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Discussions

Which data for quantitative landslide susceptibility mapping at operational scale? Case study of the Pays d'Auge plateau hillslopes (Normandy, France)

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Abstract

The objective of this paper is to assess the impact of the datasets quality for the landslide susceptibility mapping using multivariate statistical modelling methods at detailed scale. This research is conducted in the Pays d'Auge plateau (Normandy, France) with a scale objective of 1 / 10 000, in order to fit the French guidelines on risk assessment. Five sets of data of increasing quality (considering accuracy, scale fitting, geomorphological significance) and cost of acquisition are used to map the landslide susceptibility using logistic regression. The best maps obtained with each set of data are compared on the basis of different statistical accuracy indicators (ROC curves and relative error calculation), linear cross correlation and expert opinion. The results highlights that only high quality sets of data supplied with detailed geomorphological variables (i.e. field inventory and surficial formations maps) can predict a satisfying proportion of landslides on the study area.

1 Introduction

For the natural hazards management, scientists, stakeholders and government authorities need detailed information about the future possible location of damaging phenomena at large scale. In France, as in many countries disposing of national Risk Assessment Methods (RAMs), the scale of analysis is imposed by official guidelines. The French RAM (i.e. PPR, Plan de Prevention des Risques) imposes a minimum scale of 1 / 10 000 which was selected to fit the municipality cadastral maps (MATE/METL, 1999). The PPR is divided into 3 main steps: (1) hazard mapping, (2) vulnerability mapping, and (3) risk levels mapping.

The first step of hazard assessment is the susceptibility analysis and mapping (i.e. landslide spatial probability). For the landslide hazard analysis, detailed information on historic records of both landslides occurrences and rainfall or/and earthquake are necessary to determine triggering thresholds. The non-availability of these data often constitutes an operational limitation (Brabb, 1984; Mudler, 1991; Guzzetti et al., 1999; Van Westen et al., 2006). Over large areas, these data are difficult to obtain or requires important measurements (e.g. field investigations, geophysical measurements, climatic time series analysis, etc.). Therefore, most of the time, the operational hazard maps are susceptibility maps, considered as "relative hazard maps" (Soriso Valvo, 2002; Guzetti, 2006).

There is a broad consensus since twenty years that defines two main approaches for the susceptibility mapping (Van Westen et al., 2006). (1) The direct susceptibility mapping, where the geomorphologist or engineer, based on his own experience of terrain knowledge determines and depicts directly the degree of susceptibility. This method is the most widely used for establishing of official susceptibility and hazard maps in operational contexts. (2) The indirect susceptibility mapping, often considered more objective by scientists. These methods uses GIS integrated statistical models based on the spatial relationship between the landslide location and a set of controlling factors. The indirect methods have been applied and improved by scientists (e.g. Carrara et al., 1991; Guzzetti et al., 1999; Van Westen, 2000, 2003) but still few in official RAMs (Malet and Maquaire, 2008). These statistical approaches can be sometimes used complementarily with the direct approaches. They can assist in choosing the most revealing datasets to take into account in the susceptibility/hazard zoning (Van Westen et al., 2008; Ercanoglu et al., 2008). These studies are generally conducted at the 1 / 25 000 or 1 / 50 000 scale using the directly available datasets (Van Westen et al., 2006; Fell et al., 2008). Even if these spatial statistical approaches (bivariate or multivariate) give good results, a problem of compatibility of the scale of analysis can easily arise between the 1 / 10 000 scale (mapping objective) and the 1 / 25 000 or 1 / 50 000 scale (most accurate datasets available). Some studies have shown that it is possible to apply these methods at the 1 / 10 000 scale with an adapted procedure and a particular attention on the model calibration (Thiery et al., 2007). Nevertheless, two main steps increase the cost of these approaches and limit their use in operational contexts: (1) the construction of accurate database and (2) the calibration and

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validation of the models. These methods are generally developed in complex mountainous environments (for example the Apennines or the Umbria region in Italy, Atkinson and Massari, 1998; Guzzetti et al., 2006). Nevertheless, the plateau and hilly regions of the north west of Europe are as well affected by slope instability phenomena as for example, among others, the Champagne-Ardennes in France (Mare et al., 2002; Van Den Eeckhaut et al., 2010), the Yorkshire in England (Foster et al., 2007), the Flemish Ardennes in Belgium (Van Den Eeckhaut, 2006), the Pays d'Auge in France (Fressard et al., 2010, 2011). Instead of a known activity and serious management issues, still few scientists have studded them compared to mountain or coastal regions.

This research is conducted on Pays d'Auge plateau hillslopes which are characterized by the frequent triggering of shallow landslides. Some attempts to map susceptibility with indirect methods were conducted in this region (Fressard et al., 2010), but remains in the exploratory research framework. However, there's a demand from the stake holders in obtaining tools that could help in landslides hazard managements (CARIP, 2005). It is then necessary to assess the possibility of defining an adapted and operational procedure to map the landslide susceptibility using statistical methods in this region.

Instead of comparing different quantification methods of the susceptibility, we propose a comparison of the results obtained with various sets of data with different quality. The variations of the quality of the datasets are referred to the resolution and accuracy of the data, but also to the cost (both economical and time spent for the databases construction). These two aspects are important for the scale fitting and reliability of the results. Due to the difficulty of obtaining accurate data and landslides inventories, this study concentrates on a relatively small area (i.e. 24 km^2). This area is considered as a test study site that aims to calibrate the methodology and identify the necessary data to expect going further in the susceptibility mapping over larger areas in a statutory framework.

The selected mapping methodology is the logistic regression, considered as robust by many authors (e.g. Süzen and Doyuran, 2004; Brenning, 2005; Van Den Eeckhaut et al., 2009; Rossi et al., 2010; Nandi and Shakoor, 2010; Oh et al., 2010; Pradhan and Lee, 2010) and has already given good results in similar hilly environments (Van Den Eeckhaut et al., 2009, 2010). The method is simple to apply and can be directly implemented into GIS (Kemp et al., 2001; Sawatzky et al., 2009a,b).

The model is run with five sets of data with an increasing quality. The improving quality considers all the thematic data, i.e. inventory, landuse data, topographic data and geomorphological data. The statistical performance, but also the general aspects and shapes of the map are assessed and analysed through the receiver operator characteristic (ROC) curve, the relative error calculation and expert opinion. All final modelled maps are compared on the basis of the previous quality indicators, linear bivariate correlation (V Cramer and Pearson tests) and expert opinion. Finally, the possibility of using the data driven methods and expected improvements in operational landslide hazard management is discussed.

2 Study area and landslides

2.1 General presentation and geomorphology

The pays d'Auge is an agricultural region of Normandy of approximately 2500 km^2 (Fig. 1). The main activity consists in cattle and horse breeding that shaped this typical hedgerow landscape, as in many regions of the north west of Europe. This region has a maritime temperate climate with a mean annual rainfall around 700 $mm\,yr^{-1}$ regularly distributed over four seasons.

The regional topography, lithology and hydrology are important environmental factors controlling slope stability (Lautridou, 1971). The Pays d'Auge is a homogeneous geomorphologic entity characterized by a plateau with soft slopes and a massive cuesta constituting its western termination (Fig. 1). Hillslopes are generally not very steep. Only 10 % of the hillslopes have a gradient over 10°, and 70 % area ranked between 5°

and 10°. In the late tertiary and early quaternary, differential erosion shaped the actual topography of the area (Debrand-Passard et al., 1987).

The lithology consists in four major entities covering five main stratigraphic periods, from Oxfordian to Cenomanian. This plateau is characterized by a monocline structure with a soft bedding of 3 degrees and a general north east orientation (Debrand-Passard et al., 1987). The main formations are, from downslope to upslope (Fig. 1): (1) oolitic limestone, (2) marls and clays with intercalated limestone beds, (3) glauconitic clays and ferruginous sands, and (4) chalks, constituting a perched ground water (Fig. 1).

The bedrock is covered by various types of surficial deposits that can be classified in three groups: (1) very surficial (i.e. around 60 cm) alteration of the marls and clays. (2) Aeolian loess deposits located on the plateau and punctually on the downslope breaks. (3) Formations flowed on the upper part of the hillslopes derived from the local substratum alteration (i.e. chalks, clays and sands). This dynamic is the result of the low mechanical properties of the flint clays, the glauconitic clays and the ferruginous sands, combined with the upslope water discharge. On the upper part of the hillslopes, the surficial formations are often a complex mix between the upper flint clays, glauconitic clays and ferruginous sands. This general flow dynamic was initiated during the quaternary (Lautridou, 1971), and is sometimes still active nowadays (Porcher and Guillopé, 1979). The thickness of the formations is extremely variable and is function of the upstream materials, water supply and of the evolution and age of the process. They are considered as the most sensitive to landsliding on the study area.

From a regional point of view, the repartition of these surficial formations is relatively unknown. As a result, no detailed mapping has already been engaged. This point has locally necessitated detailed investigations that would be described on the methodology section of this paper.

2.2 Landslides typology and activity

A detailed landslide inventory was performed during the winters 2010 and 2011 over 130 km^2. Morphology, nature, freshness and size of the scarps and fractures of the landslides were described to estimate the type and relative age of the events. The assessment of the landslides activity consists in four classes as proposed by McCalpin (1984); i.e. active, inactive young, inactive mature and stabilized (Fig. 2).

Two main types of mass movements were identified on the study area, solifluction and landslides (Figs. 2 and 3). No detailed investigations were engaged on the solifluction processes as they were considered inherited from quaternary and stable. For the landslides processes, three main types can be identified (Cruden and Varnes, 1996; Maquaire and Malet, 2006): (1) deep seated landslides, (2) shallow landslides and more rarely (3) bank shallow landslides (Figs. 2 and 3). The field campaigns have permitted observing that the deep seated landslides are mostly old and were therefore mostly considered as naturally stabilized and were not integrated in the model. Some examples of reactivations can be found in the literature, but they often corresponds to human actions (excavations, road buildings etc.) (Masson, 1976; Brosseau et al., 2011).

The most frequent and active landslides are shallow translational and rotational landslides representing respectively 45 % and 20 % of the observed landslides phenomena (Fig. 2). Very similar predisposing factors were supposed for the two types of shallow landslides.

3 Datasets and methodology

3.1 Database available for the landslide susceptibility mapping

For the landslide susceptibility analysis, four main types of data are generally employed: (1) landslide inventory, (2) topographic data (e.g. slope angle, slope aspect, slope curvature; extracted from DEMs), (3) materials data (geology and/or surficial formations) and (4) landcover data. These data can be provided by different institutes, commercial companies or specifically created for the study. The source and the methodology employed in the production of these datasets have a significant impact

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on the quality/accuracy and on the cost of the data (Glade and Crozier, 2005). For this study, five sets of data of different quality and cost are tested (from directly available and free, to specifically created or purchased). A summary of the sources, original scale or pixel resolution and relative estimated cost for each set of data can be found in the Table 1. Some cartographic examples of the available data are provided in the Figs. 5 and 6. The Table 2 show the different data combinations that were used to compile the five different datasets (DS). For the analysis, a small study area of 24 km^2 was selected (Fig. 1). The selection of this study area was guided by the amount of data available, its accessibility and its important landslide activity.

3.1.1 Landslides data

Three landslides inventories were acquired using different methods. These inventories show large differences regarding to the accuracy and number of identified landslides (Fig. 4):

1. The first landslide inventory was obtained using the directly available BDMvt (French geological survey landslide data base, Couëffé et al., 2005). This is a free database that can be directly downloaded on the BRGM website. The only landslides referenced by the BRGM in the database with a high degree of certainty and a reasonable spatial accuracy were used for the analysis. Finally, 61 landslides are identified on the area without any distinction of type and activity.

2. The second landside inventory was obtained using only the air photo-interpretation (A.P.I). This inventory contents a low number of landslides (i.e. 15 without any distinction of type and activity). The landcover limits the landslide recognition and identification. Moreover, the distinction of type and activity of the landslides is difficult and imprecise on the only basis of the photo-interpretation of the ortho-images (quality and resolution of the images, landcover).

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3. The third landslide inventory was compiled at the 1 / 5000 scale through air-photo interpretation and systematic field survey. The landslides were mapped in the field using a cartographic GPS with 1 meter of accuracy. The landslides boundaries were classified into two zones: (1) landslide initiation zone and (2) landslide accumulation zone (Atkinson and Massari, 1998; Van Den Eeckhaut, 2006; Thiery et al., 2007). Morphological parameters, landslide type and state of activity were stored in a GIS database. This inventory is considered exhaustive and contains 52 mass movement phenomena: 12 solifluction processes, 13 deep seated landslides and 27 shallow landslides (Fig. 4).

3.1.2 Topographic data

Three DEMs were obtained from different providers and methods. These DEMs allow extracting the various topographic parameters that would be integrated in the models (e.g. slope angle, slope curvature, slope aspect etc.):

1. The first DEM is the BDAlti®, provided for free by the French Geographic Institute (I.G.N) with a pixel resolution of 25 m (Figs. 5 and 6).

2. The second DEM was extracted from the digitalized contour lines of the I.G.N topographic maps at the 1 / 25 000 scale (Figs. 5 and 6) using the modified spline algorithm proposed by the ANUEDM software (Hutchinson, 1996; Hutchinson and Gallant, 2000). Different interpolations were realized and compared. The best DEM was selected following the procedures of Carrara et al. (1995) and Hutchinson and Gallant (2000).

3. The third DEM is obtained via IFSAR imagery (InterMap, 2008). The initial resolution of this DEM is 5 m (Figs. 5 and 6) and is then more in accordance with the objective of a 1 / 10 000 scale map resolution (McBratney et al., 2003; Hengl, 2006). The DEM was corrected using the denoising algorithm of Stevenson et

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al. (2010) in order to avoid the artefacts related to the radar data (Maire et al., 2003).

3.1.3 Materials data

Two maps representing the materials of the study area were acquired (Fig. 5):

1. The 1 / 50 000 scale geological maps (BRGM, French geological survey) were digitalized and classified according to the lithology.

2. For the shallow landslide susceptibility mapping, surficial formations map was considered more relevant than the traditional ground geology map. This surficial formations map was created using extensive field survey and 108 boreholes and augurings of various depths on the study area (81 boreholes available from the BRGM database and 27 specific augurings). These boreholes were interpreting along representative profiles to identify the rules of deposition and dynamics of the surficial formations. These rules were then applied to the entire study area to map the surficial formations (Fig. 5). A particular attention was paid to the definition of the boundaries of the formations and their link with the topography in order to obtain a map that fits with the 1 / 10 000 scale.

3.1.4 Landuse data

Two different landuse maps were tested in this research and show large differences regarding to their quality (Fig. 5).

1. The landuse data were obtained throughout the Corine Landcover database provided free of charge by the European Environment Agency (EEA).

2. Because the Cornine landcover data is not very accurate (Thiery et al., 2003), interpretation and digitalizing on the 2009 orthorectified images of the French Geographic Institute (I.G.N) were performed to obtain detailed landuse data. Six

landuse classes were identified: forest, grassland, cropland, orchards, fallow fields and urban areas.

3.2 Selecting the right pixel size

A grid cell model was used to map the susceptibility as they are the most commonly used spatial representation to model susceptibility. To compare the models, all thematic layers were resampled at the same cell size and all data perfectly overlap. The choice of the raster images pixel size was guided from both reference to the imposed cartographic scale and the original scale/resolution of the available datasets. As pointed out Hengl (2006), no ideal grid resolution exists. This author suggests that the cell size should be the equivalent of 0.0005× the scale number; i.e. a pixel should represent the quarter of the maximum location accuracy on the map, usually set at one millimetre (McBratney et al., 2003). In our case, mapping at the 1 / 10 000 scale leads to work with a 5 m cell size. Regarding the original cell size and contour lines density on the available thematic maps, it was considered few realistic selecting such a detailed pixel size. The production of the thematic maps will necessitate, for most of them, an important resampling that leads to serious artefacts. On the basis of several resampling tests, it has been chosen to work with a 10 m cell size (Fig. 6). This pixel size is a good compromise between the original cell size of the available raster data and the recommended accuracy for the detailed scale analysis (Florinski and Kurakova, 2000). In this case, one pixel will represent the exact maximum location accuracy on the map, which appears fairly accurate.

3.3 The modelling method

The logistic regression is the method used in this research. The method is often cited in the comparative studies as one of the most efficient data driven technique to map susceptibility (Süzen and Doyuran, 2004; Brenning, 2005; Rossi et al., 2010; Nandi and Shakoor, 2010; Oh et al., 2010; Pradhan and Lee, 2010), moreover this technique

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has given good results in similar hilly environments (Van Den Eeckhaut et al., 2006, 2009, 2010).

The logistic regression describes the relationship between a dichotomous response variable (Y, i.e. the presence or absence of landslides) and a set of predictive variables ($x_1, x_2, \ldots, x_n$). The predictive variables may be continuous or discrete and do not need a normal frequency distribution. The logistic response function can be written as (Allison, 2001):

$$P(Y=1) = \hat{p} = \frac{1}{1+e^{-(\hat{a}+\hat{\beta}_1 x_1+\hat{\beta}_2 x_2+\ldots+\hat{\beta}_n x_n)}} \quad (1)$$

where $\hat{p}$ is the spatial probability of occurrence of a landslide, $\hat{a}$ is the intercept and $\hat{\beta}_i$ is the coefficient for the independent variables x_i estimated by maximum likelihood. More details can be found in Hosmer and Lemshow (1989); or more specifically for the landslides studies in, e.g. Atkinson and Massari (1998), Ayalew and Yamagishi (2005).

3.4 Modelling strategy

The statistical model was implemented in ArcGIS 10® through the ArcSDM extension (Kemp et al., 2001; Sawatzky et al., 2009a, b). The proposed methodology consists in four major steps (Fig. 7):

1. The first step aims to select the predictive variables and sample landslides representative cells. The predictive variables of each simulation are selected according to their accuracy, availability and cost. All collected data were split in five datasets detailed in the Tables 2 and 3. In order to preserve a set of landslides data for the validation step, only 80 % of the triggering zones cells were used for the model calibration. The other 20 % were used for the validation step (Chung and Fabri, 2003). This sampling was performed using a random selection.

2. Successive model iterations were realized with a stepwise introduction of the predictive variables in order to obtain the best combination of predictive variables

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based on the statistical performance of the models (Ayalew and Yamagishi, 2005). As a result, a set of raw probability maps were obtained representing the calculation of each predictive variables combination into the logistic model. Each map was classified into four susceptibility classes, i.e. null, low, moderate and high, to match the French RAM official guidelines (MATE/MATL, 1999). This classification was realized by identifying natural thresholds on the cumulative-area posterior probabilities (CAPP) curve (Bonham-Carter, 1994; Sawatzky et al., 2009a, b). This curve plots the modelled posterior probabilities on a log scale versus the cumulative percentage of the study area (Fig. 8). The raises in the CAPP curve can be used to define class breaks, and the flat sections define the class intervals supported by the data (Bonham-Carter, 1994).

3. The accuracy of the models is evaluated using the ROC curves (Fig. 9) and the area under the ROC curve (AUC). ROC curves plot the "sensitivity" versus the "specificity", where the sensitivity is the proportion of correctly classified known landslides grid cells as unstable, and sensitivity is the proportion of grid cells outside a mapped landslide that is correctly classified as stable (Metz, 1978; Swets, 1988; Lasko et al., 2005). The higher the curve is above the diagonal line (corresponding to AUC = 0.5), the better the model is. Relative error ξ calculation (Table 2) was performed between the highest susceptibility classes and the response variables to complete the ROC curve analysis. This indicator provides the proportion of landslides mapped outside the high susceptibility class and then gives an indicator on the quality of the classified maps. The best result of each simulation is preserved for the comparison with the other modelled maps.

4. The best results of each simulation are then compared on the basis of the obtained accuracy indicators (i.e. ROC curves, relative error), linear cross correlation tests and visual interpretation (expert opinion). Two linear cross correlation tests were computed with the R software (Akgun, 2012). These tests are applied on both unclassified (Pearson's correlation coefficient) and reclassified

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maps (V Cramer test of association). These tests aim to highlight some general similarities between maps. Both coefficients range from 0 to 1, 0 indicating the absence of correlation and 1 indicating a perfect correlation. For the expert opinion, we consider that a good susceptibility map should be able to predict a maximum of landslides in the highest class. This class should be as small as possible and should be characterized by a homogeneous zoning. We consider that to be accepted, a susceptibility map should depict a regular and simple zoning. The zones have to be composed of clustered pixels on the same classes and avoid "isolated pixels effect" generated by the artefacts of the introduced data.

4 Results

Five final simulations are successively obtained using the different sets of data presented on the Sect. 3 of this paper (i.e. DS 1, DS 2, DS 3, DS 4 and DS 5). From a general point of view, the results show a large variation of the posterior probabilities, regression coefficients, statistical and visual results. These are directly linked to the accuracy, the resolution and the scale fitting of the introduced datasets. The resulting quality indicators (i.e. AUC, relative error and size of the high susceptibility class) are presented in the Table 3. The Tables 4 and 5 show the results of the bivariate statistical tests of association (V Cramer and Pearson coefficients). The graphic result of the modelled maps is presented on Fig. 10, as well as an illustrative zoom showing the final displaying scale (i.e. 1 / 10 000).

4.1 Description of the simulations results

The simulation DS 1 has an area under the ROC curve for the calibration dataset (AUC-cal) of 0.73 and of 0.66 for the validation dataset (AUC-val). These results indicate a fair to poor classification accuracy (Metz, 1978). The relative error for the calibration variables (ξ-cal) is 0.48 and 0.67 for the validation variables (ξ-val). This means that

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respectively 48 and 67 % of the analysed landslides are falling out of the high susceptibility class. Some flat (i.e. < 5 %) and valley bottoms sectors are identified in the high and moderate susceptibility class.

For the DS 2 simulation, the AUC-cal and AUC-val are respectively of 0.85 and 0.64. This indicates a good to poor classification accuracy. The relative error remains high with values of 0.41 for the ξ-cal and 0.64 for the ξ-val. The forest variable, considered as a stabilizing factor (Masson, 1976; Fressard et al., 2011) is not identified by the model.

The introduction of an accurate landslide inventory (model DS 3) significantly improves the accuracy of the model which can be considered as good to fair (AUC-cal = 0.89 and AUC-val = 0.77). The relative error is still high with a value of 0.41 for the ξ-cal and 0.64 for the ξ-val. In using the field inventory, the zoning is more in accordance with the expert opinion and do not indicates high susceptibility levels on flat areas, valley bottoms and forested slopes. Nevertheless, the high susceptibility class is strongly influenced by the slope variable (i.e. classes 10 to 15 % and 15 to 20 %) that leads to a very complex and heterogeneous zoning (Fig. 10).

The use of the detailed surficial formations map in the simulation DS 4, improves the accuracy of the model. The AUC-cal value is 0.92 and the AUC-val value is 0.79 which means that the model has an excellent to fair accuracy. The relative error is decreasing and reaches an acceptable threshold for the ξ-cal, i.e. 0.19. The result is better for the ξ-val (0.44) but remains relatively high. In using the surficial formations map the model trends to focus more on the reworked slope deposits and glauconitic sands to determine the high probabilities. This is more in accordance with the expert assumptions (Masson, 1976; Fressard et al., 2010) and this leads to a homogeneous zoning.

The last simulation DS 5 is obtained in using a more accurate DEM. The AUC results are 0.92 for the AUC-cal and 0.86 for the AUC-val. This means that the model has an excellent to good accuracy. The relative error is 0.24 for the ξ-cal and 0.36 for the ξ-val, which is the best result obtained. The IFSAR DEM is more adapted to the

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scale of analysis as it is more accurate and less affected by artefacts. The obtained susceptibility map takes more into account the local subtle slope changes that cannot be represented in the contour lines extracted DEM (Figs. 6 and 10).

4.2 Landslide susceptibility maps comparison

The maps obtained with the simulations DS 1 and DS 2 are not considered satisfying from both quantitative and expert point of view. These results are good for the calibration (i.e. the models well identify the introduced landslides) but lacks of accuracy for the validation (i.e. the models have difficulties to predict the location of future landslides). These results are even more problematic when analysing the classified maps. For calibration and validation relative error, the maps do not success to predict an acceptable amount of landslides in highest class of susceptibility (Table 3). Visually, the two maps have very complex zoning characterized by serious artefacts, brutal changes in the susceptibility over very small zones and do not permit identifying a realistic and applicable zoning (Fig. 10).

The model DS 3 is better considering the AUC values. The relative error remains high. Nevertheless, from an expert point of view, the map is more realistic. No flat areas, valley bottoms and forested slopes are identified in the high susceptibility class which show the importance of using a complete and field validated inventory. Nevertheless, the zoning remains complex and not easily readable. The simulation DS 4 and DS 5 are very similar regarding the quality of the ROC curves and relative error calculations (Table 3). They can be considered satisfying given the quality of the output results. The detailed surficial formations map simplifies the zoning of the high susceptibility class. The accurate mapping of the reworked slope deposits and glauconitic sands increase de predictive power. On both maps, the high susceptibility class is small and predict a large majority of the observed landslides (Table 3 and Fig. 10). The DS 5 map is considered slightly better than the DS 4. The statistical tests (i.e. AUC and ξ) are better except for the ξ-cal with 0.05 of difference to the advantage of the DS 4. The last model is, from and expert point of view, more realistic due to the better accuracy of the introduced topographic data.

The cross correlation analysis shows a low association between maps on both V Cramer and Pearson's tests (Tables 4 and 5). This was confirmed by the visual interpretation and shows that the quality and accuracy of the data are strongly constraining the models. The correlation coefficients are much higher in comparing the DS 3 and DS 4 (Tables 4 and 5). Even if these two maps appear similar with the statistical correlation tests, a visual analysis allow identifying obvious differences on the high and moderate susceptibility classes. In this case, a direct correlation can clearly be indentified only on the null and low probabilities.

5 Discussion

These results allow discussing several points relative to the introduced data, their cost and the logistic regression method in the framework of operational landslide susceptibility mapping.

5.1 The susceptibility maps and datasets

The landslide inventory is the most important data in the models. The BDMvt of the French geological survey cannot be considered reliable at the 1 / 10 000 scale as it was produced with archive documents and questionnaires to municipalities. A lot of errors and imprecision can be identified when compared with detailed field inventories (i.e. several points mapped for the same landslide event, rock fall, collapses or solifluction lobes mapped as landslides, inaccurate location of the landslides etc.).

In this case, the use of API is also inappropriate for the landslide mapping. Few landslides can be identified and the distinction of type and activity of the landslides is difficult. In this plateau context, only the extensive field inventories can provide satisfying landslides data.

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The simulations obtained with low and average cost sets of data (DS 1, DS 2 and DS 3) are often affected by artefacts mostly produced by the lack of accuracy of the DEMs. These artefacts are directly imputable to the gap between the available resolution of the thematic layers and the imposed modelling resolution (i.e. 1 / 10 000 scale). The low density of contour lines in this region characterized by a smooth topography forces the integration of smoothing factors during the DEM interpolation. This generally leads to simplified DEM outputs that necessarily propagate in the modelled susceptibility maps. The IFSAR-DEM is few affected by artefacts compared to the contour lines extracted DEM. This DEM (with an original resolution of 5 m per pixel), is more adapted to the 1 / 10 000 scale as it is more able to represent detailed topography, local irregularities and small slope breaks.

The use of the detailed surficial formations map simplifies the zoning of the high susceptibility class, which are often the most challenging areas in the framework of applied mapping and landuse planning discussions. This justifies clearly the interest in using surficial deposits maps to predict the prone to landsliding areas.

The statistical quality tests, usually used to assess the quality of the susceptibility maps (e.g. ROC curve, success and prediction rate etc.) are interesting indicators on the reliability of the modelled maps, but is not always sufficient (Lobo et al., 2007). To be accepted by local authorities, the maps must be simple and understandable; therefore, the expert validation remains and essential step in the susceptibility analysis.

5.2 Cost of the datasets

The cost of the datasets is directly correlated to the quality (Table 6). The accurate geomohological variables have and important cost (Table 1) that strongly impacts the overall cost of the datasets (Table 6). This is especially due to the extensive field campaigns and associated data processing that are necessary to the geomorphological mapping. For the topographic data, the recent progress in remote sensing permits obtaining accurate data with a reasonable cost. Then, more accurate IFSAR-DEMs are considered cheaper than the usual contour lines extracted DEMs that necessitates long

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procedures of digitalizing and interpolation. Nevertheless, obtaining high quality maps that can satisfy the end-users demand necessitates an important cost. The cost acquisition of these data is apparently uncompressible as it is mainly due to the necessity of detailed geomorphologic studies.

This study shows the difficulty in obtaining data that are causally related to the landslides predisposing factors. This problem has already been discussed by several authors (Chacón et al., 2006; Van Westen et al., 2006; Akgun, 2012). In an operational context, the time, labour and cost associated to the inventory, surficial formations and/or geomorphological mapping are often limiting the use of specifically created maps to the benefit of directly available data. From perspective of engineering, the pressure to solve a problem in the shortest period of time with the most reliable data in the most economical way forces the use of the direct heuristic mapping, which is often considered as less effective and conservative by the scientists. On the other hand, the government authorities and end users are demanding accurate maps that can predict with a high confidence the potential occurrence of landslide on their territory. The mapping method, the predisposing factors and the type of data should then be consciously selected regarding to the objectives (scale and expected accuracy) and the amount of money attributed to the study. Nevertheless, for detailed studies pretending having an operational and statutory purpose, the use of high quality data is unavoidable. This necessarily leads to an effective cost (Table 6).

5.3 The logistic regression method

Logistic regression is often presented in comparative studies as one of the most effective method to map susceptibility. Nevertheless, this method (as most of the data driven methods) lacks of confidence for the definition of the low probabilities. When the relationship between landslides and the predisposing factor is obvious, no questions arise and the probabilities are considered as robust. But when this relationship becomes more subtle, not enough training points landslide training points are available and the robustness of the model can be questioned (Thiery et al., 2007).

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In spite of these problems, the logistic regression remains a good alternative to indentify the most susceptible areas which are often the most challenging zones for the statutory mapping process. Usually, on the one hand, the expert trends to protect themselves in proposing a conservative zoning with the traditional direct mapping. On the other hand, stake holders and populations try to obtain the less constraining zoning as possible (Tricot and Labussière, 2009). The use of data driven techniques could be in such cases a good way of selecting the most objective zoning on the basis of mathematical computations and avoid compromises not always justified by scientific results.

6 Conclusions

This study has demonstrated the possibility of assessing landslide susceptibility at the 1 / 10 000 scale with the use of logistic regression in a plateau region of Normandy. This statistical multivariate data driven method is appropriate to identify areas prone to landsliding but necessitates a particular attention in the introduced datasets to produce reliable maps at detailed scale. The role played by the predisposing factors has to be clearly identified and understood. Without this, the statistical analysis cannot be confidently pursued and produce misleading results (Cascini, 2008; Fell et al., 2008). This research has shown the importance of different key parameters mostly supplied by detailed geomorphologic investigations. These key parameters can be ranked by priority order: (1) the quality of the landslide inventory, (2) the availability of a surficial deposits maps, (3) the quality/accuracy of the DEM, and (4) the quality of the landuse map.

In using data driven techniques, the inventory remains the most important parameter because supplying the model with detailed and reliable observations. The quality of this inventory strongly impacts weights attributed to each predisposing factor and then directly impacts the shape of modelled maps (Ardizzone et al., 2002; Glade and Crozier, 2005; Zêzere et al., 2009). They should be then the most accurate and exhaustive as possible.

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We show that the use of the surficial formations map was very important in identifying areas prone to landsliding and in simplifying the final susceptibility maps. The maps modelled with the surficial formations parameter are then more homogeneous regarding to the zoning and are more in accordance with the expert opinion. These maps have then more chances being accepted by end-users as they are more understandable (Thiery et al., 2007).

The topographic data supplied by the DEM is also an important factor to take into account. The direct available DEM in France are still too coarse (i.e. 25 m resolution) to be adapted to the 1 / 10 000 scale. Extracting DEMs from contour maps is a very current technique to obtain DEM, but necessitates long time procedures of digitalizing and interpolation. This is a time consuming procedure that gives moderate results. We would then suggest the use of Radar DEMs as they are relatively low cost images (i.e. ±9 Euros km^{-2} over Europe) and of a good quality to work at operational scale. Lidar images are still too expensive to expect specific acquisitions in such operational context.

For the landuse data, CorineLandcover does not obviously fit the expected 1 / 10 000 scale as they are provided at the 1 / 100 000 scale. The manual photo-interpretation can be a good alternative over small areas. In this study, we did not assess the potential time variability of the landuse. Pays d'Auge, the landuse has strongly changed during the last 70 yr and constitute an important limitation in mapping the susceptibility. It should be then considered the assessment and mapping of the landuse evolution and then integrate the landcover trajectory to the susceptibility analysis (Beguería, 2006; Guns and Vanacker, 2012).

In any case, the maps obtained with low and moderate cost data cannot be used into a statutory mapping framework. These maps have to be carefully presented to the end-users as informative maps (Cascini, 2008; Fell et al., 2008). For the Pays d'Auge plateau it is essential, despite the selected mapping method, to use both field inventory and surficial deposits to obtain suitable susceptibility maps that could be integrated to statutory mapping procedures.

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Following this research, discussions were engaged with the BRGM to assess the possibility of producing a regional detailed surficial deposits map. This map should be a powerful tool not only to assess the landslide susceptibility over large areas, but also to deal with other types of natural hazards as for example swelling and shrinkage of clays.

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Table 1. Presentation of the source, resolution or scale and estimated cost and accuracy of the available datasets. – very low, + low, ++ high, + + + very high.

Data	Source	Scale/ resolution	Cost or time of acquisition	Accuracy
LS inventory				
BDMvt	BRGM	1 / 100 000	–	–
API[b]	SC[c]	1 / 5000	+	–
Field mapping	SC[c]	1 / 5000	++	+ + +
Topography				
BDAlti	IGN	25m	–	+
CL-DEM	SC[c]	15 m	++[a]	++
IFSAR-DEM	InterMap	5 m	+	+ + +
Materials				
BRGM map	BRGM	1 / 50 000	–	+
FS map	SC[c]	1 / 10 000	+ + +	+ + +
Landuse				
CLC	EEA	1 / 100 000	–	–
API[b]	SC[c]	1 / 5000	+	+ + +

[a] Low cost of acquisition, but time consuming procedure.
[b] Air-photo interpretation.
[c] Specifically created for the study.

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Table 2. Combination of the sets of data use for each simulation.

Data	Landslides	Topography	Materials	Landuse
DS 1	BDMvt	BDAlti	BRGM Map	CLC
DS 2	API	CL-DEM	BRGM Map	API
DS 3	Field mapping	CL-DEM	BRGM Map	API
DS 4	Field mapping	CL-DEM	FS map	API
DS 5	Field mapping	IFSAR-DEM	FS map	API

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Table 3. Summary of the quality statistics calculated for each landslide susceptibility map.

Simulation	AUC-cal	AUC-val	ξ-cal	ξ-val	High class (%)
DS 1	0.73	0.66	0.48	0.67	14.7
DS 2	0.85	0.64	0.41	0.66	9.1
DS 3	0.89	0.77	0.41	0.64	7.2
DS 4	0.92	0.79	0.19	0.44	7.0
DS 5	0.93	0.86	0.24	0.36	7.6

Relative error ξ = (total number of triggering zones cells-total number of high susceptibility triggering zones cells)/total number of triggering zones cells.

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Table 4. Correlation matrix of the linear correlation coefficients (V Cramer) for the 5 final susceptibility maps, classified probabilities.

	DS 1	DS 2	DS 3	DS 4	DS 5
DS 1	1.00				
DS 2	0.24	1.00			
DS 3	0.36	0.30	1.00		
DS 4	0.37	0.29	0.70	1.00	
DS 5	0.39	0.47	0.46	0.47	1.00

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Table 5. Correlation matrix of the linear correlation coefficients (Pearson coefficients) for the 5 final susceptibility maps, raw probabilities.

	DS 1	DS 2	DS 3	DS 4	DS 5
DS 1	1.00				
DS 2	0.26	1.00			
DS 3	0.45	0.26	1.00		
DS 4	0.43	0.28	0.90	1.00	
DS 5	0.35	0.24	0.48	0.54	1.00

Table 6. Cost/accuracy analysis, quality of the model and comments and suggestions for the operational mapping for the five simulations.

Models	DS 1	DS 2	DS 3	DS 4	DS 5
Data accuracy*	6 (+)	10 (+)	13 (+)	15 (+)	16 (+)
Estimated cost*	4 (+)	8 (+)	9 (+)	12 (+)	11 (+)
Statistical accuracy of the model	Fair to poor	Good to poor	Good to fair	Excellent to fair	Excellent to good
Expert opinion	Not acceptable. Serious artefacts, unrealistic. classifications	Not acceptable. Complex zoning, key predisposing factors not identified.	Moderately acceptable. Realistic zoning, but very complex, artefacts.	Acceptable. Realistic and clear zoning, artefacts.	Acceptable. Realistic and clear zoning, few artefacts.
Recommendations/ Comments for statutory mapping at the 1 / 10 000 scale	Not recommended important lack of accuracy.	Not recommended. Not enough training data, might be used for informative zoning at small scale.	Not recommended. Lack of readability of the maps, might be applicable for advisory mapping at small scale.	Might be recommended when contour lines are sufficient on the study area.	Recommended. Accurate and readable maps, the cost is lower than the DS 4.

* Sum of the cost and accuracy estimated on Table 1.

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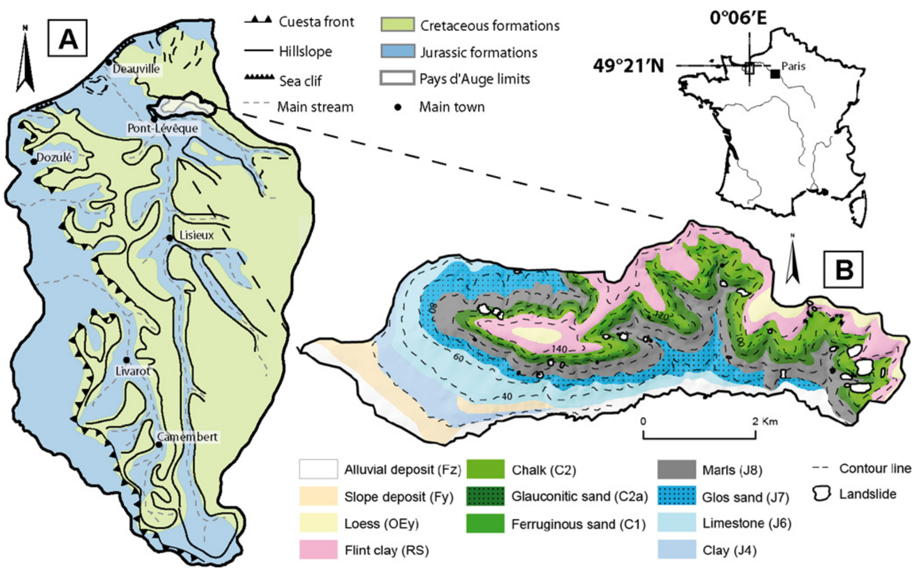

Fig. 1. Geomorphological sketch of the Pays d'Auge plateau **(A)** and **(B)** geological map of the selected study area (Debrand-Passard et al., 1989).

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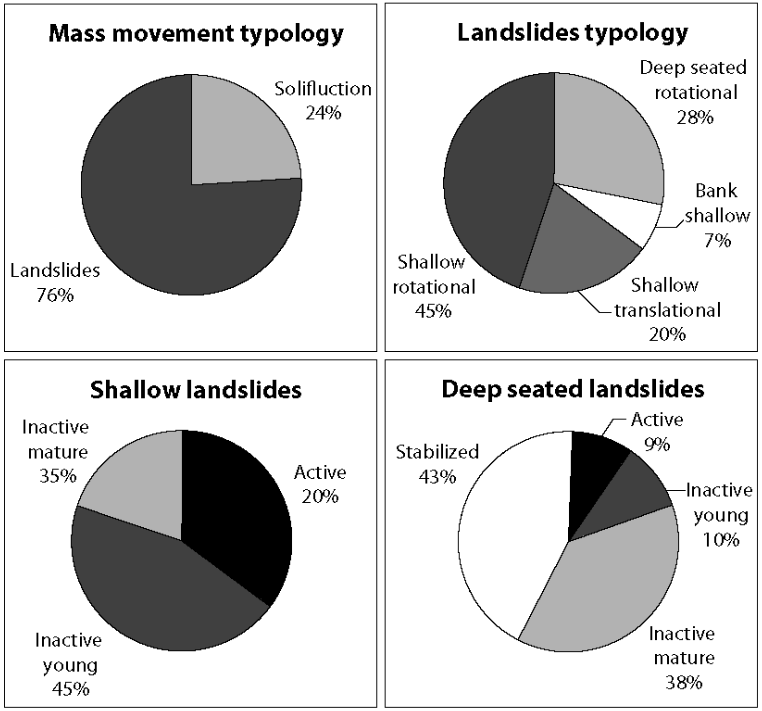

Fig. 2. Observed mass movement characteristics and states of activity.

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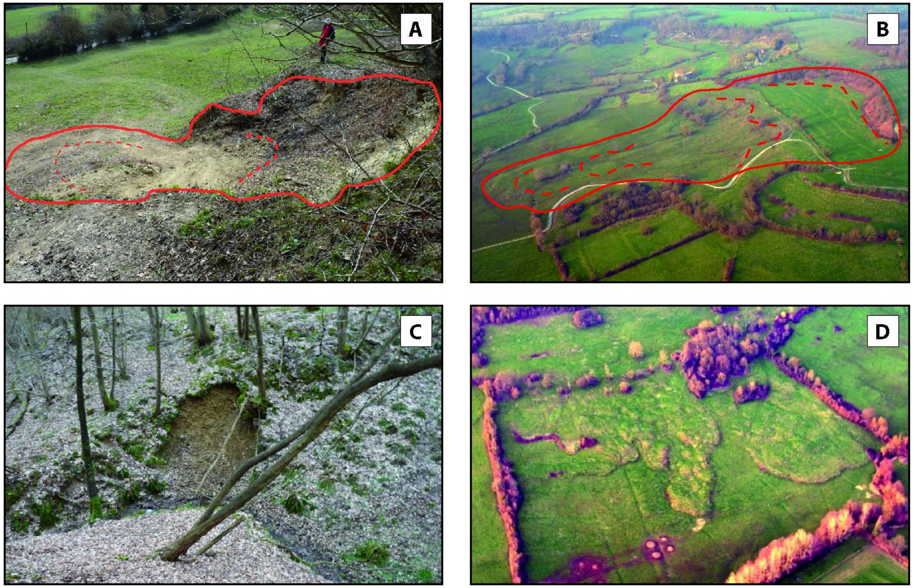

Fig. 3. Ground and oblique aerial view of typical landslides of the Pays d'Auge plateau. **(A)** Shallow landslides, **(B)** deep seated landslide, **(C)** bank shallow landslide and **(D)** solifluction.

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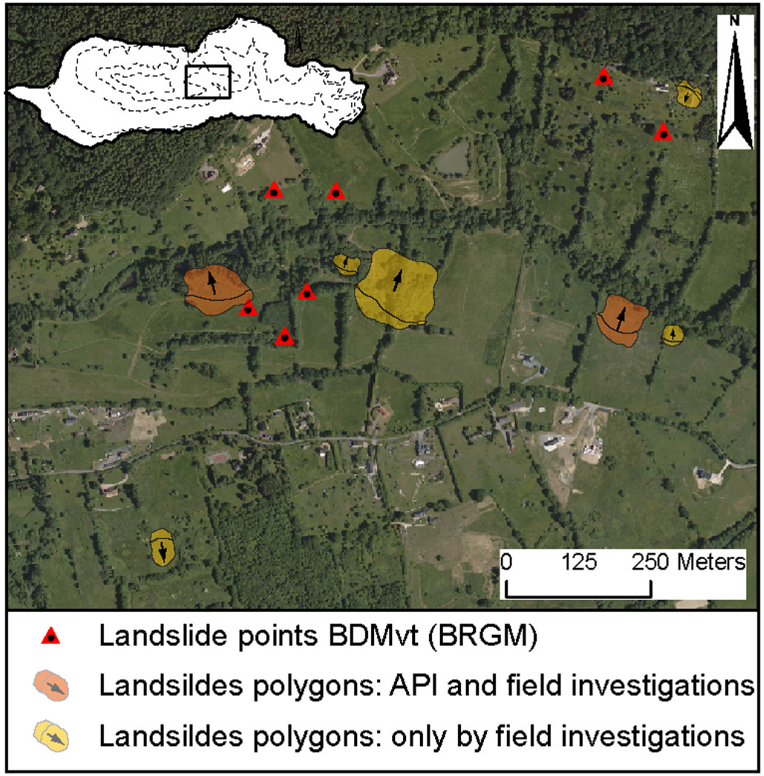

Fig. 4. Example of the different landslide inventories obtained from various sources of investigation.

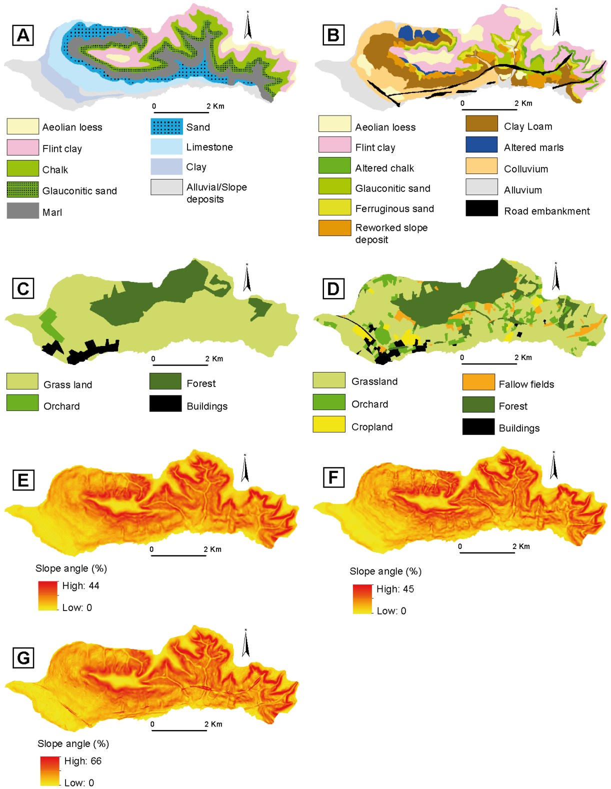

Fig. 5. Comparison of the sets of data available for the three main categories: materials, landuse and topography. **(A)** 1 / 50 000 scale geological map, **(B)** 1 / 10 000 scale surficial formations map, **(C)** 1 / 100 000 scale Corine landcover, **(D)** 1 / 5000 scale landuse map, **(E)** slope map of BDAlti® DEM, **(F)** slope map of the DEM extracted from the digitalized contour lines and **(G)** slope map of the radar DEM.

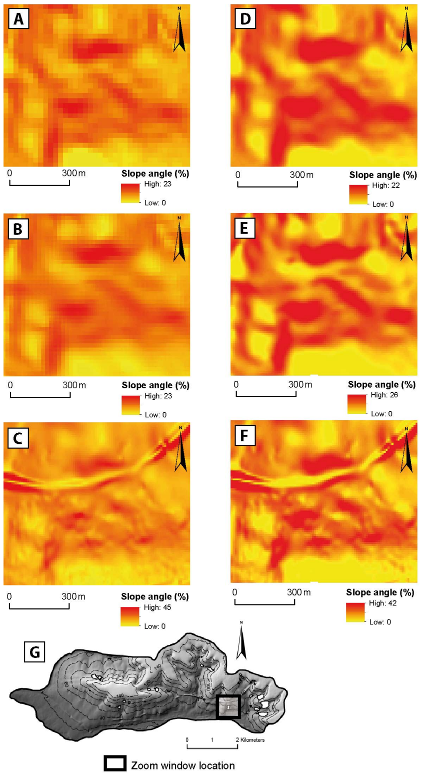

Fig. 6. Example of the three different slope maps generated from the available DEMs in their original cell size resolution and after bilinear resampling at 10 m; detailed zoom on a representative area. **(A)** Raw BDAlti® 25 m, **(B)** raw contour lines DEM 15 m, **(C)** raw radar DEM 5 m, **(D)** resampled BDAlti® slope map 10 m, **(E)** resampled contour lines DEM slope map 10 m, **(F)** resampled Radar slope map 10 m and **(G)** location of the illustrative zoom in the study area. (Note: road embankments are not visible on the two first DEMs.)

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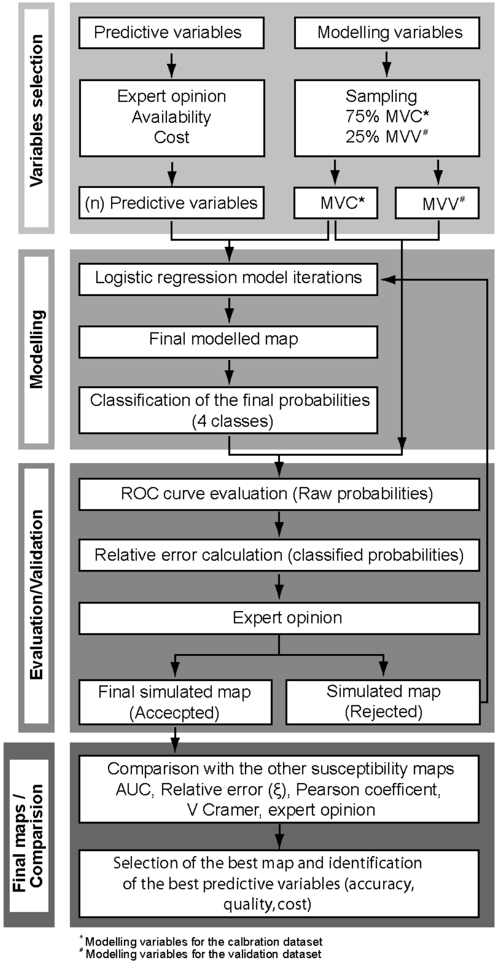

Fig. 7. General flow chart of the employed methodology.

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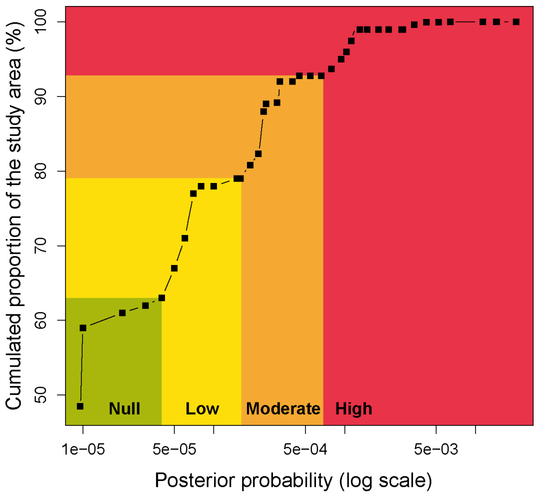

Fig. 8. Example of CAPP curve classification in four classes based on natural thresholds of the posterior probabilities, case of the DS 5 simulation.

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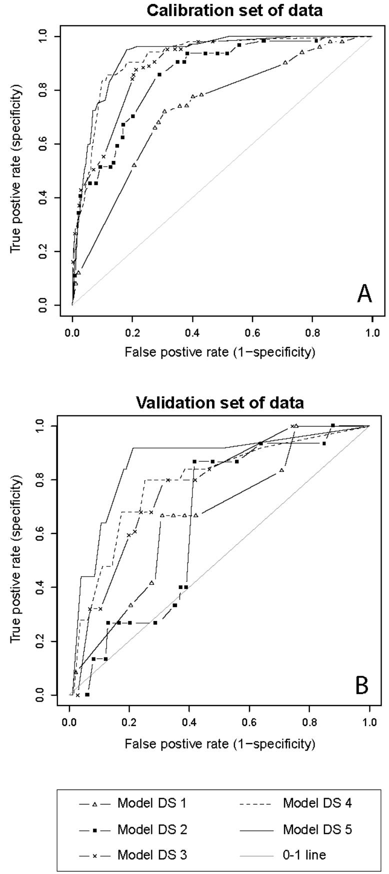

Fig. 9. Receiver Operator Characteristics (ROC) curves obtained for the different simulations, **(A)** calibration datasets and **(B)** validation datasets.

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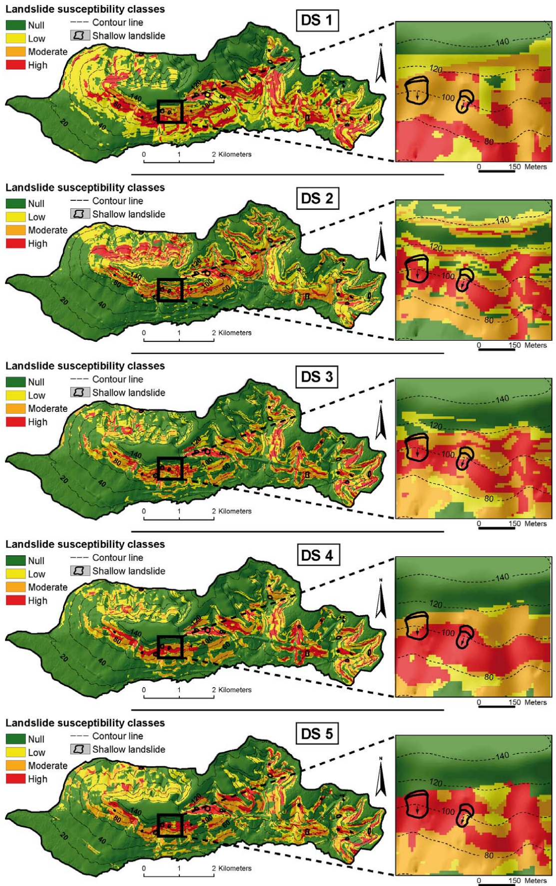

Fig. 10. Final classified modelled susceptibility maps for each simulation and illustrative zoom at the 1 / 10 000 scale on a representative zone.

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