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Evaluation of debris flow susceptibility in El Salvador (CA): a comparison between Multivariate Adaptive Regression Splines (MARS) and Binary Logistic Regression (BLR)

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Abstract

In the studies of landslide susceptibility assessment, which have been developed in recent years, statistical methods have increasingly been applied. Among all, the BLR (Binary Logistic Regression) certainly finds a more extensive application while MARS (Multivariate Adaptive Regression Splines), despite the good performance and the innovation of the strategies of analysis, only recently began to be employed as a statistical tool for predicting landslide occurrence. The purpose of this research was to evaluate the predictive performance and identify possible drawbacks of the two statistical techniques mentioned above, focusing in particular on the prediction of debris flows. To this aim, an inventory of debris flows triggered by the passage of the hurricane IDA and the low-pressure system associated with it 96E, on 7th and 8th November 2009, in an area of about 26 km^2 close to the Caldera Ilopango, El Salvador (CA), was employed. Two validation strategies have been applied to both statistical techniques, thus obtaining four models – BLR (I), MARS (I), BLR (II) and MARS (II) – to be compared in pairs. Model performance was assessed in terms of AUC (area under the receiver operating characteristic (ROC) curve), Sensitivity, Specificity, Positive Prediction Value and Negative Prediction Value. Moreover, to evaluate the robustness of the modelling procedure, 50 replicates were created for each model and standard deviation was calculated for each of them. The results show that both techniques allow for obtaining good or excellent performances so that it is not possible to define one of the two techniques as absolutely better. However, the validation procedure reveals slightly better performance of the MARS models, with greater sensitivity and greater discrimination among True Negatives (TNs).

Keywords: landslide susceptibility, debris flows, Multivariate Adaptive Regression Splines (MARS), Binary Logistic Regression (BLR), hurricane Ida, El Salvador

Introduction

Landslide susceptibility is defined as the probability of the occurrence of landslides in a given area according to local geo-environmental variables (Brabb, E.E. 1984; Carrara, A. *et al.* 1995; Guzzetti, F. *et al*. 1999).

For defining landslide susceptibility, both direct and indirect methods can be used. Direct methods are based on analyses performed by expert geomorphologists who divide the territory into areas with different susceptibility, defining the latter in qualitative terms (Verstappen, H.T. 1983; Van Westen, C.J. *et al.* 2003). By using indirect, deterministic or statistical methods, it is instead possible to obtain a quantitative classification of landslide susceptibility (Chung, C.J.F. *et al.* 1995; Ohlmacher, G.C. and Davis, J.C. 2003; Conoscenti, C. *et al.* 2008).

Landslide susceptibility assessment, developed in recent years, has seen an increasingly frequent use of the statistical approach. This method is based on the assumption

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that new landslides occur in areas with geo-environmental conditions that have caused landslides in the past (Carrara, A. *et al.* 1995; Guzzetti, F. *et al*. 1999; Van Westen, C.J. *et al.* 2003, 2008). In light of this, geo-environmental variables can be considered as predictors or independent variables while the past/present distribution of landslides as the dependent variable. The covariates are selected to reflect the variability of geo-environmental factors that are considered related to the activation of landslides and, moreover, the choice is also a function of the quality and resolution of available data. The landslide archive can be generated through field mapping or detection from high resolution remotely-sensed images. In this study, we employed the landslide archive produced by Rotigliano, E. *et al.* (2018), which was obtained through remote mapping of the Google Earth™ image dated 11/21/2009 (DigitalGlobe Catalog ID: 101001000AA5D801).

The statistical method is therefore aimed at determining relationships existing between the covariates and the dependent variable. For the determination of relationships, statistical analysis of bivariate (logistic regression, binary logistic regression [BLR]) or multivariate type (e.g., Multivariate Adaptive Regression Splines [MARS], cluster analysis, discriminant analysis) can be used. In the literature, a number of examples of landslide susceptibility studies performed using bivariate (e.g., Guzzetti, F. *et al.* 1999; Rotigliano, E. *et al.* 2012; Costanzo, D. *et al.* 2014) or multivariate analysis (e.g., Vorpahl, P. *et al.* 2012; Felicísimo, Á.M. *et al.* 2013; Conoscenti, C. *et al.* 2015, 2016) can be found. Comparative studies of the two methods are however rare (e.g. Conoscenti, C. *et al.* 2015) and, as far as we know, no comparison has ever been made in the case of evaluation of susceptibility from debris flow.

The main objective of the study is to show the difference in terms of predictive performance of the two methods, i.e. BLR and MARS, by using two different validation schemes (Chung, C.J.F. and Fabbri, A.G. 2003). Firstly, we created 50 datasets consisting of balanced samples of event and non-event pixels. In the first validation scheme, each dataset was exploited for both calibration and validation of the models. In the second scheme, each archive was split in two: the first, containing 75 per cent of the positive and negative cases, was used for the calibration of the models; the second, containing the remaining 25 per cent of the balanced archive, was used for validation. The performance of the models was assessed through the analysis of AUC (area under the receiver operating characteristic (ROC) curve) values and the confusion matrices.

The two validation schemes have been developed for both BLR and MARS models. The creation of 50 models for each procedure also allowed us to evaluate the robustness of the analysis (Costanzo, D. *et al.* 2014).

Materials and methods

Study area

The study area is a small drainage basin of about 26 km^2, located along the slopes of the Caldera Ilopango, El Salvador, CA *(Figure 1).* The slopes of the area are covered by levels of tefra and ignimbrite, derived from the most recent Quaternary eruptions of the Caldera *(Figure 2).* In the area are found deep V-shaped valleys *(Figure 3)*, whose formation is linked to intense weathering and mass movements that affected the volcanic bedrock. The latter, characterized by poor mechanical properties, can be in fact easily eroded by water especially during extreme meteorological events (cyclones and hurricanes), which occur very frequently in the region.

The climate regime of El Salvador is tropical-humid, with average annual rainfall above 1,500 mm and average annual temperature between 20 °C and 30 °C. Under these conditions, physical degradation is favoured, with further deterioration of the geotechnical properties of the pyroclastics. The meteorological phenomena are then responsible for the saturation of the degraded material and thus for a signifi-

Fig. 1. Location of the study area

cant decrease of cohesion. Due to these environmental conditions, the study area is particularly prone to landsliding, especially to debris flow type landslides. Unregulated deforestation and intensive cultivation of the area, even in very steep slopes, further promotes soil erosion as well as landslide processes.

Landslide inventory

Between 7th and 8th November 2009, El Salvador was affected by the simultaneous passage of Hurricane Ida and the 96/E low-pressure system. The greatest damage occurred in an area of about 400 km^2 around the Caldera Ilopango, where more than 300 mm of rainfall in 12 hours were recorded at the Ilopango rain gauge station. Such an intense rainfall event triggered more than two thousand debris flows and caused flooding of the valleys, causing approximately 200 fatalities and immense economic loss with destruction of houses, roads and crops (MARN 2010).

The landslide archive used in this study is a database of landslide phenomena that occurred in the catchment due to the concomitant passage of Ida and 96/E. The archive has already been used in Rotigliano, E. *et al.* (2018). The recognition of the landslides and their mapping has been carried out remotely, using a high-resolution satellite image available on the Google Earth software, which is dated 11/21/2009 (DigitalGlobe Catalog ID: 101001000AA5D801). This image, acquired only 2 weeks after the passage of Ida-96/E, allowed the identification and mapping of 2231 debris flows triggered by the aforementioned rainfall event.

Each failure has been mapped by using a landslide identification point (LIP), located at the point of origin of the movement. In the case of evaluation of susceptibility to debris flow, according to Rotigliano, E. *et al.* (2011), LIPs allow us to obtain the most reliable landslide prediction as their environmental characteristics are those that best represent pre-failure conditions and thus can be considered the best diagnostic areas for calibrating (and validating) landslide predictive models (Rotigliano, E. *et al.* 2011, Lombardo, L. *et al.* 2014; Cama, M. *et al.* 2015). For this reason, it was decided to use the archive without making any changes with respect to the initial characteristics.

Statistical modelling

In the last 20 years, many studies have dealt with landslide susceptibility modelling and a number of them have used a statistical modelling approach. Binary logistic regression (BLR) is among the most frequently used statistical techniques in geomorphology, and in particular in the field of landslide susceptibility assessment (e.g. Bai, S.B. *et al.* 2010; Atkinson, P.M. and Massari, R. 2011; Costanzo, D. *et al.* 2014). On the other hand, Multivariate Adaptive Regression Splines (MARS) (Friedman, J.H. 1991), has been employed only a few times in geomorphology (e.g., Gómez-Gutiérrez, Á. *et al.* 2009, 2015; Conoscenti, C. *et al.* 2016, 2018; Garosi, Y. *et al.* 2018).

Both BLR and MARS make it possible to identify relationships between a set of independent variables (predictors), both continuous or categorical, and a dependent dichotomic variable, which is usually coded as 0 (non-event) or 1 (event).

The aim of BLR is to describe the linear relationship between the logit (or log odds) of the dependent variable and the set of n independent variables (Hosmer, D.W. and

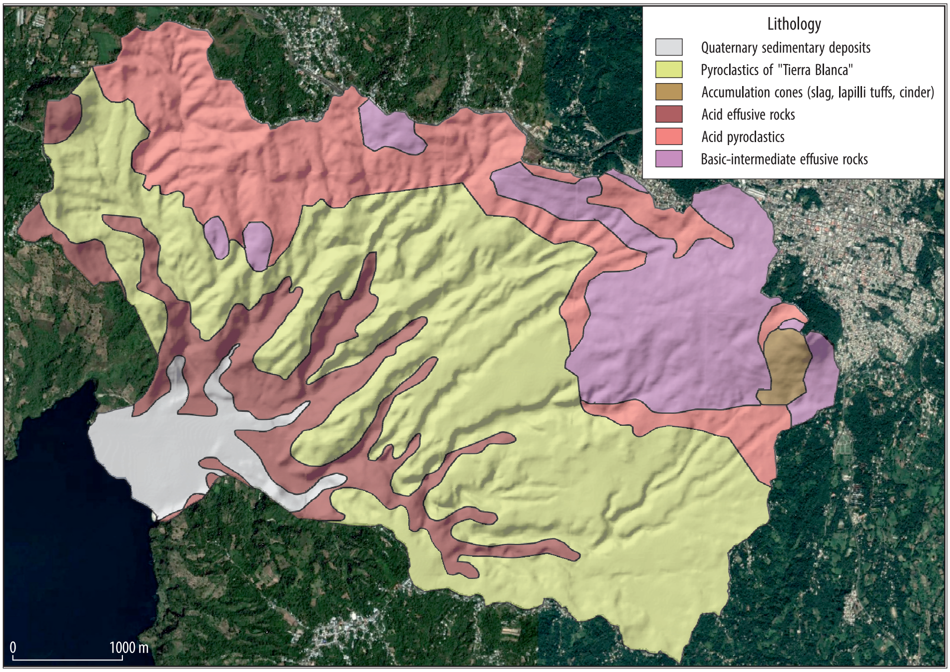

Fig. 2. Outcropping lithology in the study area (from Weber, H.S. *et al.* 1978)

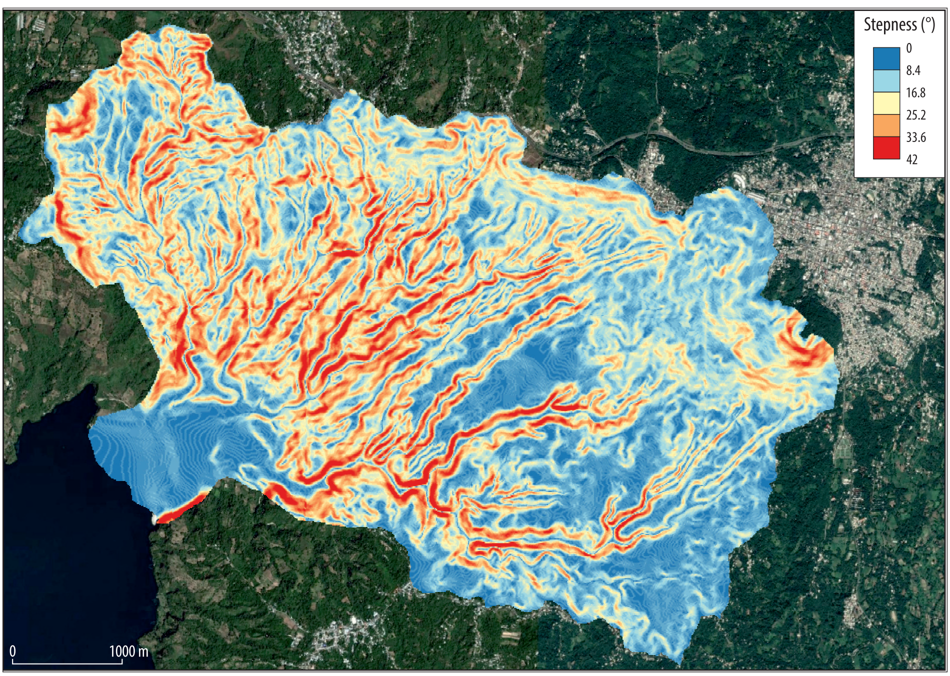

Fig. 3. Slope gradient map of the study area

Lemeshow, S. 2000). This is described by the following equation:

$$y = \ln\left(\frac{\pi(x)}{1-\pi(x)}\right) = \alpha + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n$$

where π (x) is the conditional mean of the response given specific values of x, α is the constant or intercept, x_i (i = 1, 2, ... n) is the n^{th} independent variable and β_i (i = 1, 2, ... n) is the n^{th} coefficient of the independent variable.

To optimize the values of y having certain independent variables, or rather to identify the value of α and β_i, the maximum likelihood technique is used, actually the log-likelihood (LL) function (Menard, S. 1995).

MARS is a non-parametric regression technique capable of identifying non-linear adaptation relationships between independent variables and dependent variables. MARS divides the range of the predictor values into regions and generates a linear regression equation for each region. The "nodes" are the extreme values of each region while each distinct interval is called "basis function" (BF). The latter can take the form:

$$\max(0, x - c) \text{ o}$$
$$\max(0, c - x),$$

where x is an independent variable and c is a constant corresponding to a knot. The general expression of MARS can be written as follows:

$$y = \alpha + \sum_{n=1}^{N} \beta_n h_n(x_n),$$

where y is the dependent variable, α is the constant, N is the number of terms, β_n is the coefficient of the n^{th} term and h_n (x) is a single basic fiction or a product of two or more BFs.

MARS builds the model in two phases. In the first step (forward pass) a complex model is produced in which basis functions generated for each variable are added. In the second phase (backward pass) a leaner model is established through generalized cross validation (GCV) (Craven, P. and Wahba, G. 1979). Basically, MARS removes the least influential pair in the creation of the best model and the GCV allows the identification, among the models generated, of the one offering the best compromise between adaptation (low RSS) and complexity/completeness of the model (Briand, L.C. *et al.* 2004; Gómez-Gutiérrez, Á. *et al.* 2009).

Both regression techniques and related analysis have been implemented using the software R (R CoreTeam, 2017). For the BLR analysis the "stats" package has been used, for MARS analysis the "earth" package (Milborrow, S. *et al.* 2011; Milborrow, S. 2015).

Predictors

The predictor variables were chosen according to their expected influence on slope instability and to their control on slope failure mechanisms (e.g., Conoscenti, C. *et al.* 2015; Cama, M. *et al.* 2016; Prokos, H. *et al*. 2016).

A set of ten geo-environmental variables was employed to predict debris flow susceptibility in the Caldera Ilopango. This set includes lithology (LIT) and land use (USE), in addition to the following eight terrain attributes: landform classification (LCL), elevation (ELE), slope steepness (STP), slope aspect (ASP), plan curvature (PLN), profile curvature (PRF), topographic wetness index (TWI) and terrain ruggedness index (TRI).

The outcropping lithology was obtained through the acquisition and processing of a 1:100,000 geological map (Weber, H.S. *et al.* 1978), which was derived from field survey 1: 25,000 scale. An up-to-date land use map was created on the basis of field surveys and analysis of ASTER and Google Earth images. The terrain attributes were extracted from a digital elevation model (DEM) with a ground resolution of 10-m, by using the software SAGA-GIS. All terrain attributes were extracted as continuous variables with the exception of LCL, which was classified into 10 classes, namely: streams, mid-slope drainages, upland drainages, valleys, plains, open slopes, local ridges, mid-slope ridges, high ridges. The 10-m cells of the DEM were employed as mapping units of the debris flow susceptibility in the studied area.

In order to detect collinearity among the chosen covariates, we calculated the Variance Inflation Factor (*VIF*) by using the "usdm" package (Naimi, B. 2015) implemented in the software R. A *VIF* value equal or higher than 10 indicates collinearity among the selected covariates (Heckmann, T. *et al.* 2014; Jebur, M.N. *et al.* 2014; Bui, D.T. *et al.* 2016). As *VIF* values calculated for our variables were below this threshold, all were included in both BLR and MARS models.

Model building and validation strategy

Landslide susceptibility assessment requires a validation procedure in order to evaluate the accuracy of the predictive models. This is generally performed in two steps: i) calibration of the models and ii) validation of the models (Chung, C.J.F. and Fabbri, A.G. 2003).

In this study, we evaluated adaptation, accuracy and robustness of the models generated with BLR and with MARS. To this aim, two validation strategies were developed, applying a random partition to the same landslide archive.

First, the study area was divided into 249,994 10-m grid cells corresponding to the pixels of the employed DEM. This data set includes 2,231 "event" or "positive" cells (i.e. cells hosting at least one LIP) and 247,763 "non-event" or "negative" cells (i.e. cells not intersecting any LIP). Through random selection, 50 balanced data sets were created, each of them containing all event cells and an equal number of randomly selected negative cells (Conoscenti, C. *et al.* 2016), thus including in total 4,462 cells.

The first validation strategy involved the calibration and validation of one model for each of the 50 data sets. Therefore, each data set was exploited as both learning and validation data set. In the second validation scheme, each of the 50 data sets was randomly divided into two balanced subsets: a training set, including 75 per cent of the cases, and a test set, including the remaining 25 per cent of the cases.

For both the validation schemes, it was possible to obtain a pair of models, one generated with the BLR and one with MARS, for each balanced data set *(Figure 4* and *5)*. This allowed us to analyse the difference in terms of performance and robustness between the two employed statistical techniques. As training and test datasets were the same, these differences were assumed as due only to the different characteristics of the two statistical techniques. Statistical analyses were carried out to evaluate and quantify the goodness of fit, the prediction skill and the robustness of the models.

By comparing the prediction image of each model with the spatial occurrence of the event cells, the confusion matrix and thus the number of true positive, true negative, false positive and false negative cases (TP, TN, FP and FN, respectively) for each model, applying a Youden index optimized cut-off (Youden, W.J. 1950).

To evaluate the goodness of fit and prediction skill of the susceptibility models the AUC (area under the receiver operating characteristic [ROC] curve) (Goodenough, D.J. *et al.* 1974; Hanley, J.A. and McNeil, B.J. 1982; Lasko, T.A. *et al.* 2005) was used. A ROC curve plots the true positive rate (sensitivity) against the false negative rate (1 – specificity), at any given cut-off value. For the AUC values, Hosmer, D.W. and Lemeshow, S. (2000) identify the threshold values of 0.7, 0.8 and 0.9 corresponding to acceptable, excellent and outstanding predictions respectively.

Finally, to evaluate the robustness of the models, the validation procedures have been applied to all the model runs (50 for BLR and 50 for MARS, for each validation strategy) in order to analyse the accuracy and reliability of the models through the study of the average and standard deviation of the AUC values. These validation tools have already been successfully used in previous studies with the aim of comparing different methods and models (e.g., Von Ruette, J. *et al.* 2011; Conoscenti, C. *et al.* 2015, 2016; Cama, M. *et al.* 2017).

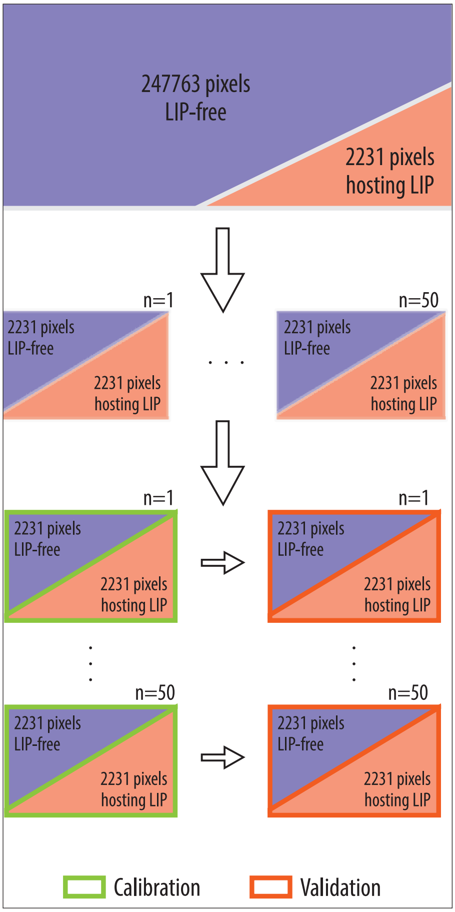

Fig. 4. Graphical summary scheme of the first adopted validation strategy

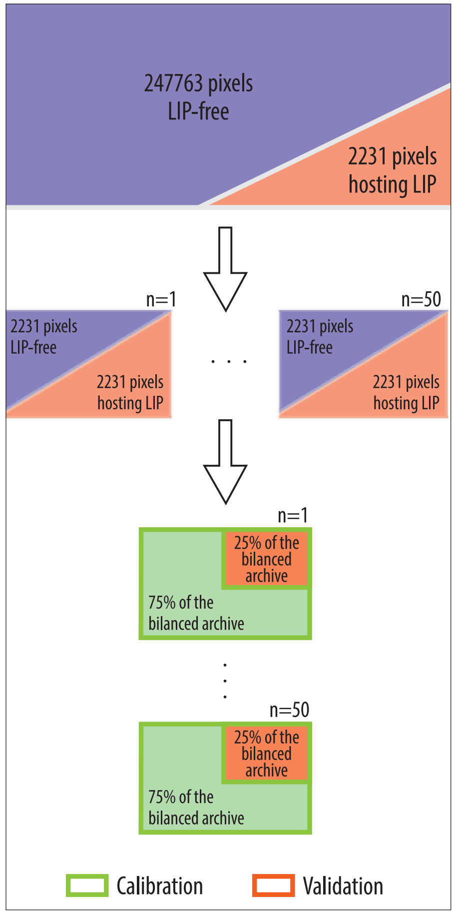

Fig. 5. Graphical summary scheme of the second adopted validation strategy

Results

For the description of the developed models and the relative results, a subscript (I) is adopted for those generated through the first validation strategy, while subscript (II) is used for those created with the second validation strategy.

The mean AUC values of the BLR (I), MARS (I), BLR (II) and MARS (II) models are 0.796, 0.821, 0.789 and 0.811, respectively. According to the classification proposed by Hosmer, D.W. and Lemeshow, S. (2000), these values indicate excellent (> 0.8) and acceptable (> 0.7) performance of the models. As shown by the AUC standard deviation values (*Table 1*), the performance of both modelling techniques is quite stable. The boxplots of *Figure 6* show a low degree of dispersion in the AUC values, which, as expected, appears slightly higher for the second validation strategy. *Figure 7* shows the ROC curves obtained from the replicates of each model (grey) while the average ROC curves are plotted in red.

Table 2 shows the cumulative confusion matrices extracted by applying the models to the 50 validation data sets of both validation strategies. *Table 3* shows the average values

Table 1. Characteristics of the AUC values for the four susceptibility models

Models	Accuracy	AUC-mean	AUC-min	AUC-max	AUC SD*
BLR (I)	0.720	0.796	0.783	0.806	0.005
MARS (I)	0.744	0.822	0.805	0.833	0.006
BLR (II)	0.716	0.789	0.754	0.815	0.012
MARS (II)	0.736	0.811	0.779	0.836	0.012

*SD = Standard deviation.

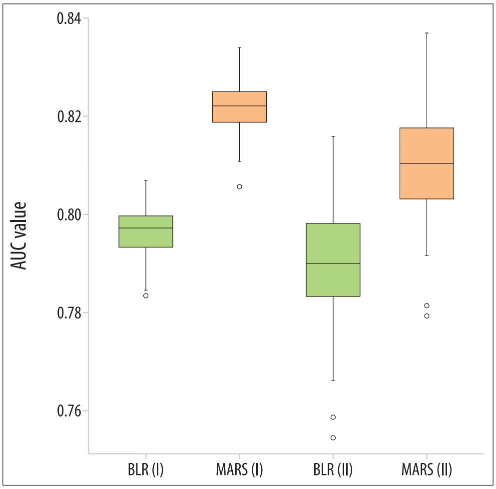

Fig. 6. AUC boxplots for the four models

of sensitivity, specificity, positive prediction value (PPV) and negative prediction value (NPV) and the relative Youden index cut-off.

The accuracy of the models can be considered good, with values between 0.71 and 0.74. Sensitivity values between 0.76 and 0.82, attest to a good predictive power of positive cases while slightly lower is the ability to discriminate the true negatives (specificity in the range 0.66–0.67). On the other hand, it is noteworthy that the NPV values, which are between 0.74 and 0.78, reveal acceptable predictions of the TNs whereas the PPV values, which are approximately 0.7, attest to a slightly worse ability to predict the TPs.

Discussion

For the discussion of the results of model validations we have to take into account that in the first validation strategy the training and the test data sets coincide whereas in the second strategy, learning and validation sets do not share any pixels and they are randomly extracted from the training/test data sets employed in the first procedure.

Models validation using the first validation strategy

MARS (I) demonstrate slightly better performance than BLR (I). It should be noted that the difference in terms of AUC is very small, being between 0.02 and 0.05. The accuracy of MARS (I) is only 0.02 higher than the accuracy of BLR (I), whereas the difference of average AUCs is only 0.03. Regarding the ability to predict event cells, a greater difference is recorded: the average sensitivity of MARS (I) is indeed 0.82 whereas that of BLR (I) is 0.77. However, PPV values reveal the same ability for both BLR (I) and MARS (I). On the other hand, although the specificity values suggest similar abilities of BLR (I) and MARS (I) to predict the non-event cells, NPV values demonstrate better performance of MARS (I) (0.78) compared to that of BLR (I) (0.74).

Models validation using the second validation strategy

Also the second validation strategy reveals a slightly better performance of MARS compared to that of BLR, although the observed differences are once again weak. The difference of both accuracy and AUC values are indeed approximately 0.02. Again, the difference in terms of sensitivity between MARS (II) (0.81) and BLR

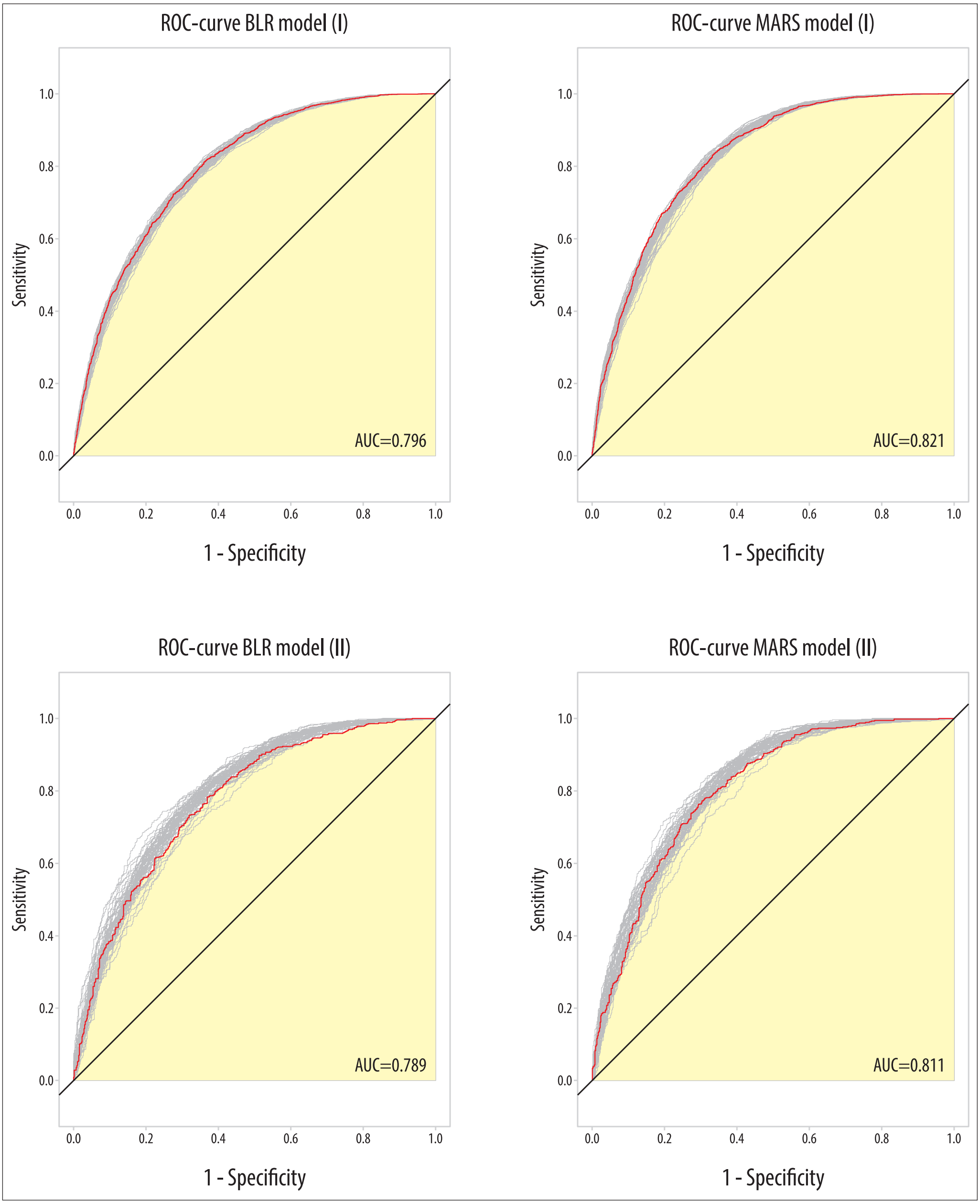

Fig. 7. ROC-plots for the four models

Table 2. Confusion matrices of the four susceptibility models

BLR (I)	Reference			MARS (I)	Reference		
		0	1			0	1
Prediction	0	74,786	25,594	Prediction	0	74,558	20,004
	1	36,764	85,956		1	36,992	91,546
BLR (II)	Reference			MARS (II)	Reference		
		0	1			0	1
Prediction	0	18,569	6,490	Prediction	0	18,453	5,234
	1	9,331	21,410		1	9,447	22,666

Table 3. Summary of the validation metrics for the four susceptibility models

Models	Youden index cut-off	Sensitivity	Specificity	Positive	Negative
				prediction value	
BLR (I)	0.48	0.77	0.67	0.70	0.74
MARS (I)	0.46	0.82	0.66	0.71	0.78
BLR (II)	0.48	0.76	0.66	0.69	0.74
MARS (II)	0.46	0.81	0.66	0.70	0.77

(II) (0.76) does not result in a greater discriminatory power of TP (the difference of PPV is 0.01). Finally, the two techniques show the same specificity (0.66), but the discriminatory ability of TN is higher for MARS (II), with NPV values equal to 0.77 versus 0.74 of BLR (II).

Concluding remarks

The use of statistical methods in landslide susceptibility assessment raises the problem of the type of analysis to perform and which one is the best modelling approach and technique. BLR has been proven a useful technique for achieving reliable assessment of landslide susceptibility. In recent years, however, several other statistical techniques have also demonstrated equally good, and sometimes even better, performance. MARS, which is a relatively new technique, has been employed in few cases for assessing landslide susceptibility but it has already been demonstrated to provide very good accuracy in predicting the occurrence of slope failures. However, as far as we know, MARS has never been employed to predict debris flows.

The aim of this study was to highlight the differences in terms of predictive performance between BLR and MARS and, thus, identify the best method for the assessment of debris flow susceptibility in the area of Ilopango Caldera.

The obtained results show that both methods achieve good to excellent predictive performances. Although MARS demonstrated slightly better performance, the difference is too small to be able to define this technique as clearly better than BLR.

Rotigliano, E. *et al.* (2018) hypothesize that in the 2009 dataset there is a problem related to a secondary triggering of a number of phenomena due to incision or lateral erosion produced by debris flows activated directly by the storm event. In fact, even in this study, the models obtained are affected by this problem, as shown by the low specificity values. In light of this, however, the performance in terms of NPV is higher than expected. MARS, in fact, with the same dataset, is able to discriminate TN with better ability than BLR. This is probably due to the ability of MARS of identifying different relationships between the dependent and the independent variables, for different regions of the predictors' ranges. This allows MARS to overcome, even if only slightly, the problem of secondary triggering of landslides, certainly with a better distinction of cases with respect to BLR. Furthermore, both validation strategies, albeit with subtle results, show a greater ability of MARS to identify positive cases compared to BLR.

In light of this, although the differences are not marked and certainly the results do not allow the definition of a modelling technique as absolutely better than the other, it is possible to identify more merits in the MARS technique than in the BLR.

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