



# INSYDE-content: a synthetic, multi-variable flood damage model to household contents

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**Abstract.** This paper introduces INSYDE-content, a novel, probabilistic multi-variable synthetic flood damage model designed to analyze physical damage to household contents on a component-by-component basis. The model addresses a critical gap in current modeling tools, which often overlook the significance of household contents in overall damage assessments. Developed through an expert-based approach and grounded in the scientific and technical literature, INSYDE-content leverages desk-based data to characterize model features, including uncertainty treatment arising from incomplete input data. A sensitivity analysis and a benchmark test against observed losses demonstrate the robust performance of the model and highlight the contribution of different features to damage mechanisms affecting house contents. While in this study INSYDE-content is tailored for illustrative purposes to the hazard, vulnerability and exposure characteristics of Northern Italy, the model is highly adaptable, allowing for its application to different regional contexts through appropriate customization.

## 1 Introduction

Floods have been one of the major natural disasters around the world for centuries (Brázdil et al., 2006; Tanoue et al., 2016). With the changing weather patterns associated to climate change, both the frequency and severity of floods have been on the rise (Hirabayashi et al., 2013; IPCC, 2023). Several flood management approaches have been formulated and implemented over the years to mitigate losses, with a shift from focusing solely on flood hazard control to a more holistic flood risk management (Plate, 2002; Sayers et al., 2002; Grallepois et al., 2016; Disse et al., 2020). In this change, damage estimation has become a key element in formulating effective policies for flood risk mitigation in both rural and urban sectors (Merz et al., 2010; Marín-García, 2023).

Flood damage models allow quantifying the extent of damage in both relative and absolute terms. They can be classified as univariable or multi-variable based on the number of variables involved in the model. A further classification distinguishes between empirical and synthetic models based on the adopted methodology for their development: empirical models use historical data to relate vulnerability and hazard variables to damage, while synthetic models are founded on an expert judgment that adopts a what-if approach for the definition of the expected damage (Merz et al., 2010; Jongman et al., 2012;



Dottori et al., 2016; Gerl et al., 2016; Martínez-Gomariz et al., 2021). Synthetic models have better flexibility in transferability in both space and time if their modeling assumptions and data are properly adapted (Merz et al., 2010; Scorzini et al., 2021; Di Bacco et al., 2024), while multi-variable models allow more reliable estimations (Schröter et al., 2014; Wagenaar et al., 2018; Amadio et al., 2019; Paulik et al., 2023; Xing et al., 2023).

35 Among the various exposed assets, damage modeling for the residential sector has been the most extensively investigated and developed, with numerous models available in the literature (Gerl et al., 2016). Nevertheless, most of these models are devised to assess building damage only, often neglecting or adopting a simplified approach to household contents (i.e., those items within the house that are not permanently installed in it, such as the furniture and appliances). The report of the US Army Corps of Engineers, “Catalog of Residential Depth-Damage Functions” (Davis and Skaggs, 1992), is one of the early  
40 efforts to address the difficulties of appraising flood damage to house contents, linked to the many economic, social, and structural factors involved in the modeling. By inventorying the contents of sample houses and pricing them, the report suggested that damage to contents can reach up to roughly 50% of the building damage, thus highlighting the importance of house contents on the overall damage figure in inundation scenarios.

More recently, a few studies have attempted to address the research gaps on modeling flood damage to contents across  
45 various spatial scales by adopting different approaches. Zhai et al. (2005) analyzed flood damages for the 2000 Tokai flood in Japan, identifying inundation depth, duration and household income as key explicative variables of flood damage to both buildings and contents. Similar results were found by Wahab and Tiong (2016), who proposed a multivariate flood damage model for the residential sector in Jakarta, Indonesia.

Romali and Yusop (2020) developed an empirical multiple regression flood damage model for Kuantan, Malaysia,  
50 incorporating residents’ occupation, household income and house types as explanatory variables. They found that content loss was positively correlated with inundation duration along with household income and inundation depth. Shrestha et al. (2021) used household surveys in Myanmar’s Bago region to create new local flood damage functions based on building characteristics. Ahadzie et al. (2022) studied flood impacts on residential buildings in urban settlements across five flood-prone regions in southern Ghana, with data showing significant damage to contents, such as furniture and clothes.

55 Mosimann et al. (2018) developed and cross-validated two linear regression models based on insurance data to estimate building and content losses in Switzerland. Their findings revealed that content losses accounted for 21% to 36% of total losses and even surpassed building losses in cases of low-severity damages.

Endendijk et al. (2023) developed empirical, multivariate vulnerability models to assess flood damage to buildings and household contents in the Netherlands, incorporating the influence of flood mitigation measures on damage outcomes.

60 Nofal et al. (2020) addressed the issue of data scarcity and the challenges of deterministic models by developing synthetic uni- and multi-variable component-based flood fragility functions. The method involved dividing the building into 65 components, with some of them representing household contents, such as chairs, desks, TVs, electric appliances, sofas, kitchen cabinets, beds and mattresses. Each component was assessed across five predefined damage states ranging from DS0 (insignificant damage) to DS4 (complete damage). The proposed approach was applied on a hypothetical single-family



65 residential wood building, with contents distributed in it based on practical considerations. However, these basic assumptions significantly limit the model's real-world applicability, as they fail to account for the substantial variability in housing characteristics and household contents.

Carisi et al. (2018) highlighted the challenge of developing comprehensive flood damage models for buildings and contents in the Italian context. Using ex-post data from the 2014 Secchia flood in the Emilia-Romagna region, they created empirical  
70 uni- and multi-variable flood damage models for buildings. Damage to contents was instead assessed indirectly using a simple square root regression relationship to building damage. By overlooking the complex induction mechanisms leading to damage and the related key factors, such as content distribution within the building, this approach, although practical, significantly hinders the model's ability to provide insights into content vulnerability in flood scenarios.

Overall, the literature highlights that modeling flood damage to contents presents a significant challenge due to the inherent  
75 variability of exposed items within buildings and the complexity of describing their susceptibility to floods. This variability increases across different regions, further complicating the spatial transferability of models. Nonetheless, current research in this area remains limited, underscoring the necessity for continued exploration and refinement of methodologies and tools.

The present study addresses this gap by introducing INSYDE-content, a micro-scale, multi-variable synthetic flood damage model for household contents. Similar to the original INSYDE model for buildings (Dottori et al., 2016), INSYDE-content  
80 employs a component-wise, probabilistic, “what-if” approach, characterized by a flexible design that can be adjusted to the local features and data availability of the region in which it is implemented, enhancing its applicability across different geographical areas. The clarity and explicitness of input data and assumptions play a crucial role in models' applicability.

The paper is structured to first outline the methodology for model development, exemplified for the context of Northern Italy (Po River District, Figure S1 of the Supplement 1). Insights on the influence of the different input variables on household  
85 contents losses and their relationships to building damage are then derived based on a probabilistic sensitivity analysis. Finally, the model's performance is evaluated using ex-post loss data from two flood events that occurred in the region.

## 2 Methodology

### 2.1 Model development

INSYDE-content adopts the general model framework proposed in the original INSYDE for buildings (Dottori et al., 2016),  
90 where damages are first modelled component-wise in physical terms and then converted into monetary values using the full replacement costs derived from reference price lists. The overall economic damage  $D$  to house contents in each building is calculated by summing the replacement costs  $C_i$  for each of the  $n$  content items within the building that is expected to be damaged:

$$D = \sum_{i=1}^n C_i = \sum_{i=1}^n \text{no. dam. items}_i \cdot \text{unitprice}_i$$



95 where  $no.dam.items_i$  represents the number of damaged items for each specific household content  $i$  and  $unitprice_i$  the corresponding unit replacement prices. The value of  $no.dam.items_i$  depends on flood event features (such as inundation depth and duration, flow velocity, and water quality, in terms of the presence of pollutants or sediments), as well as on the vulnerability and exposure of the affected objects:

$$no.dam.items_i = f(event\ features, content\ features)$$

100 Based on practical considerations derived from household surveys, INSYDE-content includes 11 standard items: beds, sofas, wardrobes, dining table setup (dining table and chairs), kitchen setup (lower and upper cabinets), TVs, washing machine, oven and microwave oven, dishwasher and refrigerator.

Since information on the actual number and distribution of contents within buildings is typically not known at large spatial scales, in model development it is necessary to introduce a probabilistic method that estimates their presence based on more commonly available data, such as building features. This approach allows for a more accurate assessment of the exposed items without needing for detailed, point-wise evaluations, which are often impractical due to the variability in individual choices of households on content selection for their properties. To this aim, in the tailored INSYDE-content model for Northern Italy (Po River District), empirical data derived from virtual surveys of buildings have been used to establish reliable estimates of content distribution as a function of certain building features. The virtual surveys involve analyzing real estate listings to extract key information from advertised posts, architectural drawings and photos detailing the buildings and their contents (Scorzini et al., 2022). Given the potential inconsistency in data completeness and quality across real estate platforms, only listings with complete information about the building and its contents have to be considered. To qualify for selection, the advertisement has to include at least information on interior details, main geometrical attributes and architectural layout and profiles, as well as a sufficient number of photos taken from various angles to cover most of the areas within all rooms. The applied criteria in the analyzed case resulted in only 60 houses being deemed suitable for analysis out of approximately 500 examined. Indeed, in many cases, only partial information could be obtained due to either a lack of data or privacy issues. Additionally, geometrical features did not always align with secondary data, such as building footprints available from other databases.

The information collected during this process can be classified into two categories: housing characteristics (e.g., location, number of floors, building type, finishing level, inter-story height, footprint area, surface area, external perimeter, year of construction) and house contents (e.g., number and size of beds and sofas, number of furniture pieces, placement height of appliances). For more detailed examples, please refer to the Supplementary Material 2 included in this study.

For practical reasons, the raw data acquired from the survey need to be transformed into more standardized variables on a component-by-component basis. For instance, different types of beds (single and double) have been represented by the single standard variable called  $BEDLeq$ , where 1  $BEDLeq$  equals 1 large double bed or 2 single beds. The same approach was applied to other items, such as sofas, wardrobes and dining setups (for details, please refer to the Supplementary Material 1).



At this stage, it becomes possible to identify empirical relationships allowing for the assessment of the number of exposed contents per building by using regression functions that relate the standardized variables for each item to the characteristics of the building. A straightforward approach might involve correlating the number of specific items to the number of rooms designated for them (e.g., beds to the bedrooms). However, since the number of rooms per building is often unknown in flood risk assessments, it is essential to establish a relationship between the number of exposed items and more general independent variables to enhance the practical applicability of the model. The most straightforward approach is to relate item quantities to building size, expressed as either footprint area (FA) or surface area (SA). Footprint area refers to the total ground area occupied by the building, while surface area is the total horizontal built-up area across all floors. For single-story buildings, FA and SA are the same. For multi-story buildings, if each floor is occupied by separate households, the SA for each unit corresponds to the individual floor area. In cases where a single household occupies multiple floors, SA becomes more representative of the total contents, as it comprises the total floor area of the entire building ( $SA = NF \cdot FA$ , with NF indicating the number of floors).

For Northern Italy, a power regression function of SA was found effective in describing the number of exposed beds, sofas, wardrobes and dining tables (Supplementary Material 1). For these elements, a stochastic component derived from a normal distribution with a mean of 1 and a standard deviation of 0.2 was applied to account for the inherent variability in the distribution of household contents. The other items were instead treated as constant functions based on practical judgment supported by empirical observations: for instance, it is expected that each housing unit may contain only one kitchen setup. The functions thus obtained can be then converted into step functions to more realistically represent the increments in the number of exposed objects with changes in SA. This means that for a specific range of SA, the standardized variable related to a certain content can assume only a physically sound constant value (e.g., the predicted *BedLeq* is expressed in increments of 0.5 *BedLeq* to capture the increase in the number of beds corresponding to a single bed unit).

Once the number of exposed items ( $exp_i$ ) is defined, it is possible to determine  $no.dam.items_i$  through the identification of the primary driving factors for damage induction for each content type, and the subsequent definition of the corresponding damage. To this aim, INSYDE-content adopts a probabilistic approach based on the use of fragility functions. The model assumes a binary damage state: an undamaged state ( $ds_0$ ) or a fully damaged state ( $ds_1$ ). For each content type, fragility functions express the probability of reaching a fully damaged state, based on the event intensity measure(s) (IM). To combine this probability with the actual occurrence of a damage state for the individual exposed elements, a random value  $P_i$ , accounting for the survival probability of each item, is sampled from a uniform distribution between 0 and 1 and compared to the damage probability derived from the fragility function for the corresponding content type. The random nature of the implemented process serves to capture the inherent uncertainty in the damage mechanisms, reflecting the intrinsic variability in content vulnerability to the same event intensity. Consequently, if  $P_i$  falls below the damage probability calculated from the fragility function, it is considered fully damaged ( $ds_1$ ), otherwise, it remains undamaged ( $ds_0$ ).



160 The formulation of the fragility functions is based on expert knowledge, practical experience, as well as available technical and scientific documentation. Assigning the thresholds for the event feature driving the damage mechanism is not trivial and the lack of relevant research in this field added further complexity to it. However, given the practical considerations surrounding the damage process for contents, it is feasible to establish lower and upper bounds for the IM.

Tables 1 and 2 describe the building and event features used in the model, including their range of values and the assumptions regarding the dependencies between the variables in case of missing information. Indeed, similar to the original

165 INSYDE for buildings, the model can automatically assign default values when certain input data are not available. This is achieved by either leveraging the implemented relationships among the variables (e.g., for SA or  $h_i$ ) or by sampling from user-defined distributions that reflect the characteristics of the region under analysis. In the version presented in this study, the model incorporates the distributions proposed by Di Bacco et al. (2024), which are based on a combination of physically-

170 informed approaches and empirical survey data for northern Italy (reported for completeness in Figures S2-S3 of the Supplementary Material 1).

**Table 1: Building features in INSYDE-content for estimating exposed household items.**

| Variable | Description                     | Range of values                                             | Default dependencies |
|----------|---------------------------------|-------------------------------------------------------------|----------------------|
| NF       | Number of floors [-]            | $> 0$                                                       |                      |
| FA       | Footprint area [ $\text{m}^2$ ] | $> 0$                                                       |                      |
| SA       | Surface area [ $\text{m}^2$ ]   | $> 0$                                                       | $SA=f(SA, NF)$       |
| IH       | Inter-floor height [m]          | $> 0$                                                       |                      |
| GL       | Ground floor level [m]          | $\geq 0$                                                    |                      |
| BT       | Building typology [-]           | 1: Detached House<br>2: Semi-Detached House<br>3: Apartment |                      |
| FL       | Finishing level [-]             | 0.8: Low<br>1: Medium<br>1.2: High                          |                      |
| GU       | Ground use [-]                  | 1: Residential use<br>2: Other use (garage, storage, etc.)  | $GU=f(BT)$           |
| HU       | Number of housing units [-]     | $\geq 1$                                                    | $HU=f(FA,BT)$        |

**Table 2: Event features in INSYDE-content.**

| Variable | Description                                               | Range of values | Default dependencies |
|----------|-----------------------------------------------------------|-----------------|----------------------|
| he       | Inundation depth outside the building [m]                 | $\geq 0$        |                      |
| hi       | Inundation depth inside the building (for each floor) [m] | $[0:IH]$        | $hi=f(he,GL)$        |
| d        | Inundation duration [hours]                               | $\geq 0$        | $d=f(he)$            |
| s        | Indicator for the presence of sediments [-]               | 0: No<br>1: Yes |                      |
| q        | Indicator for the presence of pollutants [-]              | 0: No<br>1: Yes |                      |

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Additionally, for a more comprehensive analysis, this study also employed the non-region-specific synthetic distributions proposed by the same authors (Figures S4-S5 in Supplementary Material 1). By covering a wider range of values, these distributions facilitate a deeper investigation into the model's sensitivity to input variables beyond the specific context of northern Italy. The fragility functions and general assumptions are detailed in Supplementary Material 1, while Table 3 summarizes the variables that affect both the determination of exposed elements and the damage mechanisms in the model. It is worth noting that that flow velocity does not appear among the event features considered in INSYDE-content (Table 2), despite its potential relevance to content damage. The decision to exclude it as an input variable was guided by practical considerations. Firstly, the impact of flow velocity on content damage should ideally be assessed based on water velocity inside the building. However, this information is neither available in standard flood risk analyses nor are there reliable methods to estimate it indirectly from external flow velocities (Dewals et al., 2023; Zhu et al., 2023). Furthermore, the mechanism of flow intrusion into a building generally leads to a significant reduction in velocity, making its effect negligible when assessing content damage. Conversely, when the external flow velocity is extremely high and capable of washing away the entire building, flow velocity may become critical as it would lead to the complete destruction of both the structure and its contents. However, this extreme scenario has not been included in the current version of INSYDE-content due to its rarity in fluvial floods, particularly for masonry and reinforced concrete buildings. Additionally, the lack of well-established criteria defining the threshold for washing away (based on a combination of water height and velocity) makes it challenging to quantify a situation where content damage would be complete.

**Table 3: Variables that affect the determination of exposed elements (EXP) and the damage mechanisms (i.e., fragility functions (FF)) in INSYDE-content.**

| Damage component                        | Variables affecting the component                                                      |
|-----------------------------------------|----------------------------------------------------------------------------------------|
| Beds, wardrobes, dining setup           | <i>EXP</i> : SA=f(FA,NF), BT, HU=f(FA,BT), NF, GU<br><i>FF</i> : hi=f(hc, GL), d, s, q |
| Sofas                                   | <i>EXP</i> : SA, BT, FL, HU, NF, GU<br><i>FF</i> : hi, d, s, q                         |
| Kitchen setup                           | <i>EXP</i> : HU, NF, GU<br><i>FF</i> : hi, d, s, q                                     |
| Washing machine, TV, oven, refrigerator | <i>EXP</i> : HU, NF, GU<br><i>FF</i> : hi                                              |
| Dishwasher, microwave oven              | <i>EXP</i> : HU, FL, NF, GU<br><i>FF</i> : hi                                          |

## 2.2 Model evaluation

### 2.2.1 Sensitivity analysis to the input variables

A sensitivity analysis of INSYDE-content was conducted to evaluate how the selected explanatory variables influence damage estimation and to determine how the absence of certain input data contributes to uncertainty in these estimates. This



analysis was performed using two synthetic portfolios, each consisting of 250,000 buildings exposed to hypothetical  
200 flooding scenarios, as described in Di Bacco et al. (2024). The first dataset represents more general, non-region-specific  
inundation and building characteristics (referred to as the “extended dataset”, hereinafter), while the second focuses on the  
specificities of northern Italy (Po River District, “Po dataset”, hereinafter). This approach enabled the identification of a  
more general ranking of the variable importance within the model and allowed for subsequent observations of how this  
ranking might change based on the specific characteristics of the region in which the model is implemented.

205 The sensitivity analysis followed these steps: first, INSYDE-content was applied to calculate damages for both building  
portfolios, with all required model variables known. For each  $j$ -th building in the dataset, the estimated damage value in this  
step was taken as reference value,  $D_0$ . Then, one input variable was sequentially removed and replaced, for each building in  
the datasets, with values sampled from the distributions given by Di Bacco et al. (2024). This process was repeated for each  
variable, with damage recalculated each time ( $D_i$ ). The absolute difference in damage compared to the reference value was  
210 recorded for each of the  $j$  buildings ( $|D_0 - D_i|$ ), facilitating the determination of the variance each feature contributes to the  
model’s outcome.

### 2.2.2 Model validation

The model was validated using loss data from two historical flood events that occurred in Northern Italy: the 2002 flood in  
Lodi and the 2010 flood in Caldogno. These events have been analyzed in previous studies regarding building damage  
215 (Amadio et al., 2019; Molinari et al., 2020), but never for household contents. In this study, only buildings without  
basements were considered, coherently with the model’s assumption that does not account for their presence. The validation  
dataset includes 194 buildings for the Lodi event and 169 buildings for the Caldogno event, with total actualized losses to  
year 2023 amounting to about 3.1 million euro for both cases.

The loss data were derived from the forms for damage quantification distributed by the authorities as part of the state’s loss  
220 compensation process, which were filled in by affected citizens. These forms provided actual restoration costs, certified by  
original receipts and invoices. The types of content damage eligible for compensation aligned with the 11 components  
identified in the model formulation. The unit prices for content items were taken from the decree issued by the delegated  
commissioner responsible for damage compensation following the Caldogno flood. These prices were then applied to the  
Lodi case after being adjusted for inflation to the event date.

225 In addition to loss data, the dataset includes information on external water depth at building’s location. As regards the other  
event features required by INSYDE-content, qualitative data from previous studies allowed to determinate an approximate  
value for inundation duration equal to one day for both cases (Di Bacco et al., 2024). Accordingly, the sampling of  $d$  values  
was obtained from a truncated normal distribution centred at 24 hours and spanning between 16 and 48 hours. The  
information on the presence of fine-graded sediments allowed for assigning  $s=1$  (yes) for both cases, while local data on  
230 pollutants was available only for Lodi.



Concerning building features, the dataset includes footprint area (FA), number of floors (NF), building type (BT) and finishing level (FL). For the remaining missing variables, the model was applied by leveraging the established relationships among the variables and the built-in sampling process from pre-defined distributions, as outlined by Di Bacco et al. (2024).

To account for uncertainty arising from the sampling process of unknown inputs and from the implemented assumptions on exposure and damage mechanisms, content losses were calculated probabilistically for each building over 1,000 iterations, resulting in confidence intervals for the estimated values which were compared to reported losses.

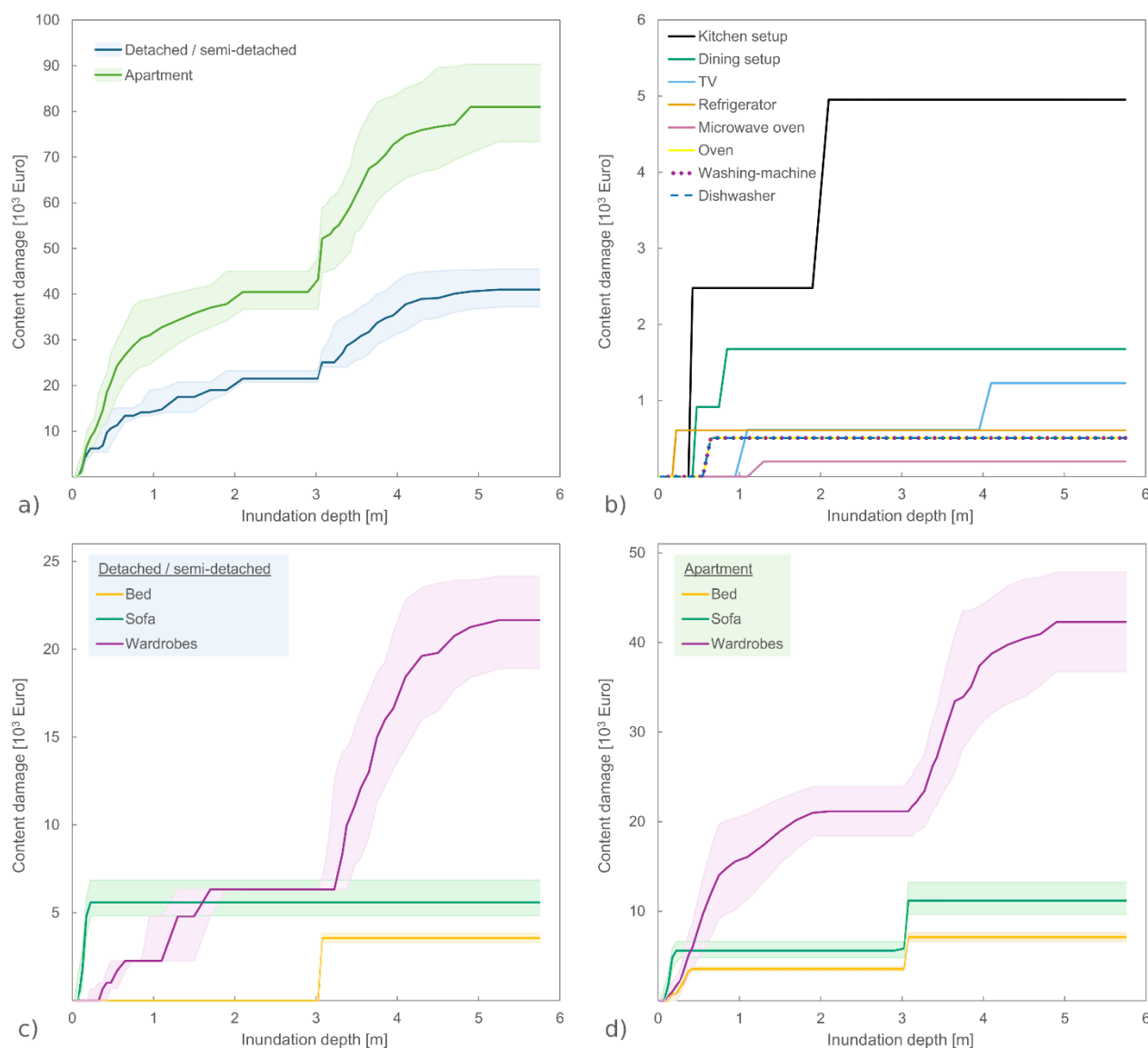
### 3 Results and discussion

#### 3.1 Examples of resulting damage functions

Figure 1 illustrates an example of traditional damage functions resulting from the application of INSyDE-content, broken down by components and in terms of total damage. The functions correspond to a scenario involving both apartment and single-family, detached or semi-detached residential buildings with a surface area of 200 m<sup>2</sup>, distributed across two floors, with IH=3 m, GL=0 m and a high finishing level. In the total damage functions, the interquartile range is shown alongside the median damage values to represent the variability induced by the probabilistic modeling of the damage mechanism. For each water depth, damage values were calculated over 1,000 iterations by randomly assigning  $q$  as either 0 or 1 and generating random samples of inundation durations based on water depth scenarios, with  $d$  assumed to be relatively short for shallow inundations and extending from 6 hours to 2 days for depths greater than 2 meters. The trends shown in Figure 1 effectively highlight the assumptions on the damage mechanisms implemented into the model for the various items, as described in the Supplementary Material 1. For instance, focusing on detached and semi-detached buildings, damage to beds only occurs when the inundation depth exceeds 3 meters, consistent with the assumption that bedrooms are located on the upper floors for this type of dwelling. Similarly, sofas, assumed to be in the downstairs living area, appear to be highly vulnerable to flood, necessitating a full replacement even under very shallow water depths. The pattern for wardrobes and their contents is more complex, as they include different types of furniture, ranging from small and decorative pieces in the living room to full-height wardrobes in bedrooms, each with varying thresholds for damage onset. This results in the stepped function shown in Figure 1, panel c) similar to the one for kitchens, where the steps represent the damage occurring to lower and upper cabinets. Electrical components display a similar behavior across all items, with only different activation thresholds based on their varying vulnerability. For apartments, the overall damage is higher compared to single-family buildings with the same surface area, due to the presence of multiple housing units within the same space, each containing its own furniture and appliances. To ensure clarity in Figure 1, panel b) focuses exclusively on the damage functions for electrical components and kitchen setup in a single-family building, which correspond to those of a single housing unit of an apartment building. For the other components, distinct patterns emerge between the two building types, reflecting different assumptions regarding the distribution of contents across the floors. For example, in the case of apartments, a non-null



damage to beds can be recognized even on the first floor, with a stepped increase in damage between floors, as observed for sofas.

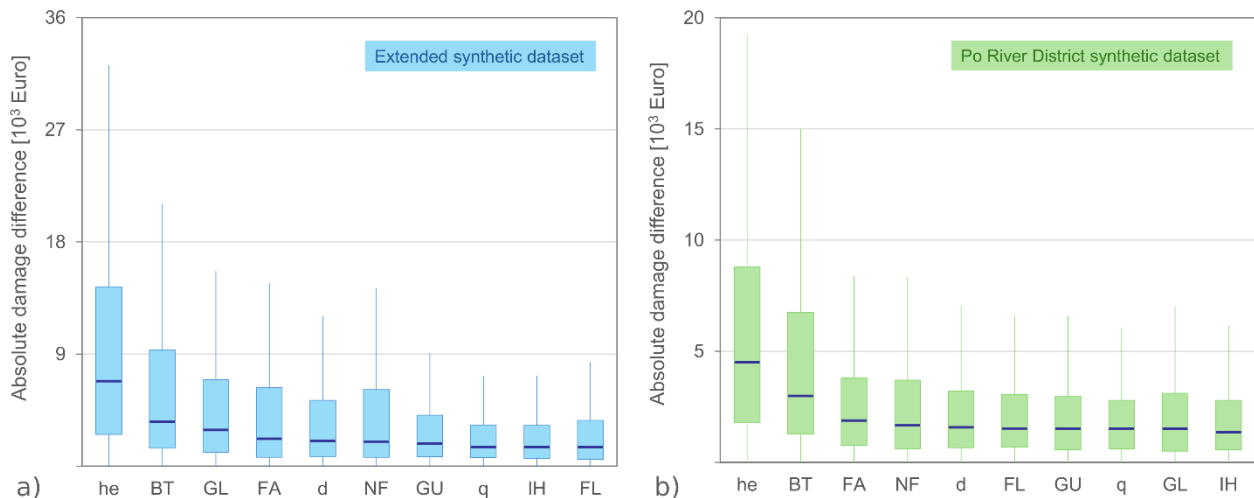


265 **Figure 1: Example of traditional damage functions resulting from the application of INSYDE-content for different building types: a) total content damage; b) damage to kitchen and damage setup as well as electric appliances; c) damage to beds, sofas and wardrobes to a detached/semi-detached building; d) as panel c), but for an apartment building.**



### 3.2 Sensitivity analysis to the input variables

This section reports on the sensitivity of damage estimation to the variables considered in INSYDE-content and on the uncertainty arising from potential missing input data in model implementation. Figure 2 summarizes the findings by illustrating the difference in computed damage when the model is applied to the reference portfolios of 250,000 buildings and to their replicas obtained by replacing the values of one input variable at a time with a sampling from the predefined distributions implemented in the model. The left and right panels of Figure 2 correspond, respectively, to the extended synthetic dataset, which encompasses a broader range of values for the input features, and the Po dataset, tailored to the characteristics of northern Italy. In Figure 2 features are ranked by the median value of  $|D_0 - D_i|$ , where  $D_0$  represents the reference damage for the  $j$ -th building and  $D_i$  the corresponding value calculated after removing and resampling the  $i$ -th variable from the predefined distributions developed by Di Bacco et al. (2024). Dependent variables, such as SA or  $h_i$ , are not shown in the figure as their effects are inherently accounted for through the independent variables with which they are assumed to be linked. Similarly, the influence of sediments, represented by the binary variable  $s$ , is not reflected in the figure; this is because the distributions generated by Di Bacco et al. (2024) for representing the fraction of sediments on water volume always yield a non-null value in the analysis, which implies a constant  $s=1$  (i.e., presence of sediment, of any gradation) in INSYDE-content. Overall, Figure 2 demonstrates a feature importance pattern that remains relatively consistent across the two tested datasets, with the most influential variables (he, BT, FA, and d) consistently appearing among the top five in both cases. As expected, higher values of  $|D_0 - D_i|$  are observed in the extended dataset, where missing data sampling (especially for extensive and intensive variables) can span a broader range of variability than in the Po scenario (Di Bacco et al., 2024).



**Figure 2: Variable importance in INSYDE-content. Results obtained with sampling from the two different datasets developed by Di Bacco et al. (2024): a) case for the extended synthetic dataset; b) case for the Po River District synthetic dataset. Variables are ordered according to the median value of the absolute damage difference.**



Inundation depth ( $h_e$ ) emerges as the primary contributor to uncertainty in damage estimation, with median absolute damage differences ranging from approximately 4,500 to 6,800 euro, confirming the well-known significance of such variable in direct flood damage assessment for various types of assets, including household contents (Merz et al., 2013; Schröter et al., 2014).

Building type (BT) plays a crucial role in determining the exposed value of contents by shaping the distribution of items within the building (e.g., the assumption regarding bed placement in single- and multi-family buildings discussed earlier). This effect is evident in the median  $|D_0 - D_i|_j$  shown in Figure 2, which range from approximately 3,000 to 3,500 euro, establishing BT as the second most influential feature in INSYDE-content, in contrast to its minimal impact on building damage mechanisms (Dottori et al., 2016; Di Bacco et al., 2024). The minor influence of ground use (GU) is partly masked by the effect of BT, as the model differentiates the use of the ground floor only in the case of apartment buildings, where it is more common for the ground floor to be allocated for non-residential purposes (e.g., garages, communal areas, etc.).

Closely related to inundation depth is the role of ground level (GL), which influences the water depth inside the building and subsequently affects damage. In the extended dataset, GL ranks as the third most important feature, with median absolute damage differences of about 2,900 euro. On the other hand, in the Po dataset, the lower variability of GL makes its impact less significant, resulting in an estimated damage variation of about 1,500 euro, which is comparable to the variations observed for other variables such as FL, GU, and  $q$ .

Regarding the number of floors (NF), while the quantitative effects on damage calculations are similar in both datasets, with a median  $|D_0 - D_i|_j$  of approximately 1,700 – 2,000 euro, greater variability is observed in the extended dataset (with an interquartile range of 5,400 euro, compared to 3,100 euro for the Po case), as a consequence of the higher probability of damage affecting upper floors, given the broader range of inundation depths represented in this dataset.

In the Po dataset, a relatively stronger influence is observed for the two variables affecting the number of exposed contents - either directly through footprint area (FA) or indirectly via finishing level (FL) (see Supplementary Material 1 for the corresponding functions) - with these variables occupying the third and fifth positions, respectively. The relatively limited impact of FL, as shown in Figure 2, can be attributed to the fact that the model considers its effect only for the estimation of the number of exposed contents, without accounting for potential increases in their unit price. This modeling choice was guided by practical considerations: first, for household contents, it is virtually impossible to establish a clear upper limit on the economic value of an item as its luxury level increases; second, this approach aligns with the application of the model in flood risk management contexts (e.g., under the European Floods Directive) or in government compensation schemes for flood damage, where standard average costs are used, regardless of the actual quality of the damaged items.

### 3.3 Insights into content-to-building damage relationship

This section expands on the model's performance by analyzing the relationship between content and building damage, aligning with previous studies that aimed to establish connections between the two (Thieken et al., 2005; Carisi et al., 2018;



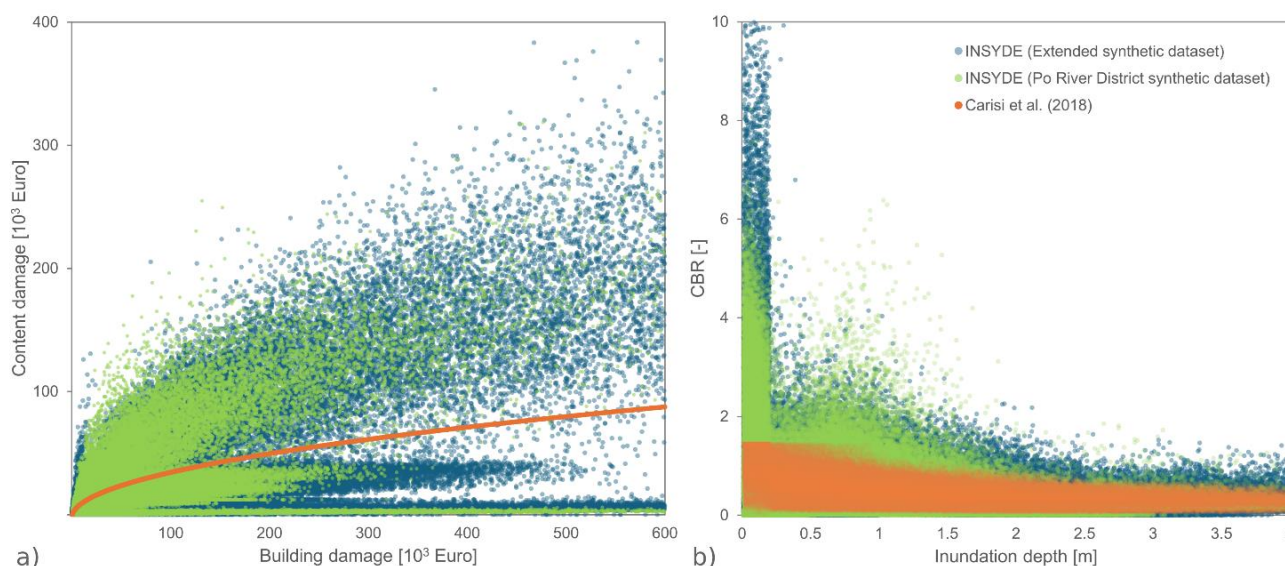
Mosimann et al., 2018). To this end, building damage was calculated using the INSYDE 2.0 model (Di Bacco et al., 2024) and paired with content damage estimates for the two synthetic datasets used in the sensitivity analysis.

Figure 3a illustrates the results, plotting estimated content damage against building damage for both datasets and comparing them with the equation proposed by Carisi et al. (2018), based on post-event observations from the 2014 Secchia flood in Emilia Romagna, Italy.

INSYDE results reveal substantial variability in content damage for same levels of building damage, highlighting the complex, multi-variable nature of damage mechanisms that cannot be fully represented by simple univariate functions. Interestingly, the root function proposed by Carisi et al. (2018) aligns at a median level with INSYDE results, although in a region with lower sample density. Conversely, INSYDE allows discerning distinct patterns in the relationship between building and content damage, shaped by the combined effects of inundation duration thresholds and building characteristics (such as BT and FL) triggering specific damage mechanisms to certain components, as previously described for INSYDE 2.0 by Di Bacco et al. (2024).

Furthermore, Figure 3b illustrates the content-to-building damage ratio (CBR) as a function of inundation depth, offering insights into the limitations of using a univariate approach based solely on building damage, especially in case of shallow inundation depths ( $< 0.5$  m), where the higher vulnerability of contents can lead to CBR values exceeding 5. However, as inundation depth increases, overall damage becomes predominantly driven by building damage, leading to a reduction in the differences between the two approaches.

Median CBR values for INSYDE across the two datasets range from 0.26 (calculated on inundation durations exceeding 48 hours) to 0.36 and 0.42, respectively for the extended and Po River datasets at shorter durations.



**Figure 3: a) Content to building damage calculated with INSYDE models on the two tested datasets and comparison with the root function of Carisi et al. (2018); b) Content to building damage ratio (CBR) expressed as a function of inundation depth with INSYDE models and Carisi et al. (2018).**



350 These findings are consistent with post-event observations in Switzerland and Germany (Thieken et al., 2005; Mosimann et al., 2018), which reported CBR values around 0.28-0.29, with higher values for lower-entity damages, as illustrated here in Figure 3b. Nonetheless, the results presented in Figure 3 highlight the importance of detailed knowledge regarding the vulnerability and exposure characteristics of potentially impacted assets to achieve accurate content damage estimations with minimized uncertainty. The probabilistic sampling approach implemented in INSYDE-content addresses the practical  
355 challenges of obtaining such detailed information in large-scale applications by effectively managing unknown missing data through calibrated distributions of the input features, while also explicitly accounting for uncertainties associated with predictions and thereby mitigating the false sense of certainty that, instead, often accompanies deterministic models.

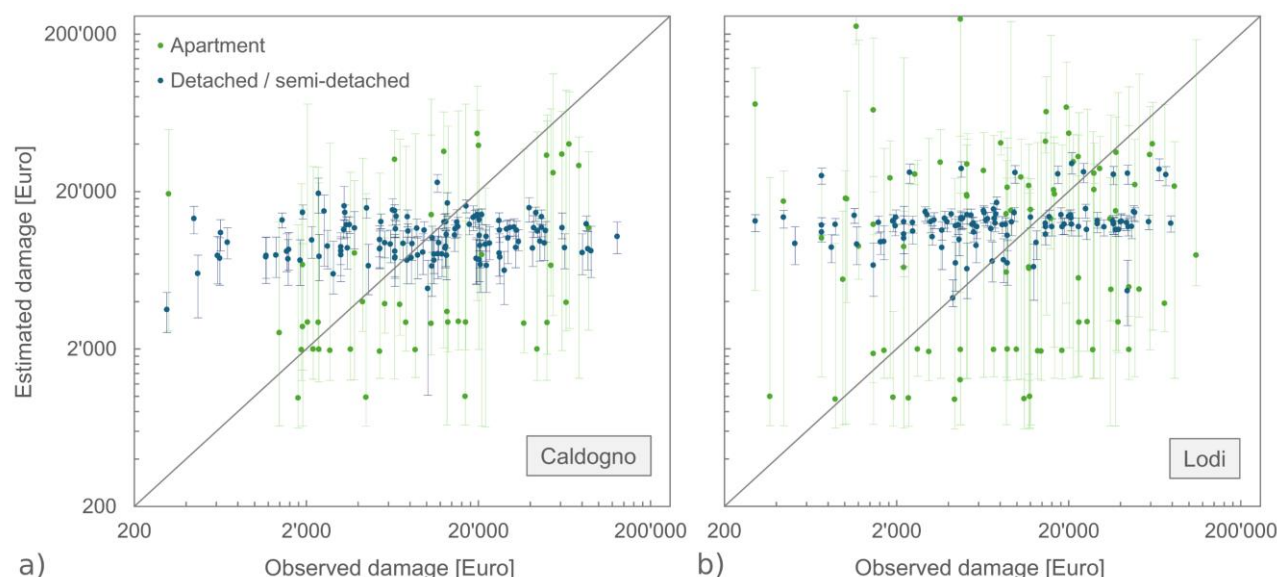
### 3.4 Model validation

The validation outcomes are summarized in Table 4, presenting the statistics of damage estimates from INSYDE-content,  
360 based on 1,000 replicates for each building with missing input features, alongside observed damage values. Figure 4 complements these findings with a detailed visualization of the differences between individual building-level estimations and actual observations.

Table 4 indicates a good alignment between the total estimated damages and observed values. In Lodi the median of calculated losses aligns closely with reported values, while for Caldogno reported losses approach the third quartile of  
365 estimates. Beyond the overall convergence, Figure 4 highlights notable scatter at the individual building level, especially for apartment buildings, where the absence of ground-level usage information (GU) introduces large variability in the estimates, as the model randomly samples residential or non-residential use over the iterations, impacting both the exposed contents and expected damage. However, it is worth noting that such building-level differences between estimates and observations are a common outcome in flood damage validation exercises, especially for lower-magnitude damages, where models often  
370 tend toward overestimation, as also described in previous studies on building damage (Merz et al., 2008; Molinari et al., 2020; Pinelli et al., 2020). From another perspective, this discrepancy may be also attributable to poor representativeness of claim data, particularly for lower entity losses, as highlighted by several authors (Molinari et al., 2020; Pinelli et al., 2020; Wing et al., 2020; Museru et al., 2024). Such findings are even more expected for contents compared to buildings, given that they exhibit much greater variability and less standardization than structural or non-structural building components.

375 **Table 4: Results of the probabilistic validation of INSYDE-content for the case studies of Caldogno and Lodi: statistics of total estimated damage versus reported damage.**

|          | Estimated damage [M€ 2023] |        |                          | Observed damage [M€ 2023] |
|----------|----------------------------|--------|--------------------------|---------------------------|
|          | 1 <sup>st</sup> quartile   | Median | 3 <sup>rd</sup> quartile |                           |
| Caldogno | 1.10                       | 1.76   | 3.50                     | 3.15                      |
| Lodi     | 1.75                       | 3.30   | 6.87                     | 3.06                      |



**Figure 4. Results of the probabilistic validation of INSYDE-content: a) Caldogno event; b) Lodi event. Median computed damage (dot) and corresponding interquartile range (line) are plotted for each building against observed damage (expressed in 2023 euro).**

In addition to confirming INSYDE-content's robustness in estimating total damages across the two events, this analysis highlights the importance of incorporating input data uncertainty when validating and evaluating model performance. Indeed, presenting results with well-defined uncertainty bounds not only increases model transparency and reliability, but also prevents the potential for a misleading impression of certainty, a limitation often found in simpler deterministic models (Pappenberger and Beven, 2006; Merz et al., 2015).

## 4 Conclusions

Modeling flood damage to household contents poses significant challenges due to the inherent heterogeneity of such items, which contrasts to the more standardized geometry and features of buildings. This complexity is further exacerbated by the need to account for a wide range of factors influencing damage mechanisms (including flood characteristics, the vulnerability of both buildings and their contents, as well as broader economic aspects), demanding a more comprehensive approach than traditional univariate damage assessments.

This study aimed to address such complexities by introducing INSYDE-content, a probabilistic, multi-variable flood damage model, specifically designed for household contents. The model was developed through a structured, multi-phase process including: (i) an extensive data collection on household contents and flood characteristics; (i) the probabilistic estimation of



the presence of household contents to reflect their variability and distribution across different building types; (iii) the development of fragility functions for individual items based on their driving factors; and (iv) a price analysis to obtain monetary damage estimations. Although the model presented in the paper has been tailored to the context of Northern Italy (Po river district), its components and basic input data can be adapted or adjusted to the specific characteristics of other regions, ensuring its generalizability.

Sensitivity analysis and validation exercises provided insights into the model's performance. One of the key findings emerging from this study is the critical importance of accounting for the multi-variable nature of flood damage to household contents, with the primary factors being inundation depth (and, to a lesser extent, inundation duration) and the variables that quantify and distribute exposed items within buildings, such as those representing building size, type and use. Additionally, the study confirms that in cases of shallow inundation, content damage can exceed building damage, with content-to-building damage ratios largely exceeding 1, thus highlighting the often-overlooked vulnerability of household contents in flood risk assessments.

The probabilistic nature of INSYDE-content effectively addresses uncertainties arising from potential missing input data, offering a more robust alternative to traditional deterministic models. By employing sampling techniques of input features, the model can estimate damage even in the absence of certain data, providing information on estimation uncertainty while maintaining transparency.

Additionally, the validation results confirmed the reliability of INSYDE-content, with its damage estimates aligning with observed claim data from two flood events in Italy. From another perspective, the analysis performed in this study also highlighted the importance of incorporating input data uncertainty when validating and evaluating model performance. Presenting damage estimations with clearly defined uncertainty bounds not only enhance model transparency and reliability, but also helps preventing a false sense of certainty, which is typical of simpler deterministic models. On the other hand, comparing observed data within a plausible range of estimates allows to properly consider also the uncertainty that is inherent in claim data.

By offering an integrated approach that combines the complex interactions between flood characteristics, building features and household contents, while also addressing the challenges posed by data variability and uncertainty, INSYDE-content then provides a robust and reliable tool for supporting more comprehensive flood risk assessments. Future work should focus on expanding and customizing the input datasets for household contents across different geographical contexts, refining and validating component fragility functions for a wider range of flood scenarios, and exploring the role of additional socio-economic factors in shaping damage patterns.

### Code availability

During the review process, the code of INSYDE-content is available at the following link:



<https://drive.google.com/file/d/1T8XPF5UPALxJ0JGUYj2rodl7TStRP9Pz/view?usp=sharing> and it will be made available on Mendeley data upon final acceptance.

#### 430 **Author contribution**

Pradeep Acharya: Data curation; Formal analysis; Investigation; Software; Visualization; Writing - review and editing.

Mario Di Bacco: Conceptualization; Methodology; Data curation; Investigation; Software; Writing - review and editing.

Daniela Molinari: Conceptualization; Investigation; Writing - review and editing.

Anna Rita Scorzini: Conceptualization; Methodology; Investigation; Visualization; Writing - original draft.

#### 435 **Competing interests**

The authors declare that they have no conflict of interest.

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