Strategies to estimate ground susceptibility to landslide reactivation. A probabilistic application in W Belgium (Oudenaarde)

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ABSTRACT: In the hilly region of the Flemish Ardennes in western Belgium, no new big deep-seated landslides have occurred for decades, whereas several reactivation episodes were recently observed in ancient landslides. We selected a test area comprised of 13 rotational landslides located close to the town of Oudenaarde in order to predict the susceptibility of their main scarp to retreat.

We propose here two probabilistic models based on a fuzzy set approach. The models use empirical distribution functions (EDFs) as favourability values to build membership values and combine them by using the fuzzy Gamma operator. Based on Kolmogorov-Smirnov tests applied to these EDFs to select the most relevant data, a first model was obtained bases on a combination of 5 quantitative variables: slope angle, distance from cultivation located upstream of the main scarp, slope aspect, elevation and profile curvature. Another, more empirical approach based on the a posteriori analysis of the prediction-rate curves was applied to select the 4 variables of a second model: slope aspect, plan curvature, vegetation index and focal flow. According to the prediction-rate curves and the resulting susceptibility maps, the empirical model appears more efficient in locating the main scarp areas most prone to reactivation.

KEYWORDS : Landslide reactivation, susceptibility, probability, fuzzy set membership function.

1. Introduction

Several conditioning parameters (geomorphic, geologic, environmental) are generally required in landslide prediction studies. Whatever the criterion used (empirical, heuristic or statistical) to select the most appropriate combination of conditioning variables to build a pertinent landslide susceptibility map, this task requires a particular attention.

Knowing that reactivation of ancient big deep-seated landslides is a more frequent phenomenon than new landslide occurrences and therefore represents a higher hazard in West Belgium (Dewitte, 2006; Van Den Eeckhaut, 2006), the aim of this research is to locate the parts of pre-existing landslide scarps most susceptible to reactivation. Strictly speaking, our study area corresponds thus to the main scarps of the landslides and the reactivated zones are those scarp parts undergoing renewed collapse.

2. Study area

This study focuses on two hills of the Flemish Ardennes situated along the river Schelde close to the town of Oudenaarde (Fig. 1). These 60-m-high hills culminate between 75 and 85 meters. In the north, the Leupegem hill is affected by 3 landslides. To the south, 10 landslides developed on the slopes of the Rotelenberg hill.

These 13 landslides extend in subhorizontal (dip to the north < 1°) Eocene sediments composed of alternating clays and clayey sands on which a perched water table can develop. Within these formations, the Aalbeke Member consists of 10-m-thick homogeneous blue massive clays, and has been recognized as the layer most sensitive to landsliding (Fig. 1).

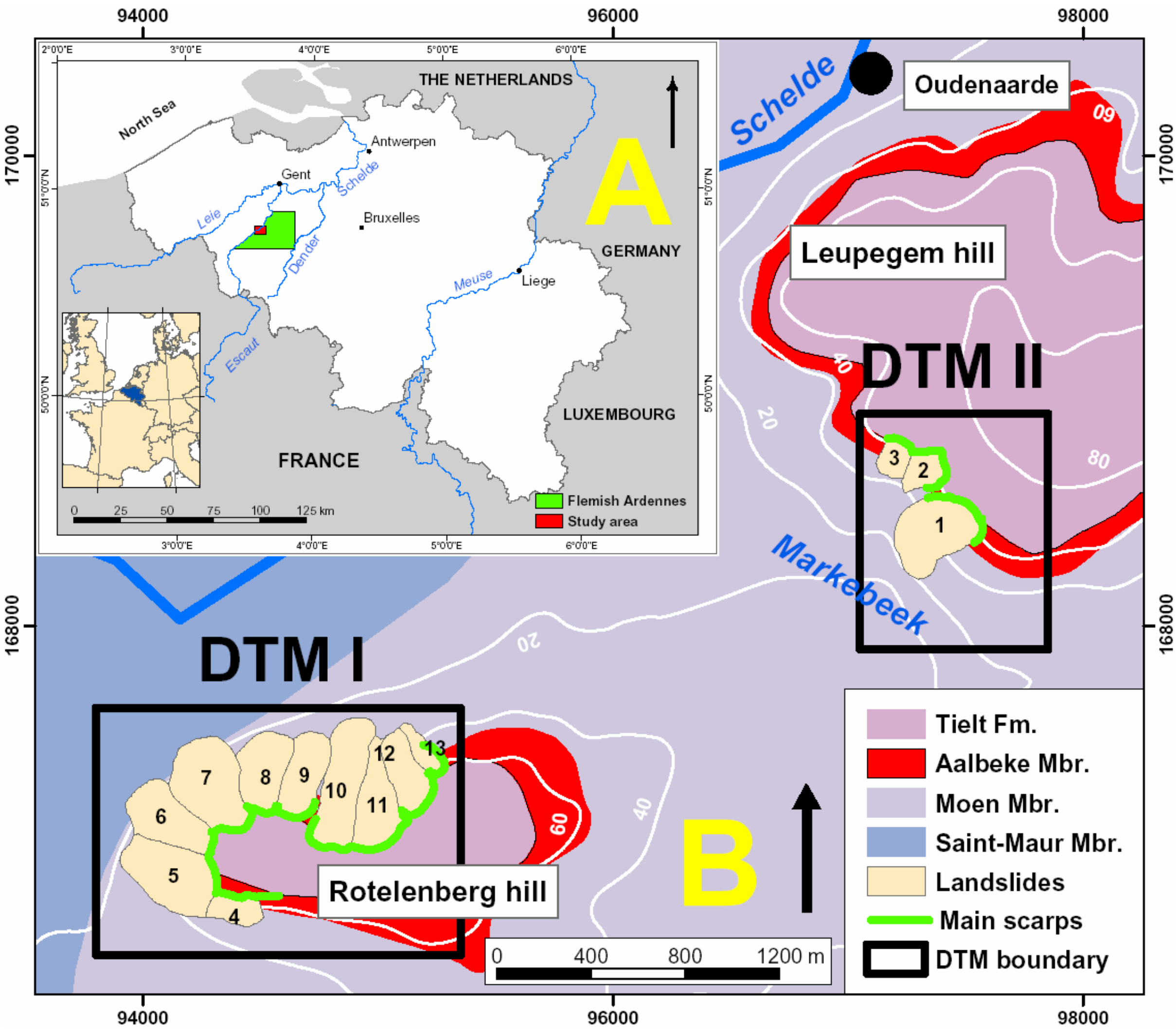

Fig. 1. (A) Location map of the Flemish Ardennes and the study area. (B) Location of the two hills of the study area with the lithological setting and the boundaries (scars) and the main scarps of the 13 landslides considered in the analysis. The quadrangles I and II locate the two DTMs used in the analysis.

3. Data and methodology

3.1. Data collection

The scarp reactivations were identified from the comparison of stereophotogrammetrically obtained DTMs (2 m resolution) for 1952 and 1996 (Dewitte and Demoulin, 2005; Dewitte, 2006). The reactivated scarp segments (26 occurrences) were used as the dependent variable in the modelling. We also considered 13 independent variables as potential conditioning variables, all of them taken at the same resolution (2 m) and computed for 1952 and 1996: elevation, slope angle, slope aspect, flow accumulation, focal flow, profile curvature, planform curvature, distance from stream network, land use, lithology, distance from cultivation upstream of the main scarp, distance from Aalbeke Member and vegetation index (Dewitte et al., 2006).

For each variable of 1952, two empirical distribution functions (EDFs) were computed, respectively for the reactivated (EDF-R) and non-reactivated ($\overline{\text{EDF-NR}}$) pixels as shown in Fig. 2 for the slope angle data layer. The values of the EDFs were then used to compute the favourability values necessary to the prediction.

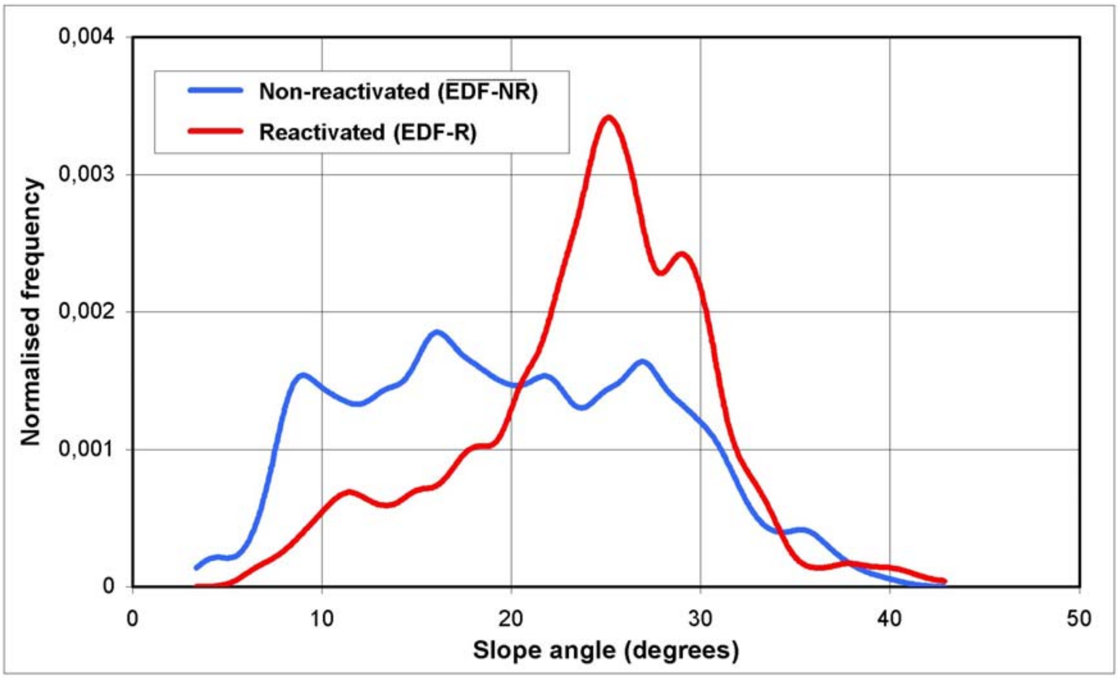

Fig. 2. Empirical frequency distribution functions of the slope angles within reactivated and non-reactivated pixel population.

3.2. Fuzzy set model

The fuzzy set prediction model combines the favourability values by using the fuzzy set theory of Zadeh (1965). In order to give to each pixel of each input data layer a membership value ranging from 0 to 1, we have computed a membership function $\mu(x)$ for each input data layer as follow:

$$\mu(x) = \frac{\text{EDF-R}}{\text{EDF-R} + \overline{\text{EDF-NR}}} \tag{1}$$

where EDF-R is the empirical distribution function of the reactivated areas and $\overline{\text{EDF-NR}}$ is the empirical distribution function of the non-reactivated areas.

A variety of operators can be employed to combine the membership values $\mu(x)$ obtained for each input data layer (Zimmermann, 1991; Bonham-Carter, 1994). Following Chung and Fabbri (2001), we used here the fuzzy Gamma operator which was defined by Zimmermann and Zysno (1980) as a combination of the fuzzy algebraic product and the fuzzy algebraic sum. The joint membership function $\mu_S(x)$ of the fuzzy set S for a particular pixel x is defined as:

$$\mu_S(x) = \left[\prod_{j=1}^{m} \mu_{S_j}(x)\right]^{1-\gamma} \times \left[1 - \prod_{j=1}^{m}\left(1 - \mu_{S_j}(x)\right)\right]^{\gamma} \qquad (2)$$

where γ is a parameter chosen in the range [0, 1], $\mu_{S_j}(x)$ is the fuzzy membership function for the j^{th} map, and j = 1, 2, …, m are the maps (i.e. data layers) that have to be combined. This Gamma operator was used in the modelling with γ = 0.5 to ensure a compromise between the "decreasing" effects of the fuzzy algebraic product and the "increasing" effects of the fuzzy algebraic sum (Dewitte et al., 2006).

4. Comparison of the models

The model comparison was performed according to their prediction rate and the relevance of their susceptibility map.

The Kolmogorov-Smirnov two-sample test applied to the EDFs used in the modelling revealed that five data layers seem to best explain the main scarp reactivation (Dewitte, 2006): slope angle, distance from cultivation located upstream of the main scarp, slope aspect, elevation and profile curvature. The model computed with these five data layers (called "K-S model") was compared with the four data layers model exposed by Dewitte et al. (2006) which results from an empirical selection of the variables considering the prediction rate of each individual data layer. The conditioning variables included in this second model (referred as the "empirical model") are: slope aspect, planform curvature, vegetation index and distance from cultivation located upstream of the main scarp.

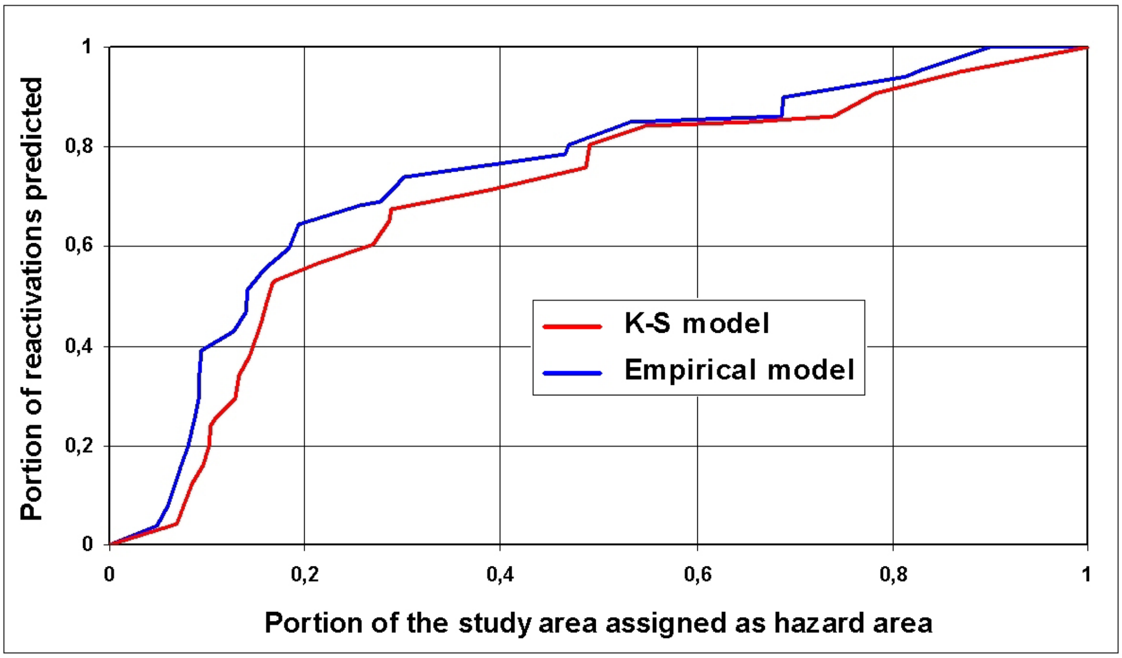

Fig. 3. Prediction-rate curves obtained by cross-validation. For the empirical model, the highest hazardous 20% of the study area contain 65% of the predicted reactivations.

First, two susceptibility maps were constructed with the data layers of 1952. With respect to their prediction-rate curve, the empirical model appears to be most appropriate to predict the main scarp reactivations (Fig. 3). These prediction curves were obtained by the same cross-validation procedure as that described by Dewitte et al. (2006).

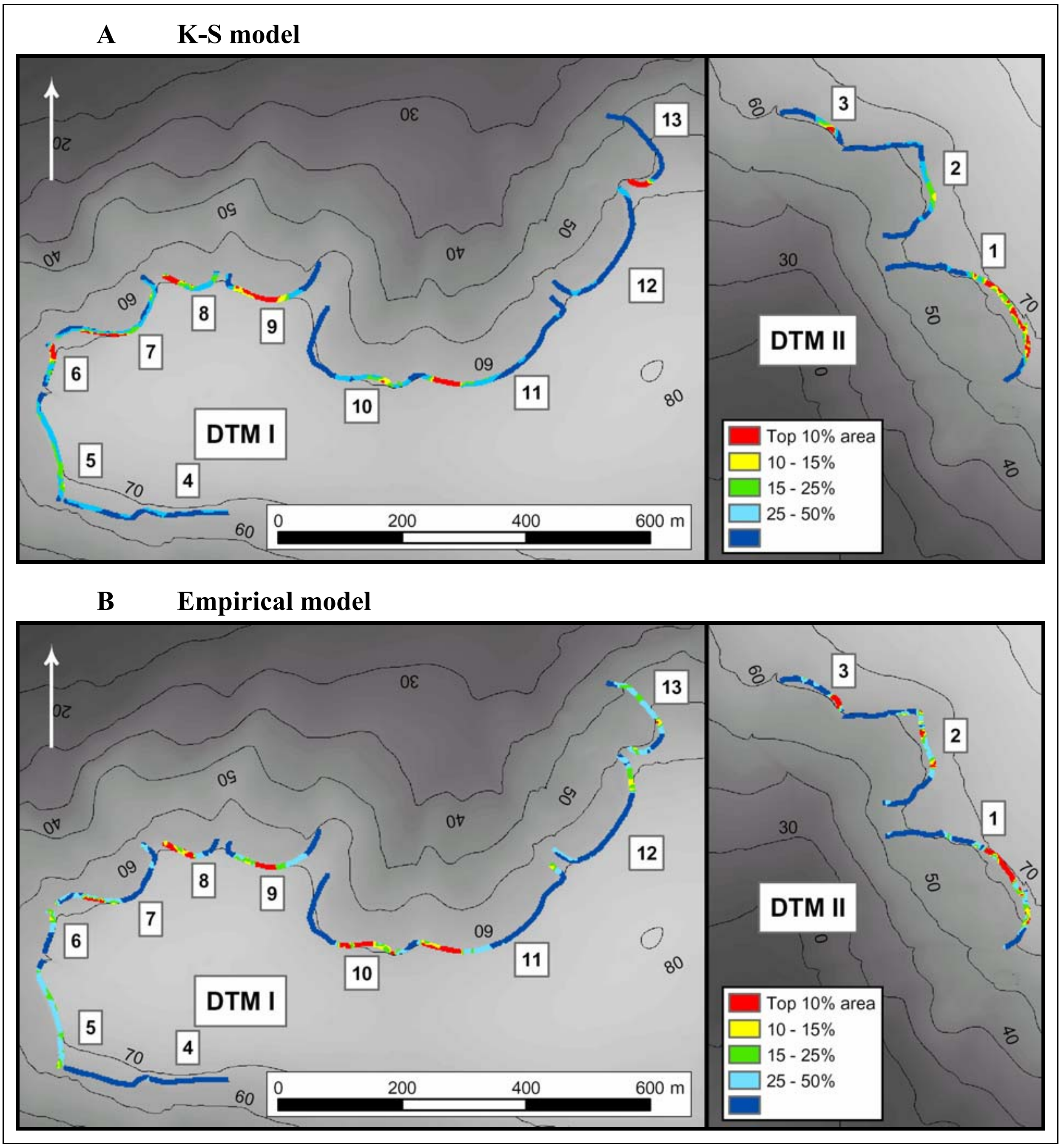

Fig. 4. Susceptibility maps of the landslide reactivation hazard obtained with the statistics of the 1952 models.

However, since the prediction curves of the two models appear only marginally different, the comparison of their respective susceptibility map is an essential step to know which one best performs.

The two susceptibility maps corresponding to the present-day situation (i.e. 1996) presented at Fig. 4 were obtained in two steps. The susceptibility maps of 1952 were built first and the statistics (i.e. membership values) of these models were then applied to the 1996 data layers.

The 10% most hazardous areas located on the two susceptibility maps presented at Fig. 4 correspond fairly well to the reactivated areas delimited between 1952 and 1996. However, according to the susceptibility maps (Fig. 4), the empirical model appears to be more realistic in the sense that the top 10% most hazardous areas are predicted across the whole height of the main scarp. This susceptibility configuration reflects better what has been recently observed (after 1996) than that of the K-S model, notably in the landslide 1, but also in other landslides of the Flemish Ardennes (Dewitte, 2006; Van Den Eeckhaut, 2006). The reactivations indeed affected the whole height of the scarp.

According to the prediction-rate curves and the resulting susceptibility maps, the empirical model appears therefore more appropriate to locate the main scarp areas most prone to reactivation.

5. Conclusions

This research on the landslide reactivation hazard in the hilly area of the Flemish Ardennes has shown that the way in which we select the conditioning variables determining the main scarp displacements has an influence on the retained set of variables and therefore on the resulting susceptibility maps.

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