Nat. Hazards Earth Syst. Sci. Discuss., doi:10.5194/nhess-2017-92, 2017
Manuscript under review for journal Nat. Hazards Earth Syst. Sci.
Discussion started: 6 March 2017

Natural Hazards and Earth System Sciences
Open Access
Discussions

Flood loss modelling with FLF-IT: A new Flood Loss Function for Italian residential structures

Roozbeh Hasanzadeh Nafari[1,2], Mattia Amadio[3,4], Tuan Ngo[5] and Jaroslav Mysiak[3,4]

[1]Centre for Disaster Management and Public Safety (CDMPS), Department of Infrastructure Engineering, University of Melbourne, Melbourne, 3010, Australia
[2]Bushfire & Natural Hazards Cooperative Research Centre, Melbourne, 3002, Australia
[3]Fondazione Eni Enrico Mattei (FEEM) and Euro-Mediterranean Centre on Climate Change (CMCC), San Giorgio Maggiore, Venice, Italy
[4]Ca' Foscari University, Venice Centre for Climate Studies (VICCS), Venice, Italy
[5]Director of the Advanced Protective Technologies for Engineering Structures (APTES) Group, Department of Infrastructure Engineering, University of Melbourne, Melbourne, 3010, Australia

Correspondence to: R. Hasanzadeh Nafari (rhasanzadeh@student.unimelb.edu.au)

Abstract. The damage triggered by different flood events costs the Italian economy millions of dollars each year. This cost is likely to increase in the future due to climate variability and economic development. In order to avoid or reduce such significant financial losses, risk management requires tools which can provide a reliable estimate of potential flood impacts across the country. Flood loss functions are an internationally accepted method for estimating physical flood damage in urban areas. In this study, we derived a new Flood Loss Function for Italian residential structures (FLF-IT), on the basis of empirical damage data collected from a recent flood event in the region of Emilia-Romagna. The function was developed based on a new Australian approach (FLFA), which represents the confidence limits that exist around the parameterized functional depth-damage relationship. After model calibration, the performance of the model was also validated for the prediction of loss ratios and absolute damage values. In this regard, a three-fold cross-validation procedure was carried out over the empirical sample to measure the range of uncertainty from the actual damage data. The validation procedure shows that the newly derived function performs well (no bias and only 10% mean absolute error). Results of these validation tests illustrate the importance of model calibration.

The advantages of the FLF-IT model over other Italian models include calibration with empirical data; consideration of the epistemic uncertainty of data; and the ability to change parameters based on building practices across Italy.

1 Introduction

Floods and storms are natural hazards that cause the largest economic impact in Europe today (European Environment Agency, 2010). Italy is no exception, with about 80% of its municipalities being exposed to some degree of hydrogeological hazards (Zampetti et al., 2012). Regarding flood hazard frequency, 8% of Italy's territory and 10% of its population are exposed to a medium probability (ANCE/CRESME, 2012). This issue is reflected in over a billion Euros spent from 2009 to 2012 on recovery from extreme hydrological events (Zampetti et al., 2012). Italy is, in fact, the European country where floods generate the largest economic damage per annum (Alfieri et al., 2016). This is especially worrisome considering that the frequency of extreme flood losses may be doubled at least by 2050 in Europe due to climatic change factors and urban consolidation (Jongman et al., 2014). Climate variability already affects rainfall extremes and the peak volumes of discharge in rivers (Alfieri et al., 2015). Relentless urban sprawl within catchments alters the water run-off speed and propagation while increasing the value of exposed land use (Barredo, 2009). In order to effectively prevent massive losses, disaster risk management requires estimation well in advance of the frequency and magnitude of potential flood events, and their consequences in terms of economic damages (Elmer et al., 2010; Kaplan and Garrick, 1981; Neale and Weir, 2015; Thieken et al., 2008; UNISDR, 2004). Therefore, it is indispensable to provide decision-makers with reliable assessment tools that are able to produce such knowledge, after which an efficient risk reduction strategy can be adequately planned (Emanuelsson et al., 2014; McGrath et al., 2015; Merz et al., 2010).

In general, flood losses are classified as marketable (tangible) or non-marketable (intangible) values, and as direct or indirect (Kreibich et al., 2010; Meyer et al., 2013; Molinari et al., 2014a; Thieken et al., 2005). Direct damage takes place when the floodwater physically inundates buildings and structures, whereas indirect damage accounts for the consequences of direct damage on a wider scale of space and time (Hasanzadeh Nafari et al., 2016c). The tools employed to assess flood risk consist of a variety of damage models, with differing methods depending on the type of accounted losses. While I-O models, Computable General Equilibrium models and other econometric tools are often used to estimate indirect economic losses (Carrera et al., 2015; Hallegatte, 2008; Koks et al., 2015), the focus of most flood damage models is still on the estimation of direct, tangible losses using stage-damage curves. Stage-damage curves or flood loss functions are used to depict a relationship between water depth and economic damage for a specific kind of structure or land use (Jongman et al., 2012; Kreibich and Thieken, 2008; Merz et al., 2010; Messner et al., 2007; Thieken et al., 2009). Damage curves can be empirical or synthetic. Empirical curves are drawn based on actual data collected from one specific event. Due to the differences in flood and building characteristics, they cannot be directly employed in different times and places (Gissing and Blong, 2004; McBean et al., 1986). To resolve this issue, general synthetic curves based on a valuation survey have been created for different types of buildings. Valuation surveys assess how the structural components are distributed in the height of a building (Barton et al., 2003; Smith, 1994). Afterwards, the magnitude of potential flood losses is estimated based on the vulnerability of structural components and via "what-if" questions (Gissing and Blong, 2004; Merz et al., 2010). Damage functions can also be distinguished as absolute or relative. The first type states the damage directly in monetary terms, while the relative type states the damage as a percentage of the total exposed value, which can refer to the total replacement value or the total depreciated value (Kreibich et al., 2010). Relative functions have an advantage over absolute functions, namely that they are more flexible for transfer to different regions or years since the damage ratio is independent of the changes in market values (Merz et al., 2010). Still, both types are developed on sample areas which have particular geographical characteristics that affect both the quality of the exposed value and the flood phenomena (McGrath et al., 2015; Proverbs and

Soetanto, 2004). Therefore, transferred models may carry a high level of uncertainty, unless they are calibrated with an empirical dataset collected from the new study area (Cammerer et al., 2013; Hasanzadeh Nafari et al., 2015; Molinari et al., 2014b).

Although Italy has seen several flood disasters in recent years, flood records do not enable development or validation of a national loss flood function because the information is still poor, fragmented and inconsistent. This issue largely depends on the lack of an established official procedure for the collection and the storage of damage data (Molinari et al., 2014b). Another obstacle is the heterogeneity across different regions of digital geographic information, which is the key to correctly represent the driving factors of exposure and vulnerability influencing the sustained damage. Few attempts at drawing a depth-damage relation from post-disaster reports have been made (Amadio et al., 2016; Molinari et al., 2014b, 2012; Scorzini and Frank, 2015), while other uncalibrated synthetic functions have been derived from pan-European studies (Huizinga, 2007). The use of such uncalibrated functions on the Italian territory has proven troublesome (Amadio et al., 2016), showing a large degree of uncertainty.

Our research aims to calibrate and validate a new relative flood loss function for Italian residential structures (FLF-IT) based on real damage data collected from one large river flood event in the region of Emilia-Romagna at the beginning of 2014. The focus of this study is on direct tangible damage, and the spatial scale is on the order of individual buildings. This research builds on a newly derived Australian approach called FLFA (Hasanzadeh Nafari et al. 2016a, 2016b).

2 The FLFA method

The FLFA method is based on a simplified synthetic approach called the sub-assembly method, proposed by the HAZUS technical manual (FEMA, 2012). This method measures the extent of losses for each stage of floodwater and suggests a flexible curve that accounts for the variability in the characteristics of structures. In the first step, one or more representative building categories are selected from the study area. The ratio of damage for every stage of water and within each category of the building is a function of the vertical distribution of structural components (i.e., vulnerability and the total value exposed to flood) (Lehman and Hasanzadeh Nafari, 2016). More specifically, each structural component starts suffering damage after a specific stage is reached. Commonly the first decimetres of water cause damage to some of the most valuable items such walls, floors, insulation and electrical wiring (FEMA, 2012). Accordingly, the relationship between the damage percentage (d_h) and water depth can be described by a root function (Cammerer et al., 2013; Elmer et al., 2010; Kreibich and Thieken, 2008). The following function (1) is developed by Hasanzadeh Nafari et al. (2016a) for the Australian case study:

$$d_h = \left(\frac{h}{H}\right)^{\frac{1}{r}} \times D_{max} \qquad (1)$$

The root (r) controls the rate of alteration in the percentage of damage relative to the growth of the water depth (h) over a total height (H) of the floor. The D_{max} is the total percentage of damage corresponding to the total height of the floor. A higher value of r means a slower increase in the rate of damage. The obtained curve is then adjusted and calibrated using the empirical data collected from the selected study area. Hence, this approach is defined as an empirical-synthetic method. Due to the inherent uncertainty in the data sample, the study has employed a bootstrapping approach, which produces three stage-damage functions (i.e. most likely, maximum and minimum damage functions) for each type of building. This range of estimate describes confidence limits around the functional parameters and represents the uncertainty that exists in the data sample. The advantages of this simplified synthetic approach include calibration with empirical data, a better level of transferability in time and space, consideration of the epistemic uncertainty of data, and the ability to change parameters based on building practices across the world.

3 Case study

The region of Emilia-Romagna is in North Italy, on the southern side of the Po River, the longest of all Italian rivers. This region has the greatest flood prone area both in relative and absolute terms: about 10 thousand km^2, including 64% of the population are exposed to a medium flood probability, while 2.5 thousand km^2 and 10% of the population are exposed to a high probability (Trigila et al., 2015). This includes more than half of the region's territory. Our empirical data comes from a flood generated by the Secchia river in 2014 near the town of Modena, in the central part of Emilia-Romagna.

3.1 Event description

January 2014 was a dramatic month for floods in Italy, with 110 flood events recorded over a span of 23 days due to extreme meteorological conditions. Severe precipitations hit central Emilia-Romagna between the 17th and the 19th of January, with a total of 125 mm of rain flowing in the Secchia catchment. The increase in the river flow volumes caused heavy stress on the levees, which stand 7-8 meters over the flood plain. At around 6 am, approximately 10 meters of the eastern Secchia levee were overwashed and breached at the top by one meter, thereby starting to flood the countryside. In 9 hours, the levee section was completely destroyed for a length of 80 meters, spilling 200 cubic meters per second in the surrounding plain and flooding nearly 6.5 thousand hectares of rural land (Figure 1) (D'Alpaos et al., 2014). Seven municipalities have been affected, with the small towns of Bastiglia and Bomporto suffering the largest share of losses. Both towns, including their industrial districts, remained flooded for more than 48 hours. The total volume of water inundating the area was estimated to be around 36 million m^3 (D'Alpaos et al., 2014).

3.2 Data description

The information about cumulative water depths comes from the hydrological simulation of the event produced by the technical-scientific committee in the official report (D'Alpaos et al., 2014; Vacondio et al., 2014). The extent of the simulated flood is nearly five thousand hectares, with an average depth of one meter. The flow volume at the breach is calculated using the 1-D model HEC-RAS calibrated on recorded observations from the event. The evolution of the flooding is simulated by a bi-dimensional hydrological model using the finite-volume method over a Digital Terrain Model (DTM)

Nat. Hazards Earth Syst. Sci. Discuss., doi:10.5194/nhess-2017-92, 2017
Manuscript under review for journal Nat. Hazards Earth Syst. Sci.
Discussion started: 6 March 2017

obtained by LiDAR scans at one-meter resolution. The simulation also accounts for the gradual change in the size of the breach from 10 to 80 meters (Vacondio et al., 2014).

A database of damage declared by residential properties has been made available for this research by the local authorities. Damage records are listed by address for the three municipalities of Bastiglia (70% of the total damage), Bomporto (24%) and Modena (6%). The total damage sums up to EUR 41.5 million, of which: 54% is damage to structural parts, including installations; 33% is damage to movable contents, meaning furniture and common domestic appliances; and 13% is represented by registered vehicles, such as cars and motorcycles. For the purpose of our study, only the structural damage is considered. The recorded damage is compared to the mean depreciated value of the residential properties, as reported by cadastral records before the flood event (Agenzia delle Entrate, 2014). The majority of residential structures in the area share the same general characteristics: they are brick or concrete buildings built in the last 30 years, with no underground basement or parking (slab-on-ground). Houses have at least two or three floors. However, only the ground floors have been affected in this particular event.

Data of the mean water depth, total structural damage and average market value are linked together at the building scale (Figure 2). Accordingly, the damage addresses are georeferenced and aggregated within the corresponding building features in the digital technical map from the regional administration. This procedure is successful for EUR 21.7 million, corresponding to 97% of the total residential damage. The remaining 3% of records are excluded due to incomplete addresses or inconsistency with the spatial data.

4 Calibration and validation of FLF-IT

Based on the formula represented previously, the model calibration process includes choosing the most appropriate values for the root of function and the maximum percentage of damage (i.e., r and D_{max}), with reference to the empirical dataset (Hasanzadeh Nafari et al., 2016a). The selection will be made by the chi-square test of goodness of fit, to minimise predictive errors. Also, instead of a deterministic regression analysis, this study has relied on the probabilistic relationship among the percentage of damage and other damage-related parameters (i.e. building and flood characteristics) (Hasanzadeh Nafari et al., 2016b). In this regard, a bootstrapping approach has been employed to resample the damage data 1,000 times. This method assists in exploring the confidence limits around the parameters and illustrates the epistemic uncertainty of the empirical damage data (Lehman and Hasanzadeh Nafari, 2016). To be more specific:

- First, the dataset was resampled using a bootstrapping approach;
- For the new resample, the most appropriate value of the root function and the maximum percentage of damage were selected by the chi-square test of goodness of fit;
- The two previous steps were repeated 1,000 times, and 1,000 sets of parameters (i.e., r and D_{max}) were generated as the result;

- Finally, by the above iteration, the averages of the 1,000 calibrated parameters converged to a fixed value considered as the most likely scenario. The most likely parameters produce the smallest cumulative error compared to the actual damage data.

- Also, from the 1,000 sets of parameters generated above, the function that maximises the depth-damage relationship was taken as a maximum damage curve, and the observation that created the minimum depth-damage relationship was considered for the minimum depth-damage function.

Results of the model calibration are presented in Table 1 and Fig. 3.

Table 1. Number of samples and range of r and D_{max} values, calculated by the bootstrap and chi-square test goodness of fit.

Number of Samples	Parameters	Range of parameters		
		Minimum	Most likely	Maximum
613	r	2.7	2	1.7
	D_{max}	10%	20%	40%

After model calibration, its performance should be validated in contrast to real damage data. Due to the lack of an independent dataset, a three-fold cross-validation technique was employed for this purpose (Seifert et al., 2010). Accordingly, the damage records were first shuffled and partitioned into three equally sized subsets. Then, three iterations of model calibration and model testing were performed. In each iteration, one subset was singled out for model testing, while the remaining two parts were used for model calibration (Refaeilzadeh et al., 2009). Model calibration in each iteration was performed based on the approach explained earlier, with values of r and D_{max} for the most likely function calculated by averaging over 1,000 resampled damage records and using the chi-square test of goodness of fit. Eventually, the loss ratio of the held-out subset was estimated by the FLF-IT model calibrated without it, and the results were compared with the actual records. Errors including the mean bias error (MBE), the mean absolute error (MAE) and the root mean square error (RMSE) were calculated and averaged over all three iterations. The MBE illustrates the direction of the error bias (i.e. a positive MBE shows an overestimation in the predicted values, while a negative MBE depicts an underestimation); the MAE shows how close the estimates are to the actual damage ratios; and the RMSE signifies the variation of the predicted ratios from the actual records (Chai and Draxler, 2014; Seifert et al., 2010). The results are presented in Table 2. As summarised, the three-fold cross-validation procedure shows that FLF-IT performs well. The average of the MBE over all iterations shows no bias and represents only around 1% bias in each iteration. The MAE is 10% on average, and RMSE alters between 12 and 16% (14% on average).

Table 2. Error estimation for the performance of the FLF-IT model (MBE: Mean Bias Error; MAE: Mean Absolute Error; RMSE: Root Mean Squared Error).

Nat. Hazards Earth Syst. Sci. Discuss., doi:10.5194/nhess-2017-92, 2017
Manuscript under review for journal Nat. Hazards Earth Syst. Sci.
Discussion started: 6 March 2017

Natural Hazards and Earth System Sciences
Open Access
Discussions

	MBE	MAE	RMSE
Iteration 1	0.015	0.092	0.119
Iteration 2	-0.010	0.104	0.157
Iteration 3	-0.009	0.091	0.133
Average	0.00	0.10	0.14

In addition to the above comparison on the loss ratios, the performance of the model is also validated for predicting the absolute damage values. In this regard and for each iteration, the absolute damage records are resampled using the bootstrapping approach 10,000 times, and the 95% confidence interval of the total losses was calculated. If the total damage value estimated by FLF-IT falls within the 95% confidence interval, its performance is accepted. Otherwise, it is rejected (Cammerer et al., 2013; Seifert et al., 2010; Thieken et al., 2008). It is worth noting that the predicted absolute damage values are calculated by multiplying the estimated loss ratio by the mean depreciated value and the area of each property. The results are presented in Table 3, which shows that the results of all iterations with the most likely functional parameters *r* and D_{max} lie within the 95% confidence intervals and the FLF-IT model has an acceptable performance.

Table 3. Comparison of total absolute losses estimated by FLF-IT with the 95% confidence interval of the resampled damage records.

		Absolute damage values (in EUR m)	Within 95% interval
Iteration 1	**Estimated Loss**	6.5	Yes
	Damage records	4.88 (2.5th percentile)	6.8 (97.5th percentile)
Iteration 2	**Estimated Loss**	7.7	Yes
	Damage records	5.81 (2.5th percentile)	7.8 (97.5th percentile)
Iteration 3	**Estimated Loss**	10.1	Yes
	Damage records	8.07 (2.5th percentile)	10.4 (97.5th percentile)
All records	**Estimated Loss**	24.3	Yes
	Damage records	19.94 (2.5th percentile)	24.5 (97.5th percentile)

Results of these validation tests illustrate the importance of model calibration, especially when the water depth is the only hydraulic parameter taken into account (Cammerer et al., 2013; Chang et al., 2008; McBean et al., 1986). In other words, flood damage, being a complicated process, could be dependent on more damage influencing parameters than those considered here (Grahn and Nyberg, 2014; Hasanzadeh Nafari et al., 2016c). However, by calibrating the loss function with an actual damage dataset and providing an empirically-based model, the function estimations are good (i.e. low predictive error, low variation and acceptable reliability in results) and its performance is validated for use in flood events with the same geographical conditions (i.e. flood characteristics and building specifications) as the area of study (Hasanzadeh Nafari et al., 2016b; McBean et al., 1986).

5 Conclusion

Floods are frequent natural hazards in Italy, triggering significant negative consequences on the economy every year. Their impact is expected to worsen in the near future due to socio-economic development and climate variability. To be able to reduce the probability and magnitude of expected economic losses and to lessen the cost of compensation and restoration, flood risk managers need to be correctly informed about the potential damage from flood hazards on the territory. A loss function that can reliably estimate the economic costs based on available data is the key to achieving this objective. However, despite a significant number of flood disasters hitting Italy every year, few attempts at developing a flood damage model from post-disaster reports have been made.

Flood loss functions are an internationally accepted method for estimating direct flood damage in urban areas. Flood losses can be classified as marketable or non-marketable values, and as direct or indirect damages. This study focused on direct, marketable damage due to riverine floodwater inundation. We employed a newly derived Australian approach (FLFA) with empirical damage data from Italy to develop a synthetic, relative flood loss function for Italian residential structures (FLF-IT). The FLFA approach takes empirical data of damage and depth, stratified by building classifications and uses the chi-square test of goodness of fit to fix a parameterized function to compute depth-damage estimates. Parameters include the height of the stories, maximum damage as a percentage and the starting elevation for damage. Additionally, FLFA illustrates a bootstrapping approach to the empirical data to assist in describing confidence limits around the parameterized functional depth damage relationship. Accordingly, the advantages of the new model (FLF-IT) include calibration with empirical data, consideration of the epistemic uncertainty of data and the ability to change parameters based on building practices across Italy. After model calibration, its performance was also validated for predicting the loss ratios and absolute damage values in Italy. In this regard, a three-fold cross-validation procedure and the usual bootstrap approach were applied to the empirical sample to measure the range of uncertainty from the actual damage data. This validation test was selected to compensate for the lack of comparable data from an independent flood event. The validation procedure shows that estimates of FLF-IT are good (no bias, 10% mean absolute error and 14% root mean square error) and its performance is acceptable.

Results of these validation tests depict the importance of model calibration, especially when the water depth is the only hydraulic parameter considered. In other words, by calibrating the loss function and providing an empirically-based model, the function performs well (i.e. low predictive error, low variation and acceptable reliability) and its performance is validated for use in events with the same geographical conditions as the area of study. Awareness of these issues is necessary for decision-making in flood risk management. Further research will be aimed at considering some additional parameters that may govern the significance of the damages for a given depth. An independent dataset will be used to evaluate the predictive capacity and transferability of the model.

Acknowledgment

The authors would like to acknowledge the ongoing financial contribution and support from the Bushfire & Natural Hazards Cooperative Research Centre. The research leading to this paper has also received funding from project ENHANCE (Grant Agreement N° 308438) and the People Programme (Marie Curie Actions) of the European Union's Seventh Framework Programme FP7 (Grant Agreement number 609642). The authors want to thank the local administrations of Emilia-Romagna for providing the official damage records of the 2014 flood event.

References

Agenzia delle Entrate, 2014. Osservatorio del Mercato Immobiliare - Quotazioni zone OMI [WWW Document]. URL http://www.agenziaentrate.gov.it/wps/content/Nsilib/Nsi/Documentazione/omi/Banche+dati/Quotazioni+immobiliari/ (accessed 7.1.15).

Alfieri, L., Burek, P., Feyen, L., Forzieri, G., 2015. Global warming increases the frequency of river floods in Europe. Hydrol. Earth Syst. Sci. 19, 2247–2260.

Alfieri, L., Feyen, L., Salamon, P., Thielen, J., Bianchi, A., Dottori, F., Burek, P., 2016. Modelling the socio-economic impact of river floods in Europe. Nat. Hazards Earth Syst. Sci. 16, 1401–1411.

Amadio, M., Mysiak, J., Carrera, L., Koks, E., 2016. Improving flood damage assessment models in Italy. Nat. Hazards 82, 2075–2088.

ANCE/CRESME, 2012. Lo stato del territorio italiano 2012. Insediamento e rischio sismico e idrogeologico 284 p.

Barredo, J.I., 2009. Normalised flood losses in Europe: 1970–2006. Nat. Hazards Earth Syst. Sci. 9, 97–104.

Barton, C., Viney, E., Heinrich, L., Turnley, M., 2003. The Reality of Determining Urban Flood Damages. In: NSW Floodplain Management Authorities Annual Conference. Sydney.

Cammerer, H., Thieken, a. H., Lammel, J., 2013. Adaptability and transferability of flood loss functions in residential areas. Nat. Hazards Earth Syst. Sci. 13, 3063–3081.

Carrera, L., Standardi, G., Bosello, F., Mysiak, J., 2015. Assessing direct and indirect economic impacts of a flood event through the integration of spatial and computable general equilibrium modelling. Environ. Model. Softw. 63, 109–122.

Chai, T., Draxler, R.R., 2014. Root mean square error (RMSE) or mean absolute error (MAE)? -Arguments against avoiding RMSE in the literature. Geosci. Model Dev. 7, 1247–1250.

Chang, L.F., Lin, C.H., Su, M.D., 2008. Application of geographic weighted regression to establish flood-damage functions reflecting spatial variation. Water SA 34, 209–216.

D'Alpaos, L., Brath, A., Fioravante, V., 2014. Relazione tecnico-scientifica sulle cause del collasso dell' argine del fiume Secchia avvenuto il giorno 19 gennaio 2014 presso la frazione San Matteo.

Elmer, F., Thieken, a. H., Pech, I., Kreibich, H., 2010. Influence of flood frequency on residential building losses. Nat. Hazards Earth Syst. Sci. 10, 2145–2159.

Emanuelsson, M. a E., Mcintyre, N., Hunt, C.F., Mawle, R., Kitson, J., Voulvoulis, N., 2014. Flood risk assessment for infrastructure networks. J. Flood Risk Manag. 7, 31–41.

European Environment Agency, 2010. Mapping the impacts of recent natural disasters and technological accidents in Europe - An overview of the last decade, EEA Technical report.

FEMA, 2012. Multi-Hazard Loss Estimation Methodology, Flood Model: Hazus-MH Technical Manual. Washington, D.C.

Gissing, A., Blong, R., 2004. Accounting for variability in commercial flood damage estimation. Aust. Geogr. 35, 209–222.

Grahn, T., Nyberg, R., 2014. Damage assessment of lake floods: Insured damage to private property during two lake floods in Sweden 2000/2001. Int. J. Disaster Risk Reduct. 10, 305–314.

Hallegatte, S., 2008. An adaptive regional input-output model and its application to the assessment of the economic cost of Katrina. Risk Anal. 28, 779–99.

Hasanzadeh Nafari, R., Ngo, T., Lehman, W., 2015. Results comparison and model validation for flood loss functions in Australian geographical conditions. Nat. Hazards Earth Syst. Sci. Discuss. 3, 3823–3860.

Hasanzadeh Nafari, R., Ngo, T., Lehman, W., 2016a. Calibration and validation of FLFArs – a new flood loss function for Australian residential structures 16, 15–27.

Hasanzadeh Nafari, R., Ngo, T., Lehman, W., 2016b. Development and evaluation of FLFAcs – A new Flood Loss Function for Australian commercial structures. Int. J. Disaster Risk Reduct.

Hasanzadeh Nafari, R., Ngo, T., Mendis, P., 2016c. An Assessment of the Effectiveness of Tree-Based Models for Multi-

Variate Flood Damage Assessment in Australia. Water 8, 282.

Huizinga, H.J., 2007. Flood damage functions for EU member states. Technical report implemented in the framework of the contract # 382441-F1SC awarded by the European Commission - Joint Research Centre.

Jongman, B., Hochrainer-stigler, S., Feyen, L., Aerts, J.C.J.H., Mechler, R., Botzen, W.J.W., Bouwer, L.M., Pflug, G., Rojas, R., Ward, P.J., 2014. Increasing stress on disaster-risk finance due to large floods. Nat. Clim. Chang. 1–5.

Jongman, B., Kreibich, H., Apel, H., Barredo, J.I., Bates, P.D., Feyen, L., Gericke, A., Neal, J., Aerts, J.C.J.H., Ward, P.J., 2012. Comparative flood damage model assessment: Towards a European approach. Nat. Hazards Earth Syst. Sci. 12, 3733–3752.

Kaplan, S., Garrick, B.J., 1981. On the quantitative definition of risk. Risk Anal. 1, 11–27.

Koks, E.E., Carrera, L., Jonkeren, O., Aerts, J.C.J.H., Husby, T.G., Thissen, M., Standardi, G., Mysiak, J., 2015. Regional disaster impact analysis: comparing Input-Output and Computable General Equilibrium models. Nat. Hazards Earth Syst. Sci. Discuss. 3, 7053–7088.

Kreibich, H., Seifert, I., Merz, B., Thieken, A.H., 2010. Development of FLEMOcs – a new model for the estimation of flood losses in the commercial sector. Hydrol. Sci. J. 55, 1302–1314.

Kreibich, H., Thieken, A.H., 2008. Assessment of damage caused by high groundwater inundation. Water Resour. Res. 44, 1–14.

Lehman, W., Hasanzadeh Nafari, R., 2016. An Empirical, Functional approach to Depth Damages. In: FLOODrisk 2016, the 3rd European Conference on Flood Risk Management. Lyon, France.

McBean, E., Fortin, M., Gorrie, J., 1986. A critical analysis of residential flood damage estimation curves. Can. J. Civ. Eng. 13, 86–94.

McGrath, H., Stefanakis, E., Nastev, M., 2015. Sensitivity analysis of flood damage estimates: A case study in Fredericton, New Brunswick. Int. J. Disaster Risk Reduct. 1–9.

Merz, B., Kreibich, H., Schwarze, R., Thieken, a., 2010. Review article “assessment of economic flood damage.” Nat. Hazards Earth Syst. Sci. 10, 1697–1724.

Messner, F., Penning-rowsell, E., Green, C., Tunstall, S., Veen, A. Van Der, Tapsell, S., Wilson, T., Krywkow, J., Logtmeijer, C., Fernández-bilbao, A., Geurts, P., Haase, D., 2007. Evaluating flood damages : guidance and recommendations on principles and methods principles and methods. Flood Risk Manag. Hazards, Vulnerability Mitig. Meas. 189.

Meyer, V., Becker, N., Markantonis, V., Schwarze, R., Van Den Bergh, J.C.J.M., Bouwer, L.M., Bubeck, P., Ciavola, P., Genovese, E., Green, C., Hallegatte, S., Kreibich, H., Lequeux, Q., Logar, I., Papyrakis, E., Pfurtscheller, C., Poussin, J., Przyluski, V., Thieken, a. H., Viavattene, C., 2013. Review article: Assessing the costs of natural hazards-state of the art and knowledge gaps. Nat. Hazards Earth Syst. Sci. 13, 1351–1373.

Molinari, D., Ballio, F., Berni, N., Pandolfo, C., 2012. Implementing the Floods Directive: the case of the Umbria Region. In: FLOODRisk 2012. Rotterdam, pp. 1–7.

Molinari, D., Ballio, F., Handmer, H., Menoni, S., 2014a. On the modeling of significance for flood damage assessment. Int. J. Disaster Risk Reduct. 10, 381–391.

Molinari, D., Menoni, S., Aronica, G.T., Ballio, F., Berni, N., Pandolfo, C., Stelluti, M., Minucci, G., 2014b. Ex post damage assessment: an Italian experience. Nat. Hazards Earth Syst. Sci. 14, 901–916.

Neale, T., Weir, J.K., 2015. Navigating scientific uncertainty in wildfire and flood risk mitigation: A qualitative review. Int. J. Disaster Risk Reduct. 13, 255–265.

Proverbs, D.G., Soetanto, R., 2004. Flood Damaged Property; A Guide to Repair. Blackwell Publishing Ltd.

Refaeilzadeh, P., Tang, L., Liu., H., 2009. “Cross-Validation.” In: Encyclopedia of Database Systems. Springer US, pp. 532–538.

Scorzini, A.R., Frank, E., 2015. Flood damage curves: new insights from the 2010 flood in Veneto, Italy. J. Flood Risk Manag. n/a-n/a.

Seifert, I., Kreibich, H., Merz, B., Thieken, A.H., 2010. Application and validation of FLEMOcs – a flood-loss estimation model for the commercial sector. Hydrol. Sci. J. 55, 1315–1324.

Smith, D., 1994. Flood damage estimation. A review of urban stage-damage curves and loss function. Water SA 20, 231–238.

Thieken, A.H., Müller, M., Kreibich, H., Merz, B., 2005. Flood damage and influencing factors: New insights from the August 2002 flood in Germany. Water Resour. Res. 41, 1–16.

Thieken, A.H., Olschewski, A., Kreibich, H., Kobsch, S., Merz, B., 2008. Development and evaluation of FLEMOps – a new Flood Loss Estimation MOdel for the private sector. Flood Recover. Innov. Response, WIT Press 315–324.

Thieken, a. H., Ackermann, V., Elmer, F., Kreibich, H., Kuhlmann, B., Kunert, U., Maiwald, H., Merz, B., Müller, M., Piroth, K., Schwarz, J., Schwarze, R., Seifert, I., Seifert, J., 2009. Methods for the evaluation of direct and indirect flood losses. In: RIMAX Contributions at the 4th International Symposium on Flood Defence (ISFD4). pp. 1–10.

Trigila, A., Iadanza, C., Bussettini, M., Lastoria, B., Barbano, A., 2015. Dissesto idrogeologico in Italia: pericolosità e indicatori di rischio. ISPRA – Istituto Superiore per la Protezione e la Ricerca Ambientale.

Nat. Hazards Earth Syst. Sci. Discuss., doi:10.5194/nhess-2017-92, 2017
Manuscript under review for journal Nat. Hazards Earth Syst. Sci.
Discussion started: 6 March 2017

UNISDR, 2004. Terminology. Basic terms of disaster risk reduction. United Nations Int. Strateg. Disaster Reduct. (UNISDR), Geneva 1–30.

Vacondio, R., Dal Palù, A., Mignosa, P., 2014. GPU-enhanced finite volume shallow water solver for fast flood simulations. Environ. Model. Softw. 57, 60–75.

Zampetti, G., Ottaviani, F., Minutolo, A., 2012. I costi del rischio idrogeologico. Dossier Legambiente, Roma.

Nat. Hazards Earth Syst. Sci. Discuss., doi:10.5194/nhess-2017-92, 2017
Manuscript under review for journal Nat. Hazards Earth Syst. Sci.
Discussion started: 6 March 2017

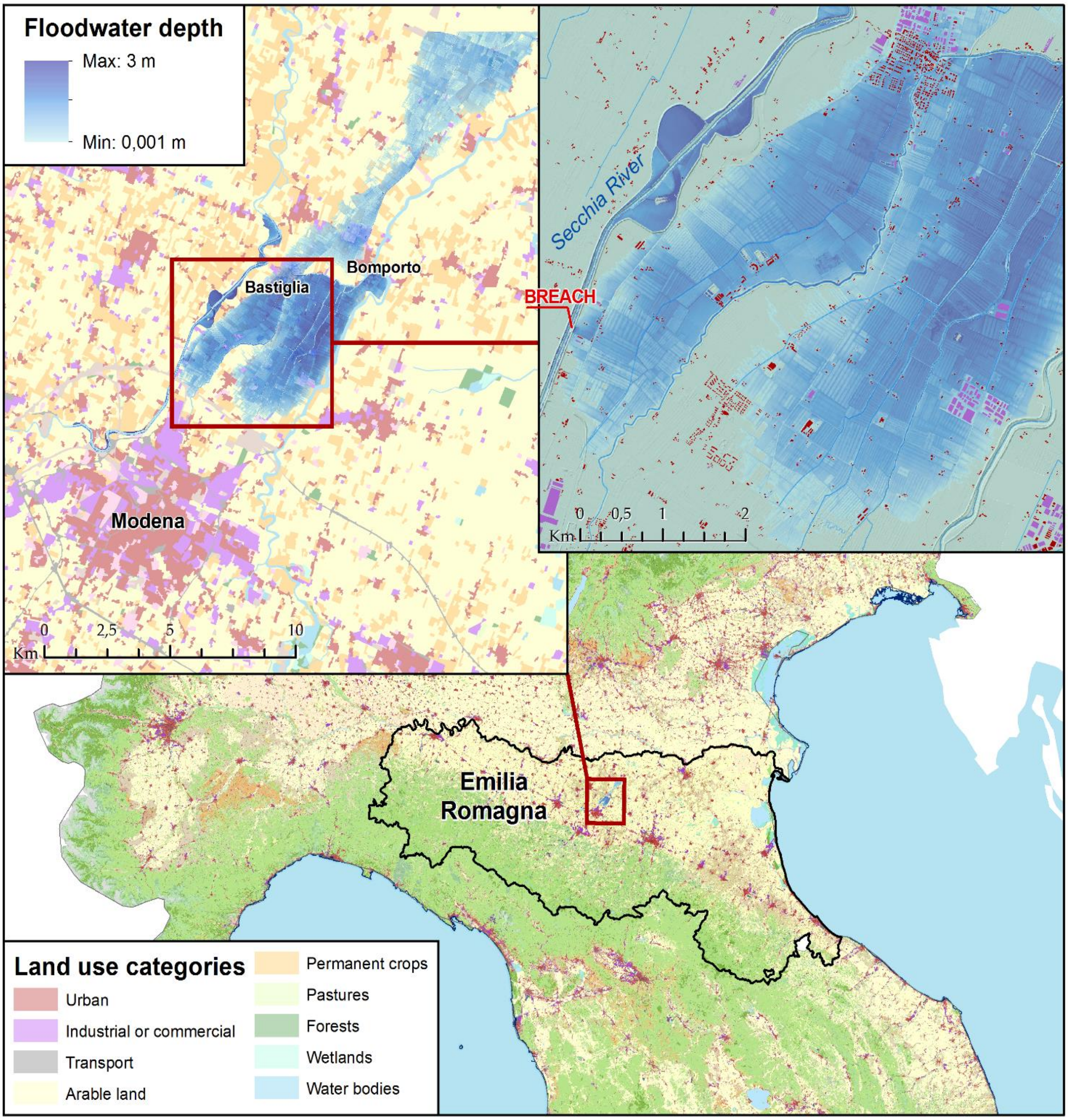

Figure 1. Identification of case study, flooding from the river Secchia during January 2014 in central Emilia-Romagna, Northern Italy.

Nat. Hazards Earth Syst. Sci. Discuss., doi:10.5194/nhess-2017-92, 2017
Manuscript under review for journal Nat. Hazards Earth Syst. Sci.
Discussion started: 6 March 2017

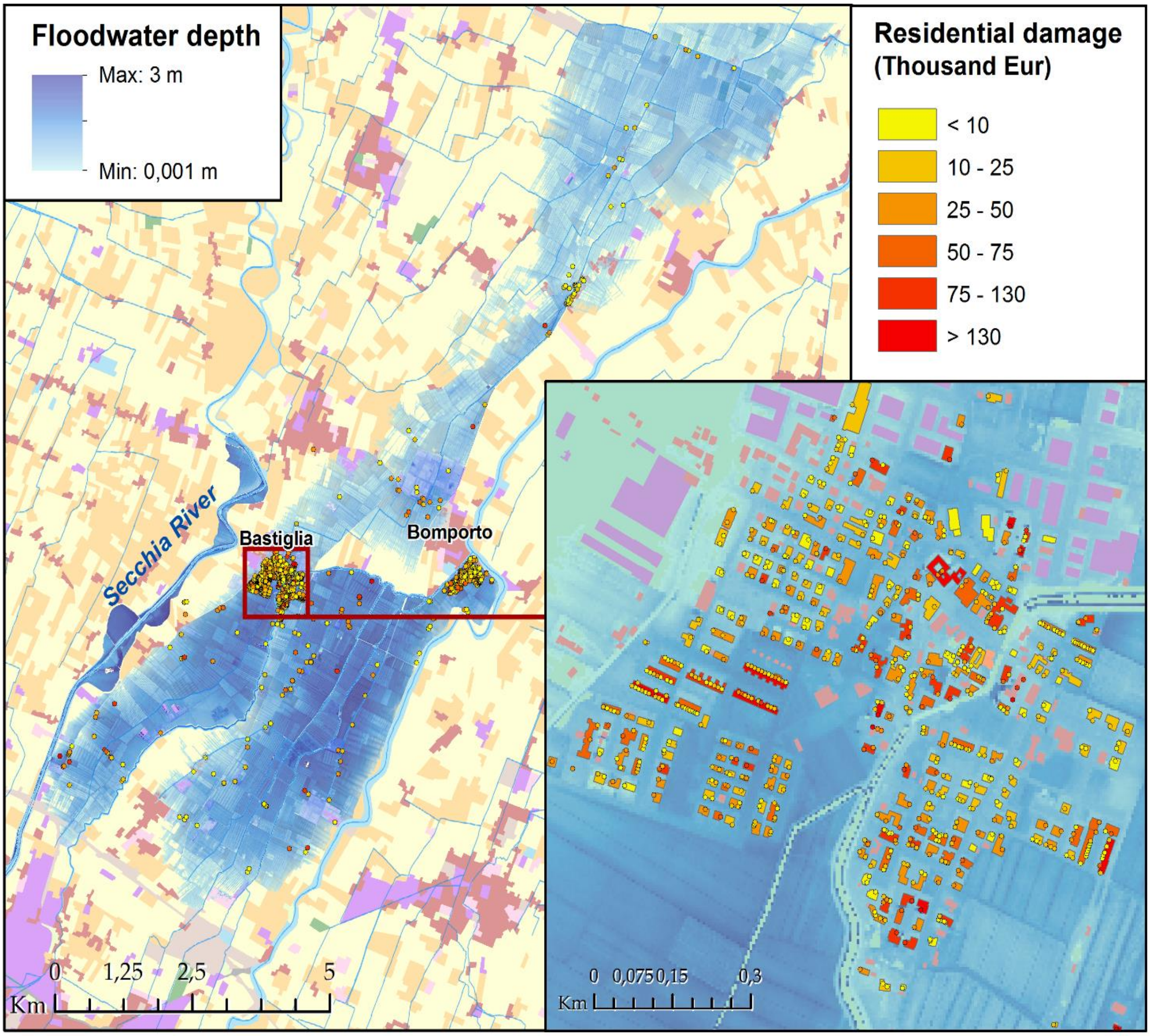

Figure 2. Georeferencing of recorded damage within building units. 97% of records are correctly projected, 3% is discarded.

Nat. Hazards Earth Syst. Sci. Discuss., doi:10.5194/nhess-2017-92, 2017
Manuscript under review for journal Nat. Hazards Earth Syst. Sci.
Discussion started: 6 March 2017

Natural Hazards and Earth System Sciences
Open Access
Discussions

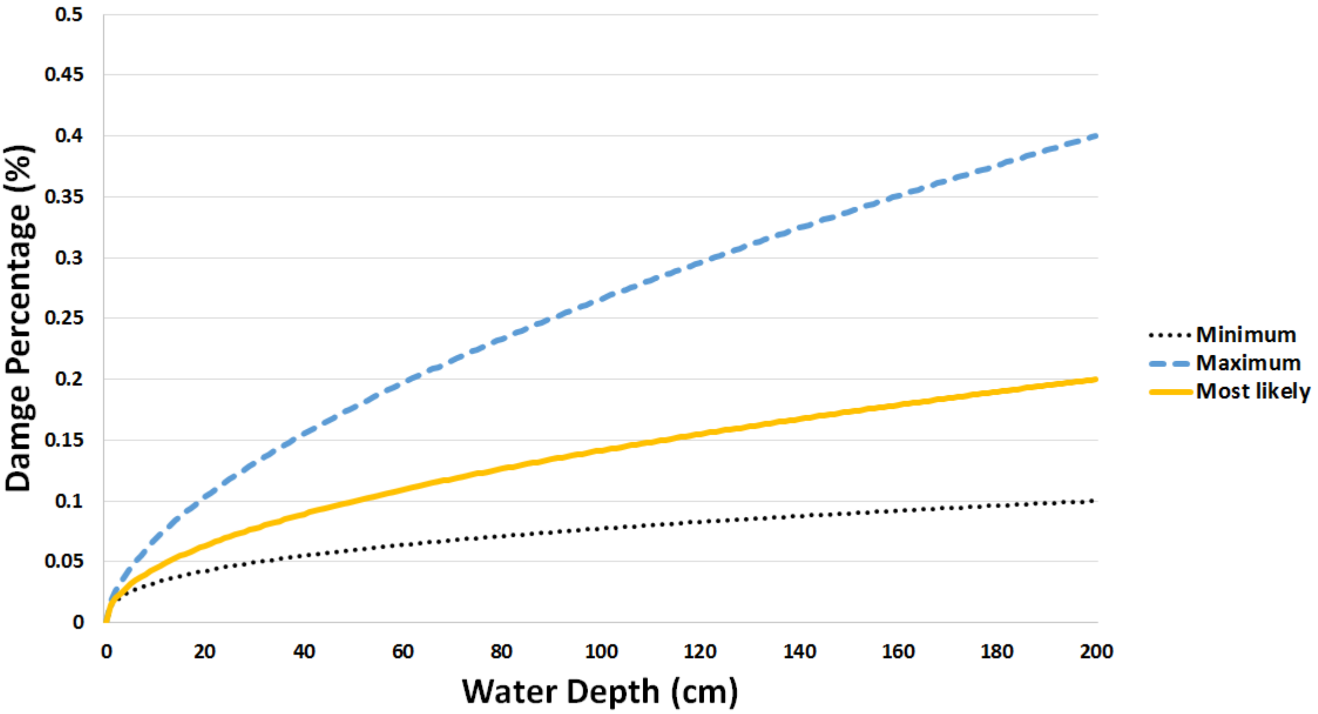

Figure 3. Visualisation of minimum, most likely and maximum damage functions, calculated by bootstrap and chi-square test of goodness of fit.