la unidad morfodinámica (los valores de las celdas individuales no tienen sentido si se tiene en cuenta fenómenos de pendientes parcial o total);
2. Las unidades de la pendiente son los dominios espacial correctos para implementar un enfoque determinista físico útil para evaluar el factor de seguridad, en las laderas más susceptibles;
3. Las actividades de mitigación en general se esperan en las escalas de ladera o de la cuenca (una representación de la susceptibilidad de las celdas es inútil para la administración territorial!).

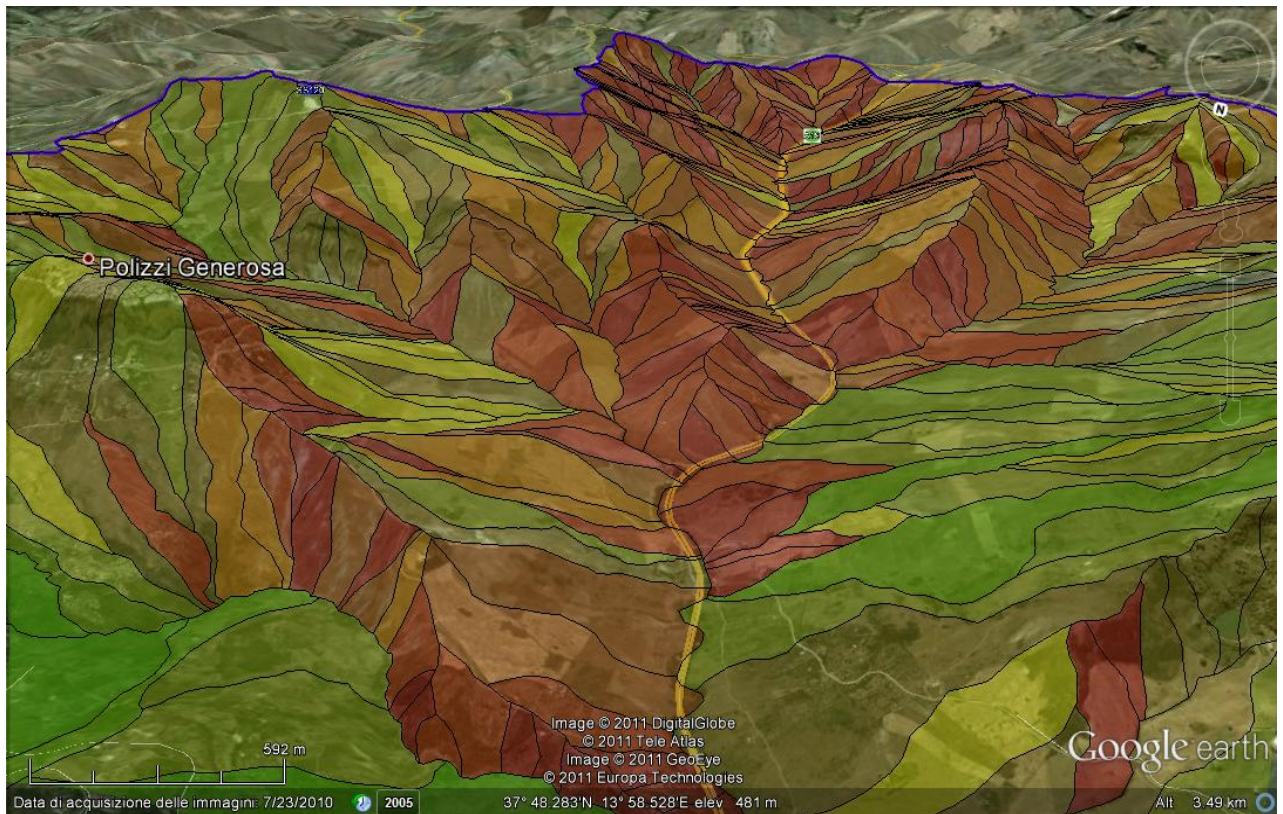


Fig 6.3 - Detalle de una porción de la cuenca, para lo cual las unidades de la pendiente se jerarquizan en función del grado de susceptibilidad a los deslizamientos.

La adopción de elementos específicos para representar a la inestabilidad conduce a importantes ahorros en términos de recursos económicos y tiempo para crear un inventario, que también se caracteriza por un mayor grado de objetividad, ya que no se no esté obligado por las habilidades interpretativas de la operador en la forma y la evolución de los deslizamientos de tierra. Obviamente, la SLU y centroides pueden verse afectadas por un gran número de problemas tales como las relativas a la definición de sus características geo-ambientales en términos de cálculos estadísticos de los datos disponibles en formato raster.

La calidad general de los resultados de las operaciones para la construcción de un modelo de susceptibilidad depende directamente de la calidad de los datos introducidos en el modelo (DEM, los factores de inestabilidad, deslizamientos de tierra), y en la actualidad no existe una metodología definitiva y única, por el contrario, existen

diferentes métodos que pueden utilizarse en relación con i) la escala de análisis, ii) la calidad y iii) la cantidad de datos y iv) el tiempo y los recursos financieros.

Es importante para todos aquellos interesados en la planificación, la protección del suelo y de protección civil para empezar a considerar la posibilidad de formalizar métodos para la evaluación de las áreas sujetas a movimientos gravitativos, una opción mucho más preferible que la situación actual, con mapas que muestran sólo el estado de inestabilidad actual, sin ninguna consideración por las activaciones en el futuro. Por otro lado, más vehemente y más sentimos la necesidad de un inventario sistemático de todas las activaciones que ya han sucedido, así como estar preparados para la adquisición de nuevas metodologías para la activación en un futuro próximo a fin de preparar escenarios más fiables y realistas y los modelos de estabilidad de taludes.

El conocimiento del estado inestabilidad actual y la capacidad de predecir los escenarios de inestabilidad en el futuro son herramientas útiles a jugar un papel crucial en las decisiones de uso de la territorio. A partir de una evaluación cuidadosa de la literatura, he notado que todos los estudios que tienen como objetivo evaluar y cuantificar la tendencia de inestabilidad de las laderas se basan en el concepto que tiene la intención de identificar y clasificar los factores de conectados, directamente y/o indirectamente a la inestabilidad geomorfológica. Las aplicaciones creadas en las áreas de la muestra indican que la opción de utilizar Google EarthTM para crear un inventario de los fenómenos gravitativos. Los procedimientos estadísticos para la selección de los factores más determinantes, las técnicas de representación deslizamientos de tierra, la elección de la unidad de mapeo basado en unidades hidro-morfométricos y la capacidad de exportar el modelo creado en áreas espacialmente remoto o con diferentes extensiones, son herramientas deseables y compatibles plenamente en consonancia con las políticas y actividades de las agencias del gobierno que debe lidiar con los problemas geomorfológicos. Los modelos creados con la susceptibilidad a la identificación de las zonas más propensas a la inestabilidad de evaluar la posibilidad de imponer restricciones a la explotación con fines de conservación de suelos y protección del medio ambiente. En una etapa posterior a los mapas de susceptibilidad y riesgo es evaluar la presencia y el valor de los bienes queridos por el hombre. La identificación de los

objetos expuestos (naturales o antropogénicos) se utiliza para definir el grado de vulnerabilidad de la zona o zonas donde, en caso de un deslizamiento de tierra, que están en mayor riesgo de pérdida en términos económicos o, mucho más grave, la pérdida de vidas.

Cada vez es más importante que el presupuesto en cualquier nivel de gobierno (municipal, provincial, regional o nacional) debe incluir recursos financieros específicos dedicados a la protección del suelo y el territorio, aunque sólo sea para actualizar el estado de los mapas de deslizamientos de tierra del territorio o los mapas existentes, en virtud del desarrollo de las infraestructuras y los asentamientos humanos.

El territorio siempre ha sido afectado por fenómenos naturales y actividades que son consistentemente más agresivos y más o menos afectan profundamente el territorio hasta el punto de poner en peligro su integridad, a veces reduciendo la posibilidad de utilizar parte de ella o la totalidad de la comunidad.

La ausencia de una cultura ambiental en la gestión de las transformaciones territoriales se manifiesta en la frecuencia de ocurrencia de los fenómenos hidrológicos que amenazan la integridad del territorio en sus diferentes personajes, y se puede evaluar la magnitud de los efectos que causan tanto en los artefactos y el propio medio ambiente. Una práctica común para la urbanización de los espacios naturales de relevancia río o inundables con facilidad, es la eliminación de la red hidrográficas de menor importancia, la reducción de las secciones hidráulicas de los ríos. Muchos asentamientos humanos se llevó a cabo en las zonas de inestabilidad de las laderas bien conocido. Del mismo modo, la construcción de ampliaciones se han producido en zonas de alto riesgo.

En los últimos años, los diferentes métodos y técnicas para la evaluación de la susceptibilidad a los deslizamientos y el riesgo de peligro han sido propuestos o ensayados. La mayoría de estos enfoques se basan en técnicas multivariantes que se puede estimar la influencia sinérgica de factores de control diferentes, y mostrar cómo los enfoques pueden ofrecer modelos más objetiva y realista de las representaciones de las condiciones de susceptibilidad a los deslizamientos. La susceptibilidad es una

característica intrínseca de la pendiente, dependiendo de la combinación de las variables ambientales.

6.2 Discusión y recomendaciones para la futura aplicación de escalas múltiples enfoques de evaluación de la susceptibilidad en Sicilia: el proyecto SUFRA

La identificación completa de las posibles situaciones de riesgo en función de las condiciones hidrogeológicas de un área se puede lograr a través de metodologías complejas, adecuado para predecir la ocurrencia en las áreas nunca se fue interesada en el pasado por estos fenómenos

El Departamento de Medio Ambiente y Territorio de la Región Siciliana, ha puesto en marcha el Proyecto PAI (Plan de Cuenca del Extracto de activos hidrogeológicos) desde el año 2003, la producción en el Departamento de Medio Ambiente y Territorio, una organización dedicada compuesta por unidades de varios funcionarios, incluyendo geólogos, ingenieros, arquitectos y peritos, coordinados por técnicos y administradores. Ese proyecto se llevó a cabo en el territorio siciliano , con un mapa a escala 1:50.000 de cobertura en las áreas de diferentes niveles de riesgo se definen. Para estas zonas también se definen las intervenciones dirigidas a la seguridad de las infraestructuras amenazadas (centros urbanos, grandes infraestructuras, edificios estratégicos, áreas de conservación de importancia, arqueológico, histórico-artístico, etc) y para la protección de las personas.

Entre los diversos enfoques utilizados en la clasificación de las condiciones de susceptibilidad de un área, es necesario el uso de métodos que garanticen, junto con la capacidad para caracterizar adecuadamente las condiciones de vulnerabilidad, un objetivo, una expresión cuantitativa, verificable y extensible de susceptibilidad a los resgos geomorfologicos. Desde este punto de vista, los protocolos de procedimientos armonizados generalizable se definen a escala europea.

En particular, un enfoque estabilizado en niviles (TIERS) fue preparado recientemente por el comité de expertos creado en el JRC (Centro Común de Investigación) de la

Comisión Europea. Este enfoque se compone de tres niveles anidados (de TIER₁, Tier₂ y Tier₃) con un grado de resolución de aumento gradual de los modelos predijeron, y los resultados del mapa a una escala mayor (Hervás et al, 2007). Al variar el nivel, la resolución de los niveles de información de los factores, la especificidad de las unidades de mapeo, así como la complejidad de las técnicas utilizadas para clasificar el nivel de aumento de la susceptibilidad.

El enfoque armonizado para la clasificación de la susceptibilidad en el procedimiento de TIERS, mientras que por un lado es un punto de referencia de seguridad importante para las administraciones nacionales y regionales, para lo cual es aconsejable iniciar una fase inicial de aplicación tan pronto como sea posible, por otro lado sufre de una excesiva disminución de la calidad de los datos y, por tanto, los modelos obtenidos, causada por el hecho de que el grupo de expertos que desarrolló el método tenía que tener en cuenta la disponibilidad de datos sobre un gran número de regiones. Desde este punto de vista, los datos iniciales adecuadas para aumentar de forma significativa el detalle de nivel están disponibles en el ARTA-Sicilia. .

Del análisis de estas consideraciones, un acuerdo marco de cooperación, llamado **SUFRA** (“*SUSCETTIBILITÀ da FRANA*”) fue propuesta por primera vez y luego firmó en 2011 con el Departamento mencionado y en el cual he conducido mi programa de doctorado (DISTeM), siguiendo el ejemplo de estas reflexiones, la identificación de una primera fase de aplicación del método, con la realización del nivel TIER₁ en una escala regional, utilizando los datos de origen identificado por el JRC, para una escala de 1:500.000, y los datos disponibles para el territorio de Sicilia, para que un TIER₁ a 250.000, se creará. El modelado de la susceptibilidad se basará en el análisis heurístico.

Para la realización de los niveles Tier₂ y Tier₃, los datos de origen identificado por el jrc se utilizarán, como un área de muestra de referencia, se formó en la zona que entran en el hoja CARG a 1: 50.000 escala "Termini Imerese-Capo Plaia".

El enfoque multi-nivel velará por la coherencia entre los escenarios creados. Los escenarios descritos por la susceptibilidad de los mapas también se compararán y se homogeneizan con los riesgos derivados del PAI, de proceder a un análisis puntual y

detallada de todas las posibles discrepancias que puedan generarse. Por la zona identificada, el siguiente procedimiento se ha propuesto, que luego pueden ser validados y verificados, incluso con activaciones en el futuro. Después de la fase de validación y prueba la solidez de las directrices científicas se proponen a continuación, las habilidades y la experiencia adquirida puede ser utilizado como base para la elaboración de mapas de susceptibilidad, periculosidad y riesgo.

6.2.1 Desglose de las actividades

Para las áreas de investigación, El Departamento de Medio Ambiente tiene a su disposición para los fines de investigación, los siguientes datos:

- Los mapas topográficos, geológicos (CARG), y el suelo (incluyendo la adquisición de los mismos en la versión digital);
- Las fotos aéreas (las consultas y la posible adquisición de copias en formato digital);
- Los datos digitales aéreos;
- DEM ATA07/08 (adquisición);
- IFFI archivo del los movimientos (de adquisición);
- PAI archivo del los movimientos (de adquisición)
- Los informes geológicos y geotécnicos presentados ante la ARTA-Sicilia (consultation)
- Difusores persistente de datos de Interferometría
- de datos LIDAR.

Dos archivos computarizados ya están disponibles para todo el territorio siciliano (IFFI y PAI), es posible proceder de las áreas de estudio a una homogeneización de la estructura de datos mediante la transferencia de datos de PAI en IFFI, por lo menos en el primer nivel. Además, con el vuelo 2007/08 (análisis de dos fotografías aéreas e imágenes aéreas), será posible proceder a una actualización y la homogeneización temporal del archivo.

El inventario de los movimientos que se utilizarán serán divididos en un archivo alfanuméricos, organizada en fichas del censo y una base de datos SIG, estructurado de acuerdo a las especificidades IFFI (detallados a nivel de: PIFF, el nivel poligonal: AREA, el nivel lineal: la dirección).

En la fase de modelado de la susceptibilidad, simplificado o blanco modo de archivo en función de la escala y el tipo de mapas prevé que se producirán serán consideradas.

6.2.2 Definición de los factores de control

La capa de información sobre los factores de control determinará lo siguiente, de los cuales las variables de predicción será obtenida, que se utiliza para definir los modelos de la susceptibilidad a diversas escalas:

- Las características geológicas
- Uso del suelo y características de textura
- Las características climáticas
- Las características sísmicas
- Características hidrográficas
- Características Litotecnic
- Las características topográficas

6.3 SUFRA250 (TIER1_SICILIA609)

El territorio siciliano se divide en una malla cuadrada de lado 2,5 km. Para cada celda de un nivel de susceptibilidad se calcula mediante la clasificación de los niveles de información sobre la base heurística relativos a la geología, uso de la tierra, el clima, las características hidrográficas y morfométricos.

Para definir las características de la célula, los datos de origen se utilizarán los siguientes:

- Geología: modelo estructural de Italia; afloramiento litología.
- Uso del suelo: Corinne, mapa de uso de la tierra (Fierotti).
- Clima: Atlas Climatológico de la Región Siciliana.
- Hidrografía: Los límites de la red hidrográfica y cuenca.
- morfométricos: DEM celular 250 (IGMI) y celda 40x40 m (Vuelo Italia 2000)

La unidad de mapeo estará formado por células de 2,5 kilómetros cuadrados, mientras que el corte se hará hasta 1:250.000, a los límites de la zona de la cuenca principal o los límites provinciales.

La clasificación del peso de cada factor y las tasas de incidencia para cada clase de cada factor se llevará a cabo de manera heurística, la optimización de sus marcas, incluso sobre la base de las áreas de la ampliación y la calibración del método, el cual será utilizado para la SCAI, AVI, IFFI y PAI o archivos DiSTeM.

6.2.4 SUFRA₅₀ (TIER₂_SICILIA609)

Por la zona que entran en la hoja 609, un modelo de susceptibilidad a los deslizamientos se hará, que se llevará a cabo en distintas unidades de asignación: una celda de la cuadrícula de 500 m de lado, con 50 celdas m cuadrados, las unidades hidrográficas (cuencas de primer orden), hidro-unidades morfológicas. Con el uso de las redes, después de realizar la clasificación del nivel de susceptibilidad, se procederá a disolver las unidades hidrográficas. El enfoque SUFRA₅₀ es un tipo estocástico y modelos por lo tanto, se definirá el uso de diferentes métodos multivariantes de clasificación: el análisis condicional, el análisis discriminante y regresión logística.

Con el fin de definir las características de la unidad de mapeo, el origen de datos se utilizarán los siguientes:

- Geología: geología CARG.
- Uso del suelo: Corine2006 nivel.

- **Clima.**
- **Hidrografía:** Índice de la fuerza erosiva de los ríos.
- **Morfología:** celads DEM 20x20m (Vuelo Italia 2000) y la celda 2x2 (Vuelo 2007/08)

Para definir el archivo de deslizamientos de tierra, un IFFI actualización 2007 se llevará a cabo (con el vuelo 2007 en color a escala 1:20.000 medio), a partir de los datos disponibles (SCAI, AVI, IFFI, PAI, DiSTeM).

El modelo de susceptibilidad estarán sujetos a la validación, la obtención de información sobre la adaptabilidad, la capacidad predictiva de resolución, y la estabilidad. El modelo se compara con los mapas de PAI.

El mapa de susceptibilidad se reducirá de acuerdo con la hoja a 50.000, de los límites municipales y los límites de la zona de la cuenca.

6.2.5 SUFRA_{10/25} (TIER₃_SICILIA609)

Desde el escenario producido en SUFRA₅₀ nivel, con algunas áreas de interés, tales como aquellos con alta susceptibilidad, se procederá a una clasificación más detallada que se llevará a cabo en un modelo estocástico, lo que aumenta el detalle de la entrada de información. Las escalas de análisis puede ser 1:25.000, en el caso de las áreas de interés en el desarrollo lineal 1:10.000, en el caso de las áreas de interés tales como cuencas o zonas de interés urbano. El nivel SUFRA_{10/25} aspira a ser el nivel de mapa base sobre la que poner en práctica cualquier estrategia determinista a la evaluación de la susceptibilidad a deslizamientos de tierra, basado en el modelo geotécnico de las laderas.

Las zonas estudiadas se dividirá en unidades de la pendiente, que se clasifican de acuerdo a sus características físico-ambientales.

Para definir las características de la unidad de mapeo, el origen de datos se utilizarán los siguientes:

- **Geología:** geología CARG, complejos litotecnic (regulación de los planes de datos).

- Uso del suelo: Corine2006 nivel.
- Clima.
- Hidrografía: Índice de la fuerza erosiva de los ríos.
- Morfología: ceeldas DEM 2x2m (Vuelo 2007/08-derived)

Incluso la clasificación SUFRA_{25/10} es un tipo estocástico y por lo tanto, se llevará a cabo usando diferentes métodos de clasificación multivariante: análisis condicional, el análisis discriminante y regresión logística.

Para definir el deslizamiento de tierra, archivar y IFFI actualización de 2007 se llevará a cabo (con el vuelo 2007 de color en escala 1:20.000 medio), a partir de los datos disponibles (SCAI, AVI, IFFI, PAI, DiSTeM).

6.2.6 SUFRAMON (SICILIA609)

El área que entran en la hoja 609, se divide en unidades de vigilancia. Estos corresponden a las unidades de la pendiente y para cada una de estas condiciones de susceptibilidad y deslizamientos de tierra se definirá mediante la identificación de un procedimiento para transferir a los municipios el comienzo de la supervisión directa de la inestabilidad gravitatoria, de acuerdo con un protocolo que participen en conjunto con ARTA y la DiSTEM en un proyecto común.

List of figures

Figure n°	Caption	Page
1.1	World Population Growth Chart	2
2.1	Schematic classification of landslides.	15
2.2	Schematic model of rock fall movements	17
2.3	Schematic model of fall in the over-consolidated soil stratification and present varying degrees of cohesion. The elements, can stop in the impact or be involved in movements for the next bounce or roll (b, c, d) falls in over-consolidated soil Beiro River Basin (Spain).	18
2.4	Schematic model of tilting coherent material intensely fractured.	19
2.5	Schematic model of a lateral spreading. A cohesive soil or rock mass (a) lays on soft materials (c) confined by the underlining bedrock (d), producing the outflowing of soft materials (b).	20
2.6	Photograph of lateral spread damage to a roadway caused by liquefiable layer underlying the road surface.	20
2.7	A typical rotational slide occurs when the underlying rock fails due to earthquake movement or an increase in water pressure. A large area of hillsides drops down and sideways, leaving a sheer exposed wall of earth and rock material ('headscarp') behind.	22
2.8	Rotational component in a landslide in a sub-basin of the river Platani.	22
2.9	Scheme of a translational slide type movement with disarticulation in multiple blocks of shifted material.	23
2.10	Geomorphological elements and kinematics of translational slide Cartuja-Granada (Spain). From Chacòn et al, 2012).	24
2.11	Kinematics reconstruction of the translational slide, Cartuja-Granada (Spain).	25
2.12	Examples of surface flow landslides identified and counted in Tumarrano river basin during field-survey in April 2009.	26
2.13	Scheme of detritic material incorporated in a debris flow.	27
2.14	Representation of detritic material incorporated in a debris flow.	28
2.15	Different parts of debris flow movement	29
2.16	View on rapid debris flows that triggered on the slopes, channeled into the river below in full for the heavy rains. The material set in motion is propagated downstream with increasing speed, expanding its	30

	volume. Altolia, October 2009.	
2.17	Overview of a slope affected by the rapid development of multiple coalesced debris flows, triggered during flood event that hit the town of Altolia (Me) in 2009. The material to be considered coincides with the layer of loose material. These materials are often placed on very steep slopes and are in poor stability. In association with intense weather events, dangerous flows of feed with a high destructive power may be generated.	31
2.18	Examples of rapid debris flows (a) and debris slides (b)	32
2.19	Activation for loss of cohesion (a), undercutting (b) and piping (c).	33
2.20	Examples of flows triggered by rapid dripping with arched crown (a, b) or straight (c, d).	34
2.21	Flows with crown of debris avalanches associated with rectilinear flow and geometry box-activation (a, b). Landslides of the slope (c, c ') and channelized landslides (d, d'). Figure 2.22 (bottom)-Hillslope (a) and channelized (b) debris flow.	35
2.22	Individual landslides (a) multiple parallel (b) multiple confluent (c) and multiple convergent (d, e).	36
2.23	Classification of landslide types.	37
2.24	Different techniques of pattern recognition, gravitational using open source software and traditional techniques; a, b) Beiro river basin; c) Platani sub-basin	43
2.25	Scheme of the landslides classification used for the construction of landslide inventories in the study areas.	45
3.1	Schematic flow of a model	52
3.2	Schematic representation of the main methods used for the evaluation of landslide susceptibility	53
3.3	An example of division of territory into morphodinamical slope units.	63
3.4	An example of division of territory into square grid cells.	65
4.1	Representation of the areas identified as a diagnostic area of statistical computing. a) Debris flow in the basin of the stream Tumarrano (Ag).	76
4.2	If only the Orange unit is affected by the slope rupture, the green unit is considered as not susceptible! Only the rupture surface should be considered as the diagnostic area for the susceptibility assessment and large and middle-scale mapping.	77

5.1	Location and geological map of the study area.	86
5.2	a) Detail of an outcrop of the Serravallian-Tortonian clays (equivalent Castellana Fm.); b) Trubi Fm. Outcrop in a Tumarrano basin.	88
5.3	Calcareous levels in the south sector of the Basin Tumarrano.	89
5.4	Excerpt of landslide inventory maps for comparison between the 2007 landslide archives obtained from field survey (in blue) and Google Earth™ remote analysis (in red). 2006BLIPs are also shown as purple circles.	90
5.5	Spatial distribution of buffered landslide identification points (BLIPs), obtained for the Tumarrano river basin by Google Earth™ remote analysis on 2006 images (a); field examples (b, c).	91
5.6	Excerpt of the landslide inventory maps for comparison, between the landslide archives obtained from PAI database (in blue) and Google Earth™ remote analysis (in red).	92
5.7	Frequency distribution of areas based on slope classes. It can be seen as the dominant class is the one with values ranging from 10° to 20°.	93
5.8	Frequency distribution of landslide density for each class of slope.	94
5.9	Frequency distribution of landslide density for each class of TWI.	95
5.10	Frequency distribution of landslide density for each class of CURPLAN	96
5.11	Frequency distribution of the density of landslides for different classes of lithological outcrops.	97
5.12	Spatial distribution of the four selected controlling factors.	98
5.13	Frequency distribution of the density of landslides for different classes of lithologies in different behavior. Predominantly litotecnic class is pseudocoherent behavior.	99
5.14	Susceptibility map, chrono-validation and cross-validation graphs obtained for the source area. The susceptibility map a was produced by computing the BLIPs density for each UCU using the whole Google_2006BLIP data set. In the chrono-validation graph b, the success rate curve is produced from the model trained by using the whole Google_2006BLIP data set, and the prediction rate curve results by comparing the susceptibility map with the spatial	104

	distribution of the Field_2007BLIPs. In the crossvalidation graph c, the success rate curve is produced from the model trained by using a randomly selected (50%) training subset of the Google_2006BLIP data set, and the prediction rate curve results by comparing the susceptibility map with the spatial distribution of the randomly selected test subset of the Google_2006BLIPs (the ones not selected for training the model). EFR values are also reported in both the two validation graphs.	
5.15	Susceptibility map and validation graphs obtained for the target area. The susceptibility map was produced by extending the BLIPs density values computed for each UCU in the source area using the Google_2006BLIP data set. In the validation graph b, the success rate curve is produced by comparing the susceptibility map and the spatial distribution of the Google_2006BLIPs in the target area; the prediction rate curve results by comparing the susceptibility map with the spatial distribution of the Google_2006BLIPs in the target area. In the cross-validation graph c, the success rate curve is produced from the model trained in the whole target area, by using a randomly selected (50%) training subset of the Google_2006BLIP data set and the prediction rate curve results by comparing the susceptibility model (whose map is not shown) with the spatial distribution of the randomly selected test subset of the Google_2006BLIPs. EFR values are also reported in both the two validation graphs	106
5.16	Earth flow landslides map (a); examples of LIPs generation (b).	110
5.17	Field and remote (Google Earth) examples of earth flow landslides in the Tumarrano river basin.	111
5.18	Example of seasonal re-activation cycles of earth flow landslides in the Tumarrano river basin: a, 2000, b, 2005; c, 2006; d, 2007; e, 2009 (from field).	112
5.19	Spatial distribution of the randomly selected stable cells included in the model suite.	121
5.20	Geographical setting of the study zone	126
5.21	Geological setting of the study zone. Regional geology (a) (modified after Vera 2004); Beiro river basin (b).	127
5.22	Granulometric curve derived from tests performed on some of the samples taken during the field-survey.	128
5.23	Beiro translational slide view by different techniques	130
5.24	Landslide inventory. Spatial distribution of landslide, obtained for the Beiro river basin by Google Earth™	132

	remote analysis.	
5.25	Correlation between ARPA and SHIFT morphometric indexes for suite models; Falls (a); Debris flows (b).	118
5.26	Comparison of best and best +1 model . With validation curves fall best model (a); fall best+1 model (b); debris flows best model (c); debris flows best+1 model (d). Degree of fit between susceptibility range and falls (e) or debris flows (f).	147
5.27	Degree of fit for the five different types of movement.	128
5.28	Landslide susceptibility map (a) and validation (b)	149
5.29	Location of the test area (a); 40-m DEM of the area (b); lithology map (c): ALV Quaternary alluvial deposits; TCL Terravecchia Fm. clays; VCL Varicolori clays; TCN Terravecchia Fm. conglomerates; TSL Talus slope; NFC Numidian Flysch clays; PML Polizzi Fm. marly limestones; NFS Numidian Flysch sandstones; TSN Terravecchia Fm. sandstones; CLD Carbonate limestones and doloarenites; SSC Siliceous successions.	150
5.30	Mean monthly rainfalls in mm/month for Caltavuturo and Scillato Station.	151
5.31	Mean annual rainfalls in mm/year for the basin area.	152
5.32	774 Slope Units (SLU) Semi-automatically derived.	153
5.33	Layers of the controlling factors: lithology (a); mean slope angle (b); Stream Power Index at the foot of SLU (c); mean Topographic Wetness Index (d); altitude range (e); slope length (f); mean profile curvature (g). The table shows break values used for the topographic factors (h).	155
5.34	An example of flow-type landslides; b landslide map showing landslide bodies and centroids (LCs).	156
5.35	Landslide centroids map; b) spatial relationship between SLUs, landslides and LCs (pif) in a representative sector.	157
5.36	Validation graphs (success and prediction rate curves; effectiveness ratio) of the single-parameter based susceptibility models (a-g). Table showing values of curve-quality indexes (h). For all the validation graphs: X-axis = portion of predicted area, Y left axis = portion of predicted landslides; Y right axis = effectiveness ratio.	160
5.37	Prediction rate curves (solid) and effectiveness ratio (dotted) for EFF, NEF, and ALL multiparametric susceptibility models, compared with the best single predictor (REN). X-axis = portion of predicted area, Y left axis = portion of predicted landslides; Y right axis =	161

	effectiveness ratio. The table shows curve-quality index (ARPA and T20) values. Error bars of the EFF model shown for each susceptibility class, differences between the number of predicted (train LCs) and occurred (test LCs) landslides, normalized to the total number of the latter: (train LCs-test LCs)/test LCs.	
5.38	Landslide susceptibility map for the best (EFF) multiparametric model (a). Training LCs-derived prediction image and test LCs spatial distribution (b).	163
6.1	Location of study areas. a) in Sicily; b) in Spain	165
6.2	Flowchart of the methodology. For each of the steps is shown the section of Chapter 4 where we affront the problem. Where the problem is approached	168
6.3	Detail of a portion of the basin, for which the slope units are hierarchized according to the degree of landslide susceptibility.	179

List of the tables

Table n°	Caption	Page
1.1	Report on the status of geomorphological risk areas in Italy (Legambiente, 2010).	9
3.1	The three main scales of analysis proposed by JRC guidelines (Hervas and others, 2007)	69
5.1	Location and sample results.	87
5.2	Most diffused UCU's in the source and target areas	100
5.3	Descriptions and codes of the independent categorical (a) and continuous (b) variables.	118
5.4	Performances of the model suite: error rate, -2LL test, McFadden and Nagelkerke pseudo R ² , AUCs of the ROC curves.	124
5.5	Confusion matrix for the model suite.	124
5.6	Predictors selected by the forward logistic regression of the model suite.	125
5.7	Size classification of sampled material.	109
5.8	Landslide inventory, extension of landslide and lithology affected by slope ruptures.	131
5.9	Correlation between the source area of the landslide and the determining factors. Factors highlighted in gray show the best models.	136
5.10	Summary of classification of the determining factors for each type of slope failure. FLL: falls; TSL: Translation slides; EFL: Earth flows; DFL: Debris flows; FSL: Flow slides	140
5.11	The two suites of models allowed high coherence between the progressive addition of variables to the multivariate models and variation of ARPA; falls (a); debris flows (b).	141
5.12	Summary of results. Validation and suite of susceptibility models for best and for best and best+1. FLL: falls; TSL: Translation slides; EFL: Earth flows; DFL: Debris flows; FSL: Flow slides.	144
5.13	Description of the 40 m grid layers from which the seven controlling factors were derived	154
6.1	Statistics for the different study zones	166

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A

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