SHALLOW LANDSLIDE SUSCEPTIBILITY MODEL USING LOGISTIC REGRESSION

A case of study in the Oria river basin, Basque Country (North of the Iberian Peninsula) and comparison with previous studies

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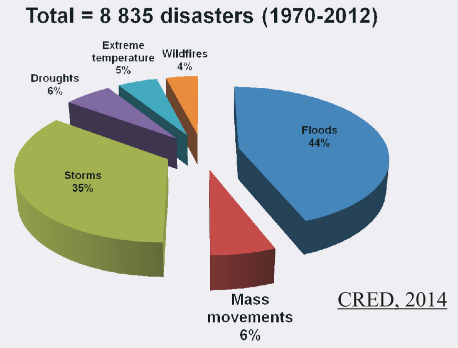
INTRODUCTION

According to the international disaster database (EM-DAT) the amount of natural disasters has considerably increased during the last decades. All around the world, landslides represented 6 % of the total amount of natural disasters between 1970 and 2012 causing an economic loss of US $ 23,900 million (CRED, 2014). Likewise, in the Oria basin landslides are very frequent and they produce several roadblocks and damages in the infrastructures, causing big economic loss every year.



CRED, 2014

In the Oria basin the following two landslide susceptibility maps were available until present:

ELSUS: It is a European landslide susceptibility map based on bibliographic landslide point information and developed by semi-quantitative methodology. Spatial resolution 1000 x 1000 m. (ELSUS 1000 version 1, 2013)

GIPUZKOA: It is a province scale landslide susceptibility map based on the geomorphologic map's landslide information and developed by discriminant analysis methodology with final expert criteria modifications. Spatial resolution 10 x 10 m. (Provincial Council of Gipuzkoa, 2007)

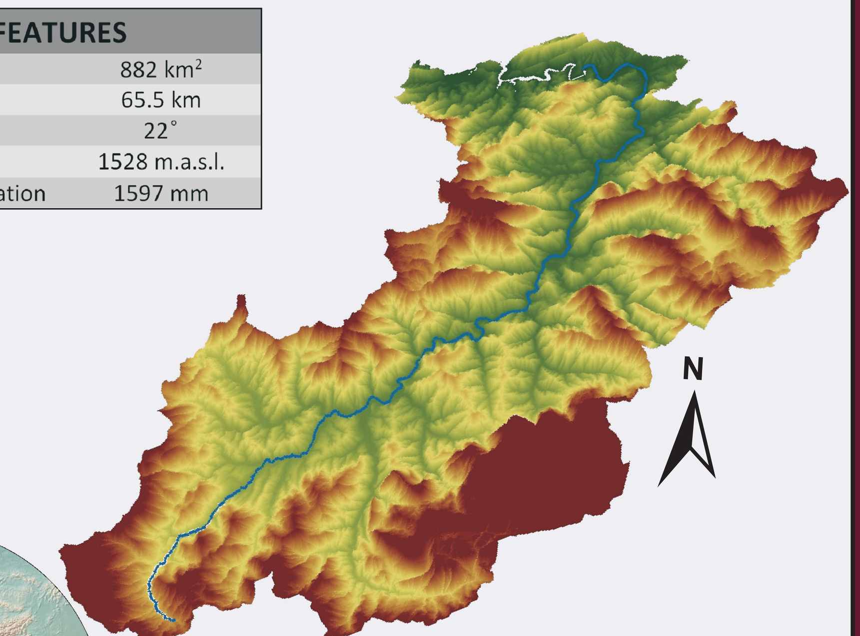
This work presents an application of an objective and reproducible quantitative methodology, the logistic regression (Trigila et al., 2015) , based on an updated field work landslide inventory data.

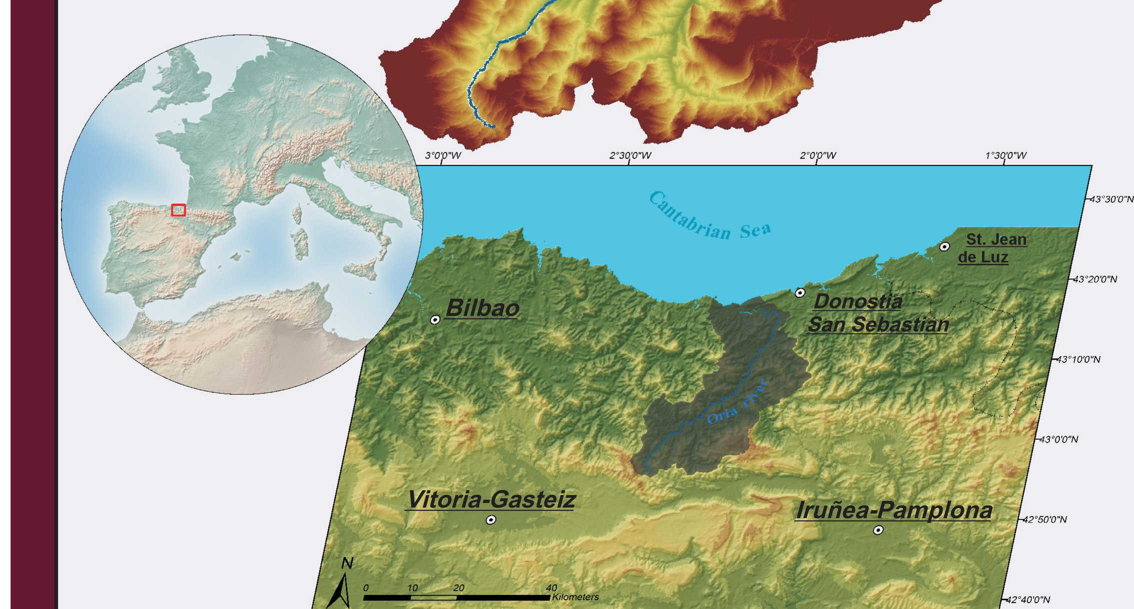
OBJECTIVES

- ✓ **To identify the most prone landslide places in the study area**
- ✓ **To test the logistic regression methodology as an objective and reproducible option**
- ✓ **To check whether the proposed map offers a significant improvement comparing with the previous existent susceptibility maps**

THE ORIA RIVER BASIN

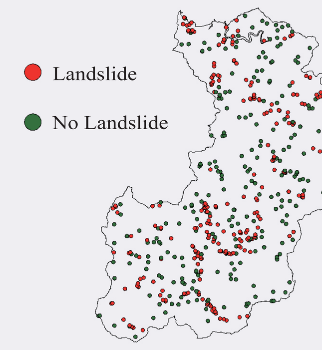
BASIN FEATURES	
Basin area	882 km^2
River longitude	65.5 km
Mean slope	22°
Max. Altitude	1528 m.a.s.l.
Annual mean precipitation	1597 mm



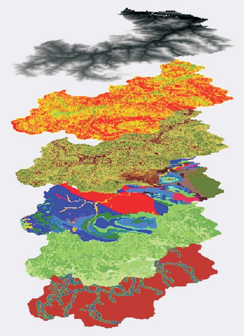


METHODOLOGY

a) MODEL CONSTRUCTION



To begin, the position of the highest points of the main scarps of each landslide have been inventoried (Landslides) (260), along with the stable points (No Landslide) (260), by fieldwork and satellite imagery analysis.



Inventory		Altitude (m)	Senoidal Slope	NDVI	Lithology	Land Use	Distance Transp.
No Landslide	0	624.018	0.8962	0.2078	0.5994	0.4361	0.6732
Landslide	1	605.171	0.8742	0.2235	0.5994	0.5323	3.0149
Landslide	1	489.240	0.5226	-0.1922	1.3561	0.5323	4.6428
Landslide	1	489.979	0.6704	-0.1451	1.3561	2.8446	4.6428
No Landslide	0	444.076	0.2770	0.0902	1.3561	2.8446	4.6428
No Landslide	0	805.107	0.9091	0.0745	0.5356	0.4361	0.2682
Landslide	1	462.784	0.4356	-0.1373	0.5994	2.8446	4.6428
...	...	...	...	...	...	...	...

Later on, for each point, different environmental information has been collected using digital spatial layers in the ArcGIS 10.0 software. Categorical variables (like lithology) have been codified giving for each class a numerical value refering to its landslide density (Bai et al. 2010). Afterwards, a sample data base has been created for the statistical analysis in SPSS XXII software. To do so, the logistic regression option has been chosen following the INTRO method.

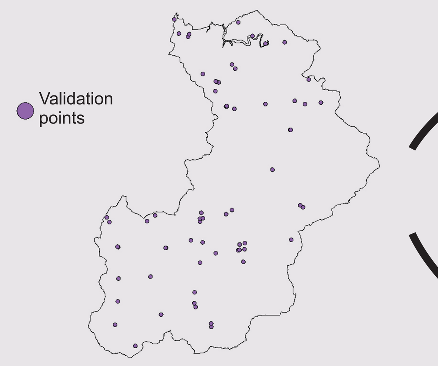
	β coef.
Altitude	-0.002
Senoidal Slope	5.312
NDVI	-4.574
Lithology	0.615
Land Use	0.559
Distance to transport network	0.499
Constant	-5.850

$$Z = \beta_0 + \beta_1 X_1 + \cdots + \beta_n X_n$$

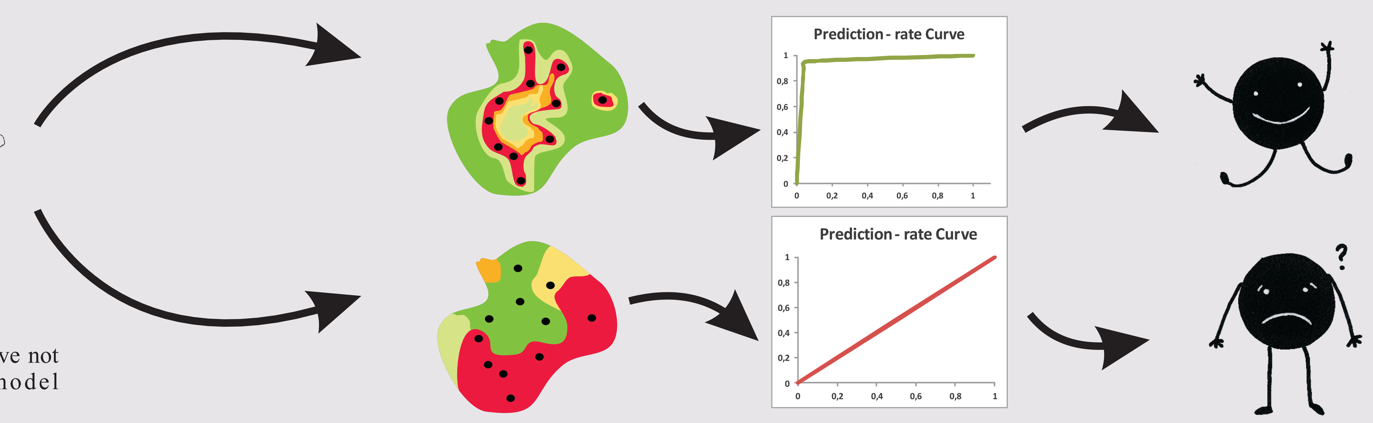
$$P = \frac{1}{1 + e^{-Z}}$$

Finally, the statistical software output the results in the form of coefficients to be applied in the logistic regression expression. Hence, in the ArcGIS software each environmental layer has been multiplied by his coefficient and the logistic equation have been represented as a P probability that a given point in the study area have of suffering a shallow landslide.

b) MODEL VALIDATION



These validation points (65) have not been used during the model production.



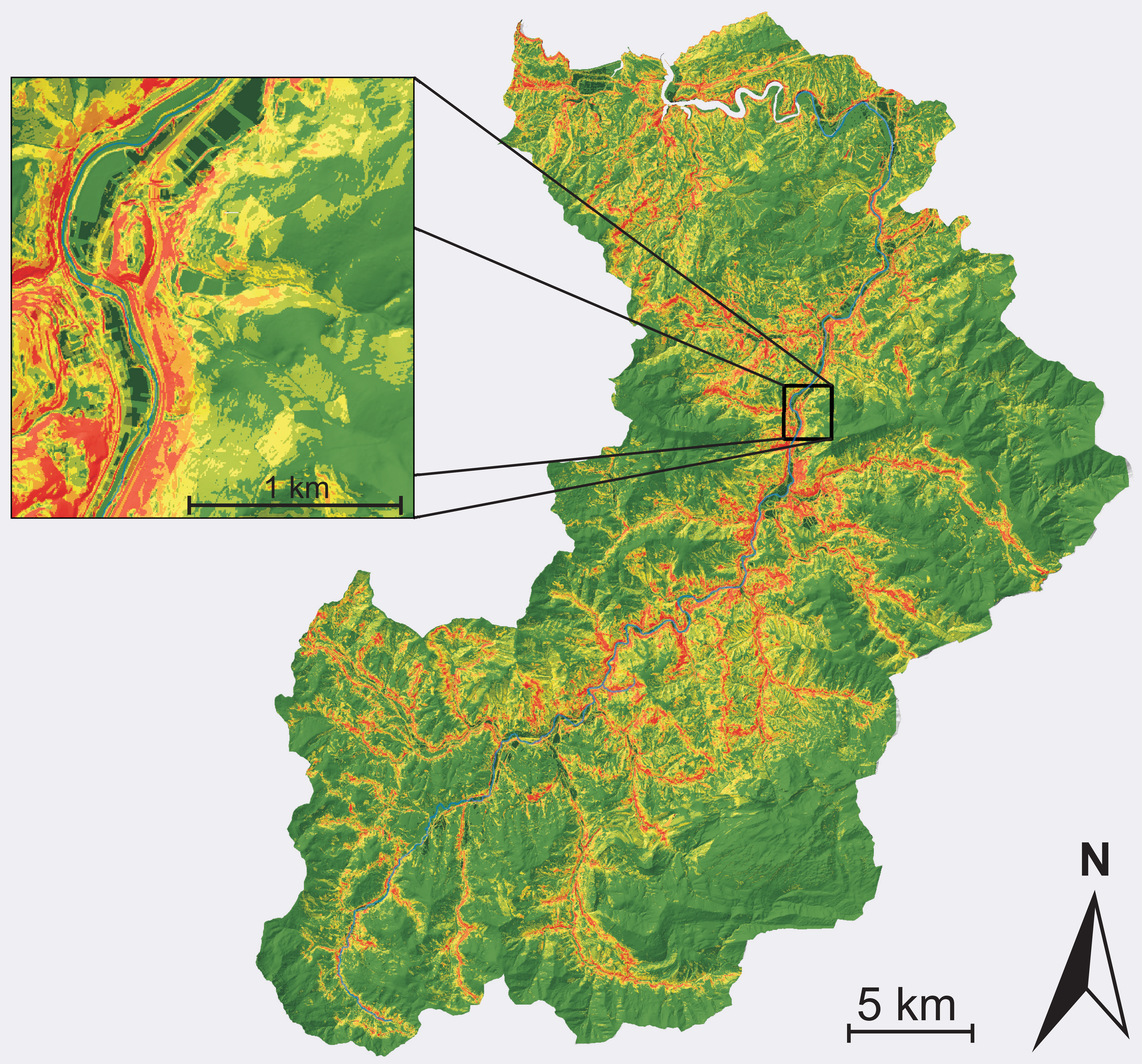
Following the validation procedure (Chung & Fabbri, 2003), the cumulative percentage of validation points falling in each susceptibility class, ordered from very high to very low, have been related with the cumulative percentage of the area of each susceptibility class.

When most of the landslides are located in the pixels included in high susceptibility classes, and these susceptibility classes cover the smallest possible area, the area under the prediction rate curve is close to 1 (see green curve), and so, it is considered that the prediction capacity of the model is satisfactory.

Otherwise, if the validation landslide points fall in low susceptibility classes or the high susceptibility classes are too extensive, then the area under the prediction rate curve will be close to 0.5 (see red curve), which means a random prediction capacity.

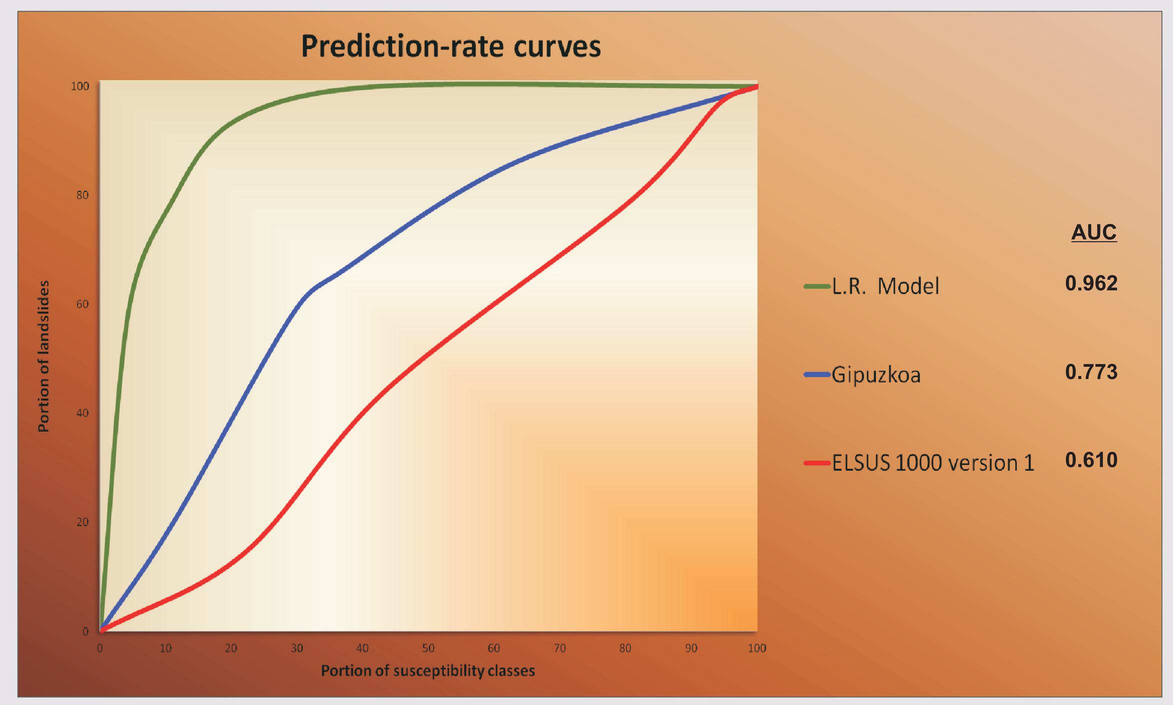
RESULTS AND DISCUSSION

Logistic Regression (L.R.)



Susceptibility class

Very low | Low | Middle | High | Very high

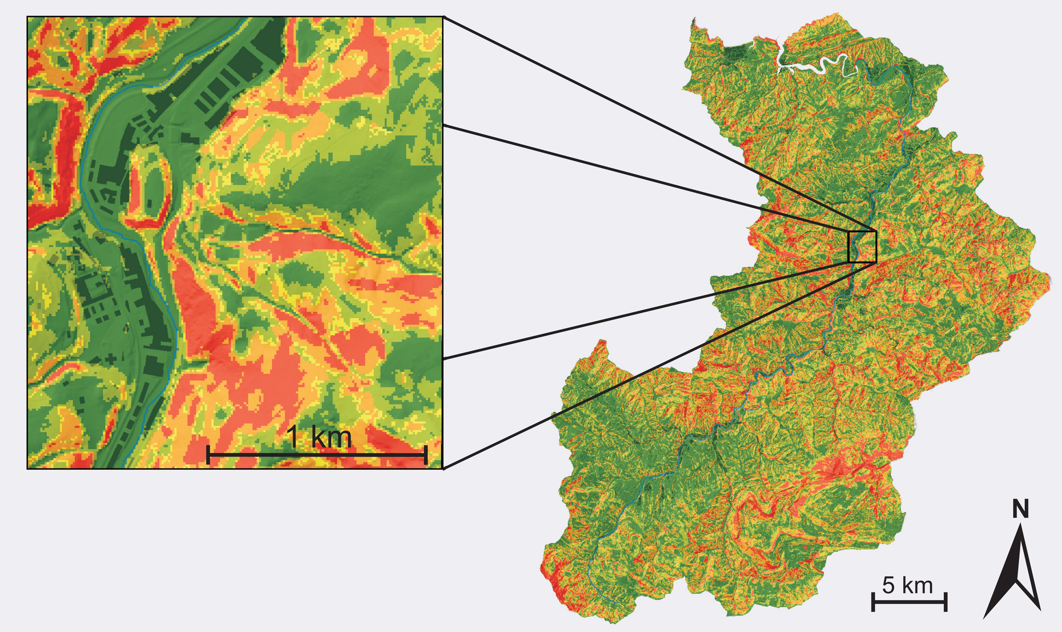


Regarding the β coefficients resulting from the logistic regression analysis (see Methodology) it can be highlighted the importance of Senoidal Slope and NDVI variables in contrast with the low significance power of the Altitude, which means that the shallow landslide's spatial distribution is generally related with high senoidal slope values and low NDVI values, and specific differences appear depending on the lithology, land use or distance to the transport network.

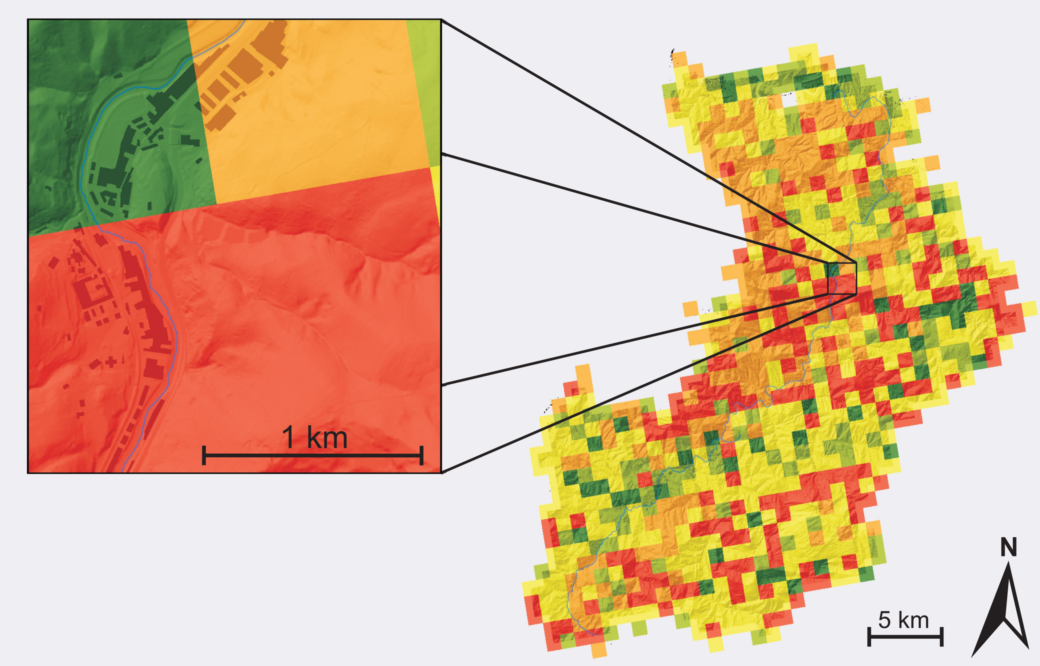
Available previous susceptibility maps in the study area show to be very different. The model ELSUS 1000 version 1 shows too low spatial resolution, which makes it inadequate for this working scale. On the other hand the Gipuzkoa model shows an adequate spatial resolution, although, as it can be appreciated in zoomed boxes, the susceptibility zonation differs a lot.

The prediction rate curves illustrates very well that there is an evident difference between the tested models. Obviously, given its spatial resolution, the ELSUS 100 version 1 model shows the worst prediction capacity. With an acceptable prediction capacity, there is the Gipuzkoa model, whose limitations may be related to the fact that high susceptibility classes take too much space. And finally, the L.R. model shows an excellent prediction capacity which means that high susceptibility classes takes as most reduced space as possible, and additionally the most part of validation landslides fall in those classes.

GIPUZKOA



ELSUS 1000 version 1



CONCLUSIONS

- ✓ **The L.R. model gives a very satisfactory prediction capacity. So the most prone landslide places have been identified.**
- ✓ **It has been confirmed the logistic regression as a valid methodology in shallow landslide susceptibility studies.**
- ✓ **The ELSUS 1000 versión 1 model does not offer useful information for the landslide management in a regional scale.**
- ✓ **The GIPUZKOA model, offers a prediction capacity which is considerably lower (19%) than the L.R. model, so it is concluded that the proposed model improve considerably the previous susceptibility models.**

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