Reviewer #1

I have now read the article titled "Estimating flood damage in Italy: empirical vs expert-based modelling approach". The article focuses on the comparison of different models (empirical vs expert based and Multi-, Bi and Univariate models aiming at the estimation of flood losses in Italy. Given the plethora of models and approaches in the field the paper is important and interesting. Furthermore, the paper is well structured and written. I recommend it for publication following minor revision. Please consider the following comments before publication:

1. The title should be revised and become more attractive. How about: "Putting flood loss models to the test: the case of Italy" or something like that….(just a suggestion)

Thank you, the title has been revised as "Testing empirical and synthetic flood damage models: the case of Italy"

2. Chapter materials and methods: 3.1 data description – consider a few introductory sentences before listing the datasets used for the study.

> Added: "Our purpose is first to draw a detailed, homogeneous description of the hazard and exposure features involved in the three hazard events in order to evaluate their relationship with measured impacts. Several datasets are required for this task. These have been collected from different sources and spatially projected to the building level (i.e. micro-scale) for each one of the three study areas. The dataset we compiled for this analysis comprises:"

3. Subchapter 3.2: This is a chapter full of dense information. I would prefer two chapters instead: one, giving an overview of the existing models and explaining their characteristics and, two, a chapter describing the method used by the authors focusing on the reasons why they chose to test the particular models.

> 3.2 has been split into 3 sub-chapters (3.2. Damage models overview; 3.3 Models from Literature; 3.4 Models trained on observed records)

4. In the proposed "method" chapter a schematic description of the model used or work flow would be good and very practical for the reader (a figure showing the models used, the category they belong to expert-based/empirical and UVM, BVM or MVM or a table with a short description of the models and their characteristics).

> A workflow figure has been added as 3.4.3.

5. Page 8, line 4: "exposure indicators" why are these "exposure" and not "vulnerability" indicators?

> "Indicators related to exposure and vulnerability"

6. Page 8, Table 1. What is "finishing level"?

> Finishing level represent the state of quality of a buildings, as described in INSYDE.

7. Page 9, line 16: Age and heat system are not in table 1. If you do not use them do not mention them at all.

➢ deleted

8. Is "number of floors" named "FN" as in table 1 or "NF" as in Figures 4 and 7?

➢ NF is the right acronym. Thanks for having spotted it, the revised version is now consistent.

9. The language is overall good. There are, however, some small typos that have to be edited. E.g. page 9, line 23: "such as high prediction accuracy" and not "such prediction accuracy".

➢ Thank you. We checked the overall manuscript and we hope to have fixed all the typos.

10. Page 14, line 17: "micro-scale". What is considered a micro-, meso- and macro-scale? The issue of scale should be further discussed in the discussion chapter and conclusions.

➢ Added in page 7, line 18: "Models can further be classified in relation to the scale of their development and application (de Moel et al., 2015): "micro-scale" usually refers to a model built to account impacts over buildings individual components and it is commonly applied for local assessment; "meso-scale" refers to sub-national analysis which commonly relies on data aggregated on provincial or regional administrative units; "macro-scale" concerns assessments at country level." Added specification of scale in conclusions.

11. Page 14, lines 18-19: the authors refer to one of the case study areas and suggest that the differences in the model results may be subject to the different type of flood that these areas experienced. This issue should be further discussed. Where all the events similar? What is the difference of the impact of a flash flood? What about the presence of debris? Are these models reliable for all these types of processes?

➢ Added explanation: "In fact, Luino's model was produced based on a flash flood event characterised by higher flow velocities and larges relative impacts". In all other cases, we speak of river floods and not flash floods, we specified in text. Also added in the conclusion: "The results have shown important errors when transferring models derived from different countries and scales such as the JRC-IT curve, or from events with different characteristics: the model from Luino is based on a flash-flood event where flow velocity has likely a significant role on the event impact."

Reviewer #2

The manuscript "Estimating flood damage in Italy: Empirical vs expert-based modelling approach" validates different types of flood damage models for Italy and discusses the advantages and disadvantages of these models. This is a very interesting paper and the most extensive comparison of flood damage models for a specific area I have seen so far. I therefore believe this paper is a useful contribution to the scientific literature. I do however have some comments/questions regarding the setup of the study and some discussion points to be considered.

More important points:

• Currently the data-driven models developed in this study have been produced with data points from the same event it is validated on, hence no model transfer of the data-driven models is included. In practice a model transfer from one event to another is always

required for flood risk studies, it would therefore be fairer to always train the models on 2 events and validate it on the third event. Such an approach is also carried out in Schröter et al., (2014) and Wagenaar et al., (2018) and both studies show that multi-variable models typically have more difficulties in such a transfer setting.

> ➢ Thank you for this very important comment. What the Reviewer suggests is definitely a valuable alternative for independent model validation. However, in case of adopting the suggested approach, one must consider that the results would depend on the selection of the calibrating events, since the available events are inevitably different in terms of data amount and quality. On the contrary, merging all the data and selecting two thirds in a Monte Carlo framework overtakes the problem of selecting one out of 3 available events. We believe this approach might increase the utility of the collected records and the statistical significance of the trained models.

> ➢ Added to 3.4 (page 9, Line 9):
>
> Trained models share the same sampling approach for validation: the observation dataset is split in three parts, where two thirds are used to train the model and one third for validation. This process is iterated 1,000 times, scrabbling the data and resampling the training set at each cycle. The output takes the mean of all iterations and provides a curve which represents the empirical damage relationship for the three events. This cross-validation approach has been previously employed in Hasanzadeh Nafari et al. (2017) and in Seifert et al. (2010) in order to optimise the statistic utility of the collected sample.

• I think the data-driven UVMs wouldn't perform so well in a transfer setting because the main advantage of MVMs seems their transferability (Wagenaar et al., 2018). In the current setup this advantage of MVMs isn't used. Also if the model setup is changed some discussion is required on how significant the model transfer is between the events and whether a MVM is required or whether the events are so similar that a UVM would do.

> ➢ As specified in 3.4 (now improved), all trained models share the same scrambling-and-resampling iterative approach. Changing the training approach for the UVM would mean to change it also for the MVMs in order for the comparison to remain meaningful. The advantage of MVMs is that they consider location-specific indicators and more hazard variables in addition to water depth; by feeding the MVMs with these event-specific data (10 variables), while UVM only consider water depth, we are exactly assessing the added value of MVM and thus their transferability potential. See also the previous comment on that.

• For the wider applicability of the results of this research some more discussion is required on to what extend the good performing literature models are tailored to the specific flood event and setting. These expert-based models seem to be made for Italy and for similar flood events to the one seen in this study. Are these models for example also made for the same region, did the developers have access to the damage data of these events or did they carry out surveys in the region? Point here is to help the reader identify when you can take a model from the literature and when you can't and for this we need more information about the good performing literature models.

➢ Thank you for pointing out this. More details have been added to the description of literature models and the source of their data. Also, additional explanations have been added in the discussion section.

Minor points:

• The abstract currently mostly summarizes the method, as a reader I would be very curious about the findings (what works better). Could you summarize these in the abstract.

➢ Thank you, we updated the abstracts with details about the findings.

• Page 2 line 16-18: Can you clarify this sentence, it is unclear and seems very crucial for the story so I wouldn't want to look up the references to get this clarification.

➢ The sentence has been rewritten as: "Synthetic models, on the other hand, are based on ''what-if analyses'', relying on expert-based knowledge in order to generalise the relation between the magnitude of a hazard event and the resulting damage estimate. That means, synthetic models have a higher level of standardisation and thus are better suited for both temporal and spatial transferability."

• Page 3, line 32: You mention 1000 flood events in 45 years, that seems way too much, what do you mean here by the word "events"?

➢ Correct observation, the number of events refer to the AVI catalogue from CNR and in their records there are more than 1,000 unique event codes, however some of them refer to the same date. We then aggregated events in the same date and corrected the number to 300 events.

• Page 6, line 27: You choose to use relative flood damages rather than absolute flood damages. This is a common choice, but I think not an obvious one, can you motivate this decision?

➢ We chose to measure impacts in relative terms so to make them easier to compare through different times (inflation effect) and places (different currencies).

• Section 3.2 introduction: Nice overview on UVMs and MVMs but I think this needs something on the transferability advantage of MVMs (see above).

➢ Improved the intro:
"[…] other parameters may influence the flood damage process, [...] a large number of other non-hazard factors can be significantly different from one place to another [...] Multivariable models (MVMs) can account for such additional factors and thus are able to adapt the damage estimate to the characteristics of a specific event and location. Therefore, they may be better-suited to describe the complexity of the flood-damage process for transferability purpose."

• Section 3.2.1: Can you make a heading for each literature model.

➢ Sub-chapters have been split differently

• Section 3.2.1: Huizinga got his damage curves from the literature also, could you reference to the study that Huizinga got his damage function from.

> That's quite a long list of studies that have been averaged, none of which related to Italy; for this reason, we prefer to keep it shorter.

• Page 9, line 2: Change "observation" in "observed"

> Changed "observation datasets" into "observed records"

• The Random Forests and ANN both have all sorts of tuning parameters. Like number of neurons (ANN), minimum number of observations per leaf (RF), learning rate (ANN) and more. Could you describe how you determined these settings?

> Unless specified, RF and ANN run on default parameters. We added the minimum number of observations per leaf in RF (5). We also added to ANN: "The learning rate is controlled by coefficient μ: when μ is very small, the training process approximates the Gauss-Newton optimization algorithm (i.e. fast learning, low stability), while when μ is very large, the training process resembles the steepest descent algorithm (i.e. slow learning, high stability) (Wilamowski & Irwin, 2011). The value of μ starts as 1 and is updated during each training epoch. In case a training epoch is successful in reducing the SSE in the output layer, then μ is reduced by half; otherwise, the value of μ is increased by a factor of two and a new training attempt is performed."
> The number of neurons in ANN is already specified: "the initial number of hidden neurons per hidden layer is approximated as two-thirds of the summation of the number of neurons in the previous and next layers".

• On page 11, from line 20. You describe something about the setup of the study. I think this should be somewhere else in the manuscript as this probably applies to all data-driven models (that would be most fair to do this the same for all data-driven models). If not why did you do that differently for the other models?

> The referenced setup is specifically related to the ANN model; we explained better the training procedure that is shared among the trained models (3.4, pg 9 line 11:) "All these models share the same sampling approach for training and validation: the observation dataset is split in three parts, where two thirds are used to train the model and one third for validation. This process is iterated 1,000 times, scrabbling the data and resampling the training set at each cycle."

• Sometimes you use the word "water velocity", sometimes "flow velocity" and sometimes "water flow velocity", I think commonly the word "flow velocity" is used. Can you unify this throughout the paper.

> Yes, thank you

• Page 16, line 14. Not all these citations fit a root function to data they just all have damage curves that have the shape of a root function. So please rephrase the sentence before the citation (message can be the same).

➢ Thanks for the comment. The sentence has been rephrased as the following: "Our findings confirm previous results indicating that the curve shape described by the root function is the most adequate to describe the flood damage process".

• In this study a limited number of variables was available for the MVMs. If more variables had been available the models might have performed better. Can you make this point somewhere.

➢ Added to discussion: "We can't exclude that the performances of MVMs would benefit from the inclusion of additional predictive variables, such as those related to the early warning system and precaution measures, or social vulnerability; however, the availability of such information is limited for our case study."

Schröter, K., Kreibich, H., Vogel, K., Riggelsen, C., Scherbaum, F. and Merz, B. (2014), How useful are complex flood damage models? Water Resour. Res. 50, 3378–3395. doi:10.1002/2013WR014396, 2014.

Wagenaar, D., Lüdtke, S., Schröter, K., Bouwer, L., Kreibich, H., 2018. Regional and Temporal Transferability of Multivariable Flood Damage Models. Water Resources Research. Volume 54, Issue 1. https://doi.org/10.1029/2017WR022233

➢ Very interesting thank you, these have been added to the discussion.

Testing empirical and synthetic flood damage models: the case of Italy~~Estimating flood damage in Italy: empirical vs expert-based modelling approach~~

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Abstract

Flood risk management generally relies on economic assessments performed using flood loss models of different complexity, ranging from simple univariable to more complex multivariable models. These latter accounts for a large number of hazard, exposure and vulnerability factors, being potentially more robust when extensive input information is available. ~~In this paper w~~We collected a comprehensive dataset related to three recent major flood events in Northern Italy (Adda 2002, Bacchiglione 2010 and Secchia 2014), including flood hazard features (depth, velocity and duration), buildings characteristics (size, type, quality, economic value) as well as reported losses. The objective of this study is to compare the performances of expert-based and empirical (both uni- and multivariable) damage models for estimating the potential economic costs of flood events to residential buildings. The performances of four literature flood damage models of different nature and complexity are compared with ~~the performance~~those of univariable, bivariable and multivariable models ~~empirically~~ trained and tested using empirical records~~developed for Italy and tested at~~ from Italy ~~the micro scale based upon observed records~~. The uni- and bivariable models are ~~produced~~ developed using~~testing~~ linear, logarithmic and square root regression ~~while~~ whereas multivariable models are based on two machine learning techniques, ~~namely~~Random Forest and Artificial Neural Networks. Results provide important insights about the choice of the damage modelling approach for operational disaster risk management. Our findings suggest that multivariable models hold better potential for producing ~~a~~ reliable damage estimates when extensive ancillary data for flood event characterisation are available, while univariable models can be adequate if data are scarce. ~~Performance metrics~~The analysis also highlights that expert-based synthetic models are likely better suited for transferability to other areas compared to empirically-based flood damage models.

Key-words: flood risk assessment empirical expert-based model machine learning stage damage curves

1. Introduction

Among all natural hazards, floods ~~historically~~ cause the highest economic losses in Europe (EEA 2010; EASAC 2018). In Italy alone, a country with the largest absolute uninsured losses among EU countries (Alfieri et al., 2016; EEA, 2016; Paprotny et al., 2018), around EUR 4 billion of public money were spent over a 10 years period to compensate the damage inflicted by major extreme hydrologic events (ANIA 2015). From 2009 until 2012, the recovery funding amounted to about EUR 1 billion per year; about half ~~fraction~~ of

the total estimated damage of around EUR 2,2 billion (Zampetti et al., 2012). In this context, and particularly compelled by the EU Flood Directive (2007/60/EC) and the Sendai Framework for Disaster Risk Reduction (Mysiak et al., 2013, 2016) , sound and evidence-based flood risk assessments should ~~provide the means to~~ support the development and implementation of cost-effective flood risk reduction strategies and plans.

Several ~~different~~ approaches of varying complexity exist to estimate potential losses from floods, depending mainly on the category of damage (e.g. direct impacts or secondary effects, tangible or intangible costs, etc.) and the scale of application (i.e. macro, meso or micro scale) (Apel et al., 2009; Carrera et al., 2015; Hallegatte, 2008; Koks et al., 2015; de Moel et al., 2015). Direct tangible damages to assets are typically assessed using simple univariable models (UVMs) that rely on deterministic relations between a single descriptive variable (typically maximum water depth) and the economic loss mediated by the type/value of buildings or land cover directly affected by a hazardous event (Huizinga et al., 2017; Jongman et al., 2012; Jonkman et al., 2008; Merz et al., 2010; Messner et al., 2007; Meyer and Messner, 2005; de Moel and Aerts, 2011; Scawthorn et al., 2006; Smith, 1994; Thieken et al., 2009). Empirical, event-specific damage models are developed from observed flood loss data. A major drawback of empirically-based damage models ~~re~~lies on its low transferability to other study areas or regions, as significant errors are often verified when these are used to infer damage in other regions than those for which they were built to (Amadio et al., 2016; Apel et al., 2004; Carisi et al., 2018; Hasanzadeh Nafari et al., 2017; Jongman et al., 2012; Merz et al., 2004; Scorzini and Frank, 2015; Scorzini and Leopardi, 2017; Wagenaar et al., 2016). Synthetic models, on the other hand, are based on ''what-if analyses'', relying on expert-based knowledge in order to generalise the relation between the magnitude of a hazard event and the resulting ~~economic~~ damage estimate. That means , synthetic models have a higher level of standardisation and thus are ~~An advantage of synthetic models over empirically-based models relies on the fact that the first are less sensitive to the input data, thus being~~ better suited for both temporal and spatial transferability (Smith 1994; Merz et al. 2010; Dottori et al. 2016).

Both empirical and synthetic models can be configured as uni- or multivariable. The vast majority of univariable flood damage models account for water depth as the only explanatory variable to explain the often complex relation between the magnitude of a flood event and the resulting damages; however~~, a non-exhaustive literature search shows that~~. other parameters may influence the flood damage process, such as flow velocity (Kreibich et al., 2009), flood duration, and water contamination (Molinari et al., 2014; Thieken et al., 2005), just to name ~~just~~ a few. In addition, ~~a large number of other~~ non-hazard factors can be significantly different from one place to another, such as type and quality of buildings, presence of basements, density of dwellings, early warning systems and precautionary measures (Cammerer et al., 2013; Carisi et al., 2018; Figueiredo et al., 2018; Kreibich et al., 2005; Merz et al., 2013; Penning-Rowsell et al., 2005; Pistrika and Jonkman, 2010; Schröter et al., 2014; Smith, 1994; Thieken et al., 2008; Wagenaar et al., 2017b). ~~Therefore, Mm~~ultivariable model~~s~~ (MVM~~s~~) can account for such additional factors and thus are able to

adapt ~~the damage estimate~~ to the characteristics of a specific event and location. Therefore, they are ~~are~~ ~~potentially~~ better-suited ~~alternatives~~ to describe the complexity of the flood-damage ~~relation~~process and be transferred to other contexts (Apel et al., 2009; Elmer et al., 2010; Schröter et al., 2014; Wagenaar et al., 2018). Common techniques applied in a context of MVM are machine learning (e.g., Artificial Neural Networks and Random Forests) (Merz et al. 2013; Spekkers et al. 2014; Kreibich et al. 2017, Carisi et al. 2018), Bayesian networks (Vogel et al., 2013), and Tobit estimation (Van Ootegem et al., 2015). Moreover, some MVMs support probabilistic analysis of damage (Dottori et al., 2016; Essenfelder, 2017; Wagenaar et al., 2017a). MVMs need to be validated against empirical records ~~in~~ from the region ~~of~~ where they are applied ~~the model application~~ in order to produce reliable estimates (Hasanzadeh Nafari et al., 2017; Molinari et al., 2014, 2019; Scorzini and Frank, 2015; Zhou et al., 2013). However, greater sophistication of MVMs requires more detailed hazard, exposure and losses description. Due to the lack of consistent and comparable observed flood data, this kind of models are still ~~seldom~~ rarely applied. This is why it is necessary to compile comprehensive, multivariable datasets with detailed catalogue of flood events and their impacts (see Amadio et al., 2016, Molinari et al., 2012 and 2014, and Scorzini and Frank, 2015).

Our study contributes to this end by assembling detailed data on three recent flood events in Northern Italy. For each event, our dataset comprises the following ~~building~~micro-scale data: 1) hazard characteris~~z~~ation derived from observational data and/or hydraulic modelling, 2) high-resolution exposure in terms of location, size, typology, economic value, etc. obtained from multiple sources, and 3) declared costs per damage categories. Building upon this extensive dataset, we employ supervised learning algorithms to explore the parameters of hazard, exposure and vulnerability and their influence on damage magnitude. We test linear, logarithmic and square root regression to select the best fitting Uni-Variable (UVM) and Bi-Variable (BVM) models, and two supervised machine learning ~~techniques~~algorithms, namely Random Forest (RF) and Artificial Neural Networks (ANN), for training and testing the empirical MVMs. The models developed on the three considered case studies provide a benchmark to test the performance of four literature models of different nature and complexity, specifically developed for Italy. The results of this study provide important insights to understand the feasibility and reliability of flood damage models as practical tools for predictive flood risk assessments in Italy.

2. Study area

With an extent of 46,000 km², the Po Valley is the largest contiguous floodplain in Italy. It extends from the Alps in the north to the Apennines in the south-west, and the Adriatic Sea to the east. It comprises the Po river basin, the eastern lowlands of Veneto and Friuli, and the south-eastern basins of Emilia-Romagna. The Po Valley is one of the most developed and populated areas in Italy, generating about half of the country's gross domestic product (AdBPo, 2006). In the lower part of the Po river, flood-prone areas are protected by a

1 complex system of embankments and hydraulic works that are part of the flood defence system in the Po

2 Valley, extending for almost 3,000 km as a result of centuries-long tradition of river embanking (Govi and

3 Turitto, 2000; Lastoria et al., 2006; Masoero et al., 2013). However, flood protection structures generate a false

4 sense of safety and low risk awareness among the floodplain residents (Tobin, 1995). As a result, exposure

5 has steadily increased in flood prone areas of the Po Valley (Domeneghetti et al., 2015). Records of past flood

6 events (1950-1995) maintained by the National Research Council (Cipolla et al., 1998) show that more than

7 3,300 individual locations were affected by approximately 1,0300 flood events within the Po Valley.

8 Three of the most recent flood events within the Po Valley (figure 1) have been chosen as case studies for this

9 analysis: the 2002 Adda flood that affected the province of Lodi (**1**); the 2010 Bacchiglione flood which

10 involved the area of Vicenza (**2**); and the 2014 Secchia flood in the province of Modena (**3**). All three locations

11 have been subject to frequent flooding between 1950 and 2000 according to the historical catalogue. A short

12 description of these three events is provided hereinafter to understand the dynamics and the impacts of each

13 flood.
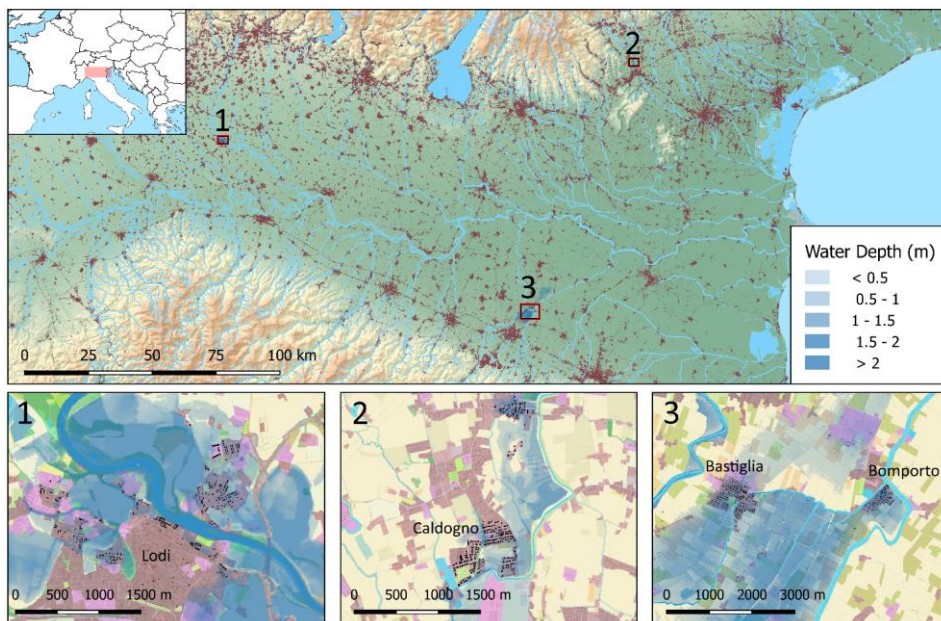
14
15 **Figure 1.** Case studies in Northern Italy (Po Valley). 1: Adda river flooding the town of Lodi, 2002; 2: Bacchiglione river
16 flooding the province of Vicenza, 2010; 3: Secchia river flooding the province of Modena, 2014. Flooded buildings for
17 which damage records are available are shown in black.

18 *2.1.1   Adda 2002*

19 On the 27th of November 2002, the province of Lodi (Lombardy) was struck by a flood caused by the

20 overflow of the Adda river. The flood-wave reached a record discharge of about 2,000 m³/s, corresponding to

4

1 a return period of 100 years (Rossetti et al., 2010). The river overtopped the embankments and flooded the

2 rural area first, later reaching the residential and commercial areas within the capital town of the province,

3 Lodi. The low-speed flood waters rose up to 2.5-3m. The inundation lasted for about 24 hours and affected a

4 large area of the Adda floodplain, including 5.5 ha of residential buildings. There were no reported

5 casualties, but several families were evacuated during the emergency and important service nodes such as

6 hospitals were severely affected. The reported damage to residential properties, commercial assets and

7 agriculture summed up to EUR 17.7M, out of which EUR 7.8M relate to residential buildings.

8 *2.1.2   Bacchiglione 2010*

9 From the 31st of October to the 2nd of November 2010, persistent rainfall affected the pre-Alpine and foothill

10 areas of Veneto region exceeding 500 mm in some locations (ARPAV, 2010). As a result, about 140 km[2] of

11 land were flooded, involving 130 municipalities (Belcaro et al., 2011). The Bacchiglione river, in the province

12 of Vicenza, was particularly negatively affected. Heavy precipitation events and early snow melting

13 increased the hydrometric levels of the Bacchiglione river and its tributaries, surpassing historical records

14 (Belcaro et al., 2011). On the morning of November 1st, the water flowing at 330 m³/s opened a breach on the

15 right levee of the river, flooding the countryside and the settlements of Caldogno, Cresole and Rettorgole

16 with an average water depth of 0.5 m (ARPAV, 2010). Then the river overflowed downstream, towards the

17 chief-town of Vicenza, which was inundated up to its historical center. The inundation lasted for about 48

18 hours, and its extent was about 33 Ha, of which 26 Ha consisted of agricultural land and 7 Ha were urban

19 areas. The total damage including residential properties, economic activities, agriculture and public

20 infrastructures was estimated to be around EUR 26M, while dwellings alone accounted for EUR 7.5 M

21 (Scorzini and Frank, 2015).

22 *2.1.3   Secchia 2014*

23 In January 2014 severe rainfall endured for two weeks on the central part of Emilia-Romagna region,

24 discharging the annual average amount of rain in just a few days. On the 19th, at around 6 AM, the water

25 started to overtop a section (10 m) of the of the right levee of the Secchia river, which stands 7-8 meters over

26 the flood plain. Later in the morning the levee breached at the top by one meter, flooding the countryside.

27 After 9 hours, the levee section was completely destroyed for a length of 80 meters, spilling 200 m³/s of

28 flooding around six thousand hectares of rural land (D'Alpaos et al., 2014). Seven municipalities were

29 affected, with the small towns of Bastiglia and Bomporto suffering the largest impact. Both towns, including

30 their industrial districts, remained flooded for more than 48 hours. The total volume of water inundating the

31 area was estimated to be around 36 million m³, with an average water depth of 1 meter (D'Alpaos et al.,

32 2014). The economic cost inflicted to residential properties according to damage declaration amounts to EUR

33 36M.

3. Materials and methods

3.1 Data description

We have first collected detailed and uniform data portraying hazard and exposure in the areas affected by the three events in order to evaluate their relationship with measured impacts. Several datasets have been ~~The~~ compiled from different sources, harmonised and geographically projected to the building level (i.e. micro-scale) for each one of the three study areas. The dataset ~~we compiled for this analysis~~ comprises:

- Detailed hazard data, including the flood extent, depth, ~~persistence~~duration, and flow velocity.
- High-resolution spatial exposure data, including type, location and value of affected buildings.
- Comprehensive vulnerability data, including the characteristics of building and dwellings in terms of material, quality and age.
- Reported damage in terms of replacement and reconstruction costs ~~of reparation or replacement of damaged goods~~.

The main hazard features (extent, depth, flow velocity and duration) are obtained from flood maps produced by 2D hydraulic models based on observations performed during and after the events. In detail, the ~~hydraulic~~flood simulation for the Adda river has been produced by means of River2D model (Steffler and Blackburn, 2002) using ~~a 5m resolution digital terrain model~~10m computational mesh based on a ~~and~~ high-resolution LiDAR ~~data~~DEM ~~for the description of the floodplains obtained from the river basin district authority (Scorzini et al., 2018)~~(Scorzini et al., 2018). The Bacchiglione flood have been simulated using the 1D/2D model Infoworks RS (Beta Studio, 2012). The 1D river network geometry comes from a topographic survey of cross-sections, while the 2D floodplain morphology (5 m resolution) is obtained from LiDAR ~~data produced by the Italian Ministry of Environment (Molinari et al., 2018)~~. The reliability of the simulations for the Adda and Bacchiglione floods was verified using hydrometric data, aerial surveys of inundated areas and photos/videos from the affected population (Rossetti et al., 2010; Scorzini et al., 2018; Scorzini and Frank, 2015). The Secchia flood event has been simulated using an innovative, time-efficient approach (Vacondio et al., 2016) which integrates both river discharge and floodplain characteristics in a parallel computation. The simulation was performed on a 5 ~~meters~~m grid and its results were validated against several field data and observations, including a high-resolution radar image (Vacondio et al., 2014, 2017). The information needed for the ~~characterization~~ characterisation of exposure is collected from a variety of sources and then spatially projected to have a ~~homogeneous,~~ georeferenced dataset for each case study. External buildings perimeter and area are obtained from the Open Street Map database (Geofabrik GmbH, 2018) and associated with official street-number points containing addresses. The land cover is freely available as perimeters classified by the CORINE legend (4th level of detail) (Feranec, J. Ot'ahel', 1998) obtained from Regional Environmental Agencies databases. Land cover information is used to discriminate housing from other buildings

1   (industrial, commercial, etc.). In addition, indicators for building characteristics (Table 1) have been selected

2   from the database of the ~~official~~ 2011 ~~Italian~~ population ~~C~~census ~~of 2011~~ (ISTAT, 2011). ~~CR~~Reconstruction and

3   restoration costs as EUR/m² are obtained for the case study areas from the CRESME database

4   (CRESME/CINEAS/ANIA, 2014). They are used to convert the absolute damage values into relative damage

5   shares. We chose to measure impacts in relative terms so to make them easier to compare through different

6   times (inflation effect) and places (different currencies). Empirical damage records have been collected by

7   local administrations after the flood events in relation to households' street numbers. The records falling

8   outside the simulated flood extents are filtered from the dataset. Each record includes: claimed; verified; and

9   refunded damage to residential buildings. Since actual compensation often covers only a fraction of the

10   damage costs, claimed damage is preferred in order to measure the economic impact (see Carisi et al. 2018).

11   We restricted our analysis on direct monetary damage to the structure of residential buildings, excluding

12   furniture and vehicles. Economic losses, building values and construction costs for the three events have

13   been scaled to EUR2015 inflation value.

3.2   Damage models overview

15   Empirical damage models are drawn based on actual data collected from specific events (e.g. Luino et al.

16   2009; Hasanzadeh Nafari et al. 2017); in some regions they represent the only knoweldge base for the

17   assessment of flood risk. However, they carry a large uncertainty when employed in different times and

18   places (Gissing and Blong, 2004; McBean et al., 1986). Differently, synthetic models are based on a valuation

19   survey which assesses how the structural components are distributed in the height of a building (Barton et

20   al., 2003; Oliveri and Santoro, 2000; Smith, 1994). In such expert-based models, the magnitude of potential

21   flood loss is estimated based on the vulnerability of structural components via "what-if" analysis and in the

22   evaluation of the corresponding damage based on building and hazard features (Gissing and Blong, 2004;

23   Merz et al., 2010). Most empirical and synthetic models are UVMs based on water depth as the only

24   predictor of damage; yet recent studies (Dottori et al., 2016; Schröter et al., 2014; Wagenaar et al., 2018) ~~(see~~

25   ~~e.g. Dottori et al., 2016 and Merz et al. 2013)~~ suggest that MVMs developed using expert-based or machine-

26   learning approaches outmatch the performances of customary univariable regression models. However, the

27   development of MVMs requires a comprehensive set of data in order to correctly identify complex

28   relationships among variables. Models can be further ~~be~~ classified in relation to the scale of their

29   development and application (de Moel et al., 2015): "micro-scale" usually refers to a model built to account

30   impacts over individual buildings ~~individual~~ components and it is commonly applied for local assessment;

31   "meso-scale" refers to sub-national analysis which commonly relies on data aggregated on provincial or

32   regional administrative units; "macro-scale" concerns assessments at country level.

33

3.2.13.3 Models from literature

There are few models in the literature that are dedicated to the economic assessment of flood impacts over Italian residential structures (see e.g. Oliveri and Santoro 2000; Huizinga 2007; Luino et al. 2009; Dottori et al. 2016). All Tthese models have been developed independently using different approaches, assumptions, scale and base data. The first model we selected for testing (Luino et al., 2009) is an empirical UVM based on the official impact data collected at micro-scale after the flash-flood event of May 2002 in the Boesio Basin, in Lombardy. One stage-damage curve was generated for structural damage to the most common building type in the area using loss data measured after the flood combined with estimates of water depth from a 1D hydraulic model. In this model, the estimation of building value is based on its geographical location, use and typology, based on market value quotations by the official real estate observatory of Italy (Agenzia delle Entrate, 2018). Market values of residential stocks for specific areas. The second model (OS - Oliveri and Santoro 2000) is a synthetic UVM developed for a study performed at the micro-scale -in the city of Palermo (Sicily). The model is based on describes damage in relation to water depth and consists of two curves, one for buildings with 2 floors and one for those with more than 2 floors. It considers water stage steps of 0.25 m; for each stage, the model computes the overall replacement cost as the result of damage over different components (internal and external plaster, fixtures, floors and electric appliances) plus the expenses for dismantling the damaged components. This model is based on an estimate of the average reconstruction value of exposed properties, a hydraulic simulation of potential flood hazard and expert-based assumptions about the damage process, but it has not been validated on empirical damage data. The third model we included in our analysis is part of a stage-damage curve database developed for the meso-scale by the EU Joint Research Centre (Huizinga, 2007; Huizinga et al., 2017) on the basis of an extensive literature survey. Damage curves are provided for a variety of assets and land use classes on the global scale by normalising the maximum damage values in relation to country-specific construction costs. These are obtained by means of statistical regressions with socioeconomic development indicators. The JRC curves are suggested for application at the supra-national scale but can be a general guide to carry on assessments at the meso-scale in countries where specific risk models are not available. We select the curve provided for Italian residential buildingsy (JRC-IT) to be tested on our dataset, although .JRC curves have been already tested at the micro-scale in Italy, revealing some large uncertainty in the estimates (Amadio et al., 2016; Carisi et al., 2018; Hasanzadeh Nafari et al., 2017; Scorzini and Frank, 2015).

The fourth model considered is INSYDE, *In-depth Synthetic Model for Flood Damage Estimation* (Dottori et al. 2016), which is a synthetic MVM developed for residential buildings and released as open source R script. Repair or replacement costs are modelled by means of analytical functions describing the damage processes for each component as a function of hazard and building characteristics, using an expert-based "what-if" approach at the micro-scale. Hazard features include physical variables describing the flood event at the building location, e.g. water depth, flood duration, presence of contaminants and sediment load.
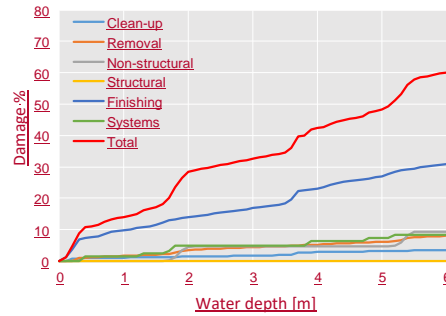

Figure 2. Examples of damage curves in relation to water depth produced by INSYDE for riverine floods in relation to a building with FA=100 m², NF=2, BT=3, BS=2, FL=1, YY=1990, CS=1.

1 Exposure iIndicators related to exposure and vulnerability include building characteristics such geometry
2 and features. Building features affect costs estimation either by modifying the damage functions or by
3 affecting the unit prices of the building components by a certain factor. Damage categories include clean-up
4 and removal costs, damage to finishing elements, windows, doors, wirings and installations (Figure 2). The
5 model adopts probabilistic functions for some of the buildings' components for which it is difficult to define
6 a deterministic threshold of damage occurrence in relation to hazard parameters. The curves are calibrated
7 on damage micro-data surveyed from a flood event in central Italy (Umbria) (Molinari et al., 2014). Despite
8 the large number of inputs, the model proved to be adaptable to the actual available knowledge of the flood
9 event and building characteristics (Molinari and Scorzini, 2017). The list of explicit inputs variables
10 accounted by INSYDE is adopted to select the variables accounted by all MVMs assessed in our analysis
11 (shown in Table 1)., with the indication of their respective data sources. Despite the large number of inputs,
12 the model proved to be adaptable to the actual available knowledge of the flood event and building
13 characteristics (Molinari and Scorzini, 2017).

Variable	Description	Source	Unit	Name
Hazard features				
Water depth	Maximum depth	Hydro model	m	he
Flow velocity	Maximum velocity	Hydro model	m/s	v
Duration	Hours of inundation	Hydro model	h	d
Exposure and vulnerability of buildings				
Replacement value	Economic value of the building structure	CRESME	EUR/m²	RV
Area and perimeter	Footprint area and external perimeter	OSM/CTR	m², m	FA, EP
Basement	Presence (1) or absence (0) of basement	CRESME	-	B
Number of floors	1, 2, 3 or more than 3 floors	Census/Inspection	-	FNF
Building type	Flat (1), semi-detached (2) or detached (3)	Census/Inspection	-	BT

9

Building structure	Bricks (1) or concrete (2)	Census/Inspection	-	BS
Finishing ~~level~~level	Low (0.8), medium (1) or high (1.2)	Census/Inspection	-	FL
Conservation status	Bad (0.9), normal (1) or good (1.1)	Census/Inspection	-	CS
Observed damage				
Damage claims	Private and shared structural parts	Official survey	EUR	D

1   **Table 1.** List of variables included in the multivariable analysis.

2   *3.2.23.4* **Models ~~developed and~~ trained on ~~the~~ observ~~ationed~~ records ~~dataset~~**

3   This section provides an overview ~~about~~ on the empirical damage model s obtained from our events dataset,

4   namely two supervised learning algorithms (Random Forest, Artificial Neural Network) and three uni- and

5   bivariable regression models used to assess the importance of variables (listed in ~~t~~Table 1) as damage

6   predictors. ~~All~~ Trained ~~these~~ models share the same sampling approach for ~~training and~~ validation: the

7   observation dataset is split in three parts, where two thirds are used to train the model and one third for

8   validation. This process is iterated 1,000 times, scrabbling the data and resampling the training set at each

9   cycle. The output takes the mean of all iterations and provides a curve which represents the empirical

10   damage relationship for the three events. This cross-validation approach has been previously employed in

11   Hasanzadeh Nafari et al. (2017) and in (Seifert et al. (~~,~~ 2010) in order to optimise the statistic utility of the

12   collected sample.

13   *3.2.2.13.4.1 Multivariable models: supervised learning algorithms*

14   A probabilistic approach is required in damage estimation in order to control the effects of data variability

15   on the model uncertainty. This is useful to overcome the limitations associated with the choice of a singular

16   model and to increase the statistical value of the analysis (Kreibich et al., 2017). The algorithms we employed

17   to deal with the empirical data share an iterative scrambling and resampling approach (1,000 repetitions) in

18   order to draw the confidence interval of the models independently from source data variability. For the

19   setup of empirically-based MVMs we selected ten variables from those listed in Table 1, excluding those

20   with small variability (basement, conservation status) or those for which an adequate level of detail is not

21   possible in our case studies ~~(age, heat system)~~. These ten variables serve as input for two supervised

22   machine learning algorithms, namely Random Forest (RF) and Artificial Neural Network (ANN), described

23   in the next paragraphs. Both algorithms are trained on our empirical dataset and produce a distribution of

24   estimates for each record, from which the mean value is calculated.
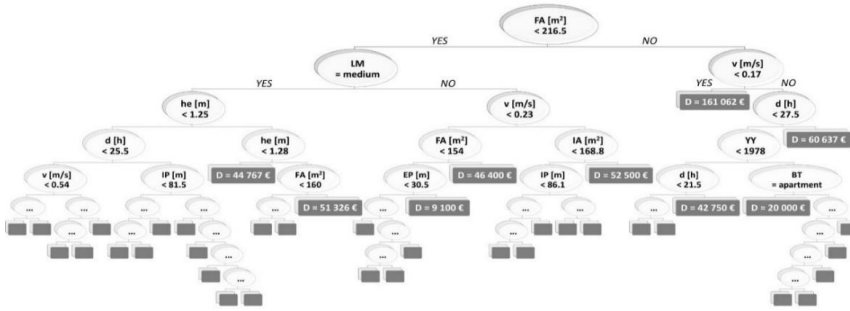
25   *3.4.1.1 Random Forest*

26   The RF is a data mining procedure, a tree-building algorithm that can be used for classification and

27   regression of continuous dependent variables (CART method - see Breiman 1984) like the one used by Merz

28   et al. (2013). RF has numerous advantages, such as accuracy of ~~high~~ prediction ~~accuracy~~, tolerance of outliers

29   and noise, avoidance of overfitting problems, and no need of assumptions about independence, distribution

30   or residual characteristics. Because of this, it has already been employed in the context of natural hazards,

10

1 including earthquake-induced damage classification (Tesfamariam and Liu, 2010), flood hazard assessment

2 (Wang et al., 2015), and flood risk (Carisi et al., 2018; Chinh et al., 2015; Kreibich et al., 2017; Merz et al., 2013;

3 Spekkers et al., 2014).

4
5 **Figure 3.** Example of one of the regression trees produced by the Random Forest model.

6 We use the algorithm implemented in the R package *RandomForest* by Liaw and Wiener (2002). The Random

7 Forest algorithm builds and combines many decision trees (500 in our case), where each tree has a non-linear

8 regression structure, recursively splitting the input dataset into smaller parts by identifying the variables

9 and their splitting values which maximize the predictive accuracy of the model. The tree structure has

10 several branches, each one starts from the root node and includes several leaf nodes, until either a threshold

11 for the minimum number of data points in leaf nodes is reached or no further splitting is possible (see Liaw

12 and Wiener, 2002 for details about the default values used, e.g. the size of the leaves). The minimum number

13 of observations per leaf is 5. Each estimated value represented by the resulting terminal node of the tree

14 answers to the partition question asked in the previous interior nodes and depends on the response variable

15 of all the parts of the original dataset that are needed to reach the terminal node (Merz et al., 2013). In order

16 to reduce the uncertainty associated with the selection of a single tree, the RF algorithm (Breiman, 2001)

17 creates several bootstrap replicas of the learning data and grows regression trees for each subsample,

18 considering a limited number of variables at each split (normally this number is equal to the root of the

19 number of the total variables). This will result in a great number of regression trees, each based on a different

20 (although similar) set of damage records and each leaving out a different number of variables at each split.

21 The mean value among all prediction of the individual trees is chosen as representative output. An example

22 of a built tree for the present study is shown in Figure 3. Another important strength of RF is its capability to

23 evaluate the relative importance of each independent variable in the tree-building procedure, i.e., in our

24 case, in representing the damage process. By randomly simulating the absence of one predictor, the RF

25 algorithm calculates the decreasing of the performance of the model and thus the importance of the variables

26 in the prediction.

11

3.4.1.2 Artificial Neural Network

ANNs are mathematical models based on non-linear, parallel data processing (Haykin, 2001). They have been applied in several fields of research, such as hydrology, remote sensing, and image classification (Campolo et al., 2003; Giacinto and Roli, 2001; Heermann and Khazenie, 1992). The model used in this study (Essenfelder, 2017) consists of a Multi-Layer Perceptron (MLP) neural network model, using back-propagation as the supervised training technique and the Levenberg-Marquardt as the optimization algorithm (Hagan and Menhaj, 1994; Yu and Wilamowski, 2011) (see figure 4 for the structure of the model).
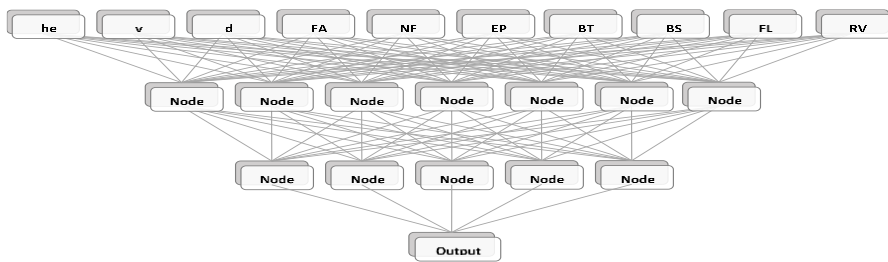
Figure 4. Structure of the Artificial Neural Network model applied in this study using two neurons (nodes) layers.

The developed ANN model evaluates the Sum of Squared Errors (SSE) of the model outputs with regards to the targets for each training epoch as a way of assessing the generalization property of a trained ANN model (Hsieh and Tang, 1998; Maier and Dandy, 2000). The ANN runs in a multi-core configuration and provides an ensemble of trained ANN models as a result, thus being suitable for probabilistic analysis. The input and target information are normalized by feature scaling before being processed by the model, while the initial number of hidden neurons per hidden layer is approximated as two-thirds of the summation of the number of neurons in the previous and next layers (Han, 2002). Regarding the activation functions, a log-sigmoid function is used for the connection with neurons in the first and second hidden layers, while a linear function is used for the connections with neurons in the output layer, allowing values to be either lower or greater than the maximum observed valued in the target dataset. This configuration is interesting as it does not limit the output range of the ANN model to the range of normalized values. The input data is randomly split between three distinct sets, namely training, validation, and test. The training dataset is used to calibrate the ANN model, meaning that the weight connections between neurons are updated with respect to the data available in this dataset. The learning rate is controlled by coefficient μ: when μ is very small, the training process approximates the Gauss-Newton optimisation algorithm (i.e. fast learning, low stability), while when μ is very large, the training process resembles the steepest descent algorithm (i.e. slow learning, high stability) (Wilamowski & Irwin, 2011). The value of μ starts as 1 and is updated during each training epoch; μ is reduced by half if training epoch is successful in reducing the SSE in the output layer, otherwise the value of μ is increased by a factor of two and a new training attempt is performed. The validation set is utilized utilised to avoid the overtraining or overfitting of the ANN model, being used to stop the training

12

process. The test set is not presented to the model during the training procedure, being used only as a way of verifying the efficiency of a trained ANN when stressed by new data. In order avoid any possible bias coming from the random split of the original dataset into training, validation, and test datasets, about 1,000 training attempts are performed, each with a different initial weight initialization and training dataset composition. The resulting ANN model consists of an ensemble of 4 models, representing the best overall results after the training procedure, that are used to define the confidence interval.

3.2.2.23.4.2   *Univariable and bivariable models*

In order to understand if the added complexity of MVMs brings any improvement in the accuracy of damage estimates, we compare them with traditional, deterministic univariable (UVM) and bivariable (BVM) regression models that are empirically derived from the observation dataset. Considering the first (water depth) or the first two variables (water depth and ~~water~~ flow velocity), we investigate whether a linear, logarithmic or exponential function has the best regression fit to the records. All functions that consider water depth are forced to pass through the origin, because most buildings have no basement and, accordingly, no water means no damage. Similarly to what we did for the MVM training, we uses an iteration of 1,000 scrambling and resampling cycles which is repeated using the two different sampling strategy: first the models are trained on 2/3 of the data and validated on the remaining 1/3 of the records.

3.4.3   *Workflow of the study*

The main elements of the ~~proposed~~ study are represented in the workflow shown in Figure 5. The dataset collected from flood events is presented for training the UV, BV and MV models by iterative cross-fold procedure. The trained RF provides the relative importance of predictive variables. Hazard and exposure variables are then used to test the performance of both trained and literature models. Simulated damage is compared to observed costs in terms of error metrics.
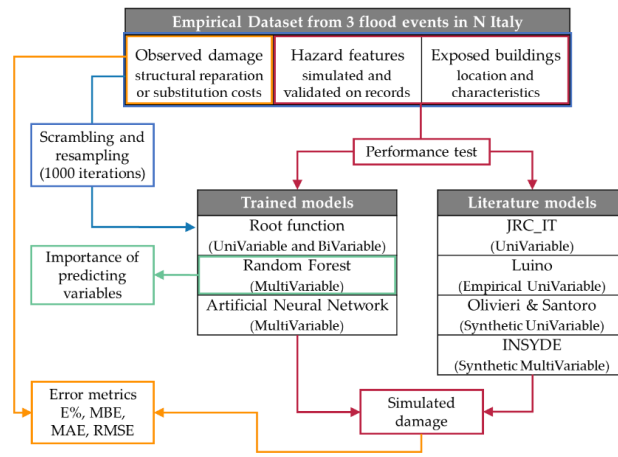

Figure 5. Workflow of the analyses performed in this study.

4. Results and discussion

4.1 Observed damage records

Our combined dataset contains records of 1,158 damaged residential buildings (Table 2). More than a half of these were damaged by the Secchia flood, which affected the largest residential area (17.7 ha) and caused the largest total losses. Only verified, spatially-matching records are accounted; economic losses are scaled to EUR2015 inflation value. Note that these losses are related to the structural damage of residential buildings, thus they do not represent the full cost inflicted by of these events.

Case study [River basin, year]	Affected buildings [n]	Flood extent [ha]	Avg. water depth [m]	Declared damage [M EUR 2015]
Adda, 2002	270	5.5	0.8	4.7
Bacchiglione, 2010	294	7.1	0.5	7.9
Secchia, 2014	594	17.7	1	21.1
Total	1,158	30.3	2.3	33.7

Table 2. Summary of residential buildings affected by the three investigated flood events according to hydraulic simulations and damage claims.

Boxplots in Figure 65 show the variance of variables driving the damage. Water depths range from 0.01 to about 2 meters, with most records falling in the interval 0.4 – 1.2 meters. Water velocities range between 0.01 and 1.5 m/s. Footprint areas and observed relative damages have similar average values for all three events, however the Secchia case study presents the longer count of records as well as the largest spread of outliers.
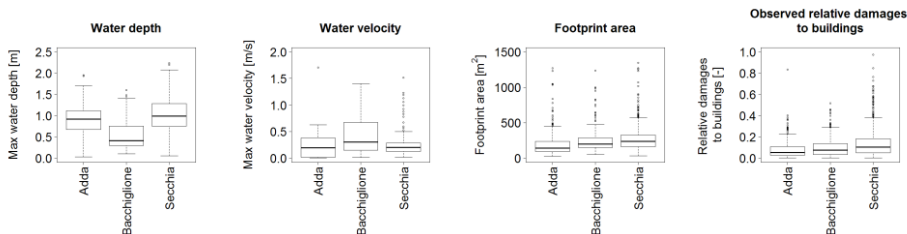

Figure 65. Data distribution for four variables from the three sample case studies.

The scatterplot in Figure 76 better shows the density of observed damages records in relation to the maximum water depth. The increase in depth corresponds to a larger range of variability in the economic damage.
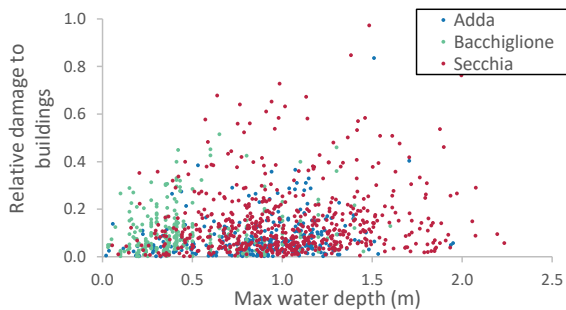
14

Figure 7. Scatterplot of relative damage (y-axis) in relation to maximum observed water depth (x-axis). Records from the same event are shown with the same color.

4.2 Influence of hazard and exposure variables on predicting flood damage

Water depth (*he*) is identified by RF as the most important predictor of damage (factor 3.4) among the ten examined variables (Figure 8~~7~~). This confirms previous findings (Wagenaar et al., 2017b) and justifies the use of depth-damage curves for post-disaster need assessment. Flow velocity and geometric characteristics of buildings (area and perimeters) are also important (factor 2.7 to 2.3), followed by other predictors such as building value, flood duration, number of floors, finishing ~~level~~ level (quality) and type of structure (factor 1 or less). Although water depth is the most influential variable, it is only moderately more important than other predictors. That substantiates the efforts to test the applicability of multivariable approaches to improve the estimation of damage.
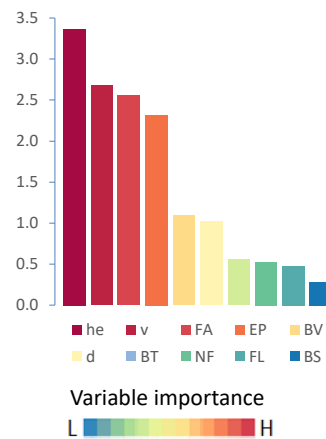

Figure 8~~7~~. Relative importance of variables as predictors of damage according to the RF model.

4.3 Performance of ~~the~~ damage models

For assessing the predictive capacity of the four selected literature models, we compare them with empirically-based, data-trained models structured on the same variables, i.e. the evaluation of the models' performances is carried out by measuring and comparing the error metrics from the aforementioned models (JRC-IT, Luino, OS and INSYDE) to those provided by the empirical MVMs obtained from supervised learning algorithms, the BVMs and traditional UVMs (depth-damage curves) developed on our dataset. The performances of each model are evaluated by using three metrics, namely Mean Absolute Error, Mean Bias Error and Root Mean Square Error. The MAE indicates the precision of the model in replicating the total recorded damage. The MBE shows the systematic error of the model, which is its mean accuracy. The RMSE measures the average magnitude of the error, enhancing the weight of larger errors. In addition to these error metrics, the total percentage error (E%, difference between observed and simulated damage divided by observed damage) is shown in tables.

15

4.3.1   Literature models

As first step, estimates of empirical and synthetic models from literature are compared with observed damages and the results in terms of total loss and total percentage error are shown in Table 3. JRC-IT is the worst performing model, largely overestimating damage from the three events (E% 143-417). This confirms previous findings about the scarce suitability of JRC meso-scale models for application at the micro-scale without previous validation (as in Amadio et al., 2016; Carisi et al., 2018; Hasanzadeh Nafari et al., 2017; Scorzini and Frank, 2015). The UV empirical model from Luino overestimates damage with a percentage error ranging from 44 to 177. This probably happens because the damage curve is based on observations forom~ a flash flood event characterised by higher flow velocities and larges relative impacts, proving that empirical models should be ~~carefully~~ transferred with caution on flood events with characteristics different from those from which the models are generated.

Case study	Unit	Obs.	JRC-IT	LUINO	OS	INSYDE
Adda 2002	M EUR 2015	4.7	24.3	13.0	8.1	5.6
	E%		417.0	176.6	72.3	19.1
Bacchiglione 2010	M EUR 2015	7.9	19.2	11.4	6.5	8.3
	E%		143.0	44.3	-17.7	5.1
Secchia 2014	M EUR 2015	21.1	64.5	44.1	19.8	28.8
	E%		205.7	109.0	-6.2	36.5
Full set	M EUR 2015	33.7	108.0	68.5	34.4	42.7
	E%		220.5	103.2	2.0	26.7

Table 3. Estimates and error from literature models compared to observed damage. Monetary values are in Million Eur, E% is total percentage error.

~~JRC-IT is the worst performing model, largely overestimating damage from the three events (E% 143-417), followed by the UV empirical model from Luino which overestimates damage with a percentage error ranging from 44 to 177. These results indicate that meso-scale models are not suitable for application at the micro-scale and that empirical models should be carefully applied for flood events with different characteristics from the ones for which they are developed. In fact, Luino's model was produced for a flash-flood event, with higher velocities and impacts.~~ The two synthetic models, OS and INSYDE, perform much better, yet showing a large variability of the error factor, depending on the considered case. In detail, OS provides better results for the Secchia event (6% underestimation) and worse for the Adda set (72% overestimation), resulting in an estimate that is very close to the observations in terms of percentual error on the total dataset, although this is mainly due to compensation of positive and negative errors for the different events. Differently, the INSYDE model exhibits a better performance for the Bacchiglione event (5% overestimation) and worse for the Secchia case study (37% overestimation). Figure 9~~8~~ compares the estimated and observed damages for the entire dataset for the two best performing literature models (OS and INSYDE).
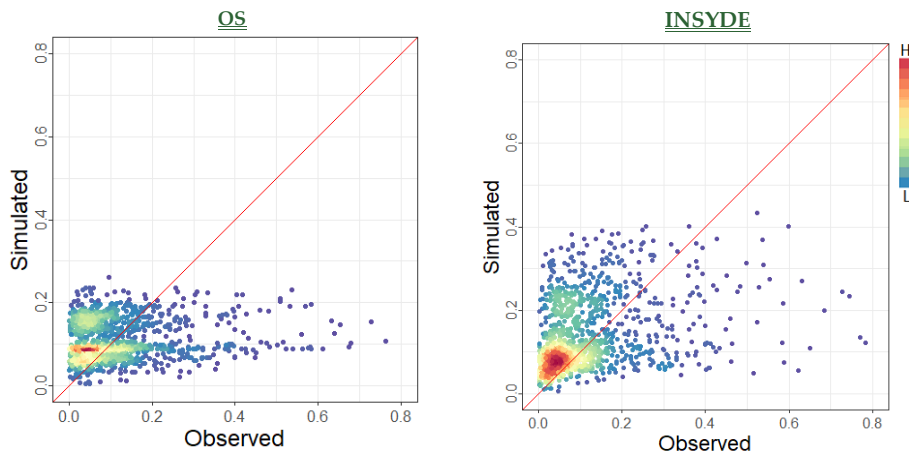
16

OS   **INSYDE**

Figure 98. Scatterplot comparing relative damage estimates produced by the two best performing literature models, OS **(left)** and INSYDE **(right).** Simulated damage on the y-axis, observed damage on the x-axis. Colors represent records density.

1 It is worth noting that, although the accuracy of the OS model is higher than of the INSYDE model for the

2 full set, the latter is more accurate for two out of the three case studies (i.e. Adda 2002 and Bacchiglione

3 2010). Moreover, the INSYDE model provides more precise results, with a variance in errors 10 times lower

4 than of the OS model and with maximum errors never exceeding an absolute value of 40%. However,

5 INSYDE seems to consistently overestimate the total damages. Figure 8 compares the estimated and

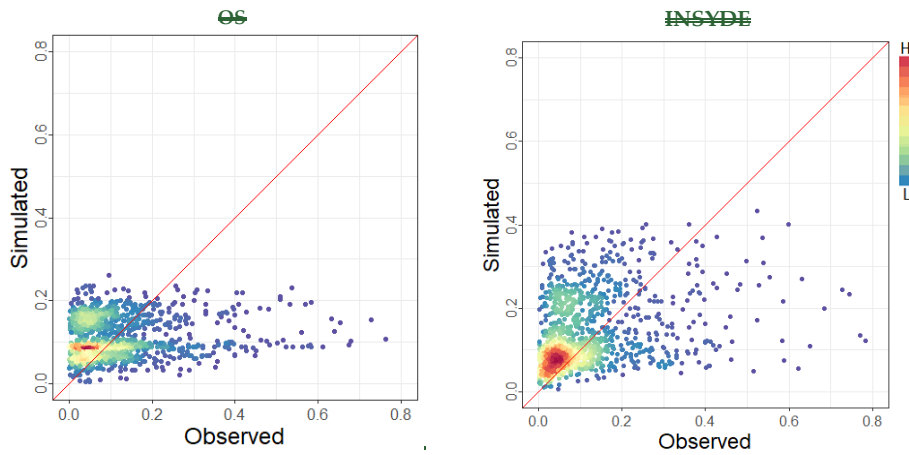6 observed damages for the entire dataset for the two best performing literature models (OS and INSYDE).

OS   **INSYDE**

Figure 8. Scatterplot comparing relative damage estimates produced by the two best performing literature models, OS **(left)** and INSYDE **(right).** Simulated damage on the y-axis, observed damage on the x-axis. Colors represent records density.

1   *4.3.2   Data-trained univariable, bivariable and multivariable models*

2   In this section, damage values estimated by empirical, data-trained UVMs, BVMs and MVMs are compared

3   with observed damage data. The results provided by these empirically-based models are used as a

4   benchmark to understand the capability of tested literature models in predicting damage. The error metrics

5   chosen for comparing the models' performances are presented for relative damage based on official

6   estimates of replacement value, however training and validation were carried out also in terms of monetary

7   damage with similar results, not presented for the sake of brevity.

Function	UVMs			BVMs		
	MBE	MAE	RMSE	MBE	MAE	RMSE
Linear	-0.015	0.087	0.127	-0.012	0.087	0.126
Log	-0.046	0.080	0.131	-0.046	0.080	0.131
Root	-0.003	0.086	0.123	-0.002	0.086	0.123

8   **Table 4.** Error metrics for the Univariable and Bivariable models.
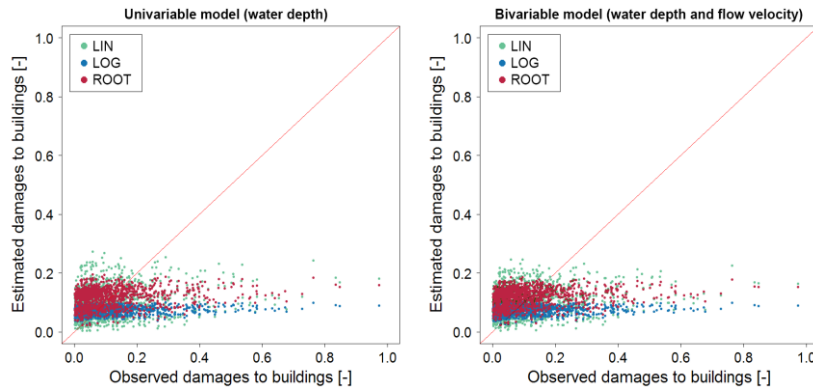

9
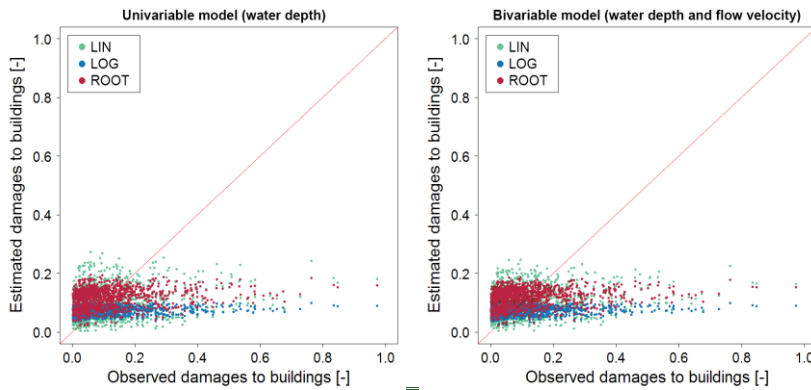
10   ~~**Figure 9.** Testing the predictive capacity of uni- and bivariable models: estimated relative damage (y-axis) from the UVM~~
11   ~~**(left)** and BVM **(right)** are plotted against observed relative damage (x-axis) according to the three tested regression~~
12   ~~functions (LINear, LOGarithmic and ROOT function).~~

13   The results shown in Table 4 and figure 9 indicate no significant differences between UVMs and BVMs. We

14   can affirm that the inclusion of ~~water~~ flow velocity as complementary explanatory variable does not improve

15   the performance of simple regression models in our case study. For this reason, BVMs are dropped from

16   further discussion from now on, to focus on a direct comparison between UVMs and MVMs.

17   Taking into consideration only UVMs, MAE and RMSE are very similar for the three tested regression

18   functions. However, the root function described by the general formula $y = b(\sqrt[a]{x})$ has a slightly better fit

19   (correlation is higher, MBE is lower) compared to linear and log functions. We select the function described

20   by the equation $y = 0.13(\sqrt{x})$ as the best performing UVM to be included in the comparison with MVMs.

21   Our findings confirm previous results indicating that the curve shape described by the root function is the

22   most adequate to describe the flood damage process ~~Our findings confirm previous results indicating that~~

18

1 ~~the root curve as the most adequate to describe the flood damage process~~ (Buck and Merkel, 1999;

2 Cammerer et al., 2013; Elmer et al., 2010; Kreibich and Thieken, 2008; Penning-Rowsell et al., 2005;

3 Scawthorn et al., 2006; Sluijs et al., 2000; Thieken et al., 2008; Wagenaar et al., 2017b).

4
5 **Figure 10**~~9~~. Testing the predictive capacity of uni- and bivariable models: estimated relative damage (y-axis) from the
6 UVM **(left)** and BVM **(right)** are plotted against observed relative damage (x-axis) according to the three tested
7 regression functions (LINear, LOGarithmic and ROOT function).

8

9 Figure 10~~9~~ shows a direct comparison between the damage estimated by the empirically-based models

10 against observed damage. The upper panel shows the output from the UVM described by the root function.

11 The lower panels show the output of the RF (left) and ANN (right) algorithms. The two machine learning

12 algorithms produce comparable results, with both RF and ANN models tending to slightly overestimate the

13 average damage (higher density of points, in red) and to significantly underestimate extreme values (lower

14 density of values, in blue). This is a common result of data-driven models, where better results are biased to

15 high-frequency values in comparison to low-frequency values due to the larger sample of those data in the

16 calibration dataset. In Figure 10, the range of estimates, shown as min-max, describes the confidence of the

17 model for individual records. In the case of RF, it shows the min-max range over all the 1,000 iterations of

18 the model, while in the case of ANN only an ensemble of the four best-fit models is shown (see Section

19 3.2.2.1).

20 Theoretically, MVMs should simulate the complexity of the flooding mechanism better than UVMs. In our

21 test, the ANN model has the best fit to the data, but UVMs (depth-damage curves) appear to perform

22 similarly: the MVMs describe recorded damage with a percentage error between 0.2 and 10, while UVMs'

23 error is around 12 (see table 5 in the next paragraph). Accordingly, when extensive descriptive data are not

24 available, UVMs appear to be a reasonable alternative to describe the flood damage process. These

25 empirically data-driven models are useful to understand the capability of multivariable approaches in

1 <u>predicting damage, i.e. which is the range of uncertainty that can be expected when assessing the flood</u>

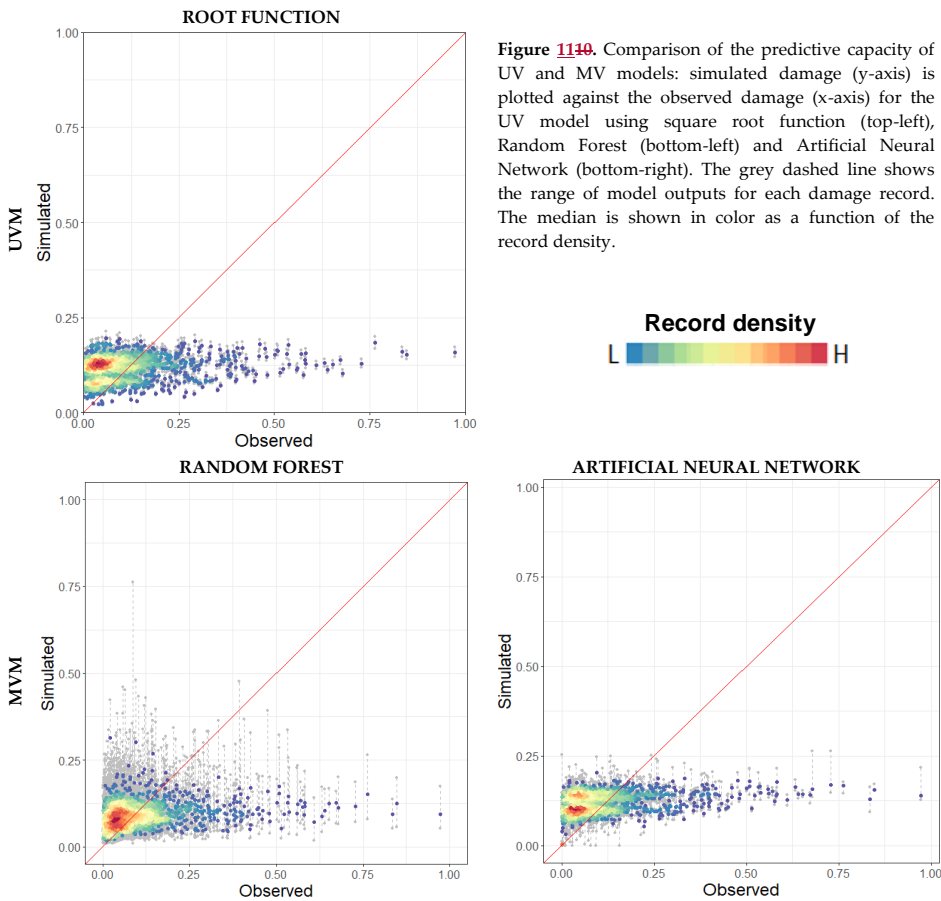2 <u>damage process, comparing to simpler models like UVMs.</u>

3

Figure 1110. Comparison of the predictive capacity of UV and MV models: simulated damage (y-axis) is plotted against the observed damage (x-axis) for the UV model using square root function (top-left), Random Forest (bottom-left) and Artificial Neural Network (bottom-right). The grey dashed line shows the range of model outputs for each damage record. The median is shown in color as a function of the record density.

4 ~~Theoretically, MVMs should simulate the complexity of the flooding mechanism better than UVMs. In our~~

5 ~~test, the ANN model has the best fit to the data, but UVMs (depth damage curves) appear to perform~~

6 ~~similarly: the MVMs describe recorded damage with a percentage error between 0.2 and 10, while UVMs'~~

7 ~~error is around 12 (see table 5 in the next paragraph). Accordingly, when extensive descriptive data are not~~

8 ~~available, UVMs appear to be a reasonable alternative to describe the flood damage process. These~~

9 ~~empirically data driven models are useful to understand the capability of multivariable approaches in~~

10 ~~predicting damage, i.e. which is the range of uncertainty that can be expected when assessing the flood~~

11 ~~damage process, comparing to simpler models like UVMs.~~

1 *4.3.3   Comparing models' performances*

2 First, we evaluate how selected literature UVMs (JRC-IT, Luino and OS) compare to the root function trained

3 on the empirical dataset. Figure 11~~10~~ shows the distribution and the density of observed relative damage as

4 a function of water depth for the full dataset, together with the UV curves selected for testing. This figure

5 explains the results presented in Section 4.3.1, with the JRC-IT and Luino models growing too fast for

6 shallow water depths, as opposed to OS (shown as two separate curves for different number of floors of the

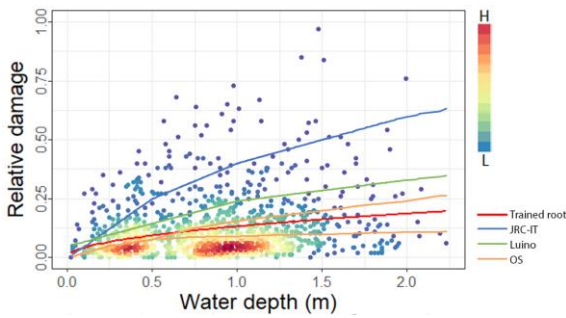7 building), which has a good mean fit to the data.

Figure 12~~11~~. Scatterplot of relative damage records (y-axis) and water depth (x-axis). Points color represents record density. The red line shows the empirical root function ($y = 0.13(\sqrt{x})$, selected as best fit. The other lines represent the three UV literature models (JRC-IT, Luino, and OS) selected for the test. OS model is made of two curves, in relation to the number of floors of the building.

8 Table 5 summarises the main results from all the models in terms of error metrics. Specifically, among all

9 models, MVMs RF and ANN are those with the lowest MAE and RMSE, followed by UVM ROOT with a

10 MAE of 0.086 and a RMSE of 0.123. In terms of percentage error, the ranking is the same, with the only

11 exception of OS, whose result in terms of this metric lies between the two empirical data-trained MVMs.

12 Overall, the two expert-based literature models OS and INSYDE, are the best performing ones when

13 ~~compared~~ benchmarked against~~to~~ empirically-trained models, as shown by MAE, MBE and RMSE. As

14 mentioned before, the performance of the UVM OS is very close to those of the MVM INSYDE, although this

15 result may depend on the fact that the large share of records come from the Secchia event, for which OS

16 outperforms INSYDE.

	Model	MBE	MAE	RMSE	Est. dmg [M EUR 2015]	Abs. error [M EUR 2015]	Percent error [%]
Trained models	**UVM (ROOT)**	-0.003	0.086	0.123	37.8	+4.1	+12.3
	MVM (RF)	-0.024	0.081	0.126	30.4	-3.3	-9.8
	MVM (ANN)	+0.009	0.091	0.115	33.8	-0.1	-0.2
Literature models	**UVM (JRC_IT)**	+0.217	0.239	0.27	108	+74.3	+220.5
	UVM (Luino)	+0.082	0.13	0.154	68.5	+34.8	+103.2
	UVM (OS)	-0.009	0.088	0.127	34.4	+0.8	+2.0
	MVM (INSYDE)	+0.019	0.093	0.132	42.7	+9.0	+26.7

17 **Table 5.** Comparing error metrics between empirically-base models and INSYDE.

Based on these results, the synthetic models INSYDE and OS currently represent ~~very~~ good alternatives for flood risk assessment in Italy, in cases where no empirical loss data are available to develop specific damage models. Indeed, our analysis has shown that particular care should be taken when transferring models derived from specific events (Luino curve) or from different scales (JRC-IT), while synthetic models can be considered more robust tools, relying on a physically-based description of flood damage mechanisms. Overall, for the investigated dataset, the synthetic MVM INSYDE has ~~not been~~ found to not provide much ~~different an improvement in the accuracy of damage estimates~~ performances compared to those of the UV OS. However, the results of INSYDE are more precise if considering the different flood events, with a general, although limited, damage overestimation in all the cases, as opposed to OS which exhibited more accurate performance only for the Secchia flood and larger variability for the other two events, consequently being less precise. Thus, caution should be used in the generalisation of this finding. Further validation exercises, combined with the application of standardised and detailed procedures for damage data collection (e.g. Molinari et al. 2014) could improve INSYDE's predictive accuracy; being an open-source model, it is possible to modify the damage functions for the different building components; for example, the availability of datasets with building losses subdivided into different categories (e.g. structural/non-structural elements, finishing, systems, etc.) could help to identify which damage components are responsible for the larger share of the error. The same cannot be said for OS, which is presented as a simple stage-damage curve, without a detailed explanation of the modelling assumptions on the considered flood-damage mechanisms.

We can't exclude that the performances of MVMs would benefit from the inclusion of additional predictive variables, such as those related to the implementation of early warning system and precaution measures, or social vulnerability; however, the availability of such information is limited for our case study. As a final consideration, the accuracy and precision of damage observations are key aspects for the correct development of an MVM. This makes synthetic and empirical MVMs better fit for applications at the micro-scale (up to the census block scale (Molinari and Scorzini 2017)), where explanatory variables can be spatially disaggregated. Indeed, the aggregation scale is of primary importance in the application of MVMs: if we can compare our results to those reported in other studies applying similar multivariable approaches on an extensive damage dataset (bagging of regression trees), as in Wagenaar et al. (2017a) and in Kreibich et al (2017), we observe that our range of uncertainty is drastically smaller. This difference is likely imputable to the fact that, in the referred studies, information is aggregated at the municipality level, as opposed to our case, where each variable is precisely linked to buildings' location.

5. Conclusions

Risk management requires a reliable assessment tool to identify priorities in risk mitigation and adaptation. Such tool should be able to describe potential damage based on the available data related to hazard features

1 and exposure characterisation. Recent studies suggest that multivariable flood damage modelling can

2 outperform customary univariable models (depth-damage functions). In this study we collected a large

3 empirical dataset at the micro-scale (i.e. individual buildings) which includes multiple hazard and exposure

4 variables for three riverine flood events in Northern Italy, including the declared economic damage to

5 residential buildings. On this basis, we produced three univariable, three bivariable and two multivariable

6 models that are compared in terms of predictive accuracy and precision. We found that water depth is the

7 most important predictor of flood damage for the assessed events, followed by secondary variables related

8 to hazard (flow velocity, duration) and exposure features (area, perimeter and replacement value of the

9 building). However, our results suggest that the inclusion of one additional variable (flow velocity) does not

10 improve the estimates produced by simple regression models in a bivariable setup. On the other side, the

11 analysis confirms the literature notion that the root function is the best fitting curve to describe damage in

12 relation to water depth. Two MVMs were trained using two different machine learning algorithms, namely

13 Random Forest and Artificial Neural Network. These empirically-trained MVMs performed well (with an

14 error ranging from 1 to 10%) in reproducing the damage output from the three events and thus were set as a

15 reference for assessments in the same geographic context. In this perspective, other case studies are needed

16 to confirm their robustness. Moreover, our results corroborate previous findings about the advantages of

17 supervised machine learning approaches for developing or improving flood damage models. Still, their

18 application remains limited by the availability of the data required for the MVM setup. In case of scarce

19 number of variables, however, simple univariable models trained on the specific contexts seem to be a good

20 alternative to MVMs.

21 We then considered four literature models of different nature and complexity to be tested on our extended

22 case study dataset. We compared their error metrics with those of the empirically-trained UVMs and MVMs

23 in order to evaluate their performance as predictive tool for flood risk assessment. The results have shown

24 important errors when transferring models derived from different countries and scales such as the JRC-IT

25 curve, or from events with different characteristics, as the empirical ~~: the~~ model from Luino, which is based

26 on a flash-flood event where flow velocity has likely a significant role on ~~the event~~flood impacts. On the

27 other hand, we found that both UV (Oliveri and Santoro 2000) and MV (INSYDE, Dottori et al. 2016)

28 synthetic models can provide ~~similar~~ similar results (although with ~~obviously~~ larger uncertainty) ~~errors~~ to

29 those observed from the empirically-trained models. ~~On the contrary, we found important errors when~~

30 ~~transferring models derived from other specific events (Luino curve) or different scales (JRC-IT). Therefore,~~

31 ~~t~~The tested synthetic models can be currently considered as the best option for damage prediction purposes

32 in the Italian context, in cases where no extensive loss data are available to derive a location-specific flood

33 damage model. Overall, we found that errors produced by synthetic models were ~~smaller than~~within 30% of

34 observed damage, with MVM INSYDE providing more precise results over the ~~different,~~ single case study

23

events (with a percentage overestimation of 19, 5 and 37% of observed damage for Adda, Bacchiglione and Secchia, respectively) and is more accurate for two out of the three case studies (i.e. Adda and Bacchiglione), while the OS model is generally less precise but more accurate for the Secchia flood event only (2% error, as opposed to a 72% overestimation for the Adda and 18% underestimation for the Bacchiglione event).

Observed errors depend in part on the inherent larger variability found in the dataset related to that particular event. Nevertheless, the collection of additional independent flood records from different geographic contexts in Italy would help to further evaluate the adaptability of these models, estimate their uncertainty, especially of the open source INSYDE, to estimate their uncertainty, and to increase their predictive accuracy. The open-source INSYDE model INSYDE holds the best potential in this sense. FinallyTo conclude, the work presented here has assembled a dataset that is currently one of the most extended and advanced for Italy; empirical damage data is the most important piece of information that allows to improve and validate damage models. Onon this track, we aim to promote a shared effort towards an updated catalogue of floods that includes hazard, exposure and damage information at the micro-scale. To this purpose, the adoption of a standardised and detailed procedure for damage data collection is a mandatory step.

Data availability

The INSYDE model is available as R open source code from https://github.com/ruipcfig/insyde

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