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A GIS-Based Multivariate Statistical Analysis for Shallow Landslide Susceptibility Mapping in La Pobla de Lillet Area (Eastern Pyrenees, Spain)

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Abstract. This paper presents a GIS-aided procedure for shallow landslide susceptibility mapping at a regional scale. Most of the input data for the susceptibility assessment have been captured automatically. A total of 13 parameters, related to the slope geometry, have been derived from the digital elevation model (DEM) while vegetation cover and thickness of superficial formations have been obtained from photointerpretation and field work. The susceptibility assessment is based on multivariate statistical techniques (discriminant analysis), which has been tested in a pilot area in La Pobla de Lillet (Eastern Pyreenes, Spain). The results obtained using a random sample show that 82% of all the cells, and 90% of cells including slope failures, have been properly classified. A susceptibility map based on the discriminant function has given consistent results. The susceptibility assessment is very sensitive to the parameters selected. Compared to the traditional methods, the main advantage of the GIS-aided procedure is the rapidity provided by the automatic capture of parameters. It also has the capability of covering large areas, and the objectivity and reproducibility of the results. The main drawback is that, at present, not all regions have DEM accurate enough to cope with small landslides.

Key words: landslide-susceptibility map, shallow landslides, GIS, multivariate techniques, DEM

1. Introduction

Landslide susceptibility is defined as the proneness of the terrain to produce slope failures. Susceptibility is usually expressed in a cartographic way. A landslide susceptibility map depicts areas likely to have landslides in the future by correlating some of the principal factors that contribute to landsliding with the past distribution of slope failures (Brabb, 1984). These maps are a basic tool for land-use planning, especially in mountain areas.

Several approaches have been traditionally used to assess landslide susceptibility. Early attempts defined susceptibility classes by qualitative overlaying of geological and morphological slope-attributes to landslide inventories (Nilsen *et al.*, 1979). More sophisticated assessments involved multivariate analysis (Jones *et al*., 1961; Neuland, 1976; Carrara, 1983). Development of Geographic Information Systems (GIS) has enhanced the capabilities for susceptibility assessment of large regions. The performance of neighbourhood operations with the GIS allows extraction of morphometrical and hydrological parameters from Digital Elevation Models (DEM), that otherwise would have been difficult to obtain. Parameters such as slope gradient, slope aspect, slope convexity, watershed area, drainage network order, among others can be easily included for susceptibility analyses. Complete overviews of the use of GIS for landslide susceptibility assessment can be found in Van Westen (1994) and Carrara *et al*. (1995).

We present here a methodology to assess shallow landslide susceptibility by means of multivariate statistical techniques (discriminant analysis) used by Baeza and Corominas, (2001). In this research, however, the procedure will be implemented in a GIS. The main goal was the automatic capture of most of the parameters in relation to the occurrence of slope failures. The methodology has been tested in the area of La Pobla de Lillet, Spanish Eastern Pyrenees that was hit in November 1982 by heavy rains that caused catastrophic floods and countless landslides (Gallart and Clotet, 1988).

2. The Study Area

The lithology of the La Pobla de Lillet area is composed of sandstones, limestones, marls and flysch formations from Devonic to middle Eocene ages. These formations belong to thrust sequences arranged in east-west bands, dipping towards the north (Muñoz *et al*., 1986).

The spatial distribution of the landslides in the area is controlled by the lithology and by both morphological and hydrological characteristics of the slopes. The most affected lithostratigraphic units are clayey and sandy formations of Cretaceous-Palaeocene age, which produce both translational and rotational slides and marls of Lower Eocene age, also affected by translational failures. However, most of the slope failures take place on colluvial deposits though some of them also affect underlying weathered clayey formations.

The slope failures considered in this study belong to different landslide types. Following Cruden and Varnes (1996) terminology, movements are mostly translational slides (debris slides, earth block slides) and debris flows. Mobilised volumes are small (less than 10,000 m^3), failure surfaces are usually located at a depth up to 2 metres, and have an average length of 70 metres. All the movements show a D/L (maximum depth/length of the scar) ratio of less than 0.1. The failures occur preferentially on slope between 20° and 40°.

Rock falls and large landslides have not been included in the analysis presented here because these movements take place under geological, geomorphological, and hydrological conditions different to shallow landslides.

3. Landslide Susceptibility Assessment

We selected shallow landslides due to their simplicity and because of previous knowledge of the conditioning factors (Baeza, 1994). The term shallow landslides is used here in a generic way and includes both small size translational slides and debris flows. As has been already mentioned, in La Pobla de Lillet area the occurrence of landslides is controlled by the lithology. Bedrock is almost unaffected whereas slope failures take place mostly on colluvium blanketed slopes and less frequently on weathered marls and flysch formations.

The overall analysis is based on the hypothesis that failures occur due to the increase of pore water pressures in the soil that reduces the soil strength, which can be eventually overcome by slope driving forces. Slope geometry (slope angle, watershed size, degree of concavity), lithology and land-use are expected to affect the amount of rainfall that infiltrates into the soil and the groundwater flow path.

The landslide susceptibility assessment has been carried out in a test area by means of multivariate analysis. The slope failures are considered the result of the interplay of several factors that can vary in space and time. Multivariate analysis is performed to evaluate the relative weight of each factor contributing to the instability using a random sample of cells in the study area. As a result, a discriminant function is obtained. Each cell of the random sample will take a value of the function according to the characteristics of factors present in it. Ideally, cells associated with slope failures will have values of the discriminant function well apart from cells associated with unfailed slopes. After checking the validity of the results, the function is then applied to the whole study area. It is assumed that factors that cause slope failure are the same in both the random sample and the whole study area.

In order to proceed to the susceptibility assessment, first of all it is necessary to have a set of variables covering the whole area. Classical procedures for susceptibility mapping use variables gathered from aerial photointerpretation and fieldwork. These procedures are costly and time consuming and it becomes evident that, because of this, the extent of the area analysed is often restricted. On the other hand, the coverage of large areas often requires the contribution of different expert teams that may add some degree of heterogeneity and error. In that respect, the development and availability of GIS has increased the capabilities of producing and handling large amount of data. Automatic data capture, especially from the Digital Elevation Models (DEM), allows the extraction of variables from large areas with greater objectivity than former methods. The DEM used here is a grid of 15×15 m supplied by the Catalonian Cartographic Institute. It was obtained by restitution of aerial photographs at 1 : 22,000 scale taken in summer of 1983. GIS-generated variables can be easily exported to powerful statistical packages and perform the susceptibility analysis. Recent versions of GIS also incorporate several statistical commands and functions, thus allowing an integrated analysis.

In the following sections, the procedure for obtaining variables and the susceptibility analysis is described.

3.1. SELECTION AND ACQUISITION OF VARIABLES

Several terrain parameters related to the occurrence of the slope failures have been selected for their inclusion into the multivariate statistical analysis. A total of 17 variables have been produced. From them, 14 are digital terrain models (DTM) derived directly or with simple algorithms from the DEM. Six DTMs (cell height, slope angle, slope aspect, curvature, transverse curvature, and longitudinal curvature) were obtained directly from the DEM or with commands available in the GIS used (Arc/Info version 7.2.1). We used the Grid module, a cell-based geoprocessing toolbox integrated in the Arc/Info package. As shown in Table I, eight parameters (sinusoidal slope angle, solar radiation, slope roughness, watershed angle and both watershed length and area of the whole basin and that of the colluvial deposits) were created from algorithms that we have especially defined. Two parameters, watershed length and area of the colluvial deposits, required additional field information to be created from the DEM (Santacana, 2001). Finally, variables not derived from the DEM were obtained by means of photo-interpretation and fieldwork (land use, thickness of the superficial formations and landslide inventory). This information was digitised and then converted into raster format to carry out the analysis. Table I shows variables used in the analysis while Figure 1 is a sketch explaining some of the variables used. The next paragraphs describe the expected relationships between the variables used and the occurrence of slope failures.

Precipitation is the main triggering mechanism of shallow landslides in the Eastern Pyrenees. Several researchers have found an increase of rainfall with altitude and a consequent increase in the number of slope failures (Gallart and Clotet, 1988). The slope angle is the main geometric instability. The higher the angle the greater is the shearing component of the forces acting at the potential surface of failure (Jones *et al.*, 1961). The geological and morphological diversity of the study area has a particular effect on the threshold angle for slope failures. The latter occur in colluvium blanketed slopes or on weathered argillaceous formation. It appears that, even though a minimum angle is needed to cause slope failures, such failures are absent on very steep slopes (over 45°). This is because neither colluvium nor weathered clay can stand on these slopes. Steep slopes are made of resistant bedrock and are stable. To reflect this effect, a sinusoidal function of slope angle ($\sin 2\beta$) has been also used (Baeza, 1994). In order to determine which is the most significant variable, slope angle and sinusoidal slope angle were included separately in the discriminant analysis.

Both slope aspect and solar radiation are related to available soil moisture, amount of vegetation and rainfall storm paths. High roughness slopes are more prone to landsliding because gradient changes favour rainfall infiltration into the soil. The slope curvatures indicate the capability of water run-off concentration or dispersion. Several studies suggest that shallow landslides mostly occur in

Table I. Variables derived and non-derived from DEM, used in the analysis.

Variables derived from DEM				Variables not derived from DEM
	Variable	GIS function	Algorithm	
DEM	Height above mean sea level (m)	×		
Slope	Slope angle (^{P}°)	×		
Geometry	Sinusoidal slope angle		×	
	Slope aspect (°	×		
	Solar radiation (0–255)		×	
	Roughness (0–1)		×	
	Curvature	×		
	Longitudinal curvature	×		
	Transverse curvature	×		
Watershed	Watershed area (logarithm)		×	
Dimension	Watershed length (log)		×	
	Area of deposits (log)		×	×
	Length of deposits (log)		×	×
	Mean watershed angle		×	
Land use				Density of vegetation
Geology				Presence of surficial fm
				Thickness of surficial fm
Landslides				Rupture zone (inventory)

topographic hollows where subsurface flow concentrates (Reneau and Dietrich, 1987).

The watershed area is related to the amount of water that the soil can collect and infiltrate. A greater area is associated with more water infiltrated and higher chances of landsliding (Oyagi, 1984). The length of watershed indicates the size of watershed area, the capability to concentrate groundwater and to accumulate sediments. A close relationship has been found between the distance to water divide and location of the slope failures (Oyagi, 1984). Both area and length of superficial deposits show the extent where the water may infiltrate into the material susceptible to failure. Finally, the mean slope angle of the watershed indicates the capacity to help water infiltration into the soil.

Land use (density of vegetation) has a twofold influence on the stability of superficial deposits: hydrological (capacity of infiltration into the soil, soil moisture, groundwater level, etc.) and mechanical (root strength) (Greenway, 1987). The

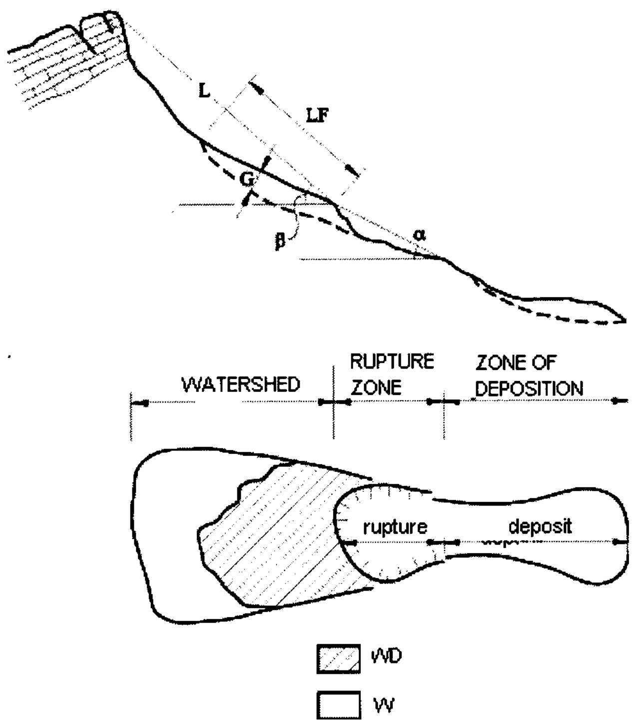

Figure 1. Cross-section with some variables used for the analysis (WD: area of superficial deposits; W: watershed area; L: watershed length; LF: length of superficial deposits; G: thickness of superficial deposits; β: mean watershed angle, and α: slope angle).

variable thickness of superficial deposits indicates the capability of generating pore water pressures and the presence of susceptible material.

3.2. STATISTICAL TREATMENT

Statistical analysis can only be undertaken with those cells having a landslide status (failed or unfailed). The data treatment in the GIS will work with raster format. Slope failures (shallow landslides) are points that have been rasterized and converted to cells (failed cells). The rest of the cells have been defined as unfailed.

In the 1982 rainfall event, 280 shallow landslides were triggered in the study area, and all of them have been used in the analysis. The number of cells showing slope failures is much smaller that the number of cells of the study area (about 170,000 cells). In order to avoid the bias of the function obtained, the discriminant analysis requires population sets having a similar number of individuals (Dillon and Goldstein, 1986). Therefore, because the number of failed cells is small, the sample set of stable slopes must be also small. Consequently, to derive the discriminant function, we have selected a random sample of 140 failed cells and the same number of unfailed cells, while we have reserved the remaining 140 failed cells for validation purposes. The sample was obtained by the GIS with an algorithm created for sampling.

Before proceeding with the statistical analysis, variables non-derived from the DEM have been weighted according to our expert criterion (i.e., land use). Furthermore, some variables derived from the DEM have been transformed in order to avoid errors or senseless results by the operations of the statistical analysis (i.e., zero values have been substituted by very small quantities to allow multiplication and division).

From the GIS, the random sample has been exported to the SPSS statistical package for treatment and to obtain the discriminant function. The value that the function takes at each cell is used as susceptibility rating. The data treatment involved the following steps:

(a) Test of normal distribution of variables (Kolmogorov-Smirnov test) and transformation of those that are not normally distributed. Both watershed area and length showed a skewed distribution and were transformed using logarithms to normal ones
(b) The Factorial Analysis (Principal Component Analysis) was performed to determine possible correlations between variables. Three of the groups of variables have shown colinearity (Table II): those related with watershed dimension, slope angles and slope curvatures
(c) The variable showing the highest significant level was selected from each group, to form a set of independent variables. The selection was made by means of the contrast analysis (T-test and One-Way test). Considering F-values of the One-Way test, variables with highest significance were (Table III): thickness of superficial deposits, height, sinusoidal slope angle, slope angle and mean slope angle of the watershed. Instead, slope roughness and longitudinal curvature were the lowest ones.
(d) The discriminant analysis was performed using the selected independent variables. The discriminant capability of each variable was analysed with the Stepwise Method. The discriminant function finally selected was that giving the best classification of the failed cells while taking the lowest number of variables

It must be taken account that the relative weight of the variables within the discriminant function may not correspond to their significance given by the One-Way test. The latter evaluates the significance of isolated variables while the discriminant function quantifies the weight of a set of variables. As sinusoidal slope angle and slope angle have similar F-values, both have been considered in the discriminant analysis. Slope angle has shown slightly better results and, consequently, it has been chosen for the definitive discriminant function.

The discriminant function selected and the main statistical parameters are shown in Table IV. Discriminant scores of the random sample, obtained from unstandardised coefficients, range from -3.1 to 3.4, with -0.739 as centroid value of the non- failed cells and 0.916 that of the cells including slope failures. The

Table II. Varimax rotated factor matrix with loads over 0.4 of Pobla de Lillet area.

	Varimax rotated factor matrix				
Variables	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
Slope height				−0.782	
Slope angle		0.981			
Sinusoidal slope angle					
Slope aspect					0.860
Solar radiation		−0.738			0.548
Roughness			0.476		
Curvature			0.888		
Longitudinal curvature			−0.822		
Transverse curvature	−0.468		0.677		
Watershed area (log)	0.910				
Watershed length (log)	0.931				
Area of deposits (log)	0.905				
Length of deposits (log)	0.914				
Mean watershed angle	0.764	0.477			
Land-use					−0.677
Thickness of deposits				0.864	

resultant classification of the random sample, according to its discriminant value, shows that 82% of the overall cells and 90% of the cells including slope failures were correctly classified. These results demonstrate the suitability of the variables selected and of the procedure.

Standardized coefficients of the variables in the discriminant function indicate the influence and the relative contribution to landslide susceptibility. Positive discriminant values are associated with slope failures while negative ones are associated with unfailed slopes. Slope angle is the most powerful discriminant variable with a coefficient of 0.820, followed by the thickness of the superficial deposits with 0.689 and the average slope angle of the watershed with −0.440.

In the function, the greater the slope angle, colluvium thickness, and watershed length, the greater the score, and consequently, the chances of slope failure. Instead, the increase of the average slope angle of the watershed, slope convexity, and vegetation will reduce the score, thus favouring more stable conditions. Summing up, shallow landslides are more likely to occur in steep unforested slopes, with large watershed, covered with colluvial deposits, and preferably in hollows.

Table III. Results of T-test and one-way test of La Pobla de Lillet area (UN: unfailed group; F: failed group).

Variable	T-test		One-Way		Variable	T-test		One-way	
(group)	Mean	SD	F	Sig.	(group)	Mean	SD	F	Sig.
UN	1165.9	163.6			UN	0.08	1.3		
Slope height			40.5	0.0000	Trans. curv.			11	0.001
F	1051.5	155.8			F	−0.39	1.2		
UN	23.8	8.4			UN	2.4	1.4		
Slope angle			27.8	0.000	Waters. area			6	0.015
F	28.4	6.5			F	2.7	1.2		
UN	0.7	0.19			UN	1.4	0.8		
Sin. angle			30.7	0.0000	Waters. length			6	0.015
F	0.8	0.13			F	1.7	0.7		
UN	107.4	56.1			UN	2.02	1.5		
Aspect			4.5	0.034	Deposit area			14.1	0.000
F	120.1	48.8			F	2.62	1.3		
UN	151.8	12.5			UN	1.2	0.9		
Solar radiation			4.6	0.032	Deposit length			14.2	0.0000
F	149	10			F	1.6	0.8		
UN	0.99	0.01			UN	19.7	12.2		
Roughness			1.1	0.298	Mean w. angle			7.7	0.006
F	0.98	0.01			F	23.3	10.5		
UN	0.08	2.05			UN	12.4	4.1		
Curvature			5.2	0.023	Land use			2.8	0.095
F	−0.45	2.1			F	11.7	3.1		
UN	0.003	1.1			UN	2.8	1.1		
Long. curv.			0.123	0.726	Thickness			103.2	0.000
F	0.05	1.2			F	3.9	0.3		

4. Susceptibility Map

The discriminant function has been used to prepared the landslide susceptibility map of La Pobla de Lillet. The function has been solved at each individual cell using the unstandardised coefficients of its variables. With this operation, a discriminant cell grid has been obtained. The whole range of values that the function is able to take has been divided in segments of the same size, which define the susceptibility levels. Each cell is assigned to a susceptibility level according to the value of the discriminant function takes in it. Figure 2 is the susceptibility map obtained with these susceptibility levels.

Table IV. Discriminant function with standardised and unstandardised coefficients, classification and other statistical parameters of La Pobla de Lillet area.

Variables	Function coefficients	
	Standardised	Unstandardised
Slope angle	0.820	0.108
Thickness of deposits	0.689	0.761
Mean watershed angle	−0.440	−0.038
Transverse curvature	−0.336	−0.257
Slope height	−0.320	−0.078
Land use	−0.291	−0.078
Watershed length constant		−1.927

Eigenvalue	Wilks-λ	χ^2	Prob. %	Success classification ($F = 0$)	Unfailed	Failed
0.682	0.595	162.438	0.000	Stable cells	75.1%	24.9%
				Unstable cells	9.9%	90.1%
				Global	81.8%	

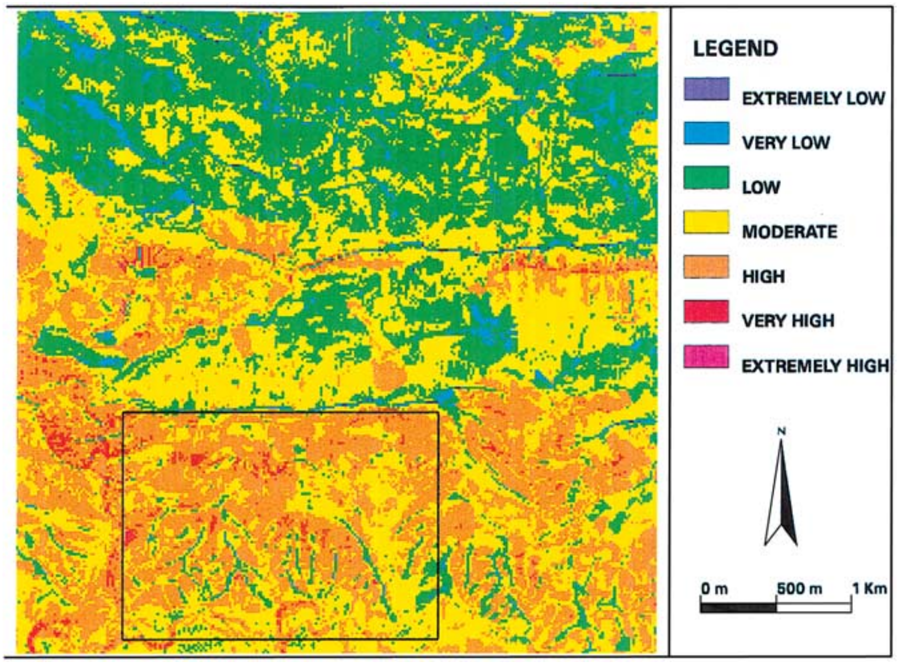

Figure 2. Landslide susceptibility map of La Pobla de Lillet area (about 179,000 cells).

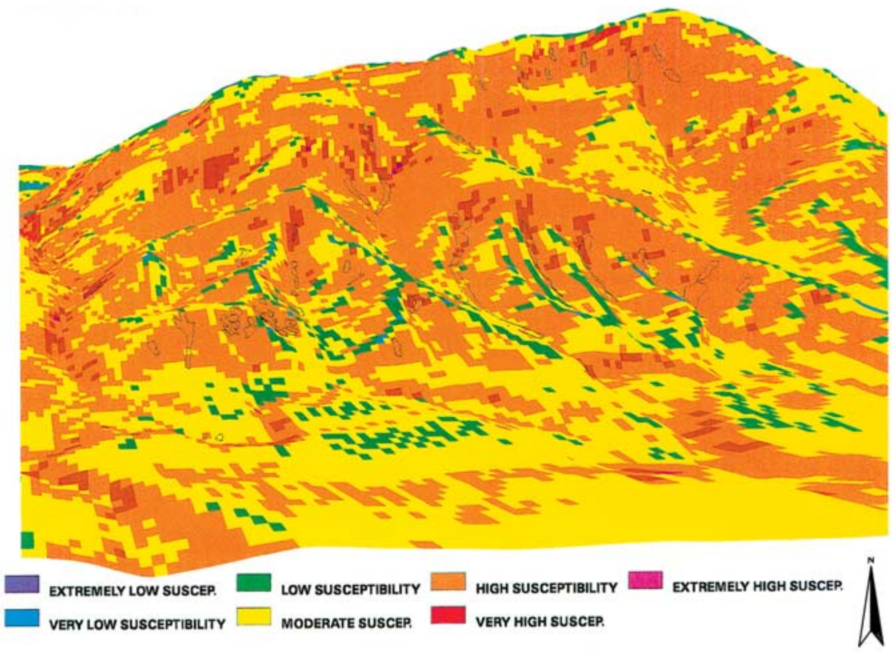

Figure 3. Partial 3-D view of the La Pobla de Lillet landslide susceptibility map. The area corresponds to that included in the frame of Figure 2. Landslides (irregular contours) have been overlapped to visualise their adjust to the most landslide-susceptible cells.

The consistency of this map has been checked using landslides of the 1982 event that were not included in the random sample. In order to do so, a mask was created to exclude the cells of the random sample. Therefore, the susceptibility map (Figure 2) has been created with the rest of cells of the study area, about 170,000 cells. Figure 3 shows a partial 3-D view of the map. Landslides have been included to visualise whether they coincide with the most landslide-susceptible cells.

An index of relative landslide-density (R) has been used to validate the results. The index is defined as follows (Baeza and Corominas, 2001):

$$R = ((n_i/N_i)/\Sigma(n_i/N_i)) \times 100,$$

where n_i = number of landslides in susceptibility level "i", N_i = area occupied by the cells of susceptibility level "i".

It may be expected that slope failures will appear in cells having higher discriminant scores (from moderate to extremely high-susceptibility levels). Table V shows the R index for each susceptibility level. The index shows an increase of the number of landslides with the level of susceptibility. We may thus conclude that the distribution of slope failures observed in these levels indicates that susceptibility levels are consistent.

Table V. Results of the relative-density index in the susceptibility map of La Pobla de Lillet area.

Susceptibility level	No. of landslides	No. of cells	*R* Index
Extremely low	0	258	0.00
Very low	0	6,634	0.0
Low	1	55,124	0.24
Moderate	18	74,685	3.26
High	100	38,582	35.01
Very high	9	1,977	61.49
Extremely high	0	49	0.00

Table VI. Number of labour days required for acquiring variable data. One field-work day allows acquisition of data from 3 slope failures or stable slopes. Labour days for aerial photo interpretation, and data manipulation in the office are not included.

Data acquisition Procedure	No. of failures	No. of unfailed slopes	Slope failures labour days	Unfailed slopes labour days	Total labour days
Field work	150	50	50	16	66
Automatic capture	272	136,000	1	3	4

5. Discussion

The results also show the significant discriminant capability of some variables, such as colluvium thickness. The inclusion of this variable improves the number of cells properly classified with the function between 5 to 10%. Even though this type of variable can not be easily gathered, it must be included in the susceptibility assessment.

The main advantage of the presented procedure is the rapidity provided by the automatic capture of most of factors from the DEM in front of traditional methods. Table VI shows a comparison between the time needed to collect data by photointerpretation and field work, and the automatic data capture from DEM. We estimate that we can obtain, in a traditional way, data from 3 landslides or 3 stable slopes per day. Field gathered parameters belong to Baeza (1994) and automatic ones to this study (Santacana, 2001). The Table VI only shows used days for fieldwork but it does not include the time involved in other processes as photointerpretation or digitalisation. Besides the capability of covering large areas, the objectivity and the repetitiveness of the analysis with different samples are clear advantages in front of traditional methods.

The discriminant function based on data captured automatically has allowed us to correctly classify 90% of cells, which may be considered as good classification although it is slightly worse than that obtained with the same procedure, 96% of cells, using data gathered directly in the field (Baeza and Corominas, 2001). Furthermore, although resultant classification of the area is acceptable, the statistic controls as Lambda of Wilks or eigenvalue (Table IV) suggest that the selected function has lower discriminant capability than the traditional method (Baeza, 1994). With the GIS-aided procedure, failed and unfailed populations overlap in a great range of discriminant values of the selected function and of the created susceptibility map. There are two main reasons to explain this: the use of variables derived from DEM and the use of a sample without previously confirmed stable cells.

Most of the variables derived from DEM are obtained from neighbourhood operations and the resultant values of cells are usually mean values. Because of this, the range of values from variables derived from DEM is smaller than those obtained directly in the field, and it is close to average values. It happens usually when using values obtained from areas (such as cells in variables derived from DEM) instead of values obtained from points (as the information gathered from field work).

The sample used to derive the discriminant function included a 50% of unfailed cells. These cells were those that had no slope failure during the 1982 rainfall event. However, it does not mean that some of them could be susceptible to produce a slope failure in the future. The 1982 rainfall event was not homogeneously distributed throughout the study area and some cells might have not received the critical amount of rainfall to produce the failure of the slope. Therefore a part of the unfailed population that overlap the failed one might include susceptible cells in which the critical rainfall to produce landsliding was not reached.

6. Concluding Remarks

The results of this investigation can be summarized as follows:

(1) The automatic capture of most of variables related to the occurrence of shallow landslides by derivation from DEM has several advantages, namely: the rapidity of the procedure, the objectivity and reproducibility of the results. The results of the susceptibility analysis are only slightly worse than those obtained in using data gathered in the field.

(2) The meaning of the discriminant function indicates that shallow landslides are more likely to occur in steep unforested slopes, having both large and gentle watershed, covered with thick colluvial deposits, and preferably in hollows.

(3) The results of the susceptibility map have been checked with landsides that occurred in the 1982 rainfall event. The distribution of the landslide density among the different susceptibility levels is coherent. Landslides do not occur

in the lowest susceptibility levels while their density increases in the highest levels.

(4) The main drawback is that, at present, only few regions have availability of DEM with enough accuracy and resolution to cope with small size landslides.

(5) This method is efficient because shallow landslides have simple failure mechanism, essentially controlled by slope angle and thickness of superficial deposits. Extension to other phenomena has to be undertaken carefully.

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