Strategy to Reduce Subjectivity in Landslide Susceptibility Zonation by GIS in Complex Mountainous Environments

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SUMMARY

In the last decade, statistical modelling of landslide susceptibility by GIS has become a major topic of research. Despite some advancements, particularly through the bayesian approach based on the concept of "weight of evidence", some unsolved questions may be asked: (i) what is the influence of the input data set on the quality of the simulations and (ii) how can we resolve the effect of violating the conditional independence assumption. This paper presents a strategy to collect relevant geographical information for reducing subjectivity in landslide susceptibility zonation in complex mountainous environments and stresses the different ways to reduce information redundancy.

KEYWORDS: *landslide susceptibility, geographical information, GIS modelling, conditional independence.*

INTRODUCTION

Risk assessment and modelling through GIS (floods, Shanker *et al.*, 2003; earthquakes, Recifea & Capolongo, 2002) has become a key topic of interest for geoscientists, engineers and end-users in the last decade (Agent, 2004). Especially, most relevant progress has been accomplished in landslide susceptibility assessment at both medium (1:25 000) and large (1:10 000) scales (Carrara *et al.*, 1995; Soeters & van Westen, 1996; Aleotti & Chowdury, 1999). At these scales three methods have been developed to locate and characterise landslide-prone areas (ie. recognition of the slope instability factors, Aleotti & Chowdury, 1999):

- a qualitative approach, based on expert knowledge (Wachal & Hudak, 1999; van Westen *et al.*, 2000);
- a deterministic approach, incorporating geotechnical data to evaluate a safety factor of the hillslope, used at very large scales (1:5 000 and less) (Terlien & van Westen, 1995);
- a statistical or probabilistic approach, used at medium scales (1:25 000 or 1:10 000, Aleotti & Chowdury, 1999; van Westen *et al.*, 2003), and based on the observed relationship between each factor and the past and present landslide distribution (Carrara *et al.*, 1995).

The underlying concept of these GIS-based (raster) methods is the "terrain unit" or "homogeneous unit" (Carrara *et al.*, 1995) the portion of land surface which contains a set of ground parameters which differ from the adjacent units across definable boundaries. The aim is to predict the behaviour of a dependent variable (landslide susceptibility) through a set of known *a priori* independent variables (ground parameters). The statistical approach has been the object of several studies and is often considered as the most objective method avoiding the problem of the expert subjectivity (Soeters & van Westen, 1996). Moreover, statistical methods are useful in landslide mapping because a few set of data

can produce meaningful results (van Westen, 2000). Nevertheless, the strength of this functional approach is directly dependent on the quality and quantity of data collected (map scale, typology, precision, Carrara *et al.*, 1995). The strategy to collect relevant geographical information for reducing subjectivity in landslide susceptibility zonation at 1:10 000 scale in complex mountainous environments is discussed in this paper.

POSITION OF THE PROBLEM AND OBJECTIVES

The statistical approach can be applied following different techniques, either bivariate (weight of evidence, logistic regression, fuzzy logic), or multivariate (multiple regression, discriminant analysis), which differs on the statistical procedure used (Carrara *et al.*, 1995; van Westen *et al.*, 2003); they are all based on conditional analysis which attempts to assess the probabilistic relationship between relevant factors and the occurrence of landslide over a given region. Bivariate techniques are generally based on the *Bayes* theorem according to which frequency data, such as landsliding area or number of landslides, can be used to calculate probabilities that depend on knowledge of previous events. Therefore the technique is dependent on the quality of data and on the assumption of their statistical independence. However, few studies show (i) how to define a set of information sources adapted and (ii) how to avoid the problem of conditional independence (CI) (Bonham-Carter, 1994). When the evidence from several ground parameters is combined, the weight of each parameter is calculated independently and then combined in a single equation (Agterberg *et al.*, 1993; Bonham-Carter, 1994) through which posterior probabilities are calculated, that may not be identical as those calculated directly from the data. Therefore, this type of calculation requires the assumption of CI in order to reduce the redundancy of information. In practice, the assumption of CI is always violated, and, following Bonham-Carter (1994), some questions arise: How serious is this violation? What can be done to mitigate the effects of violating CI? What is the magnitude of the problem and what are the maps causing the most difficulty? This can be evaluated through the analysis of a pairwise test supported by a χ^2 statistical test (Spiegelhater & Kill-Jones, 1984; Bonham-Carter, 1994).

The objective of this article is to propose an overall strategy of relevant data collection, especially through (i) the identification of the input data causing the most problems on CI violation, (ii) the definition of the minimal number of landslides to introduce in the modelling study, (iii) the certainty of the map, in order to obtain a robust representation of landslide susceptibility for a given area. The article discusses the choice of the best dataset to obtain reliable results at 1:10 000 scale (national or regional end-users products, built database) and stresses the different ways to reduce information redundancy. The study site is the Barcelonnette Basin (South French Alps) known for its numerous slope instabilities and its complex morphology (Maquaire et al., 2003).

METHODOLOGY

Landslide susceptibility maps are computed according to the bayesian "weight of evidence" (WofE) method proposed initially by Agterberg et al. (1993) and Bonham-Carter (1994) for mineral exploration mapping, and adapted by Sterlacchini (2000) and van Westen et al. (2003) for landslides zonation. The model is based on the following assumptions (Carrara et al., 1995): (i) future landslides will be triggered under the same circumstances as in the past, (ii) all controlling factors are known and included in the model, (iii) all past and actual landslides are identified in the study area.

Weight of evidence modelling: principles

The WofE modelling technique is the log-linear version of the general bayesian theorem which uses a probability framework, based on the idea of prior and posterior probability, to solve the problem of combining multiple data sets. The prior probability is the probability that a terrain unit contains the response variable (Rv, the landslides) before considering the existing predictor variables (Pv, the favourable ground conditions factors). This model is fundamentally based on the calculation of positive

and negative weights (W_+ and W_-), the magnitude of which depends on the measured association between the response variable and the predictor variables.

$$[1] \ W_+ = \ln \frac{P(B|D)}{P(B|\bar{D})} \qquad\qquad [2] \ W_- = \ln \frac{P(\bar{B}|D)}{P(\bar{B}|\bar{D})}$$

where B is the class of the Pv and D is the Rv. The symbol " ‾ " represents the absence of the Pv and/or Rv. The model is expressed in an odds form (ratio of the probability that an event will occur to the probability that it will not occur).

Being the model in a log-linear form, the weights can also be added. Therefore the contrast C ($C = W_+ - W_-$) gives an overall measure of the degree of spatial association between the predictor variables and the response variable, in each precise geographic location. The contrast C has a null value when a predictor variable has a distribution which is spatially independent in relation to the response variable. So the contrast value is a first important basis for accepting (or rejecting) the Pv as a real predictor themes, evaluating the level of spatial correlation between a precise Pv and the Rv. The calculation of the W_+ and W_- values for all the selected predictor evidences allows the calculation of the posterior probability, which updates (increases or decreases) the prior probability. When several predictor themes are combined, the areas with the greatest coincidence of low/high weights produce the lowest/greatest probability of occurrence of the Rv.

Stepwise map combination

The model is implemented in an ArcView 3.2® free extension called *ArcSDM* (Kemp *et al.*, 2001). The model calculates automatically the posterior probabilities for each terrain unit and the χ^2 value to determine whether the assumption of CI is satisfied. Calculation are performed on a per-pixel basis. The procedure to determinate the best dataset (*Vp*) incorporates the stepwise combination of maps, added one by one. The stepwise resulting scores are analysed on a cumulative curve representing the cumulative area versus the posterior probability; three susceptibility classes are defined (low, average, high).

In order to accept or to reject each *Pv*, the CI test is based on a pairwise test and χ^2 test for each new *Pv* introduced in the model. The pairwise test between two *Pv* involves a contingency tables calculation, applicable only at locations at which pixel of *Rv* occur. The rows of the contingency table are the classes of the first *Pv* (*Pv1*), and the columns of the contingency table are the classes of the second *Pv* (*Pv2*). Each cell (*i, j*) of the table records the number of *Rv* occurring for a specific overlap of the *i*-th class of *Vp1* and the *j*-th class of the *Vp2*. The calculation of the χ^2 test involves estimating the expected number of pixel of *Rv* in each cell, under the assumption that *Pv1* is independent of *Pv2*. The expected value in a cell is calculated as the product of the marginal pixels divided by the grand total number of pixels. χ^2 test is a measure of the differences between the observed and expected frequencies, summed over all cells of the table. The null hypothesis of CI is tested by determining if the measured χ^2 value exceeds a theoretical $\chi2$ value, given the number of degrees of freedom (*υ*) and the level of significance (α).

$$[3] \ υ = [(r\text{-}1)(c\text{-}1)]$$

where *υ* is the degree of freedom; *r* the number of class for *Pv1* and *c* the number of class for *Pv2*; the *ls* is taken as 95% or α = 0.05.

In order to evaluate the success rate of the model, the relative error is calculated for each simulation. The triggering zone of each landslides are compared with the zone considered as the more susceptible (high susceptible class) following the equation [4]. It is assumed that the landslides map give the "true" situation.

$$[4] \ \xi = \frac{x - y}{y}$$

where ξ is the relative error, x the real value (number of pixel of the landslide triggering zones) and y the calculated value (number of pixel of the high susceptible class considered).

Certainty of simulations

In order to obtain very robust model a test of uncertainty is performed on the basis of the variance of the weights (Bonham-Carter, 1994). As indicated by Bonham-Carter (1994), the variance of the weights can be used to calculate the variance of the posterior probability (pp) at each location, and to generate an uncertainty surface linked to the simulation. This measure is based on the calculation of the Studentized value (Sv) of the pp. This Sv is obtain by dividing the pp by its standard deviation [5]:

$$[5] \; Sv = \frac{pp}{s(pp)}$$

where Sv is the Studentized value, pp is the posterior probability and s the standard deviation. This ratio is sued in order to test the hypothesis that pp=0. As long as the ratio is relatively large, implying that the posterior probability is large compared with the standard deviation, then the pp is more likely to be "real". For Bonham-Carter (1994) the ideally ratio must be larger 1.5 or even 2, either a certainty calculation between 92.5% and 97.5% (Davis, 2002). In the case of the Barcelonnette Basin and according Davis (2002), some thresholds for the Sv (1.28; 1.64; 1.96; 2.33) have been used to know the calculation certainty of the pp (90%; 95%; 97.5%; 99%). The confidence area obtained is compared to the high susceptibility class area defined by the cumulative curve. This "certainty test" gives an information about the confidence of the classes defined by the analysis of the cumulative curve.

STUDY AREA AND DATA ACQUISITION

Study area

The study focused on the north facing slope of the Barcelonnette Basin (French South Alps). The area extends over 100km^2. Surrounding crests are capped by limestone, sandstone and flyschs. Below the crests lower slopes are underlain by less resistant callovo oxfordian black marls. Slope angles are comprised between 8° and 36°, they are covered by morainic deposits (77% of the surface) and by forest (62%). Geomorphological forms comprise very steep (>45°) naked badlands areas, regular slopes and hummocky topography due to heterogeneous accumulations zones (Maquaire *et al*., 2003). Various factors including lithology, tectonics, climate and the evolving land use have given rise to numerous slope movements like rotational landslides, earthflows or debris flows. The behaviour of these slope instabilities have been studied during the last ten years by several research teams (Flageollet *et al*., 1999; Buma, 2000). More than 350 active landslides have been inventoried and only rotational and translational landslides, which represent the majority of the active landslides (71% of the total number of observed active landslides in 2000), are considered in this study. Complex landslides such as rockfalls, earthflows and debris flows are not discussed. It is assumed that rotational and translational landslides have the same controlling factors. Firstly, the best set of data to minimize the problem of CI is identified; secondly, the area representing the landslide complex is stressed; thirdly, the minimal number of landslides to introduce in the simulation is discussed on the basis of a random sampling, fourthly the certainty of simulation is discussed.

Data acquisition

The landslide susceptibility maps are built through the statistical computation of six categories of ground parameters (also controlling factors, Table 1). These input data are derived from existing national databases, from the digitization of aerial photographs, from the statistical treatment of satellite imageries, from the interpretation of maps and from field observations (Table 1). Originally, data are computerized in different formats (raster format, vector format, data needed to be digitized before rasterization, Table 1). The best way to produce the initial dataset is discussed in the following sections.

Best dataset to optimise CI assumption

Several combinations of data are tested in order to increase the quality of the dataset. Calculation were performed by introducing successively the maps which require the longest pre-processing. To test the performance of the model, the simulated susceptibility maps are compared to a map of the observed events (called inventory map) in 2000. Results indicate that the available (existing) databases are not adapted to landslide susceptibility assessment at a 1/10 000 scale for complex environments (topography, vegetation). It is necessary to adapt the data to the particularities of the site, in terms of spatial resolution, accuracy and nomenclature (Thiery *et al*., 2003). The optimal dataset is represented on Figure 1.

Data format	Ground parameters	Layers	Available	Source of information	Acquisition method
Raster data	Landcover	CLC[1][2,3]	Yes	LANDSAT MSS and TM + SPOT XS imagery + Public Database + AP[2]	Visual interpretation od satellite images
		CRIGE[3]	Yes by CRIGE[3]	LANDSAT 7 ETM+ imagery (1999) + IRS-1D (1999) + Public Database + AP[2]	Automatic and semi-automatic processing
		L AND	No	LANDSAT ETM+ imagery (2000) + 2 SPOT imageries (1994) orthorectified Public Database + vegetation map + AP[2]	Automatic and semi-automatic processing + field survey
	DTM	BD Alti ®	Yes by CRIGE[3]	Topographic maps	G + D + I [4] by IGN[5]
Vector data	Landslide	LA1	No	AP[1] (2000) + topographic maps (1/10.000)	API[6]
		LA2	No	AP[1] + topographic maps (1/10.000)	API[6], field survey
	Geology	Superficial deposits	No	Geological map + topographic maps (1/10.000) + AP[2]	Interpretation of geological map + field survey + API[6]
		Lithology	No	" " "	" "
		Faults	No	" " "	" "
	Hydrography	Humid area	No	Topographic maps + AP[2]	Analysis of topographic maps + field survey + API[6]
		Hydrographic network	No	" " "	" "
	DTM	DTM IL	No	Topographic maps (1/10.000)	G + D + I [4]
		DTM KL	No	" "	"
		DTM KV	No	" "	"
		DTM RBF	No	" "	"

[1]CLC: Corine Land Cover ; [2] AP : Aerial Photographs ; [3] CRIGE : Centre Régional de l'Information Géographique ; [4] G +D +I : Georeferenced + Digitization + Interpolation ; [5]IGN : Institut National Géographique ; [6] API : Aerial Photograph Interpretation

Table 1: Input data retained for susceptibility assessment.

Area of landslides to model

Simulations are performed taking into account as Rv (i) the area of the landslides (AL), (ii) the area of the triggering zone (ATZ), (iii) one pixel representing the barycentre of the landslide complex (BL), (iv) one pixel representing the barycentre of the triggering zone (BTZ), (v) one pixel representing the most frequent linear combination of factors of the triggering zone (CTZ).
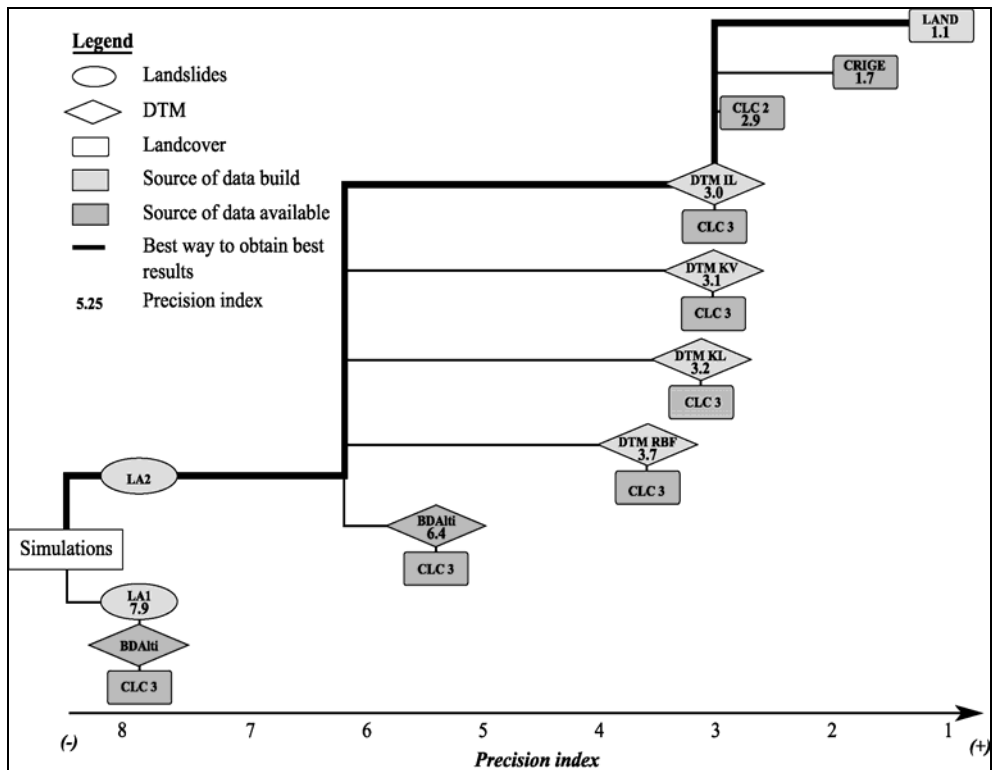

Figure 1: Flow-chart of the best way to obtain good results and precision
index depending on the databases (Thiery et al, 2003).

Simulations with AL and ATZ are rejected with the null hypothesis H_0. For the two simulations, it is impossible to determined the Pv which causes problem of conditional dependence. Nevertheless, for simulation with AL, cumulative curve presents some thresholds and the three susceptibility classes can be identified. But, for this map the relative error is very high, some flat zones are considered by the model with high susceptibility because the accumulation area of each landslides with low slopes are taking into account in the simulation.

Simulations with one pixel (BL, BTZ, CTZ) give best results, and especially with CTZ. However, some problem of conditional dependance appears when the Pv "lithology" and "stream with buffer" are introduced in the model. The null hypothesis H_0 is rejected at each time. The best combination is obtained with the 234 CTZ (relative error ξ represents 7%)., slope map, aspect map, topographical concavities and convexities, deposit thickness map, landcover map.

	SLO	**SD**	**LAND**	LIT	STR	**CUR**
SD	*del =54* 72.1 **31**					
LAND	*del = 72* 92.8 **13.9**	*del =108* 133.5 **31**				
LIT	*del = 36* 51 **54.2**	*del = 54* 72.1 **5.5**	*del = 72* 92.8 **10.9**			
STR	*del = 12* 21 **4.7**	*del = 14* 23.7 **4.4**	*del = 24* 36 **48.9**	*del = 12* 21 **1.7**		
CUR	*del = 12* 21 **11.7**	*del = 14* 23.7 **7.3**	*del =24* **13.9** 36.4	*del = 52* 69.8 **5.7**	*del = 4* 9.4 **1.4**	
ASP	*del = 42* 82.5 58.1 **23.7**	*del = 63* 82.5 **17.3**	*del = 84* 106.4 **21.1**	*del = 48* 65.1 **89.5**	*del = 16* 26.3 **28.2**	*del = 14* 23.6 **9.1**

Table 2: Selection of the *Pv*. In bold the *Pv* retained for the best simulation; SLO: slope classes map; SD: Surficial Deposits map; LAND: Landcover map; LIT: Lithology map ; STR: Stream map with 5 buffer classes; CUR: Curvature map (concavities, convexities); ASP: Aspect map.
With $\alpha = 0.05$. *del* = degree of freedom, 72.1= theoretical χ^2 , **31**= measured χ^2.

Minimal number of landslides

To optimise the collection and pre-processing of data (mapping time, document analysis, field survey), the minimal number of landslides to introduce in the model is estimated through a random sampling of the 234 CTZ. The different simulation indicate that 125 landslides (somehow 50% of the total number of observed landslides) can be considered as a indicative threshold for an acceptable landslide zonation in the Barcelonnette Basin with a relative error ξ of 17%. The figure 2b reinforces this opinion, cumulative curves with less than 125 CTZ do not give identifiable thresholds, it is difficult to define the three susceptibility classes. Nevertheless, cumulative curves with 125 CTZ or more present the same thresholds as the best cumulative curve obtained with 234 CTZ.
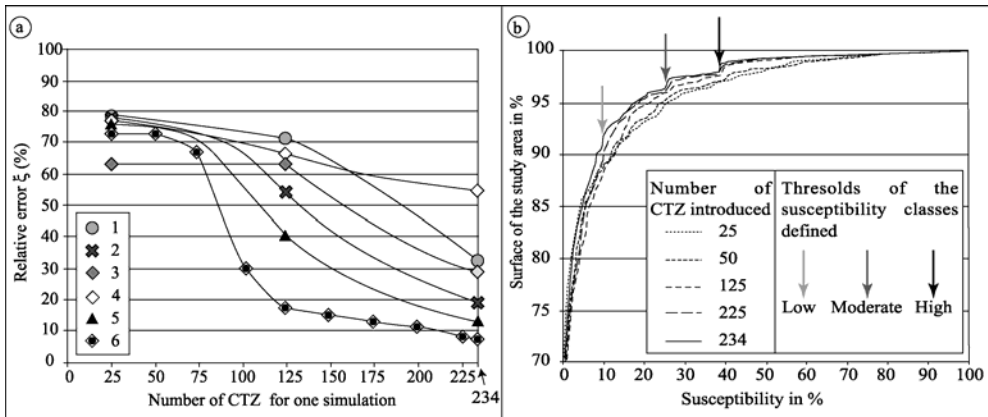

Figure 2: Result of simulations. (a) Relative error for different number of CTZ and for different combination of predictive variable (Pv) with this following Pv: SLO, SD, LAND, LIT, STR, CUR. ASP.
1 = SLO + SD. 2 = SLO + SD + LAND. 3 = SLO + SD + LAND + LIT. 4 = SLO + SD + LAND + STR.
5 = SLO + SD + LAND + CUR. 6 = SLO + SD + LAND + CUR+ ASP.
(b) cumulative curves with the surface area versus the posterior probability following
the number of CTZ introduced in the model.

Certainty of the susceptibility class

In order to check the certainty of susceptibility map, the high susceptibility class is compared to the certainty calculation at different levels of certainty.

The figure 3 shows results obtained for different simulations. The most interesting results are obtained with the simulations with 125 CTZ and 234 CTZ. The simulation with 125 CTZ gives good certainty up to 95% level. For simulation with 234 CTZ the different "certainty test" for high susceptibility class are better for the four certainty thresholds, with a little decrease of the certainty calculation from 95% to 97.5% (89.5% to 89%). This is mainly due to the number of CTZ introduced in the model. More CTZ are introduced in the model, more the certainty increases. As mentions Bonham-Carter (1994), if the degree of certainty is comprised between 92.5% and 100% the simulation are good in a statistical point of view. In our case this comparison confirm the relative error calculated for 125 CTZ and 234 CTZ. The test with this two simulations shows that the high susceptibility class chosen by analysis of cumulative curve is good. It shows that with 50% of CTZ, statistic calculation and simulation map are very robust. Nevertheless this test must be used as a relative indicator. It is a guaranty to have high susceptibility class defined by subjective opinion closest the certainty of statistical calculation.
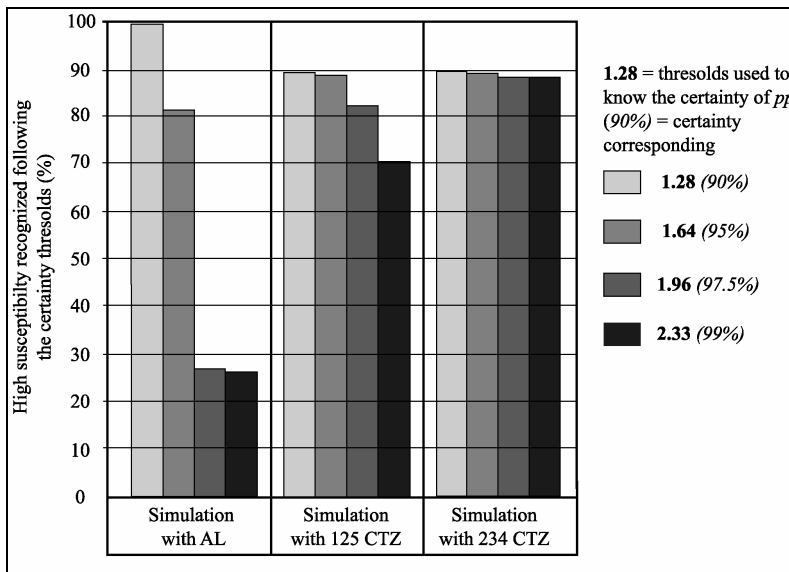

Figure 3: Results of certainty test for simulation with AL, 234 CTZ and 125 CTZ.

DISCUSSION AND CONCLUSION

The relative error analysis with the best dataset indicates that the use of the Pv "landcover" (LAND) raised the overall accuracy of the susceptibility map from 32% to 19%. This result confirms some studies about the sensitivity of this modelling technique for this variable type (Sànchez, 2002; van Westen et al., 2003).

The use of others Pv such as "curvature map" and "aspect map" decrease respectively the relative error from 19% to 12.5% and from 12.5% to 7%. This type of Pv doesn't need a laborious work of field
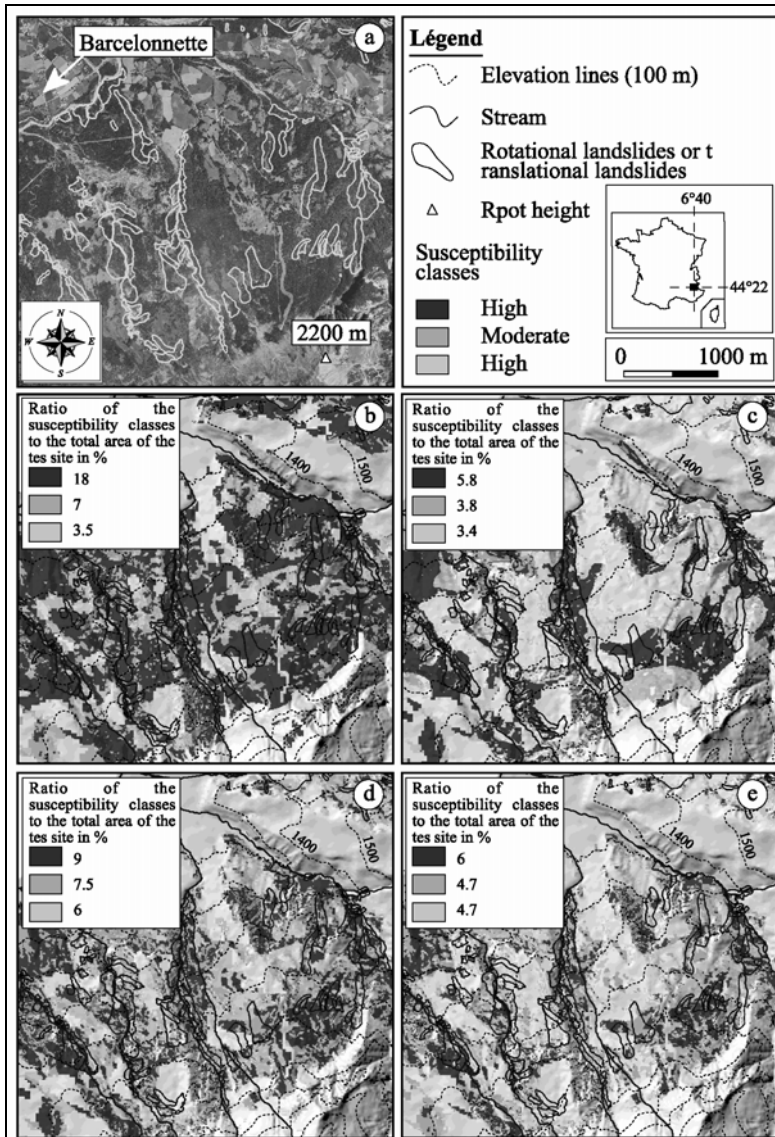
Figure 4: Susceptibility maps obtained by combination of different Pv;

(a) Location of the study site. (b) Map obtained with the totality of the landslide areas. (c) Map obtained with SLO, SD,LAND and 234 CTZ. (d) Map obtained with SLO, SD,LAND, CUR, ASP and 234 CTZ. (e) Map obtained with the same Pv as (d) and 125 CTZ.

observation, and/or imagery treatment as the landcover data. This information is derived from a DTM which gives some indication about the terrain morphometry according the algorithms used. The information derived from the DTM are very useful for statistical model, but they are available only if the DTM has good precision for the scale of work. For example the National Height Elevation Database BDAlti ® (spatial resolution of 50m) is not adapted, in particular for complex mountainous environments.

The relative error is very large and final results are very biased. In this specific case, a new DTM was elaborated by digitization of elevation lines from topographic maps at 1:10 000 scale. Different algorithms were performed and compared (Borgefors distance method, radial basis method, kriging method). Best results were obtained by complex interpolation method as kriging method with specific variogram. Also it is essential to have precise and adapted topographic information (metric resolution, and elevation precision close to the meter), built either by precise digitisation of elevation lines (time-consuming task), or derived from expensive technical image processing (photogrammetry, laser scanning) to obtain good simulation for this scale.

For the Pv "lithology" the different simulations indicate a conditional dependence with the Pv "slope classes map" then the relative error increases (Table 2). In order to reduce the conditional dependence problem, a combination of this two Pv was attempted, as recommended by Bonham-Carter (1994). Despite this combination, the χ^2 test is rejected. The model based on the use of Pv "lithology" increases only the high susceptibility on area with slope between 8° to 27° and decreases the probability on other zones with slopes above 27°. Contrary to scientist belief, the lithology is not a good predictive variable for all study case, especially when the slope morphology depends on the surficial deposits. Besides, majority of Barcelonnette landslides occurs in surficial deposits as morainic deposits, de facto the Pv "lithology" is rejected of simulations.

The procedure described in this analytical study stresses the importance of the Rv and of the Pv on the output simulations. The bayesian "Wofe" statistical method with the χ^2 test, calculation of relative error and certainty test appears as an efficient tool for landslide susceptibility assessment at 1:10 000 scale, once the quality on the input data has been evaluated. But as mentioned by van Westen et al. (2003), this type of model needs an expert opinion. Landslide data are the result of the subjective interpretation of the scientist. For instance, if landslide location is very different because another people has collected information, the calculation of posterior probability can be very diverse.

This error can be reduced by a careful field survey. Another point very important lies in the choice of the response variable (Rv) and the predictor variable (Pv). If the Rv is complex and/or if some Pv are not precise enough or have no relations, in an expert point of view, the method presents some limitation, especially for the combination of Pv recommended by Bonham-Carter (1994). For the Barcelonnette Basin, this limit has been solved (i) by a strong analysis on the part of landslides to model, (ii) by statistical analysis and expert reflection on each Pv which causes conditional dependence problem. Thus, the strategy adopted on Rv and Pv for this complex area gives a new approach to reduce redundancy problem and to obtain a robust statistical model and landslides susceptibility maps closest the reality at 1:10 000 scale. Nevertheless, despite field verification, statistical analysis and expert reflection, some unstable areas are not predicted by the model. This mismatch can be explained by the following: a few landslides occurs in areas represented by low posterior probability values for some classes of factors (i.e. low slope angles, landcover with low posterior probability values such as natural grassland and pastures, colluvium for surficial deposits).

As calculation is based on the number of landslides observed in each class, classes characterized by a wide area and a small number of landslide locations result in low posterior probability. Hence, the simulated maps underestimate landslide susceptibility in few locations. Nevertheless, the different tests used (pairwise test, certainty test) indicate that the model seems robust to predict landslide location; it could be improved by introducing temporal data on landslides.

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