Avances de la Geomorfología en España 2012-2014

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(editores)

UNIVERSIDAD DE EXTREMADURA

Sociedad Española de Geomorfología

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XIII Reunión Nacional de Geomorfología, Cáceres, 2014.

ISBN: 978-84-617-1123-9

XIII REUNIÓN NACIONAL DE GEOMORFOLOGÍA

Cáceres, 9-12 de Septiembre de 2014

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EARTH-FLOW SUSCEPTIBILITY ASSESSMENT IN THE MARVELLO RIVER BASIN (SICILY, ITALY)

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Abstract: In this study, statistical models of earth-flow susceptibility were prepared using logistic regression. The analyses were carried out in a small (51 km^2) basin of western Sicily, where 1,376 earth-flows were identified. To predict the spatial distribution of the mapped landslides, outcropping lithology and seven topographic attributes were exploited as explanatory variables. Before calculating these variables, a reconstruction of the pre-failure topography was performed. To evaluate the predictive skill and the robustness of the models, two groups made of five random subsets of earth-flows and stable cells were prepared. Absences of the first group were selected as individual cells whereas those of the second group where picked up using circular areas randomly distributed within the stable portions of the basin. The largely satisfactory accuracy and stability of the models demonstrated the reliability of the reconstructed pre-landslide topography. Furthermore, models prepared with the circular groups of absences showed better predictive skills.

Key words: Landslide susceptibility; Earth-flows; Geographic Information Systems (GIS); Logistic regression; Sicily

1. INTRODUCTION

The statistical modeling of landslide susceptibility relies on the assumption that new failures are more likely to occur under the same environmental conditions that led to landsliding in the past (Carrara et al., 1995). Hence, if the objective is to identify statistical relationships between terrain morphology and occurrence of landslides, the pre-failure topography has to be defined. Since slopes are modified by landslide occurrence, this task is not easily achievable if the date of the events is unknown, as happens when a landslide archive is prepared by visual interpretation of aerial/satellite imagery. To solve this problem, many investigators proposed to relate the occurrence of slope-failures to the topography of their surroundings (e.g. Süzen and Doyuran, 2004; Conoscenti et al., 2008; Nefeslioglu et al., 2008; Bai et al., 2010; Rotigliano et al., 2011; Costanzo et al., 2012, 2014). Conversely, Gorum et al. (2008) employed a reconstructed pre-landslide topography to calculate the probability of occurrence of deep-seated landslides.
In this research, Logistic Regression (LR; Hosmer and Lemeshow, 2000) was employed to evaluate susceptibility to earth-flows in a basin of Sicily. This method has been among the most adopted for assessing landslide susceptibility in the recent past (e.g. Ohlmacher and Davis, 2003; Lee, 2005; Van Den Eeckhaut et al., 2006; Nefeslioglu et al., 2008; Bai et al., 2010; Atkinson and Massari, 2011; Costanzo et al., 2014). To investigate the relationships between landslide occurrence and terrain morphology we carried out a reconstruction of the pre-failure topography. Moreover, as LR requires both presences and absences, we tested two different methods of selecting the negative cases. Hence, the main goals of the research are: i) to achieve accurate models of earth-flow susceptibility in the study area; ii) to verify the reliability of the reconstructed topography; iii) to compare the two methods adopted to select the absences.

2. MATERIALS AND METHODS

2.1. Study area

The experiment was carried out in the basin of the Marvello River, which is a tributary of the Belice River (Fig. 1). The basin extends for 51 km^2 in a hilly sector of western Sicily, characterized by gentle slopes and large outcrops of clays and marls. Water erosion and mass movements are the dominant denudation processes in the basin. Landslides mainly consist of earth-flows that are typically triggered by intense rainfall events occurring in autumn and winter. Earth-flows cause a serious economic damage to farmers as they reduce the extent of land surface available for cultivation.

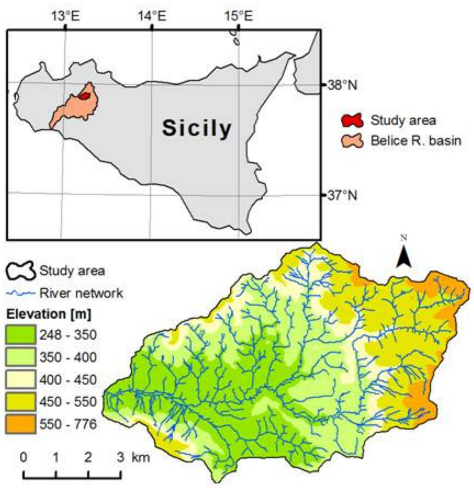

Fig. 1. Location and elevation of the study area.

2.2 Earth-flow inventory

An inventory of 1,376 earth-flows (average size: 3,335 m^2) occurred in the basin was prepared by analyzing high-resolution (pixel: 0.25 m) orthophotos dated 2008 and by carrying out field checks. Landslide mapping was also supported by the analysis of contour lines and hillshade images. These were extracted from a Digital Terrain Model (DTM), with a spatial resolution of 2 m, which is also dated 2008. As physical conditions favoring the occurrence of the landslides are those of their initiation zone, we identified the source areas of each of the mapped earth-flows.

2.3 Pre-failure topography

A reconstruction of the pre-failure terrain morphology was performed starting from the DTM cited above. Since this DTM (hereafter called DTM_2008) is more recent than the mapped landslides, we assumed that the elevation of the cells hosting earth-flows has been modified by their occurrence. Hence, a pre-failure DTM (hereafter called DTM_pre) was prepared by changing the values of the cells affected by the earth-flows. The pre-landslide elevation of these cells was calculated by exploiting the interpolation algorithm *topo-to-raster*, which is provided by the software ArcGIS 9.3.

2.4 Statistical modeling

A grid layer with a spatial resolution of 10 m was employed to map earth-flow susceptibility in the basin. For each cell of this layer, the values of the dependent and of the independent variables were defined. The dependent variable is dichotomous: 1 for cells intersecting source areas; 0 for cells outside landslide areas. As explanatory variables we selected outcropping lithology and the 7 topographic attributes, namely: i) elevation; ii) slope angle; iii) catchment slope angle; iv) convergence index; v) Topographic Position Index (TPI); vi) Topographic Wetness Index (TWI); vii) Stream Power Index (SPI). These attributes were extracted from the DTM_pre. SPI was calculated only on river cells and the average value of each stream segment was assigned to the grid cells of its contributing area.

To assess the accuracy of the likelihood models and the robustness of the method, we prepared two groups made of five subsets of presences and absences. The first group, named A, was obtained by joining five random samples of source areas with five samples of absences that were randomly picked up as individual cells (Fig. 2a). The second group, named B, was prepared by combining the same samples of positives of the group A with five samples of negatives that were selected using random circles with a size equal to the average size of the source areas (Fig. 2b). Each of the subsets was used to train a predictive model and to test the models trained on the other four subsets of the same group.

The spatial probability of landslide occurrence was calculated using LR with a backward stepwise selection of the variables. A LR-model was prepared for each of the ten subsets of cells. The predictive performance of these models and their fit to the training data were assessed by preparing Receiver Operating Characteristics (ROC) curves and by computing the area under the ROC curve (AUC). To interpret the AUC values we employed the classification proposed by Hosmer and Lemeshow (2000), who consider a model as acceptable, excellent or outstanding, if AUC values are higher than 0.7, 0.8 and 0.9, respectively.

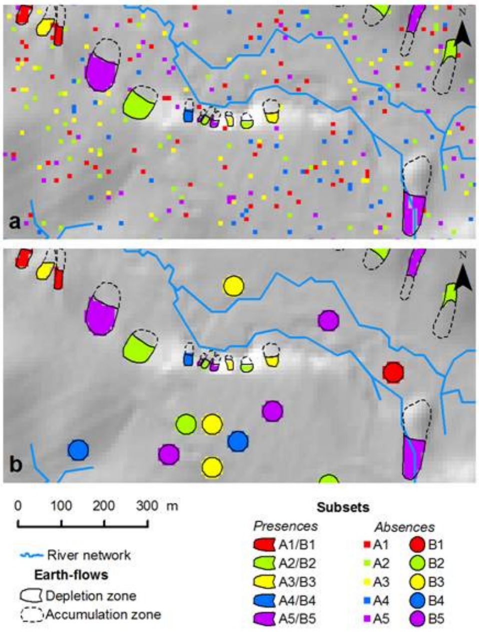

Fig. 2. Presences and absences of subsets A (a) and B (b) in a sample sector of the basin.

3. RESULTS AND DISCUSSION

Fig. 3 shows a portion of the grid layer calculated as the difference between the DTM_pre, which is assumed to reflect terrain elevation before landslide occurrence, and the DTM_2008. The cells of this grid layer have a value of zero outside landslide areas whereas assume positive and negative values within depletion and accumulation zones, respectively.
Table 1 reports the AUC values obtained by comparing each of the ten LR-models and the occurrence of presences and absences within the training subset and the four test subsets.
These values indicate an excellent predictive skill of all the models trained on the subsets of group B (AUC range: 0.819 – 0.866) whereas models calibrated using the A subsets show a slightly lower accuracy that is from acceptable to excellent (AUC range: 0.782 – 0.819).
The goodness-of-fit is excellent for all the models, but again those trained on the B subsets (AUC range: 0.857 – 0.881) have a better discriminating power than the models calibrated on the A subsets (AUC range: 0.802 – 0.827).

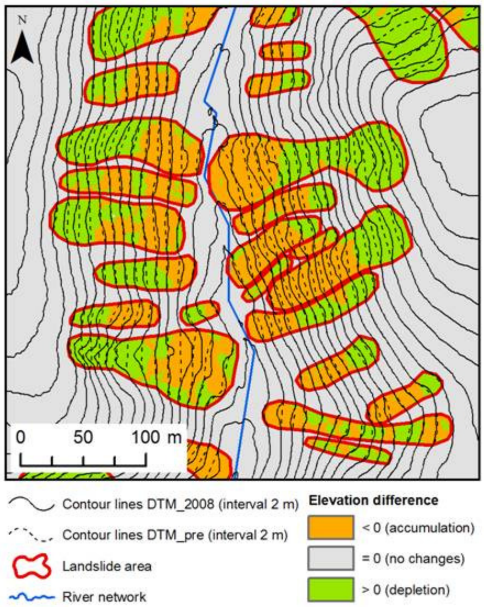

Fig. 3. Grid calculated as the difference between the DTM_pre and the DTM_2008.

Table 1. AUC values calculated for both training (in bold) and test subsets.

	LR-models				
Subsets	LR(A1)	LR(A2)	LR(A3)	LR(A4)	LR(A5)
A1	**0.825**	0.819	0.818	0.816	0.814
A2	0.792	**0.802**	0.782	0.791	0.783
A3	0.813	0.810	**0.823**	0.807	0.803
A4	0.799	0.800	0.796	**0.808**	0.788
A5	0.804	0.806	0.804	0.802	**0.827**
	LR(B1)	LR(B2)	LR(B3)	LR(B4)	LR(B5)
B1	**0.879**	0.862	0.862	0.853	0.860
B2	0.839	**0.861**	0.842	0.836	0.845
B3	0.859	0.866	**0.877**	0.841	0.860
B4	0.838	0.842	0.819	**0.857**	0.827
B5	0.846	0.859	0.843	0.839	**0.881**

However, as the difference between apparent accuracy (measured on the training data) and validated accuracy (measured on the test data) is small for all the models, we can conclude that the procedure has not suffered from overfitting. Furthermore, within both the groups of subsets, the LR-models show a similar predictive skill, demonstrating that the method is robust when changes of the learning and validation data are performed.

In light of the better performance of the models calibrated on the B subsets, these were used jointly to fit a further LR-model that allowed us to prepare the earth-flow susceptibility map of the Marvello River basin (Fig. 4).

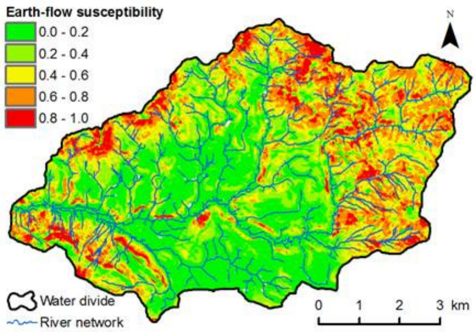

Fig. 4. Earth-flow susceptibility map of the Marvello River basin.

4. CONCLUSIONS

The method adopted allowed us to prepare earth-flow susceptibility models that effectively predict the spatial occurrence of these slope-failures in the study area. Furthermore, the largely acceptable accuracy of the models attests for the reliability of the method used to reconstruct the pre-landslide topography. Finally, the selection of the absences intersecting random circles provided LR-models with a higher accuracy than those trained on absences randomly picked up as individual cells.

Acknowledgements

This research was developed in the framework of the projects: FLUMEN (project number: 318969), funded by the EU (FP7-PEOPLE-2012-IRSES); SUFRA_SICILIA funded by the Department of Earth and Marine Sciences of the University of Palermo and by the Sicilian Government.

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