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Influence of Digital Elevation Models on Landslide Susceptibility with Logistic Regression Model

Influência dos Modelos Digitais de Elevação na Susceptibilidade a Escorregamento com Modelo de Regressão Logística

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***Abstract**: This paper focuses on the influence of Digital Elevation Models on the landslides susceptibility assessment in agricultural terraces, using Logistic Regression statistical model.This study was performed in a watershed located at Carvalhas Estate in Douro Valley, using an inventory of 109 landslides. To analyse the influence of the digital elevation model (DEM) resolution we used three DEMs, (A), (B) and (C). The DEMs (A) and (B) were directly obtained by processing aerial images and extracting different resolutions, 1 and 5 meters, respectively. The DEM (C), with 5m resolution, was processed with Topo to Raster interpolation method, using as input data contour lines of 10 m interval, elevation points and hydrography. The Logistic Regression was performed using two models which are distinguished by the independent variables selection. At model 1 was used the slope, curvature, raiser slope, riser height, contributing areas and topographic wetness index. In model 2 we decide remove the independent variables related with the terrace geometry, riser slope and riser height. The result seems to indicate that there is no significant influence of different resolutions of Digital Elevation Models in susceptibility modelling at this small scale and using statistical methods. The independent variables riser slope and riser height provide information of the terraces geometry and the construction techniques that enter the modelling process with more detailed information.*

***Keywords**: Statistical Modelling; Landslides; Agriculture Terraces; Douro Demarcated Region.*

Resumo: O artigo demonstra a influência dos Modelos Digitais de Elevação na avaliação da suscetibilidade a movimentos de vertente em terraços agrícolas, utilizando o modelo de base estatística -Regressão Logística. O estudo foi realizado numa bacia hidrográfica localizada na Quinta das Carvalhas, no Vale do Douro, utilizando um inventário de 109 movimentos de vertente. Para analisar a influência da resolução do Modelo Digital de Elevação (MDE), utilizaram-se três MDE's, (A), (B) e (C). Os MDE's (A) e (B) foram obtidos diretamente pelo processamento de imagens aéreas e extração de diferentes resoluções, 1 e 5 metros, respetivamente. O MDE (C), com resolução de 5 m, foi processado com o método de interpolação Topo to Raster, utilizando como dados de entrada curvas de nível com equidistância de 10 metros, pontos cotados e a hidrografia. A Regressão Logística foi realizada utilizando dois modelos que se distinguem pela diferente seleção das variáveis independentes. No modelo 1 utilizaram-se o declive, curvatura, inclinação do talude, altura do talude, área contributiva e índice topográfico de humidade. No Modelo 2, removeram-se as variáveis independentes relacionadas com a geometria do terraço, nomeadamente a inclinação do talude e a altura do talude. Os resultados indicam que não existe influência significativa na modelação da suscetibilidade com métodos estatísticos, a uma pequena escala, utilizando diferentes resoluções dos MDE´s. As variáveis independentes, inclinação do talude e altura do talude, fornecem informações relativas à geometria e técnicas de construção dos terraços, e permitem um processo de modelação com informações mais detalhadas.

Palavras-Chave: Modelação Estatística; Movimentos de Vertente; Terraços Agrícolas; Região Demarcada do Douro.

1. Introduction

The Porto wine production is the most important economic activity of the Douro Demarcated Region (DDR), and the associated landscape is partially classified as a world heritage since 2001. The topography, modified by the construction of the ground frame systems, has very steep slopes (**Figure 1**). This morphological modification has important consequences on the soil hydrological and stability conditions (Fernandes et al., 2017). The ground frame systems, based on the construction of agricultural terraces, is capable to allow the mechanization of agricultural work. The terrace platform is divided into two sections: one excavated and another filled. The desegregated materials of the filled section is under the influence of a high subsurface flow hydraulic gradient that promotes instability, (Fernandes et al., 2017).

The landslides susceptibility cartography can be produced through direct mapping methods (geomorphological and heuristic method) or indirect (inventory analysis, statistical modelling and geotechnical models), (Guzzetti et al., 1999). However, the spatial resolution has to be adapted in order to be representative of the surface features and patterns. The choice of spatial resolution may lead to misinterpretation of the surface features. Thus, coarse spatial resolutions will overlook reduced scale surface features and, on the other hand, high resolutions provide a detail that is not adjustable to all analysis scales, (Mora et al., 2014), Zhang and Montgomery (1994), used TOPMODEL to build DEM's - (Digital Elevation Models) in hydrological modelling with 2, 4, 10, 30 and 90m resolution. The result suggests that the data with a 10 meters resolution provide a better relationship with the volume of data for simulation of geomorphological and hydrological processes. Guzzetti et al. (1999), proposed that should be tested different pixel sizes according to the subject of study in order to use the most suitable DEM resolution for the susceptibility evaluation methods. Li and Zhouh (2003), modelled the susceptibility of landslides in Hong Kong (Latau) with DEM resolution of 5m, 10m, 20m, 40m and 80m using as condition factors, the slope, aspect, type of vegetation, geology, altitude and distance to the water line. They concluded that the 20 m of DEM resolution is the best fit for this assessment. The authors indicate that the choice of pixel size should be in accordance with the study area spatial dimension. Lee et al. (2004) used DEM, (for evaluation of susceptibility to landslide at Bour (Korea)), with 5, 10, 30, 100 and 200 meters resolution and concluding that the spatial resolutions of 5, 10 and 30 meters showed similar results. Moreover, resolutions of 100 and 200 m resulted in lower precision and as consequence inferior results. The authors concluded that the input DEM has a great influence on the final modelling outcome in this study was 30 meters. Claessens et al. (2005) used four DEM with 10, 25, 50 and 100 meter resolution for a 12 km2 area of study (in New Zealand). They conclude that the selection of DEM resolution depends on data availability adapted to the context and scale of analysis. Tian et al. (2008) evaluated the susceptibility of slips occurrence using the informative value method with eleven different resolutions DEM's (5, 10, 30, 50, 70, 90, 110, 130, 150, 170 and 190 meters). They concluded that the curvature and slope are the variables, directly derived from the DEM, that have more dependence of resolution DEM. Moreover, the same influence does not appear on variables such as the land use or geology, which dependence is lower in these cases.

The relationship between the resolution and the study area shows that the 90 meters resolution has better performance, considering the necessity to find acceptable threshold between the size of the study area and the DEM resolution. Stefanescu et al. (2012) applied the TITAN 2D model with DEM input resolutions of 5, 10, 30, 50 and 90 meters. They concluded that the highest resolution DEM show better results in the definition of the water flow lines while the coarser DEM resolution do not has accurate results.

There are several methods of assessing landslides susceptibility. The stochastic models perform statistical relationships that quantify and combine the distribution of previous landslides events to a set of geoenvironmental variables, (Constanzo et al., 2013; Zêzere et al., 2017). The statistical approaches are gaining increasing importance, particularly for basin-scale, (Costanzo et al., 2013).

Logistic regression, models the relationship between a dichotomous variable (presence/absence of landslide) and a set of independent physical variables (controlling factors), (Guns and Vanacker, 2012). Many authors have used the logistic regression model in landslides susceptibility, (Carrara, 1983; Carrara et al., 1991; Ayalew and Yamagishi, 2005). Constanzo et al. (2014), used logistic regression to produce earth-flow susceptibility model defined by the statistical relationship between 760 slip events and a set of 20 predictors. From the results, they concluded that the model is adequate with a robust prediction demonstrated in the validation process. Sangchini et al. (2015), used logistic regression to determine landslides susceptibility areas in a watershed. From the study the authors concluded a high prediction accuracy of the model that can be useful in watershed management. Zêzere et al. (2017) evaluated the differences between the susceptibility maps produced by statistical methods. The authors consider that, the main errors in statistical models application are the inaccuracy of the inventory, the selection of statistical method, the terrain mapping unit and the type of inventory representation (point or polygon). They reinforce the idea that single point per landslide proved to be efficient to generate accurate landslide susceptibility maps, providing that landslides are small size, thus minimizing the possible existence of heterogeneities of predisposing factors within the landslide boundary.

The main objective of this study is the analysis of the influence of the DEM resolutions and construction methods, to assessment the landslides susceptibility in agriculture terraces. Was used the logistic regression applied to two models with different independent variables.

2. Study Area: Carvalhas Estate

Carvalhas Estate is located in the Douro valley (county of S. João da Pesqueira in the Viseu district, Portugal), on the left margin of the Douro river (**Figure 1**). Integrated in the Central Iberian Zone, one of the five geotectonic regions of the Hesperian Massif, (Ribeiro, 1979), is constituted by shale-greywacke complex of pre–Ordovician age, currently designated as Dúrico-Beirão super-group (Esteves, 2006). The Douro Group includes the Bateiras formation as the dominant lithological subtract. This is an allochthone formation about 900m thick from Proterozoic age of the lower Cambrian. It consists of an alternation of laminated phyllites with metagrauvaques and interbedded limestones, black phyllites and metaquartzovaques.

Carvalhas Estate present a total area of 306 hectares, that about 37% occupied by vineyard. The slopes are organized by different types of ground frame system that have evolved as necessary to combat pests, and to improve the plant cultivation according to technological developments. In the agricultural area exist a predominance of vineyard in terraces (43%), followed by the traditional vineyard (or post-phylloxera) (30%) and vertical vineyard planting, (27%) (**Figure 1**).

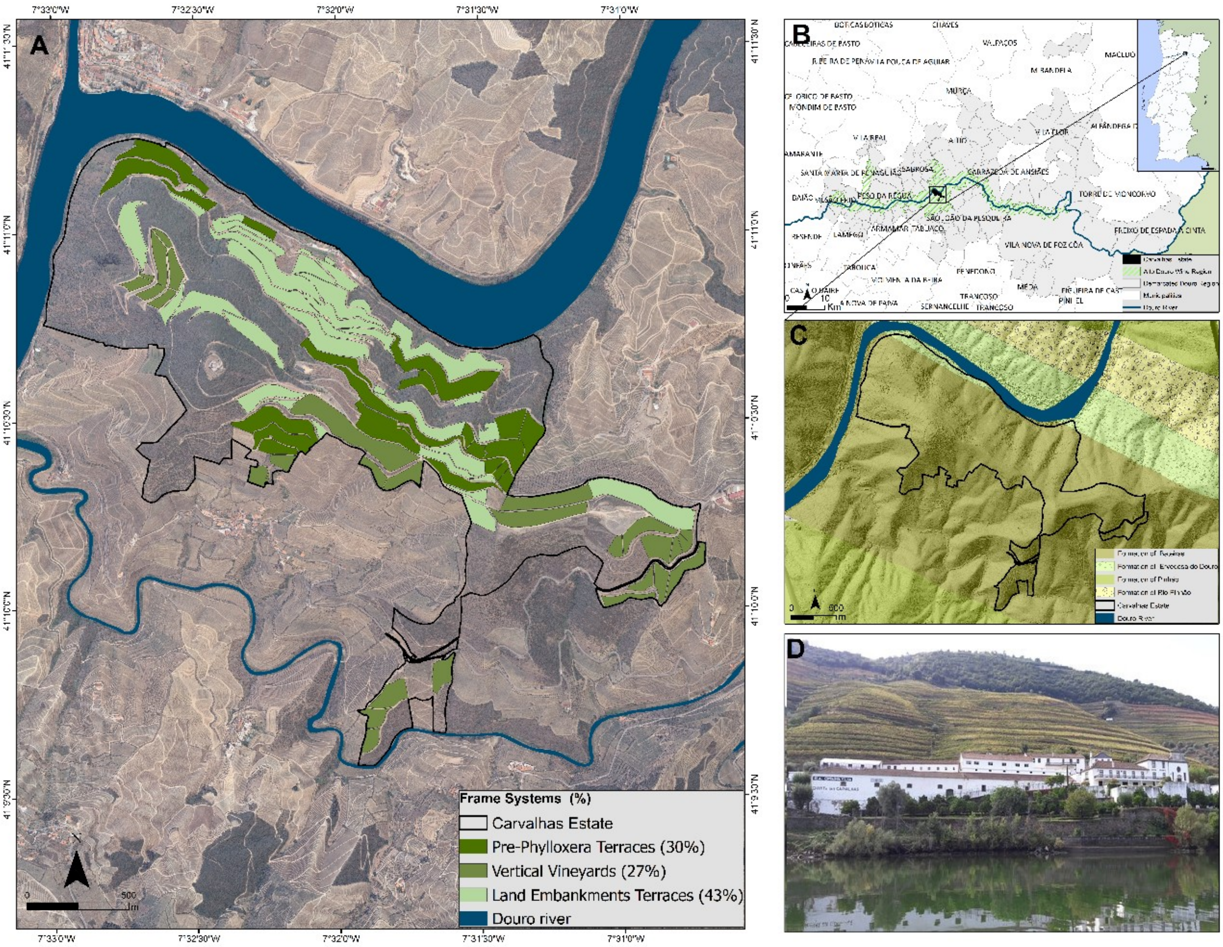

Figure 1: Study area framework. A – Study watershed and frame system; B - Location of Carvalhas Estate, in the spatial perimeter of the DDR; C - Lithology and tectonics; D - Overview of Carvalhas Estate.

The soil of this area is characterized as anthrosols due the long and intensive agricultural activity with the agricultural terraces construction, (world reference base for soil resources, 2006). The soil texture varies between muddy gravel (mG) and gravelly mud (gM), according to the Folk (1954) classification, which reveals a silt and clay percentages ranging from 45% to 69% respectively. The sand varies between 7% to 16% and gravel between the 25% to the 40% (**Figure 2**).

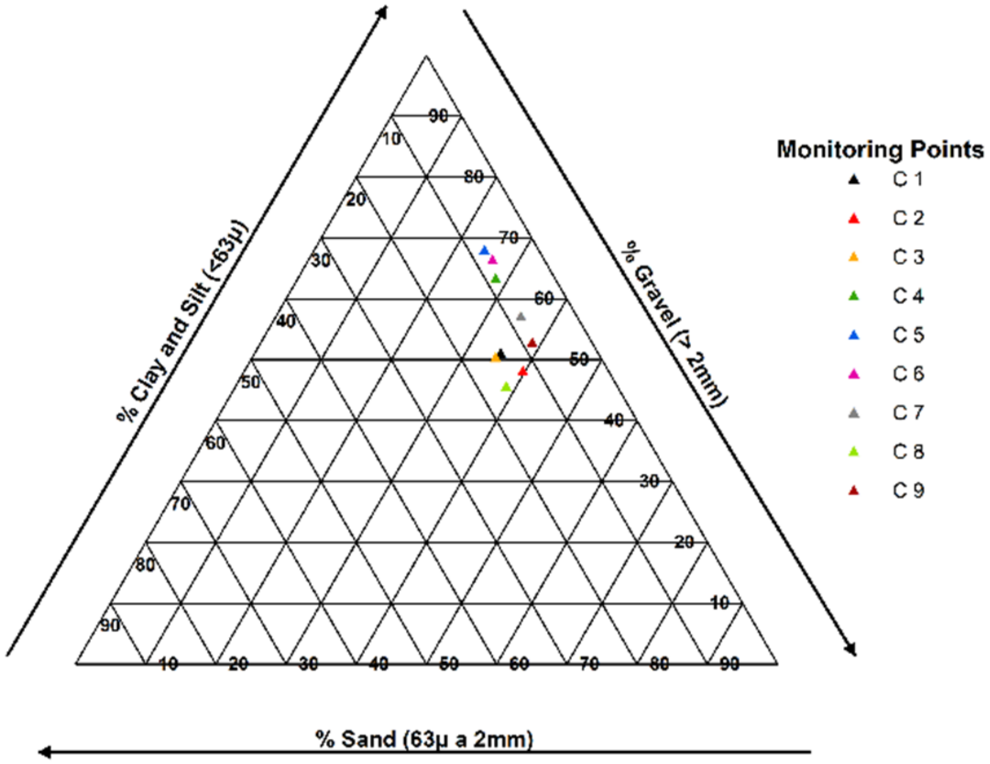

Figure 2: Soil Texture in Carvalhas Estate.

3. Materials and methods

3.1 Digital Elevation Models Processing

To analyse the influence of the DEM spatial resolution, on the landslide susceptibility modelling, will be used three models (A), (B) and (C). The DEM (A) and (B) were constructed from a stereo pair of aerial photographs with a pixel size of 50 cm, obtained on 23 June 2012 between 10h 47m and 12h 26m. The flight made about 5000 m high, has a longitudinal and lateral overlapping of 60% and 30%, respectively. The DEM obtained automatically by processing images in Agisoft Photoscan ® program and by a stereo matching procedure in order to obtain a dense point cloud, and finally, a regular grid DEM. There were extracted two digital elevation models with different resolutions, the DEM A with 1 meter and DEM B with 5 meters of resolution.

The DEM (C), with 5m resolution, was processed with *Topo to Raster* interpolation method that uses an interaction technique of finite differences, combining the advantages of local and global interpolation using a continuity of surface (Huntchinson, 1989). For that we use the *Topo to Raster* tool, in ArcGis 10.2 software, using as input data the contour lines of 10 m interval, elevation points and hydrography. The source of the topographic data was provided by Portuguese official organizations.

3.2. Landslides Inventory

The identified landslides inventory was performed along the terraces risers (**Figure 3**). There were 109 occurrences registered mostly shallow landslides. The scar wide and length varies from 1 m to 3 meters and are up to 1.5 m depth. Generally, the slipped materials are retained on the terrace platform below. Due to agricultural activity, the terrace instability along risers is quickly repaired. So, it is not possible register the old landslide occurrences.

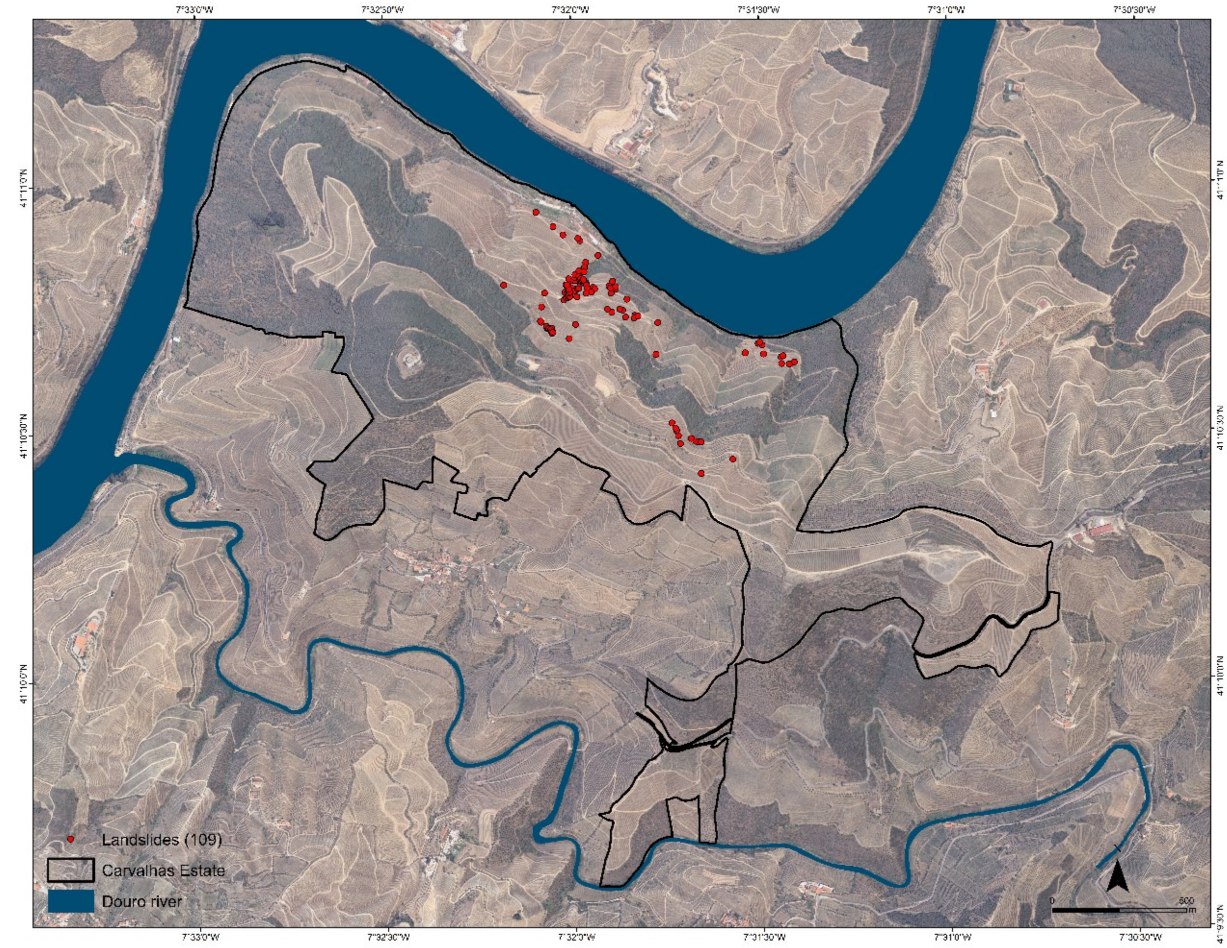

Figure 3: Landslides inventory performed at Carvalhas Estate.

3.3. Susceptibility modelling - Logistic Regression

The logistic regression is the statistical model chosen to perform the susceptibility assessment to landslide. This multivariate method involves the study of the relationship between the dependent variable (the landslide) with a set of independent variables (conditioning factors), analysing their influence on a particular occurrence, (Zêzere et al., 2017). The inventory of the instability points will have the value of 1 (presence of landslide), and the absence of landslide is provided by a serial of random points (defined as “no points”) that will take the value of 0. The logistic regression results on a probability of occurrence defined in a range between 0 and 1 (Landau and Everitt, 2004) represented by the following equation:

$$Pi = \frac{1}{1+e-(\beta_0+\beta_1 x_{1,i}+\cdots+\beta\kappa\, x_{\kappa,i})} \qquad \text{Eq. [1]}$$

To model with the logistic regression we used two models which are distinguished by the independent variables alteration (**Figures 4, 5 and 6**). At model 1 the independent variables, obtained from the three DEMs mentioned above (A, B and C), are the slopes, the curvature, raiser slope and high, contributing areas and topographic wetness index. In the model 2 we decide to use the same variables excluding the variables riser and high of the slope, since they are variables that represent the geomorphological detail of the terraces and, therefore, the exclusion allow us to test their influence on logistic regression susceptibility assessment.

The curvature map was processed in ArcGis 10.2 software. The high and slope of the riser was achieved by an implanted toolbox in ArcGIS 10.2. The high of riser was obtained through general slope inclination, the wide of the platform measure on the Orto photomap, and the slope of the riser terrace, following **Equations 2 and 3**.

$$H = tg(\beta)T \qquad \text{Eq. [2]}$$

$$T = tg\ (\alpha)\frac{P}{(tg(\beta) - tb(\alpha))} \qquad \text{Eq. [3]}$$

Where:

T is the riser wide;

P is the platform wide;

$\boldsymbol{\alpha}$ is the general slope of the terrain;

$\boldsymbol{\beta}$ is the riser slope.

The riser slope was obtained through the platform width and the general inclination of the slope. The high of the riser was classified into six classes: <1,7 m; 1,7 to 2,2; 2,2 to 2,6; 2,6 to 3; 3 to 3.4 and> 3.4 and the slope of the riser was classified into seven classes: <40º; 40º to 45º; 45º to 50º; 50º to 55º; 55º to 60º; 60º to 65º and > 65º (**Figures 4, 5 and 6**).

The contributing areas used at this study was based on D-Infinity method proposed by Tarboton (1997), represents the flow to two directions based on an single angle taken as the steepest downward slope on the eight triangular facets centred at each pixel. This method takes into account the proportion of flow of each cell between the nearest neighbours of maximum gradient. The early concentration promoted by this method, a major part of the slope is classified with low values of flow accumulation, suggesting a better representation of the internal flow by diffuse runoff.

Contributing areas were classified into nine classes: <25, 25 -50, 50 - 100, 100 - 200, 200 - 400, 400 - 1000, 1000 - 2000, 2000 - 4000 and > 4000 (m2) (**Figures 3, 4 and 5**).

The Topographic Wetness Index (TWI) was developed by Beven and Kirkby (1979), based on the hydrological model TOPMODEL (**Figures 4, 5 and 6**). It is defined as:

$$ln = \frac{\mathbf{a}}{\mathbf{tan(s)}} \qquad \text{Eq. [3]}$$

Where:

a are contributing areas;

$\mathbf{tan(s)}$ is the tangent of the angle of the topographic surface.

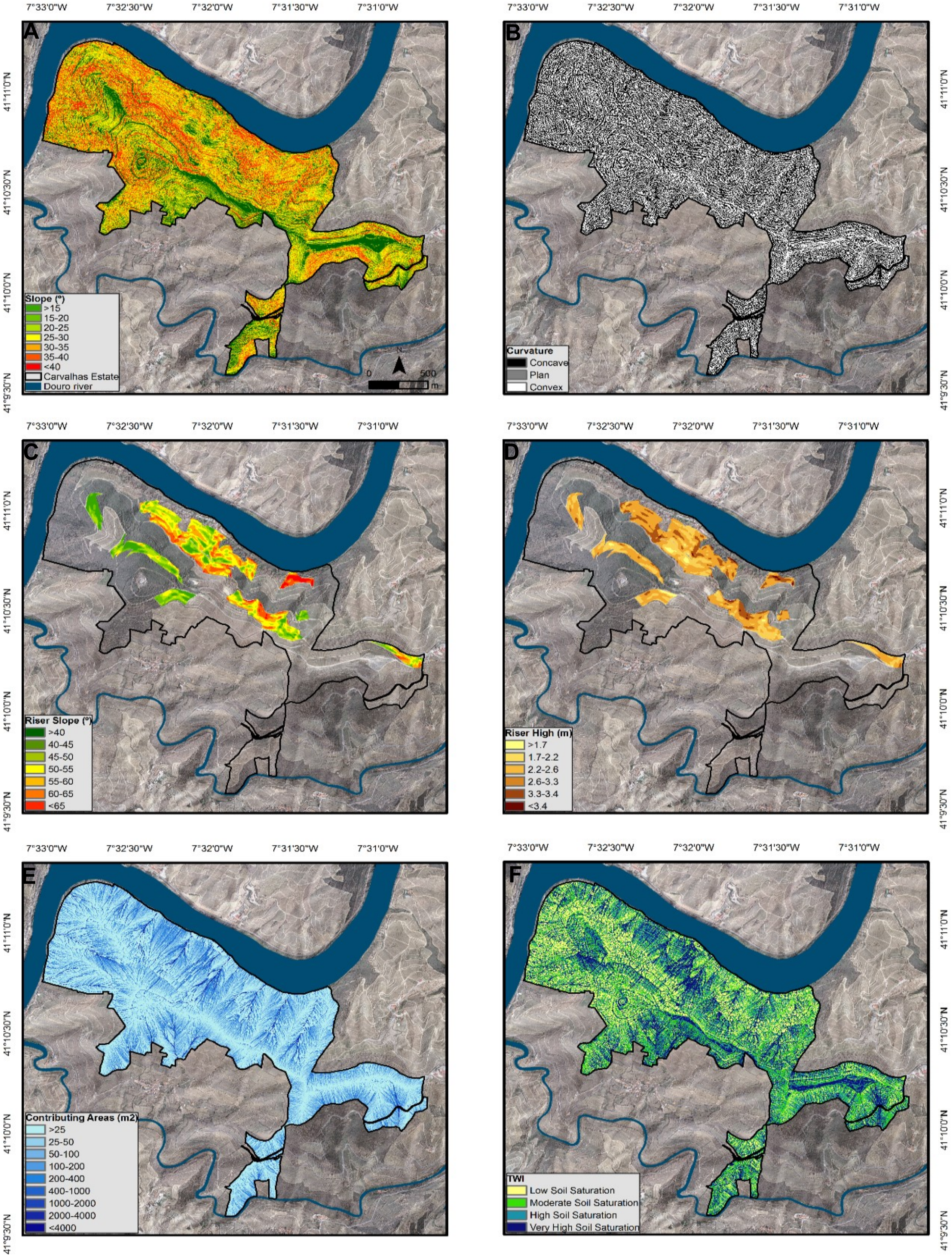

Figure 4: Landslide independent variables, with 1 meter resolution DEM, used to model logistic regression: A – Slope; B- Curvature; C – Riser Slope; D – Riser High; E – Contributing Areas; F - Topographic Wetness Index.

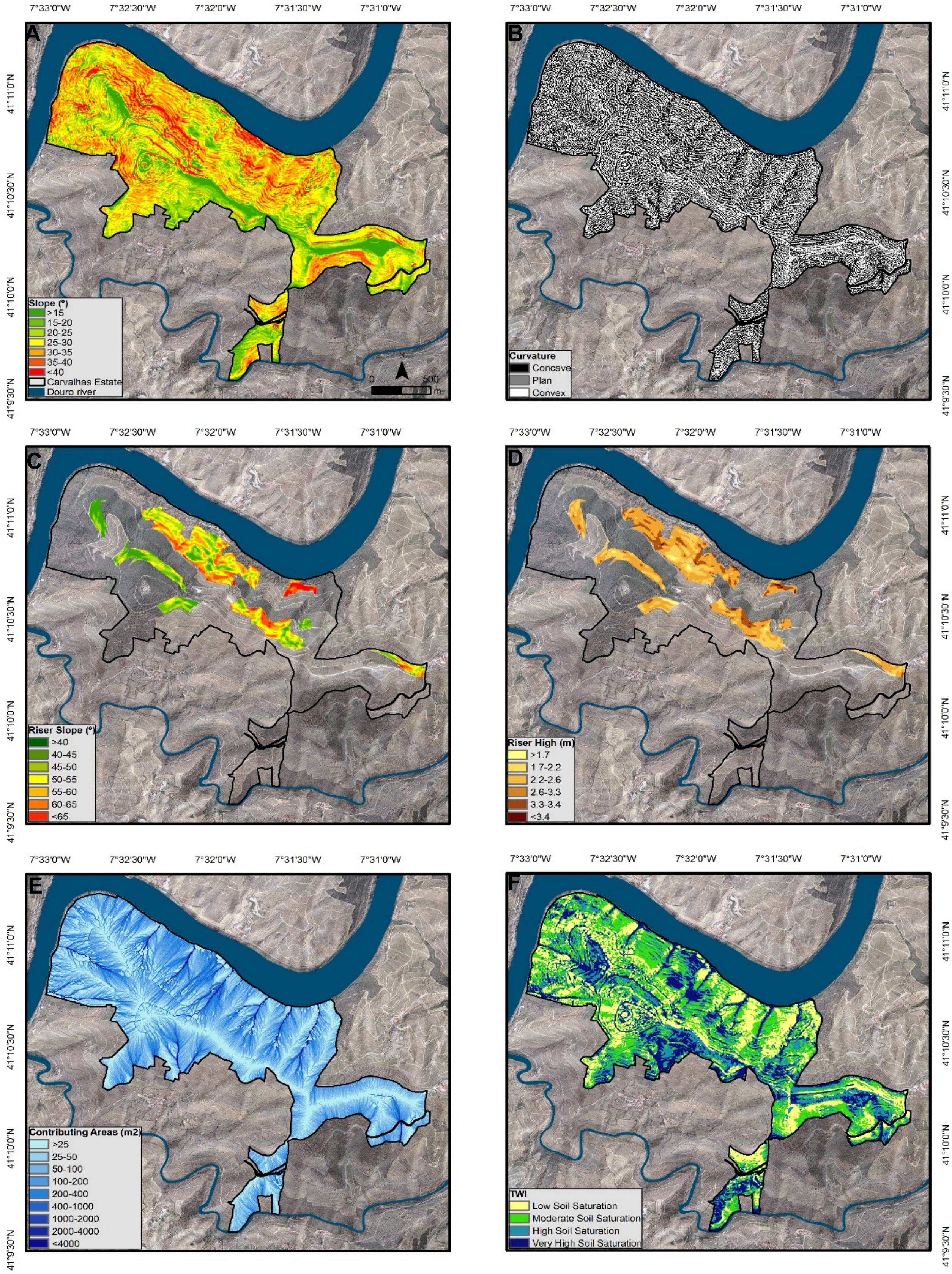

Figure 5: Landslide independent variables, with 5 meter resolution DEM, used to model logistic regression: A – Slope; B- Curvature; C – Riser Slope; D – Riser High; E – Contributing Areas; F - Topographic Wetness Index.

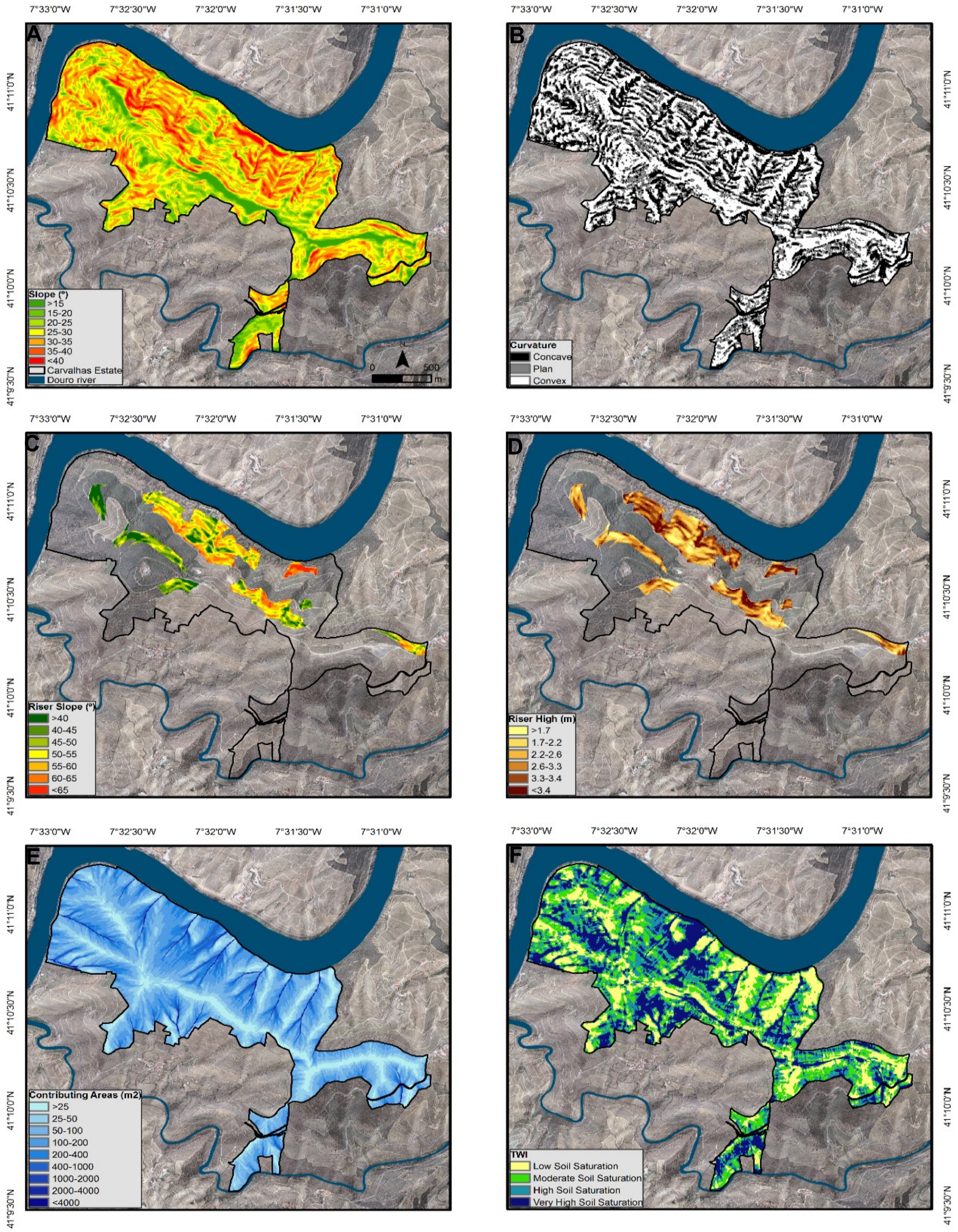

Figure 6: Landslide independent variables, with 5 meter resolution DEM obtained by topo to raster method from contour lines with equidistance 10m, used to model logistic regression: A – Slope; B- Curvature; C – Riser Slope; D – Riser High; E – Contributing Areas; F - Topographic Wetness Index.

3.4. Validation

The susceptibility modelling validation use the contingency matrix ratios described by Fawcett (2006). We use TPR (true Positive Ratio) and FPR (false positive Ratio).The value of TPR (TP/TP+FN) concerns the percentage of events that occur in areas classified as unstable. The FPR (FP/FP+VN) value refers to the percentage of the area considered unstable without landslides in the total area without landslides. The PPV (Precision =TP/ (TP+FP)) refers to the ratio of the slipped area correctly classified over the whole area classified as unstable. The ACC ((TP+TN)/ (P+N)) analyzes the areas that were correctly classified on the total area, so a higher value represents a better performance of the model. Finally, the TPR/FPR index identify the model with a high prediction capability with the smaller area classified as unstable.

In addition, we obtained the sensitivity and specificity, the two most appropriate metrics to analyze the performance of binary statistical analysis such as logistic regression, through the ROC (Receiver Operating Characteristic) curve. The sensitivity is the true positive rate (TPR=TP/TP+FN) and specificity is the true negative rate (TNR= TN/(TN+FN) identified by the percentage of the negative values correctly predicted over the total of negative values (Fawcett, 2006).

4. Results and Discussion

The results of logistic regression application on landslides susceptibility assessment do not differ significantly when using the three DEM (A, B and C), at the models 1 and 2, similar conclusion to (Lee et al. 2004) (**Figure 7**). In this case, the DEM (A) with 1 meter resolution did not contribute to a significant increase in susceptibility model precision. According to Jacobs et al. (2018), an increase in resolution does not necessarily improve the model performance. Furthermore, when landslide location precision is weak, the finer DEM resolution does not contribute to increase landslide susceptibility analysis, (Lin et al., 2017). In this case, an incomplete inventory and the landslide representation with a centroid point, considering they are very small, may the main reason to justify this similitude of the final results. . Moreover, Guzzetti et al. (2012) advocate that the detection of landslides has limitations and the uniformitarianism principle may not be applicable where large land cover changes have occurred. In this study the inventory also is conditioned by the agricultural terraces maintenance and the machinery used to vineyard cultivation, which erases the landslides scars.

Also, other DEM sources and lower resolutions show differences which can reflect in the output derivate that may be resolved better at higher resolutions, (Mahalingam and Olsen, 2016). The DEM (C) with coarser resolution provided a higher accuracy in the representation of the independent variables, especially those that relate to the terraces geometry.

Evaluating the susceptibility areas, it is clear that DEM (A) reveals a greater area classified as high and very high susceptibility to landslides, (34%), followed by DEM (B) with 33% and DEM (C) with 31%, in the considered classes. This scenario is reversed when considering the low and moderate susceptibility areas, where the DEM (C) presents 70% of the areas, the DEM (B) 67% and finally the model (A) 66% (**Figure 7**).

Analyzing the validation process, with contingence matrix, DEM (B) is the one that presents the higher values of TPR (69%). However, the values, at this index, are not very different, so, DEM (C) shows the lowest result with 67%. Considering the FPR index the DEM (C) presents better results, considering 31% is the lower value of the unstable areas without registered landslides on the total area without landslides. In contrast, DEM (A) obtains the highest FPR value with 34%, so, finer DEM resolution classifies more landslide areas which increases the number of false negative pixels, (Pawluszek et al., 2017). Regarding the PPV index, the DEM (C) is more assertive and presents the higher value (0.0047) with the higher landslide area well predicted over the area classified us unstable. The lower value of PPV index is the DEM (A) and according to Tarolli and Tarboton (2006) the landslide identification decreases at finer resolutions with localized topography not representative of the processes governing landslide initiation. Concerning the accuracy, (ACC), the DEM C presents a better performance by classifying a greater number of areas correctly classified (69%). Relatively to the relationship present in the ratio (TPR/FPR), the DEM (C), exhibit the higher value (2.19) and shows better results (**Table 1**).

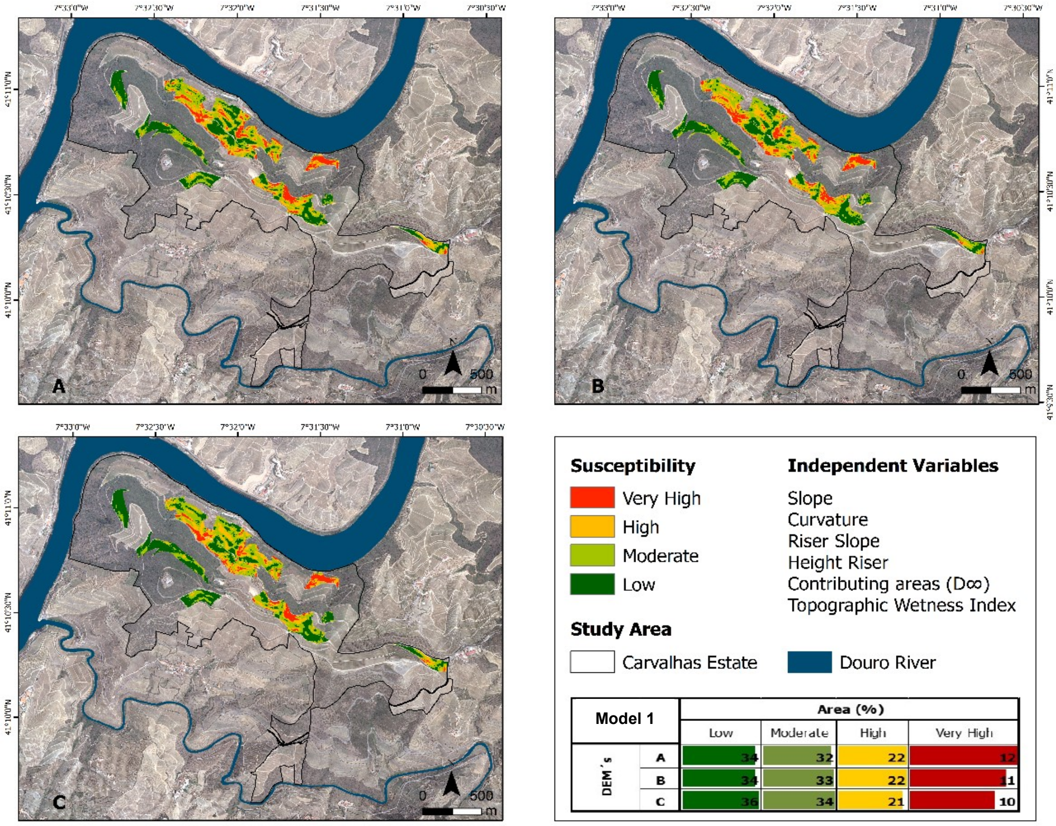

Figure 7: Landslide susceptibility maps obtained with logistic regression for model 1.

Table 1: Susceptibility modelling validation using contingency matrix (model 1)

	TPR	FPR	PPV	ACC	TPR/FPR
Model A	0,68	0,34	0,00043	0,66	1,97
Model B	0,69	0,33	0,00044	0,67	2,09
Model C	0,67	0,31	0,00047	0,69	2,19

Through ROC curve validation, several authors refer that the area under the curve (AUC) is used to evaluate the quality of the model. In this the sense, higher the value, more discriminating is the model, (Braga, 2001). From the ROC curve application, we observe that do not exist a marked difference between the logistic regressions modelling using the three DEM´s. However, it appears that DEM (C) is the most discriminant with 76% (**Figure 8**).

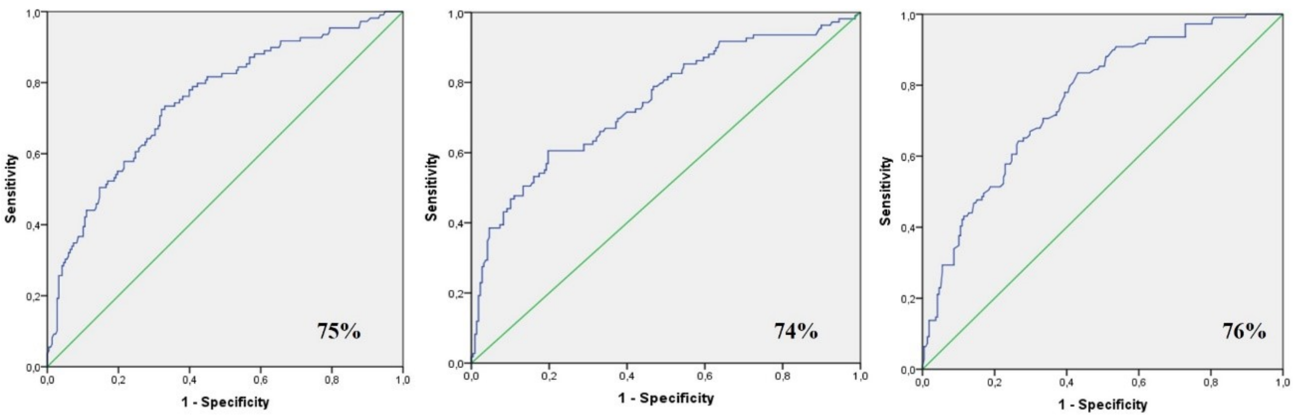

Figure 8: Susceptibility modelling validation using Roc curve (model 1).

In relation to model 2 we extracted the variables height and slope riser in order to verify the influence of them in the final model (**Figure 9**).

From the results we can see that, when using only four variables (slope, curvature, contributing areas and topographic wetness index), in general, there is an increase of areas classified as unstable, (considering very high and high classes), compared to model 1. Obviously, there is a decrease of stable areas (classified as moderate and low), relatively to the model 1 (**Figures 7** and **9**).

As a result of models validation, for model 2, it is possible verify that DEM (C) presents better results in the TPR (70%) and FPR (43%) (**Table 2**). However, we have a better relationship in the classification of occurrences and non-occurrences in the DEM (B) that also shows the best performance with TPR / FPR ratio (1.72).

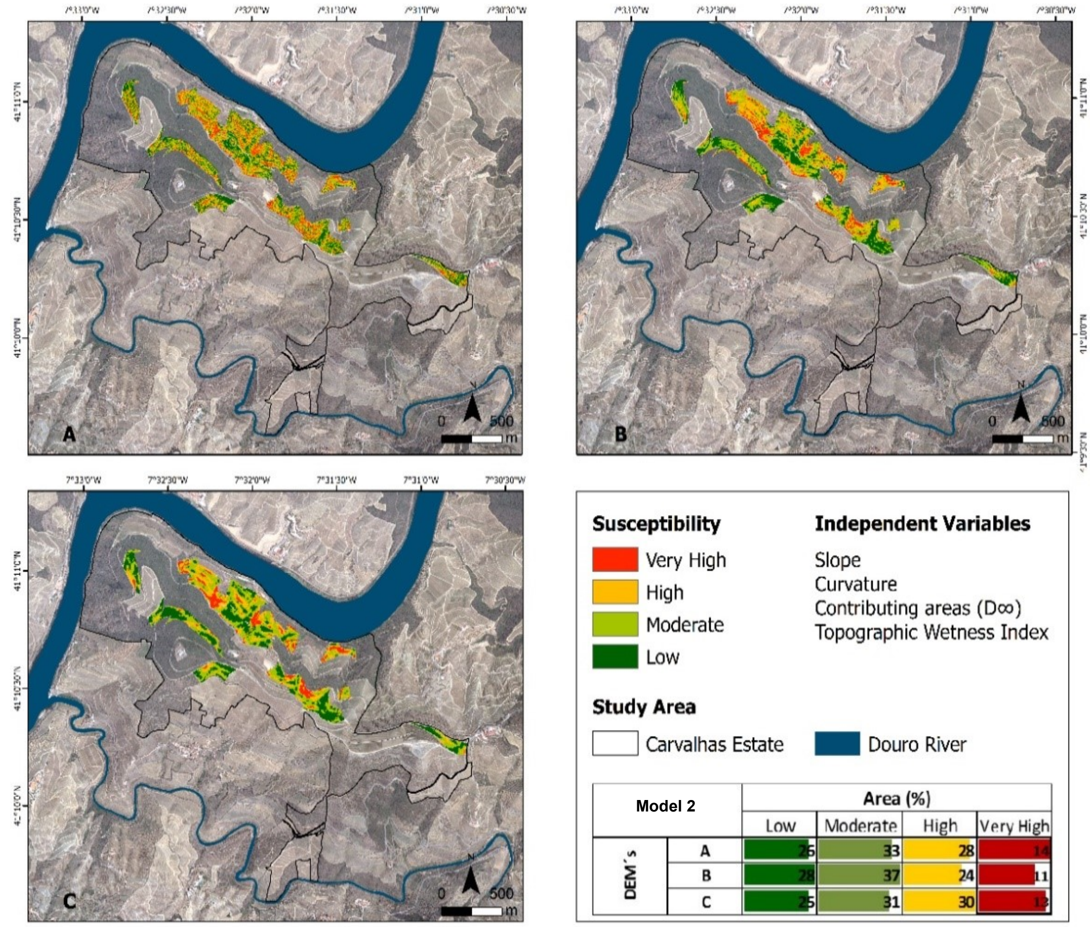

Figure 9: Landslide susceptibility maps obtained with logistic regression for model 2.

Table 2: Susceptibility modelling validation using contingency matrix (model 2).

	TPR	FPR	PPV	ACC	TPR/FPR
Model A	0,61	0,41	0,000316	0,59	1,48
Model B	0,60	0,35	0,000363	0,65	1,72
Model C	0,70	0,43	0,000344	0,57	1,62

When analyzed the ROC curve (**Figure 10**), it is confirmed that the DEM (C) is the one that better discriminate the model, with the value of 72% below the curve. Contrary, the DEM (A) presents the lower value of the two models (65%).

The results of model 2 are lower than those obtained in model 1. This reflects, as Duman et al. (2006) argues, the importance to use the topographic parameters well representative of the physiographic reality of study area to obtain a better performance in the susceptibility landslide model. This idea assume higher importance since the area is under an intensive human intervention.

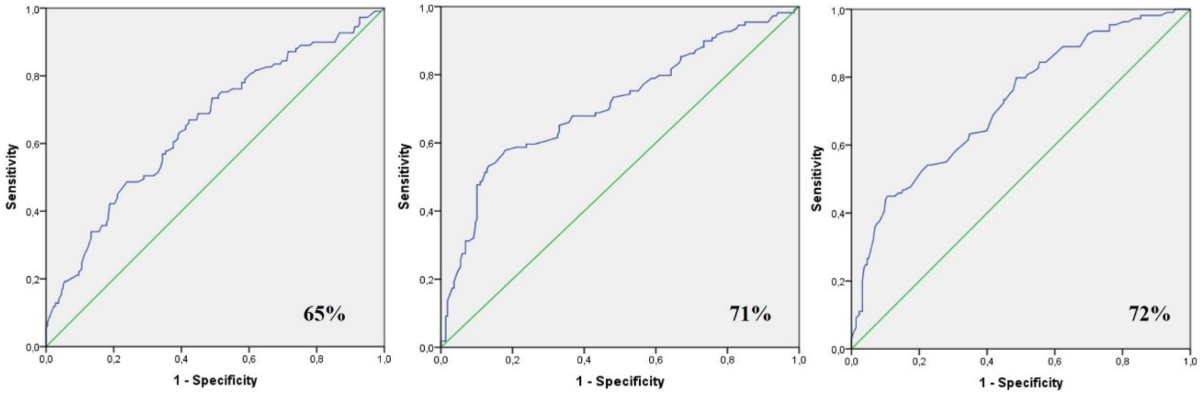

Figure 10: Susceptibility modelling validation using Roc curve (model 2).

5. Conclusions

The obtained results seem to indicate that there is no significant influence of different resolutions of Digital Elevation Models in susceptibility modelling at this scale, using statistical methods. Even with DEMs with high detail resolution, there is no model that stands out significantly.

At model 1, the DEM that has slight edge in the correct prediction of landslides is DEM (B), (with a TPR of 0.69). However, the relationship between the landslides occurrences and the unstable area predicted (TPR / FPR) highlights the DEM (C), (2, 19). In model 2, the DEM that stands out, with a better prediction of landslides, is the DEM (C). However, in the TPR/FPR index the DEM (B) reveals the highest value. Analyzing the ROC curve, mainly in DEM (A), the AAC decreases from 75% to 65%, following the DEM (C) which decreases from 76% to 72% and, finally, DEM (B) 74% to 71%, relatively to model 1.

Comparing the influence of different digital elevation models construction methods, it was concluded that the DEM obtained with better performance in the two models was DEM C. It is important to point out that this DEM was constructed from an interpolation of elevation points and contour lines with 10m equidistance as input data. It should be noted that this method, coupled with the 5 meters DEM resolution, provides the necessary geomorphologic detail for independent variables riser slope and riser height representation. These variables reflect the geomorphological context of the terrace construction. In addition it also reveals a higher performance in the other independent variables that reflects the general trend of slopes in agriculture terraces. For these reasons model 1 presents better results.

The inventory is incomplete and be noted that the landslide occurrences are often erased due to agriculture practices. For this reason, TPR values do not exceed 75%. We believe that, with a more reliable inventory can be achieved better results.

With this work we are able to state that it is possible to use statistical methods at large scales. On the agricultural terrace susceptibility analysis is important the use of the terrace geometry since it represents the geomorphologic features of the terrain. The conditioning variables selection is another key element along the workflow. The use of so high scale to developing the modelling process it is important to identify the relevant elements that define the spatial variation of susceptibility processes. The choice of the spatial resolution and the conditioning factors is the key to a good performance of the statistical models.

Thus, we intend to develop the applied methodology in order to evaluate more precisely the influence of slope and height of the risers, and others independent variables of the terrace geometry in landslides susceptibility.

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