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Artificial Neural Networks and Robustness Analysis in Landslide Susceptibility Zonation

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Abstract— **This contribution focuses on the application of Artificial Neural Networks (ANNs) in landslide susceptibility zonation taking into consideration both the prediction capability assessment and the sensitivity to measurement errors in the obtained models. We suggest a general procedure to perform susceptibility analysis by means of ANNS, introducing robustness analysis as the final step in the susceptibility modelling in order to test the reliability of the obtained maps with respect to errors in measuring, and calculating, the conditioning factors. Such robustness analysis has been performed by calculating a robustness index both for each conditioning factors and for the total model; this allowed us to find the errors in the conditioning factors which affect the neural computation in a greater way and the overall robustness of the model. The experimental results, obtained on the Deba Valley database, suggest that ANNs are a proper method to analyze a complex relationship between conditioning factors and landslides, and that the robustness analysis is a crucial step in the susceptibility modeling, specially as an iterative procedure for variables selection.**

I. Introduction

All over the world, landslide phenomena represent one of the most serious problems in terms of economic damages. Due to the temporal and spatial frequency, landslides every year cause higher economic loss than other natural disasters, such as earthquakes and floods. For that reason, the need for landslide cartography at different scales has increased in the last years to support decision makers at every level of the territorial management.

This contribution focuses on the basin scale landslide cartography and in particular on quantitative techniques to analyse and model landslide phenomena. The main idea of these techniques is to predict future landslides knowing the conditions that have caused the mass movements in the recent past, following the common idea of landslide analysis that the past is the key to the future.

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In the last years, the widespread use of Geographical Information Systems (GIS), the ease in collecting, manipulating, and updating data in a GIS, and the development of software tools have increased the production of landslide cartography at the basin scale. Despite those clear advantages, essential problems in the basin scale cartography has not yet been solved, e.g., the uncertainty in collecting and mapping the conditioning factor and the landslides, the difficulty in generalizing the property of rocks to lithology units, the inconsistency of the data, etc. By means of statistical techniques it is possible to study and analyze the relationships between a conditioning factor, or a combination of conditioning factors, and the presence of mass movements. However, as most of the natural processes, landslides are complex phenomena whose mechanisms are not yet completely understood. The landslides occurrence depends on the relationship among different conditioning factors, some of which are well known, others are not well known, or totally unknown [1].

Due to these reasons, the landslide prediction has to be based on complex, unknown, and non linear relationships between mass movement distribution and conditioning factors. The ability to learn non linear functions from the data is a key point in the problem of classifying landslide prone areas.

In this contribution the landslide analysis has been performed by means of Multi-Layer Perceptron (MLP) networks. ANNs are data-driven models and universal non linear function approximators [2]. Moreover, ANNs are able to give a good prediction even though trained with noisy and uncertain data.

We have introduced as final step an analysis of robustness to investigate with a quantitative approach, how errors in input data could affect susceptibility computation once applied on a real case study. This analysis of robustness has been performed to evaluate error sensitivity for each conditioning factor, thus giving a sensitivity characterization to the data in terms of which errors could affect the network output in a greater way. Robustness analysis has been introduced to evaluate the reliability of the final susceptibility map. This evaluation is crucial, since a susceptibility map too much influenced by errors in the data can not be used to support territory planning and the decision making.

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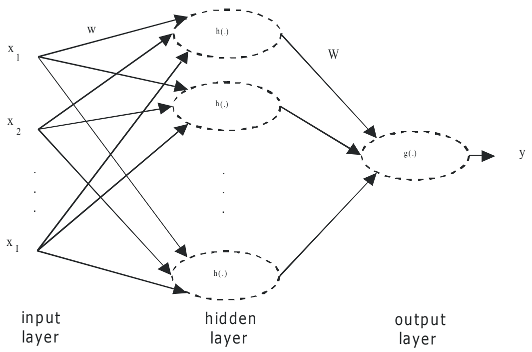

Fig. 1. Schematic representation of a simple feed-forward topology.

We have also trained the networks both using all the variables and using only the input variables selected during a previous analysis with the Logistic Regression [3]. The comparison between the reduced and the complete models has been carried out evaluating the prediction capability and using the results of the robustness analysis.

Herein (Section II) we will describe the methodology used to perform the analysis and to evaluate the results . Section 3 gives a general overview about the geological and geomorphological characteristics of the study area and describes the variables selected for the analysis. The results of the prediction capability and robustness indexes are discussed in Section IV.

I. Methodology

A. Artificial Neural Networks

ANNs are generic non-linear function approximators extensively used for pattern recognition and classification [2]-[4]. A neural network is a collection of basic units, called neurons, computing a non-linear function of their input. Every input has an assigned weight that determines the impact this input has on the overall output of the node.

By interconnecting a proper number of nodes in a suitable way and by setting the weights to appropriate values, a neural network can approximate any non-linear function with arbitrary precision [5]. This structure of nodes and connections, known as network topology, together with the weights of the connections, determines the final behavior of the network. Fig. 1 describes a simple feed-forward topology (i.e., no loops are present) with a single hidden layer (i.e., a layer of neurons neither connected to the input nor to the output). Given a neural network topology and a training set, it is possible to optimize the values of the weights in order to minimize an error function by means of any back-propagation algorithm [6], standard optimization techniques [7], or randomized algorithms [8].

The topology of a neural network plays a critical role in whether or not the network can be trained to learn a particular data set. A simple topology will result in a network that can not learn to approximate a complex function, whereas a complex topology is likely to result in a network losing its generalization capability. This loss of generalization is the result of overfitting the training data, i.e., instead of approximating the function that generates the data, the neural network memorizes the training set resulting in inaccurate predictions on future samples. In this paper to improve generalization we use the early stopping technique [9], consisting in using a validation set to stop the training algorithm before the network starts learning noise in the data as part of the model. The error on the validation set can be used also as an estimate on generalization error and thus can be used to select a proper network topology.

B. Methods to evaluate the prediction capability

To evaluate the capability classification and discrimination of the ANNs and to evaluate the prediction capability of the obtained susceptibility maps, we used: sensitivity, specificity, overall accuracy, ROC curves, and the validation curves of the susceptibility map. In the following we introduce each of these measures and illustrate their meaning.

We have selected as performance measures sensitivity, specificity and accuracy to represent the percentage of correct classified samples. In particular, the sensitivity is the percentage of correct classified landslides (i.e., true positive); the specificity is the correct samples classified as no landslide (i.e., true negative); the accuracy assesses the goodness of the classification, since it evaluates the correct samples classified as landslide or as not landslide. Since the network was designed to have output in the range [0, 1], it represents the probability of each sample to belong to the landslide class. In order to calculate the performance measures, a threshold of 0.5 has been chosen to separate the two classes (i.e., landslide versus not landslide).

The ROC curve is obtained by calculating Sensitivity and 1-Specificity for different thresholds. One important parameter of the ROC curve is the ROC value representing the area under the curve. The ROC value is a measure of the discrimination capability and the accuracy of the classifier.

The validation curve aims to evaluate the prediction capability of the obtained susceptibility maps and to compare different maps. The first step in calculating the validation curve consists to simulate the trained network on the whole study area. The susceptibility map is produced first ordering the output values in increasing order and then ranking the values in classes with the same number of pixels [10]-[11]. The 0-0.1 class includes the 10% of the pixels with highest mean output value. The 0.1-0.2 class includes the following 10% more susceptible, and so on. Finally, the validation curve is evaluated by calculating the percentage of corrected classified landslides for each susceptibility class. Since that curve measures the prediction capability, the calculation is performed on the landslides of the test set.

C. Robustness Analysis in ANNs

The robustness analysis is aimed at estimating the variation in accuracy due to perturbation in the computational flow. Because of the already discussed presence of high uncertainty in the conditioning factors, we have decided to consider the variation in accuracy due to perturbation affecting the input variables. We have modified and applied the robustness index proposed in [12], where a randomized algorithm [13]-[14] was introduced to solve the intractable problem of evaluating the robustness of a generic neural network with respect to a generic and continuous perturbation affecting the weights. In this contribution we have applied the index to estimate variation of sensitivity due to perturbation affecting the input variables.

In general, the robustness analysis requires the evaluation of the loss in performance due to a generic perturbation. Let be $f(x_\Delta, \theta)$ the perturbed network answer and $f(x,\theta)$ the not perturbed answer, where Δ is a generic perturbation m-dimensional vector of the perturbation space D. Each component of the vectors represents each independent perturbation of the input. D is characterized in stochastic terms by means of a probability density function pdf_Δ. The first step is selected a loss function $U(\cdot)$ that measures the discrepancy between $f(x_\Delta, \theta)$ and $f(x,\theta)$. Since the aim of susceptibility analysis is to classify landslide areas, we have selected as loss function the discrepancy between the sensitivity of the perturbed model and the sensitivity of the not perturbed model:

$$U(\Delta,\theta) = \left|Sen(f(x_\Delta,\theta)) - Sen(f(x,\theta))\right|$$

The impact of the perturbation on the network performance is evaluated by introducing a robustness index $\bar{\gamma}$. The network is robust at level $\bar{\gamma}$ in D, when $\bar{\gamma}$ is the minimum positive value for which:

$$U(\Delta,\theta) \le \bar{\gamma}, \forall \Delta \in D, \forall \gamma \ge \bar{\gamma} \qquad (1)$$

The main problem to evaluate $\bar{\gamma}$ is from the computational point of view, since we have to calculate $U(\Delta,\theta) \forall \Delta \in D$. This problem can be solved by associating a probabilistic interpretation to Equation (1). The network is robust at level $\bar{\gamma}$ in D with confidence η, when $\bar{\gamma}$ is the minimum positive value for which:

$$P(U(\Delta) \le \bar{\gamma}) \ge \eta, \forall \Delta \in D, \forall \gamma > \bar{\gamma} \qquad (2)$$

Equation (2) means that not more than $100(1-\eta)\%$ of the perturbations $\Delta \in D$ will generates a loss in performance larger than $\bar{\gamma}$.

The non linearity with respect to Δ and the lack of priori assumptions on the neural network do not allow the computation of Equation (2) and this issue can be solved by using the randomized algorithm.

Denote with p_γ the probability that the loss in performance induced by perturbation in D is below a arbitrary value γ:

$$p_\gamma = P(U(\Delta) \le \gamma)$$

The probability p_γ can be estimated by sampling in D according to the pdf_Δ with N independent and identically distributed samples Δ_i. For each Δ_i the following triplet is generated:

$$\{\Delta_i, U(\Delta_i), I(\Delta_i)\}, i = 1, \ldots, N$$

Where:

$$I(\Delta_i)\begin{cases} 1, if U(\Delta_i) \le \gamma \\ 0, if U(\Delta_i) > \gamma \end{cases}$$

The probability p_γ can be estimated:

$$\hat{p}_N = \frac{1}{N}\sum_{i=1}^{N} I(\Delta_i)$$

When N tends to infinity, $\hat{p}_N$ converges to p_γ; if N is finite, the discrepancy between $\hat{p}_N$ and p_γ is $\left|p_\gamma - p_N\right|$. By introducing accuracy ε and confidence level $1-\delta$ the following inequality is required to be satisfied for $\forall \gamma \ge 0$:

$$P\left\{\left|p_\gamma - p_N\right| \le \varepsilon\right\} \ge 1-\delta$$

This relationship holds when N satisfies the Chernoff inequality:

$$N \ge \frac{\ln \frac{2}{\delta}}{2\varepsilon^2}$$

The main assumptions we made in the robustness analysis is then that the errors in the data could be modelled by a generic perturbation Δ_i and that this error model is the same for all the input variables. In this work we have calculated the robustness indexes assuming an error proportional to the input magnitude:

$$\bar{x}_{j,\Delta_i} = x_j(I + \overline{\Delta}_i), \forall i = 1,...,n$$

Where $\bar{x}_j$ is the vector for the j-th input variable, $\overline{\Delta}_i$ is the perturbation vector and I is the identity vector. The robustness index has been calculated for each variable and for the total model by perturbing all the input variables at the same time.

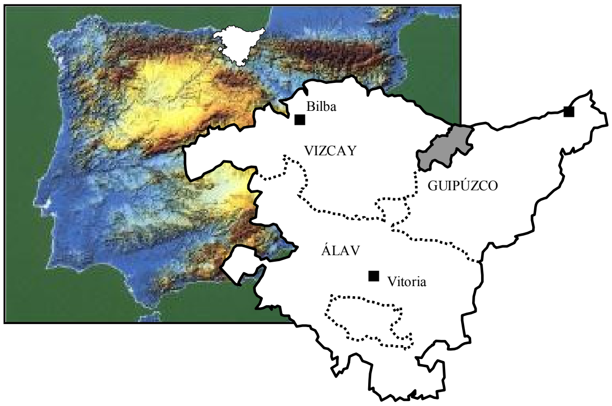

Fig. 2. Location of the study area. The Deba Valley is visualized in grey.

II. Case Study

The susceptibility analysis and robustness assessment have been applied to the Deba Valley area, located in northern Spain (Fig. 2). The Deba Valley covers approximately 140 km^2 and the mean annual rainfall is in the order of 1,500 mm. The lithology is mainly sedimentary (limestone, marl, claystone, sandstone and flysh) and volcanic. The average slope is about 22° and the regolith thickness is in the range from 0.5 to 3 m. The landslides affecting the area are several types, the shallow translation slides and flow are the most common. A landslide susceptibility analysis in this area is particularly interesting because of the high density of population and because of the presence of intense human activity.

The landslides analysed in this work are the debris slides, affecting the weathered and colluvial materials. In the study area the main triggering factor for those types of landslides is intense rainfall, that increases pore water pressure and lowers the shearing resistance of surface formation. The geometrical characteristics of the slopes play a crucial role on conditioning landslide because they influence the water concentration capacity. Vegetation is important because it influences the soil infiltration capacity, the soil humidity and its cohesion. Lithology is another important factor for the cohesion. According to that rupture hypothesis, different variables related to lithology, vegetation, and geometric characteristics of the slopes have been selected in order to perform the susceptibility analysis (Table I).

Before performing the analysis, all the input variables have been scaled into the range [0, 1]. The categorical variables (i.e., vegetation and lithology) have been converted in numerical value by using expert knowledge [15]-[3]. The landslides inventory map was convert in a binary output layer (i.e., presence/absence of landslides).

III. Analysis and Results

The analysis was performed using an MLP network and the Levenberg–Marquardt training algorithm [16]-[17]. We used the early stopping technique [18]-[9] to improve the generalization of the network. This technique consists of using a data set (i.e., validation set) to stop the training algorithm before the network starts learning noise in the data, so thus to find the network with the highest generalization capability.

TABLE I
DESCRIPTION OF THE VARIABLES USED IN THE ANALYSIS

Variable	Description
Mass movement (MOVPT)	Represent landslide used in the analysis
Elevation (DEM)	Altitude asl
Slope gradient (PEND)	Slope gradient at failure zone
Aspect (ORIENT)	Slope aspect
Insolation (INSOL)	Solar radiation on June, 21
Roughness (RUGOS)	Divergence of vectors normal to pixel surface
Curvature (CURVAR)	Degree of concavity/convexity
Regolith presence (FS)	Presence of surface deposits
Regolith thickness (ESPE)	Thickness of surface deposits
Upstream area (ACUENCA)	Area of upstream drainage basin
Basin length (LONG)	Upstream basin length
Upstream surface deposit area (AFS)	Upstream basin area with surface deposits
Upstream surface deposit length (LFS)	Length of upstream area with surface deposits
Average slope gradient (PENDM)	Avarage slope gradient of the upstream basin
Vegetation (VEGET)	Land cover type and density
Lithology (LITO)	Bedrock and surface deposit

The first step in the this study aimed at finding the best architecture for the data analysis. Fig. 3 individuates the relationship between the MSE (Mean Square Error) on the validation set and the number of neurons in the hidden layer. We selected the architecture with 6 neurons corresponding to the smallest network with the minimum MSE (i.e., network that guarantees the best generalization).

In order to obtain and discuss results not influenced by a particular partition of the database, we partitioned the database 10 times in training, validation and test set. In [3] we used in the LR analysis the likelihood ratio criteria to select only the statistically significant variables. That criteria

Fig. 3. MSE on the validation set .

TABLE II
PERFORMANCE MEASURES OBTAINED FOR REDUCED AND NOT REDUCED MODELS

	Not reduced variables			*Reduced variables*		
	Sen	***Spe***	***Acc***	***Sen***	***Spe***	***Acc***
Subdivision 1	64	75	70	71	68	69
Subdivision 2	70	65	68	71	67	69
Subdivision 3	73	66	70	68	70	69
Subdivision 4	73	65	69	69	69	69
Subdivision 5	70	63	66	71	68	70
Subdivision 6	70	70	70	74	64	69
Subdivision 7	64	75	70	72	68	70
Subdivision 8	74	63	68	72	68	70
Subdivision 9	76	61	69	76	66	71
Subdivision 10	70	65	67	68	68	68
Minimum	64	61	66	68	64	68
Maximum	76	75	70	76	70	71
Average	70	67	69	71	68	70

selected the same variables 9 times out of 10. Since the excluded variables should be not statistically significant, we decided to perform again the analysis by mean of the ANNs using only the variables selected by the LR. For each obtained model (i.e., reduced and not reduced) the performance measures, the ROC curve and the validation curve were calculated.

As final step of the susceptibility modelling we have performed the robustness analysis [12]-[13]. The robustness index was designed specifically to evaluate the sensitivity to errors of neural networks. In spite of that, the index is not strictly related with the use of the ANNs, but it can also be applied to estimate the errors sensitivity in each statistical model. We used a uniform (probability density function) and a range error of ±5% to extract the perturbations and by selecting a 5% in accuracy and a 99% in confidence we extracted 1060 samples from the perturbation space.

A. Evaluation of the prediction capability

All the method used to estimate the prediction capability of the tested models have shown similar results for the comparison between the reduced and not reduced models; in particular, the prediction is slightly better if the analysis is performed with a reduced number of inputs. In details we can notice that the mean values of the performance measures (Table II) have been increased, mainly because the worst models (i.e., minimum values) obtained reducing the variables show higher prediction capability than the worst models obtained using all the available input variables. Similar results were obtained for the ROC value (Table III) that confirms a slightly better discrimination between the two classes (i.e, presence/absence of landslides) for the reduced model. Nevertheless, that difference is not so significant because in all the tested model the ROC value is in the range 0.7 – 0.8 representative of a acceptable

TABLE III
ROC VALUES OBTAINED FOR REDUCED AND NOT REDUCED MODELS

	Not reduced variables	***Reduced variables***
Subdivision 1	0.75	0.76
Subdivision 2	0.74	0.76
Subdivision 3	0.76	0.77
Subdivision 4	0.76	0.77
Subdivision 5	0.74	0.76
Subdivision 6	0.76	0.78
Subdivision 7	0.76	0.78
Subdivision 8	0.74	0.77
Subdivision 9	0.77	0.78
Subdivision 10	0.73	0.75
Average	0.75	0.77

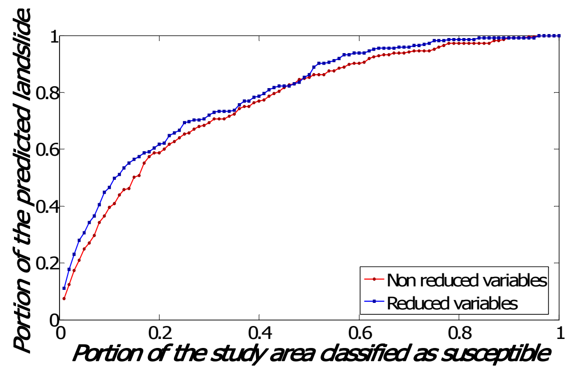

Fig. 4. Example of validation curves obtained for models with reduced and not reduced variables.

discrimination. Concerning the results obtained for the validation curves, they have shown for 6 database sub-sampling out of 10 better prediction, specially for the more susceptible classes.

One example is shown in Fig. 4: the 10% most susceptible area (0-0.1 class) predicts the 10% more landslide for the model trained with a reduced number of variables.

The prediction capability does not decrease after removing the Afs, Curvar, Lfs, Orient, Pendm, Rugos variables and those variables contain only noise and not useful information to model landslide presence.

B. Robustness analysis

Table IV (a) and IV (b) show the robustness index values (partial and total index) obtained for the networks trained with all 15 variables. It is possible to notice that the index value depends on the considered variable and on the selected subdivision.It depends on the variable since the index has approximately the same value in all the database subdivisions. In fact, the variables the model is more sensitive to errors are the roughness and the curvature in all the subdivisions, whereas the index has always value 0 for the variables Acuenca and Afs. The index value depends on the selected subdivision, since the rank of the influence that

TABLE IV (a)
PARTIAL AND OVERALL ROBUSTNESS INDEXES FOR THE COMPLETE MODELS (1-5 DATABASE SUBDIVISIONS)

	Database subdivision				
	1	***2***	***3***	***4***	***5***
Acuenca	0	0	0	0	0
Afs	0	0	0	0	0
Curvar	9.99	7.12	5.78	7.56	7.12
Dem	1.34	1.34	1.78	1.34	0.89
Espe	1.78	0.89	0.89	1.34	0.89
Fs	2.67	3.56	0.89	3.12	1.78
Insol	3.12	1.78	3.12	2.23	2.67
Lfs	0	0	0	0.89	0
Lito	1.34	0.89	1.78	1.78	0
Long	0	0	0	0.45	0
Orient	0	0.45	0.45	0.45	0
Pend	2.23	0.45	1.78	1.34	1.34
Pendm	0.45	0	0.45	0.45	0
Rugos	4.89	2.67	4.01	6.67	3.12
Vege	0.45	0.45	0.89	1.34	1.34
Total	9.99	9.34	7.12	9.78	7.56

TABLE V (a)
PARTIAL AND OVERALL ROBUSTNESS INDEXES FOR THE REDUCED MODELS (1-5 DATABASE SUBDIVISIONS)

	Database subdivision				
	1	***2***	***3***	***4***	***5***
Acuenca	0	0	0	0	0
Afs	/	/	/	/	/
Curvar	/	/	/	/	/
Dem	0.89	1.34	1.34	1.34	1.78
Espe	0.45	0	0.45	0.45	0.45
Fs	4.45	2.23	1.78	3.12	3.12
Insol	1.34	2.67	1.78	2.67	2.67
Lfs	/	/	/	/	/
Lito	1.34	0.45	0.89	1.34	0.89
Long	0	0	0	0.45	0
Orient	/	/	/	/	/
Pend	1.34	1.78	0.45	0.89	1.34
Pendm	/	/	/	/	/
Rugos	/	/	/	/	/
Vege	1.34	1.78	1.34	1.78	1.34
Total	4.45	3.56	2.67	4.89	3.56

TABLE IV (b)
PARTIAL AND OVERALL ROBUSTNESS INDEXES FOR THE COMPLETE MODELS (6-10 DATABASE SUBDIVISIONS) AND MEDIUM PARTIAL INDEX VALUE CALCULATED ON THE 10 SUBDIVISIONS

	Database subdivision						
	5	***6***	***7***	***8***	***9***	***10***	***Average***
Acuenca	0	0	0	0	0	0	0
Afs	0	0	0	0	0	0	0.00
Curvar	7.12	5.78	6.67	3.56	4.01	6.23	5.56
Dem	0.89	0.45	1.34	1.34	1.78	0.45	1.04
Espe	0.89	0.45	0.89	0.45	1.34	0.45	0.75
Fs	1.78	3.12	2.67	4.89	2.23	2.23	2.82
Insol	2.67	1.78	1.78	1.78	2.23	1.34	1.93
Lfs	0	0	0	0.45	0	0.45	0.15
Lito	0	0.45	1.34	0.45	1.34	0.45	0.67
Long	0	0	0	0	0.45	0.45	0.15
Orient	0	0	0.45	0	0.45	0.45	0.23
Pend	1.34	1.78	0.89	1.34	1.78	0.45	1.26
Pendm	0	0.45	0.89	0	0.45	0.45	0.37
Rugos	3.12	7.12	5.34	6.67	4.01	6.23	5.42
Vege	1.34	0.45	1.34	0.45	1.78	0.89	1.04
Total	7.56	9.34	6.67	8.89	5.78	9.99	8.04

TABLE V (b)
PARTIAL AND OVERALL ROBUSTNESS INDEXES FOR THE REDUCED MODELS (6-10 DATABASE SUBDIVISIONS) AND MEDIUM PARTIAL INDEX VALUE CALCULATED ON THE 10 SUBDIVISIONS

	Database subdivision					
	6	***7***	***8***	***9***	***10***	***Average***
Acuenca	0	0	0	0	0	0
Afs	/	/	/	/	/	/
Curvar	/	/	/	/	/	/
Dem	1.78	0.89	1.78	1.78	1.34	1.48
Espe	1.78	0.45	0.89	2.23	0.89	1.13
Fs	4.01	4.89	2.67	2.67	2.23	3.12
Insol	3.12	3.12	1.34	1.78	2.23	2.30
Lfs	/	/	/	/	/	/
Lito	1.34	0.89	1.78	0	0.45	0.84
Long	0	0	0.45	0.45	0	0.15
Orient	/	/	/	/	/	/
Pend	1.34	2.23	1.78	1.78	0.89	1.47
Pendm	/	/	/	/	/	/
Rugos	/	/	/	/	/	/
Vege	2.67	0.89	0.89	1.34	0.89	1.29
Total	4.45	5.34	2.67	4.01	3.12	3.80

each variable has on the networks behaviour changes with the changing of the selected database subdivision. Moreover, it is possible to notice that the total index is not the sum of the partial indexes, but its value is approximately the maximum value of the partial indexes. We could conclude that the total variation in the model performance is mainly due to the most noisy variable.

The Table V (a) and V (b) show the results of robustness analysis performed on the reduced neural models. As already discussed for the Table V (a) and V (b), the partial indexes are influenced by the selection of the database, showing that they are not only a property of the considered variable. Finally, we can notice that the total index is lower than the index for the model including all the variables: the reduction of the input have increased the robustness of the neural model.

IV. Conclusions

To consider the uncertainty in collecting and in computing the conditioning factors, in this paper we have introduced robustness analysis in landslide susceptibility mapping. Errors have been inserted in the model input by means of stochastic perturbation of the network and the impact of such perturbation is quantified introducing a robustness index. Such a robustness index is calculated by measuring the change in the network performance induced by input perturbation. The networks were trained using all the variables and using a reduced number of variables and the prediction capability and the robustness of the two different types of models were tested and compared.

The calculation of robustness indexes allowed the understanding that some of the variables excluded in the LR analysis are mainly source of noise. We claim that the introduction of the robustness analysis in a susceptibility model is a key to analyze the real applicability of the obtained models, since a susceptibility model too much influenced by the noise in the data (i.e., not robust) can not be used in territory planning and management.

Moreover, the robustness index value has allowed to deeply understand the network behaviour on the selected data. It has been often underlined that a vantage in using the ANNs is that they do not need assumption on data distribution, absence of correlation and they can have a good response even when trained with noisy data. The robustness analysis has shown that even though the variables selection is not necessary, it can be introduced in a preliminary phase of the analysis in order to improve the robustness and the prediction capability of the final models.

Reducing the number of variables increases the robustness of the models obtained by means of the neural networks, even when it does not increase the prediction capability of the models. This calls for the introduction of robustness analysis in an iterative process of variables selection and analysis aimed to exclude the variable not significant and noisy. Moreover, since the chosen index is not strictly related to the use of ANNs, we suggest a more intense introduction and investigation of the robustness analysis in the landslide susceptibility zonation an model assessment in general.

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