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Landslides susceptibility change over time according to landuse and terrain condition in a mountain area of the tropic region

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ABSTRACT

Susceptibility to landslides in mountain areas is the result of the interaction of various factors related to relief formation and soil development. The assessment of landslide susceptibility has generally been done taking into account individual events, or it has been oriented at establishing relationships between a landslide inventory map and maps of factors related to the occurrence of landslides, without considering that these relationships change in space and time. In this work, temporal and space changes in landslides were analysed in eight different scenarios (combinations of year and geomorphological unit) were analysed in two different geological formations to determine the terrain susceptibility for landslide occurrence. For that, landslide inventories of different years of the Southern Central Coast Range of Venezuela were analysed by means of multiple logistic regression analysis. The logistic regression showed that the variables related to the triggering of landslides in the study area were: slope, aspect, LS factor, and the vegetation cover estimated through the normalized difference vegetation index o NDVI (as activating factors) and flow direction, elevation and planform curvature (as conditioning factors). These acted as either activating or conditioning factors depending on the scenario. This shown the complexity of assessing landslide occurrence even at the same location, which were associated with changes in the causes and the mechanisms that activate them over time.

KEYWORDS: Logistic regression, mass erosion, hydrographic basin, activating factor, conditioning factor

1. INTRODUCTION

Landslides are common geomorphic processes in mountain areas and are responsible for mass movements involving rock materials, regolith and/or soil debris. They usually occur under specific conditions of soil moisture content, having gravity as the main engine. Although the causes of these different types of mass movement are usually known, the degree to which an area is susceptible to mass movements and the spatial distribution of such events is difficult to establish, largely because the relationships between the activating and conditioning factors are complex (Carrara et al. 1991; Guzzetti et al. 2005; Can et al. 2005; Federici et al. 2006). According with Varnes (1984) the keys to determine the occurrence of future landslides depend on the geological, geomorphological and hydrological processes that led to instability in the past and also at present. Reason why the objective of the landslide susceptibility assessment is identify in the land surface the probability of failure caused by mass-movement (Varnes, 1978, Guzzetti et al. 1999, 2005).

To date, research into susceptibility to mass movements has generally been performed with respect to individual events and has been spatially orientated. The assessment of individual cases includes the study of each type of mass movement in a specific area while spatial assessment is usually performed by establishing relationships between the spatial distribution of related factors with reference to a landslide inventory map (Guzzetti 2003; Chacón et al. 2006). This requires the use of statistical tools in combination with geographic information systems (GIS) and remote sensing imagery (Carrara 1983; Carrara et al. 1999; Ostir et al. 2003; Guzzetti et al. 2005; Alexander 2008; Budetta et al. 2008).

To evaluate terrain susceptibility to landslides, a number of different techniques are used, ranging from qualitative assessments based on expert judgment (Gupta and Sah 2008; Budetta et al. 2008; Magliulo et al. 2009), which are intrinsically subjective (Van Westen 2000; Magliulo et al. 2009); to quantitative assessments based on advanced statistical techniques or mathematical models. The latter can only be applied in detailed investigations with the required available data, but are less effective at regional scale (Carrara et al. 1992; Zhou et al. 2002; Gorsevski et al. 2006; Abdallah et al. 2007).

Among the statistical analyses used, the most common are: bivariate statistical analysis (Budetta et al. 2008; Magliulo et al. 2009); multivariate analyses, such as multiple regression and discriminant analysis (Greco 2007; Carrara et al. 2008; Frattini 2008); bivariate and multiple logistic regression (Rowbotham and Dudycha 1998; Dai and Lee 2002; Can et al. 2005; Akgün and Bulut 2006; Carrara et al. 2008); multiple regression (Ohlmacher and Davis 2003; Yilmaz 2009); and factorial analysis (Duman 2005). Other more recent techniques include: artificial neural networks, which

have been mainly applied to analyse shallow landslides and debris flows (Ermini et al. 2005; Chacón et al. 2006); fuzzy Logic (Remondo et al. 2003; Gorsevski et al. 2003); uncertainty analysis; reliability analysis; and fractal analysis (Chacón et al. 2006).

The relationship between landslides and causative factors is not linear, unique, or constant in either space or time (Carrara, 1983; Carrara et al. 1991; Dai and Lee 2002; Zhou et al. 2002; Ohlmacher and Davis 2003; Duman 2005; Guzzetti et al. 2005; Can et al. 2005 and Federici et al. 2006) and although, as mentioned above, statistical analysis techniques have been used to study several aspects of landslide susceptibility, the multitemporal aspect has hardly been studied to date (Guzzetti 2003, Ayalew et al. 2004; Chau and Chan 2005; Chacón et al. 2006; Felicísimo et al., 2012). Currently, the interest has been focused on the comparison of methods with the idea of selecting the most accurate (Choi et al. 2012; Das et al. 2012; Devkota et al. 2012; He et al., 2012; Calvellido et al. 2013; Kavzoglu et al. 2013).

A temporal evaluation of a landscape tends only to be included when there is a perceived need to predict the changes that might occur in it (Parise 2001). To evaluate the time factor, some authors have performed inventories of landslides for different periods, using remote sensing images corresponding to different dates. The objective is to predict when landslides may occur based solely on the location of past movements, without taking changes on environmental conditions into account. However, changes do not only affect the determination of risk, but also susceptibility, since the temporal and spatial responses of mass movements may vary considerably both within, and especially between, basins (Carrara et al. 1992) and over time (Guzzetti 2003). As a result, factors that may not have initially been decisive may subsequently become activating and conditioning factors.

The present research has the purpose to determine factors associated with susceptibility to landslides in mountainous areas of the Caribbean, the changes that occur in these factors and their relationships over time. For this, a case study was conducted in the Caramacate River Basin, located in the southern part of the Central Coastal Range of Venezuela. This area was selected because it is a strategic basin within the country for water resource (it satisfies more than 60% of the demand for drinking water of the city of Caracas and its metropolitan area) (Machado et al. 2010) and is frequently affected by landslides.. The basin also contains important farming and livestock activity, which have caused severe erosion and land degradation due to the existence of steep slopes with reduced vegetation cover. The

objective of this work was to evaluate the impact of the changes that have occurred in this area on the natural environment and to assess how they have influenced susceptibility to landslides in both space and time.

2. MATERIAL AND METHODS

2.1. Study area

The study area covered 6760 ha in the Caramacate River Basin (Datum Sirgas Regven, 9.55 to 10.09 m North and -67.12 to -67.03 m East) located in the mountains of north-central Venezuela (Fig. 1). Elevation ranges from 334 to 1405 m a.s.l., with an average slope angle of 40%. The average annual rainfall is 1100 mm and the average annual temperature is 22 °C (Pineda et al. 2011b). The dominant vegetation is herbaceous, but is subjected to extensive grazing. It is only interrupted by forest corridors following waterways and areas of evergreen forest in the highest areas. The geology of the study area is dominated by two major formations (Pineda et al. 2011b): “El Chino-El Caño metatobas” (VCcn) and “El Carmen metalavas” (Vcca), which belong to the Villa de Cura group (metavolcanic and metasedimentary rocks) (Urbani and Rodríguez 2003). The VCcn consists of basalts and metavolcanic rocks associated with sedimentary rocks and the VCca of mafic metalavas intercalated with metasedimentary and metavolcanic rocks (Shagam 1960).

Fig. 1 Location of the Caramacate River Basin and the study area

2.2. Cartographic information

Table 1 shows the images used for this analysis. The aerial photographs taken in 1941 and 1971 were scanned in greyscale (8 bits) at a resolution of 600 dots per inch. The georeferencing of the aerial photographs was carried out with MiraMon ® Software v.7.0b, using 52 control points, which were taken from the 2008 SPOT image (orthorectified). In the georeferencing, we used first-degree polynomials with an estimated root mean square error of <12.5 m for the scale of 1: 25 000 (USGS 1993). Corrections were made taking into account the elevation provided by a digital elevation model (DEM). A DEM with a 20 m cell size generated from 1:25 000 topographic charts by means of the ANUDEM algorithm (Hutchinson 1989) included in the TOPOGRID command of ArcGIS (version 9.2, Environmental Systems Research Institute, Redlands, CA, USA). The aerial photographs were then related to the DEM through colinearity equations. The different combinations of years and geomorphological unit were called scenarios

2.3. Evaluation of susceptibility to landslides

In order to evaluate susceptibility to mass movements, an inventory of landslide evidence was made using the aerial photographs (from 1941 and 1971) at 1:25,000, orthophotomaps (1992) at 1:25,000 and a satellite image (SPOT, 2008). Eight different locations were considered based on the geological formations and the dates of the landslide inventories. The VCnc formation was not covered by the 1941 and 1971 aerial photographs.

The identification of landslides was based on image interpretation of the respective digital images, determining points corresponding to scars and blocked soil masses. The studied landslides were of rotational type (Hutchinson 1968; Varnes 1978; EPOCH, 1993). These mass movements produce scars of concave form (spoon shape) and the material slipped in this case is soil. In this case study, due to the working scale (1:25,000), only the scars wider than 5 meters were mapped. Then, the points with landslide scars were identified with the code or value 1. Also points without evidence of landslides were identified for each location outside a 50 m radius buffer zone drawn around each scar (Dai and Lee 2002) (Table 2). The points were coded with value 0. The interpretations were then validated in the field by testing some of the points (30 points) identified in the image corresponding to the year 2008 (Fig. 2) because of the appearance of these landslides change over time. Finally, a data table with points without landslide scars (WOLS) was generated, which were similar in number to those in the data table for landslide scars (WLS), shown in the Table 2.

Fig. 2 Left (a) landslide scars close to the drainage network; this situation particularly occurs on the slopes of the VCca geomorphic unit. Right (b) landslide scars observed near the peak of the hill slopes in the VCnc geomorphic unit.

2.3.1. Landslides' activating and conditioning factors

The present research considered the following activating and conditioning factors: A) Geomorphometric parameters that have been related to the occurrence of landslides, which are detailed in Table 1 (Adediran et al. 2004; Di Crescenzo and Santo 2005; Bolongaro-Crevenna et al. 2005; Van Asselen and Seijmonsbergen 2006; Ardiansyah Prima et al. 2006; Iwahashi and Pike 2007).

Table 1 Geomorphometric parameters related to the occurrence of landslides

Parameters	Calculation	Author
Elevation (ALT)	Z Value (m)	Hutchinson (1989)
Relative position (RP)	$([DEM]-[DEMMin])/([DEMMax]-[DEMMin])$	Böhner (2004)
Slope gradient (SLO)	Magnitude in m/m of the steepest gradient in both the X and Y directions	Burrough and McDonell (1998)
Slope aspect (ASP)	direction in radians towards which the slope faces	Lee and Talib (2005)
Profile curvature (PFC)	curvature in m/m^2 in the direction of the slope	
Planform curvature (PC)	curvature in m/m^2 perpendicular to the direction of the slope	
Curvature (C)	combination of profile curvature and planform curvature	Moore et al. (1991); Zevenbergen and Thorne (1987)
Convergence index (CI)	The convergence index gives a measure of how flow in a cell diverges (convergence index < 0) or converges (convergence index > 0)	Claps et al. (1994)
Sediment transport index (STI)	$(As / 22.13)m (\sin \text{slope}^\circ / 0.0896)n$, where m and n are constants that depend on slope length	Moore and Wilson (1993)
Flow direction (FWD)	Flow goes from the center of a cell to the center of one (and only one) of the surrounding cells. Flow directions are, therefore, restricted to multiples of 45°	O'Callaghan and Mark (1984)
Catchment area (AS)	As, the local upslope area in m^2 draining through a certain cell of the model	Tarboton et al. (1991)
Topographic wetness index (TWI)	Calculated as $\ln (As/\tan \beta)$, where β is the local slope in degrees	Wilson and Gallant (2000)

Calculations involving these parameters were made using the Software Systems for Automated Geoscientific Analyses (SAGA) v2.0.4 and a DEM (Pineda et al. 2012).

B) Distance to the drainage network, obtained through contour curves plotted every 50 m from the drainage lines (Dai and Lee 2002). This factor was considered because previous observations suggested a possible influence of this variable with the occurrence of landslides close to the drainage network. For that, the methodological approach of D'Amato Avanzi et al. (2004) and Shrestha and Zinck (1999) was [used](#).

C) The Normalized Difference Vegetation Index (NDVI) calculated from satellite images corresponding to the dates of each scenario (Rouse et al. 1973).

D) Landforms identified at two different scales (1:50000 corresponding to types of landscape and 1:25000 corresponding to types of relief) (Pineda et al. 2011b).

It is important to take into account the fact that the (activating or conditioning) behaviour of the geomorphometric parameters depends on the study area. For this reason, the classification of these parameters into groups according to their behaviour was one of the results of the present work.

2.3.2. Relationships between activating and conditioning factors and the occurrence of landslides

The relationship between the set of variables considered as possible activating or conditioning factors and the existence or absence of landslides was established on the basis of the "Zonal Statistics" algorithm (ArcMap 9.2, Environmental Systems Research Institute, Redlands, CA, USA). The presence or absence of landslides (Table 2) was considered the dependent variable and the other thematic variables were considered as independent variables.

A multiple logistic regression analysis, using the SPSS v12 (SPSS Inc., Chicago, IL, USA), was then performed to analyse the relationship between the factors and the occurrence of landslides. Multiple logistic regression analysis was applied by means of the maximum likelihood model (Chung, 2006; Lee et al., 2007; Dewitte et al., 2010), which refers to that the coefficients that made the observed results most "likely" were selected (Choi et al., 2012). Initially, all the variables (whether continuous or categorical) were considered and the multiple logistic regression coefficients of the different factors were calculated.

Models to predict landslide susceptibility ($\hat{g}$) were generated using 90% of the sample points in each study area. The remaining points (10%) were used for validation (Table 2). The probability of a landslide occurrence was interpreted as landslide susceptibility (e.g. Dai and Lee 2002; Can et al. 2005; Carrara et al. 2008; Nefeslioglu et al. 2008; Pradhan and Lee 2010; Chauhan et al. 2010; Bai et al. 2010), where P was the probability and $\hat{g}$ was the multiple logistic regression equation generated by the model. According to Can et al. (2005), P must be interpreted as landslide susceptibility and not as the probability of occurrence because it does not take into account the time factor. The regression equations generated, called " $\hat{g}$ ", and their respective probabilities were applied to the whole study area using the ArcMap 9.2 program. Finally, quantitative landslide susceptibility maps (one map for each scenario) were generated. These were then classified into four levels of susceptibility to landslides, based on the procedure proposed by Tangestani (2003).

2.4. Validation of the landslide susceptibility model

Two validations were performed: an internal one, using input data from the models, and an external one, based on the data that were separated for validation. The internal validation was used to estimate the sensitivity of the model. In this case, the value of the predicted probability for each of the points used to build the model was compared with the observed value (input data). This validation was performed for all of the model's entry points. For the external validation, a confusion matrix was created using the points not included in the generation of the model (Meyer and Martínez-Casasnovas 1999; Pearce and Ferrier 2000; Frattini et al. 2008) (Table 2). The accuracy of each logistic regression model was computed as the ratio between the number of points correctly classified (true positive or true negative) and the total number of validation points. The precision of the model was calculated as the ratio between the number of points classified as true negative and the number of points classified either as true negative, or false positive. This was done for seven of the eight scenarios. It was not applied to the 1941 scenario because of the lack of enough data.

3. RESULTS AND DISCUSSION

3.1. Landslides' activating and conditioning factors

Table 3 presents the variables included in each of the multiple logistic regression models. The results show that, when the B coefficient of each variable in the model was negative, the value of $\exp(B)$ was less than 1. This interpreted as a conditioning factor, because it increased the resistance of the system to landslides. On the contrary, when B was positive, the values of $\exp(B)$ were greater than 1 and the variable was therefore considered as an activating factor (Pineda et al. 2011a).

The continuous variables related to landslides in the proposed scenarios were (Table 3): elevation, relative position, slope, slope aspect, convergence index, sediment transport index, planform curvature and NDVI. These acted as either activating or conditioning factors depending on the scenario in question. The categorical variables were: the geomorphic unit, the landscape type, the relief type and the distance to the drainage network. These were included in the analysis but were not selected to form part of any of the models, except the variable flow direction.

This shows that the characteristics of geomorphic unit and the landscape type were not determining the susceptibility to landslides in the study area, when the two units were evaluated together. This is in disagreement with findings by other authors, which state that lithology was, among other factors, a determining factor leading to landslide occurrence (Ozdemir and Altural 2013; Kavzoglu et al. 2014).

The susceptibility to landslides in the VCca geomorphic unit was evaluated for the years 1941, 1971, 1992 and 2008. The variables included in the models for the years 1941 (scenario 1) and 1971 (scenario 2) were different from those selected for 1992 (scenario 4) and 2008 (scenario 7) and did not behave in the same way. This shows the complexity of assessing landslide occurrence even at the same area, which are associated with changes in the causes of landslides and the mechanisms that activate them over .

(Fig. 3).

Among the relief variables evaluated, flow direction played an important role in 1941, when it acted as a conditioning variable for the occurrence of landslides. However, the negative value of its coefficient indicated that landslide susceptibility decreased when values of this variable increased. For this year, the activating variables were not identified. In 1971, the susceptibility to landslide occurrence was related to the slope and aspect (activating variables) and to elevation and the convergence index (conditioning variables). The first three, generally played major roles in landslide occurrence and distribution, as found Ozdemir and Altural (2013) in the Sultan mountains. In this year, slope steepness was a circumstance that predisposed the increase in the susceptibility level, while convex areas with diverging flow were less susceptible to landslides. For 1992 (scenario 4), sediment transport index and NDVI were the activating variables (positive coefficient sign). No conditioning variables were identified for this year. In 2008 (scenario 7), the planform curvature acted as a conditioning variable (negative coefficient sign) instead of the convergence index, nevertheless these variables reflect the same relief characteristics. The slope and aspect were considered to be activating variables.

In the VCnc geomorphic unit, susceptibility to landslides was only assessed for the years 1992 (scenario 3) and 2008 (scenario 6). In 1992, the variables sediment transport index, flow direction and convergence index were included in the model, while in 2008, slope and relative position were the related variables. In both scenarios, NDVI was included in the prediction models as an activating variable of landslide occurrence. In this geomorphic unit, sediment transport index (STI), NDVI, slope and convergence index acted as activating factors in both dates (1992 and 2008).

The susceptibility to landslides in the VCnc geomorphic unit therefore increases in line with the sediment transport index, NDVI value and slope angle. In contrast, in the VCca geomorphic unit, the CI variable acted as an activating variable. In this case, the convex areas (positive coefficient sign) would therefore be more susceptible to landslides. Joint evaluations of the VCca and VCcn geomorphic units were performed for the years 1992 and 2008, respectively (Table 3). In 1992, the most sensitive areas had higher STI and NDVI values. Also water flows mainly ran towards the south or southwest. The values of NDVI relating to riparian forests were associated with drainage. The models differed from those calculated by Pineda et al. (2011b), using logistic multiple regression, and Pineda et al. (2012), using multiple logistic regression and also from Bayesian networks for the same area such as that corresponding to the year 1992. In the first (Pineda et al. 2011b), the relief type, the distance to the drainage system, and the vegetation cover (NDVI) were conditioning variables, while rainfall was the activating variable. In this case the susceptibility increased on concave landforms located at distances less than 50m from the drainage network. In the second (Pineda et al. 2012), the variables associated with susceptibility to landslides were the shape of the slope, the lithology, the type of relief, distance to the drainage network, the topographic wetness index and the NDVI. The precipitation and sediment transport index (STI) were not included in these analyses (Pineda *et al.*, 2012). However, the final interpretation of the results was similar, as it was found that susceptibility to landslides increased on concave slopes in poorly vegetated areas and close to the drainage network.

Fig. 3. Logistic multiple regression model relating environmental variables to scars associated with landslides in the VCnc, VCca or both formations, for each of the years evaluated.

In summary, when comparing the two study areas, it was observed that flow direction was a conditioning variable of landslide occurrence, inducing greater susceptibility on slopes facing S, SW and SE. The vegetation cover estimated through the NDVI was an activating variable, perhaps due to the location of scars in areas that were closer to the drainage network. This agrees with the results found by He et al. (2012), who found that areas around rivers were highly susceptible to the occurrence of landslides in the Qinggan River delta. In these areas, high NDVI values were found in association with riparian forest cover and an increase in the number of activating variables was observed over time. This can be most clearly seen in the VCca geomorphic unit where the higher degree of intervention increased the surface with low vegetation coverage associated with grasslands. The convergence index (scenario 2) and planform curvature (scenario 7) were also included amongst the conditioning variables in the VCca geomorphic unit as these two variables could also be interpreted in a similar way. In the VCca unit, the lower values of the variables (concave area) indicated a higher susceptibility to landslides, whereas in the VCnc unit (scenario 3), the lower values of the variables (concave areas) indicated a lower susceptibility to landslides. The increase in susceptibility to landslides in the VCca unit was apparently associated with concave areas, while in the VCnc unit these areas were less susceptible to landslides than convex areas. In the convex areas, susceptibility could be associated with slopes on which landslides coincide with areas of terracing or cattle tracks (Fig. 3).

The results also showed the contradictory role of NDVI as an indicator of vegetation cover in association with landslides. Dai and Lee (2002) and Zhou et al. (2002) also found distinct results in the relationship between the occurrence of landslides and vegetation cover. In the present case, NDVI acted as an activator factor, so it would be expected that higher NDVI values would result in higher susceptibilities to the occurrence of landslides. Taking into account the considerations highlighted by Pla (1997), one would infer that areas with greater vegetation cover should present better structured soils which the infiltration and distribution of water within the soil profile should improve. These are conditions which have been considered as landslide activating factors (Ayala 2006). Alternatively, the activator character of the NDVI could be associated with the existence of riparian forests in the neighbouring drainage networks; a large number of similar landslides were found in the study area in these zones.

Additionally, the behaviour of the different land cover types in the occurrence of landslides can be as activating or conditioning, as shown in the study area Inje, Korea, where farmland, mixed forest, coniferous forest, cropland was

considered as conditioning coverage, and the mixed forest of soft and hardwood pine forest and larch forest as activating coverage (Park et al. 2013).

3.2. Validation of the models

Table 4 shows the predictive power of each of the multiple logistic regression models generated for environmental variables related to the presence or absence of landslides. The predictive power of these models ranged between 78 and 89%.

The proposed models discriminated between points with and without landslides with a varying degree of precision and accuracy. Table 4 shows that the model with the greatest accuracy (0.8) and precision (0.87) was that for scenario 5, which corresponded to values for the VCnc and VCca geomorphic units for the year 1992. This was followed by the model generated for the VCca geomorphic unit corresponding to the same year. Both of these models included variables that indicated flow directions: south (4) and southwest (5), combined with high length and slope gradient values and also high vegetation cover values related to the areas that were most susceptible to landslides. The true negative for this model varied between 0.89 and 0.92 and the false negative, or commission error, ranged from 0.35 to 0.38. The model therefore accurately predicted landslide susceptibility at seven of the ten sites, while at the three remaining sites it either underestimated or overestimated this susceptibility.

Both the type and number of the variables included in each model and the variation in the accuracy and precision of each model suggest that the factors that condition or activate landslides do not only vary with location but also in function of time. Nevertheless, the limited accuracy of these models may have been related to the number of points used to generate and validate them.

The results obtained for each of the scenarios showed that the variables related to the occurrence of landslides change over time, and even change their behavior. This is because the variables and their interactions change over time, which is logical, given that we are evaluating a dynamic environment. In this respect, the purpose of this work was to show that care should be taken when setting the variables related to landslide susceptibility, because the application of statistical methods for a given time locality and not conclusive.

4. CONCLUSIONS

The temporal assessment of the occurrence of landslides showed that in a same geographic area different patterns of activating and conditioning factors can be found in space and time. This may question the use of use a single model to assess the susceptibility of landslides in large regions. The different models that were obtained revealed that there were distinct mechanisms responsible for landslide activation, even at the same location and at the same time. The selection of the most influential factors associated with the occurrence of landslides depended not only on the intrinsic characteristics of their formation, but also on variables related to the configuration of the local relief, drainage network and vegetation cover. The main variables related to the triggering of landslides were slope, orientation, sediment transport index (STI). The changes that occurred in the landscape affected the susceptibility to landslides, and even induced changes in the activity of some factors.

The variables selected for the regression models were relevant to the study area. Although the methodology can be used in other study areas, the models could have to consider other factors according to the intrinsic characteristics of theses areas.

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Table 2 Number of points with and without landslide scars and validation points at each combination of geological formations and the date of the landslide inventory.

Image	Year	Scenario	Geomorphic unit	With Landslide Scars	Without Landslide Scars	For Validation
Aerial photographs	1941	1	VCca	16	10	-
Aerial photographs	1971	2	VCca	91	90	18
Orthophotos	1992	3	VCnc	160	139	33
		4	VCca	50	53	12
		5	VCnc & VCca	110	192	45
Satellite image SPOT	2008	6	VCnc	159	177	32
		7	VCca	73	65	16
		8	VCnc & VCca	232	242	48

VCcn=El Chino-El Caño metatobas

VCca=El Carmen metalavas

Table 3 Variables included in each model of binomial multiple logistic regression analysis and predictive power.

Year	Geomorphic unit	Scenario	Variables	B ¹	P-value ²	Exp (B)
1941	VCca	1	FWD	-0.57	0.05	0.56
			Constant	1.22	0.20	3.39
1971	VCca	2	ALT	-0.012	0.00	0.99
			SLO	0.14	0.00	1.15
			ASP	0.008	0.00	1.00
			CI	-0.035	0.03	0.97
			Constant	3.82	0.00	45.44
1992	VCnc	3	STI	0.04	0.00	1.04
			FWD	-0.28	0.00	0.77
			NDVI	8.38	0.00	4351.12
			CI	0.03	0.03	1.03
			Constant	-4.35	0.00	0.01
	VCca	4	STI	0.03	0.01	1.03
			NDVI	17.64	0.00	4.58E7
			Constant	-6.39	0.00	0.00
	VCnc & VCca	5	STI	0.03	0.00	1.03
			FWD	-0.21	0.00	0.81
			NDVI	8.87	0.00	7098.04
			Constant	-3.72	0.00	0.02
2008	VCnc	6	SLO	0.26	0.00	1.29
			RP	-0.01	0.00	0.99
			NDVI ³	10.05	0.00	23 244.658
			Constant	-5.06	0.00	0.01
	VCca	7	PC	-195.13	0.00	0.00
			SLO	0.20	0.00	1.22
			ASP	0.01	0.01	1.01
			NDVI	24.40	0.00	3.96E10
			Constant	-10.15	0.00	0.00
	VCnc & VCca	8	SLO	0.19	0.00	1.20
			RP	-0.01	0.00	0.99
			NDVI ³	10.34	0.00	30 903.27
			Constant	-2.32	0.00	0.09

¹: Coefficient of each variable in the model; ²: significance level for the chi-square test; VCcn=El Chino-El Caño metatobas; VCca=El Carmen metalavas; Elevation (ALT); Slope gradient (SLO); Slope aspect (ASP); Convergence index (CI); Sediment transport index (STI); Flow direction (FWD); Normalized Difference Vegetation Index (NDVI); Planform curvature (PC); Relative position (RP).

Table 4 Confusion matrices: accuracy and precision of the landslide susceptibility models.

Year	Geomorph ic unit	Scenarios	Total	A	P	TP	TN	EO	EC	PP
1971	VCca	2	18	0.56	0.50	0.38	0.70	0.30	0.63	79
	VCnc	3	33	0.78	0.80	0.62	0.89	0.11	0.38	81
1992	VCca	4	12	0.58	1	0.29	1	0	0.71	80
	VCnc & VCca	5	35	0.80	0.87	0.65	0.92	0.08	0.35	78
	VCnc	6	32	0.66	0.31	1	0.59	0.41	0	85
2008	VCca	7	13	0.85	0.67	1	0.78	0.22	0	89
	VCnc & VCca	8	48	0.69	0.36	0.89	0.64	0.36	0.11	84

A= Accuracy; P= Precision; TP= True positive; TN= True negative; EO= Error of Omission; EC= Error of Commission; PP= Predictive power (%); VCcn=El Chino-El Caño metatobas; VCca=El Carmen metalavas