THE INFLUENCE OF DEM PROPERTIES IN LANDSLIDE SUSCEPTIBILITY ASSESSMENT AT A REGIONAL SCALE

Influencia de las Propiedades del Modelo Digital de Elevaciones en la evaluación de los Modelos de Susceptibilidad a Deslizamientos a escala regional

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Resumen: El objetivo de este trabajo es evaluar la influencia de los MDE con diferentes propiedades en la capacidad de predicción de los modelos de susceptibilidad a deslizamientos rotacionales, a través de uno de sus parámetros derivados más importantes en la inestabilidad de laderas (pendiente). Los resultados indican que los diferentes MDE influyen en la distribución de frecuencias de valores de pendiente. No obstante, la capacidad para predecir deslizamientos rotacionales permanece casi inalterada. La razón de esto es que las mayores diferencias de pendiente encontradas se producen en las zonas donde generalmente no hay deslizamientos. Así, la evaluación de la susceptibilidad a deslizamientos es relativamente independiente de la complejidad de la construcción del MDE. Sin embargo, esta conclusión solo es cierta si la calidad de los datos de las curvas de nivel para la elaboración del modelo está garantizada y los deslizamientos ocurren en las zonas de mayor pendiente.

Key words: DEM, slope angle, landslide, susceptibility, regional scale
Palabras clave: MDE, pendiente, deslizamiento, susceptibilidad, escala regional

1. INTRODUCTION

Digital Elevation Models (DEMs) are essential for landslide susceptibility assessment, directly through altitude data but also indirectly because some parameters derived from altitude are predisposing landslide factors.

Thus, the aim of this work is to assess the influence of different DEM characteristics in the predictive capacity of susceptibility to rotational slide modelling at the basin scale, using as a proxy the predictive ability of slope angle.

2. DATA & METHODOLOGY

2.1. Study area and data

The study area is the Alenquer river basin (Fig. 1), located north of Lisbon (Portugal). The catchment is 118 km^2 in area, and is a hilly landscape with altitudes ranging between 0 and 373 m. The major relief elements are strongly controlled by differences in the resistance and plasticity of the rocky formations, such as sandy-marls, sandstones and limestones.

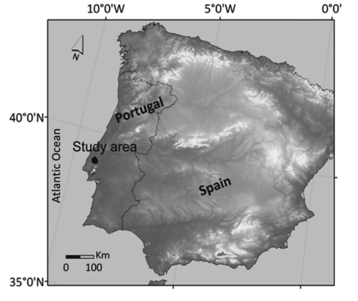

Fig. 1. Alenquer river basin.

Field work and interpretation of orthophotomaps (0.5 m resolution) allow the identification and mapping of 116 rotational slides (0.98 landslides/km^2), with a total unstable area of 663,508 m^2 (0.56% of the study area).

2.2. Digital Elevation Model (DEM)

The original elevation data used was a 1:10,000 contour map (5 m equidistance lines) and spot height data. In order to avoid distortion problems near the boundaries, all the DEMs are wider than the study area, and were computed using a

Triangular Irregular Network (TIN) model. These models allow a very accurate representation of relative complex topographical surfaces (Reis, 2006). However, these models may have difficulty in correctly representing flat areas, such as valley bottoms and hilltops. These areas are known to be responsible for the major altimetric errors in DEMs (Carrara et al., 1997), due to the lack of data inside closed contours or irregular reliefs.

In order to decrease the areas lacking data, automatic or semi-automatic procedures can be adopted (Eastman, 2003; Bonin and Rosseaux, 2005). In this work two different procedures were tested: (1) the production of an artificial auxiliary spot height network using a parabolic function; (2) an automatic sinkholes removal operation. The artificial network allows the calculation of about 50,000 additional height spots. However, many of these spots are superfluous as they are spatially redundant using the original contours and spot height data. For this reason, filters were used to remove points and avoid excessive and erroneous information.

Thus, auxiliary height spots which are within a buffer zone of 5 and 10 m from the original contours and spot data were removed. With this correction 30,000 spots were maintained with the 5 m buffer and only about 19,000 with the 10 m buffer.

The various approaches resulted in four DEMs with different amounts of input data: (a) single contours (CN), which often are the only available topographic data; (b) original contours and height spot data (CN+S); (c) additional artificial network height spots associated with 5 m buffering zones (CN+S+ASN5); and (d) similar to (c) but using a 10 m buffering zone (CN+S+ASN10). An automatic correction to remove sinkholes was applied to each, resulting in four further DEMs to be tested. Thus, 8 different DEMs were used to derive slope angles.

2.3. Slope angle and predictive capacity

Slope data extracted from DEM grid structured files (5 m cell sizes), were classified in 1º range classes. First, slope angle values were compared by means of absolute frequencies as well as the correlation percentage between maps based on different DEMs. Secondly, the landslide predictive capacity was assessed by plotting the success rate curves (Fabbri et al., 2002) and computing the area under the curve (Bi and Bennett, 2003). The susceptibility ranking of each slope class was performed based on the conditional probability to find a rotational slide in a specific slope angle class.

3. RESULTS & DISCUSSION

The visual comparison of the DEMs produced showed that there are slight differences between them (Fig. 2). However, the automatic removal of sinkholes (depressions) did not produce significant differences. This is due to the fact that, regardless of DEM analysed, the amount of corrected cells had no impact over the whole study area, with the percentage of corrected cells equal or lower to 0.11 (Table 1).

Table 1. Number of corrected cells by the removal of depressions

DEM	# corrected cells	% corrected cells
CN	650	0.01
CN+S	3544	0.07
CN+S+ASN10	3727	0.08
CN+S+ASN5	4969	0.11

Similar results were obtained for slope angle frequency distributions, as shown in Fig. 3. The absolute frequencies of slope angles clearly show that the higher the density of altimetry input data, the lower the frequency of values close to zero (Fig. 3A). Indeed, the main differences are observed for gradients lower than 15º. This results from the increased amount of elevation data, especially in flatter areas (hilltops and valley bottoms), which no longer have slope angles near zero but slightly higher gradients.

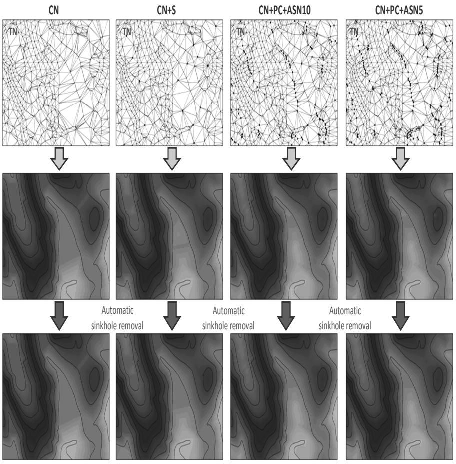

Fig. 2. Different input data DEM (1:10,000) in Alenquer river basin (CN – Contours; S-Height spots; ASN-Auxiliary Height Spot Network buffer 10 or 5m; TN-Triangulation network).

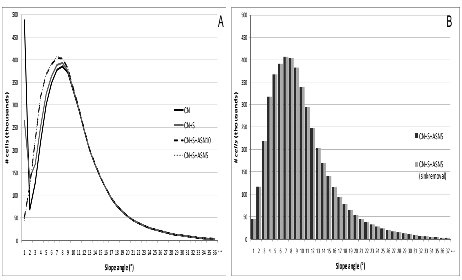

Fig. 3. Frequency distribution of slope angle derived from different DEMs in an Alenquer river basin.

Nevertheless, the comparison between DEMs with or without sinkhole removal reveals that the final results are almost identical and there were no significant differences in slope angles obtained with either DEMs (see Fig. 3B, for example).These results are further reinforced when analysing the agreement percentage between slope angle maps (Table 2). Comparison of DEMs with different input data shows that differences increase as more artificial height spots are added. Whilst the lowest spatial similarity found is 75%, if an error of ±1º of slope angle value is accepted, then the minimum agreement increases to 85% (Table 2). Once again the changes produced by automatically removing depressions have no significant impact on the percentage of agreement (> 98%) as shown in Table 3. However, the main question remains: will the small differences encountered affect the slope angle prediction ability in landslide modelling?

Table 2. Degree of overlap between tested DEMs (%)

±1°\=	CN	CN+S	CN+S+ ASN10	CN+S+ ASN5
CN	---	89.2	77.9	75.4
CN+S	94.3	---	83.3	80.1
CN+S+ASN10	86.7	91.0	---	94.7
CN+S+ASN5	85.4	89.5	98.0	---

Upper right – equal slope values (=); lower left – slope values with ±1°.

Table 3. Degree of overlap between DEM with or without sinkhole removal (%)

DEM/Slope angle	=	± 1
CN vs CN[c]	99.96	99.97
CN+S vs CN+S[c]	98.8	99.6
CN+S+ASN10 vs CN+S+ASN10[c]	98.6	99.1
CN+S+ASN5vs CN+S+ASN5[c]	98.4	99.0

Equal slope values (=); Slope value error of ±1°.

Analysis of the success rate curves shows that the differences in predictive ability are minimal (Fig. 4).

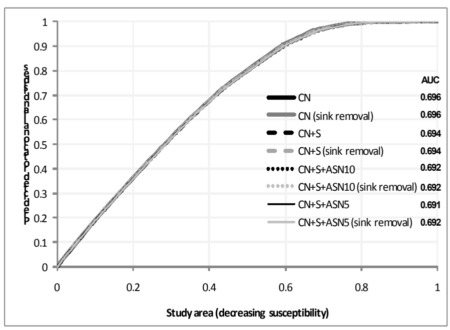

Fig. 4. Success rate curves and Area Under the Curve (AUC) of models using slope angles derived from different DEMs in the Alenquer river basin.

Nevertheless, the AUC reflects that DEM characteristics have some impact on the modelling results. In fact, it seems that

DEMs with more input data have the least predictive ability (Fig. 4). Results highlight that the areas in which slope values change are areas where landslides do not tend to occur, i.e. flat areas. Thus, using more altimetry data in those areas will increase the slope angle values and classify them as areas that are more prone to the occurrence of landslides. This reduces the discriminatory capacity of flat areas, which generally leads to a worse predictive capacity. Additionally, it should be pointed out that the use of an artificial height spots network forces all hilltops and valley bottoms to have a parabolic shape, which possibly introduces further errors.

4. CONCLUSIONS

The results obtained clearly show that slope angle frequency distributions obtained from different DEMs have several differences, which are mainly found in areas with low gradients (<15º). The removal of depressions has no significant impact on general gradient distributions. Nevertheless, differences in slope angle values have little impact in the predictive ability of rotational slides. Furthermore, it appears that the increment of altimetry data to produce DEMs leads to reduced predictive ability. This is due to differences in slope angle values being found mainly in areas where landslides tend not to occur (flat tops and valley bottoms). Therefore, more complex DEMs do not have a positive impact on regional landslide susceptibility modelling, which allows a higher confidence in the use of gradient data obtained from simple contours. Nevertheless, this idea is strongly dependent on the availability of good contour data and on the morphology of the study area. Additionally, further studies should be done to verify if results hold true for other morphometric variables derived from DEMs commonly used as predisposing factors in landslide susceptibility models.

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