Swift Delineation of Flood-Prone Areas over Large European Regions

SYSTEM RISK ETN

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Ricardo Tavares da Costa (1, 2), Attilio Castellarin (2), Salvatore Manfreda (3), Caterina Samela (3), Alessio Domeneghetti (2), Paolo Mazzoli (1), Valerio Luzzi (1) and Stefano Bagli (1)
(1) GECOsistema Srl, Viale Giosuè Carducci, 15, 47521 Cesena, Italy (ricardo.tavarescosta@gecosistema.it, www.gecosistema.com), (2) DICAM, University of Bologna, School of Engineering, Viale del Risorgimento, 2, 40136 Bologna, Italy, (3) University of Basilicata, Viale dell'Ateneo Lucano 10, 85100 Potenza, Italy

Introduction

According to the European Environment Agency (EEA Report No 1/2016), a significant share of the European population is estimated to be living in, or near to, a floodplain, with Italy having the highest population density in flood-prone areas among the countries analysed. This tendency, tied with event frequency and magnitude and the fact that river floods may occur at large scales and at a transboundary level, where data is often sparse, presents a challenge in the management of flood-risk. The availability of consistent flood hazard and risk maps during prevention, preparedness, response and recovery phases is a valuable and important step forward in improving the effectiveness, efficiency and robustness of any evidence-based decision making process. In this work, **we test and discuss the usefulness of pattern recognition techniques based on geomorphic indices** (Manfreda et al., 2011, Degiorgis et al., 2012, Manfreda et al., 2016; Samela et al., 2017) **for the simplified mapping of riverine flood-prone areas at large scales**. Results are compared to the Pan-European flood hazard maps derived by Alfieri et al. (2013) using a set of distributed hydrological (LISFLOOD, van der Knijff et al., 2010, employed within the European Flood Awareness System, www.efas.eu) and hydraulic models (LISFLOOD-FP, Bates and De Roo, 2000). **This work is developed under the System-Risk project** (www.system-risk.eu).

Objectives

1. Implement a pattern recognition technique for large scale delineation of flood-prone areas
2. Identify challenges and limitations of such a simplified methodology, applications and the way forward
3. Investigate how machine learning techniques may be used to evaluate flood risk (incl. ungauged basins)

The 3 Case Studies

Within the European context, the **Danube, the Po and the Severn river basins** were selected for three distinct scales of application of the geomorphic classification, as shown in Table 1. Each case is different in area, which, along with resolution, influences pre-processing times. Each basin Digital Elevation Model (DEM), at 25 m resolution, was obtained from the Copernicus data and information, funded by the European Union – EU-DEM layers. The Catchment Characterisation and Model layer (Vogt, J.V. et al., 2007) was used as clipping mask.

Table 1: Raster details of the Danube, Po and Severn river basins.

	Danube	Po	Severn
Area	~804303 km²	~75399 km²	~11381 km²
#pixels	66856x33916 ~2B	18776x11368 ~213M	7348x6404 ~47M
File size	~9 Gb (BigTIFF)	~500 Mb	~75 Mb

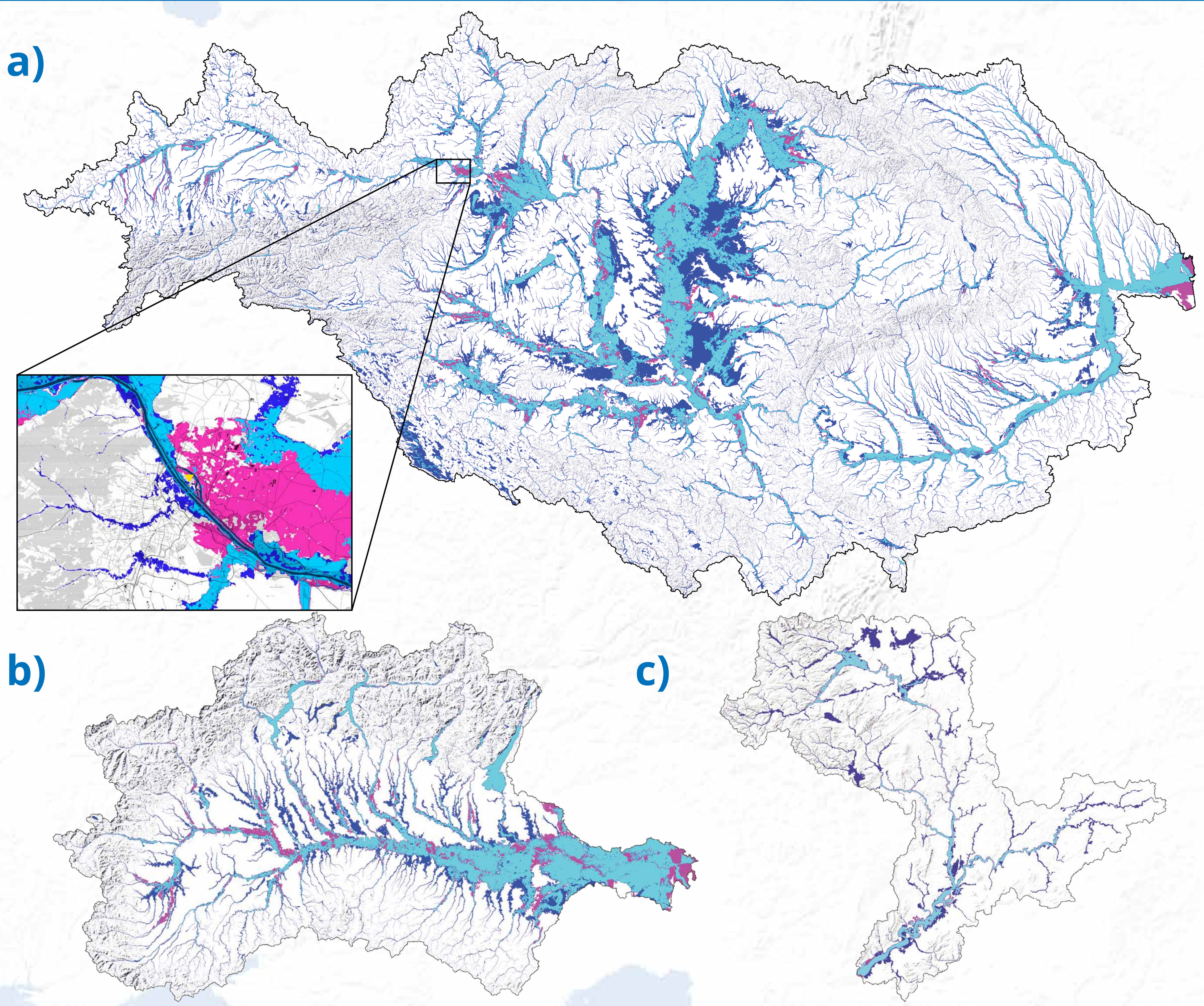

Figure 1: Comparison of flood-prone areas resulting from the linear binary classification of the Geomorphic Flood Index and flood extent derived from the EC JRC flood hazard map for a return period of 500 years (Dottori et al., 2016). Cyan colour corresponds to an optimal geomorphic classification, with reference to the EC JRC map, while dark blue and magenta correspond to overestimation and underestimation, respectively. a) Danube River Basin and zoomed inset of Vienna region (incl. EGU venue); b) Po River Basin; c) Severn River Basin. Note that different map scales were used.

Methodology

The complete workflow is composed of a **pre-processing stage, calibration of a cutoff value and the final classification of flood-prone areas**. The Geomorphic Flood Index pre-processing, as proposed by Samela et al. (2017), requires a set of static inputs extracted from a DEM by terrain analysis: slope, flow direction and upslope contributing area. The calibration stage is then performed using whole basins by comparing a reference flood hazard map (e.g. Dottori et al., 2016) to several Geomorphic Flood Index cutoff values to determine the optimal one (Degiorgis et al., 2012). In our case the optimal cutoff maximizes an objective function: the Youden's index. The final stage is a binarization of the Geomorphic Flood Index using the optimal cutoff, its output represents the final delineation of the flood-prone areas showed in Figure 1.

Validation

In this section, we summarize some of the validation results for each case study. In Figure 2, the Receiver Operating Characteristic (ROC) curve and respective Area Under the ROC curve (AUROC) resulting from the calibration stage are presented. The closer the curve is to the top-left corner of the box, or the AUROC is to 1, the better is the prediction. In Table 2, we present some measures of uncertainty, obtained by comparing the final delineation of the flood-prone areas to the reference flood hazard map (Dottori et al., 2016). The hit rate is the percentage of flood-prone areas correctly predicted, while the specificity is the percentage of areas not prone to flood correctly rejected.

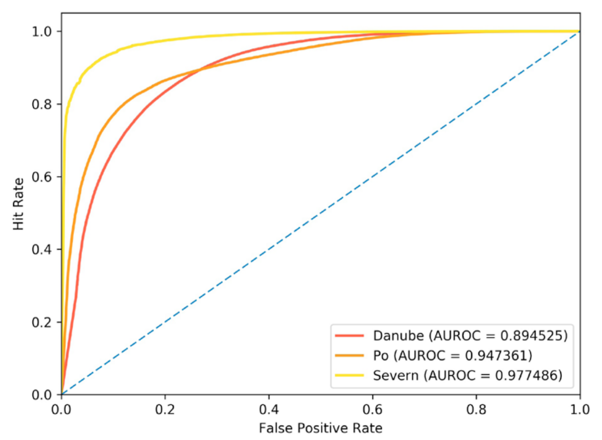

Figure 2: Receiver Operating Characteristic (ROC) and Area Under the ROC curve (AUROC) for the Danube, Po and Severn river basins.

Table 2: Cut-off values and error metrics for the Danube, Po and Severn river basins resulting from the linear binary classification of the GFI.

	Danube	Po	Severn
Cut-off	33.8%	33.5%	34.2%
Hit rate	84.5%	79.1%	91.9%
Specificity	95.1%	96.0%	97.7%
Accuracy	94.4%	94.7%	97.6%

Conclusions

The Geomorphic Flood Index represents a simple methodology for the swift delineation of flood-prone areas (e.g. with pre-processing accomplished, the Danube River Basin took approx. 7 min on a 2.3 GHz Intel® Core™ i7 with 16GB of RAM). The methodology reveals the potential for water conveyance from the main source of hazard to all hydrologically connected cells. It implies that the two main driving factors of riverine flooding are channel flood water heights (obtained from a hydraulic scaling relation) and elevation difference. We have demonstrated how such methodology is useful in the identification of flood-prone areas for three distinct European basins, even at an early stage of development where other driving factors are neglected. We have derived for the first time, comprehensive large scale flood extent maps for the whole Danube, Po river and Severn river basins with high prediction accuracy 94-98%. The advantages of this methodology are clearly its cost-effectiveness and easiness of application, minimum knowledge and data requirements, comprehensiveness of the results, high-resolution and virtually unlimited scales of application; but also, its potential suitability for application in data-scarce regions, for the use in a machine learning framework and for effortlessly plug in more features. We envision that a step forward would be to factor-in water losses, particularly through infiltration, presence of hydraulic infrastructures and effects of land use and land cover. But even more crucially would be to find a way to spatially quantify hazard; essential for the assessment of flood risk.

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