

A Model Taxonomy for Flood Fragility and Vulnerability Assessment of Buildings

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ABSTRACT

In the last two decades, probabilistic approaches to flood risk modeling have emerged, often as an extension of more consolidated methods used in probabilistic seismic risk assessment. Nonetheless, only a few studies deal with best-practice methodologies for flood physical vulnerability assessment, and existing approaches/models often lack appropriate guidance for their selection/rating and use. These concerns underline the need for a rational, integrated and comprehensive compendium of existing flood-related fragility (*i.e.*, the likelihood of various damage states as a function of hazard intensity measure(s)) and vulnerability (*i.e.*, the likelihood of loss levels as a function of hazard intensity measure(s)) models to be used in probabilistic flood risk assessment. To this aim, and following the approach used in the guidelines recently developed by the Global Earthquake Model (GEM) project, this paper proposes a model taxonomy for flood fragility and vulnerability assessment of buildings. A review of major state-of-the-art large-scale models for flood vulnerability assessment is first carried out. A discussion on the main factors affecting the reliability of empirical fragility and vulnerability relationships is presented, focusing on data sources, building classification, statistical techniques for data collection/fitting, and damage scales/loss metrics. As a proof of concept, a compendium of existing studies dealing with empirical fragility and vulnerability models for buildings is finally developed and discussed based on the proposed model taxonomy. This type of database can benefit (re)insurance companies interested in flood loss assessment and various decision-makers (*e.g.*, governmental agencies) committed to mitigate flood risk and communicate its level to various stakeholders.

KEYWORDS: Flood risk assessment; Fragility; Vulnerability; Buildings; Loss assessment.

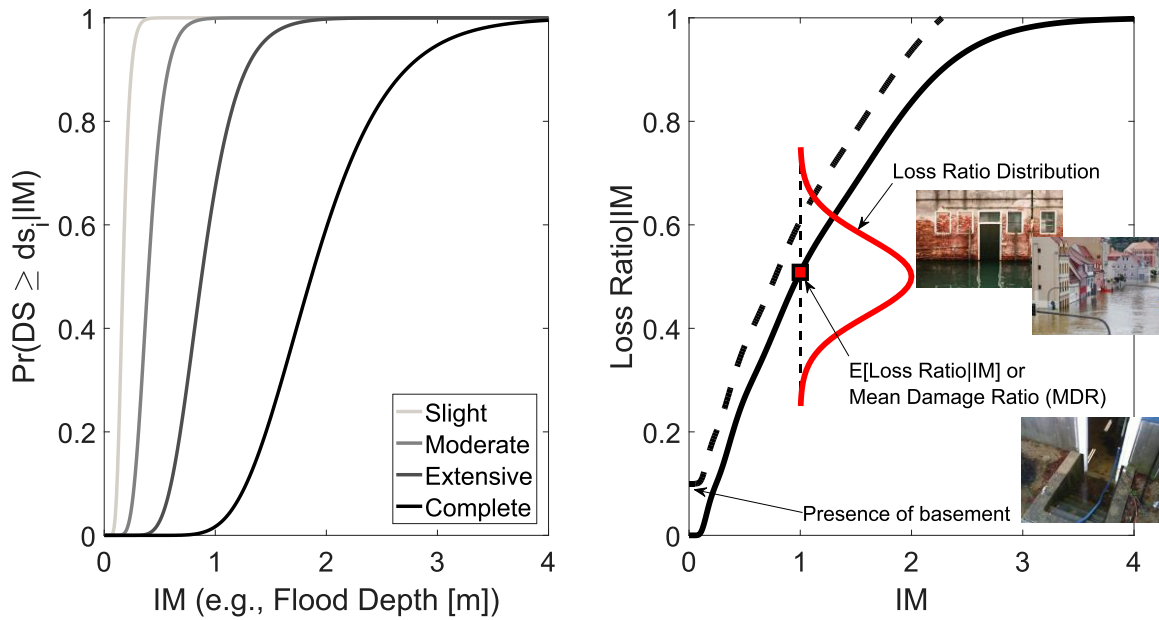
1. INTRODUCTION AND MOTIVATIONS

One-third of the economic losses due to natural hazards in Europe are related to flooding, one of the most frequent hazards with windstorms (*e.g.*, Munich Re, 2017; EEA *et al.* 2016). Quantifying the potential impact of floods on portfolios of assets located in flood-prone regions is of primary interest to various stakeholders, such as property owners, (re)insurance companies, and local government agencies, among others. It is critical that potential loss estimates, on which risk management and decisions on possible risk-mitigation/resilience-increasing strategies are based, are as accurate as possible given the available scientific knowledge. Indeed, “understanding disaster risk” is the first priority for action of the *Sendai Framework for Disaster Risk Reduction 2015–2030* (United Nations Office for Disaster Risk Reduction, 2015), endorsed by the Member States of the United Nations in 2015, with the aim of “preventing new and reduce existing disaster risk”. Disaster risk management and reduction need to be based on understanding disaster risk in all its dimensions of vulnerability, capacity, exposure of people and assets, hazard characteristics, and the environment.

Probabilistic catastrophe risk models are popular tools for estimating potential human and economic losses due to natural hazards. Such models incorporate detailed databases and scientific understanding of the highly complex physical phenomena related to natural hazards and engineering expertise on how those hazards impact buildings/infrastructure and their contents (*e.g.*, Grossi and Kunreuther, 2005). Until the 1980s, portfolio loss estimates associated with natural hazards such as earthquakes, windstorms, and floods were usually extrapolated from historical loss data. Nevertheless, the limited span covered by historical catalogs, the lack of systematically gathered loss data, and the changes in terms of exposure in hazard-prone regions worldwide have led to a severe underestimation of such losses. As a result, purely actuarial approaches (*e.g.*, based on claim data as in the case of automobile or fire insurance policies) for the estimation of losses generated by rare natural hazards have been

53 progressively abandoned in favor of simulation-based models integrating all the relevant science, data, and
 54 engineering knowledge. Moreover, as uncertainty lies at the heart of catastrophe risk modeling, it requires an
 55 appreciation at all modeling stages. Thus, a probabilistic approach is nowadays recognized as the most appropriate
 56 to model the complexity of natural hazards and their impact on the built environment.

57
 58 Within catastrophe risk modeling, several different approaches have been developed to link hazard intensities to
 59 the expected level of damage (fragility) or, more ambitiously, directly to the level of monetary loss (vulnerability).
 60 In particular, vulnerability relationships/curves (Figure 1b) express the likelihood that assets at risk will sustain
 61 varying degrees of loss (e.g., in terms of direct economic consequences of physical damage) over a range of hazard
 62 intensities. In some cases, developing vulnerability relationships requires the use of (1) fragility
 63 relationships/curves (Figure 1a), expressing the likelihood of different levels of damage (i.e., damage states, DSs)
 64 sustained by a given asset/asset type over a range of hazard intensities; and (2) damage-to-loss models, which
 65 convert damage estimates to loss estimates.
 66



67
 68 **Figure 1. Illustration of a) fragility curves corresponding to four damage states (DSs) for a given**
 69 **asset/asset type (or class); b) a vulnerability curve for the given asset/asset type. A vulnerability curve**
 70 **correlates a flood intensity measure (IM) to the percentage of an asset’s replacement cost (in the class)**
 71 **needed to repair the damage. An example of flood IM is the flood depth (in m). The figure also shows a**
 72 **representative probability distribution of a loss ratio at a given IM level.**
 73

74 In its generic form, this indirect approach enables the derivation of intensity-to-loss relationships by coupling
 75 damage probabilities for a given asset/asset type at specified intensities to damage-to-loss models by using the
 76 total probability theorem:
 77

$$78 \Pr(L > l | IM) = \sum_{i=0}^n \Pr(L > l | ds_i) \Pr(DS = ds_i | IM), \quad (1)$$

79
 80 where $\Pr(L > l | IM)$ is the complementary cumulative distribution function (CCDF) of the loss given a hazard
 81 intensity measure IM; $\Pr(L > l | ds_i)$ is the CCDF of loss given a damage state ds_i ; $\Pr(DS = ds_i | IM)$ is the damage
 82 probability. In some practical applications, the uncertainty in the damage-to-loss function is neglected, and the
 83 focus is on the estimation of the expected (average) loss at discrete IM levels:
 84

$$E(L | IM) = \sum_{i=0}^n E(L | ds_i) \Pr(DS = ds_i | IM), \quad (2)$$

where $E(L | ds_i)$ is the mean loss L suffered by an asset/class of assets for a given damage state; $E(L | IM)$ is the mean loss for a given intensity IM .

The damage probability term in both equations (*i.e.*, $\Pr(DS = ds_i | IM)$) can be easily linked to fragility relationships/curves expressing the probability of a level of damage being reached or exceeded given a range of IM levels:

$$\Pr(DS = ds_i | IM) = \begin{cases} 1 - \Pr(DS \geq ds_i | IM) & i = 0 \\ \Pr(DS \geq ds_i | IM) - \Pr(DS \geq ds_{i+1} | IM) & 0 < i \leq n-1, \\ \Pr(DS \geq ds_i | IM) & i = n \end{cases} \quad (3)$$

where $\Pr(DS \geq ds_i | IM)$ is the probability of a level of damage ds_i (out of n total DSs) being reached or exceeded given the intensity IM . It is worth noting that in the (re-)insurance industry, vulnerability relationships are also known as damage functions, implicitly emphasizing economic damage. Therefore, these two definitions will be used interchangeably in this paper.

Fragility and vulnerability relationships are derived from statistical analysis of damage/loss values recorded, simulated, or assumed over a range of hazard intensities. In practice, damage/loss statistics can be obtained from observation of past events (empirical approaches), analytical or numerical studies (based on engineering models of structural loads/demands and resistances/capacities), expert judgment, or a combination of these (hybrid approaches). Empirical approaches based on post-event surveys of asset classes' performance are commonly regarded as the preferred source of damage/loss statistics as they are based on actual post-event observations. Even though considerable efforts have been spent and progress has been made on post-flood damage data collection/post-processing and model development in recent years (*e.g.*, Ballio *et al.*, 2018; Menoni *et al.*, 2016, among many others), the main challenge in using available models for future applications is how to identify, rate, select, and, if necessary, combine suitable fragility and vulnerability relationships with different characteristics and, often unknown, reliability (*e.g.*, Rossetto *et al.*, 2014b).

Following the approach used in the bulk of research developed by the Global Earthquake Model (GEM; *e.g.*, Rossetto *et al.*, 2013, 2014a) and building on the preliminary results of Pregolato *et al.* (2015), this study aims at addressing the challenges discussed above by proposing a model taxonomy for flood fragility and vulnerability assessment of buildings. A similar review of flood loss models as a basis for harmonization and benchmarking is presented in Gerl *et al.* (2016), who offer a comprehensive review of flood loss models to 2015 containing nearly a thousand vulnerability relationships. However, the study of Gerl *et al.* (2016) considers different scales (spatial resolution/unit of analysis), and the vast majority of the models considered in such a review (about 60%) refers to aggregated land-use classes and various derivation methods (*i.e.*, empirical and synthetic approaches). The study presented in this paper focuses on empirical fragility and vulnerability models for buildings, resulting in a more extensive and more recent (up to 2019) compendium of existing studies dealing with the topic. This type of assessment/focus is common in smaller investigation areas (local or object-based scale); on this scale, building types are often differentiated by building age, construction material, or floor space, among many other parameters, with separate damage functions often available regarding building structure and building content.

The paper is organized as follows. An overview of the fundamentals of catastrophe risk modeling in the context of flood risk is first presented (Section 2). This is followed by (i) a description of the existing methods for the development of fragility and vulnerability relationships for flood, including a review of some state-of-the-art large-scale models for flood vulnerability assessment around the globe; (ii) a discussion on the main factors affecting the reliability of empirical fragility and vulnerability relationships, with a focus on data sources, building classification, statistical techniques for data collection/fitting, and damage scales/loss metrics (Section 3). The

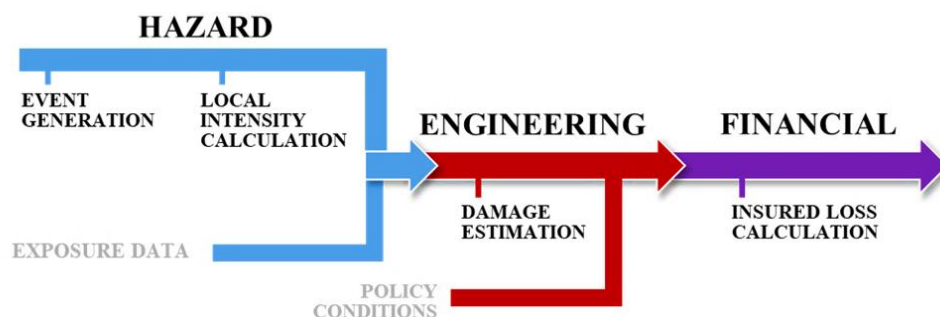
132 proposed model taxonomy for flood fragility and vulnerability assessment of buildings is then introduced (Section
 133 4). As a proof of concept, a compendium of existing studies dealing with empirical fragility and vulnerability
 134 models for buildings is finally developed and discussed based on the proposed model taxonomy (Section 5). This
 135 type of database can benefit (re)insurance companies interested in flood loss assessment and various decision-
 136 makers (e.g., governmental agencies) committed to mitigate flood risk and communicate its level to various
 137 stakeholders. For instance, the resulting collection of comparable flood vulnerability models can serve as a
 138 reference framework against which damage curves from catastrophe risk models for flood can be evaluated for
 139 various regions and construction types.

141 2. FLOOD RISK MODELING

142 2.1. Fundamentals of Catastrophe Risk Modeling

143 Flood is one of the most challenging hazards to model among all the natural perils because of the complexity at
 144 each stage of the flooding process, from the precipitation modeling to the inundation at each location of interest
 145 and the estimation of damage to properties and resulting consequences in terms of financial losses,
 146 casualties/affected people, and business interruption.

147 The general framework for modeling the impact of natural hazards on asset inventories can be broken down into
 148 the following four primary components, or modules, consistently with the general catastrophe risk modeling
 149 framework (e.g., Grossi and Kunreuther, 2005; Mitchell-Wallace *et al.*, 2017): (1) exposure, (2) hazard, (3)
 150 vulnerability, and – in the case of (re-)insurance applications, (4) financial – as shown in Figure 2. Each module
 151 requires substantial amounts of data for model development and validation.



153
 154 **Figure 2. Catastrophe model components.**

155 The *exposure* module contains details on the location and characteristics of the “exposure” at risk, *i.e.*, a property
 156 at risk of damage or a business at risk of interruption (in some cases, insurance loss models may also consider
 157 human exposure to death or injury). The property exposure information, which is usually provided to the analyst
 158 by a client, has a level of detail that varies from case to case. In fact, catastrophe models can be used to estimate
 159 aggregate insured or insurable losses for the entire insurance industry, individual company portfolios, or individual
 160 buildings. In the case of critical structures, the information may be very specific, including property address (which
 161 can be easily geocoded), detailed engineering and architectural drawings/design reports, presence of mitigation
 162 measures, and both retrofit and replacement cost estimates. Suppose a large portfolio of structures is considered.
 163 In that case, exposure information may consist only of the total value of all the properties located in a - usually
 164 large - geographical area, e.g., ZIP code/postcode, county, or CRESTA (Catastrophe Risk Evaluation and
 165 Standardizing Target Accumulations; <https://www.cresta.org/>) Zone. Suppose the location and the basic
 166 characteristics of each property are not available. In that case, the analyst is forced to make simplifying
 167 assumptions, for example locating the properties at the population-weighted centroid of an often vast geographical
 168 area and disaggregating (based on statistical procedures) available census data for buildings. This results in
 169 difficulties in assessing the accuracy of loss estimates.

170
 171
 172 The *hazard* module deals with (1) simulating thousands of representative, or stochastic, catastrophic events in time
 173 and space, *i.e.*, a database of scenarios; and (2) assessing the resulting hazard IM (e.g., level of earthquake-induced

174 ground motion, wind speed, flood depth) across a geographical area at risk, *i.e.*, at each location identified in the
175 exposure module, by propagating a given event across the affected region. Each event is defined by a specific
176 “magnitude” (*i.e.*, its size/severity), location, and the probability of occurrence (event rate), or time of occurrence,
177 based on historical data often supplemented by physics-based models for the phenomenon of interest.

178
179 The (physical) *vulnerability* is the susceptibility to damage, or other forms of loss (*e.g.*, downtime and casualties),
180 of structures and their contents because of the hazard’s impact. Typically, vulnerability relationships define the
181 loss in terms of the percentage of a property value (*i.e.*, its replacement value) expected to be lost at a defined
182 hazard level, specific to the exposure category/property type. Specifically, parameters defining property
183 susceptibility to damage include construction type (material and structural/lateral load-resisting system),
184 occupancy type (*e.g.*, residential or commercial, especially for assessing damage to contents), year of construction
185 (which represent a proxy for the building-code level of the asset), and height/number of stories. Some “secondary
186 modifiers” can also be considered, such as roof and foundation type, presence of a basement, among others. Given
187 that there is considerable uncertainty in the vulnerability assessment, besides proving a predictive relationship for
188 the mean loss, it is also necessary to carry a measure of the error of the estimation, *i.e.*, to consider the probability
189 distribution of a loss ratio at a given IM level (Figure 1b).

190
191 The *financial* module – when available (*e.g.*, for insurance applications) – estimates insured losses by applying
192 policy conditions (*e.g.*, deductibles, limits) to the total loss estimates or ground-up losses (in the insurance industry
193 jargon). The estimates of insured loss are validated using loss data from actual (historical) events. Output in terms
194 of loss may be customized to any desired degree of geographical resolution and by “line of business” (*e.g.*,
195 residential, commercial, industrial), and within line of business, for instance, by construction class.

196 The main output of a probabilistic catastrophe model is the exceedance probability (EP) curve, which describes
197 the annual probability of exceeding a certain level of loss. The mean of this distribution is the average annual loss
198 (AAL), or the expected loss per year, averaged over many years. AAL is a loss statistic widely used and has a
199 diverse range of applications in catastrophe risk management.

200

201 **2.2. Flood Risk Assessment**

202 The catastrophe risk modeling framework described above can be applied to various natural hazards and can be
203 specialized for flood hazard, as shown in Figure 3.

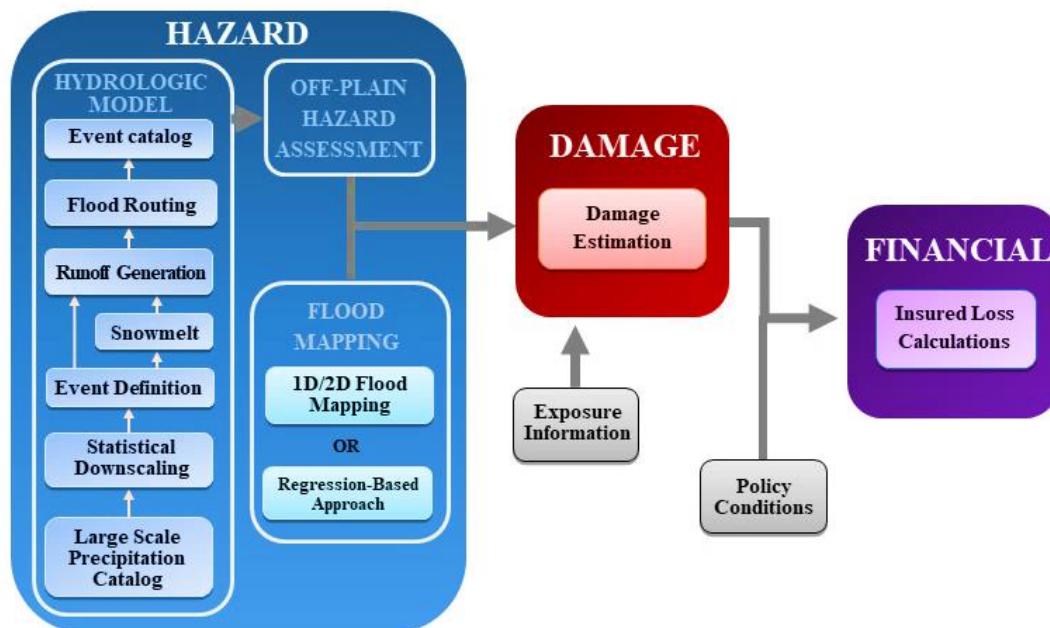
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205 The starting point for probabilistic flood loss assessment is the quantification of flood hazard to produce flood
206 depths or any other relevant IM in the floodplain-of-interest. Although different types of flooding (*e.g.*, mainstream,
207 flash, and overland) behave differently, flood-related damage fundamentally results from the depth and duration
208 of inundation as well as the water velocity. Those are the most widely used IMs in any flood model (Kreibich *et*
209 *al.*, 2009). A robust flood hazard model has to capture all the complexities inherent in a flood generation process,
210 such as the space-time patterns of rainfall input, the effects of a highly variable climate, topography, soil type, and
211 other local factors that determine the amount of rainfall drained to the rivers, as well as the effects of snowmelt
212 and man-made flood defenses (and their possible failure) on flood hazard estimation.

213

214 In the hazard module, large catalogs comprising tens of thousands of computer-simulated precipitation events are
215 generated (*event generation* sub-module), representing the broad spectrum of plausible events. Models usually
216 employ historical pluviometric data or the downscaling of various climate projection scenarios to obtain rainfall
217 statistics to be used as an input for stochastic catalog generation. For each stochastic event, the total and effective
218 runoff per catchment area is calculated, accounting for topographic and antecedent conditions (for instance, the
219 amount of prior rainfall or snowmelt, which determines the degree to which soils are already saturated), by
220 implementing a detailed *hydrologic model* converting precipitation to discharge and calibrated and validated based
221 on the available historical data (*e.g.*, European Commission, 2016). Next, a detailed *hydraulic model* is used in
222 conjunction with the hydrologic model output to define a flow versus depth relationship, *i.e.*, a rating curve, for
223 each location of interest (*local intensity* sub-module) (*e.g.*, European Commission, 2016). Rating curves are
224 typically constructed and periodically calibrated at river gauging stations, but they are not available for any
225 arbitrary “exposed” point of interest. Therefore, the role of the hydraulic model is to develop a full set of rating
226 curves for each point of interest. Typically, one-dimensional or two-dimensional hydraulic models are used for

227 flood hazard mapping in flood risk assessment, *e.g.*, LISFLOOD-LP (Bates *et al.* 2010). For example, for both
 228 industry and research applications, there are a wide variety of hydraulic models that account for varying degrees
 229 of physical complexity and offer a range of solutions to a given problem (*e.g.*, Neal *et al.*, 2012).
 230



231
 232 **Figure 3. Flood model sub-components.**
 233

234 It is worth noting the development of a hydraulic model for a large hydrological basin requires the availability of
 235 high-performance computing and efficient numerical algorithm along with detailed knowledge of topography, land
 236 cover, and canal geometry and properties. This becomes challenging in countries that lack detailed and high-
 237 resolution topography data and relevant information on stream and floodplain characteristics, for instance, in
 238 developing countries. Regression-based approaches (*e.g.*, Galasso and Senarath, 2014) can be used as an
 239 acceptable alternative for developing depth versus river discharge relationships in catchments with sparse data,
 240 provided that a suitable data set exists in another data-rich basin for the generation of the necessary regression
 241 relationships. In general, the suitability of a given assessment method depends on the characteristics of the area
 242 under study and the study's aims/requirements, and the availability of data (*e.g.*, Apel *et al.*, 2004).
 243

244 The vulnerability module, which is the focus of this paper, estimates damage and downtime caused by flood to
 245 assets of interest. The extent of damage, repair, and cleaning costs depends on many factors (Jonkman *et al.*, 2008),
 246 including debris load and silt in the water, building location and its orientation to any flow, the spacing of assets
 247 (influencing the flow velocity between buildings), materials used, and construction detailing, and how quickly a
 248 building may be cleaned and completely dried out after a flood (contributing to flooding resilience). Some of these
 249 parameters/information may not be available to the analyst – this is the case in many practical applications.
 250 Occupancy classes also play a crucial role since they can help determine the design level, the contents of a building
 251 and its basement (if present), and which local standards for flood defenses may apply to a given property.
 252 Downtime, namely the time window during which the flooded area cannot be used, also depends on the building's
 253 occupancy classification.
 254

255 Some examples of probabilistic flood risk models can be found in the literature, *e.g.*, CAPRA (Probabilistic Risk
 256 Assessment) Platform/Flood Model or HAZUS-MH Flood Module, among many others (see GFDDR, 2014 for a
 257 detailed review).
 258

259 **3. EXISTING METHODS FOR THE DEVELOPMENT OF FRAGILITY AND VULNERABILITY RELATIONSHIPS FOR**
260 **FLOOD**

261 As discussed above, fragility and vulnerability relationships express the probability of exceeding prescribed levels
262 of damage and loss, respectively, given a flood IM. In the case of flood hazard, the development of these
263 relationships is generally based on two main approaches: (i) empirical approaches, using damage and/or loss data
264 collected after flood events; and (ii) synthetic approaches, which are based on expert judgment, using damage
265 and/or loss data collected via *what-if* questions (Amadio *et al.*, 2019).
266

267 Empirical vulnerability relationships can be constructed directly from post-flood observations of losses collected
268 over sites affected by different flood intensities. If the IM level has not been recorded at each site, it can be assigned
269 using a hydraulic model (eventually combined with a hydrological model), as discussed in Section 2. Statistical
270 models are typically used to estimate a chosen functional form's parameters to fit data, although nonparametric
271 models can also be used. The central assumption in the development of empirical fragility and vulnerability
272 relationships is that past damage suffered by a particular asset class represents the damage that might happen in
273 the future to a similar asset class subjected to a similar flood event/intensity. This assumption essentially limits
274 empirical relationships' applicability to assets in geographical proximity to where empirical data was collected.
275 This poses a problem for their use in flood assessments in some countries because fragility and vulnerability
276 relationships are not evenly distributed worldwide, as discussed in Section 5.2.
277

278 What-if analyses estimate the damage expected under a flood scenario, for instance, by asking an expert: "*Which*
279 *damage would you expect if the water depth is 'X' m above the building floor?*" (Merz *et al.*, 2004). These analyses
280 are functional to explore various hazardous scenarios and evaluate their consequences, especially when empirical
281 data is not readily available or not enough. This means that empirical models can be effectively extended by
282 employing synthetic models to increase their applicability.
283

284 Recently, analytical/numerical approaches based on structural engineering principles (*e.g.*, load and resistance
285 approaches) have been proposed for flood-fragility derivation. Such approaches use a computer-based model (*e.g.*,
286 a finite element model) of the structure or a structural component of interest (*e.g.*, a wall) to increasingly apply
287 forces due to floodwater while observing the building performance (flood demand). Three main types of forces
288 due to floodwater are usually considered in analytical approaches to damage estimation: (i) hydrostatic forces
289 associated with the pressure of still water, which increases with depth; (ii) hydrodynamic forces associated with
290 the pressure due to the energy of moving water; and (iii) impact forces associated with floating debris dragged by
291 water. The flood demand at a given IM level is compared to each structural component or structural system's
292 capacity. The conditional probability of demand exceeding capacity for the given value of IM (*i.e.*, the structural
293 fragility) is determined using structural reliability concepts. Examples of such a procedure can be found in Oliveri
294 and Santoro (2000), Kelman and Spence (2003), van de Lindt and Taggart (2009), De Risi *et al.* (2013), and Custer
295 and Nishijima (2015), among others. Analytical models have also been used by, for instance, Dong and Frangopol
296 (2017) to carry out a probabilistic life-cycle cost-benefit analysis of building portfolios subjected to flood hazard.
297 As discussed above, numerical fragility models can be combined with damage-to-loss (or consequence) models to
298 finally derive vulnerability relationships.
299

300 **3.1. Overview of large-scale models for flood vulnerability assessment**

301 To develop a data scheme for fragility and vulnerability models/relationships to be practically used in flood risk
302 assessment, highlighting challenges in compiling a comprehensive compendium of existing studies, various global
303 and country-wide fragility/vulnerability models have been first selected. They are briefly reviewed in this section
304 (see Table 1). Comprehensive literature reviews of those models have been carried out by Smith (1994), Merz *et al.*
305 *et al.* (2010), Jongman *et al.* (2012), and Gerl *et al.* (2016), among others, but their detailed discussion does not fall
306 within the scope of this paper.
307
308
309
310
311

312 **Table 1. Summary of the considered country-wide models.**

Model	Type	Country	Main IM	Geographical scale	Unit of analysis	Building attributes	References
ANUFLOOD	Empirical	Australia	Water depth	Regional National	Individual buildings	Floor area Occupancy	NR&M (2002)
FLEMO	Empirical	Germany	Water depth	Local Regional National	Individual buildings Land use classes	Height Quality Occupancy	Thieken <i>et al.</i> (2008) Kreibich <i>et al.</i> (2010) Seifert <i>et al.</i> (2010)
HAZUS	Empirical-synthetic	USA	Water depth Flood duration Flow velocity Presence of debris Rate of rise Flood timing	Local Regional National	Individual buildings Land use classes	Construction material Age of construction No. of stories Presence of split floor Presence of basement	FEMA (2003, 2009) Scawthorn <i>et al.</i> (2006a,b)
JRC	Empirical-synthetic	EU Member States/Global	Water depth	Regional National European/Global	Individual buildings Land use classes	Occupancy	Huizinga (2007) Huizinga <i>et al.</i> (2017)
MCM	Synthetic	UK	Water depth	Local Regional	Individual buildings	Susceptibility Occupancy Presence of basement	FHRC (2005) Penning-RowSELL (2013)
USACE	Empirical	USA	Water depth Flow velocity Duration of inundation Contamination Frequency of inundation	Local Regional National	Land use classes	Construction material Occupancy No. of stories Presence of basement	USACE (1985)

313

314 Among the country-wide models, ANUFLOOD (NR&M, 2002) is an Australian commercial flood loss estimation
 315 model developed in 1983 on historical data from flood events in the UK and Australia. This empirical model
 316 consists of absolute damage functions (*i.e.*, functions directly providing the economic loss associated with a given
 317 flood IM) related to various classes of buildings according to their occupancy (*e.g.*, residential or commercial) and
 318 size (measured in terms of floor area). Water depth is the only IM used in the model, whereas the building
 319 vulnerability is considered dependent on the object size and “susceptibility”. The latter parameter refers to the
 320 sensitivity of a facility to the physical presence of floodwater. For example, a building cannot be removed from
 321 the flooding zone, whereas moveable objects can be protected elsewhere. In addition, the loss is not separately
 322 evaluated for each asset type (*i.e.*, buildings and contents), only enabling the estimation of the total loss in one
 323 figure.

324

325 As far as flood risk in Europe is concerned, three country-wide models were selected from the literature for their
 326 wide applicability: Flood Loss Estimation MOdel (FLEMO), the Multi-Coloured Manual (MCM) model, and the
 327 Joint Research Centre (JRC) model.

328

329 FLEMO was developed by researchers of the German Research Centre for Geoscience (GFZ) to support flood risk
 330 assessment at local, regional, and national scales. FLEMO is a modeling package consisting of FLEMOps
 331 (Thieken *et al.*, 2008) and FLEMOcs (Kreibich *et al.*, 2010; Seifert *et al.*, 2010), which are multifactorial models

332 for private and commercial sectors, respectively. The former allows the estimation of direct monetary losses related
333 to residential buildings; the latter was built up to estimate direct economic losses related to buildings, equipment,
334 and goods of companies. Such vulnerability models were developed based on empirical damage/loss data collected
335 after significant floods in 2002, 2005, and 2006 in Germany. FLEMO models apply either to single buildings at a
336 local scale or to medium/large areas for rapid damage assessment and scenario analysis at a regional or national
337 scale. The extension of those models to regional and national scales was based on census, geomarketing, and land
338 use data. The models were extensively validated at various scales employing repair cost datasets related to both
339 individual buildings and entire municipalities. In FLEMOs, the inundation depth is the primary IM that mostly
340 influences damage to residential buildings. Nevertheless, flood damage is computed over surface areas (rather than
341 for individual assets), accounting for five classes of inundation depth (*i.e.*, 0–0.20 m, 0.21–0.60 m, 0.61–1.00 m,
342 1.01–1.50 m, > 1.51 m), three types of buildings (single-family homes, semi-detached houses, multi-family
343 houses), two classes of building quality (low/medium quality, high quality), three classes of water contamination
344 (none, medium, heavy – the latter being oil or multiple contaminations), and three classes of private protection
345 (none, good, very good). Given that FLEMOs relies upon relative (rather than absolute) vulnerability functions,
346 asset values in terms of replacement costs are required, and their estimation may increase the uncertainty level. By
347 contrast, that type of function makes flood risk assessment independent of changes in the real estate market. It can
348 be used for several purposes by insurance and reinsurance companies and cost-benefit analysis by building owners
349 and government agencies.

350
351 The Multi-Coloured Manual (MCM) is the UK reference for flood damage assessment of both residential and non-
352 residential structures. It is based on a consistent data set of buildings and real data from major flood events
353 (Penning-Rowell, 2013). The MCM includes many absolute depth–loss functions, so asset values are not required
354 because the monetary loss due to a given flood scenario is directly provided. This calls for periodic recalibration
355 of these vulnerability functions to account for investments in properties and contents. Flood depth–loss
356 relationships were developed for various residential, commercial, and industrial buildings, mainly through
357 modeling and expert judgment (*i.e.*, synthetic approach). The vulnerability relationships are differentiated in terms
358 of building vulnerability (low, medium, high) and the presence of a basement. In this respect, input data for
359 buildings located in the UK can be gathered from the National Property Dataset, where residential properties are
360 classified according to their age, social class of residents, and types of buildings (detached, semi-detached), leading
361 to around 100 vulnerability functions for each building class. Information on non-residential buildings is available
362 in the Focus database. The MCM applies to both local and regional scales and uses individual assets as the analysis
363 unit. Water depth is the assumed IM, whereas the pre-flood depreciated asset value is the considered loss metric.
364 It is noted that the empirical validation of the MCM is still limited (Jongman *et al.*, 2012). As the MCM is an asset-
365 based model, the assessment provides the maximum loss per square meter of buildings, reflecting only the expected
366 repair costs to buildings rather than damage to neighboring land.

367
368 The JRC model was developed to assess flood risk at a pan-European level through depth–loss functions (*i.e.*,
369 vulnerability functions, although they are termed as depth–damage functions in the model) and maximum loss
370 values that are differentiated over European Union (EU) Member States (Huizinga, 2007). Five classes of assets
371 at risk are considered, *i.e.*, residential, commercial, industrial, roads, and agriculture. Flood depth at any location
372 of interest is multiplied with a weighted average of depth–damage functions and maximum loss values. Whilst
373 depth–damage functions of ten countries (*i.e.*, Belgium, Czech Republic, Denmark, France, Germany, Hungary,
374 Netherlands, Norway, Switzerland, UK) were collected from existing studies, those related to other EU countries
375 were assumed as the average of functions available for each class of asset at risk. It is also noted that maximum
376 loss values in EU countries with available damage functions were scaled to the gross domestic product (GDP) per
377 capita. Therefore, depth–damage functions adopted in the JRC model are uniformly distributed within each
378 country, whereas maximum damage values may vary across different regions of a country.

379
380 In 2017, the JRC released a global flood model developed according to the EU Strategy on Adaptation to Climate
381 Change (Huizinga *et al.*, 2017). Depth–damage functions were derived at both continental and country scales,
382 considering all continents and 214 countries, respectively. Continent- and country-specific functions were
383 provided for the following asset classes: residential buildings, commerce, industry, transport, infrastructure, and
384 agriculture. Regarding Europe, the depth–damage functions proposed by Huizinga (2007) were considered

385 because no publications on significant improvements related to European damage functions were found. Therefore,
386 flood damage data (*i.e.*, damage functions and maximum loss values) were searched for countries and regions
387 outside Europe. As expected, the collected data set was quite large for some countries where post-event damage
388 assessments are systematically carried out (*e.g.*, USA, Australia, Taiwan, Japan, South Africa). By contrast, the
389 amount of data across Africa was not evenly distributed, highlighting some concentrations in sub-Saharan African
390 countries according to their higher frequency of flood occurrence. When vulnerability levels of depth–damage
391 functions did not span from zero (no damage) to unity (maximum damage) for a water depth ranging from 0 to 6
392 m, the functions were normalized, and the maximum damage value was corrected. Loss values were harmonized
393 to the 2010 price level and to Euro. The average maximum loss per continent was computed after removing
394 apparent extreme values. Two sets of maximum loss values were tested: (i) maximum loss values derived from
395 country-specific models available in the literature; and (ii) construction cost values from international surveys.
396 Construction cost values were harmonized using regression analysis to use data in countries with unknown
397 maximum loss values for residential, commercial, and industrial buildings. This allows a non-biased comparison
398 of loss values between different countries. Thus, the global JRC model provides maximum loss values per
399 continent and country. Huizinga *et al.* (2017) recommend using continent-specific functions for all countries
400 within a continent and (average) maximum loss values from the literature review for risk assessments within a
401 country. In the case of countries with maximum loss values derived from the continental data, the maximum
402 continental loss value can be scaled according to the ratio between the GDPs per capita of the continent and the
403 country under consideration. Residential buildings were grouped in single-family and apartment buildings.
404 In contrast, commercial buildings were differentiated according to the following occupancy classes: shops/malls,
405 warehouse/storage, offices, education, hotels/restaurants, hospitals, other (public/sport). It is worth noting that the
406 global JRC model accounts for the uncertainty in damage functions, maximum loss values, and (observed or
407 calculated) flood extent and flood depth. Therefore, mean damage curves for each continent are provided together
408 with mean plus/minus one standard deviation curves.

409
410 In the USA, two country-wide models have been mostly used, namely the US Army Corps of Engineers (USACE)
411 model and HAZUS-MH (HAZards US Multi-Hazard) Flood Model. The USACE model (USACE, 1985), which
412 is based on guidelines published by US Water Resources Council (USWRC, 1985) allows the estimation of
413 damage to residential, commercial, industrial, and institutional property, accounting for the structure, equipment,
414 inventory (*i.e.*, warehouse stock to be sold), and content (*i.e.*, a combination of equipment and inventory).
415 Vulnerability functions for several occupancy classes (*e.g.*, residential, department store, school building, office
416 building, restaurant, lodging, clothing, service station) were derived from post-flood empirical damage data related
417 to individual districts of the USACE. Flood damage estimation procedures were compared by region and for a
418 small number of companies, highlighting wide variations between districts. Given a type of construction, the input
419 parameter (*i.e.*, the IM) of the damage function is the water depth. In the case of residential buildings, depth–
420 damage functions are provided for seven classes of structures determined by the number of stories (*i.e.*, single,
421 multiple, or split level) and presence/absence of basement, plus mobile homes. The influence of construction
422 material is also considered, *i.e.*, wood, metal, brick/block masonry, or reinforced concrete.

423
424 Nonetheless, the nation-wide damage functions developed by the Federal Insurance Agency (FIA) were considered
425 a reference model for residential buildings, so the USACE model primarily aimed at developing business-specific
426 damage functions as the FIA’s functions combined all businesses. The output of damage functions can be either
427 relative or total monetary loss, the latter to be adjusted by the time elapsed from the time and place of damage
428 function computation to application. Appendix C of the USACE model provides charts representing the
429 combination of depth–damage and overbank velocity that are likely to cause the collapse of buildings. Those
430 additional functions were developed for the following building classes: steel-framed buildings without loadbearing
431 walls (class A); reinforced concrete framed buildings without loadbearing walls (class B); masonry or concrete
432 wall buildings (class C); buildings having wood or steel studs in loadbearing walls with wood or steel frame (class
433 D).

434
435 The HAZUS-MH model is a software package developed by the Federal Emergency Management Agency
436 (FEMA; 2003, 2009) to estimate future losses from earthquakes, windstorms, floods, and tsunamis in the United
437 States of America (Scawthorn *et al.*, 2006a,b). The HAZUS-MH Flood Model was developed since 1997 and

438 applies to local (city/county) and regional (state) scales. This model provides fragility and vulnerability functions
 439 derived from modeling, expert opinion, and empirical data. Depth–damage functions for buildings were developed
 440 by (i) FIA based on empirical damage data related to a 20-year period; and (ii) the US Army Corps of Engineers
 441 for some regions of the United States. An extensive validation was carried out against historical data. Such a model
 442 allows both riverine and coastal floods to be considered and is based on more than 900 relative damage functions
 443 (*i.e.*, loss ratio vs. IM) for multiple types of constructions. Risk assessment via the HAZUS-MH Flood Model can
 444 be performed at three levels of detail, namely, “level 1” analysis based on default input data, “level 2” analysis
 445 based on default data and regional-specific information, and “level 3” analysis based on detailed engineering and
 446 economic studies by the user. The unit of analysis is either an individual asset or surface area. Several building
 447 characteristics are considered, such as building type (*i.e.*, wood frame, steel frame, concrete frame, masonry,
 448 manufactured housing), number of stories (*i.e.*, low-rise, mid-rise, high-rise, except for wood apartments and
 449 mobile homes), presence of basement and construction age. The model allows the following hydrological features
 450 to be included by univariate functions: water depth, flood duration, flow velocity, presence of debris in floodwater,
 451 rate of rise, and flood timing. The latter is an important type of damage influencing parameter because a flood
 452 event occurring, for instance, at night or during holidays, is expected to induce higher levels of damage. In addition,
 453 the user can also define the available warning time by the community and the loss metric in terms of replacement
 454 cost or depreciated asset value. It is worth noting that the HAZUS-MH Flood Model includes an additional module
 455 that allows the user to estimate indirect costs and more significant economic effects of a flood event.
 456

457 **3.2. Factors Affecting the Reliability of Empirical Fragility and Vulnerability Relationships**

458 Post-flood damage and loss databases, widely used to derive empirical fragility and vulnerability relationships
 459 described above, can be very often associated with problems such as incompleteness, misclassification errors,
 460 small sample sizes, and large aggregated building classes. In empirical fragility and vulnerability models,
 461 therefore, large epistemic uncertainties can be introduced by the low quantity and/or quality of typical post-flood
 462 damage/loss databases and the inability to account for the complete characteristics of the flood event in the
 463 selection of a particular IM. Furthermore, it is evident that existing studies/models typically do not appropriately
 464 communicate the overall uncertainty in fragility and vulnerability relationships and often cannot distinguish the
 465 effects of the two components, *i.e.*, aleatory (due to the natural variability of the flooding process and the resulting
 466 flood intensity) and epistemic.
 467

468 **Table 2** identified the main categories of factors affecting the reliability of empirical vulnerability and fragility
 469 relationships; particularly, the quality of damage/loss data is one of the major determining factors for reliability.
 470 Those factors have been identified based on a detailed analysis of the model described in Section 3.1 and their
 471 application in practical flood risk assessment studies (e.g., Mertz *et al.*, 2010, among many others).
 472

473 **Table 2. Factors determining the reliability of empirical vulnerability and fragility models.**

Factors	Description
Intensity measure (IM)	Hazard parameters and their spatial resolution. IM estimation method (<i>e.g.</i> , hydraulic model or recorded).
Damage characterization (in the case of fragility relationships)	Damage scale; consideration of nonstructural damage/contents. Number of damage states (DSs).
Building classification and sample size	Single or multiple building classes. Sample size (size of database and completeness).
Data quality/quantity	Post-flood survey method. Coverage, response and measurement errors in surveys. Quantity of data (<i>e.g.</i> , number of buildings or loss observations). Number of flood events, range of IMs and DSs covered by data.
Derivation method	Data manipulation or combination. Statistical modeling. Treatment of uncertainty (sources of uncertainty, quantification).
Documentation	Whether complete information is present that makes the study reproducible.
Cross-validation	Whether the derived model/relationship is compared with existing models/relationships or observations.

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The variation of the selected IM over a geographical unit and uncertainty in the estimation of the IM at a site arising from the use of hydrological/hydraulic models contribute to the uncertainty associated with the IM computation at a site of damage evaluation (*e.g.*, Kreibich et al., 2009). To the authors' knowledge, no existing study has yet taken this last aspect into account, and all adopt statistical models assuming that the IM is known with certainty. Moreover, due to the nature of flooding, the empirical data is typically seen to be clustered in specific ranges of IM and damage/loss values. This means that extrapolating fragility and vulnerability relationships outside those ranges may be unreliable. As a matter of good practice, empirical fragility and vulnerability relationships should not be used to estimate damage and loss outside the range of IMs of the data that has been used in their derivation.

Even large damage databases may contain errors or may be associated with a low degree of refinement in the definitions of damage scales and building classes. The damage scale used to collect the damage data from the field is important in determining the potential for misclassification errors and the usefulness of the developed relationships. In general terms, a damage scale that describes a number of damage states unambiguously in terms of structural and non-structural component/content damages will result in a more reliable and useful empirical fragility model (and eventually vulnerability model). The combination of several datasets from the same or different flood events are often combined in the construction of empirical fragility curves can often be hampered by the use of different damage scales by each database. In this case, it is best practice to map the damage states of each damage scale onto those of the damage scale with the least number of damage states (*e.g.*, Rossetto et al., 2013).

Post-flood damage data at a building-by-building level is not always available. Instead, the damage data is usually presented in aggregated form, often over geographical areas of various sizes (*e.g.*, a ZIP-code, village, district, or town) (Molinari *et al.*, 2014). In the latter case, the geographical area is assumed to have a constant flood intensity value, which is typically evaluated at its centroid (De Risi *et al.*, 2020). Nonetheless, if the geographical unit is large, there is likely to be a considerable variation in the IM values across the unit, which is not typically accounted for (Merz *et al.*, 2007).

Different statistical modeling approaches have been used by existing studies to fit parametric functions to their empirical data. The choice of statistical model is seen to have a strong influence on the reliability and validity of existing empirical fragility functions. In addition, all the necessary inputs, outputs, and derivation steps are generally not clearly documented to a level that will allow the study to be reproduced by others. Such documentation should be independently peer-reviewed and readily available to future users.

Finally, a significant shortcoming of existing models is the lack of model cross-validation to assess whether a given vulnerability model/relationship at least roughly agrees with some prior accepted model or, the observed disagreement appear reasonable in light of shortcomings in the past model, or differences between the asset classes of the past model and the one in question. Most of the existing studies do not fully document the validation process of a given model and do not clearly demonstrate the validation process's independence and impartiality. The uncertainty in the model, limitations, and required future developments are seldomly documented.

4. PROPOSED MODEL TAXONOMY FOR FLOOD FRAGILITY AND VULNERABILITY ASSESSMENT

Fragility and vulnerability relationships have been developed from post-flood data in recent years, mostly by individual researchers or small research groups rather than a joint research community. Such relationships show disparities in terms of applicability and reliability and the level of the information underlying their development, which is provided to a user and their validation. This section introduces a proposed taxonomy for flood fragility and vulnerability models/relationships.

Existing model taxonomies, such as those of Gerl *et al.* (2016) and Murnare *et al.* (2019), have been thoroughly reviewed/considered to derive the proposed model taxonomy. In particular, the proposed taxonomy is entirely consistent with the GEM exposure taxonomy (*e.g.*, Silva *et al.*, 2020) and the multi-hazard exposure taxonomy

526 proposed by Dabbeek and Silva (2020) for the purpose of probabilistic earthquake and flood loss assessment in
527 the Middle East (e.g., Dabbeek et al., 2020).

528
529 The proposed model taxonomy (Table 3) has been applied to selected studies available in the literature (Table 4),
530 excluding the large-scale models presented in Section 3.1 for simplicity. For example, both the MCM and HAZUS-
531 MH contain several hundred functions due to the numerous subcategories of individual construction/occupancy
532 classes and secondary modifiers. This would just complicate the readability of Table 4 without adding much to the
533 general discussion to support the aim of this study. More in general, the main aim here is to demonstrate the initial
534 development of a rational, integrated, and comprehensive compendium of existing flood-related fragility and
535 vulnerability models/relationships to be used in probabilistic flood risk assessment.

536
537 There are 26 fields related to six categories, described in Table 3. Each record provides information regarding an
538 existing study developing vulnerability or fragility relationships. The proposed structure contains basic
539 information regarding the type of study that developed a given model/relationship (reference, type of assessment,
540 source) and the investigated asset (i.e., type of building: material, age, flood design, etc.). It is worth noting that
541 other important building attributes such as “height between ground level and ground floor” are not generally
542 included in any exposure taxonomy available in the literature (e.g., that proposed by GEM) and, as such, they have
543 not been included in the proposed model taxonomy. The proposed model taxonomy also includes information
544 regarding the damage scale (for fragility), the loss parameter (for vulnerability), the coverage (building structure
545 and/or building contents) and the flood intensity, reporting the type of flood, adopted IM(s), the range of IM(s),
546 and the main IM estimation method. Regarding the data quality/quantity, the country(ies) where the database was
547 developed, data source(s), number of assets, and data points provide useful information regarding the model
548 reliability. Finally, the functional form and the type of analysis (statistical fitting) are described.

549
550 Once a compendium of fragility and vulnerability relationships is developed based on the proposed model
551 taxonomy, the main challenge consists in selecting/using relationships in new flood vulnerability/risk assessment
552 applications, identifying the most suitable models/relationships from the collection. For instance, in the field of
553 earthquake engineering, Rossetto et al. (2014b) and Rossetto et al. (2015) proposed a procedure for assessing the
554 robustness and quality of fragility and vulnerability relationships for seismic risk assessment within the GEM
555 project, identifying a formal framework for choosing the most appropriate model according to the asset class and
556 location. Similarly, in the context of flood loss modeling, Figueiredo et al. (2018) proposed the use of multi-model
557 ensembles to assess existing flood loss models and associated uncertainty. Specifically, the authors proposed a
558 model rating framework to support ensemble construction, based on a probability tree of model properties, which
559 establishes relative degrees of belief between candidate models. Using 20 flood loss models in two test cases, they
560 construct numerous multi-model ensembles based on the rating framework and on a stochastic method, differing
561 in terms of participating members, ensemble size and model weights. This approach enabled assessing the
562 performance of ensemble means, as well as their probabilistic skill and reliability, demonstrating that well-
563 designed multi-model ensembles represent a pragmatic approach to consistently obtain more accurate flood loss
564 estimates and reliable probability distributions of model uncertainty.

566 **5. APPLICATION OF THE PROPOSED MODEL TAXONOMY TO SELECTED FRAGILITY AND VULNERABILITY** 567 **RELATIONSHIPS FOR FLOOD**

568 As a proof of concept, a range of existing models was organized into a pilot-compendium of original relationships
569 by applying the proposed model taxonomy (Table 3) to selected studies available in the literature, Table 4. The
570 compilation of such a flood vulnerability model inventory is carried out by collecting references that include
571 original work on developing flood vulnerability relationships within a literature review.

572
573 It is worth mentioning that this is not intended to be an exhaustive compendium of all available flood loss
574 models/relationships globally. However, it represents an illustrative application providing interesting insights
575 regarding current data and its quality. Indeed, the functional forms/plots themselves have not been included in the
576 paper. Nevertheless, all necessary references are given to lead the reader to the specific formulations, if that were
577 of interest. In most cases, these references are publicly available and can be easily retrieved from the literature.

578

Table 3. Taxonomy for flood fragility and vulnerability models/relationships for buildings.

General category	Field	Description
Existing study	Reference	
	Type of assessment	Type of assessment followed by the study, <i>e.g.</i> , fragility or vulnerability.
	Source	The methodology used to obtain the functions, <i>e.g.</i> , empirical (uses loss data collected after flood events), engineering/synthetic (uses loss data collected via <i>what-if</i> -questions), or a combination of both types.
Damage and loss measures	Damage scale	The main damage scale adopted by the study (if applicable, <i>i.e.</i> , in the case of fragility relationships).
	No. of DSs	Number of damage states (DSs) used by the main damage scale.
	Loss parameter	Definition of the loss adopted by a vulnerability assessment study, <i>i.e.</i> , relative (% of total value) or absolute (currency/unit, <i>e.g.</i> \$/m ²) damage.
	Coverage	Building structure and/or building contents.
Building classification	Construction material	
	Structural system	
	Type of foundation	
	Age/Year of construction	
	Height/No. of stories	
	Floor material	
	Walls/infill material	
	Percentage of openings by floor	
	Presence of basement	
	Flood design?	Does the building class account for any flood design?
Occupancy	Sector for which a flood damage function is available, <i>e.g.</i> , residential, commercial, industrial, public/municipal, etc.	
Flood intensity	Flood type	Considered flood source: fluvial flood (water overflowing river banks when surface water runoff exceeds the flow capacity of channels), flash flood (flood peak appearing within a few hours originating from torrential rainfall), pluvial flood (caused by rainfall or snowmelt), groundwater rise (water table level rises to surface level), coastal flood (originating from incursion by the ocean), or dam break (originating by failing of dikes).
	Intensity measure	The flood intensity measure (IM) used by each study.
	Range of IM	Range of IM values of the data.
	Main IM estimation method	Recorded/surveyed or simulated (hydraulic modeling).
Data quality/quantity	Country/ies	Name of the country/ies of each dataset used.
	Source of the data	Source/s of data, <i>e.g.</i> , flood event.
	No. of assets	Number of buildings used for the construction of the relationship.
	No. of data points	Number of data points used for the construction of the regression analysis.
Method	Functional form	Type of function, <i>e.g.</i> , mean curve or probability distribution.
	Type of analysis	The analysis used by the examined study, <i>i.e.</i> , regression, univariate distribution fitting.

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5.1. Selected models

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Numerous scientific papers were selected to develop the pilot compendium. These papers were identified by only selecting studies that included original flood models. The selection was limited to functions that: (i) were related to the building sector; (ii) were developed for computing direct damages (*i.e.*, direct physical damage); (iii) were developed for floods (specifically fluvial flood). The model taxonomy proposed in Table 3 was used to catalog the

586 identified models/relationships. Not surprisingly, most of the research has been mainly conducted in a few flood-
587 prone countries, where funding and research were available to perform existing studies.
588

589 An in-depth screening of scholarly literature was undertaken using both Google Scholar and Scopus because the
590 databases of the two research engines have different characteristics. Indeed, Google Scholar covers any document
591 with a seemingly academic structure, including for example, conference proceedings, while Scopus comprises a
592 database of documents—mainly journal papers—from approximately 5,000 publishers that have been selected by
593 an independent committee. Similarly to Gerl *et al.* (2016), the following keywords were searched in the different
594 web search engines using the option “search in all fields” without imposing any date restriction: “flood catastrophe
595 risk model”, “flood vulnerability function”, “flood vulnerability curve”, “flood vulnerability model”, “flood
596 fragility function”, “flood fragility curve”, “flood fragility model”, “flood damage function”, “flood damage curve”,
597 “flood damage model”. A cross-reference approach between the identified documents was implemented to select
598 additional publications of interest. A final check of gray documentation, such as policy reports, and open-source
599 peer-reviewed papers/reports was performed.
600

601 It is worth noting that the description of the selected models/relationships is quite heterogeneous, reflecting that
602 the required information is often not provided explicitly.
603

604 **5.1.1. Europe**

605 In Europe, most flood-prone areas are located in Germany, the Netherlands, and Italy. In Germany, extensive
606 literature is available.
607

608 Merz *et al.* (2004) developed depth–damage curves and quantified the uncertainty of direct monetary flood damage
609 estimates to flooded buildings in southwest Germany. They analyzed more than 4,000 (direct, tangible) damage
610 records for nine flood-related events in the period 1978–1994 of six economic sectors (private housing, public
611 infrastructure, service, industry, manufacturing, and agriculture); for these sectors, a non-parametric regression
612 (Epanechnikov-kernel, bandwidth equal to 0.6 m) was performed between the total damage (damage to the fabric,
613 fixed, and movable inventory) and water depth. The study demonstrated that the damage data follow a Lognormal
614 distribution with considerable variability, which is only partially reduced by dividing the data into subsets based
615 on flood depth and building use. It was concluded that considering more damage-influencing factors (besides flood
616 depth and building use, *e.g.*, using building types) could improve the estimation of flood damages.
617

618 Apel *et al.* (2004) investigated the levee breaches during the Elbe catchment floods in August 2002. Within the
619 damage estimation, total direct monetary losses of different sectors (private housing, public infrastructure,
620 industry, traffic and communication engineering, buildings in agriculture, energy and water supply, agricultural
621 area) were related to the inflow water volume due to the levee failure, by combining sector-specific replacement
622 value (EUR/m², from regional authorities) and stage-damage curves (derived per m² inundated area per economic
623 sector). Monte Carlo simulations were performed to analyze uncertainty; they found that damage estimation can
624 be refined by using historical data collected in the aftermath of the event.
625

626 Buchele *et al.* (2006) discussed a multifactorial approach to damage estimation, considering damage-influencing
627 factors besides the water depth, *i.e.*, building quality, contamination, and precautionary measures. Damage data
628 from 1697 household interviews after the 2002 Elbe and Danube flood were gathered and divided into sub-samples
629 according to various factors (*e.g.*, building type, use, quality). A GIS-tool is developed to estimate damages (both
630 in absolute monetary units, *i.e.*, EUR, or percentages of damage), divided for building fabric and content; the user
631 can choose among different functions (Linear Polygon Function, Square-Root Function, or Point-based Power
632 Function).
633

634 Kreibich *et al.* (2009) examined the importance of flood velocity as an intensity measure for computing flood
635 damage since most studies are limited to consider water depth only. The study investigated damages to residential
636 buildings impacted by Elbe river floods in August 2002, finding that the energy head (*i.e.*, water depth plus the
637 square of the velocity divided by two times the acceleration of gravity) could be a suitable IM for residential

638 buildings (considering a critical depth level > 2 m). By contrast, flow velocity alone was instead not recommended
639 as an IM for estimating monetary loss.

640
641 The same 2002 dataset was used by Schwarz and Maiwald (2009, 2012) to validate a loss prediction model. They
642 developed a damage classification based on five damage grades correlated to the water depth. Six vulnerability
643 classes (from A to F) described the flood vulnerability of both masonry and reinforced concrete structures, from
644 which fragility functions were derived. Results showed a good agreement between the estimate and the reported
645 losses. This methodology was also applied for tsunami-generated water flow in Chile (2010).

646
647 For the Netherlands, Jonkman *et al.* (2008) developed stage-damage functions for computing physical damage to
648 buildings, land use (*e.g.*, agriculture) as a function of water depth and flow velocity. These functions were derived
649 from empirical flood damage data collected during the river Meuse floods in 1993.

650
651 Gersonius *et al.* (2008) constructed flood damage curves to investigate private floodproofing of residential
652 buildings through a synthetic approach. Water depth was considered as IM and simulated, employing a
653 probabilistic model. The benefit for each damage reduction measure was computed by estimating the difference
654 in expected annual loss (EAL) compared to traditional buildings.

655
656 In Italy, Scorzini and Frank (2015) developed depth–damage functions based on damage data for the 2010 flood
657 event in the Veneto Region. A coupled hydrological-hydraulic model was adopted to simulate inundation features,
658 whereas loss data were collected from a database of 319 residential reinforced concrete and masonry buildings.
659 Linear regression was used to develop original local depth–damage functions at meso- (land-use units) and micro-
660 scale (building level). The variability of the outputs was found lower for the micro-scale model. Thus, it was
661 concluded that models transferability depends on (but it is not limited to) the similarity in terms of IMs and/or
662 building characteristics.

663
664 Dottori *et al.* (2016) presented a new synthetic flood damage model named INSYDE (IN-depth Synthetic model
665 for flood Damage Estimation) to compute physical damages to buildings. The damage functions were developed
666 using expert-opinion, literature, and loss data for about 60 buildings affected by the November 2012 flood in the
667 Umbria region (central Italy). Chi-square hypothesis tests showed a high correlation between water depth and
668 building components, whereas flood duration and water quality seemed less significant. The model was validated
669 with loss data from 2010 floods in Caldugno (Veneto region, North-East Italy), related to about 300 buildings;
670 results showed a good fit with the estimations.

671
672 In Spain, Velasco *et al.* (2016) advanced synthetic absolute depth–damage curves for the Raval district (1.09 km²)
673 in Barcelona by implementing a hydrological-hydraulic model. The curves were developed for six different
674 categories (warehouses and parking areas; commercial; residential; hotels and leisure; public and cultural
675 buildings; sites of interest) and validated through surveys and data from Spanish reinsurance companies; simulated
676 damages represented an upper bound to the actual costs of the district.

677 678 **5.1.3. South America**

679 In Brazil, Nascimento *et al.* (2006) developed flood damage functions in relation to the water depth for residential
680 buildings. The functions were obtained through systematic post-event surveys (city of Itajubá, January 2000 flood
681 event), which provided information for 469 affected buildings. No validation was offered in the study.

682 683 **5.1.4. Asia**

684 In Thailand, the research of Tang *et al.* (1992) estimated the cost of flood damage using flood damage functions
685 obtained by regression. For the city of Bangkok (flood event in 1983), a survey based on a sample of 3522 buildings
686 from the residential, commercial, agricultural, and industrial sectors was used. Flood depth and duration seemed
687 the most relevant factors in relation to residential and industrial assets, whereas flood depth resulted in being
688 crucial for commercial and agricultural areas only.

689

690 In Japan, Herath (2003) derived stage-damage functions from data available in relation to past flood events or
691 analytical descriptions of flood damage. The study considered the flooded area and water depth as IMs. Stage-
692 damage functions were derived for several categories, considering both urban and agricultural damages. Dutta *et*
693 *al.* (2003) presented an integrated model for flood loss estimation based on stage-damage relationships. The model
694 accounted for tangible damage to urban, rural, and infrastructure sectors (divided into subcategories), in relation
695 to water depth. The method was applied to the Ichinomiya river basin for the 1996 flood events caused by heavy
696 rainfall. Results showed that the model performed well in urban damage estimation; however, validation was not
697 possible for rural and infrastructure damage estimation due to the lack of observed data.

698
699 Zhai *et al.* (2005) used 3036 household questionnaire-based surveys after the 2000 Tokai flood (Japan) to derive
700 damage probability functions using multivariate regression. The inundation depth was considered as the most
701 critical factor in determining the flood damage to residential buildings. In addition, other parameters like
702 preparedness or income, were considered.

703
704 In Taiwan, Chang *et al.* (2008) attempted to develop a residential flood damage function from post-event
705 interviews after the 2001 Nari Tphoon in the Keelung river basin (302 questionnaires). Flood damages were
706 related to flooding depths through a traditional regression model (Ordinary Least Squares); that regression was
707 then modified by a Geographically Weighted Regression, which introduced damage location into the function.
708 The modified model performed better than its initial version.

709 710 **5.1.5. Australia**

711 Smith *et al.* (1990) developed stage-damage functions using surveys undertaken after the Sydney flood in August
712 1986 (71 properties). Damages are computed for building (residential, commercial, and industrial), content, and
713 vehicles considering water (overflow) depth and low velocity flow. They recorded the characteristics of the
714 properties using the taxonomy of ANUFLOOD. However, such records were not presented in the paper.

715
716 Gissing and Blong (2014) studied flood damage for commercial properties in the catchment of Kempsey (NSW,
717 Australia). Three surveys were conducted after a flood in 2001 to collect data on water depths and damages. That
718 activity supported the evaluation of losses in terms of direct damage. Regression analysis allowed to relate water
719 (over-floor) depth with direct damage per square meter. Size, type of building, and contents are the factors that
720 affected businesses' vulnerability, together with the type of business.

721 **Table 4. Compendium of existing vulnerability and fragility models/relationships [Note: this table is placed here as a Figure to avoid formatting**
 722 **issues; the original .xls file is provided with the manuscript].**
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EXISTING STUDY			DAMAGE AND LOSS MEASURES				BUILDING CLASSIFICATION										FLOOD INTENSITY				DATA QUALITY				METHOD	
Reference	Type of assessment	Source	Damage scale	No. of Ds	Loss parameter	Coverage	Construction material	Structural system	Foundation	Age	Height/No. of stories	Floor/Walls material	Percentage of openings	Presence of basement	Flood Design	Occupancy class	Flood type	Intensity measure	Range of IM	IM estimation method	Country/ies	Source of data	No. of assets	No. of data points	Functional form	Type of analysis
Apel et al. (2004)	V	E	-	-	L	building	na	na	na	existing	na	na	na	na	na	residential commercial industrial	fluvial	IV	0 - 120×10 ⁶	HD	Germany	Cologne (1961-1995)	na	na	MC	UDF
Büchle et al. (2006)	V	E	-	-	DR	building	na	na	na	existing	na	na	na	Yes	Yes	residential	fluvial	WD	0 - 1.5	HD	Germany	Elbe and Danube river basins (2002)	1697	na	MC	R
Chang et al. (2008)	V	E	-	-	L	building	na	na	na	existing	na	na	na	na	na	residential	fluvial	WD	na	S	Taiwan	Keelung river basin (2001)	302	na	MC	R
Dottori et al. (2016)	V	S	-	-	L	structure content	na	na	na	existing	na	na	na	Yes	na	residential	fluvial	OFD FD WD, WV	> 0	HD S	Italy	Umbria Region (2012)	60	na	MC	na
Dutta et al. (2003)	V	E S	-	-	DR	structure content	C W	frame	na	existing	up to six stories	na	na	na	na	residential non-residential	fluvial	WD	0 - 6	HD S	Japan	Ichinomiya river basin (1996)	na	na	MC	na
Gersonius et al. (2008)	V	S	-	-	L	structure content	C	frame	na	existing	detached semidetached multistorey	C	na	No	Yes	residential	fluvial	WD	0.3 - 2.4 > 2.4	HD	Netherland	na	na	na	na	na
Gissing & Blong (2004)	V	E	-	-	L	building	na	na	na	existing	na	na	na	na	na	commercial	fluvial	OFD	0 - 2.5	S	Australia	Kempsey (2001)	94	na	MC	R
Jonkman et al. (2008)	V	E	-	-	DR	structure content	na	na	na	existing	low-rise mid-rise high-rise	na	na	na	na	residential commercial	fluvial	WD	0 - 4.5	HD	Netherland	Meuse river basin (1993)	na	na	MC	na
Herath (2003)	V	E S	-	-	DR	building	W non W	na	na	existing	na	na	na	na	na	residential industrial	fluvial	WD	na	HD S	Japan	Ichinomiya river basin (1996)	na	na	MC	na
Kreibich et al. (2009)	V F	E	Schwarz and Maiwald (2012)	5	L	building	na	na	na	existing	na	na	na	na	na	residential	fluvial	WD H	0 - 2 0 - 3	HD	Germany	Elbe and Mulde river basins (2002)	na	na	na	na
Merz et al. (2004)	V	E	-	-	L	building	na	na	na	existing historical	na	na	na	Yes	na	residential commercial industrial	fluvial	WD	0.5 - 4	S	Germany	Events during 1978-1994	4000	na	PD	R
Nascimento et al. (2006)	V	E	-	-	L	building	na	na	na	existing	na	na	na	na	na	residential	fluvial	WD	0 - 3.5	S	Brazil	Itajuba (2000)	469	na	MC	R
Schwarz & Maiwald (2009; 2012)	F	E	Developed by the authors	5	na	building	C M	frame wall	na	existing new	na	na	na	Yes	na	residential	fluvial	WD H	na	S	Germany Chile	Saxony (2002) Dichato (2010)	na	na	MC	R
Scorzini and Frank (2015)	V	E	-	-	L	building	na	na	na	existing	detached semidetached multistorey	na	na	Yes	na	residential	fluvial	WD	0 - 4	H	Italy	Caldogno (2010)	319	na	na	R
Smith (1994)	V	E	-	-	L	building	M	na	na	existing	one story	na	na	na	na	residential	fluvial	WD	0 - 2	S	Australia	Sydney (1986)	71	na	MC	na
Velasco et al. (2016)	V	S	-	-	L	building	na	na	na	existing historical	na	na	na	Yes	na	residential commercial	fluvial	WD	0 - 1 > 1	H	Spain	na	na	na	na	na
Tang et al. (1992)	V	E	-	-	L	building	W non W	na	na	existing	na	na	na	na	na	residential commercial industrial	fluvial	FD WD	na	S	Thailand	Bangkok (1983)	3522	na	MC	R
Zhai et al. (2005)	V F	E	Developed by the authors	1	DR L	structure content	W non W	na	na	existing	up to three stories	na	na	na	Yes	residential	fluvial	WD	0 - 2.1	S	Japan	Tokai area (2000)	3036	na	MC PD	R

725 Explanatory legend. In “Existing study”, Type of assessment: *F* = fragility or *V* = vulnerability; Source: *E* =
726 empirical or *S* = synthetic. In “Damage and loss measures”, *DR* = Damage Ratio, repair cost vs replacement
727 cost or *L* = loss, i.e. repair cost. In “Building classification”, Construction material: *M* = Masonry or *C* =
728 Concrete or *W* = Wood. In “Flood intensity”, Intensity measure: *WD* = Water Depth [m] or *WV* = Water
729 Velocity [m/s] or *OFD* = Over-floor depth [m] or *H* = specific energy height [m] or *FD* = flood duration [days]
730 or *IV* = inflow volume [m³]; Main IM estimation method: *S* = surveyed or *HD* = hydrological/hydraulic model.
731 In “Method”, Functional form: *MC* = mean curve or *PD* = probability distribution; Type of analysis: *R* =
732 regression or *UDF* = univariate distribution fitting.

733

734 5.2. Discussion

735 Despite considerable progress in the development of loss estimation tools since the 1980s, loss estimates still
736 reflect high uncertainties and disparities that often lead to questioning their quality. Assessing the validity and
737 robustness of loss model components is crucial as various model assumptions may affect prioritization and
738 investment decisions in flood risk management and regulatory requirements and business decisions in the
739 (re)insurance industry. Hence, more effort is needed to quantify uncertainties and undertake validations,
740 particularly in physical vulnerability modeling. These concerns emphasize the need for a rational, integrated, and
741 comprehensive compendium of existing flood-related fragility and vulnerability models to be used in probabilistic
742 flood risk assessment. This requires, in turn, an *ad-hoc* model taxonomy for flood fragility and vulnerability
743 assessment, as proposed in this study for buildings.

744

745 The proposed model taxonomy has been used to analyze a selection of studies from the literature and develop a
746 pilot-compendium of flood fragility/vulnerability models/relationships. The focus is on fluvial floods and direct
747 losses due to a flood event's direct physical impact. As expected, all the models were constructed for only a few
748 flood-prone developed countries, in particular, Australia, Germany, and Japan (Figure 4a). The developed
749 compendium contains 18 models, of which 15 include vulnerability relationships, one is a fragility model, and two
750 present a combination of both models (Figure 4b). More than 62% of the models relate to residential buildings,
751 while approximately 21% and 17% relates to industrial and commercial building, respectively. Most of the studies
752 (44%) does not report information about the number of assets used to develop the functions (Figure 4c); this
753 prevents from understanding the scale and the detail/quality of the study, as well as the reliability of the proposed
754 models, as discussed above.

755

756 Moreover, it is possible to appreciate that almost all models/relationships are based on data from a single flood
757 event/river basin; thus, those relationships often cover a small range of IM levels and typically contain few
758 observations for a high level of damage or loss. The water depth is considered by far the most important factor to
759 explain flood loss (almost 67% of the studies); although the water depth is accepted as the most relevant IM, other
760 parameters should be considered (e.g., flow velocity) to fully explain the damage. Other variables, such as flood
761 preparedness, the time of the flood event, flood alerts, could contribute to explain flood losses; however, these
762 seem to play a minor role (Zhai *et al.*, 2005; Gerl *et al.*, 2016) in loss computation.

763

764 The pilot-compendium highlighted consistency issues with data/information in terms of accuracy and
765 completeness, undermining both qualitative and quantitative assessment. Firstly, the gathered models do not
766 present a homogenous quality in terms of data and suffer from incomplete information on the structural
767 characteristics of buildings (e.g., basement presence, among many others). In particular, important factors affecting
768 vulnerability and relevant in an exposure model for flood are often not adequately considered, such as type of
769 foundations or building-specific features (e.g., type of floors, opening percentage). Secondly, details on the
770 statistical modeling used, the number of data points considered, and the treatment of the uncertainty are frequently
771 not addressed in the existing studies. As a result, “NA” tag indicates that around 48% of all the compendium
772 entries and even basic factors (like the construction age, the construction material, and the structural system) show
773 extensive missing data in the records.

774

775 This exercise results in a compendium of flood vulnerability relationships that are highly heterogeneous and
776 generally not accompanied by explicit validation at the time of their proposal. This lack of reliable information
777 particularly undermined the application of various rating systems to judge the validity and transferability of the

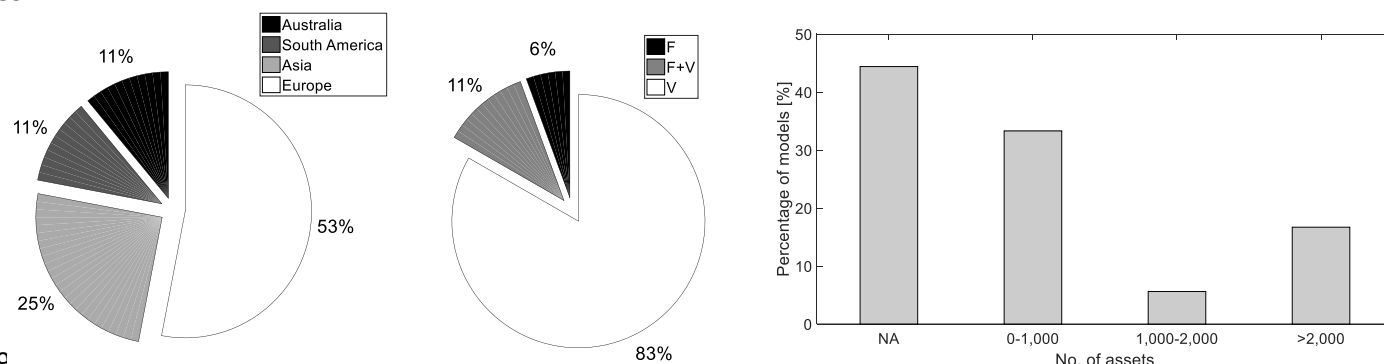
778 selected models/relationships. This can prevent from the development of robust flood risk models or perform
 779 accurate flood risk assessment exercises, as required by risk modelers or (re)insurance companies. The approach
 780 proposed by Figueiredo *et al.* (2018), relying on developing multi-model ensembles to assess existing flood loss
 781 models and associated uncertainty, is generally recommended to obtain accurate flood loss estimates and reliable
 782 probability distributions of model uncertainty.

783

784 A robust protocol of data collection and organization, particularly in post-event settings, is a prerogative for the
 785 creation of sound and flexible databases, which should also be able to accommodate future data collection via
 786 digital systems (*e.g.*, improved forms/procedures for post-event damage/loss data collection, perhaps implemented
 787 in mobile applications).

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Figure 4. Statistics derived from the compendium (Table 3): (a) country of the data source; (b) type of assessment used in the study: V – Vulnerability, F – Fragility, V+F – both; (c) number of assets used in the study/model.

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6. CONCLUDING REMARKS

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This paper has presented (i) an overview of catastrophe risk modeling, with emphasis on flood risk assessment and the methods to develop fragility and vulnerability relationships for flood; and (ii) a model taxonomy and a pilot compendium of existing fragility and vulnerability models/relationships for flood. Despite the number of relationships available, it is noted that their quality and geographical applicability may significantly vary. More specifically, existing empirical fragility and vulnerability relationships are typically based on databases associated with important quality issues, including a low level of refinement/details on the building class and damage states (if considered), scarcity of observations, especially at high flood intensities and damage states. Furthermore, there is no consensus in the literature concerning the functional form of empirical vulnerability and fragility functions or on best-practice methodologies for modeling and communicating the uncertainty related to those functions.

These observations highlight the need for improved protocols for collecting loss and damage data in post-flood scenarios to provide a sound basis for the derivation of future empirical vulnerability and fragility relationships. There is also an urgent need to develop a rational, statistically correct, widely accepted method to construct empirical fragility and vulnerability, which explicitly quantifies and models the uncertainty in the data and clearly communicates the uncertainty in the considered models.

This work has the potential for future development in multiple directions. First of all, the compendium could be reviewed to include additional available models and additional categories (*e.g.*, functions related to crops or infrastructure damages). On the condition that functional forms are made available by relevant studies, the compendium could be implemented on the internet, enabling user-friendly consultation and download.

A rating system of existing models is considered a fundamental prerequisite for using functions with confidence, thus producing meaningful results. This is extremely reliant on the quality and completeness of the compendium. Currently, the reliability of the available functions is often unknown.

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