Development and assessment of uni- and multi-variable flood loss models for Emilia-Romagna (Italy)

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Abstract.

Flood loss models are one important source of uncertainty in flood risk assessments. Many countries experience sparseness or absence of comprehensive high-quality flood loss data which is often rooted in a lack of protocols and reference procedures for compiling loss datasets after flood events. Such data are an important reference for developing and validating flood loss models. We consider the Secchia river flood event of January 2014, when a sudden levee-breach caused the inundation of nearly 52 km^2 in Northern Italy. After this event local authorities collected a comprehensive flood loss dataset of affected private households including buildings footprint and structure, damages to buildings and contents. The dataset was enriched with further information compiled by us, concerning economic buildings values, maximum water depths, velocities and flood durations for each building. By analysing this dataset we tackle the problem of flood damage estimation in Emilia-Romagna (Italy) by identifying empirical uni- and multi-variable loss models for residential buildings and contents. The accuracy of the proposed models is compared with those of several flood-damage models reported in the literature, providing additional insights on the transferability of the models between different contexts. Our results show that (1) even simple uni-variable damage models based on local data are significantly more accurate than literature models derived for different contexts; (2) multi-variable models that consider several explanatory variables outperform uni-variable models which use only water depth. However, multi-variable models can only be effectively developed and applied if sufficient and detailed information is available.

1 Introduction

According to analyses of the Centre for Research on the Epidemiology of Disasters - CRED, hydrological disasters (i.e., natural disasters caused by river and coastal floods, flash-floods, rainstorms, etc.) are the most frequently recorded natural calamities occurring worldwide in the last two decades (see e.g. Guha-Sapir and CRED, 2015). Also, the number of disasters caused by hydrological events in 2016 exceeded by far that of any other type of natural hazards (Guha-Sapir and CRED, 2016).

Flooding was the third major cause of economic loss worldwide among all natural disasters between 2006 and 2015 (the firsts were earthquakes and storms), resulting in total damages larger then \$ 300 billion. In Europe, the proportion of flood impacts was even larger during the same decade, with inundations ranked first in terms of total damage (i.e. $\sim$ \$ 51 billion; CRED). The CRED findings about the increasing amount of economic loss starting from the second half of 20^{th} century agree with the analyses carried out by the Intergovernmental Panel on Climate Change (IPCC), which highlighted that flood damages in the past ten years were ten times higher than in the period 1960-1970 (IPCC, 2001, 2014).

Future scenarios provided by IPCC (2014) and Jongman et al. (2012) suggest that extreme flood events at a global scale are expected to increase in terms of frequency and magnitude. Barredo (2009) drew an hypothetical scenario without any change in the meteorological forcing and found that loss would increase anyway in the future due to exposure and socio-economic changes (e.g. higher demographic pressure, improved pro-capita wealth and living standards).

The implementation of the European Flood Directive (2007/60/EC) led flood risk assessment and management to gain even greater interest (de Moel et al., 2015; Dottori et al., 2016b, and references therein), forcing Member States and authorities to dedicate additional resources and efforts to the assessment, mitigation and management of flood risk in the broader contexts of possible climate change, population growth and economic changes (Meyer et al., 2013; Merz et al., 2010, 2014). However, despite these efforts, there are still several open problems and limits that need to be discussed and addressed in order to better assess flood risk and its evolution in time and space.

Among the three components that define the flood risk (*hazard* , *exposure*, and *susceptibility*), this paper focuses in particular on the last two, namely the qualification and quantification of the exposed elements and the attribution of a loss value to them, as a function of one or more flood intensity parameters and resistance characteristics (damage models). The scientific literature of the last decade shows a large number of innovative damage models that are capable of estimating flood loss starting from one or more predictive variables. Nevertheless, several authors indicate that damage models still provide an important sources of uncertainty in flood damage estimates, leading to uncertainties which are comparable to or larger than those associated with any other component (Jongman et al., 2012; de Moel et al., 2012; Gerl et al., 2016; de Moel et al., 2014; Merz et al., 2004, 2007; Apel et al., 2009).

One important source of uncertainty is the simplified representation of complex damaging processes in terms of a stage-damage function (Jongman et al., 2012). Since White (1945) linked the water level to relative (i.e., the loss ratio) or monetary damages, most of the models used today stick to this concept using only water depth to estimate relative loss (see e.g. Penning-Rowsell et al., 2005; Smith, 1994; Apel et al., 2009; Kreibich et al., 2009; Merz et al., 2013). Other important influencing factors, such as flood duration and flow velocity are often not considered (de Moel and Aerts, 2011; Merz et al., 2013).

Recently, some authors (see Merz et al., 2013; Chinh et al., 2016; Hasanzadeh Nafari et al., 2016, 2017; Kreibich et al., 2017; Spekkers et al., 2014) developed multi-parameter damage models including more than one predictive variable, chosen among other hydraulic parameters (e.g. streamflow velocity, duration of the inundation, etc.), resistance performance, precautionary measures and people awareness and experience with floods (Meyer et al., 2013). These models were shown to outperform uni-variable loss models, under the condition that sufficiently large and detailed damage datasets are provided (Merz et al., 2013; Schröter et al., 2016). Bubeck and Kreibich (2011), Cammerer et al. (2013), Messner et al. (2007) and Meyer et al. (2013), among others, indicate the need for a better understanding of the damage processes as a mean to further improve multi-variable models.

A further aspect that contributes to the overall uncertainty in the flood risk assessment and modelling is the lack of sufficient, comparable and reliable high quality flood loss data (Meyer et al., 2013; Molinari et al., 2014a; Amadio et al., 2016; Scorzini and Frank, 2015; Green et al., 2011). In the absence of empirical damage data, loss models are either selected from the literature or subjectively and schematically derived by experts using a synthetic approach (see e.g. Penning-Rowsell et al., 2005; Merz et al., 2004; Thieken et al., 2008; Kreibich et al., 2010; Merz et al., 2013; Dottori et al., 2016a). In fact, data collected in the events aftermath are crucial to construct new models and validate existing ones (Meyer et al., 2013; Cammerer et al., 2013; Ballio et al., 2015), to adjust them for peculiar conditions of the study area, to improve the consistency of the models themselves (Amadio et al., 2016; Büchele et al., 2006; Gerl et al., 2016), and to provide information about their transferability in different analyses and contexts (Molinari et al., 2014a; Cammerer et al., 2013; Green et al., 2011). Many damage models developed up to now are in fact internationally accepted as standard methodologies for estimating flood damages (Merz et al., 2007; Smith, 1994; Merz et al., 2010), without being neither tested nor calibrated for the specific study area (Amadio et al., 2016). Indeed, using damage models for geographical areas, socio-economic conditions and flood events that differ from those for which the models themselves have been originally derived leads to the incorporation of large errors into the assessment of flood risk (Merz et al., 2004; Schröter et al., 2016; Merz et al., 2010). According to Gerl et al. (2016), validation analyses were performed only for about 45% of literature models included in their review by means of comparisons with observed data, while for the remaining models either the evaluation status is unknown, or the validation process is not explicitly described.

Concerning Italy, the scientific literature reports on the one hand several examples in which models developed elsewhere are applied without calibration or validation (see e.g. Amadio et al., 2016), and on the other hand it clearly states the limited exportability of empirical damage models (see e.g. Molinari et al., 2014b, on the transferability of the model developed on the basis of specific flood event data by Luino et al. (2006) and Freni et al. (2010)). Molinari et al. (2012) associate the generalized poor performance of loss models with a variety of reasons, among which two are worth recalling. First, the Italian peninsula is characterized by an extreme variability of geographical and geomorphological contexts as well as of urban textures and building typologies. Second, Italian flood-loss datasets are generally of low quality and very often characteristic of small areas, if compared to other European case studies (see Molinari et al., 2012).

The analysis described herein assesses the performance of uni- and multi-variate empirical models developed on the basis of a recently compiled Italian dataset. Our study highlights the problem of lacking consistent data and the consequent difficulty in the development of robust and reliable damage models for estimating flood loss to buildings and contents in local applications.

Furthermore, our study contributes to the understanding of potential and limitations of flood damage modeling in Northern Italy, aiming at investigating the open problem of transferability of empirical damage models to different areas and socio-economic contexts.

We consider one of the most comprehensive Italian flood damage dataset, which consists of 1330 post-event data on flooded private properties in the province of Modena (Northern Italy), collected in the aftermath of the Secchia river inundation (January 2014). The database contains information about the affected properties, such as their location and structural characteristics and the amount of loss suffered, concerning both structural and non-structural parts and installations (termed "buildings" from here on) and furniture and household appliances ("contents") of each building (see Sec. 3.1 and 3.2). The raw data collected by local authorities has been homogenized, geocoded and integrated with other useful information including the outcomes of a detailed hydrodynamic numerical simulation of the inundation event (see Sec. 3.3).

Our study is structured into three main components:

- First, concerning direct tangible economic damages to buildings, we use the above dataset to derive uni- and multi-variable damage models for the study area and compare the accuracy in estimating damages with a selection of established literature models.
- Second, we calibrate empirical uni- and multi-variable models to subsections of the study area and validate them using the data observed in different subsections (split-sample validation).
- Third, we investigate the relationship between damages to buildings and damages to contents, developing an empirical damage model also for the latter.

2 STUDY AREA AND INUNDATION EVENT

Our study focuses on a real inundation event occurred in Italy in 2014 and caused by a breach in the right embankment of the Secchia river during an intense, yet not extreme, flood event. The collapse of the right levee occurred on 19^{th} January near the town of San Matteo, in the Northern part of the Modena municipality (see yellow dot in Fig. 1), and caused inundation of the neighbouring municipalities of Bastiglia, Bomporto and Modena (violet, orange and green polygons in Fig. 1, respectively) in less than 30 hours. The overflowing volume was estimated between $36.3 \cdot 10^6$ and $38.7 \cdot 10^6$ m^3, flooding an area of about 52 km^2 (see e.g. Orlandini et al., 2015). Towns and the surrounding countryside remained flooded for more than 48 hours, until a water volume in excess of $20 \cdot 10^6$ m^3 was finally pumped out of the inundated area. According to Orlandini et al. (2015), the total estimated flood loss was about € 500 million (about € 16 million considering only residential properties).

The study area includes the municipalities of Bomporto and Bastiglia and the Northern part of the Municipality of Modena. It is located on the Secchia downriver right side and it extends for approximately 112 km^2. The area is mainly flat and main relieves consist of roads or railways embankments and minor river levees. The aspect of the area is oriented in a North-Eastern direction, along which ground elevations decrease from ca. 30 m a.s.l. in the South-Western territories to ca. 18 m a.s.l., about 20 km North-Eastwards.

The delineation of the study area relies on different topographic boundaries. The Western boundary in Figure 1 is the right levee of the Secchia river, while the Eastern boundary consists of the left levee of the Panaro river, which also flows towards North-East, almost parallel to the Secchia river. Roads, embankments and drainage channels which form the Southern and Northern boundaries are an important control for flooding dynamics (Carisi et al., 2017) and, in the Northern part, they prevented urban areas from being flooded.

The breach was first detected at 6:30 a.m. Most likely it was triggered either by direct river inflow into the riverside entrance of an animal burrow system or by the collapse of an existing animal burrow, which was separated by a 1 m earthen wall from the levee riverside and saturated during the flood event (Orlandini et al., 2015). A trapezoidal part of the embankment, with a base width of about 10 m, was removed and the embankment's top elevation became immediately 1 m lower than the river water surface. The breach reached a maximum bottom width of about 80 m and the embankment's top elevation became equal to the ground level within 9 hours (3:00 p.m. of 19th January 2014). Given the advanced state of the development of the breach when it was first discovered, no repair of the breached levee was even attempted as immediate measure.

Thanks to several eyewitness accounts, video footages and studies conducted by an ad hoc scientific committee (D'Alpaos et al., 2014; DICAM-PCREM, 2015), it was possible to identify the flood event propagation dynamics, shown by the blue arrows in Fig. 1. This data was used, together with local accounts, pictures and videos of the flooded municipalities, to reconstruct the event by means of a fully-2D hydrodynamic model (see Sec. 3.3).

3 FLOOD LOSS AND HYDRODYNAMIC DATA

In the immediate post-event period, for the purpose of compensation, authorities of Emilia-Romagna Region, Modena Province and affected municipalities started a data collection campaign to get as much information as possible on the damages caused by the flood event. According to Regional Decree n. 8 of 24th January 2014, the aim of the survey was to quantify the financial needs for the restoration of damaged public buildings, infrastructure network, hydraulic and hydrogeological works, as well as private properties for residential use, household contents, private registered goods and goods related to the productive sector. Accordingly, citizens and property owners were asked to fill forms about public properties damages, private properties, furniture and registered goods damages, as well as damages to the economic and productive activities and agriculture and agro-industrial sectors. In the present analysis, damage assessment focuses exclusively on private properties.

Authorities collected a total of 2448 forms, divided as per the affected municipalities. In order to geocode the position of every damaged property, the complete database was filtered, considering only records for which the complete address was provided. The database regards private properties affected by different kinds of potential damages: damages to buildings (structural and non-structural parts and installations), contents damages (furniture and household appliances), structural damages to common parts and registered goods damages (cars, motorcycles, etc.). Our analyses focuses only on properties affected at least by damages to buildings. The total amount of considered forms is therefore 1330 (see Table 1, second column).

The 1330 records were geocoded in a GIS environment, using the Google Maps basemap, being this one the most complete freely available map for the study area; geocoding was followed by a careful manual control activity using publicly available internet pictures, Google Street View and Google Earth. This step enabled the correction of several wrong or inaccurate geocodings, mainly in the rural areas, where distances between street numbers are higher.

The refund requests by citizens, collected from municipal authorities, were divided into different asset typologies: buildings damages, contents damages, structural damages to common parts and registered goods. We neglected structural loss to common parts and registered goods in our analyses because of the limited amount of data collected on these categories. Table 2 shows in details the different assets which could be refunded for buildings and contents damages. Table 3 summarizes all data collected and used in our study for each damaged property, providing information about the original sources and grouping the data into three different categories: observed (i.e. declared by owners in the official forms); simulated by the hydrodynamic model; retrieved from an external source. The rightmost column of the same table reports the ranges of these variables within the study area. The following sub-sections detail the information collected and summarized in Table 3.

3.1 DAMAGES TO BUILDINGS

As mentioned before, all 1330 considered records report at least damages to buildings (structural and non-structural parts and installations). Authorities defined the final compensation granted to owners in accordance to Ordinance No. 2 of 5^{th} June 2014 and Law No. 93 of 26^{th} June 2014, which specifies refund criteria. For instance, considering the total amount of money that authorities had available for the restoration of all kind of properties, the maximum coverage for each property was set to € 85 000 for damages to buildings and € 15 000 for damages to contents, setting a fixed amount of money for each different room. In addition, owners declarations about the amount of the restoration work of the damaged parts, if higher than € 15 000, were verified by authorities by means of experts technical reports. These controls probably reduced the amount of damages claimed by owners, who commonly tend to overestimate their loss and have less competency for estimating damages than professionals have.

Nevertheless, the limited availability of money and the need for an homogeneous criterion for all the affected properties led in many cases to a much higher reduction of the amount of damages refundable to the owners. In fact, refundable assets are only a cut percentage of assets that can be found in a property and, in addition, experienced damages could be higher than the maximum coverage established by authorities. The difference between overall monetary refunded and claimed damages to buildings is equal to about € 1.7 million (€ 15.2 million of declared loss vs. € 13.5 million of refunded loss). Given this significant difference, in order to preserve the representativeness and consistency in loss data, we chose to consider in our study observed damages as claimed by citizens in the forms they filled (estimation of the financial need for restoration, without knowing the refund criteria). We are aware that this choice can introduce overestimation of the damages (particularly considering damages below € 15 000) for the reason explained before, but we considered this possible error having less influence on loss estimation, both quantitatively and methodologically, relative to the distortions that would be systematically introduced by adopting the result of the compensation phase.

Together with the amount of money requested for compensation, we extracted from the filled forms also the available information on building footprint and structural typology (masonry, reinforced concrete, etc.) because of their potential impact on the damage process and therefore on damage modeling (see also previous studies, e.g. Merz et al., 2013).

In order to evaluate loss in relatives terms (as the percentage of suffered damage relative to the total value of the building), we retrieved the economic value of each property from the Italian Revenue Agency reports (Agenzia delle Entrate - AE). Every six months AE issues the open-market values [€/m^2] for different assets (e.g. civil houses, offices, stores, etc.) in each Italian administrative district (spatial scale of municipality), taking into account different classes of residential and industrial buildings and the overall economic well-being of the region. These values are different for each homogeneous geographical area (*OMI zone*) and set a minimum and a maximum market value per unit area. Focusing on residential buildings, and in particular on their structural part without including the cost of the land, we defined the buildings economic value [€/m^2] as the average of the values provided for each building in the same *OMI zone*. Only the first floor of each building was considered, being the maximum water depth always lower or equal to 2.1 m (see Table 3). It is important to notice that these economic values do not consider possible fall in price due to catastrophic events. Also, we are aware that reconstruction costs seem to be more suitable for this kind of analyses, but they are not freely available in Italy, homogeneous at a national level, differently from *OMI* values. Moreover, the use of these economic values at an aggregation level is still informative for future ex-ante damage estimation for planning activities and it is in line with previous loss analyses at different scales (see e.g. Arrighi et al., 2013; Domeneghetti et al., 2015).

3.2 DAMAGES TO CONTENTS

We also analyze the monetary loss to household un-registered contents (e.g. furniture and household appliances: refrigerator, dishwasher, oven, sink, stove, washer, dryer, TV and personal computers).

Focusing on these data and looking at the refunded loss, because of the stricter criteria for contents damages compensation of Ordinance No. 2 of 5th June 2014 and Law No. 93 of 26th June 2014, the difference between requested and refunded amount is even more evident. It is equal to about € 5.7 million (€ 10.4 million of overall declared loss to contents vs. € 4.7 million of refunded loss) and confirms the choice to consider observed damages as claimed by owners.

Concerning this dataset, it is worth noting that we do not have any specific information for each building on the items recorded under the generic expression "contents". Therefore, we can not express these damages in terms of relative loss over the overall movable property value. Also, the damage models to household contents proposed by the scientific literature are fairly rare and isolated (some examples are represented by studies performed by Penning-Rowsell et al., 2010; Thieken et al., 2008). Thus, we investigate the usefulness of an indirect modeling approach for this type of damages which is based on regressing loss to contents against loss to buildings (see Sec. 5.3).

3.3 HYDRODYNAMIC CHARACTERIZATION OF THE INUNDATION EVENT

Forms collected from authorities for the purpose of compensation do not include data on hydraulic variables, such as water depth, water velocity, etc. Being these data necessary to our analysis, the reconstruction of the flood event is performed by means of Telemac-2D, a fully-2D hydrodynamic model which solves the 2D shallow water Saint Venant equations using the finite-element method within a computational mesh of triangular elements (see Galland et al., 1991; Hervouet and Bates, 2000, for details). This computational model complies with the validation protocol by the International Association of Hydraulics

Research (IAHR) and has been successfully applied to case studies around the globe (Hervouet and Bates, 2000; Brière et al., 2007).

Concerning the inundation event, the dynamics of the wetting front were strongly influenced by the presence of topographic discontinuities (e.g. road embankments, artificial as well as natural channels belonging to the minor stream network, etc; see D'Alpaos et al., 2014). In order to correctly reproduce ground elevation and discontinuities in the model, a detailed LiDAR DEM with spatial resolution of 1 m is used and an unstructured triangular finite element mesh of the study area is generated. The mesh consists of 34 082 nodes connecting 66 596 elements with variable length side from 1 to 200 m in flatter zones, covering a total of 112 km^2. This accurate mesh ensures the correct representation of all major linear discontinuities existing in the study area.

The outflowing hydrograph of the levee breach, as reconstructed by the scientific committee that studied the event (D'Alpaos et al., 2014), is used as boundary condition, in particular as inflow to the boundary elements representing the levee breach.

The calibration of the 2D model is performed by varying floodplain roughness coefficients in order to reproduce the real extent of the inundation, at different time steps, as documented by maps and aerial images made available in the immediate post-event by competent authorities and rescuers (D'Alpaos et al., 2014), and as also confirmed by later studies (see e.g. Vacondio et al., 2016). In particular, Manning's coefficients values were differentiated between agricultural areas and urban areas, and resulting coefficients (0.033 m$^{-1/3}$s and 0.1 m$^{-1/3}$s, respectively) are in line with values reported in the scientific literature (see e.g. Vorogushyn, 2008; Domeneghetti et al., 2013).

After the event, local authorities collected information about water depths reached in different points of the inundated area. This information is used for the validation of the model, together with pictures, videos and reports made available on the Internet sites, as well as in situ interviews. In about 50 points, uniformly distributed in the study area, simulation outcomes are compared in terms of water depth with the information available. Results show a good agreement between simulated and observed flooding dynamics, being the residuals between observed and simulated water levels always smaller that $\pm$20 cm. In order to avoid errors due to the model uncertainty, we consider as "flooded" the area with simulated water depth greater than 10 cm (see e.g. Castellarin et al., 2009; Samuels, 1995).

The calibrated and validated model is then used to reconstruct the detailed spatio-temporal dynamics of the inundation event and to identify the spatial distribution of the hydraulic variables of interest. In fact, combining 2D model outcomes and geocoded locations shown in Fig. 2, it is possible to extract maximum water depth, maximum flow velocity and duration of the inundation at each site (see Table 3). Maximum water depth and the maximum flow velocity commonly refer to different time steps of the flood event.

4 DAMAGE MODELS

As already discussed in Sec. 1, damage models return the amount of loss potentially suffered by certain elements (population, buildings, economic activities, ecosystem, etc.) as a result of a specific flood event, thus providing an estimate of the objects susceptibility. These models associate relative (or monetary) loss with different input variables. The most frequently used loss models in Europe are uni-variable damage models, i.e. they estimate the amount of damages as a function of a single input variable, most commonly water depth, (Merz et al., 2010; Messner et al., 2007; Jongman et al., 2012), distinguishing between different building use, type, etc. (Gerl et al., 2016). Although each model is developed with different approaches and uses different economic values for assets, the damage values can be relativized based on each different context, in order to make the models comparable to each other.

This section briefly recalls well known and largely employed literature depth-damage models (also called "stage-damage models", shown in Fig. 3). Furthermore, it describes empirical depth-damage models and a multi-variable loss model that we derived for the Secchia loss dataset. All uni- and multi-variable models illustrated here are applied for predicting loss to buildings and household contents resulted from the January 2014 Secchia flood event.

4.1 LITERATURE DAMAGE MODELS

4.1.1 Multi-Colored Manual model (MCM)

The depth-damage curve implemented in the Multi-Colored Manual (MCM; Penning-Rowsell et al., 2005) is considered as one of the most comprehensive and detailed models for flood damage estimation in Europe and it is used as a support for water management policy and quantitative assessment of the effect of investment decisions (Penning-Rowsell et al., 2010; Jongman et al., 2012). This model estimates loss based almost exclusively on synthetic analysis and expert judgment from the insurance industry or engineers (Penning-Rowsell et al., 2005; Bubeck and Kreibich, 2011). Differently from the majority of other damage models, MCM estimates buildings damages using a monetary depth-damage curve, i.e. it defines monetary potential loss relative to water depth, rather than providing damage ratios (Penning-Rowsell et al., 2005; Bubeck and Kreibich, 2011; Jongman et al., 2012). Similarly to previous studies (see e.g. Domeneghetti et al., 2015) and aiming at performing a fair comparison between all considered models, we make use of the relative depth-damage curve as obtained by Jongman et al. (2012), who re-scaled the original MCM monetary curve by referring the total building damage (100%) to an average pre-flood depreciated building value in 2005 GBP (see Table 2 in Jongman et al., 2012).

4.1.2 Flood Loss Estimation MOdel for private sector (FLEMOps)

The "Flood Loss Estimation MOdel for private sector (FLEMOps)" (Thieken et al., 2008) is an empirical model based on an extensive dataset from 2158 private households that were significantly affected by flood events in 2002, 2005 and 2006 in Germany. According to Thieken et al. (2008), the database used for identifying FLEMOps was compiled through computer aided telephone interviews with a sample of people affected by these serious events. FLEMOps assesses relative flood damages to private households by referring to several factors: inundation depth, building types, building quality, water contamination and private precaution. Although the original FLEMOps has been developed as a multi-variable model, in this study we implemented it as a uni-variable one, by referring to the water depth as the only parameter available in our data collection. The curve taken into account in this study (see Fig. 3) is the one that considers a uniform distribution of building types in the study area (see Apel et al., 2009), while no information about building quality, water contamination and private precaution were available (concerning these last three factors, the first classes of the original model are considered).

4.1.3 Rhine Atlas damage model

The "Rhine Atlas" damage model was designed by the International Commission for the Protection of the Rhine (ICPR) for the hydraulic risk assessment within the watershed of the Rhine river, after that in 1993 and in 1995 two severe floods caused a large amount of economic damages in Germany and the evacuation of 250 000 people in the Netherlands (Bubeck et al., 2011). For developing the model, damage intensity and maximum damage values were set on the basis of collected empirical data in the two mentioned floods and experts judgments, combined with a synthetic approach (Bubeck and Kreibich, 2011). This model includes five different stage-damage functions, each of which is associated with a different land-use class derived from CORINE Land Cover project (European Environment Agency, 2007). The Rhine Atlas model used in this analysis (see Fig. 3) is the stage-damage curve associated with the residential sector.

4.1.4 Joint Research Centre (JRCs) damage models

These curves were developed by the European Commission's Joint Research Centre - Institute for Environment and Sustainability (JRC-IES) (Huizinga, 2007) as part of a project to estimate trends in European flood risk under climate change (Ciscar et al., 2011; Feyen et al., 2012). They consist of different depth-damage functions and maximum damage values which can be used by all EU countries (see Fig. 3). On the basis of land-use data retrieved from the CORINE project (European Environment Agency, 2007), stage-damage functions were identified for ten countries from existing studies (for example, depth-damage models based on Penning-Rowsell et al. (2005) and van der Sande (2001) were used to develop a stage-damage model for the United Kingdom and, regarding Germany, depth-damage functions were chosen using a combination of many existing models; see Jongman et al., 2012) and applied to the corresponding damage classes. In addition, an average of all available land-use specific curves was used to develop a model for countries, where stage-damage curves were not available ("JRC other countries"), and Italy is among these (Manciola et al., 2003; Molinari et al., 2012). We selected for our analysis seven out of the eleven JRC available curves: we neglected the curves that provide the highest and the lowest damage estimation for water depths between 0 and 2.5 m, that is the range that includes our observed data. In fact, these curves would be located respectively above and below the observed grey data points in Fig. 3, and would provide unrealistic over- and under-estimations for our case study. Therefore, the curves that we considered for our analysis are: JRC Belgium, JRC Czech Republic, JRC Germany, JRC Netherlands, JRC Switzerland, JRC UK and JRC other countries.

4.2 MODELS DEVELOPED ON SECCHIA DATASET

4.2.1 Secchia Empirical damage model (SEMP)

The "Secchia Empirical" damage model (SEMP) is an empirical stage-damage curve that we derive from the observed relative loss for the inundation event of 2014. It is obtained by binning water depth values into 25cm-wide classes (i.e. 0-

25 cm; 25-50 cm; etc.) and by calculating the median damage for each bin. Then, for each bin the median damage value is associated with the mean water depth of the bin itself (e.g. 12.5 cm; 37.5 cm; etc.), and the empirical damage curve is then obtained by linearly interpolating the binned values. This curve is obviously limited to the maximum water depth resulting from the 2D simulation. Further, the intercept is equal to zero, in order to reproduce a realistic and representative situation of the buildings in the study area where only a few affected buildings have a basement: a water depth equal to zero means no damages. Different classes subdivisions have been tested (from 10 cm to 1 m water depth) and the one chosen (25 cm) results the one with the best performance in terms of Root Mean Square Error (RMSE - see Sec. 5.1 for details) in reproducing observed loss data. Table A1 in the Appendix displays the curve's formulation.

4.2.2 Secchia Square Root Regression damage models ($\mathrm{SREG_x}$)

We obtain the "Secchia Square Root Regression" damage models ($\mathrm{SREG_x}$) by regressing observed relative loss against: maximum water depth ($\mathrm{SREG_d}$); maximum water velocity ($\mathrm{SREG_v}$); and building footprint or area ($\mathrm{SREG_a}$) recorded for every buildings, respectively. It is worth pointing out that $\mathrm{SREG_a}$ refers only to footprints of buildings that are flooded during the considered event (i.e. a real inundation or a flooding scenario). Regression curves based on water depth and building area have an intercept equal to zero: for the reason explained in Sec. 4.2.1, no damages are produced if the water depth or the footprint of the building are null. On the contrary, the intercept of the regression model based on water velocity is different from zero, because it is possible to have damages also if the water is stagnant. We tested linear, logarithmic and square root regression of observed data, obtaining the best prediction performance in terms of RMSE with the latter.

The identified regression relationships read:

$$D_{SREG_d} = 0.113\sqrt{h} \quad (1)$$

$$D_{SREG_v} = 0.007\sqrt{v} + 0.104 \quad (2)$$

$$D_{SREG_a} = 0.009\sqrt{a} \quad (3)$$

where D_{SREG_d} [-], D_{SREG_v} [-] and D_{SREG_a} [-] represent relative economic damages to buildings estimated by referring to the maximum water depth h [m], maximum water velocity v [m/s] and building area a [m^2], respectively.

For the sake of completeness, we point out that an additional curve has been developed based on the maximum intensity (i.e. water depth times velocity), but it is not reported here and in the following paragraphs, because it does not bring any improvements to the results.

4.2.3 Secchia Multi-Variable damage model (SMV)

The "Secchia Multi-Variable" model (SMV) of this study takes advantage of the Secchia 2014 dataset by applying datamining procedures used by Merz et al. (2013). While Merz et al. (2013) used Bagging Decision Trees from the Matlab toolbox implementation, the multi-variable model derived in this study uses the Random Forest algorithm implemented in the R package randomForest by Liaw and Wiener (2002).

Both Random Forests (RF) and Bagging Decision Trees are tree-building algorithms which can be used for predicting continuous dependent variables. The procedure of growing each tree consists of the approximation of a non-linear regression structure, recursively repeating a sub-division of the given dataset into smaller parts, in order to maximize the predictive accuracy of the model. The classification and regression tree (CART) methodology (Breiman et al., 1984) is used to select and split variables and to identify leaf nodes which give the prediction for the dependent variable. CART uses an exhaustive search method on a randomly chosen set of variables to identify the variable with the best split based on a measure of node impurity (in our case the RMSE of the response values in the respective parts). The splitting is stopped either if a threshold for minimum number of datapoints in leaf nodes is reached or if no further splitting is possible. These steps create a tree structure with several nodes, whereby the beginning node is called root node and the last nodes are called leaf nodes. Each resulting node of the tree represents the answer to the partition question asked in the previous interior nodes and the prediction for an input x_1, x_2, ..., x_k depends on the response variable of all the parts of the original dataset that are needed to reach the terminal node (Merz et al., 2013). A possible problem of regression trees is overfitting, i.e. growing trees that are too large and with many leaves some of which are associated with small subsamples. As a consequence, the model may work well with the training data but will show clearly worse performance for independent validation data. In order to reduce this overfitting Breiman (2001) proposed the RF algorithm which uses several bootstrap replica of the learning data for which regression trees are learned. RF consider a limited number of variables for each split to learn the trees. The responses from all trees are aggregated in terms of the mean value of all predictions. The procedure with a qualitative example for a RF is shown in Fig. 4, while an example of a built tree for the Secchia case study is reported in Fig. B1 in the Appendix.

The RF algorithm has the advantage of providing also estimates regarding the importance of variables in the tree-building procedure, and thus, in our case, of evaluating the relative importance of the contribution of each independent variable in representing the damage process: randomly permuting the values of the predictor variables, the algorithm simulates the absence of a particular variable and calculates the difference of the prediction error with and without the permutation. The variables being randomly permuted leading to a strong decrease of predictive performance are considered important for the prediction, given their influence in the prediction process is very high.

The RF algorithm was used in many different scientific fields, from flood hazard assessment (Wang et al., 2015) to computer-aided diagnosis (Mihailescu et al., 2013), passing through gene selection (Deng and Runge, 2013), earthquake-induced damage classification (Solomon and Liu, 2010) and many others. The numerous applications show the many advantages of using the RF method, including high prediction accuracy, acceptable tolerance to outliers and noise, and easy avoidance of overfitting problems. In the last years, some applications of this method to flood risk have been performed (see Merz et al., 2013; Chinh et al., 2016; Hasanzadeh Nafari et al., 2016, 2017; Kreibich et al., 2017; Spekkers et al., 2014), but literature in this field is still scarce if compared to the numerous studies that use simpler uni-variable models. Nevertheless, Merz et al. (2013) demonstrated that tree based models are able to improve the performance of existing models like stage-damage functions and to better identify the most informative independent variables and their interactions (e.g., they can identify different importance levels of a same variable, depending on the value of another variable).

Another important advantage of this algorithm is that no assumptions about independence, distribution or residual characteristics are needed. Further, RF allow to include both continuous, e.g. water depth or velocity, and categorical variables, e.g. building type. On the other hand, multi-variable models need sufficient amounts of data, in order to correctly identify complex relationships between variables. This is one of the reasons why this kind of models is scarcely used in regions where comprehensive, multi-dimensional databases are not available (Merz et al., 2013).

For RF learning, we consider all the variables that are available, collected from authorities, simulated by means of the hydrodynamic model and retrieved from external sources: maximum water depth, maximum water velocity, flood duration, building area, economic building value per unit area and building structural typology.

5 RESULTS AND DISCUSSION

5.1 LITERATURE AND EMPIRICAL DAMAGE MODELS COMPARISON

Figure 5 shows the results of the correlation analysis between relative flood loss to buildings and the available six predictive variables: maximum water depth, maximum water velocity, flood duration, building value per unit area, building area and building structural typology. Being the latter a categorical variable, it is converted to dummy variable encoding in order to calculate the correlation of continuous and categorical data together. We refer to the Spearman correlation coefficient in order to take into account also non linear relationships between variables. Empty boxes represent correlation that are not statistically significant at a 5% significance level. The variables that result significantly correlated with the relative loss to buildings are maximum water depth, building value per unit area and building structural typology. However, correlations coefficients are low, precisely lower than ± 0.18 in all the cases. Similar results were obtained in terms of Pearson's correlation, but the values are not shown for the sake of brevity.

Figure 6 shows the output of the RF evaluation of the importance of the six predictive variables within the SMV model. This concept is different from the correlation one: in fact, while the Spearman coefficient indicates how well the relationship between two variables can be described using a monotonic function, RF algorithm evaluates the importance of a variable by assessing the worsening in the performance of the model when that specific variable is not included in the database. In contrast to other studies (see e.g. Merz et al., 2013), the dataset does not reveal a distinct importance for individual variables, not even water depth stands out. The descriptive capability of water depth is only slightly stronger than water velocity and building area, while the remaining predictors show very small importance.

Figure 7 shows in the background the observed relative damage to buildings, collected in the three affected municipalities (i.e. Bastiglia, Bomporto and Modena) as a function of maximum water depth (top panel), water velocity (middle panel) and building area (bottom panel). Despite the statistically significant correlation with water depth (see Fig. 5), a very large noise can be observed in all diagrams, which implies that one variable alone explains only a very limited part of the damage process. This is confirmed from the outcomes of both the correlation assessment (see Fig. 5) and the importance analysis (see Fig. 6).

Taking the maximum water depth as the only explanatory variable, top panel of Fig. 7 represents the damages to buildings estimated by means of the uni-variable models developed on Secchia dataset (SEMP, with blue dots, and SREG_d, dark red dots). In a similar fashion, middle and bottom panels of Fig. 7 show the relative loss to buildings as function of maximum water velocity and building area, estimated by means of $\mathrm{SREG_v}$ and $\mathrm{SREG_a}$, respectively (dark red dots in both diagrams).

Results of the application of the multi-variable model (SMV), described in Sec. 4.2.3, are shown in Fig. 8, which highlights the good performance of this model.

Table 4 quantifies the discrepancy between observed and predicted loss values for local empirical models in terms of four different performance metrics, namely BIAS, Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and the difference between estimated and observed overall monetary loss to buildings (ΔLOSS), which are defined as follows:

$$BIAS = \frac{1}{n}\sum_{i=1}^{n}(P_i - O_i) \tag{4}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|P_i - O_i| \tag{5}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(P_i - O_i)^2} \tag{6}$$

$$\Delta LOSS = \frac{\sum_{i=1}^{n}(P_i \cdot BA_i \cdot BV_i) - \sum_{i=1}^{n}(O_i \cdot BA_i \cdot BV_i)}{\sum_{i=1}^{n}(O_i \cdot BA_i \cdot BV_i)} \cdot 100 \tag{7}$$

in which O_i and P_i are observed ad predicted relative damages at the *i-th* site, respectively; *n* is the number of sites in the study area; BA_i and BV_i are building area and building value per unit area at the *i-th* site, respectively (see Table 3).

SMV is associated with the lowest RMSE value (i.e. 0.062), which is less than half the RMSE value of the second to best models (i.e. $\mathrm{SREG_d}$ and $\mathrm{SREG_v}$, with an RMSE value of 0.125). $\mathrm{SREG_a}$ and SEMP provide slightly worse relative loss estimations than the previous models (RMSE equal to 0.129 and 0.130, respectively). Results are similar in terms of BIAS and MAE, although some differences can be pointed out for $\mathrm{SREG_x}$ models, which present a BIAS value that is slightly lower than the one derived from SMV estimation.

Concerning literature models described in Sec. 4.1 and illustrated in Fig. 3, Table 5 shows that FLEMOps and JRC Czech Republic outperform the others in terms of RMSE (RMSE equal to 0.125 and 0.127, respectively), and are comparable with the models developed on Secchia's dataset. RMSE values derived from the relative loss estimation with JRC Netherland, JRC Germany, JRC Belgium and Rhine Atlas are between 0.131 and 0.143, while the worst performance in terms of RMSE are associated with JRC Switzerland, JRC other countries, MCM and JRC UK (RMSE values higher than 0.2). These outcomes reflect the fact that all these latter damage curves are all in the upper part of the diagram in Fig. 3, and significantly apart from the rest of the models, which are instead close to each other. We obtained similar results in terms of BIAS and MAE.

Analogous results can be observed in terms of ΔLOSS, which is reported in the rightmost column of both Tables 4 and 5. This indicator, differently from MAE and RMSE and similarly to BIAS, highlights the tendency of models to under- or over-predict damages to buildings; yet ΔLOSS focuses on the overall monetary damage in a given area, whereas BIAS refers to relative damages. Hence, ΔLOSS clearly shows if a model is biased in predicting the overall monetary loss, that is if the model systematically predicts higher, or lower (positive and negative bias, respectively) damages for the entire study area than those observed. This is shown in Fig. 8, where most of the predictions provided by SMV, especially for observed relative damages higher than 10%, lie under the 1:1 line: it means that the model is negatively biased. Predictions obtained with the other models are spread more evenly around the 1:1 line, denoting a smaller bias. In terms of BIAS and ΔLOSS, SMV seems to have slightly worse performance than $SREG_d$, $SREG_v$ and $SREG_a$ (and FLEMOps, regarding these specific outcomes).

The large overestimation of overall losses associated with JRC UK, MCM, JRC other countries, JRC Switzerland and JRC Belgium reported in Table 5 is expected from the comparison between these models and empirical data presented in Fig. 3. The overestimation may results from morphologic and socio-economic contexts for which these models were constructed, as well as criteria adopted for their development, which might differ considerably from our case study and empirical models. For example, due to the diverse study area topographies and land-uses, floods can propagate with various dynamics, differently influencing hazard indicators. Also, buildings characteristics and the overall well-being of an area can differ considerably between regions and countries, therefore compromising the transferability of literature curves.

Another worth noting feature of the rightmost column of Table 5 is that four of the literature models that preform the best in terms of RMSE (JRC Czech Republic, JRC Netherlands, JRC Germany and Rhine Atlas) underestimate the overall monetary loss. This fact can be explained by several reasons, among which an important one is certainly comparing damages claimed by citizens with the four models listed above, that were developed on the basis of expert-based judgment only, or by considering experts knowledge together with empirical data.

An additional important factor that influences the performance of literature models applied to the Secchia case study is the different scale on which these curves are calibrated and applied: some of them are developed to be applied at the micro-scale (e.g. MCM, FLEMOps), while other at the meso-scale (e.g. Rhine Atlas, JRC curves). However, among meso-scale models there is a large variability in terms of performance. In several practical applications, identifying the best performing damage model a-priori can be an extremely difficult task. This is also complicated by difficulties in obtaining detailed information about original datasets used for developing literature models (including damage data, characteristics of the flood event and of typology of affected buildings). Deeper investigation on model properties and assumptions (e.g. hazard and vulnerability features on the context where they have been derived; values used for translating monetary damage into relative damage; level of aggregation of original data) can guide the selection of models, still a variety of them should be used to additionally obtain information on associated uncertainty (Figueiredo et al., 2018).

5.2 VALIDATION OF LOCALLY DERIVED DAMAGE MODELS

The results reported in Table 4 refer to calibrations of empirical models based on our entire dataset. We also validate all empirical models by using a split-sample validation procedure. Specifically, two thirds of the records are randomly selected from the dataset for calibrating each model, which is then applied on the remaining one third of the data. BIAS, MAE and RMSE calculated in this context and reported in Table 6 are very similar to the ones reported in Table 4 concerning $SREG_x$ and

SEMP. Results of the validation of SMV by means of the same approach, instead, indicate lower performance of this model, when calibrated on a smaller dataset (see Table 6). In fact, values of BIAS, MAE and RSME are twice as high as values reported in Table 4. These outcomes highlight the need for extensive datasets for identifying robust and reliable damage models. From the comparison of the different considered models (uni- and multi-variable), it is clear that this aspect is more evident for the multi-variable model, whose performance is significantly worse when calibrated on a smaller number of observed data. On the contrary, uni-variable models, though simpler than SMV, appear more robust in case of a smaller amount of calibration data, providing better results in the validation.

Based on the output of Sec. 5.1, it is worth noting that the application to the Secchia case study of JRC other countries, in which Italy should be included, provides very poor results in terms of building loss. This confirms how challenging the identification of a regional or large scale model with a general validity could be (see also Sec. 1 and Cammerer et al., 2013; Amadio et al., 2016; Molinari et al., 2012). This section further assesses the transferability of damage models to very similar socio-economic contexts.

In order to test the transferability of the empirical locally derived models to similar contexts, we identify analogous models ($SREG_x$, since it results to be the best model among the local derived ones, and SMV) on the basis of the buildings loss data collected in a single municipality and then apply these models for predicting flood buildings loss in a neighboring municipality. In particular, among the three municipalities considered in the study (i.e. Bomporto, Bastiglia and Modena), we consider Bastiglia (887 observed records) and Bomporto (392 observed records) because of the larger number of data available. We calibrate the models on Bomporto's subset (Bo_MV, Bo_REG_d, Bo_REG_v and Bo_REG_a) and we apply them for predicting Bastiglia's flood damages to buildings. Then, we calibrate the same models on Bastiglia subset (Ba_MV, Ba_REG_d, Ba_REG_v and Ba_REG_a) and apply them to Bomporto.

Figure 9 shows the results of these split-sampling experiments. The figure in the top panel refers to Bastiglia's relative damages to buildings, estimated via Bo_MV and Bo_REG_d, while the bottom panel indicates Bomporto's damages estimated via Ba_MV and Ba_REG_d; in each graph grey dots represent the estimation of relative loss using the multi-variable models and red dots indicate relative damages to buildings estimated with Square Root Regression models.

Square Root Regression models in Fig. 9 show rather poor performances, being capable of capturing only the average loss, while better results seem to be associated with multi-variable models in both graphs. Some differences between the two panels are worth noting: grey dots in the upper panel (application of models calibrated in Bomporto with 392 data to Bastiglia) seem to overestimate relative loss to buildings, while in the lower panel (application of models calibrated in Bastiglia with 887 records to Bomporto) they lie closer to the 1:1 line. The studies performed in terms of relative damages to buildings related to maximum water velocity and building area present very similar results and are reported in the Appendix (see Figures C1 and C2).

These outcomes are also visible in Table 7, which presents the results of the split-sampling experiments in terms of the usual BIAS, MAE and RMSE indexes. While uni- and multi-variable models calibrated on Bastiglia's data and applied to Bomporto's subset do not differ much, with slightly better performances for Ba_MV, Bo_MV is associated with much higher prediction errors when applied to Bastiglia. The worse performance of Bo_MV can be explained by the smaller size of the Bomporto subset of data used for its calibration (less than a half of the Bastiglia's sample). As already outlined in Sec. 4.2.3, in order to have robust results from multi-variable models, a large amount of empirical data is required. Furthermore, the inundated area in Bomporto is larger than in Bastiglia (see Fig. 2). This explains rather clearly the difference in terms of accuracy of Ba_MV and Bo_MV in Table 7: the higher the loss data density the more robust the relationship between different predictor variables and loss data and the higher the ability of the model to explain local characteristics of the study area (Schröter et al., 2014).

The transferability of the models is also hampered by the different distribution of the water depths in the different municipalities: Figure 10 shows that water depths in Bastiglia are lower than in Bomporto, although the quite similar distribution of observed relative damages. This might be due to the fact that, beside hazard, different buildings vulnerability plays an important role on the damage process too and it also explains prediction errors resulted in the analysis. This aspect has to be taken into consideration whenever the loss estimation is performed by using a model calibrated for a different flood event.

5.3 MODELING FLOOD LOSS TO CONTENTS

Similarly to the procedure for assessing damages to buildings, first of all we analyze the Spearman correlation between the observed flood loss to contents and all potential predictive variables, included monetary damages to buildings). Figure 11 shows the results of this assessment, where full boxes represent statistically significant correlation coefficient at a 5% significance level. On the one hand, similarly to the analysis for building loss, the maximum water depth and the structural typology result to be significantly correlated with damages to contents, although their correlations coefficients are low. On the other hand, damages to contents turn out to be significantly correlated with the building footprint (Spearman correlation coefficient equal to 0.27) instead of the building value. A noteworthy feature of Figure 11 is the very strong and statistically significant positive correlation between damages to buildings and their contents (Spearman correlation coefficient equal to 0.59).

We therefore explore the possibility to exploit the relationship between monetary loss to buildings and contents for predicting these latter. We test different types of mathematical relationships (i.e. linear, square-root, logarithmic and bilogarithmic regressions), and the square-root regression results the one with the best prediction performance in terms of RMSE, i.e. the one that best relates monetary buildings loss with damages to contents. In fact, RMSE is equal to € $10\,569$, while it resulted to be € $10\,882$, € $10\,971$ and € $15\,531$ for linear, logarithmic and bilogarithmic relationships, respectively. The identified regression relationship reads:

$$D_{contents} = 116\sqrt{D_{buildings}} - 2311 \tag{8}$$

where $D_{contents}$ [€] represents economic damages to contents, while $D_{buildings}$ [€] indicates loss to buildings. Fig. 12 depicts empirical vs. predicted monetary loss to contents with Eq. 8.

In the last component of our analysis, we apply Eq. 8 for estimating damages to contents as function of the estimates of monetary buildings loss resulted from the uni- and multi-variable damage models that we considered in our study.

Table 8 lists the performance metrics BIAS, MAE, RMSE and ΔLOSS obtained while predicting monetary loss to contents as described. The first row in Table 8 reports as a reference term the same performance indexes that can be obtained when Eq. 8

is applied to observed damages to building. In the second row, the first block of Table 8 shows the performance in estimating monetary content loss applying Eq. 8 to monetary damages to building, estimated with empirically derived models. The best performance in terms of RMSE is always associated with SMV, followed by SEMP and $SREG_x$, all of them with comparable RMSE values. The outcomes for literature models (last block of Table 8) also reflect the results that we obtained when modeling buildings loss, presented in Sec. 5.1. The ranking of the best performing literature models in terms of RMSE for an indirect assessment of contents loss is JRC Czech Republic, JRC Netherlands, JRC Germany, FLEMOps, Rhine Atlas, JRC Belgium. Evidently, models associated with poor performances in predicting monetary loss to buildings are also not reliable for indirectly predicting loss to building contents by means of Eq.Eq. 8 (see JRC Switzerland, JRC other countries, MCM and JRC UK). The performance of most considered models, with the exception of the last six in Table 8, show a difference between overall observed and predicted monetary loss to contents that does not exceed € ± 20 million. Differently from the results obtained when predicting damages to buildings, eleven damage models overestimate contents loss, while SEMP, JRC Netherlands, JRC Germany and Rhine Atlas underestimate them. Small differences in the models ranking, compared to Tables 4 and 5, are probably due to the fact that the regression curve for content damages is applied to predicted buildings damages, that are themselves affected by uncertainty.

6 Conclusions

Our study focuses on the development and validation of flood loss models based on a comprehensive database of observed loss data (1330 records), collected after a recent inundation event in Italy. We derived empirical uni- and multi-variable damage models, whose performance has been compared with that of stage-damage functions existing in the literature (MCM, FLEMOps, Rhine Atlas and JRC models for different countries).

Consistently with the findings of Cammerer et al. (2013), Dottori et al. (2016a) and Scorzini and Frank (2015), locally identified empirical models provide better estimation of relative and monetary damages to buildings. This result underlines the criticality and uncertainty associated with the application of literature damage models to different contexts from the ones in which they were originally developed. Even though some literature models have similar performance to locally identified empirical models, the difficulty to retrieve detailed information about their development data and procedures makes not easy to identify a-priori the best performing literature models. This hampers the practical utilization of literature models themselves for predictive purposes. The results of this study strengthen the need, in case a literature curve should be applied, for a more informed and rational selection of damage models, e.g. the level of detail of each input variable required should not be overlooked nor neglected.

Concerning the estimation of relative loss to buildings, the Secchia Multi-Variable model (SMV), which was developed using the Random Forest approach (RF), outperforms the other considered models. This outcome is confirmed with regards to the contents damages, estimated with a regression function applied on the monetary damages to buildings estimated with different models. Regression trees composing the multi-variable forest also provide the important advantage to avoid the need of a parametric function that works with all the data. Also, RF provides useful information about the relationship among the variables and how to exploit the local relevance of predictors. These can be a very useful information for authorities and stakeholders to define preventive measures and/or mitigation strategies.

The study on the transferability of empirical models, i.e. models calibrated on the dataset of one given municipality and applied to a different one located close by, shows that the best performance is controlled by the size and consistency of the loss dataset. This consideration is valid for all models, but especially for the multi-variable one, which requires a large amount of data to ensure a reliable loss estimation (Merz et al., 2013; Schröter et al., 2014). To completely exploit the potential of such models and sustain the possibility to export their use in different areas, it is necessary to pursue a detailed and structured acquisition of explanatory variables. According to Amadio et al. (2016), Molinari et al. (2012, 2014b) and Scorzini and Frank (2015), the most urgent need in Italy, concerning flood loss estimation, is to identify guidelines, valid for the whole country, to collect consistent and comparable data, even if they relate to different contexts. According to Ballio et al. (2015), data-collection protocols are urgently needed for harmonizing and standardizing the compilation of flood-loss datasets. These data should include further useful information in addition to those commonly collected, such as e.g.: observed water depths; flood duration; presence of sediments; contamination rate; early warning or precautionary measures adopted; as well as other indication about the buildings composition (numbers of floors, type of contents, presence of basements, building condition, etc.), preferably collected in the immediate post-event (see also Merz et al., 2010).

As it emerges from our analysis, in case of limited and uncertain information, empirically uni-variable models still represent a good compromise between model complexity and reliable damage estimations. Differently from other studies, which developed site-specific models but they rarely tested them in other regions, this analysis focuses on the transferability and demonstrates that models can be transferred to other contexts with satisfying results, provided that they are similar. e.g. in terms of territorial structure and buildings characteristics. Since the creation of a "one-size-fits-all" model is almost impossible due to large variability of geographical and geomorphological contexts as well as urban patterns and building typologies in Italy, the definition of various damage models for different standardized Italian contexts is of paramount importance to increase the reliability of future flood risk analyses. The adoption of probabilistic modeling concepts could add another useful level of detail in terms of quantitative information about the uncertainty.

Appendix A: Secchia Empirical damage model (SEMP)

SEMP is the linear interpolation of points with specific coordinates, calculated as explained in Sec. 4.2.1. These coordinates are reported in Table A1.

Appendix B: Secchia Multi-Variable damage model (SMV)

SMV is an ensemble of several regression trees, built from the bootstrap replica of the learning data, as explained in Sec. 4.2.3. Fig. B1 reports a qualitative example of one of these regression trees for the Secchia case study, cut off at an arbitrary level for the sake of clarity.

Appendix C: Validation of the locally derived damage models

Fig. C1 and C2 show the results of the validation of the locally derived models, that estimate relative damages to buildings as function of maximum water velocity and building area, respectively.

Acknowledgements. Emilia-Romagna Region, Regional Agency for Civil Protection, and Po River Basin Authority are kindly acknowledged for providing the datasets used in this study. In fact, part of the activity was performed with the support and contribution of the Civil Protection Agency of Emilia-Romagna under a five-year framework research agreement with the Department of Civil, Chemical, Environmental and Materials Engineering (DICAM) of the University of Bologna (DICAM-PCREM, 2015). The present work was developed also within the framework of the Panta Rhei Research Initiative of the International Association of Hydrological Sciences (IAHS). Funding was partly provided by the University of Bologna, the SYSTEM-RISK Marie-Skłodowska-Curie European Training Network (EU grant 676027) and the IMPREX project (EU Grant 641811). Finally, the authors would like to sincerely thank the two anonymous reviewers for their effort to improve the manuscript with valuable comments and suggestions.

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Figures

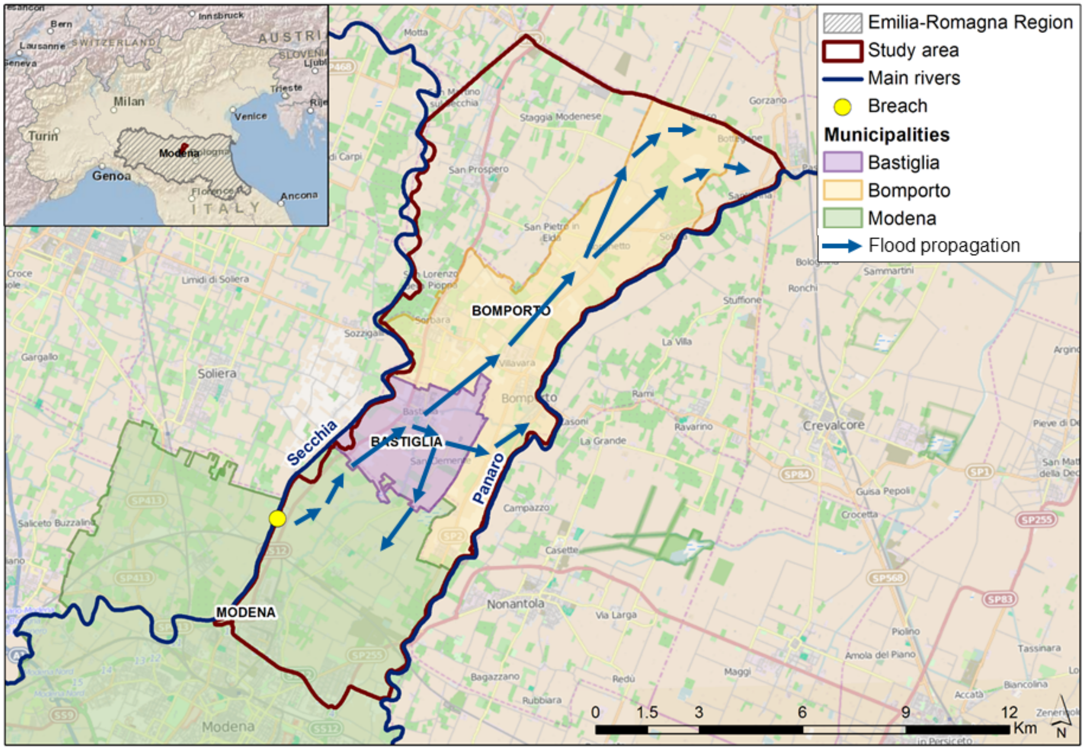


Figure 1. Study area: Secchia and Panaro rivers; location of the breach (yellow dot); municipalities of interest (i.e. Bastiglia, Bomporto and Modena); schematic of the inundation dynamics.

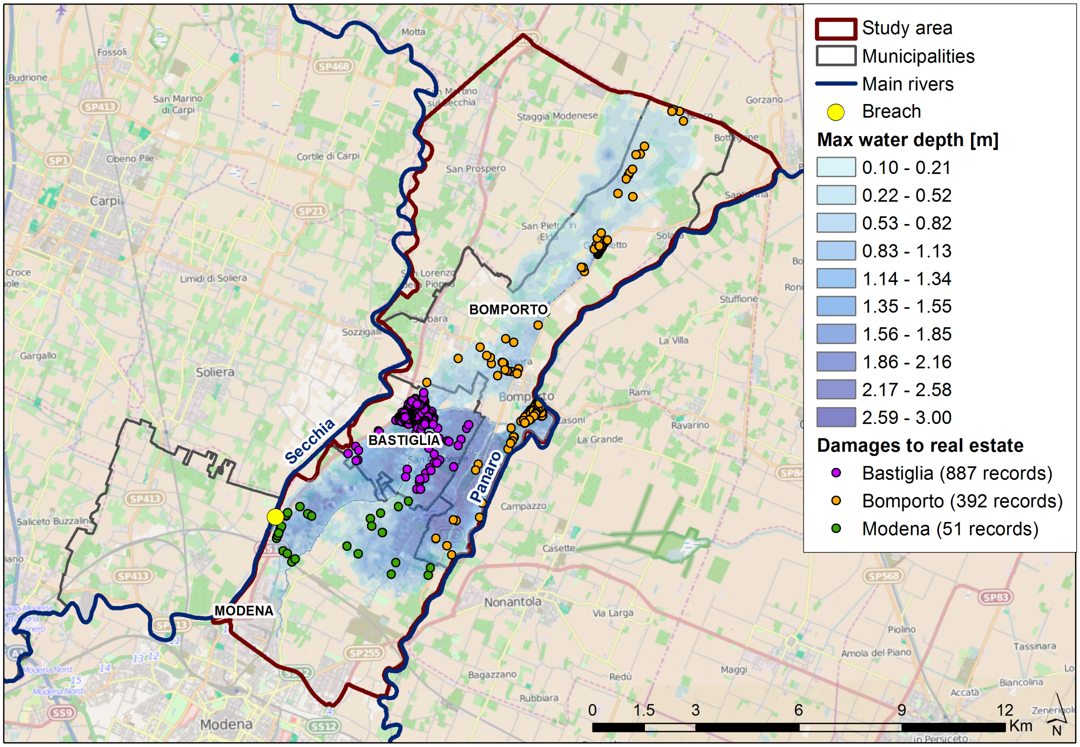


Figure 2. Maximum water depths simulated by the 2D model; geolocated buildings damages (colors reflect municipalities).

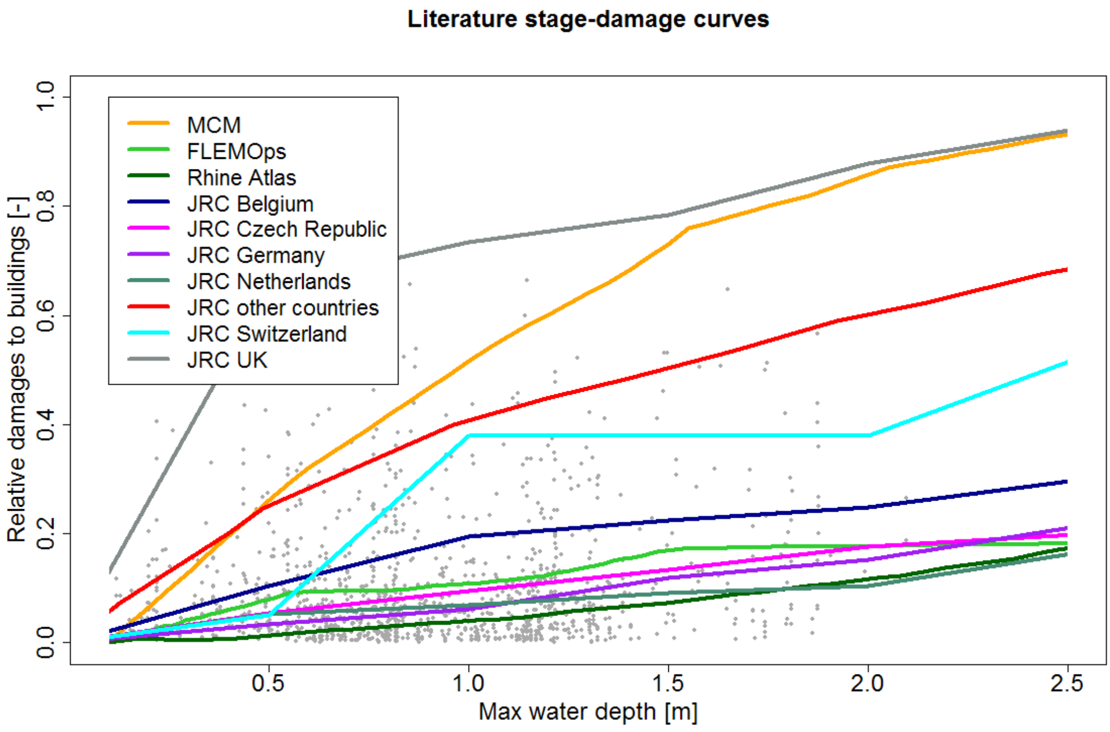


Figure 3. Literature stage-damage models and observed data: grey points in the background represent the observed relative loss (buildings only); literature models are limited to the maximum water depth reconstructed for the inundation event through the 2D hydrodynamic model (i.e. 2.5 m).

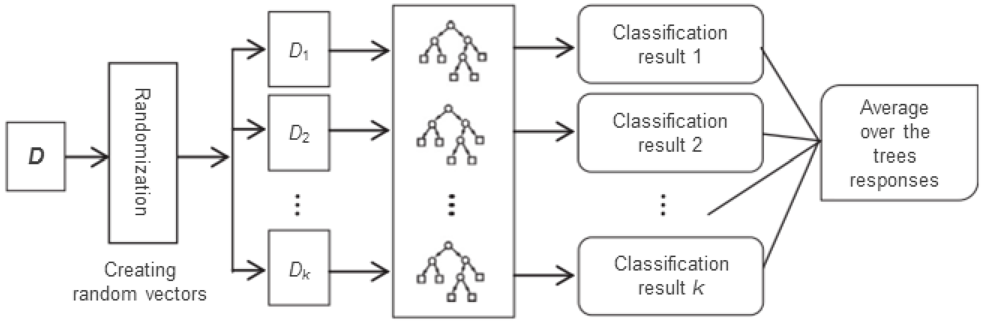


Figure 4. Random Forest method (Wang et al., 2015). An example of a regression tree built for the Secchia case study is shown in the Appendix (see Fig. B1).

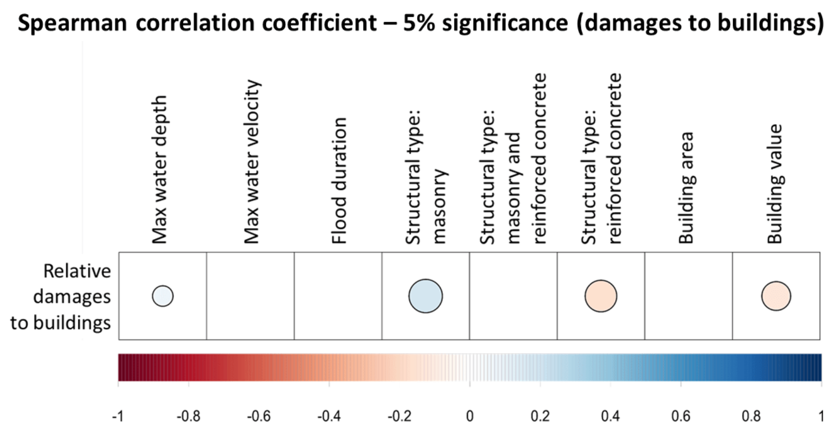


Figure 5. Spearman correlation between relative loss (buildings only) and predictive variables: maximum water depth; maximum water velocity; flood duration; structural type: masonry, masonry and reinforced concrete or reinforced concrete; building area; building value per unit area. Empty boxes indicate statistically non-significant correlation coefficients at a 5% significance level.

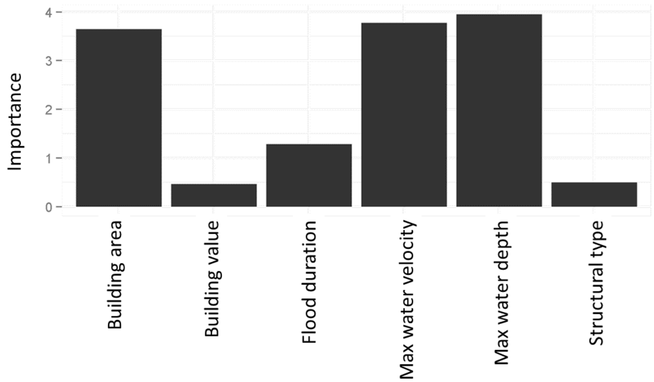


Figure 6. Importance of predictive variables considered in SMV (building area; building value per unit area; flood duration; maximum water velocity; maximum water depth; structural type).

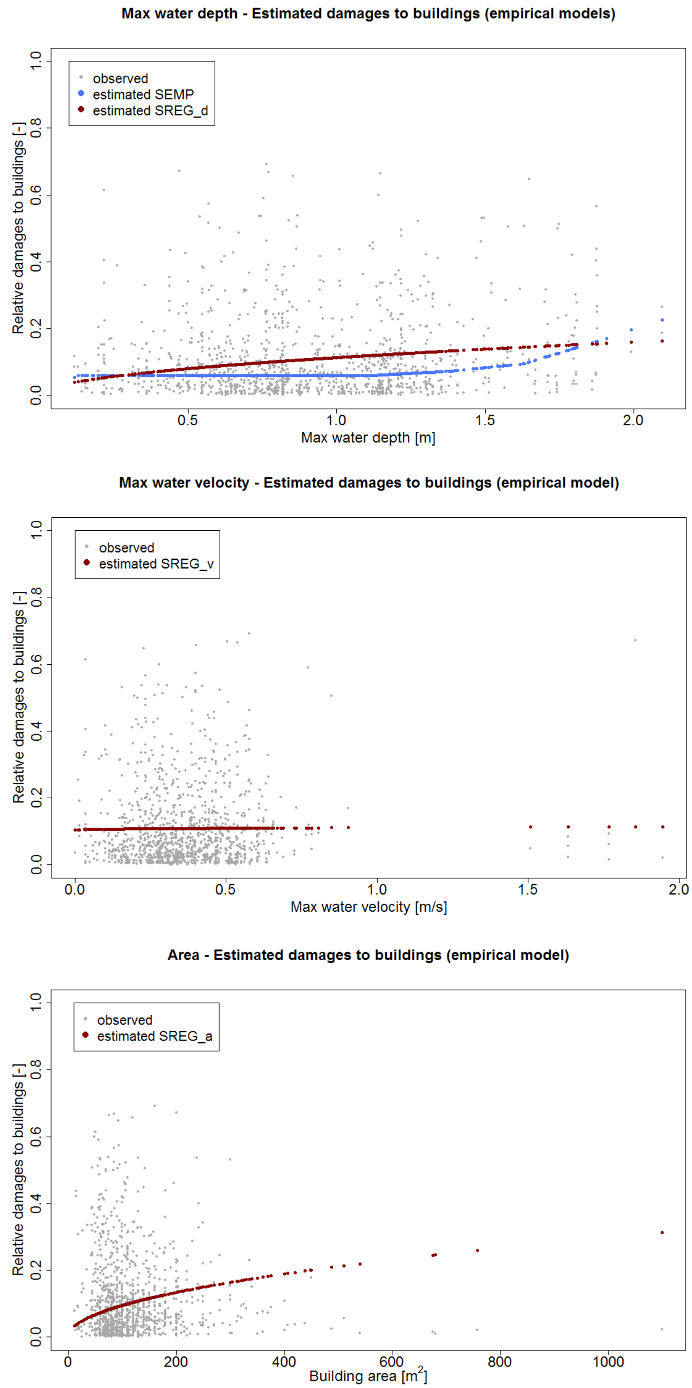


Figure 7. Relative damages to buildings estimated with SEMP (blue dots) and $SREG_d$ (dark red dots) - top panel; $SREG_v$ (dark red dots) - middle panel; $SREG_a$ (dark red dots) - bottom panel. Grey points in the background represent observed relative loss to buildings.

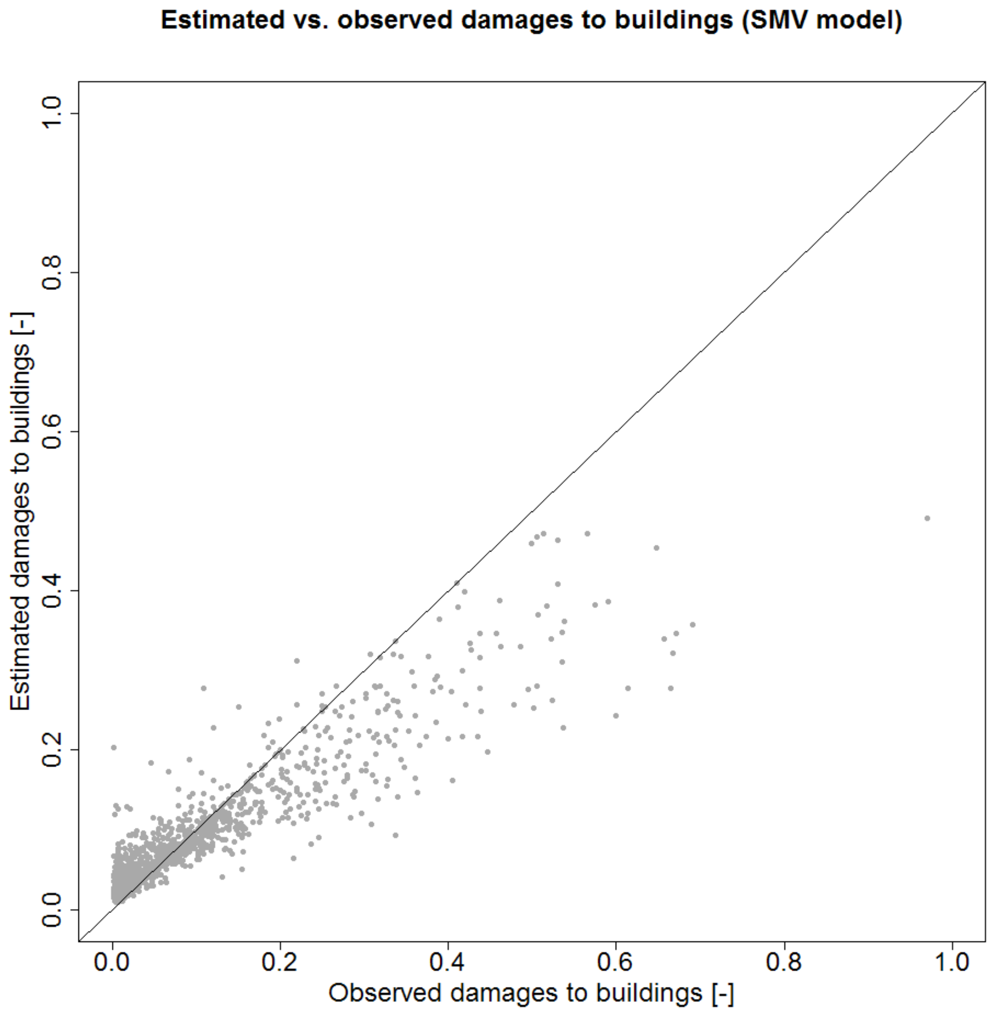
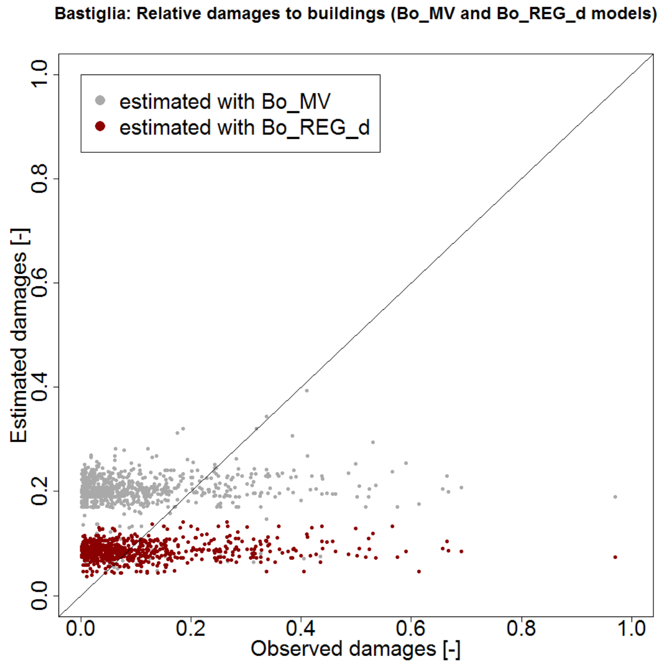


Figure 8. Relative damages to buildings estimated with SMV.



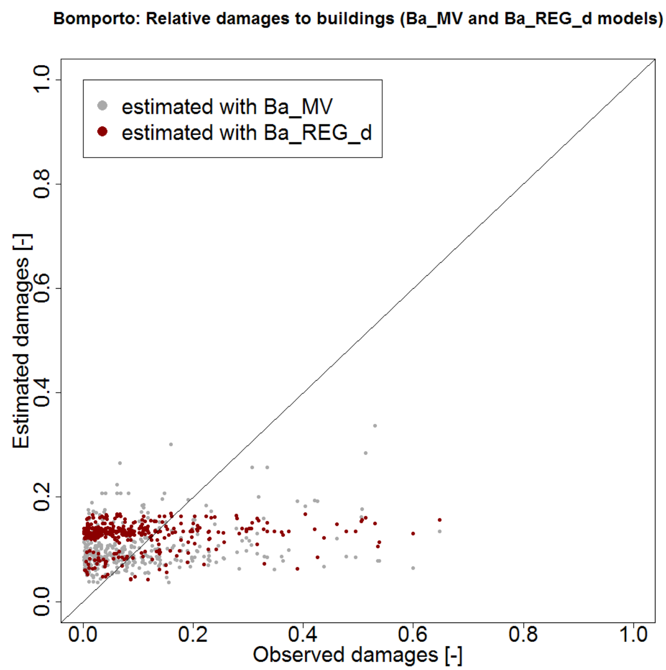


Figure 9. Top panel: Bastiglia relative damages to buildings estimated with Bo_REG$_d$ (red dots) and Bo_MV (grey dots); Bottom panel: Bomporto relative damages to buildings estimated with Ba_REG$_d$ (red dots) and Ba_MV (grey dots).

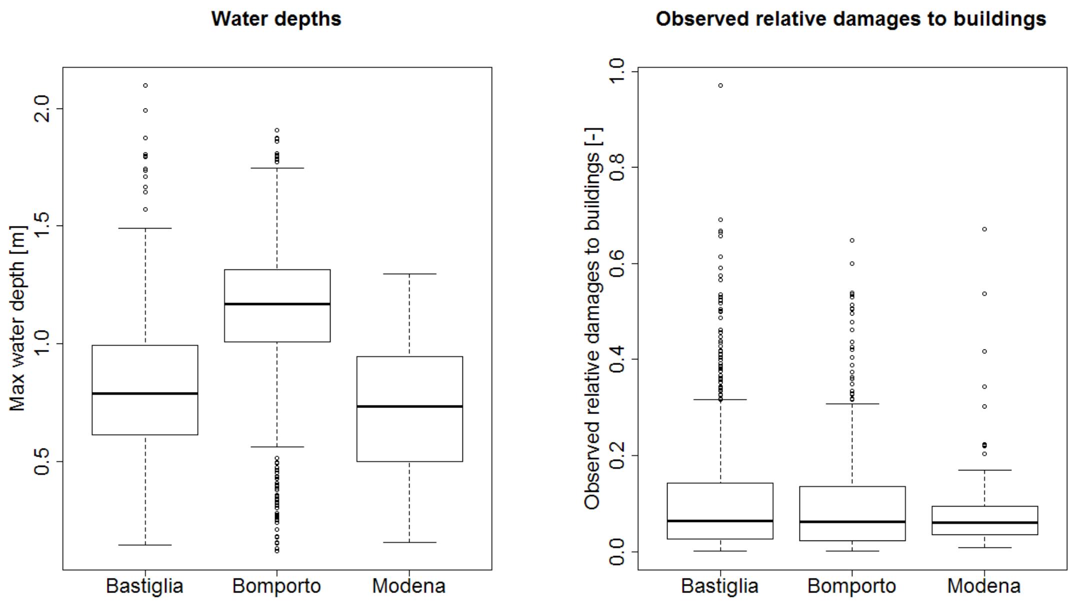


Figure 10. Distribution of water depths (left panel) and observed relative damages (right panel) in the three considered municipalities.

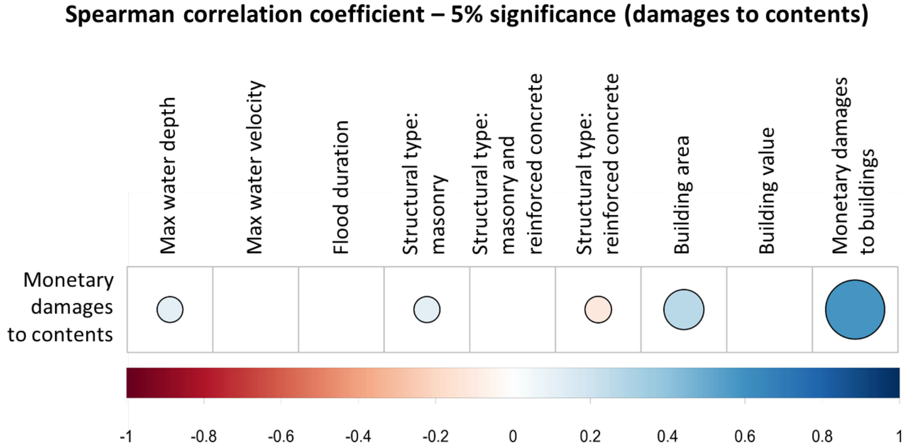


Figure 11. Spearman correlation between monetary loss (contents only) and predictive variables: maximum water depth; maximum water velocity; flood duration; structural type: masonry, masonry and reinforced concrete or reinforced concrete; building area; building value per unit area; monetary loss to buildings. Empty boxes indicate statistically non-significant correlation coefficients at a 5% significance level.

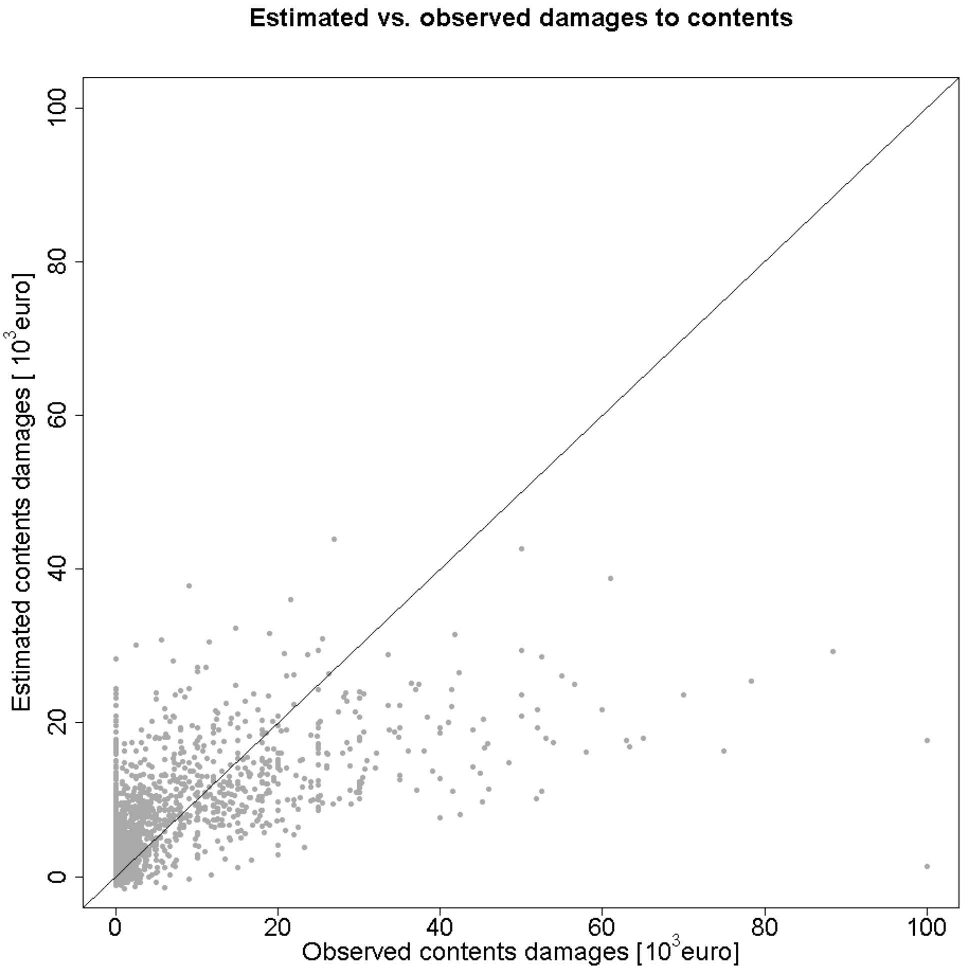


Figure 12. Empirical vs. predicted monetary loss to contents for the Secchia 2014 inundation event. Monetary loss to contents is predicted as a function of monetary loss to building through Eq. 8.

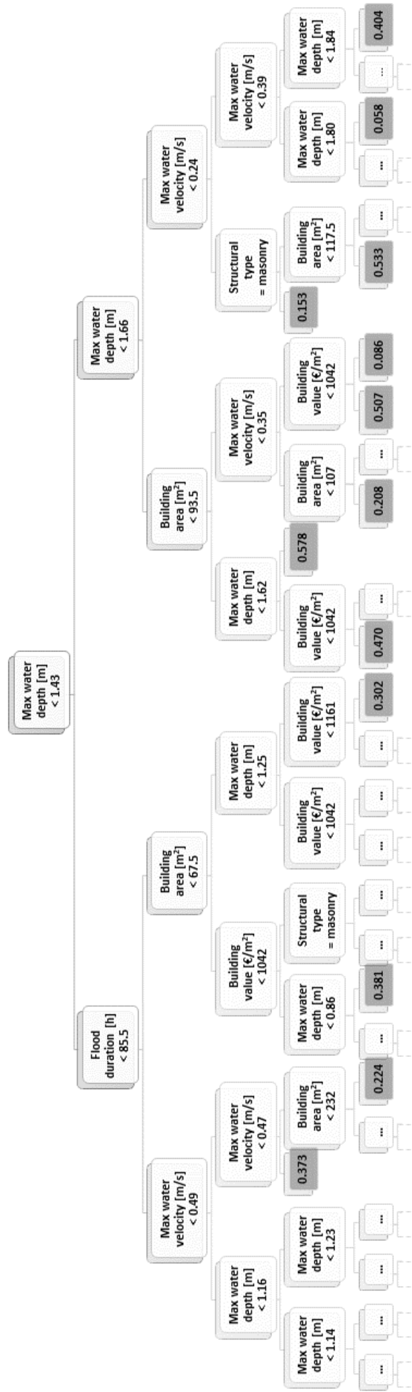
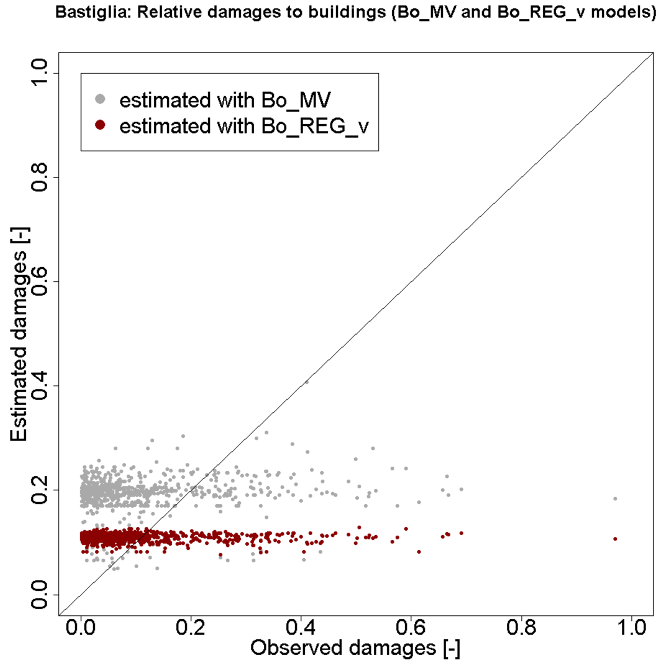


Figure B1. Example of a tree built with the RF algorithm on the base of the Secchia dataset. White boxes represent splitting nodes, together with the indication of the splitting variable and its splitting value; grey boxes represent final nodes and the estimation of the relative building damages of that branch. The tree is cut off at an arbitrary level for the sake of clarity.



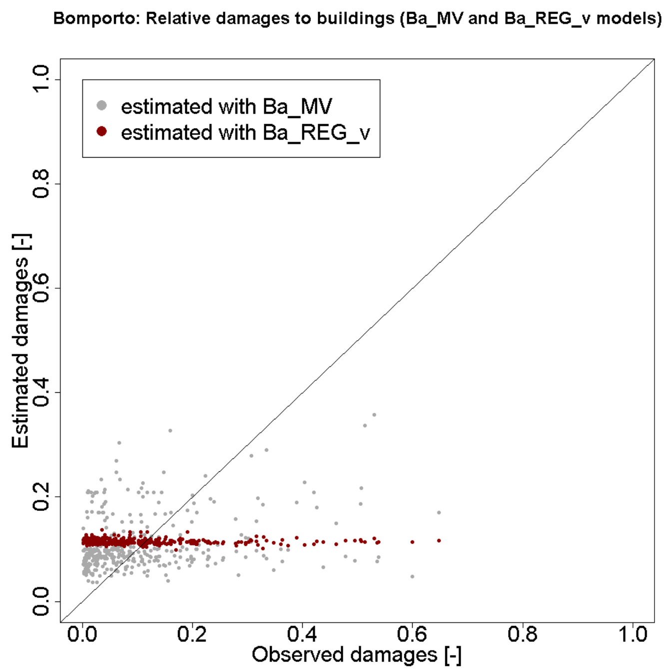
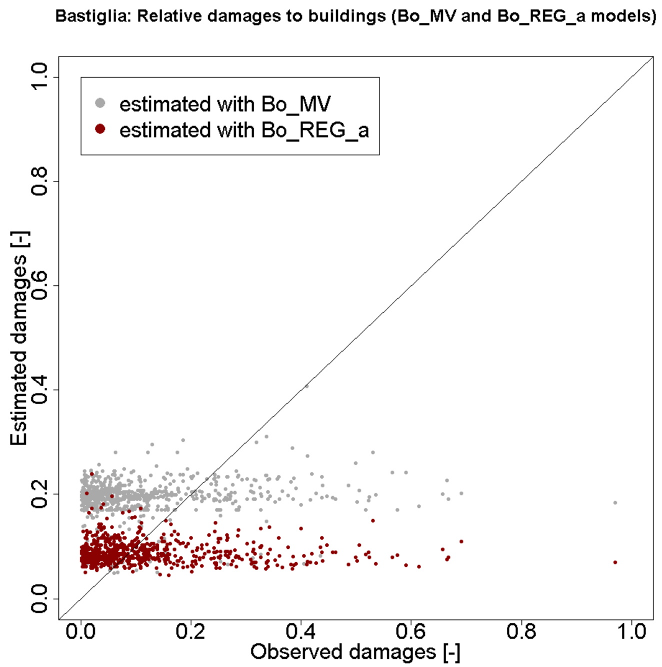


Figure C1. Top panel: Bastiglia relative damages to buildings estimated with Bo_REG$_v$ (red dots) and Bo_MV (grey dots); Bottom panel: Bomporto relative damages to buildings estimated with Ba_REG$_v$ (red dots) and Ba_MV (grey dots).



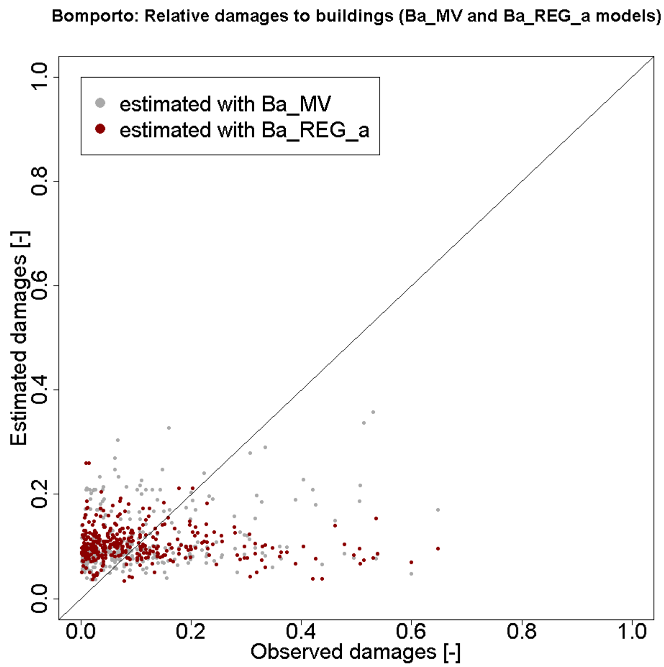


Figure C2. Top panel: Bastiglia relative damages to buildings estimated with Bo_REG$_a$ (red dots) and Bo_MV (grey dots); Bottom panel: Bomporto relative damages to buildings estimated with Ba_REG$_a$ (red dots) and Ba_MV (grey dots).

Tables

Table 1. Number of forms filled by private owners per municipality.

Municipality	Affected private properties	Affected private properties (available address and reporting at least damages to buildings)
Bastiglia	1728	887
Bomporto	624	392
Modena	76	51
Total	2448	1330

Table 2. Refundable assets in accordance to Ordinance No. 2 of 5^{th} June 2014 and Law No. 93 of 26^{th} June 2014.

Typology	**Description**	
Damages to buildings	- Structural parts:	roofs, foundations, supporting structures, interior or exterior stairs, retaining walls for the stability of the building;
	- Non-structural parts:	walls or delimitation fence, interior flooring, plastering, interior and exterior painting, interior and exterior fixtures;
	- Installations:	electrical, heating, water, TV antenna, lifts, stair lifts for disabled or elderly people.
Damages to contents	- Furniture and household appliances: refrigerator, dishwasher, oven, sink, stove, washer, dryer, TV and personal computers.	

Table 3. Considered variables and their sources and ranges, for buildings and contents damage analysis.

Variable	Observed	Simulated	External sources	Range
Maximum water depth [m]		•		0.12 - 2.10 m
Maximum water velocity [m/s]		•		0 - 1.95 m/s
Flood duration [h]		•		2 - more than 30 h
Building area [m^2]	•			12 - 1100 m^2
Building value [€/m^2]			•	902 - 1183 €/m^2
Structural typology [-]	•			masonry; reinforced concrete; combination of the two
Monetary damages to buildings [€]	•			40 - 160 000 €
Relative damages to buildings [-]	•			0.05 - 0.97
Monetary damages to contents [€]	•			0 - 100 000 €

Table 4. Performance of the uni- and multi-variable models developed on local data in estimating relative damages and overall monetary loss to buildings (see Eq. 4, 5, 6 and 7; the observed overall monetary loss is equal to € 15.2 million). Models are ranked according to RMSE values, from the lowest to the largest. Corresponding results for literature models are reported in Table 5.

	BIAS [-]	**MAE [-]**	**RMSE [-]**	**△LOSS [%]**
SMV	-0.012	0.035	0.062	-9.2
$SREG_d$	-0.003	0.089	0.125	2.6
$SREG_v$	0.000	0.090	0.125	5.9
$SREG_a$	-0.010	0.090	0.129	13.1
SEMP	-0.043	0.080	0.130	-35.4

Table 5. Performance of different literature uni-variable models in estimating relative damages and overall monetary loss to buildings (see Eq. 4, 5, 6 and 7; the observed overall monetary loss is equal to € 15.2 million). Models are ranked according to RMSE values, from the lowest to the largest. Corresponding results for uni- and multi-variable models developed on local data are reported in Table 4.

	BIAS [-]	**MAE [-]**	**RMSE [-]**	**ΔLOSS [%]**
FLEMOps	-0.003	0.089	0.125	2.1
JRC Czech Republic	-0.022	0.085	0.127	-16.4
JRC Netherlands	-0.043	0.082	0.131	-36.7
JRC Germany	-0.046	0.082	0.133	-40.0
JRC Belgium	0.056	0.119	0.142	58.4
Rhine Atlas	-0.071	0.087	0.143	-64.3
JRC Switzerland	0.149	0.196	0.232	148.2
JRC other countries	0.256	0.272	0.300	252.5
MCM	0.350	0.364	0.406	342.4
JRC UK	0.585	0.586	0.607	570.0

Table 6. Validation of the models: performance of the uni- and multi-variable models in estimating relative damages to buildings, developed on two thirds and validated on the remaining on third of the local data. Models are listed as in Table 4.

	BIAS [-]	**MAE [-]**	**RMSE [-]**
SMV	-0.021	0.078	0.120
$SREG_d$	-0.003	0.089	0.125
$SREG_v$	0.000	0.090	0.125
$SREG_a$	-0.010	0.090	0.129
SEMP	-0.042	0.080	0.130

Table 7. Transferability of the models: performance of different uni- and multi-variable models in estimating relative damages to buildings in different contexts. In the upper tables, the models were calibrated on Bomporto's dataset (392 records) and validated in Bastiglia, while in the bottom tables the models were calibrated on Bastiglia's dataset (887 records) and used to estimated damages in Bomporto. Left tables report performance of the models in the calibration phase, while right tables show performance of the validation study.

	Calibration on Bomporto's dataset (392 records)			***Validation on Bastiglia's dataset (887 records)***		
	BIAS [-]	**MAE [-]**	**RMSE [-]**	**BIAS [-]**	**MAE [-]**	**RMSE [-]**
Bo_MV	-0.011	0.031	0.053	0.094	0.140	0.159
Bo_REG_d	-0.002	0.085	0.118	-0.023	0.085	0.128
Bo_REG_v	0.000	0.085	0.118	0.000	0.092	0.127
Bo_REG_a	-0.012	0.085	0.125	-0.021	0.088	0.131

	Calibration on Bastiglia's dataset (887 records)			***Validation on Bomporto's dataset (392 records)***		
	BIAS [-]	**MAE [-]**	**RMSE [-]**	**BIAS [-]**	**MAE [-]**	**RMSE [-]**
Ba_MV	-0.012	0.039	0.068	0.007	0.084	0.115
Ba_REG_d	-0.002	0.090	0.126	0.023	0.096	0.121
Ba_REG_v	0.000	0.091	0.126	0.012	0.090	0.119
Ba_REG_a	-0.008	0.091	0.130	0.002	0.091	0.126

Table 8. Performance of different uni- and multi-variable models in estimating relative damages and overall monetary loss to contents (see Eq. 4, 5, 6 and 7; the observed overall monetary loss is equal to € 10.4 million). The first row shows the performance of Eq. 8 applied to the observed monetary damages to buildings; the first block represents the results of the application of Eq. 8 to monetary buildings damages estimated with locally derived models, while the second block to those estimated with literature ones. Models in each group are ranked according to RMSE values, from the lowest to the largest.

	BIAS [€]	**MAE [€]**	**RMSE [€]**	**ΔLOSS [%]**
Obs. buildings loss	*0*	*6 605*	*10 569*	*0*
SMV	235	7 121	10 918	2.9
SEMP	-1 066	8 111	12 314	-11.5
$SREG_d$	1 644	9 080	12 367	18.3
$SREG_v$	1 915	9 303	12 524	21.2
$SREG_a$	1 651	9 239	12 754	18.3
JRC Czech Republic	274	8 520	12 274	2.9
JRC Netherlands	-1 160	8 078	12 330	-12.5
JRC Germany	-1 608	7 970	12 382	-18.3
FLEMOps	1 523	9 034	12 432	17.3
Rhine Atlas	-3 956	7 667	12 922	-44.2
JRC Belgium	4 678	10 591	13 256	51.9
JRC Switzerland	8 032	12 871	15 632	89.4
JRC other countries	12 577	15 816	18 010	140.4
MCM	15 162	17 863	20 397	169.2
JRC UK	21 886	23 586	25 817	244.2

Table A1. SEMP model: empirical curve obtained from the binning procedure in terms of water depth (h) and relative damage to buildings (see Sec. 4.2.1 for the procedure adopted to developed the curve).

h [m]	**Relative damage [-]**
0.000	0.000
0.125	0.058
0.375	0.058
0.625	0.059
0.875	0.060
1.125	0.060
1.375	0.072
1.625	0.094
1.875	0.161
2.100	0.226