# Land use and land cover geoinformation properties and its influence on the landslide susceptibility zonation of road network

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**Abstract.** This paper evaluates the influence of land use and land cover (LUC) geoinformation with different properties on landslide susceptibility zonation of the road network in Zêzere watershed (Portugal). The Information Value method was used to assess landslide susceptibility using two models:
10  one including detailed LUC geoinformation (Portuguese Land Cover Map - COS) and other including more generalized LUC geoinformation (Corine Land Cover - CLC). A set of six fixed independent layers were considered as landslide predisposing factors (slope angle, slope aspect, slope curvature, slope over area ratio, soil, and lithology), while COS and CLC were used to find the differences in the landslide susceptibility zonation. A landslide inventory was used as dependent layer, including 259
15  shallow landslides obtained from photo-interpretation of orthophotos of 2005 and further validated in three sample areas (128 landslides). The landslide susceptibility maps were merged into road network geoinformation, and resulted in two landslide susceptibility road network maps.

Models performance was evaluated with success rate curves and area under the curve. Landslide
20  susceptibility results obtained in the two models are very good, but in comparison the model obtained with more detailed LUC geoinformation (COS) produces better results in the landslide susceptibility zonation and on the road network detection with the highest landslide susceptibility. This last map also provides more detailed information about the locals where the next landslides will probably occur with possible road network disturbances.

**Keywords** LUC; geoinformation properties; landslide susceptibility; road networks disruption, Information Value method.

## 1 Introduction

The landslides are natural processes that can cause constraints on the free movement of people and goods, when directly or indirectly affect the road network (Bíl et al., 2014, 2015; Hilker et al., 2009; Winter et al., 2013). The total or partial blockages of road network have economic and societal impacts, particularly direct damages in the infrastructure (material damages) and cause injuries and deaths of people when driving on the affected infrastructures (Guillard and Zêzere, 2012; Pereira et al., 2014, 2017) or causing indirect damages as delays, detours, material damage and raw material rising prices (Zêzere et al., 2008; Bíl et al., 2014, 2015; Jenelius and Mattsson, 2012; Winter et al., 2016).

The landslide susceptibility assessment is crucial to identify locations with higher probability of landslides occurrence (Conforti et al., 2014; Guillard and Zêzere, 2012; Guzzetti et al., 2006; Pereira et al., 2014; van Westen et al., 2008). Landslide susceptibility is the likelihood of a landslide occurring in an determined area controlled by local terrain condition, may also include a description of the velocity and intensity of the existing or potential landslide (Fell et al., 2008; Günther et al., 2013; Guzzetti et al., 1999). Landslide susceptibility reflects the degree to which terrain unit can be affected by slope movements in the future (Günther et al., 2013).

In general, the choice of geoinformation (GI) details for the landslide predisposing factors are not often explained in the landslide susceptibility assessment based on statistical methods; or some criteria defined in the literature is used for this selection, since these variables explain the occurrence of slope movements in the study area (Blahut et al., 2010; Carrara et al., 1991; Castella et al., 2007; Castellanos Abella, 2008; Guzzetti et al., 1999, 2006; Soeters and van Westen, 1996; van Westen et al., 2008; Zêzere et al., 2008, 2017).

Beyond the influence of different environmental factors (e.g. lithology, slope angle, slope morphology, topography, soils, hydrology) on spatial distribution landslides, the LUC dynamics is also an important factor on landslide susceptibility assessment (Guillard and Zêzere, 2012). Certain land use and land cover changes (LUCC) increase the number of unstable slopes (Reichenbach et al., 2014), i.e., promoting the propensity to landslide occurrence (e.g. deforestation, slope ruptures to roads construction, steep slopes), and can have an important impact on landslide activity (Beguería, 2006; Glade, 2003; Mugagga et al., 2012; Persichillo et al., 2017; van Westen et al., 2008). In short, the LUC,

while proxy variable, is very dynamic over time influenced by climate-driven changes and direct anthropogenic impacts (Promper et al., 2014).

For instance, performing a landslide susceptibility analysis with an historical inventory for long periods (e.g. decades) demands the use of a permanent set of predisposing factors along the landslide inventory time. LUC can be changeable over time; due to this reason it will be more accurate to use LUC for different periods, not using an available and most recent LUC map, in order to avoid spatial relations between past slope instability and wrong LUC classes.

Selection of the GI scale influences the map elements representation and detail, as well as the choice of the scale of analysis of final results (Leitner, 2004; Stoter et al., 2014). The choice of the GI level of detail will constrain the modeling final results. For example, Meneses et al. (2018) obtained different LUCC results in the Portuguese territory due to the use of different LUCC datasets, namely Corine Land Cover (CLC) and official Land Cover Map of Portugal (Portuguese designation and acronym: Carta de Ocupação do Solo, COS), with different properties concerning scale (1:100000 and 1:25000, respectively), minimum mapping unit – MMU (25 and 1 ha, respectively) and generalization level (Table 1).

Due to the variation of the road network morphology (length versus width of the roads typologies), the selection of appropriate GI which integrates the analysis of ruptures of the roads caused by landslides requires a systematic assessment of more detailed properties of the landslide predisposing factors (Drobnjak et al., 2016; Imprialou and Quddus, 2017; Kazemi and Lim, 2005; Orongo, 2011) in order to obtain detailed landslide susceptibility results at the local scale (roads).

In this context, the main goal of this work is the assessment of land use and land cover GI properties influence on the landslide susceptibility zonation of road network. Other two goals was defined: in the first one, we want to evaluate and quantify the landslide susceptibility results using two LUC datasets (CLC 2006 and COS 2007) with different properties (scale and MMU) in two landslide susceptibility models; in the second goal, we want to identify road sections of the main road network with the highest landslide susceptibility that will suffer future road blockages using the output results of the two landslide susceptibility models.

## 2 Material and methods

### 2.1 Study area

This research was developed in the Zêzere watershed (5063.9 km$^2$) located in the Center region of mainland Portugal (Fig. 1). The North-Northwest sector of this watershed is occupied by Estrela

5 mountain, reaching the maximum elevation of 1993 m and where high slopes can be found; in the Central sector, the relief is less irregular when compared to the previous sector, but still has high slope areas (e.g. vicinity of the Castelo de Bode reservoirs and Cabril); in the South-Southwest sector low slopes and flat areas are predominant.

The soils of the Zêzere watershed are very variable between North-Northwest, Center, and Southwest

10 sectors. In the Northwest sector cambisols predominate, with small areas of fluvisols and rankers along the Zêzere River. The central area of the watershed is characterized by the predominance of lithosols, with some areas of cambisols. In the South-Southwest sector, there are areas of lithosols intercalated with cambisols and luvisols.

According to the CLC 2006, the predominant LUC in the study area are forest and semi-natural areas

15 representing 72% of the total area, agricultural land (25.5%), artificial land (1.5%) and water bodies (1%), including an important reservoir of fresh water, such as Castelo de Bode dam (Meneses et al., 2015a). The LUC of this watershed is very dynamic, especially the LUCC in forest and agricultural areas derived from multiple socio-economic driving forces and forest fires (Meneses et al., 2017).

Due to the large extension of this watershed, three sample areas were selected – Estrela Mountain, Vila

20 de Rei and Ferreira do Zêzere municipalities (areas of 86.7, 191.5 and 190.4 km$^2$, respectively), where field work was developed to validate the landslide inventory and the disruption of roads caused by landslides. The selection of these areas was based on the criteria of higher density of landslides observed in these locations.

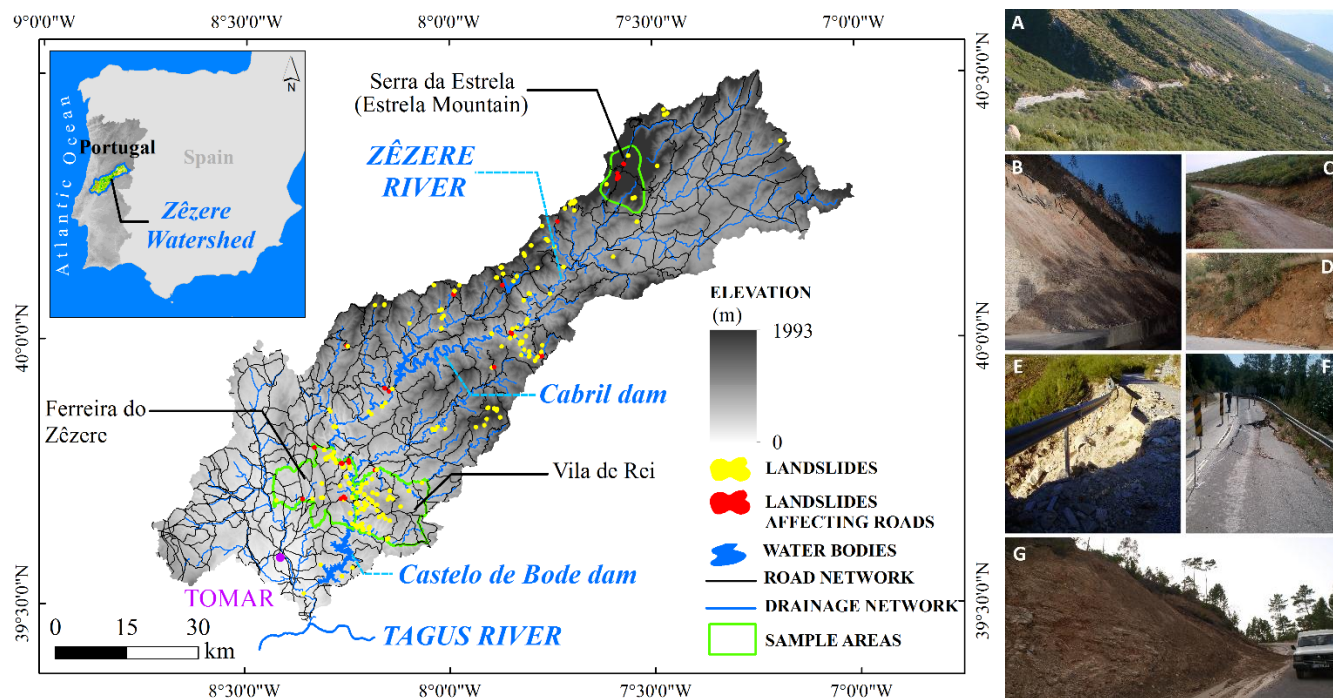



**Figure 1.** Zêzere watershed study area and landslide spatial distribution. The pictures represent landslides that affected roads: A, B, C, D and E - municipality roads of Estrela mountain; F – Ferreira do Zêzere; G – Vila de Rei.

## 2.2 Data

The predisposing factor maps (PFM) were selected after literature reviewing about the causal factors of landslides occurrence (Blahut et al., 2010; Carrara et al., 1991; Castella et al., 2007; Castellanos Abella, 2008; Guzzetti et al., 1999; Soeters and van Westen, 1996; van Westen et al., 2008; Zêzere et al., 2008, 2017). The PFM selected to the landslide susceptibility modeling in Zêzere watershed are presented in Figure 2.

Six fixed landslide predisposing factors were considered: slope angle, slope aspect, slope curvature, slope over area ratio, soil and lithology. LUC of COS and CLC were used to find the differences in the landslide susceptibility zonation. The set of landslides predisposing factors and the corresponding classes (Fig. 2) were the same in all models, only changing the LUC data.

In general terms, slope angle increasing promotes the landslide occurrence and is a very good proxy of the shear stress (Zêzere et al., 2017). Higher slope instability was identified in higher slope angles of the

Estrela Mountain and throughout Zêzere valley. Also in these areas, convex slope curvature is predominantly related with slope instability. The slope aspect is important in the spatial distribution of the different LUC types of the study area (Fig. 2) and also on slope instability, especially in northwest-facing slopes (more exposed to the rain and with higher humidity levels).

5   The slope over area ratio is a proxy variable that reflects the moisture retention, the soil water content, and the surface saturation zones (Zêzere et al., 2017), highlight in Zêzere watershed the upstream (very close of Zêzere river) and SW areas with higher ratio.

In sample areas (Vila de Rei and Ferreira do Zêzere) where high landslide density was observed, schist and metasedimentary lithology are predominant. Also slope instability in the study area is higher in the

10   hortic luvisols and in LUC classes of forest and shrubland or herbaceous vegetation associations (Fig. 1).

The official LUC GI available for the study area are the CLC, available in European Environment Agency (EEA), and the COS, available in General Directorate for Territorial Development (DGT), Portugal. This GI has different properties and has been used in several studies about landslides in

15   Portuguese territory (e.g. Guillard and Zêzere, 2012; Meneses et al., 2015b; Piedade et al., 2011; Reis et al., 2003; Zêzere et al., 2017).

Table 1 describes the main properties of this LUC GI (DGT, 2013; EEA, 2007; IGP, 2010). Among the differences of the two LUC datasets, the scale is highlighted because COS is the most detailed relatively to CLC (proportion 1/4). However, the properties are not proportional between the two LUC datasets,

20   while the COS features have 1 ha of MMU the CLC has 25 ha; and the minimum distance between lines is 20 m in COS and 100 m in CLC.

To reduce possible discrepancies in the field, LUC data was collected for near periods: CLC 2006 and COS 2007. The LUC GI was developed with base information that matches in temporal terms, for example the satellite images, orthophotos and agricultural and forestry inventories used as auxiliary

25   information. The nomenclature of this LUC GI has correspondence to the third level (see official CLC nomenclature on EEA website). In this study the second level of the CLC nomenclature was opted because it has a lower number of classes for the study area (12 of 31 classes, respectively).

**Table 1.** Properties of LUC geoinformation.

| Properties | Land Cover Maps of Portugal | Corine Land Cover |
|---|---|---|
| Acronym | COS | CLC |
| Scale | 1:25000 | 1:100000 |
| Minimum mapping unit | 1 ha | 25 ha |
| Data structure | Vector | Vector |
| Geometry | Polygons | Polygons |
| Minimum distance between lines | 20 m | 100 m |
| Base data | Orthophotos | Satellite images |
| Spatial resolution | 0.5 m | 20 m |
| Nomenclature | Hierarchical (5 levels) | Hierarchical (3 levels) |
|  | 225 classes | 44 classes |
| Production method | Visual interpretation | Semi-automated production and visual interpretation |

The soil and lithology GI were obtained on the web platform of the Environment Atlas, published by the Portuguese Environment Agency (APA) at 1:1000000 scale. Digital elevation model (DEM) was

5  built using digital topographic maps at 1:25000 scale (IGEOE), containing contour lines with 10 m equidistance. Slope angle, slope aspect, slope curvature and slope over area ratio - SOAR (topographic wetness index) layers were extracted from the DEM. Road network GI (vector lines) was extracted from the military cartography of Portugal (itinerary maps, 1:500000), available on website of the Portuguese Army Geospatial Information Center. The road network was classified according to the road network

10  hierarchy and their width. Considering the road center line, a buffer of 5 m distance was defined for municipal roads, 10 m for complementary roads and 20 m for motorways. These distances were measured in roads of study area with Geographic Information Systems (GIS) (directly on the orthophotos).

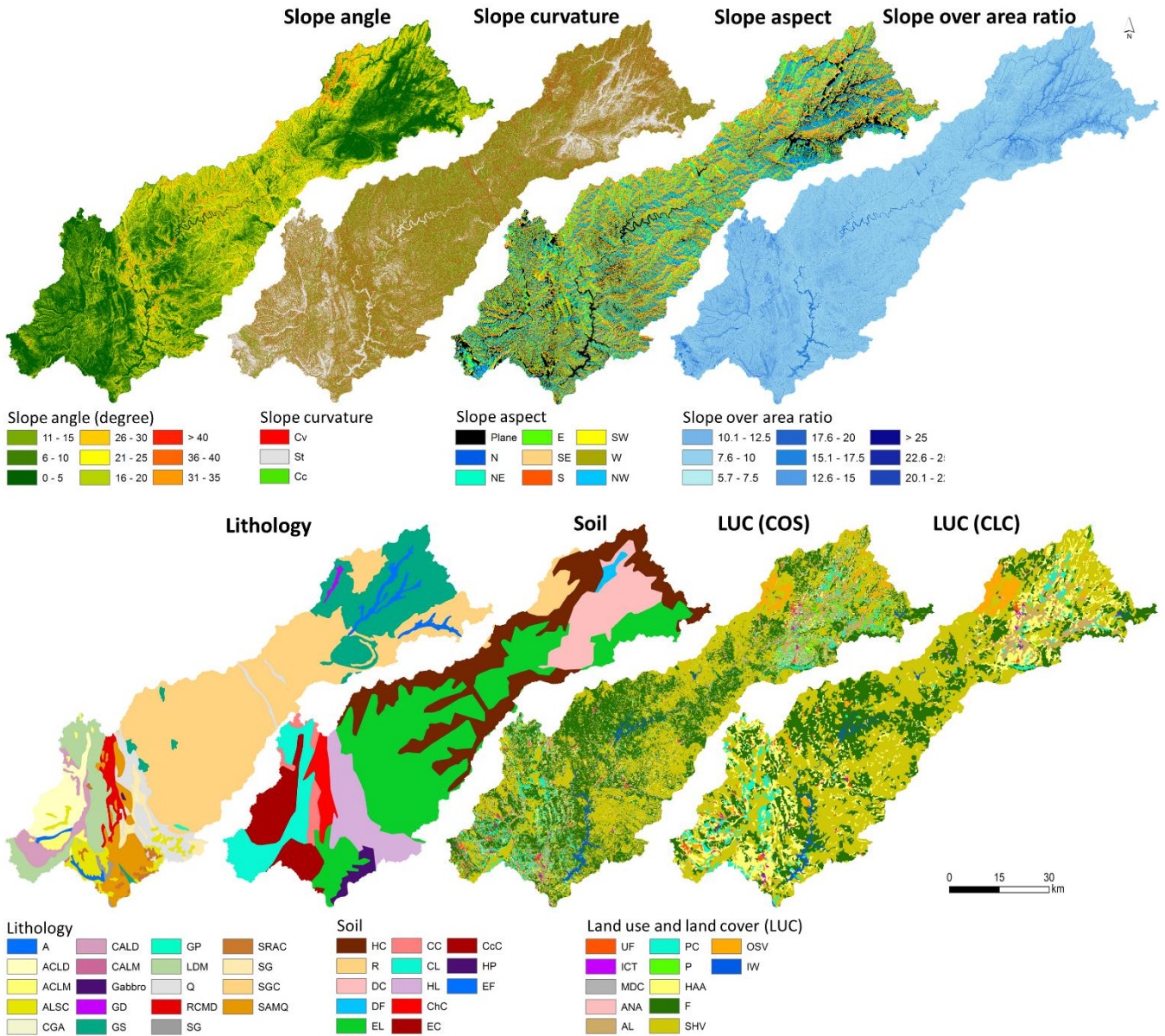



**Figure 2.** Predisposing factor maps (PFM) used in the landslide susceptibility analysis.

**PFM legend**: **Curvature** - Cv: Convex, St: straight, Cc: concave; **Lithology** - A: Alluvium, ACLD: Arenites, conglomerates, limestones, dolomitic limestone, ACLM: Arenites, conglomerates, limestones, dolomitic limestone and marl, ALSC: Arenites, limestone, sand, stony banks and clay, CGA: Clayey schist, grauwackes and arenites, CALD: Conglomerates, arenites, limestone, dolomitic limestone, marly limestone and marl, CALM: Conglomerates, arenites, white limestone and red marl, G: Gabbro, GD: Glacial deposits, GS: Granite and other stones, GP: Granite porphyritic, LDM: Limestones, dolomitic limestone, marly limestone and marl, Q: Quartzite, RCMD: Red sandstone, conglomerates, marl and dolomitic limestones, SG: Sands and gravel, SRAC: Sands, rocky, arenites and clay, SG: Schists and grauwackes, SGC: Schists and grauwackes complex, SAMQ: Schists, amphibolite, mica schists, quartzite grauwackes, carboned stones and gneisses; **Soil** - HC: Humic Cambisols, R: Rankers, DC: Dystric Cambisols, DF: Dystric Fluvisols, EL: Eutric Lithosol, CC: Calcic Cambisols, CL: Calcic Luvisols, HL: Hortic Luvisols, ChC: Chromic Cambisols, EC: Eutric Cambisols, CcC: Calcic-chromic Cambisols, HP: Hortic Podzols, EF: Eutric Fluvisols; **LUC** - UF: Urban fabric, ICT: Industrial, commercial and transport units, MDC: Mine, dump

and construction sites, ANA: Artificial, non-agricultural vegetated areas, AL: Arable land, PC: Permanent crops, P: Pastures, HAA: Heterogeneous agricultural areas, F: Forests, SHV: Scrub and/or herbaceous vegetation associations, OSV: Open spaces with little or no vegetation, IW: Inland waters.

5   The landslide inventory was obtained by photointerpretation (orthophotos of the year 2005 and Google Earth images), a process supported by ancillary topographic data and further field work validation only in the sample areas (Fig. 1) due to the extension of the study area. A total of 128 landslides (predominantly shallow translational slides) was validated during field work in sample areas (49.4% of the total inventoried landslide cases), with a total area of 74042 m$^2$. Among the landslides initially
10  inventoried by photointerpretation in sample areas more than 90% of cases were confirmed. In these sample areas roads disruptions were also validated. In the complete Zêzere watershed 259 landslides have been identified (Table 2), predominantly of shallow type. On the total, 32 landslides affected directly the road network (total or partial blockages by the material and 7 cases with partial loss of infrastructure).

15  GIS were used to convert the predisposing factors to raster (10×10 m) and to compute the landslide susceptibility zonation. Selection of cell size of the predisposing factors was based on several GI conversion tests in the Zêzere watershed previously performed by Meneses et al. (2016).

**Table 2.** Statistics description of the landslides inventory.

|  | **Total inventory** | **Landslides affecting roads** |
|---|---|---|
| Total landslides | 259 | 32 |
| Total area (m$^2$) | 104077.4 | 49029.7 |
| Minimum (m$^2$) | 7.4 | 7.4 |
| Maximum (m$^2$) | 12507.2 | 12507.2 |
| Mean (m$^2$) | 398.8 | 1532.2 |
| Standard deviation (m$^2$) | 1065.2 | 2653.5 |

## 2.3 Methods

The landslide susceptibility modeling was carried out using the Information Value (IV) method (Yan, 1988; Yin and Yan, 1988). The IV is a bivariate statistical method that has been used in several studies and different areas with good results for landslide susceptibility assessment (e.g., (Guillard and Zêzere,

2012; Oliveira et al., 2015a; Zêzere et al., 2017). The IV of each class within each explanatory variable is given by Eq. (1) (Yan, 1988; Yin and Yan, 1988):

$$IVX_i = \ln \frac{S_i / N_i}{S / N} \tag{1}$$

where $IVX_i$ is the Information Value of variable $X_i$; $S_i$ is the number of terrain units with landslides and the presence of variable $X_i$; $N_i$ is the number of terrain units with variable $X_i$; $S$ is the total number of terrain units with landslides; and $N$ is the total number of terrain units.

The IV method was applied in several landslide susceptibility zonation studies, providing good results (e.g., Che et al., 2012; Chen et al., 2016; Conforti et al., 2012) at the regional scale. This method was also applied in several studies conducted in Portuguese territory with good performance in the susceptibility assessment (e.g., Guillard and Zêzere, 2012; Oliveira et al., 2015b; Pereira et al., 2014; Zêzere et al., 2017).

Priori probability of finding a landslide unit in the study area ($S/N$) and conditional probabilities for each class of the independent variables ($S_i/N_i$) were calculated, allowing to obtain the IV for this classes. However, the IV method presents constraints on obtaining the natural logarithm for negative results; in this case the lower value calculated for each variable was assigned to classes where it has not been possible to make the calculation of IV.

The IV of all variables were combined and obtained the landslide susceptibility map (LSM). For the final landslide susceptibility assessment, i.e., the integration the information values of all independent variables, the following equation was considered:

$$IV_j = \sum_{i=0}^{n} X_{ij} I_i \tag{2}$$

where $IV_j$ is the total information value of cell $j$, $I_i$ is the information value of each cell of each independent variable, $n$ is the number of variables, $X_{ij}$ assumes the value 1 or 0 depending on the presence or not of the variable in the field unit.

Success rate curves (SRC) were produced for each final susceptibility maps (Chung and Fabbri, 1999, 2003) and the area under the curve (AUC) was computed.

The importance of each independent variable in the assessment landslide susceptibility was also determined, so that the spatial influence of each predisposition factor in the models can be understood. The accountability ($A_I$) and reliability ($R_I$) indexes have been used in different contexts to assess the importance of each independent variable in bivariate statistical methods (e.g. Blahut et al., 2010; Meneses et al., 2016).

$A_I$ explains how different classes of predisposition factors are relevant in the analysis because they contain landslide area, while $R_I$ depends on the average density of landslide area in the predisposing factors classes that are more relevant to the development of this process. In this procedure, the $A_I$ and $R_I$ were determined using Eq. (3) and (4) (Blahut et al., 2010).

$$A_I = \frac{\sum_{i=1}^{n} k}{N} 100 \qquad (3)$$

$$R_I = \frac{\sum_{i=1}^{n} k}{\sum_{i=1}^{n} y} 100 \qquad (4)$$

where $k$ is the landslides area in classes with values of conditioned probabilities superior to a priori probability; $N$ is the total landslides area; $y$ the area of each class of independent variable with conditioned probability above the a priori probability.

Two landslide susceptibility models were built using the IV method, using the same set of predisposing factors, except the types of LUC GI (Fig. 3): model 1 (M1) modelled with the COS 2007 and resulted in the LSM1; the model 2 (M2) modelled with the CLC 2006 and resulted in the LSM2. The LSM1 and LSM2 results were correlated and spatial concordance was analyzed.

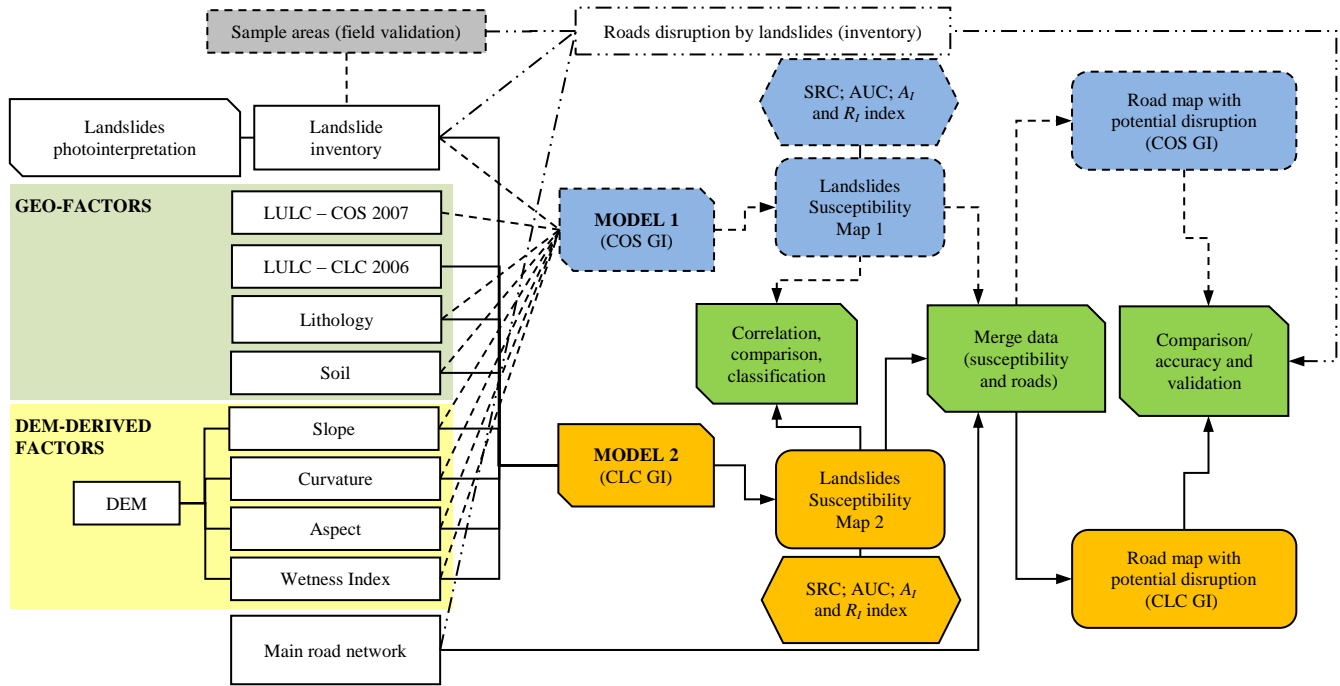



**Figure 3.** Workflow of landslide susceptibility assessment (using different LUC datasets) and the roads susceptibility data integration.

The information values of LSM1 and LSM2 was extracted for the road network (using GIS), resulting
in a road network map with the landslide susceptibility location where there is greater spatial probability
of road interruption or road interference caused by landslides. Then different outputs of the two models
(road network) were compared, i.e., the overall accuracy and Kappa coefficient (Congalton and Green,
2009) was performed, allowing to assess the consistency and agreement of the obtained results with
different LUC datasets. Road disruptions caused by landslides were used to validate these results in the
sample areas.

Landslide susceptibility maps were built and classified in 10 classes (deciles) containing equal number
of terrain units to allow the visual comparison of the results.

# 3 Results

## 3.1 Landslides susceptibility

The landslide susceptibility results show spatial contrasts in the study area. Some areas in centre (highlighting the vicinity of the Castelo de Bode reservoir) and north (Estrela Mountain) sectors present
5   the highest landslide density and landslide susceptibility (Fig. 4).

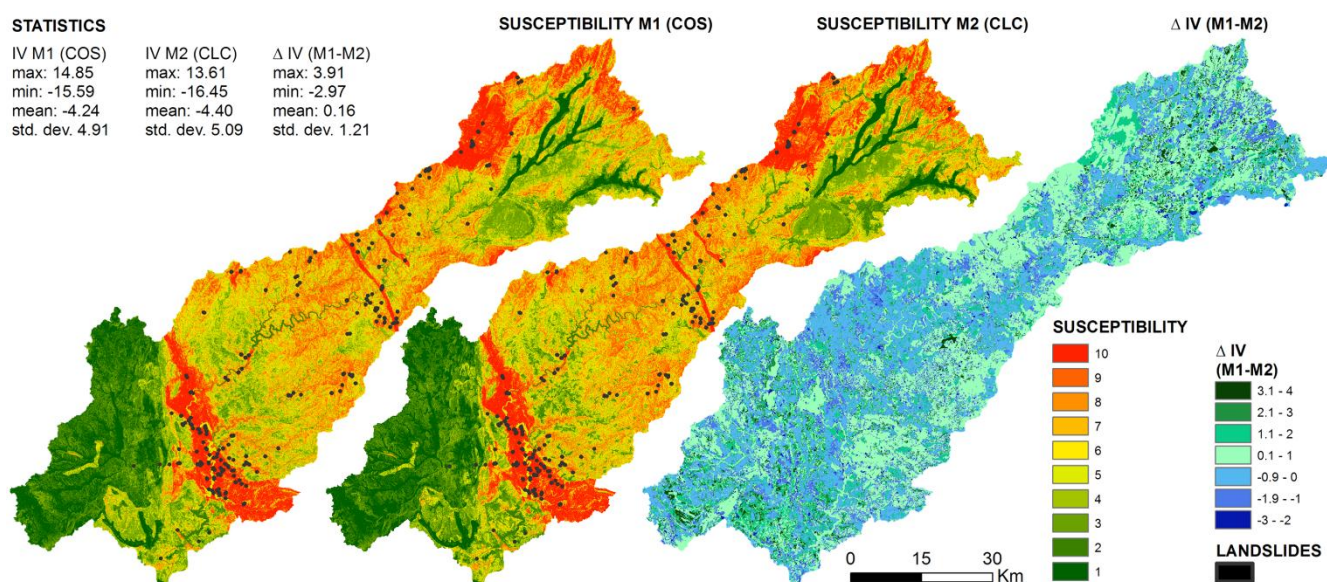



**Figure 4.** Spatial landslide susceptibility (IV represented in deciles): susceptibility M1 represent the results obtained with model 1 (COS GI) and susceptibility M2 represent the results obtained with model 2 (CLC GI). The map in the right is the variation between M1 and M2.

The results of $A_I$ and $R_I$ indexes show important differences between the predisposing factors that have integrated the landslide susceptibility models (Table 3), except $A_I$ of the LUC (COS and CLC).

The LUC predisposing factors (COS and CLC) registered the highest $A_I$ results (81.1, Table 3), showing the relevance of certain classes of this predisposition factors by the number of landslide area covered
15   (emphasis on the forests, scrubland and/or herbaceous vegetation associations and open spaces with scarcity or absence of vegetation).

In the case of $R_I$, soil SOAR and slope angle present the highest values which shows that landslide density is concentrated in a reduced number of classes of each of these predisposing factors area (e.g. Hortic Luvisols, SOAR [22.5-25] and slope [between 25 and 45 degrees]).

5   **Table 3.** Results of the accountability ($A_I$) and reliability ($R_I$) indexes.

| Factors | $A_I$ | $R_I$ |
|---------|-------|-------|
| Aspect | 71.1 | 0.32 |
| Slope | 77.5 | 0.80 |
| SOAR | 15.8 | 1.04 |
| Soil | 66.4 | 1.30 |
| Lithology | 67.2 | 0.55 |
| Curvature | 60.0 | 0.39 |
| LUC (COS) | 81.1 | 0.43 |
| LUC (CLC) | 81.1 | 0.40 |

The landslide susceptibility model's accuracy test was performed using the landslide inventory and the final outputs of each model (M1 and M2). The SRC of each final susceptibility maps (obtained from the results of GI mentioned above) show slight variations (Fig. 5), but in general terms the curves are very

10  identical, demonstrating the high performance of the models in the determination of landslides susceptibility areas.

The area under the curve (AUC) of LSM1 and LSM2 is 91.4 e 91.1%, respectively. However, the landslide susceptibility results obtained in the two models are spatially different (Fig. 4), reflecting the influence of LUC properties.

15  When the two LSM are reclassified in two classes (not susceptible IV≤0 and susceptible IV>0), the susceptible area in LSM1 correspond to 17.3% and in LSM2 to 16.9%.

With input the CLC GI, the IV results are mostly lower in comparison to the IV obtained with COS GI. The variation between the most positive and negative IV (4 and -3) (Fig. 4) shows different IV obtained in the LUC classes of two LUC datasets. The highest variations between LSM1 and LSM2 results are

20  found in places with reduced IV (low susceptibility), marking the Southwest and North sectors (Zêzere valley) of the study area. In the areas with the highest IV in LSM1 and LSM2 the variation is lower, with IV differences between 0.1 and 2.

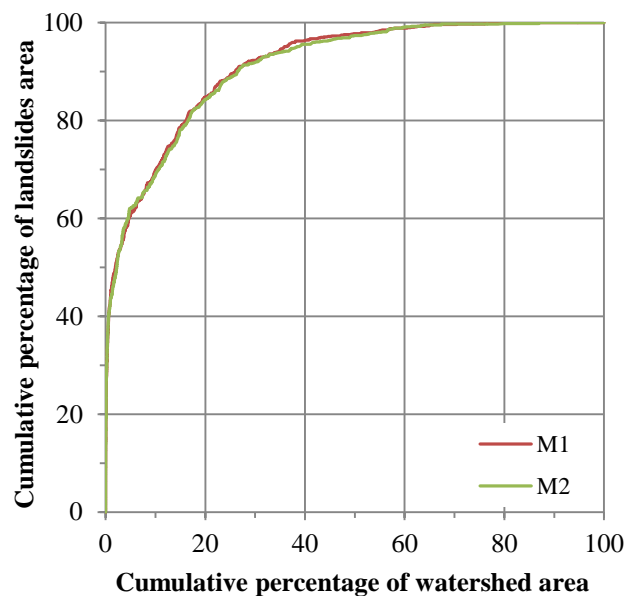



**Figure 5.** Success rate curve (SRC) of the landslide susceptibility models M1 and M2.

## 3.2 Landslides susceptibility in the road network

5 Due to the width of road network, in most cases these infrastructures are not identified in the LUC GI due to minimum distance between lines considered in the LUC cartography scale (Table 1). The class "road and rail networks and associated land" (LUC nomenclature: level III) is inserted in the class "industrial, commercial and transport units" (level II), however, different LUC datasets are crossed with the main roads it shows that most of the roads are mostly intersected by other types of LUC in COS and 10 CLC maps (Fig. 6).

When the IV of LSM1 and LSM2 was associated to the road network it was possible to differentiate the roads due to the landslide susceptibility, representing the highest IV where probably will occur the next landslides and possibly causing socioeconomic constrains, due to total or partial blockages or rupture of the road network. In this case, the differences of roads landslide susceptibility were also analyzed.

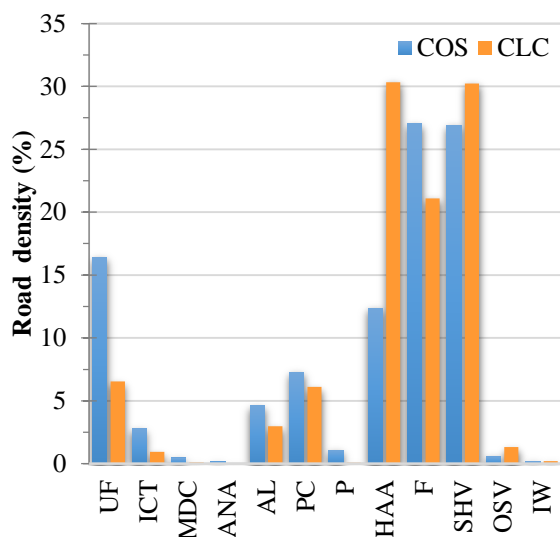
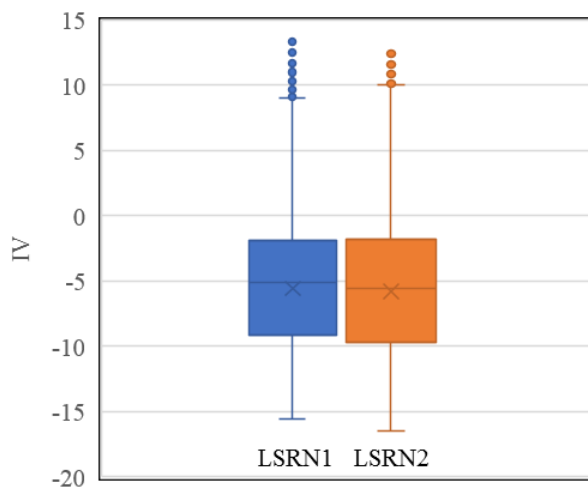



**Figure 6.** Density of roads by LUC class of CLC and COS GI (see LUC legend Fig. 2).

The IV assigned to the road network does not have agreement between two models. The difference
5   between maximum and minimum IV of the LSRN1 and LSRN2 variations is notorious, with
approximately 1 value of IV variation. The interquartile range of the IV is greater in LSRN2 than in
LSRN1 (Fig. 7). However, the IV average is smaller in LSRN2 in comparison to LSRN1.

10   **Figure 7.** Landslide susceptibility of the road network. LSRN1 – IV extracted of the LSM1; LSRN2 – IV extracted of the LSM2.

The landslide susceptibility map of the roads network obtained by LSM1 (LSRN1) (Fig. 8), i.e., IV extracted of the LSM1, the landslide susceptibility is spatially contrasted along the road network, highlighting the places where is most likely to occur the future landslides that may cause disturbances

5  on the roads.

On the other hand, in the landslide susceptibility map of the roads network obtained by LSM2 (LSRN2), the IV assigned to the road network is generally lower when compared to LSRN1, which is a result derived from LUC (CLC) generalization used in the input of M2.

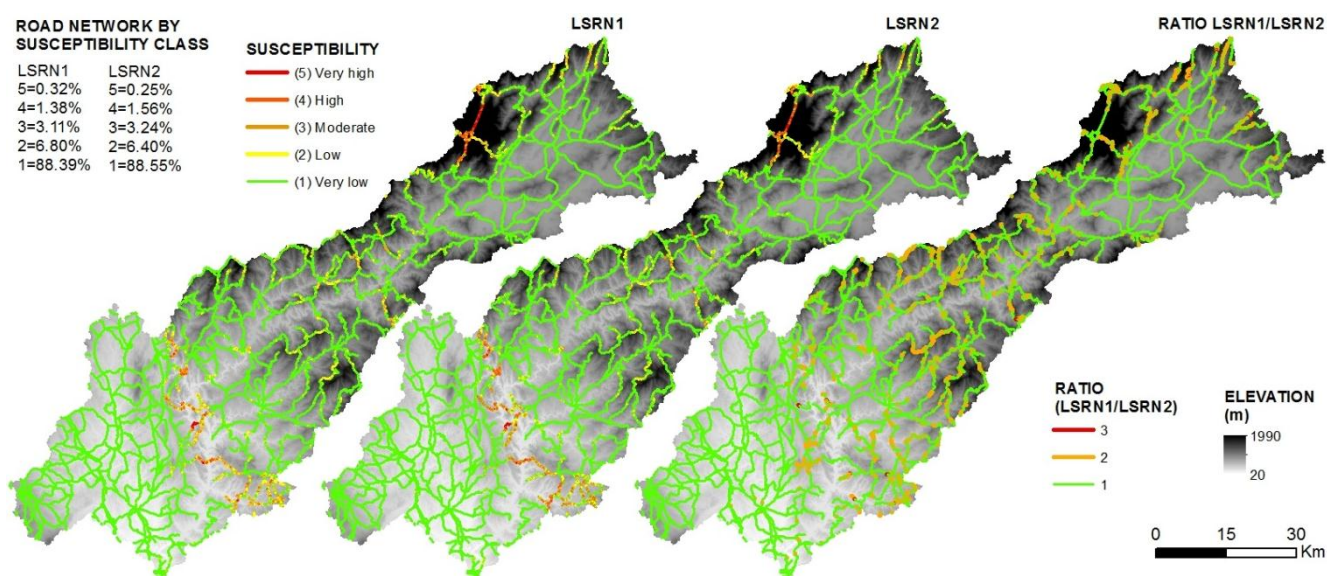



**Figure 8.** Landslide susceptibility of the road network (LSRN1 and LSRN2) and the ratio between landslide susceptibility class of the roads. LSRN1 – IV extracted of the LSM1; LSRN2 – IV extracted of the LSM2.

LSRN1 includes 11.6% of roads with positive landslide susceptibility (IV ≥ 0), and the roads with high

15  landslides susceptibility (IV > 7.5) represent only 0.32% of the total road network (Fig. 8); while in the LSRN2 case, the positive landslide susceptibility (IV ≥ 0) reduces to 11.5% in the total road network, where 0.3% of this network corresponds to high landslide susceptibility (IV > 7.5).

Landslide susceptibility in LSRN2 do not show a high variation in short distances of roads, i.e., the IV tends to be extended within each polygon of the same class of LUC of CLC (polygons larger in

comparison with COS GI) reducing the IV variation along the roads. The variation of the IV within each polygon of LUC GI is explained only by the remaining predisposing factors included in the model. On output of LSRN2, the places with high landslide susceptibility are not always identified where effectively landslides occurred (Fig. 9). The landslide susceptibility of the road network enhances the results obtained with the COS (LSRN1) in very high landslide susceptibility identification, precisely where landslides were validated in the fieldwork. These results show the importance of LUC GI properties in spatial differentiation of the landslide susceptibility.

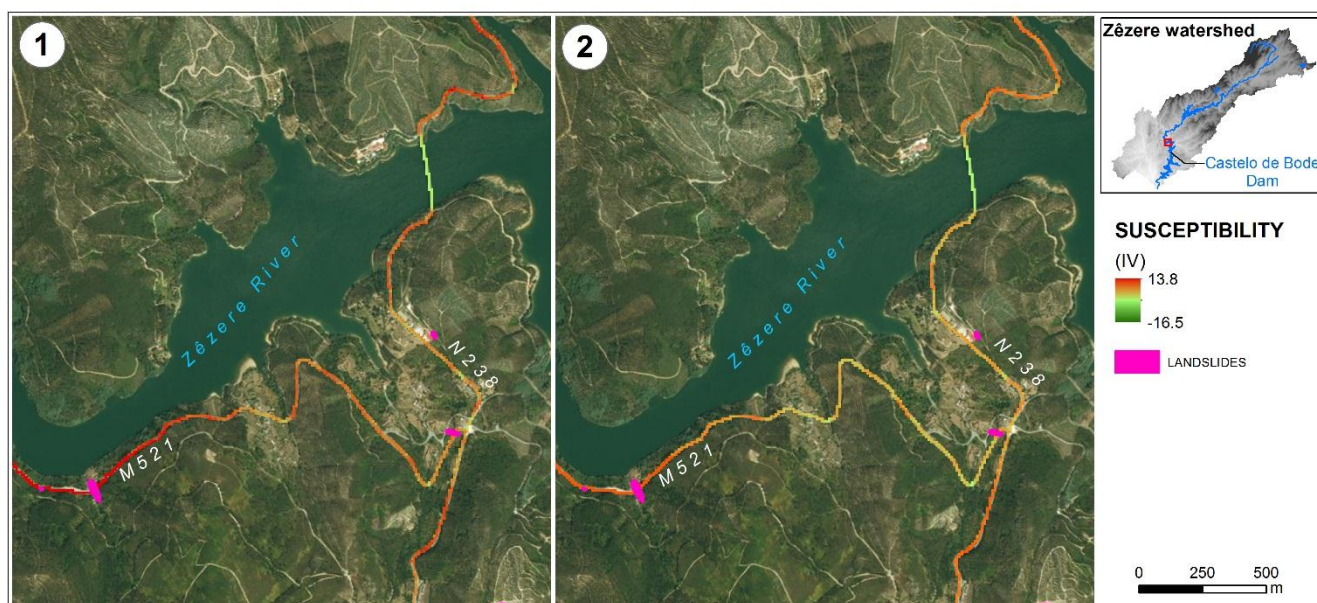



**Figure 9.** Examples of the landslide susceptibility of the road network in Ferreira do Zêzere municipality. 1 – LSRN1; 2 – LSRN2.

The overall accuracy and Kappa coefficient between landslide susceptibility classes of LSRN1 and LSRN2 are 94.8 and 76.5%, respectively (Table 4). The susceptibility class "very high" have 98% correspondence between LSRN1 and LSRN2, but the remaining susceptibility classes present approximately 70% correspondence (except the class very low in LSRN2, with 88.5 accuracy), i.e., 30% of each class not corresponding and are distributed by other susceptibility classes.

**Table 4.** Accuracy between LSRN1 and LSRN2 results (area %).

| LSRN1 | LSRN2 | | | | | Total (%) | Accuracy (%) | Commission error (%) |
|---|---|---|---|---|---|---|---|---|
| | Very high (IV >7.55) | High (IV 5-7.5) | Moderate (IV 2.5-5) | Low (IV 0-2.5) | Very low (IV < 0) | | | |
| Very high (IV >7.5) | 86.11 | 1.53 | 0.03 | 0.00 | 0.00 | 87.66 | 98.22 | 1.78 |
| High (IV 5-7.5) | 1.69 | 4.82 | 0.69 | 0.03 | 0.00 | 7.22 | 66.70 | 33.30 |
| Moderate (IV 2.5-5) | 0.07 | 0.44 | 2.44 | 0.36 | 0.00 | 3.31 | 73.62 | 26.38 |
| Low (IV 0-2.5) | 0.00 | 0.01 | 0.28 | 1.16 | 0.03 | 1.47 | 78.54 | 21.46 |
| Very low (IV < 0) | 0.00 | 0.00 | 0.00 | 0.09 | 0.23 | 0.32 | 70.89 | 29.11 |
| Total area (%) | 87.86 | 6.80 | 3.44 | 1.64 | 0.26 | | | |
| Accuracy (%) | 98.01 | 70.85 | 70.87 | 70.65 | 88.55 | **Overall accuracy: 94.8%** | | |
| Omission error (%) | 1.99 | 29.15 | 29.13 | 29.35 | 11.45 | **Kappa coefficient: 76.5%** | | |

Although it has been variations between LSRN1 and LSRN2 landslide susceptibility, the relationship between the two model's outputs is high (Fig. 10), presenting a Pearson correlation coefficient of 0.96 (significance level $p < 0.05$). The results of this correlation reflect the existence of an agreement on the spatial variation between LSRN1 and LSRN2, i.e., in general, when the IV of one outputs increases the other also increases, or vice versa, regardless of the discrepancy between the IV of the same cell of each output.

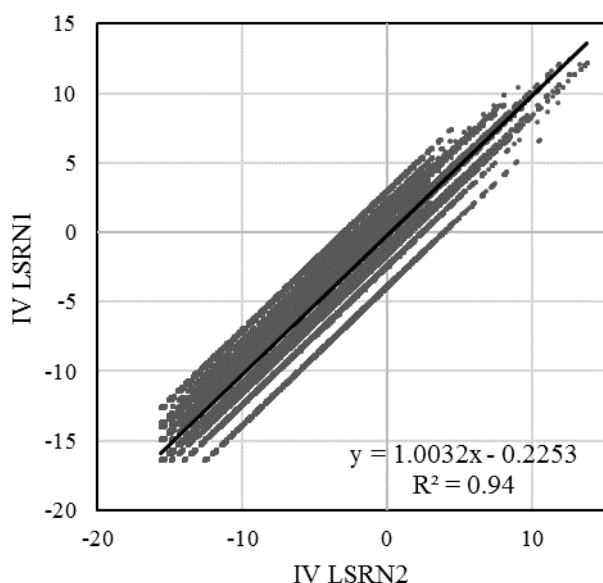



**Figure 10.** IV of the road network obtained by M1 versus IV of the road network obtained by M2. LSRN1 – IV extracted of the LSM1; LSRN2 – IV extracted of the LSM2.

The LSRN1 and LSRN2 results were crossed with the landslides that caused perturbations or disruptions of the roads network to validate the landslide susceptibility models. Overall, the results are very good, with 89.3 and 88.9% AUC for LSRN1 and LSRN2, respectively. However, LSRN1 offers slightly better results compared to LSRN2, as can be seen in the representation of the SRC (Fig. 11),

5   i.e., in 20% of the total area of the road network are validated 83.3% LSRN1, while for the same percentage of roads area is validated only 81% of LSRN2.

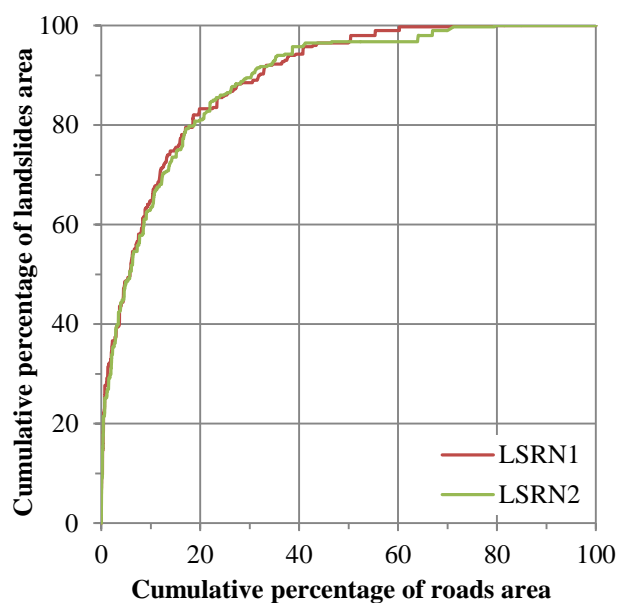



**Figure 11.** Success rate curves of the LSRN1 and LSRN2.

10  **4 Discussion**

According to this research, we showed that LUC GI detail concerning their properties in the input of the models is important in the landslide susceptibility evaluation and showed different results.

Some research works refer the quality of GI (scale and precision) in the final results changes (e.g. Etter et al., 2006). In this case, the degree of completeness, the positional, geometric, and thematic accuracy

15  of the selected LUC GI was evaluated by the different proprietary institutions, with more than 80%, i.e.,

where the semantic inconsistencies error was reduced, an important factor in the error propagation reduction and achieving product with best quality (Van Oort and Bregt, 2005; Regnauld, 2015).

The correlation between outputs of each model is high, but there are differences between them. COS GI is more detailed (1:25000) than CLC GI (1:100000), then the LUC are more differentiated in the

5    territory allowing to determine with greater detail and accuracy the areas with high landslide susceptibility, fact verified in LMS1; while in M2, the CLC GI is less detailed, resulting the LSM2 with IV tended more reduced (low and very low landslide susceptibility), comparatively with LSM1.

There was also verified a greater IV generalization along the road network at LSRN2 when compared with LSRN1, derived from the input of LUC GI more generalized, with a smaller scale. The scale of the

10   GI proves to be important in this type of modelling.

In the road network intersection with the LUC GI a high absence of roads GI was observed in the class "industrial, commercial and transport units", which is explained by the cartographic generalization due to the minimum mapping unit (MMU) and minimum distance between lines of each LUC dataset. These factors exclude the roads GI due to the minimum requirements defined in the technical specifications of

15   each LUC dataset.

However, the distribution of road network between the LUC classes is quite variable in two LUC datasets (COS and CLC), being one of the factors that also justifies the variation of landslide susceptibility observed in different outputs.

The results of success rate curves and AUC for LSM1 and LSM2 show a high quality of two models in

20   the landslides susceptibility areas determination (Guzzetti et al., 2006), but LSM1 present slightly better results. LSRN1 and LSRN2 results and respective validation demonstrates that the models effectively identify the places where the landslides occurred and the areas more likely to occur the future landslides. In this case, also noted through the SRC and AUC the high efficiency of the models (Guzzetti et al., 2006), with a slightly higher efficiency of the LSRN1.

25   Some roads in the study area were affected by landslides, a fact confirmed during the field work developed to validate the landslide inventory (examples of roads blockage or damaged: CM1064, M521, N339, municipality roads of Fernandaires and Fernande local roads in Estrela Mountain). In certain cases, the affected roads are important accesses to the most isolated villages in the study area,

and may in some cases a landslide isolates the villages, because part of the affected infrastructures are unique public access, a fact verified in the sample areas. On the other hand, the central region of Portugal, presents the lowest percentage of landslide disaster cases, but one of the highest percentage of landslide fatalities (Pereira et al., 2017), underlining the importance of the accuracy of landslide susceptibility in this area.

In the analysis of the risk associated with road transportation, the higher probability of a given event or incident, greater are the consequences (Berdica, 2002). It is in this sense that the exact determination of the locals with the largest landslide susceptibility acquires importance, enabling act preventively and to minimize these consequences, or act better reactively when dealing with emergencies, because the road closed change time of course increasing the reaction time and relief (Meneses and Zêzere, 2012).

## 5 Conclusion

Landslide susceptibility in the study area is very spatially variable, highlighting some characteristics of geo-factors of the study area in high landslide density in a specific location, for example the highest slope angles and certain types of LUC and lithology.

The properties of the GI which integrates the models is also important in landslide susceptibility assessment, since the variation of properties of the same geo-factor, in this case LUC with different properties, provided different results.

More detailed LUC GI (COS) allows better landslide susceptibility results, while LUC GI more generalized, as is the case with CLC, resulted in the IV reduction, not allowing identify some places where landslides occurred effectively.

However, the results of the two susceptibility models (M1 and M2) are good performance, a fact demonstrated by the validation of the model's results (SRC and AUC).

The merging of these results to the road network allowed identifying the locations with the highest spatial probability to the landslides occurrence, standing out the LSRN1 map with better results, because integrated the COS dataset, showing this result the importance of LUC GI detail in the specific identification of locals in the roads where landslides have occurred. In LSRN2 map, after crossing of

landslides validated in the field, it was verified that the model does not identify high landslide susceptibility in all road sections where landslides have occurred.

In general, both LSRN1 as LSRN2 show the same trend in spatial variation of landslide susceptibility of the road network in the study area, highlighting high susceptibility on the slopes of the Estrela Mountain and near the Castelo de Bode reservoir.

The results of this research are important for the emergency services in Zêzere watershed, allowing the adoption of preventive measures and alternative evacuation paths determination in case of the landslides occurrence. Knowing the locations most likely to landslide occur, the alternatives options can be created avoiding partial or complete isolation of certain localities, and allowing reduce social and economic constraints of this population.

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