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Evaluating targeted heuristics for vulnerability assessment in flood impact model chains

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Abstract

In flood risk management, the choice of vulnerability functions has a remarkable impact on the overall uncertainty of modelling flood damage. The spatial transferability of empirical vulnerability functions is limited, leading to the need for computation and validation of region-specific vulnerability functions. In data-scarce regions however, this option is not feasible. In contrast, the physical processes of flood impact model chains can be developed in these regions because of the availability of global datasets. Here we evaluated the implementation of a synthetic vulnerability function into a flood impact model. The function bases on expert heuristics on a targeted sample of representative buildings (targeted heuristics). We applied the vulnerability function in a meso-scale river basin and evaluated the new function by comparing the resulting flood damage with the damage computed by other approaches, (1) an ensemble of vulnerability functions available from the literature, (2) an individual vulnerability function calibrated with region-specific data, and (3) the vulnerability function used in flood risk management by the Swiss government. The results show that targeted heuristics can be a valuable alternative for developing flood impact models in regions without any data or only few data on flood damage.

KEYWORDS

extreme events, flood damages, floodplain, vulnerability

1 | INTRODUCTION

The analysis of flood impacts requires the combination of simulation models for natural processes (climate, meteorology, hydrology, and hydrodynamics) and models simulating the impacts of these processes on elements at risk, such as assets, citizens, and, in a broader sense, socio-economic activities. The coupling of specialised and therefore often disciplinary models for selected processes towards a coupled component modelling framework has repeatedly been proposed for integrated assessments of flood risk (Falter et al., 2015; Falter et al., 2016; Zischg, 2018). For example, Ward et al. (2015), Felder et al. (2018), and Hoch et al. (2019) provide an overview of coupling global or regional climate models, hydrologic models, and inundation models. Moreover, data availability for setting up global, continental, or basin-wide model chains for flood risk analyses increased remarkably, especially due to improved remote sensing and sensor technologies. Global or continental datasets on topography (e.g., Courty et al., 2017; Yamazaki et al., 2017; Yamazaki et al., 2019), land use, rainfall reanalyses (Andreadis et al., 2017), river network (Andreadis et al., 2013), river morphology (Yamazaki et al., 2014), runoff (Fekete et al., 2002) or even hazard maps (Alfieri et al., 2016; Hirabayashi et al., 2013) are increasingly available (Trigg et al., 2016). These data are easing the setup of flood models in various regions of the world, even in data-scarce regions.

In contrast, reliable flood impact models (i.e., exposure models and flood vulnerability functions) are still not available for many regions in the world (Fuchs et al., 2015; Jongman et al., 2014). These models rely on region-specific data such as spatial distribution of the values at risk (buildings, infrastructure; e.g., Jongman et al., 2012; Eberenz et al., 2020), the construction characteristics of buildings and infrastructure (Englhardt et al., 2019; Veerbeek & Zevenbergen, 2009; Zischg et al., 2013), and their physical vulnerabilities to floods (e.g., Aznar-Siguan & Bresch, 2019). Moreover, the choice of vulnerability functions (as well as vulnerability indictors) is still responsible for a major share in the overall uncertainties of flood impact models (Apel et al., 2004; Apel et al., 2008; Keller et al., 2019; Merz et al., 2004; Papathoma-Köhle et al., 2019; Zischg, Felder, Mosimann, et al., 2018; Zischg, Felder, Weingartner, et al., 2018).

Vulnerability functions are usually computed by means of statistical analyses of region-specific damage data (Fuchs, Keiler, et al., 2019; Papathoma-Köhle et al., 2017). However, they are rarely adjusted to different socio-economic conditions when applied to other regions (Amadio et al., 2016). Hence, the transferability of flood vulnerability functions from one region to another has been repeatedly debated (Cammerer et al., 2013; Fuchs, Keiler, et al., 2019; Mosimann et al., 2018). Besides from statistical analyses resulting in functions for assessing the physical vulnerability of buildings or other infrastructure, detailed physical modelling may also be an alternative for developing vulnerability functions. For example, Sturm et al. (2018a, 2018b) showed a model approach based on laboratory experiments to assess the physical vulnerability of buildings. Currently, also machine learning approaches are used for deriving vulnerability functions (e.g., Amadio et al., 2019; Sultana et al., 2018; Terti et al., 2017). Another alternative is the development of synthetic models for assessing the physical vulnerability of elements at risk. These models are based on "what-if analyses" and rely on expert-based assessments. Often these models are called synthetic stage-damage curves and can be deduced by expert knowledge (e.g., Naumann et al., 2009; Penning-Rowsell, 2010) or are a combination of expert knowledge and empirical data (e.g., Department of Natural Resources and Environment, 2000). For instance, Dottori et al. (2016) developed a component-by-component analysis of physical damage to buildings. Damage to the building are estimated by steadily increasing the parameters for flood magnitude based on the assessment of costs for repairing the damaged parts. They generalise the relation between the magnitude of a hazard event, the impact on the building envelope and the resulting damage. Resulting vulnerability functions were computed using an expert elicitation approach with the support of existing scientific and technical literature. A similar approach has been presented by Neubert et al. (2016) who developed synthetic vulnerability functions for different building types based on civil engineering analyses of the building constructions. Nevertheless, vulnerability functions often lack validation (Molinari et al., 2018) which results in damage assessment bias. For an extended review on recent developments in vulnerability functions see Fuchs, Keiler, et al. (2019).

Common to all these approaches for vulnerability assessment is that they rely on data in one or another form. In data-scarce regions, however, in-depth information required for developing region-specific flood vulnerability functions is usually not available (Englhardt et al., 2019; Malgwi et al., 2020). Yet, model chains for assessing hazards can still be applied and set up (although sometimes with limited reliability) because of the availability of the required input data and their given regional transferability due to the global validity of their underlying physical processes. However, the transfer of vulnerability functions to new case studies is limited due to the variety in socio-economic conditions, for example, the tradition of construction typology, construction material, or main functionality of buildings. If no damage data is available for developing or validating vulnerability functions, the only possible ways for selecting a suitable vulnerability function to implement in flood impact model chains are to develop a synthetic function based on expert-elicitation or by selecting the most representative function from existing functions by means of a model comparison.

The main aim of this study is firstly to develop a synthetic vulnerability function by targeted heuristics and to implement this newly developed function in a flood impact model chain for simulating a high number of flood scenarios. We want to show how only few buildings can be used as representatives for vulnerability assessment of a larger population, based on the location of a building within the flooded areas and on its functionality. We hypothesise that a targeted selection of representative buildings based on flood model outputs and building characteristics allows an efficient development of synthetic flood vulnerability functions in regions without flood damage data. Secondly, we aim at assessing the effects of flood event and floodplain characteristics on the evaluation of a new vulnerability function. Due to a lack of damage data available for a thorough model validation, we evaluated the new function by a comparison with other functions. We hypothesise that the evaluation of a vulnerability function is influenced by the characteristics of the flood event and the floodplain, as well as by the regional variability of building characteristics. To gain a robust evaluation, we applied the different vulnerability functions for a high number of modelled flood scenarios over multiple floodplains with different characteristics of the flood processes and with different -socio-economic settings (urban and rural, residential and industrial).

2 | METHODS

2.1 | Flood modelling

The study area consists of seven main floodplains located along the Aare River upstream of Bern, Switzerland with different flood characteristics. Two floodplains are characterised by river flooding only (Aare River and Guerbe River), two floodplains are characterised by lake flooding (lateral shores of Lake Thun and Lake Brienz), and three floodplains are characterised by combined river and lake flooding (city of Thun, city of Interlaken, floodplain of Hasliaare River, see Figure 1). In a first step, we set up the model chain for simulating the physical processes of flooding in the case study area. We used a coupled component model described in Felder et al. (2017) and Zischg, Felder, Weingartner, et al. (2018). This model aims at identifying the probable maximum flood damage on buildings under probable maximum precipitation within 3 days. The model chain applied simulates a set of different spatio-temporal rainfall patterns over the river basin with a Monte-Carlo procedure (Felder & Weingartner, 2016). The rainfall sum and the study area were set constant for all simulations. From the total set of simulations, we selected 150 flood maps related to different rainfall patterns. The resulting floods differ remarkably in terms of peak outflow from the river basin, number and locations of exposed buildings, and inundation depth at the exposed buildings.

2.2 | Targeted heuristics

The main idea underlying the concept of targeted heuristics is first to set up a flood model and simulate different

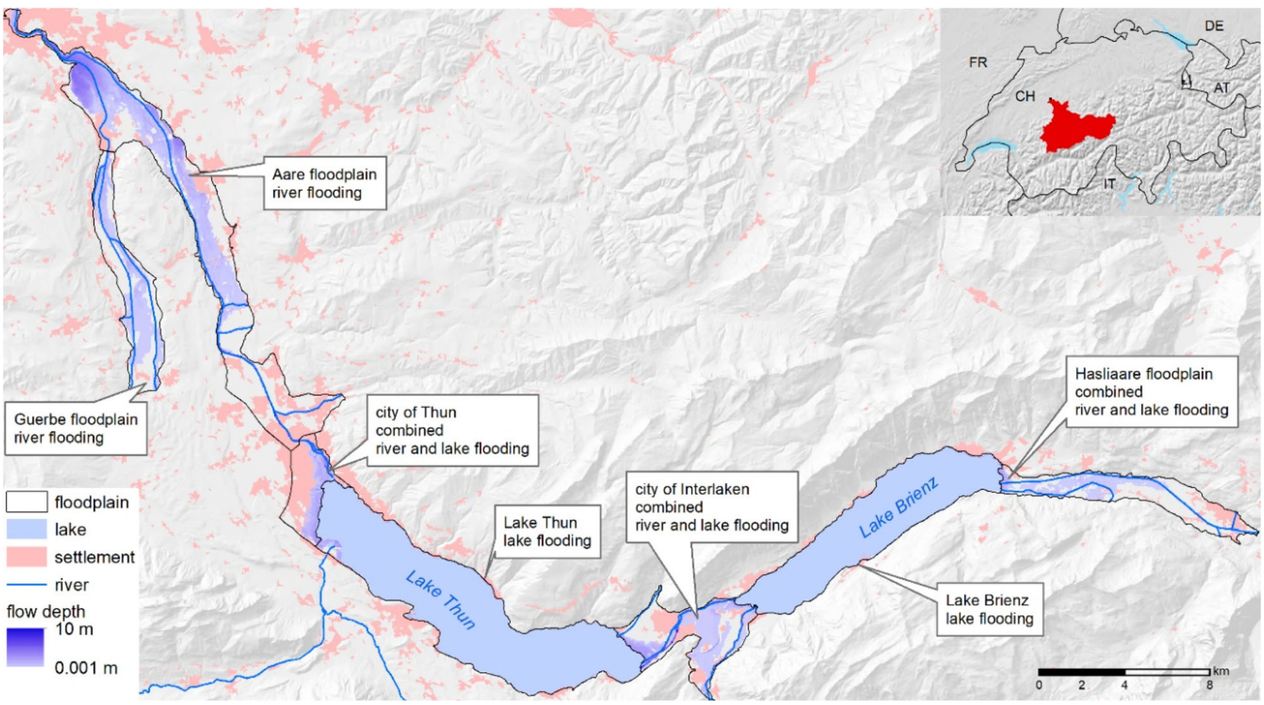

FIGURE 1 Characteristics of the floodplains in the river basin of the Aare River upstream of Bern, Switzerland. Background map: (Swisstopo, 2019). The map shows the maximum flood depth over all scenarios

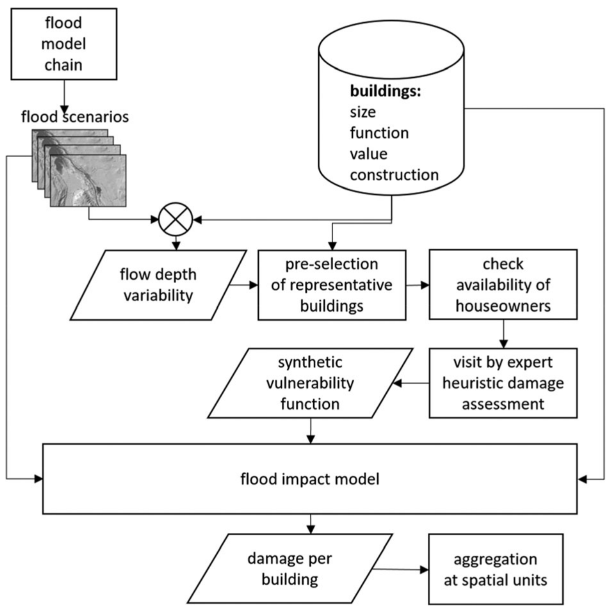

FIGURE 2 Procedure of the development of flood vulnerability functions for representative building types based on targeted heuristics

flood scenarios, and second to select representative buildings in flooded areas with a high variability of flood depths over all simulations. These selected representative buildings are then visited by a professional damage assessor and a synthetic depth-damage curve is developed in an expert elicitation approach. This targeted selection of representative buildings in flood prone areas that is used as a sample for elaborating a synthetic vulnerability function by expert reasoning is hereafter termed as '*targeted heuristics*'. The approach differs from established approaches for developing synthetic damage functions (e.g., Penning-Rowsell and Chatterton, 1977; Penning-Rowsell et al., 2005; USACE, 1997) by this targeted selection of the sample for expert assessments. The procedure is schematized in Figure 2.

2.2.1 | Targeted selection of representative buildings

In this study, we use an existing dataset of buildings with the replacement costs modelled on the basis of Swiss building insurance claim data and the building volume calculated from the footprint area of buildings and their height above ground (Röthlisberger et al., 2018). Replacement costs correspond to the financial resources needed to reconstruct damaged buildings or building parts and are used by default as building values in cost–benefit analyses in Switzerland (Bründl et al., 2009; Fuchs & McAlpin, 2005). Insurance companies in Switzerland determine the insured value of a building by the replacement costs. In addition to the size and value of the building, this dataset also contains the age of construction and the building purpose. The buildings are overlaid with the 150 flood depth maps and the flood depth of each flood scenario is attributed to each building by the maximum value at each vertex of the building footprint outline (Bermúdez & Zischg, 2018). This results in 150 different flood depths for each building. This overlay gives a range of flood depths for each building. In order to provide the damage assessor with a list of representative buildings to be visited and to heuristically estimate the damage for selected flood depths, the range in flood depths is the first criterion for selecting representative buildings. This means that a representative building should be subject to a variability of flood depths ranging from nearly >0 m to at least >1 m over the 150 flood simulations. The underlying assumption for choosing this criterion was to avoid the selection of buildings that are either located in proximity to rivers, in local terrain depressions, or at the external borders of flood-prone areas. Buildings in the close proximity of rivers or in local terrain depressions are expected to be more frequently affected by floods than buildings in other locations and were not considered as representative because of an additional high likelihood of local flood protection measures. These buildings experience high flood depths over all scenarios. In contrast, buildings located at the outer borders of flood-prone areas were supposed to show a below-average exposure and where therefore not included in the set of representative buildings. A second criterion is the building type so that the major construction typologies can be mirrored in the vulnerability assessment. Specifically, the following building types were considered:

a. old detached single-family building (constructed before 1990),
b. new detached single-family building (constructed after 1990),
c. old apartment building (constructed before 1990),
d. new apartment building with more than three housing units (constructed after 1990),
e. large commercial property with a relatively high insured value (not classified as single-family or apartment building, building value above 850,000 CHF),
f. small commercial property with a relatively low insured value (not classified as single-family or apartment building, building value up to 850,000 CHF),

The owners or residents of the primary selection of representative buildings were contacted by phone and by means of written letters. We asked the owners or the occupants for agreeing to visit their building for the purpose of this study and to report the insured value of the building. The final selection of representative buildings with permission to being inspected consisted of two buildings per category ($n = 12$). The size of the buildings sample for being visited was limited by the amount of available resources. The expert had three field days for visiting the selected buildings. An additional but not systematically considered criterion for triaging was the geographical location of the buildings within the most recent flood event in August 2005, and buildings located within the flooded area of this event were selected with a higher priority because of the possibility to compare the damage estimations with the damage experienced in 2005. If available, the damage of the affected houses caused by this flood event has been reported to the expert by the house owner. The expert used this information for a plausibility check of his own assessment.

2.2.2 | Damage assessment heuristics

The professional loss assessor inspected the buildings from outside and inside, looking mainly at the characteristics of building material, construction technology, electricity installation, status of smart home technology, building design (configuration of building openings such as doors and windows), and presence or absence of a basement. For each of the flood depth classes (>0–0.25 m, >0.25–0.5 m, >0.5–0.75 m, >0.75–1 m, >1–1.25 m, >1.25–1.5 m, >1.5 m), the assessor described the damage type (damage by moisture, direct water damage, and structural damage) and calculated the refurbishment costs by estimating separately necessary repair costs. Due to the pre-analysed flood depths, the damage assessor focused on potential damage in the basement and ground floors. We then normalised the resulting absolute damage estimation by the insured value of the building. This resulted in a synthetic vulnerability function (targeted heuristic) for determining the degree of damage from the flood depth for each representative building. We averaged the two vulnerability functions per building category into one vulnerability function per building category. The vulnerability function developed with the targeted heuristics approach was implemented into a flood impact model. We computed the damage for each building for each of the 150 flood scenarios.

2.3 | Comparison with other vulnerability functions

Due to privacy reasons, we were not allowed to assess claim data from the mandatory insurance company in the study area. To evaluate the reliability of the proposed procedure, we compared the results of the targeted heuristics approach with the results of other available vulnerability functions. Specifically, we compared the developed targeted heuristics approach with (i) an ensemble of vulnerability functions from the literature, (ii) a vulnerability function calibrated with region-specific data, and (iii) a vulnerability function used by authorities responsible for flood risk management in Switzerland. The main principle of this comparison was to keep the building dataset and the flood scenarios constant and to analyse the differences between the outcomes of the vulnerability computation. All vulnerability functions therefore computed the damage based on the predicted relative degree of damage multiplied by the same reconstruction value of the building of the used building dataset of Röthlisberger et al. (2018).

2.3.1 | Ensemble of vulnerability functions from the literature

To account for the uncertainties in flood damage assessment, Figueiredo et al. (2018) proposed combining several vulnerability functions to a multi-model ensemble. This allows also considering the uncertainties due to the transfer of flood vulnerability functions that are calibrated in one socio-economic region to another. Moreover, we expected a range of different flood processes in our study area, including lake flooding, river flooding and flooding with sediment transport. Thus, we combined the models of Dutta et al. (2003) (residential structure), Jonkman et al. (2008), Karagiorgos et al. (2016) (buildings with cellar), and Fuchs, Heiser, et al. (2019) (Figure 3b). All of them consider flood magnitude in terms of flood depths as explaining variable for calculating the degree of damage and are applicable on an object scale. Thus, they have a degree of model complexity comparable to the targeted heuristics approach. The selection of these functions was guided by the comparability of the underlying concept, the comparability of the original and the present context, the targeted spatial scale (i.e., single building scale), the diversity in the underlying formula, and by a difference in the range of degree of damage values. The outcome of these functions is the degree of damage, which can be multiplied with the replacement costs of the building to estimate the damage resulting from the flood scenario. Using this multi-model ensemble will show the upper and lower bounds of damage estimations by vulnerability functions that had been developed outside of the study area and were transferred to our case study.

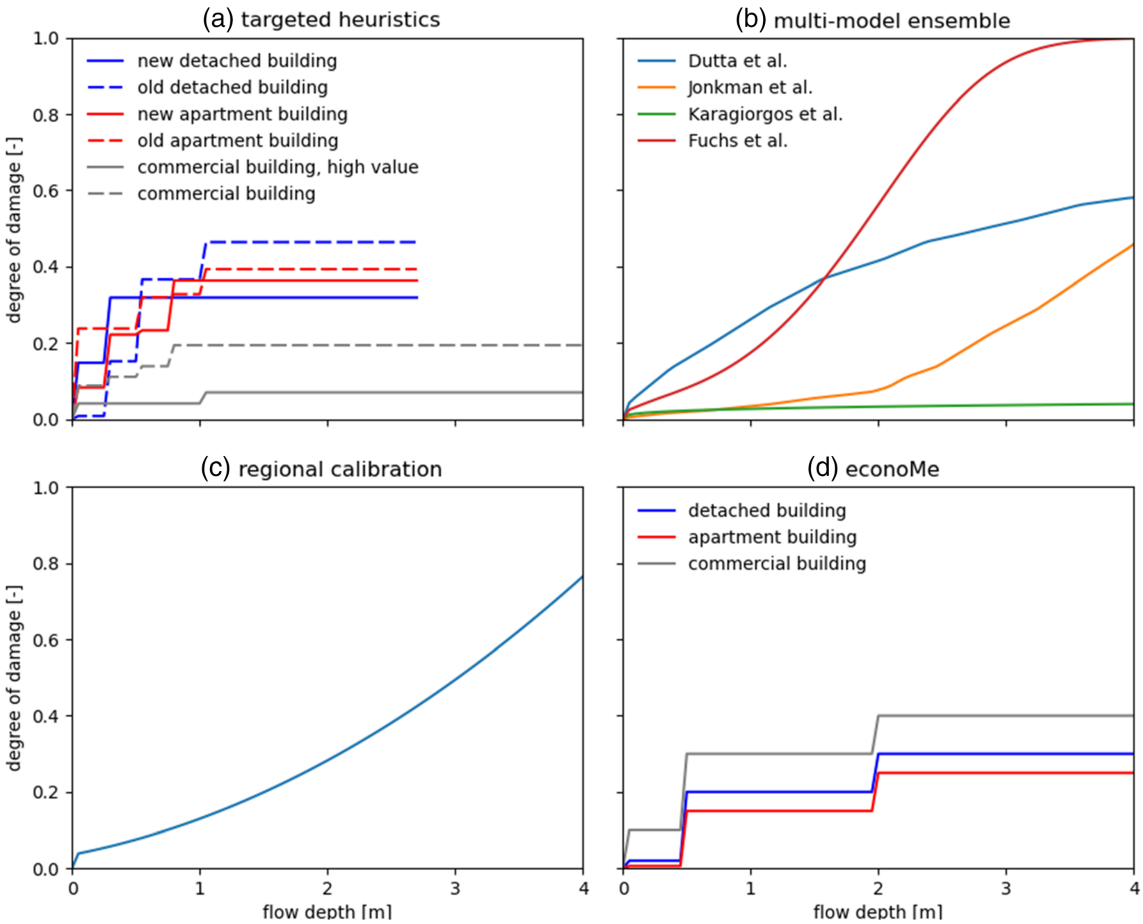

FIGURE 3 Applied vulnerability functions; (a) vulnerability function based on targeted heuristics, (b) multi-model ensemble of vulnerability functions, (c) simple function set up with region-specific insurance claim data, (d) vulnerability function used by the Swiss government for cost–benefit analyses (exemplified with flow velocity = 0 m/s)

2.3.2 | Vulnerability function calibrated with region-specific insurance claim data

An alternative to the transfer of vulnerability functions from the literature to a specific use case is the development of a region-specific vulnerability function. In this method, a common regression function is calibrated with the help of damage data, i.e., insurance claims data on structural damage to buildings in cantons (regions) located nearby of the case study area where damage data and insurance claim data were available and accessible. Due to the similarity of the flood processes and building typologies in these neighbouring regions, we therefore defined this data-driven vulnerability function "region-specific". The region-specific vulnerability function was based on three well-documented flood events including river and lake flooding (cf. Table 1) in neighbouring regions. We reconstructed the flood depths of the flood events based on event documentation reports and overlaid these data with the building stock in the flooded area. For each of these buildings the degree of damage was deduced from the insured value and the documented damage (insurance claim data). The resulting data were used to set up a regression model for the relationship between the flood depth and the degree of damage. The resulting vulnerability function was represented by a power function because this function demonstrated the best fit for describing the relationship between flood depth and degree of damage of all tested functions.

The vulnerability function resulting from the calibration with region-specific data is shown in Figure 3c and described by Equation (1) as follows with

$$dod = (0.18846 + 0.17152 * fd)^2 \tag{1}$$

where *dod* is the degree of damage and *fd* is the flood depth attributed to the building envelope.

TABLE 1 Overview of damage data from case studies used for developing the region-specific vulnerability function

Case study	No. of insurance claim data	Source of event documentation
Biel-Benken, Laufen, Liesberg, Zwingen (Canton of Basel-Country)	186	Measured flood depths and event documentation of the Canton of Basel-Country for the flood event of 8/9 August 2007 (Imhof & Heuberger, 2008)
Klosters-Serneus, Susch (Canton of Grisons)	76	Event documentation of the Canton of Grisons for the flood event of 23 August 2005 (Geotest AG, 2006; Hilker et al., 2005)
Buochs, Ennetbürgen, Hergiswil, Stansstaad	135	Lake level of Lake Lucerne of flood event of 24 August, 2005 (435.23 m a.s.l.) (Hilker et al., 2005; Oeko-B AG and Niederer + Pozzi Umwelt AG, 2006)

2.3.3 | Vulnerability function used by authorities responsible for flood risk management in Switzerland

Finally, we compared the outcomes of the previously presented vulnerability functions with the outcomes of the vulnerability function that is officially in use for cost–benefit analyses of flood protection planning in Switzerland (the '*econoMe*' tool, Bründl et al., 2009). The vulnerability function was developed based on merging individual empirical analyses of damage data of selected flood events. The function differentiates between three types of buildings (detached building, apartment building, and non-residential building). In contrast to all the other vulnerability functions applied in our study, this vulnerability function uses also flow velocity as a second parameter. It distinguishes three classes of hazard intensities. Low hazard intensity is attributed to the process if flood depth h or the product of h and flow velocity v is below 0.5 m or 0.5 m^2/s. A medium hazard intensity is attributed if 0.5 m < h < 2 m or 0.5 $m^2/s < h*v < 2\ m^2/s$. A high hazard intensity is attributed if $h \geq 2$ m or $h*v \geq 2\ m^2/s$. Here we calculated flow velocity with the Manning-Strickler formula and used the flood depth at the building as the hydraulic radius. A value of 30 $m^{1/3}/s$ for the Strickler roughness coefficient was assumed.

2.4 | Spatial variability of the model comparison

A high-magnitude flood event causes higher average flood depths at the buildings than a low-magnitude event (Keller et al., 2019). Thus, a specific vulnerability function deduced either from a high or low-magnitude flood event might reproduce well the observed damage when applied to a similar magnitude scenario but not if this function is applied to another magnitude level. The selection of the best vulnerability function for being implemented in flood impact models might be hampered if only one specific flood event is used for validating a vulnerability function or if the case study site is small and thus the variety of damage is limited. Considering a set of different flood scenarios and an adequate size of the study area mirroring different characteristics of the built environment is even more important if the number of damage data for validation is limited or/and the evaluation of a vulnerability function has to be based on a comparison. In addition, the selection of the vulnerability function might depend on the topography of the flooded areas. In mountain areas, the flood depths at the buildings vary remarkably with flood magnitude because the flooded area is laterally restricted. In contrast, in flat terrain or on alluvial fans, the average flood depth at the buildings will not vary as such with flood magnitude because the flood water can disseminate, and the spatial extent of the flooded area will increase. Consequently, the number of affected buildings will increase but the average flood depth at the buildings will not increase with the same gradient. To consider this, we compared the effects of applied vulnerability functions on the damage estimation regarding (a) flood event characteristics, (b) floodplain characteristics, and (c) the aggregation level of the results on the evaluation procedure.

We aggregated the damage estimations to the entire river basin and compared the outcomes of the different models for the set of 150 flood simulations. The high number of flood simulations with a high variability of flood magnitudes in floodplains within the river basin allows to analyse a wide range of flood depths in the different floodplains. We furthermore selected the flood scenario with the lowest average flood depth at building level and the flood scenario with the highest average flood depth for presenting detailed insights. In a next step, we compared the outcomes of the damage calculations for different floodplain characteristics considering exposure of buildings and the location in the flooded area. As suggested by Röthlisberger et al. (2017), we aggregated the damage estimations for individual buildings to hexagons of an area of 0.1 km^2, 1 km^2, and 10 km^2 to avoid the modifiable areal unit problem (Charlton, 2008; Openshaw, 1984). This problem causes a statistical bias and arises when model outcomes (e.g., flood exposure analyses) are aggregated and compared for different sizes of spatial reference units, for example, when comparing flood exposure analyses for regions or municipalities of different size and population.

Finally, we evaluated the damage estimates by the targeted heuristics model in comparison with the other model outcomes and rank the damage estimations of the targeted heuristics model at each spatial aggregation level with the other estimates, including the upper and lower boundaries of the ensemble of vulnerability functions. The ranking aimed to identify outliers in the spatial distribution of model outcomes and conditions, which cause over- or underestimation.

3 | RESULTS

3.1 | Targeted heuristics

The targeted heuristics approach led to a synthetic vulnerability function (see Figure 3a). Compared to the multi-model ensemble of vulnerability functions (Figure 3b), the synthetic function shows a stepwise increase in the degree of damage. The maximum degree of damage (0.571) is reached at a flood depth of 1.25 m. While old detached buildings have the highest degree of damage, commercial buildings have the lowest degree of damage. The vulnerability function for residential buildings is valid for flood depths of up to 2.7 m (ground floor). This upper bound results from the pre-analysis of expected flood depths in the case study region. From the multi-model ensemble, only the function of Fuchs, Heiser, et al. (2019) resulted in higher degrees of damage. The region-specific vulnerability function (Figure 3c) that was calibrated with insurance claim data showed lower degrees of damage at low flood depths (<0.5 m) than the synthetic function. Compared to the vulnerability function used by the public administration in Switzerland (the '*econoMe*' tool, Figure 3d), the synthetic function showed a slightly higher degree of damage for apartment buildings and a markedly lower degree of damage for commercial buildings. Moreover, old buildings were rated as more vulnerable than new buildings.

3.2 | Model comparison

The use of 150 flood scenarios for comparing the damage estimations of the different models showed a high variability in the outcomes. The highest damage estimation for the entire river basin over all flood scenarios and vulnerability functions was 1576.9 million CHF, while the lowest damage estimation was 59.9 million CHF. Hence, possible damage of a three-day probable maximum rainfall induced scenarios in the Aare River basin varied by the factor of 26. This considerable variability in damage estimation is related to the variability in the number of exposed buildings, the average flood depth at the exposed buildings as well as to the spatial variability of the flooded settlements. In the present case, some flood scenarios did not affect the cities of Thun and Interlaken, resulting in low overall damage. Flooding in these areas, however, resulted in a high number of flooded buildings in the whole river basin. Moreover, the variability depends also on the choice of the vulnerability function. The minimum average flood depth (0.26 m) over all flooded buildings results from scenario 73, while the maximum average flood depth resulted from scenario no. 149 (0.80 m). In scenario 73, 3868 buildings were affected and 4545 buildings in scenario 149. Scenario 73 resulted in the lowest damage estimation (over all vulnerability functions) while the highest damage estimate resulted from scenario 103 that affects a high number of buildings with high replacement costs. Figure 4a shows the average flood depth of the flooded buildings and the number of flooded buildings for each of the 150 scenarios. The relationship between average flood depth and number of exposed buildings is determined by floodplain topography. In case of smaller floods, only few buildings were affected but with generally higher flood depths. With increasing flooded area, the number of affected buildings increased but the high number of buildings in the peripheral areas of the flood extent lowered the average flood depth at building level. The compared vulnerability functions reflect the high variability of the damage estimates over the flood scenarios. However, the damage estimates of the different vulnerability functions were ranked comparably over all flood scenarios. The highest damage was mostly computed by the *econoMe* vulnerability function. Because 47% of the buildings in the study area are classified as buildings with a commercial purpose, the *econoMe* vulnerability function computed a higher degree of damage at relatively low flood depths. The damage resulting from this function is at the upper bound of the minimum-maximum range of the ensemble prediction if these factors are combined. The damage estimations of the targeted heuristics function were within the ensemble range but generally higher than the estimations of the region-specific vulnerability function and the ensemble mean. Mean bias to these both functions were 1.34 and 1.62, respectively. Thus, the targeted heuristic estimations ranked mostly second,

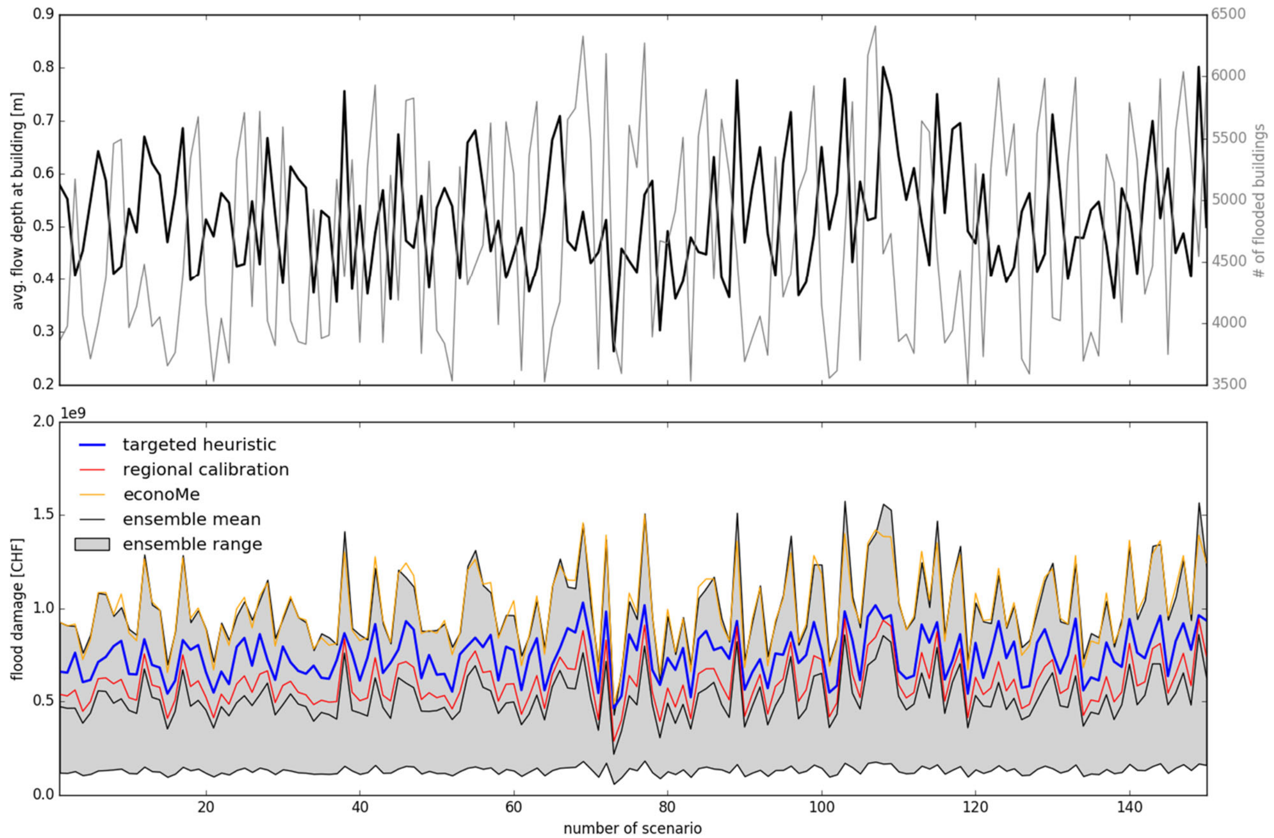

FIGURE 4 Upper: Average flood depth at buildings (black line, left axis) and the number of flooded buildings (grey line, right axis) for each of the 150 scenarios. Lower: variability of estimated damages over the 150 flood scenarios

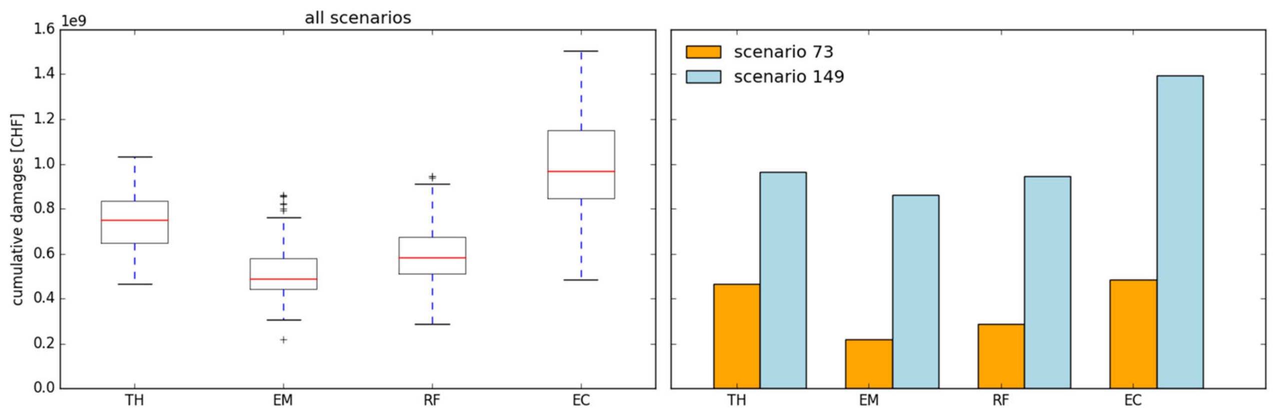

FIGURE 5 Left: damage estimates of all scenarios aggregated at river basin level (TH, targeted heuristics; EM, ensemble mean; RF, data-driven function; EC, econoMe). Right: damage estimates for the two flood scenarios with the lowest (scenario 73) and highest (scenario 149) average flood depth at building level

the region-specific model third, and the ensemble mean predictions fourth.

The ranking of the damage estimates of the compared methods is shown in Figure 5. The estimates of the targeted heuristics approach were bound by the *econoMe* function and by the region-specific function. The ranking is robust also when considering only a specific flood event for model comparison. For the flood scenarios with the lowest (73) and the highest (149) average flood depths at building scale, the damage estimates by the targeted heuristics function ranked second. However, damage estimates by the targeted heuristics function were nearly similar to the estimates computed by the *econoMe* tool for scenario 73 with the lowest average flood depth at the building footprint.

To explain this variability in the model comparison, we evaluated smaller spatial units of damage aggregation levels, starting with the aggregation at floodplain level. The floodplain characteristics reflect the different flood processes. Figure 6 shows that the targeted heuristics model ranks first in three of seven floodplains and second in four of seven floodplains in scenario 73. However, in scenario 149 the targeted heuristics model ranks first in one and last in two of seven floodplains. Of the 150 scenarios, this scenario has the highest lake level of Lake Thun. It shows that this vulnerability function underestimates damage in this situation in comparison to the other vulnerability functions. In this scenario, Interlaken is flooded by the Lütschine River. Over all flood scenarios, the targeted heuristics model ranked first in the floodplain of the Aare River downstream of Lake Thun and last in the floodplains of Thun and Lake Thun. In four of seven floodplains, the targeted heuristics model ranked in between the other models. Hence, the rank of this model is relatively constant over all flood process types but is sensitive to the floodplain characteristics of Thun and Lake Thun.

To break this down into smaller aggregation units and to test the sensitivity of the model comparison method, we further aggregated the damages computation from the individual building level to harmonised spatial units. In a first step, we compared the damage estimates of scenarios 73 and 149 at the level of the 10 km^2 hexagons. The ranking of the damage estimates at this aggregation level shown in Figure 7 varies remarkably in comparison to the aggregation level of floodplains shown in Figure 6.

The ranking of the targeted heuristics model was highest in several places across the river basin. Thus, the aggregation levels of the entire river basin and of the floodplains smoothed out the regional particularities in flood characteristics and exposure characteristics. In scenario 73, the highest rank of the targeted heuristics model can be found in the Aare River valley, in Thun, in Interlaken, and in the Guerbe River valley. Only the Aare River valley and the Guerbe River valley remained ranked highest in scenario 149. Scenario 149 has moreover a high number of hexagons with the targeted heuristics method ranked lowest.

The spatial pattern of the ranking varies over the river basin, depending on the aggregation level, that is, the size of the spatial unit for which the damages are aggregated from the individual building level (c.f. Figure 8). The smaller the size of the spatial aggregation units, the higher is the variability of the spatial pattern of the ranking. The smaller spatial units allow a more detailed view of the settlements that are determining the rankings of the damage estimates. Table 2 summarises the variation of the ranking depending on the size of the spatial aggregation units. When aggregated at 10 km^2 hexagons, damage estimates by targeted heuristics rank most

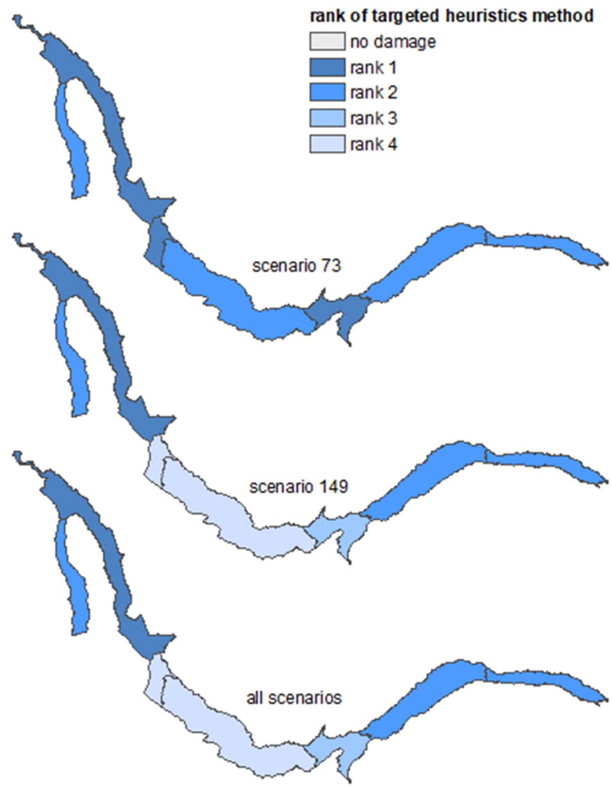

FIGURE 6 Ranks of the damage estimates by the targeted heuristics function in comparison to the other models, aggregated at floodplain level

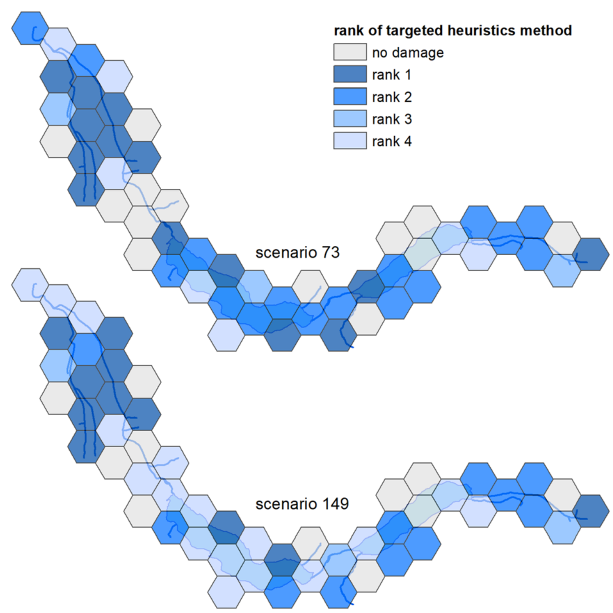

FIGURE 7 Ranks of the damage estimates by the targeted heuristics function of scenarios 73 and 149 in comparison to the other models, aggregated at hexagon level (10 km^2)

times between highest and lowest rank. This is also valid for the 1 km^2 hexagons. When aggregated at the 0.1 km^2 hexagons, damage estimates by targeted heuristics rank first in the majority of hexagons.

Figure 9 shows that the targeted heuristics function generally ranks lowest, that is, underestimates damage in comparison to the other functions, if flood depths are relatively high (Figure 9a–d) and the share of residential buildings is relatively low (Figure 9b–d). However, the average flood depths on the ranking vary with the aggregation level, especially for ranks 2–3. The ranking is not

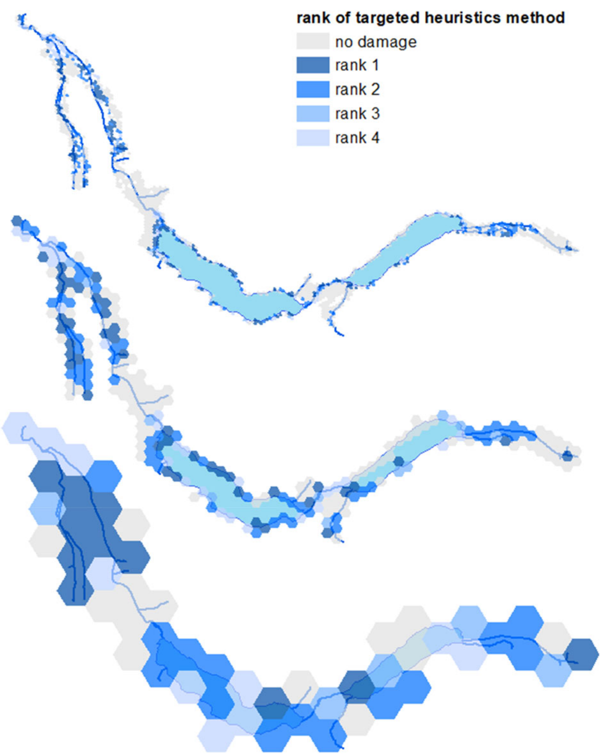

FIGURE 8 Ranks of the damage estimates by the targeted heuristics function over all scenarios, aggregated at hexagon level with different size (0.1, 1, 10 km^2)

remarkably influenced by the distance of the buildings to rivers and lakes and to the flood borders.

4 | DISCUSSION AND CONCLUSIONS

The evaluation of a newly developed flood vulnerability function is not feasible in a quantitative way without damage data of sufficient quality and quantity, for example, insurance claim data or other types of documented damage. Thus, we evaluated the newly developed vulnerability function by means of a comparative analyses as previously shown and suggested by Scorzini and Frank (2017), Carisi et al. (2018), Figueiredo et al. (2018), and Amadio et al. (2019). The comparison of the targeted heuristics models with other modelling approaches proved the applicability of an expert elicitation and heuristic reasoning approach. The damage estimations resulting from the targeted heuristics approach lay within the upper and lower bounds of the other models and within the uncertainty range of the multi-model ensemble. Furthermore, they have a relatively low positive bias against the data-driven vulnerability function as well as against the mean of the ensemble prediction. However, the proposed function is a stepwise function derived from a small sample of representative buildings and therefore, the transfer to the remaining buildings should be analysed before application. The steps in this function are determined by the characteristics of the visited sample buildings. Once a building-specific threshold of flood depth is exceeded, the damage can increase sharply because of building openings providing a pathway for water intrusion. Consequently, limitations of such a stepwise approach may occur once the floodplains are located in hilly terrain and flood characteristics become more dynamic. This fact has repeatedly also been mirrored by the high spread and skewness in models based on continuous vulnerability functions, as discussed in Fuchs,

TABLE 2 Rank of damage estimates by targeted heuristics depending on aggregation level

Rank	Hexagon 10 km^2	Hexagon 1 km^2	Hexagon 0.1 km^2	Hexagon 10 km^2	Hexagon 1 km^2	Hexagon 0.1 km^2
	Times occurring			Frequency (%)		
No damage	13	93	692	24.5	39.9	60.9
Rank 1	11	44	170	20.8	18.9	15.0
Rank 2	14	57	134	26.4	24.5	11.8
Rank 3	5	11	27	9.4	4.7	2.4
Rank 4	10	28	114	18.9	12.0	10.0

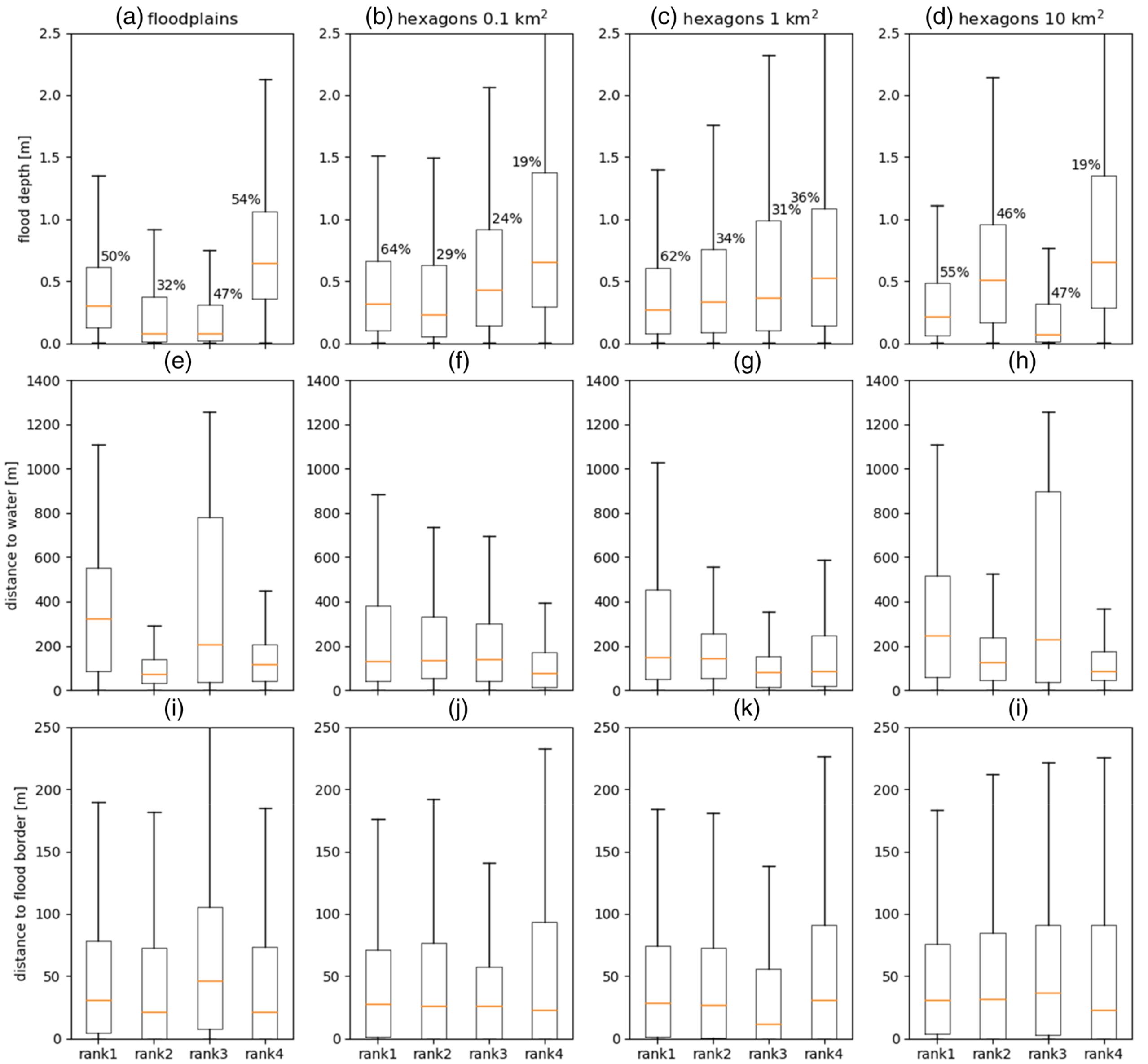

FIGURE 9 Effects of aggregation level and floodplain characteristics on the ranking of the targeted heuristic function. (a–d) flood depths, (e–h) distance of buildings to rivers and lakes, (i–l) distances of buildings to flood border at different aggregation levels. The numbers in (a–d) show the percentage of the residential buildings to all buildings in the spatial aggregation unit and the rank of the targeted heuristic function in comparison to the other functions

Heiser, et al. (2019) with respect to European data and Wing et al. (2020) focusing on the US. Moreover, the damage may have an upper bound and does not increase with increasing flood depths because some repairing costs are not varying with the flood depths. Due to the stepwise function, the comparison of the targeted heuristics approach with other models is sensitive to the flood depths at building level. However, the aggregation of building damage is smoothing the effect of the stepwise function on the ranking of the outcomes from different vulnerability functions. The aggregated damages computed with the targeted heuristics function do not show a threshold behaviour.

Here we showed a top-down approach for selecting necessary representative buildings, meaning first to run the flood simulations and second to select the representative buildings based on the flood characteristics and additional criteria. The presented targeted selection of buildings to be used as representative samples for developing the heuristic function does not remarkably influence the damage estimations. The approach for selecting the representative buildings based on flood simulations has also the advantage that the expected flood depths are known in advance for the whole study area. This allows to focus on a certain range of flood depths during the field visits. If a possibility to compare the outcomes of this approach with the outcomes of other vulnerability functions exists, the presented approach on targeted heuristics can be evaluated for being implemented in flood impact model chains. This offers options for evaluating flood impact model chains in regions where no damage data or only few data is available for model validation or for developing data-driven vulnerability functions. Targeted heuristics can therefore complement the methods for elaborating synthetic vulnerability functions (Amadio et al., 2019; Dottori et al., 2016; Neubert et al., 2016; Penning-Rowsell, 2010). The steadily increasing availability of exposure data, for example, Open Street Map data, allows to develop flood impact model chains in larger areas. The presented vulnerability function was developed with only 3 days of field investigation, which proves the applicability in regions where no damage data exist for calibrating region-specific vulnerability functions. Hence, the method is shown to be efficient in terms of extending flood model chains with vulnerability functions. However, the presented method requires data on the reconstruction values of the buildings.

The model comparison resulted to be sensitive to (a) the characteristics of the flood scenario in terms of average flood depths at the building scale and in terms of the spatial pattern of exposed settlements within the river basin and (b) the size of the spatial unit for aggregating the damage estimations from the building level. Overall damage increase with the average flood depth at the building level and the number of affected buildings. The flood patterns within the river basin, that is, the settlements affected, varied remarkably between the flood scenarios, although we used the same rainfall sum and duration. This is mirrored in the comparison of the different damage estimations. Depending on the local scale characteristics of the flood scenario and the buildings, the targeted heuristics function rank differently against the other vulnerability functions. This implies that the choice of the flood event and the case study (size) is markedly influencing the evaluation of flood impact models. Thus, the sensitivity of the model comparison against flood characteristics and exposure urges for basing a validation of flood impact models on more than one case study and on cases with different flood characteristics. We suggest validating flood impact models and vulnerability functions with data from multiple case studies and different flood event characteristics, for example, damage data from flood events with different average flood depths at building scale.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

The data that supported the development of the targeted heuristics vulnerability function study and the codes of the used flood vulnerability functions are available at github (https://github.com/zischg/targetedheuristics). The insurance claims data for calibrating the region-specific vulnerability function are not publicly available due to privacy restrictions.

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