Research Group on Environmental Hazard and Risk Assessment and Management
Centre for Geographical Studies
Institute of Geography and Spatial Planning, Universidade de Lisboa
http://riskam.ul.pt/

Development of a stream flood susceptibility index at the municipal level in mainland Portugal

SANTOS, PEDRO PINTO[1]; REIS, EUSÉBIO[1]; PEREIRA, SUSANA[1]; SANTOS, MÓNICA[1,2]

[1] RISKam, Centre for Geographical Studies, Institute of Geography and Spatial Planning, Universidade de Lisboa, Portugal (CEG-IGOT/Ulisboa)

[2] Centre for the Research and Technology of Agro-Environmental and Biological Sciences, Universidade de Trás-os-Montes e Alto Douro, Portugal, (CITAB-UTAD)

1. INTRODUCTION

Between 1998 and 2017, floods were responsible for a total of US$656 billion in economic losses (23% of the total of climate-related and geophysical disasters), only surpassed by earthquakes and storms, and caused the loss of life to 142,088 persons (11% of the total). Assessing the natural condition to the flood occurrence is the first step to understand and prevent such disasters. Constraints on time and data availability – high-resolution DEMs, permeability-related data, rainfall-runoff data or historical records, for example – or the need to assess flood hazard homogeneously on large areas limit the capacity of applying complex susceptibility assessment methods (hydrologic-hydraulic modelling, geological-geomorphological interpretation, etc.). In the so-called data scarce contexts, the application of coupled methodologies is quite often not possible, requiring the search for more expedite approaches.
The proposed multi-criteria method to assess stream flood susceptibility (*SFS*) considers 3 flood-conditioning factors: flow accumulation, average slope angle and average inverse relative permeability. After assessing *SFS* on a cell-by-cell basis, a municipal representation of *SFS* was performed to rank the 278 municipalities in mainland Portugal (Figure 1).

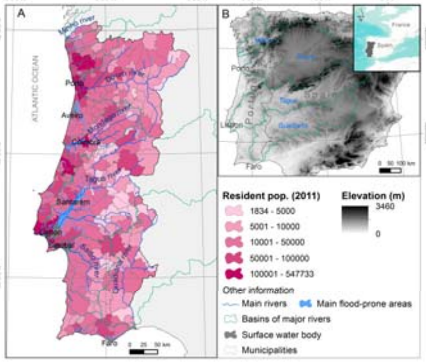

Figure 1 *Resident population (2011) per municipality in mainland Portugal (A) and elevation in Iberian Peninsula (B).*

2. DATA AND METHODS

A summary of the used data and adopted methodology is presented in Figure 2.

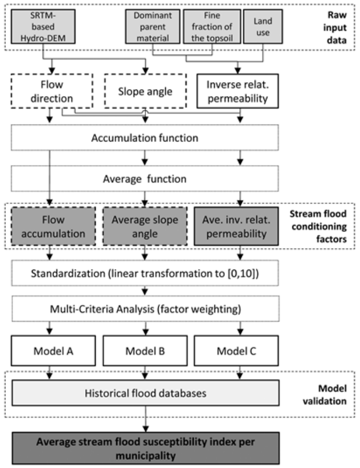

Figure 2 *Methodological scheme for the national scale stream flood susceptibility assessment.*

2.1. DEM derived data

Flow accumulation (*F_{acc}*) was calculated from the Shuttle Radar Topography Mission (SRTM) DEM for the entire Iberian Peninsula with a 3 arc-second resolution. The result ranges from 1 to 13029779 cells (each cell represents about 7482 m^2), to which the natural logarithm was applied, resulting in a range from 0 to 16.38.
Slope angle in degrees was calculated using the hydrologically corrected SRTM-based DEM. Flow accumulation was ran using as input the previously obtained flow direction raster dataset and using as weight factor the slope angle raster dataset (*S*), which results in the accumulated slope angle. Average slope angle (S_{avg}) is obtained by dividing accumulated slope by flow accumulation and clipping the raster dataset to mainland Portugal. As performed with F_{acc}, the natural logarithm was applied to the average slope raster dataset, resulting in scores ranging from [-6.3, 3.7]. The final raster dataset of average slope angle (S_{avg}) is the result of the transformation of those scores to the interval [0, 10].

2.2. Inverse relative permeability

Relative permeability was estimated using three data sources: dominant parent material (*DPM*), fine fraction of the topsoil (*FFT*) and land use (*LU*) (Figure 3). *DPM* and *FFT* were extracted from the European Soil Data Centre (ESDAC) and express the natural permeability, while *LU* (CLC2012) represents the effect of the land use coverage on infiltration.
DPM and *FFT* classes were assigned scores from 0 to 10, on the perspective of their influence to runoff and infiltration. Their mean was multiplied by *LU* (which ranges from 0 to 1), thus obtaining relative permeability (*Prel*). Similarly to the other flood conditioning factors, flow accumulation was calculated to obtain the accumulated inverse relative permeability ($Prel\_{invacc}$), in which flow direction is used as input data and the inverse relative permeability ($Prel_{inv}$) as the weight factor. The scores were divided by F_{acc} to obtain the average inverse relative permeability ($Prel\_{invavg}$). The natural logarithm was applied to these scores in order to obtain new values ranging from [-1.2, 2.3] which were transformed to the interval [0, 10].

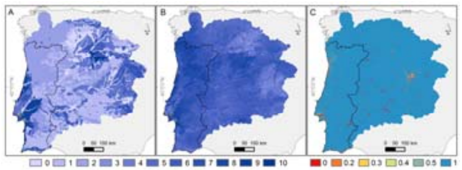

Figure 3 *Scores assigned to the three input data used on the assessment of relative permeability: dominant parent material (A), fine fraction of the topsoil (B) and land use (C).*

2.3. Historical flood records and model validation

Historical flood databases such as the DISASTER database (Zêzere et al., 2014) and other flood documental databases (Santos et al., 2018; Santos and Reis, 2018), both based on newspapers were used to select the best combination of flood conditioning factors' weights and to further validate the SFS models.
In both databases, those flood cases classified as 'urban floods' or 'other type of floods' were excluded from this analysis.
The DISASTER database includes 932 flood cases that generated human losses (1 or more casualties, missing, injured, displaced or evacuated persons), in mainland Portugal, for the period 1865-2015. The other flood databases complement the DISASTER database by adding the flood cases in which only minor losses are reported.
In sum, five validation areas were used to select the final *SFS* model (Figure 4).

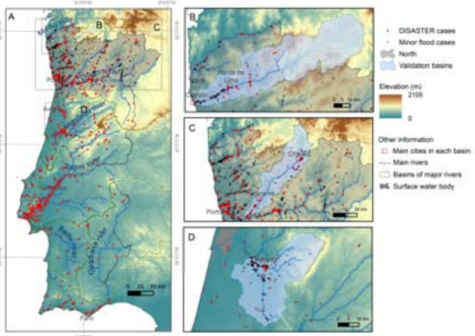

Figure 4 *Historical flood records of Disaster and North databases (A), and Lima (B), Tâmega (C) and Águeda (D) basins.*

2.4. Municipal stream flood susceptibility

The final index of *SFS* was computed using the data mapped in Figure 5, as follows:

$$SFS = F_{acc} * w_{F_{acc}} + S_{avg} * w_{S_{avg}} + Prel\_inv_{avg} * w_{Prel\_inv_{avg}}$$

Based on previous applications of this methodological approach in weighting flood conditioning factors (Jacinto *et al.*, 2014; Santos and Reis, 2018), the following three models were tested at the national scale:

- Model A, with w_{Facc} = 0.75, w_{Savg} = 0.15 and $w_{Prel\_inv\_avg}$ = 0.10;
- Model B, with w_{Facc} = 0.80, w_{Savg} = 0.10 and $w_{Prel\_inv\_avg}$ = 0.10;
- Model C, with w_{Facc} = 0.85, w_{Savg} = 0.10 and $w_{Prel\_inv\_avg}$ = 0.05.

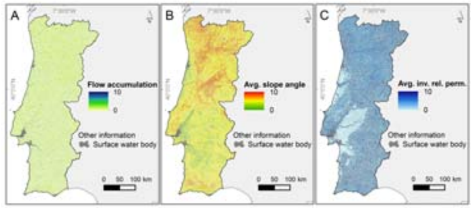

Figure 5 *Stream flood susceptibility conditioning factors: flow accumulation (A), average slope angle (B) and average inverse relative permeability (C).*

For model selection, since the models classify the stream network susceptibility, the validation points from the historical flood databases were associated to the nearest streamline resulting from each model, instead of being associated to the value of the cell where they are positioned.
Pearson correlation coefficients were calculated between the i) number of cells in each *SFS* class correlated with the number of flood cases per cell (P1) and ii) class of *SFS* (from very low to very high) correlated with the number of flood cases per cell in each *SFS* class (P2). For P1-type correlation coefficients, the more negative the correlation the better the model: in fact, the strongest association between flood occurrences and susceptibility occurs when high densities of flood cases occur in a small number of cells of high susceptibility. For P2-type coefficient correlations, the more positive the correlation the better the model because the highest densities of flood cases are expected to occur on the highest susceptibility classes.

3. RESULTS AND APPLICATIONS

Considering the 4 validation areas, model C was selected as the one that best describes stream flood susceptibility. A zoom-in of the *SFS* mapping is shown on Figure 6.

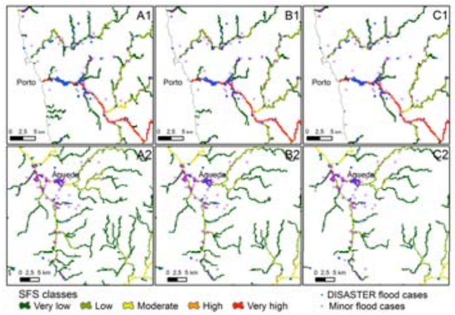

Figure 6 *Classes of SFS according to models A, B and C near the Douro River mouth (A1, B1 and C1) and on the Águeda River basin (A2, B2 and C2). Location of plots in Figure 4.*

Model C (weighting 0.85 to F_{acc}, 0.1 to S_{avg} and 0.05 to $Prel\_{invavg}$) performs a filtering effect removing from streams that are represented in models A and B but that do not have a historical record of flood cases. Higher averages of *SFS* are found on municipalities crossed by transboundary rivers, particularly the Douro, Tagus and Guadiana rivers. Some coastal municipalities located at the mouth of Portuguese river basins, particularly between the Minho and the Douro rivers, are also classified on the highest SFS quantile (scores between 6.67 and 8.86) (Figure 7).
Crossing the *SFS* municipal results with the historical flood losses from the DISASTER database allowed for the definition of municipal flood risk profiles (Figure 8 and Table 1).

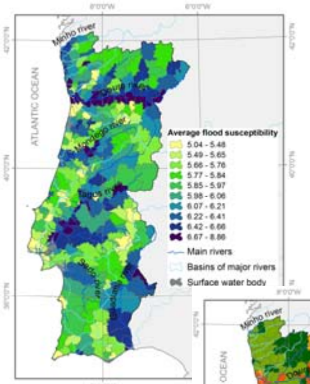

Figure 7 *Average flood susceptibility by municipality, according to SFS obtained from model C. Classification in 10 classes of equal number of individuals (quantiles).*

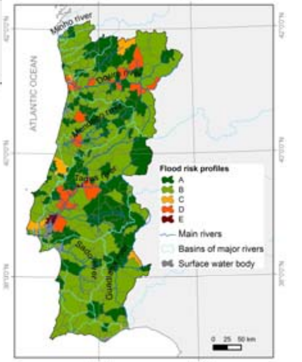

Figure 8 *Municipal flood risk profiles.*

Profiles:

A – the safest (absence of DISASTER-type cases

B – few cases, low and very low susceptibility -> high exposure?

C and D – intermediate contexts of susceptibility and losses.

E – Moderate to Very High SFS and extensive record of losses

Table 1 *Classes of average SFS per municipality and classes of DISASTER cases per municipality.*

	Classes of DISASTER flood cases per municipality				
Average SFS	0 cases	1-9 cases	10-19 cases	20-90 cases	Total
Very low [5.24, 6]	64	78	4	3	149
Low]6, 7]	39	66	8	5	118
Moderate]7, 8]	1	6	1	1	9
High]8, 9]	1	1	0	0	2
Very high]9, 10]	0	0	0	0	0
No. of municipalities	**105**	**151**	**13**	**9**	**278**

The methodology can be used in modelling the effects in *SFS* by changes in the permeability conditions – caused, for example, by land use changes; the identification of naturally priority areas of higher susceptibility for the application of hydrologic and hydraulic (1D or 2D) modeling at the local scale.
When crossed with historical records and exposure data, the cell-by-cell *SFS* results have the ability to identify priority reaches of the river network to benefit from early warning systems, additional land use regulations and local engineering mitigation structures.

Further information

This research was recently published in:

Santos PP, Reis E, Pereira S, Santos M (2019) A flood susceptibility model at the national scale based on multicriteria analysis. Science of The Total Environment 667:325-337. https://doi.org/10.1016/j.scitotenv.2019.02.328

References

Jacinto R, Grosso N, Reis E, Dias L, Santos FD, Garrett P, 2015. Continental Portuguese Territory Flood Susceptibility Index - contribution to a vulnerability index. Natural Hazards & Earth System Sciences 15: 1907–1919. https://doi.org/10.5194/nhess-15-1907-2015

Santos M, Fragoso M, Santos JA, 2018. Damaging flood severity assessment in Northern Portugal over more than 150 years (1865-2016). Natural Hazards 91(3): 983-1002. https://doi.org/10.1007/s11069-017-3166-y

Santos PP, Reis E, 2018. Assessment of stream flood susceptibility: A cross-analysis between model results and flood losses. Journal of Flood Risk Management 11: S1038-S1050. https://doi.org/10.1111/jfr3.12290

Zêzere JL et al., 2014. DISASTER: a GIS database on hydro-geomorphologic disasters in Portugal. Natural Hazards 72: 503-532. https://doi.org/10.1007/s11069-013-1018-y

Acknowledgments

This work was financed by national funds through FCT – Portuguese Foundation for Science and Technology, I.P., under the framework of the project FORLAND – Hydro-geomorphologic risk in Portugal: driving forces and application for land use planning (PTDC/ATPGEO/1660/2014), and by the Research Unit UID/GEO/00295/2019