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Compound earthquakes-floods produce non-additive urban recovery driven by financing bottlenecks

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Abstract

Recent compound disasters—for example, the 2023 Turkey–Syria earthquake sequence followed by atmospheric-river-induced flooding—show that distinct hazards with independent physical mechanisms can affect the same assets, infrastructure systems, and communities within short time frames and interact through their consequences and recovery processes. Yet regional risk and recovery models commonly treat multi-hazard events as simple superpositions. Here, we present a probabilistic framework that simulates building-portfolio recovery under multi-hazard scenarios while explicitly modelling interactions among post-disaster processes (financing, contractor mobilisation, and other impeding factors) as functions of hazard intensity and interarrival time. We adjust impeding-factor delay distributions to Italian recovery data from the 2009 L’Aquila earthquake and the 2023 Emilia-Romagna flood, and apply the framework to 3,282 residential buildings in the city of Pompei, Italy, across 20 typologies. We analyse four scenarios—two earthquake mean return periods paired with a flood of 100-year mean return period—across a range of interarrival times. Results show that neglecting interactions can systematically underestimate city-scale recovery time by up to 50%. Sensitivity analyses show recovery strongly depends on interarrival time and interaction mechanisms, with financing delays the dominant driver. Our approach enables decision-makers to incorporate recovery interactions into multi-hazard resilience planning for cities.

Keywords: compound risk, urban recovery, multi-hazard interactions, earthquake, flood

1 Main

Assessing compound impacts on engineered systems and communities from multiple interacting natural hazards—and explicitly linking that assessment to post-disaster recovery—is essential for effective urban resilience planning. Compound impacts arise when two or more hazards co-occur or strike the same area in rapid succession, producing consequences that

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exceed those of individual events and that complicate emergency response and recovery^{1–4}. The likelihood, severity, and consequences of such multi-hazard events are amplified by rapid urbanisation, increasing complexity and interdependencies within modern societies, and climate change^{5–7}. Although compound events account for only 19% of recorded disasters worldwide between 1900 and 2023, they are responsible for 59% of global economic losses, underscoring their disproportionate consequences⁸. Recent evidence from Europe highlights this trend: more than 70% of flood events involve additional hazards such as droughts, heatwaves, earthquakes, and economic losses from these compound floods are on average 2.8 times greater than for isolated floods. Specifically, between the 1980s and 2010s, the frequency of floods that occurred along with two or more additional hazards increased by 186%, compared to a 16% increase for standalone floods⁹. International policy, including the Sendai Framework for Disaster Risk Reduction (DRR) 2015–2030, therefore, calls for multi-hazard risk analysis to guide investments in mitigation and resilience¹⁰.

Multiple hazard events interact in different ways^{11,12}, producing direct consequences (for example, physical damage¹³ and population displacement¹⁴) and indirect consequences (for example, supply-chain and service disruptions^{15,16}) that shape recovery trajectories. Interactions are commonly classified as *Level I* and *Level II*^{17,18}. *Level I* interactions are due to physical trigger mechanisms: one hazard directly causes or amplifies another, independently of exposure (for example, earthquakes triggering landslides, tsunamis, or liquefaction). These interactions are conditioned by environmental state variables (for example, antecedent rainfall and slope saturation) and follow mechanistic processes that can be reliably modelled with empirical or physics-based approaches. *Level II* interactions arise when exposure and system state are taken into account. Even when hazards are physically independent, their impacts can interact through consequence and recovery pathways: prior damage can weaken assets, degrade services, and erode community capacity, thereby amplifying the effects of subsequent hazards. *Level II* therefore concerns systems rather than physics alone—damage accumulation, cascading infrastructure failures, disrupted recovery processes, and shifting vulnerability states are all *Level II* phenomena. Crucially, *Level II* interactions do not require a physical trigger; they can occur simply because independent hazards strike the same exposed community in close temporal and spatial proximity.

Level II interactions are increasingly observed. For example, the 2023 Turkey–Syria earthquakes were followed five weeks later by severe atmospheric-river-induced flooding that struck already damaged infrastructure and temporary housing, substantially delaying recovery operations¹⁹. In Pakistan (2022), an extreme heatwave strained electricity and water systems and was followed by unprecedented monsoon flooding that further disrupted services and prolonged recovery, contributing to a marked increase in poverty^{20,21}. In Japan (2024), heavy rainfall triggered flooding and landslides across the Noto Peninsula, nine months after the devastating moment magnitude 7.5 earthquake. The event damaged temporary housing and transport infrastructure, isolated communities, and disrupted reconstruction^{22,23}.

Despite their relevance, *Level II* interactions are poorly represented in operational regional risk and recovery models. Existing multi-hazard studies typically account for interactions through damage accumulation or cascading physical consequences^{24–26}, whereas interactions among post-disaster recovery processes are rarely considered^{27,28}. This gap limits our ability to predict recovery delays amplified by administrative and financial bottlenecks and other resource constraints—often referred to as impeding factor (IF) delays²⁹. Building on recent

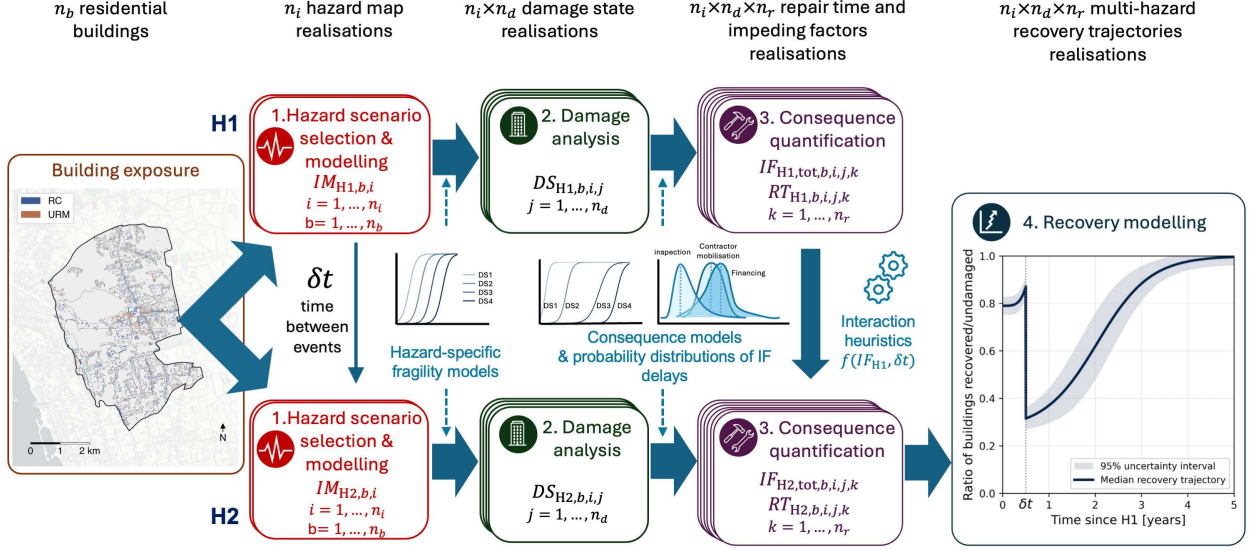


Figure 1: The proposed simulation-based framework for modelling building-portfolio recovery under multi-hazard events, i.e., H1 followed by H2, separated by a time interval of δt .

methodological advances for single-building multi-hazard recovery modelling³⁰, we extend that framework to assess portfolio-level building recovery across a city, explicitly accounting for interactions among IF delays and their effects on recovery timing and trajectories. The resulting city-scale recovery trajectories provide critical information to support climate adaptation and to assess the resilience implications of alternative DRR policy interventions in communities exposed to compound hazards^{31–35}. We demonstrate the enriched framework using the residential building portfolio of Pompei, Italy, under a suite of earthquake–flood scenarios representative of the Campania region, illustrating how interactions among recovery processes influence city-scale recovery trajectories. We focus on earthquake–flood scenarios because they combine the high-consequence impacts of earthquakes with the high frequency and broad exposure of floods, involve distinct physical mechanisms that make *Level II* (consequence and recovery) interactions especially salient, and are well represented in recent high-impact case studies and recovery datasets^{19,32,34–40}—making them both policy-relevant and tractable for model calibration.

The proposed framework

The proposed simulation-based framework (Figure 1) models building-portfolio recovery for two physically independent hazards that occur in close temporal and spatial proximity (H1 followed by H2, separated by a time interval of δt). The framework comprises four simulation stages: (1) hazard scenario selection and modelling; (2) damage analysis; (3) consequence quantification; and (4) recovery modelling. These stages build on a (pre-existing) exposure model, which details the locations, physical vulnerability characteristics, and value of the residential building inventory before the subsequent formal analyses.

First, representative scenarios—characterised, for example, by event features (e.g., rupture characteristics) or intensity level (e.g., in terms of different mean return periods)⁴¹—are

selected for H1 and H2, in line with the preparedness and emergency response planning requirements of local authorities or other stakeholders³³. For each hazard, n_i hazard footprint realisations can be generated to represent intensity measures (IMs) at the location of n_b exposed assets (e.g., buildings) for both events, $IM_{Hx,b,i}$ ($b = 1, \dots, n_b$, $i = 1, \dots, n_i$, and $x = 1$ or 2 , representing the first or second event, respectively). Hazard footprints could be produced using empirical (statistical) models or physics-based simulations, and can be conditioned on a specified scenario or drawn from a full stochastic event set to support fully probabilistic inference^{42–44}. For earthquakes, for instance, ground motion footprints can be obtained from empirical ground motion models^{45,46} or from physics-based rupture and wave propagation simulations^{47,48}. Each hazard footprint realisation yields the spatial IM field for H1 and H2 at building locations; the two events are separated by an interarrival time δt , which can be varied across scenarios (or be simulated probabilistically¹⁸) to explore the sensitivity of various impacts and recovery outcomes to temporal proximity.

Second, $IM_{Hx,b,i}$ values are translated into n_d realisations of discrete damage states $DS_{Hx,b,i,j}$ ($j = 1, \dots, n_d$) using appropriate hazard-specific fragility models^{49–51} which estimate the probability of reaching or exceeding a certain damage state for a given hazard intensity⁵². These models could be preselected from existing models or derived empirically or analytically for building archetypes of interest⁵².

Third, n_r realisations of total IF delays (the time after the occurrence of the event and before the start of repair activities where no gain in functionality is attained) for H1, $IF_{H1,tot,b,i,j,k}$ ($k = 1, \dots, n_r$), are sampled from probability distributions of individual IF delays adjusted with empirical recovery data. Total IF delays are constructed by combining individual IF components in a manner consistent with the sequential and parallel nature of recovery activities³⁰. Considered IFs depend on the local administrative context and the hazard type, but typically include event duration (e.g., the time required for floodwater to recede), inspection, permitting, financing, contractor mobilisation, restoration mobilisation, and restoration work and cleanup^{30,53,54}. The corresponding $IF_{H2,tot,b,i,j,k}$ (total IF delays for H2) values are then sampled from a second set of IF distributions. These distributions are derived from the baseline IF distributions for H1 that are modified using predefined interaction heuristics, accounting for the state of recovery from H1 at time δt , which is quantified by the proportion of buildings experiencing the same IF delays. The heuristics represent mechanisms through which ongoing recovery activities from H1 influence H2 recovery, such as increased financing delays arising from overlapping insurance claims or funding applications.

Similarly, n_r realisations of repair times, $RT_{Hx,b,i,j,k}$, are sampled from hazard-specific consequence models which map discrete $DS_{Hx,b,i,j}$ values to continuous consequence metrics⁵², e.g., Aljawhari et al.⁵⁵. Alternatively, repair times can be estimated directly from IMs using hazard-specific vulnerability models which provide probabilistic estimates of consequence given a specific hazard intensity⁵², e.g., Olmez & Deniz⁵⁶. In addition, fragility, consequence, and vulnerability models for H2 could be modified to account for the state of buildings following H1 (i.e., damage accumulation)²⁵. Such state-dependent models more realistically characterise damage for structures already weakened by H1 by estimating the probability of exceeding different DSs or consequence thresholds under H2-related IM levels, conditional on the initial DS or consequence caused by H1^{52,57,58}. However, this study specifically focuses on interactions that affect IF delays, which can arise even when hazards do not produce identical damage patterns on the same engineered components. For instance, earthquakes and floods

often produce distinct damage mechanisms: earthquakes frequently impose large structural demands (deformations, cracking, and local/global collapse⁵⁹) while floods disproportionately damage ground floor contents, façades, interior finishes, and utility services⁶⁰—effects that are especially pronounced for low rise and ground floor spaces. Because these damage patterns differ, multi-hazard interactions often emerge through overlapping repair activities, competition for contractors and materials, and financing bottlenecks rather than through identical physical damage to the same components. In earthquake–flood sequences, therefore, consequence-driven interactions among recovery processes (i.e., IF delays) can be as important as, or more important than, any direct physical coupling of damage, and must be explicitly modelled to capture realistic city-scale recovery trajectories.

Finally, these components are combined to generate $n_i \times n_d \times n_r$ multi-hazard recovery trajectories, where buildings are considered fully recovered only once repair processes associated with both events are completed following the associated compound IF delays. Each framework iteration produces a set of recovery trajectories for a specific modelling configuration, defined by parameters such as the multi-hazard scenario (and δt), the selected fragility, vulnerability, and consequence models, and the adopted interaction heuristics. Uncertainty is propagated throughout all calculation stages using Monte Carlo sampling in line with Kourehpaz et al.³⁰.

Results

We demonstrate the framework (see the Methods section for additional details) using the residential building portfolio of Pompei, Italy, which is located within the Campania region—a region highly exposed to multiple natural hazards, including earthquakes, floods, and volcanic eruptions (Figure 2). The analysis focuses on reinforced-concrete (RC) and unreinforced-masonry (URM) buildings, which together account for 92.2% of all residential buildings in Pompei. We consider multi-hazard scenarios consisting of earthquake (EQ) and flood (FL)—two of the most prominent natural hazards in the Campania region⁶¹ and Italy—which may occur consecutively and independently with overlapping consequences^{62,63}, representing a common example of *Level II* interactions.

Exposure modelling

The detailed spatial inventory for 3,282 residential buildings (see Figure 3) is generated by disaggregating census-tract-level data on physical vulnerability characteristics obtained from the Italian National Institute of Statistics (ISTAT)⁶⁴ and assigning attributes to residential building footprints via Monte Carlo sampling. The sampling process is guided by local contextual heuristics—e.g., tall, regular, small-footprint buildings are more likely RC than URM^{65,66}. Buildings are classified into typologies defined by material of the lateral load-resisting system, LLRS (i.e., RC with moment-resisting frames as the LLRS, or URM with walls as the LLRS), age class (i.e., construction era), and height class, consistent with taxonomies developed for Italian RC⁵⁰ and URM⁴⁹ residential buildings. For RC buildings, age classes are 1946–1970 (which corresponds to structural designs considering only gravity loads), 1971–1980 (i.e., low seismic design code), and post-1980 (i.e., moderate seismic design code, consistent with the introduction of seismic code provisions in Italy⁶⁷), with height classes defined as low-rise (LR, 1–2 storeys), mid-rise (MR, 3–4 storeys), and high-rise

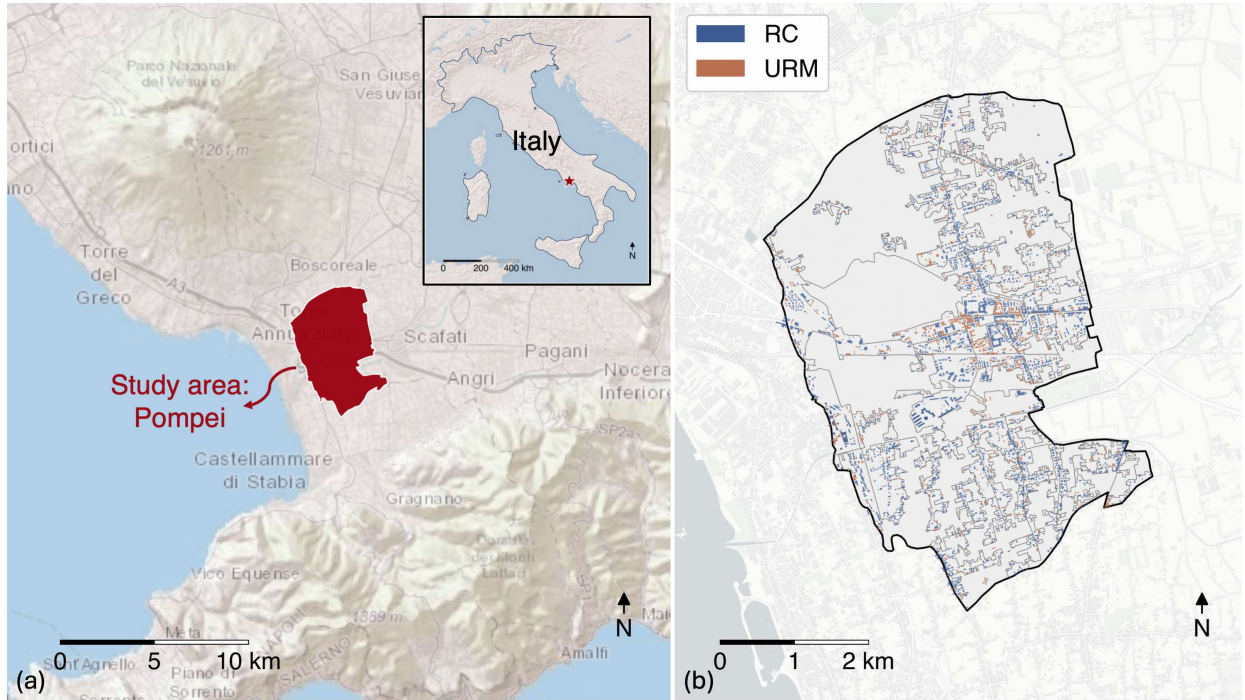


Figure 2: Study area and residential building inventory used in the analysis. (a) Geographic location of the municipality of Pompei within the Naples–Vesuvius region of southern Italy. (b) Spatial distribution of residential buildings in Pompei, classified according to the material of their lateral load-resisting systems as reinforced concrete (RC) or unreinforced masonry (URM).

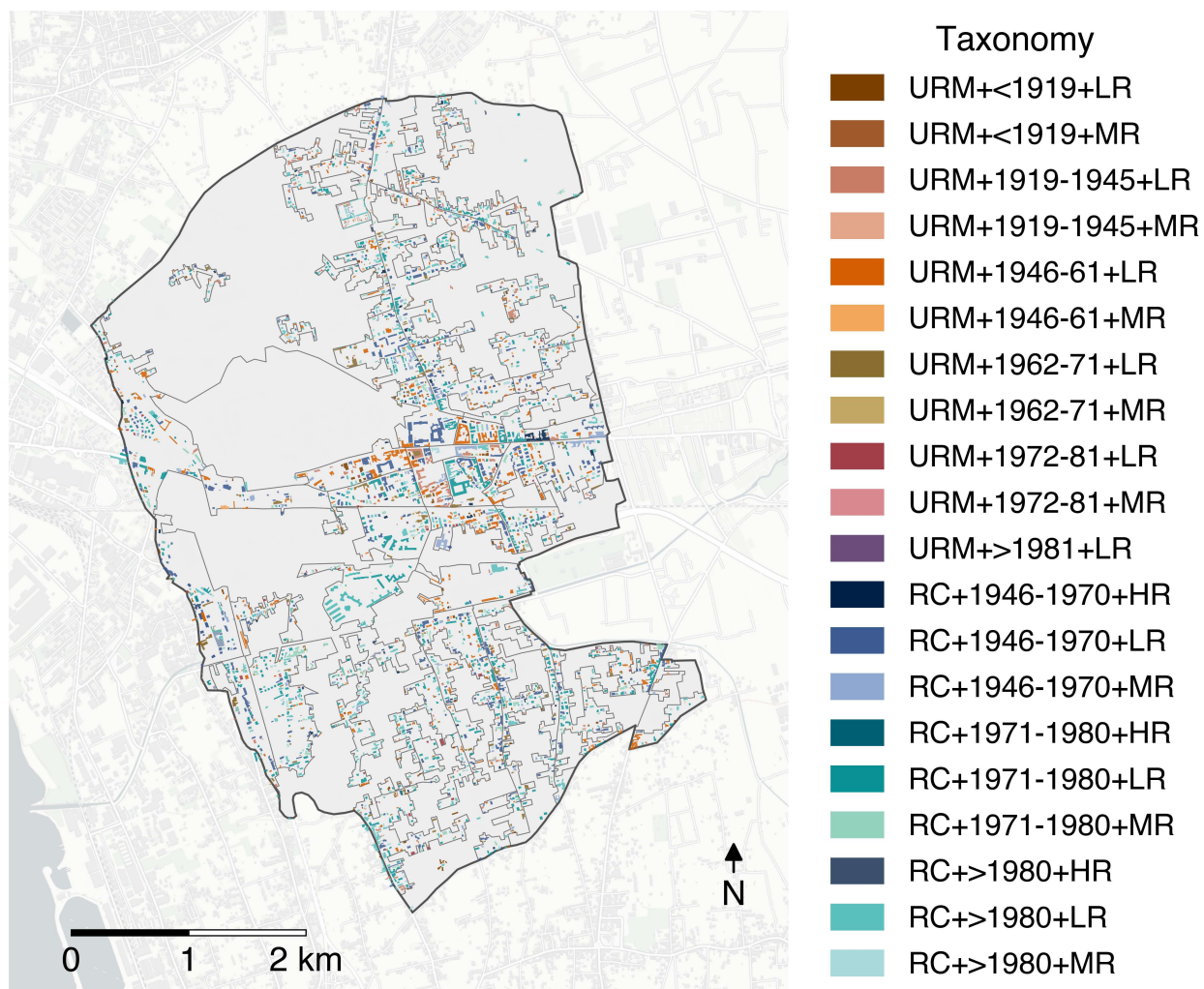


Figure 3: The residential building portfolio of Pompei, Italy, classified under an Italy-specific taxonomy, which consists of material of lateral load-resisting system + age class + height class. 'URM' and 'RC' refer to unreinforced masonry and reinforced concrete, respectively, whereas 'LR', 'MR', and 'HR' refer to low-rise, mid-rise, and high-rise, respectively.

(HR, 5+ storeys), consistent with Rosti et al.⁵⁰. For URM buildings, age classes are pre-1919, 1919–1945, 1946–1961, 1962–1971, 1972–1981, and post-1981—reflecting URM-specific building code evolution⁴⁹, with height classes defined as low-rise (1–2 storeys) and mid-rise (3+ storeys), consistent with Rosti et al.⁴⁹. Each typology is labelled as material of the LLRS + age class + height class, for example, RC+1971–1980+MR represents a mid-rise RC frame building built between 1971 and 1980.

Specifically, the spatial building inventory is constructed by integrating ISTAT statistics with geospatial building footprints through a multi-step disaggregation and assignment process. First, census-tract-level ISTAT data are combined with geopolitical boundaries of census tracts (i.e., Sezione di Censimento, SEZ) to obtain, for each SEZ, aggregate residential building counts by construction era (Step 1). Within each construction era, buildings are then proportionally allocated and integerised across LLRS material and storey count according to Pompei-wide conditional distributions (e.g., 40.1% of buildings in Pompei built between 1919 and 1945 are one-storey URM), and storey counts are grouped into the height classes of the adopted taxonomy, thereby producing a list of SEZ-level building counts for each typology (Step 2). Table 1 presents the number of residential buildings of each typology across all SEZs in Pompei.

Table 1: Number of residential buildings for each typology in Pompei.

Typology	Count	Typology	Count
RC+1971-1980+LR	571	URM+1972-81+LR	75
RC+1946-1970+LR	548	RC+1946-1970+HR	50
RC+>1980+LR	451	URM+1946-61+MR	46
URM+1946-61+LR	369	URM+1962-71+MR	27
URM+1962-71+LR	302	URM+>1981+LR	25
URM+1919-1945+LR	232	URM+1919-1945+MR	25
RC+1971-1980+MR	161	URM+<1919+MR	10
RC+1946-1970+MR	139	RC+>1980+HR	10
URM+<1919+LR	137	RC+1971-1980+HR	5
RC+>1980+MR	97	URM+1972-81+MR	2

These SEZ-level typology counts are subsequently used to assign specific typologies to individual buildings (Step 3). Building footprint datasets (which also include information on height) are spatially matched to SEZs. Building morphological attributes, including building height, footprint area, and plan irregularity, are derived or imputed where missing. Plan irregularity (I) is quantified as the inverse of circularity in line with Hauser et al.⁶⁸, given in Eq. 1:

$$I = \frac{p^2}{4\pi A} \quad (1)$$

Where P and A denote the building perimeter and area, respectively. Building typologies are then assigned to individual buildings by matching SEZ-level counts and ranking buildings according to local contextual heuristics. For each SEZ, the integerised typology counts are used as assignment quotas. Buildings are ranked based on morphological attributes, including

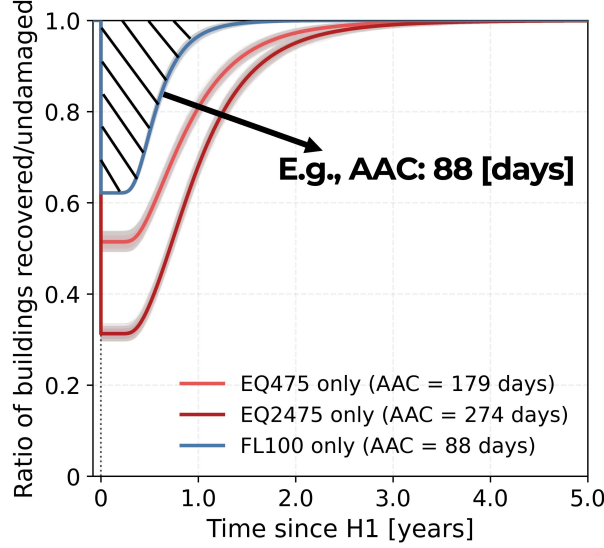


Figure 4: Recovery trajectories for the three baseline individual hazard events: FL100, EQ475, and EQ2475. Bold curves indicate median recovery trajectories, while shaded regions represent the 95% uncertainty intervals.

height, I , and A . Building height is derived from available data where possible, with missing values (104 out of 3,282 buildings; 3.2%) imputed using the median height within the same SEZ. Height and footprint characteristics guide the allocation of material classes. In contrast, construction age is not inferred at the building level but enforced through SEZ-level typology quotas defined in the disaggregation step. Candidate buildings for RC-related typologies are prioritised as those that are taller, more regular (i.e., smaller I), and have smaller A . In contrast, URM-related typologies are assigned to buildings that are shorter, more irregular, and have larger A . Typology labels are assigned sequentially in order of descending quota until all quotas are filled.

Recovery trajectories

The Area Above the median recovery Curve (AAC; days), defined by Bruneau et al.⁶⁹ as a measure of resilience loss, is used to quantify the cumulative impact on the residential building portfolio. Figure 4 presents the recovery trajectories for three standalone hazard events that we consider, a 475-year mean return period (MRP) earthquake (EQ475), a 2,475-year MRP earthquake (EQ2475) and a 100-year MRP flood (FL100). Figure 5 presents the recovery trajectories for four multi-hazard scenarios (EQ475–FL100, FL100–EQ475, EQ2475–FL100, and FL100–EQ2475), with (panels a and c) and without (panels b and d) consideration of interactions between successive events. The AAC values for the ‘no-interaction’ multi-hazard scenarios are not simply equal to the sum of the AAC values associated with the corresponding individual hazards (179, 274, and 88 days for EQ475, EQ2475, and FL100, respectively), because some buildings are affected by both hazards and therefore should not be double counted.

When interactions are considered, the AAC increases from 233 to 304 days (30.5%) for the EQ475–FL100 scenario and from 256 to 397 days (55.1%) for the FL100–EQ475 scenario. The larger increase in the latter case arises because the earthquake affects a greater proportion of

buildings and is associated with longer financing delays than the flood. Consequently, ongoing financing delays from the first event propagate more strongly into the second event, increasing overall recovery times. Although overlapping recovery activities partially reduce contractor mobilisation delays ($IF_{H2,con}$), this benefit is outweighed by the persistence of financing delays, which emerge as the dominant recovery bottleneck. The same mechanism governs the EQ2475-related scenarios, for which the AAC increases from 306 to 377 days (23.2%) for the EQ2475–FL100 scenario and from 346 to 538 days (55.5%) for the FL100–EQ2475 scenarios. The larger absolute AAC values reflect the greater extent of earthquake damage, while the substantially stronger amplification in the FL100–EQ2475 scenario arises because the amplified financing delays are experienced by a much larger portfolio of earthquake-damaged buildings.

The relatively small uncertainty observed in the portfolio-level recovery trajectories arises from the aggregation of a large number of individual building-level realisations. While recovery times for individual buildings are subject to significant variability due to stochastic IF delays and repair time, aggregating the recovery trajectories of 3,282 buildings leads to a smoothing effect: at each time step, the portfolio-level recovery is effectively the mean of many independent (or weakly correlated) recovery states, and random variations across individual buildings tend to cancel out. As a result, the aggregate recovery trajectory converges toward its expected value, which is primarily governed by the central tendency (e.g., mean or median) of the underlying distributions of IF delays, repair times, and interaction heuristics.

To illustrate this aggregation effect, Figure 6 presents recovery trajectories for progressively larger randomly selected subsets of buildings for the FL100–EQ2475 scenario. For a single building ($N = 1$), the trajectory is a binary step function and exhibits substantial uncertainty across realisations. With 10 buildings, the trajectories remain step-like and highly uncertain. As the subset size increases to 50 and 100 buildings, the recovery curves become progressively smoother, and the uncertainty interval decreases noticeably. For subsets of 200 and 500 buildings, the uncertainty intervals become considerably narrower, and the aggregate trajectories closely resemble the portfolio-level recovery curves obtained for the complete building inventory ($N = 3,282$). This convergence demonstrates that the narrow uncertainty intervals observed for the full portfolio arise primarily from statistical averaging rather than a lack of uncertainty at the individual-building level. Importantly, increasing N reduces the uncertainty interval but does not eliminate the differences between the interaction and no-interaction cases, showing that this gap is attributable to the interaction mechanisms themselves rather than stochastic variability in individual building recovery.

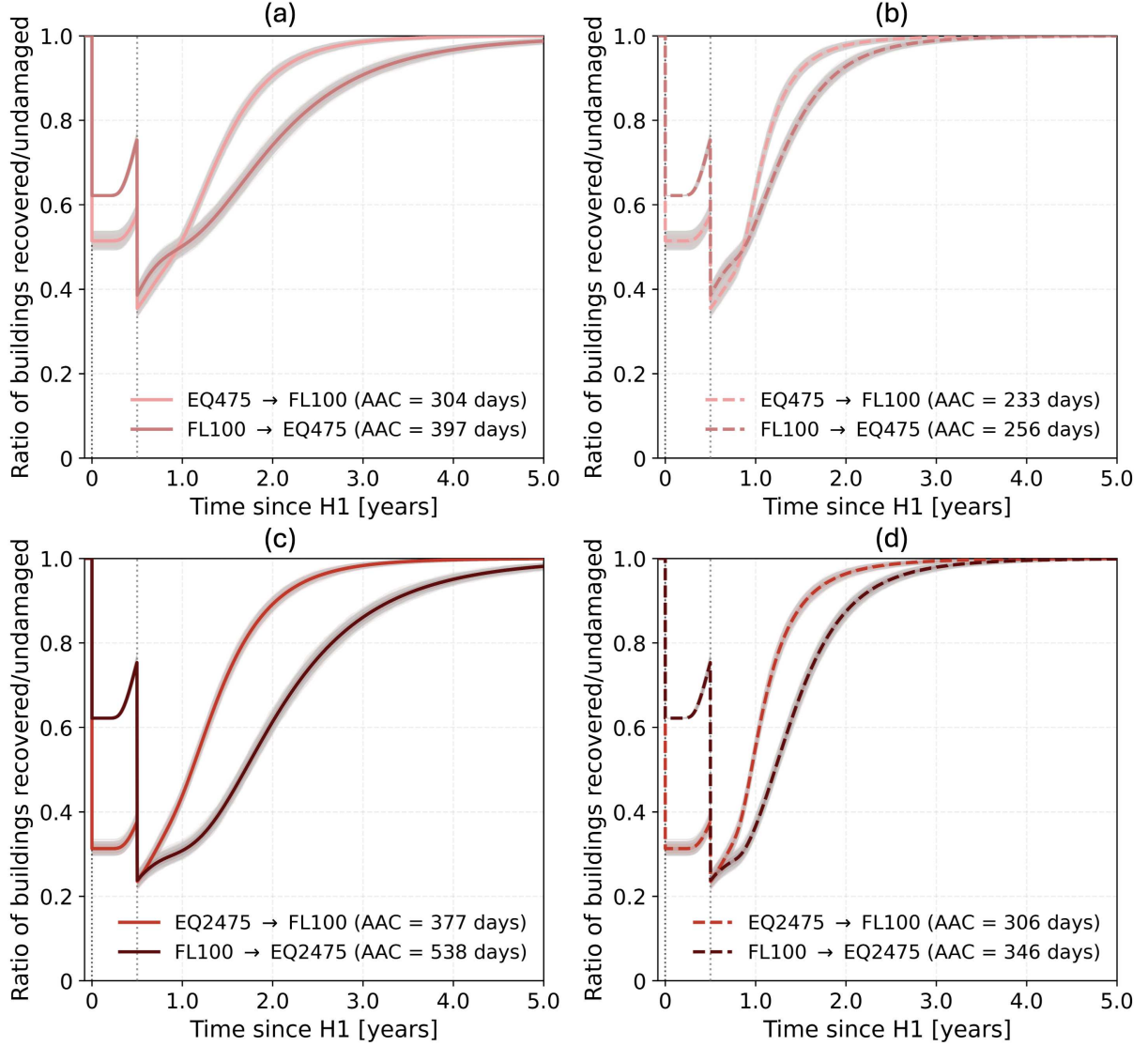


Figure 5: Recovery trajectories for four multi-hazard scenarios involving FL100, EQ475, and EQ2475: EQ475 followed by FL100 (EQ475–FL100), FL100 followed by EQ475 (FL100–EQ475), EQ2475 followed by FL100 (EQ2475–FL100), and FL100 followed by EQ2475 (FL100–EQ2475), with a six-month interval between events ($\delta t = 6$ months). Results considering interactions are shown in panels (a) and (c), while results neglecting interactions are shown in panels (b) and (d). Bold curves denote median recovery trajectories, and shaded regions represent the 95% uncertainty intervals. The vertical dotted line indicates the occurrence of the second hazard event.

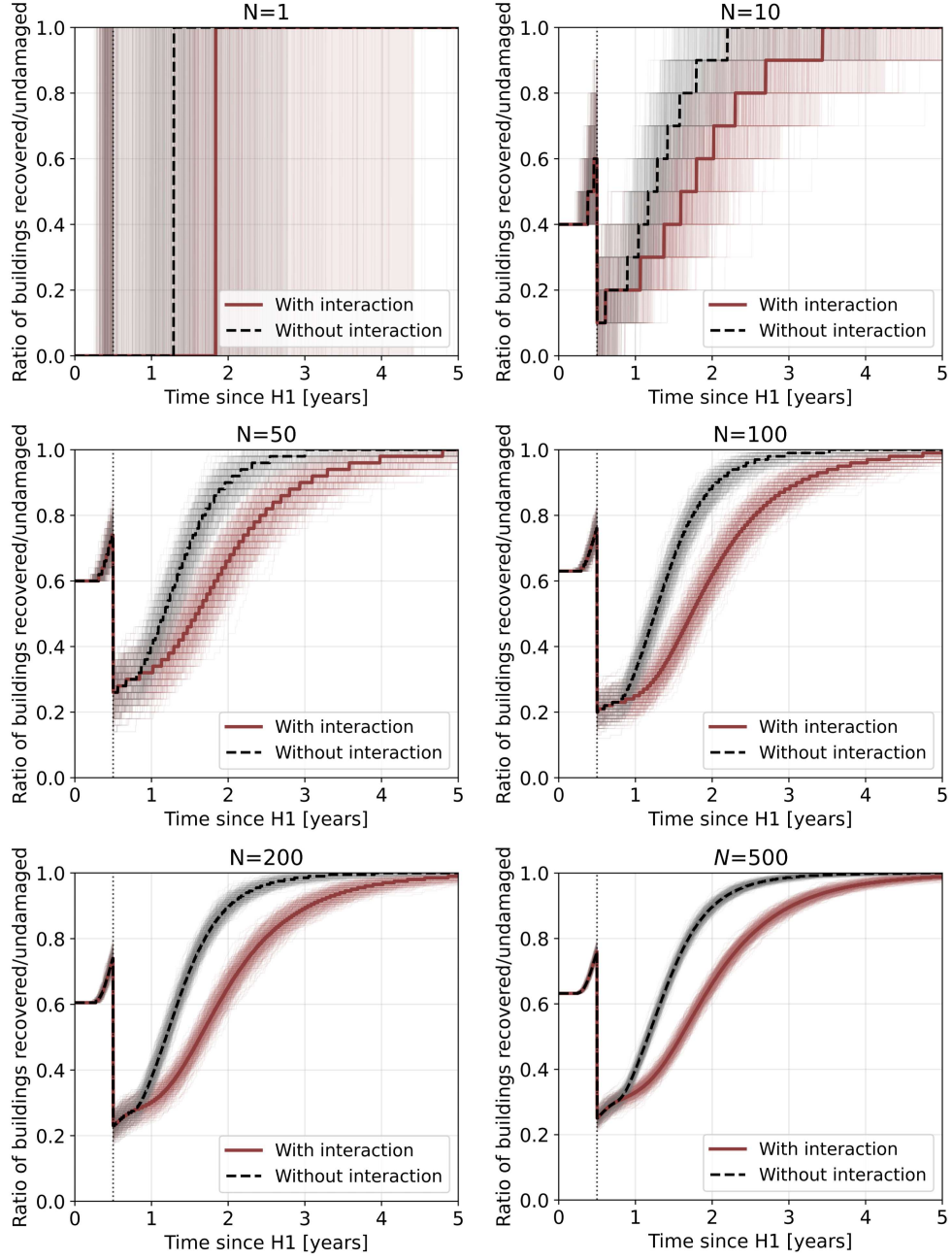


Figure 6: Recovery trajectories for progressively larger randomly selected subsets of buildings in the FL100–EQ2475 scenario, considering subset sizes of $N = 1, 10, 50, 100, 200$, and 500 buildings. The solid and dashed bold curves represent median recovery trajectories with and without interactions, respectively, while the lighter curves show the corresponding stochastic realisations. The vertical dotted line indicates the occurrence of EQ2475.

Sensitivity Analysis

We assess the sensitivity of the results to key modelling assumptions by considering three alternative cases: (1) increasing the interarrival time to $\delta t = 1$ year, with all other parameters unchanged; (2) $\delta t = 6$ months combined with a moderate interaction case, in which the baseline scaled medians of the $IF_{H2,fin}$ and $IF_{H2,con}$ distributions are multiplied by 1.5 and 0.5, respectively (e.g., resulting in a median of 394.4 days for $IF_{EQ,fin}$ and 58.9 days for IF_{EQ,con_str} when $DS_{EQ,b,i,j} \geq 2$), applied when the corresponding IF delay remains substantial (i.e., $>20\%$) across damaged buildings at time δt ; and (3) $\delta t = 6$ months combined with a severe interaction case, in which the baseline scaled medians of the $IF_{H2,fin}$ and $IF_{H2,con}$ distributions are multiplied by 2.2 and 0.1, respectively, under the same activation conditions as (2). The multipliers adopted in (2) and (3) are not intended as empirically calibrated values; rather, they represent moderate and severe interaction assumptions selected to evaluate the sensitivity of the framework to increasingly strong financing and contractor-mobilisation interactions. From a practical point of view, they reflect different post-disaster recovery dynamics and policies. Reduced amplification of financing delays for the subsequent hazard (i.e., limiting increases in $IF_{H2,fin}$) could be achieved through, for example, parametric catastrophe insurance⁷⁰, and expedited disbursement of government-backed loans and grants. Stronger contractor-mobilisation interactions (i.e., facilitating the reduction in $IF_{H2,con}$) could be achieved by enhancing contractor supply, for example, through providing temporary accommodation and incentives to attract out-of-town contractors⁷¹.

Figure 7 presents the recovery trajectories for the alternative modelling case (1). The interactions have negligible impact on the FL100–EQ475 and FL100–EQ2475 scenarios, as over 90% of damaged buildings have completed flood-induced repair within one year and, therefore, interactions are minimal. In contrast, for the EQ475–FL100 and EQ2475–FL100 scenarios, the AAC increases from 254 to 324 days (27.6%) and 339 to 409 days (20.6%), respectively, when interactions are considered. This increase arises because, after one year since EQ475 and EQ2475, only 5.1% and 9.8% of earthquake-damaged buildings remain in the contractor mobilisation phase, respectively, whereas 29.0% and 28.9%, respectively, are still awaiting financing, leading to prolonged financing delays for flood-damaged buildings. The effects of interactions on recovery trajectories are significantly smaller compared to those of $\delta t = 6$ months, which highlights the role of interarrival time in multi-hazard recovery trajectories.

Figures 8 and 9 present the recovery trajectories under the alternative interaction heuristics defined in modelling cases (2) and (3), respectively. These results are interpreted relative to results under the baseline interaction heuristics shown in panels a and c of Figure 5. In the alternative modelling case (2), the AAC decreases from 304 to 268 days (11.8%) and 377 to 341 days (9.5%) for EQ475–FL100 and EQ2475–F100, respectively, and from 397 to 326 days (17.9%) and 538 to 440 days (18.2%) for FL100–EQ475 and FL100–EQ2475, respectively. This indicates that changes in $IF_{H2,fin}$ dominate the overall effect, as the reduced amplification in $IF_{H2,fin}$ outweighs the smaller decrease observed in $IF_{H2,con}$. The effect is particularly pronounced for multi-hazard scenarios where flooding strikes first (i.e., FL100–EQ475 and FL100–EQ2475) and earthquake strikes later with more buildings affected by financing delays. This is because only 2.0% of flood-damaged buildings remain in the contractor mobilisation phase at the time of δt whereas 45.2% of the damaged buildings are still awaiting financing,

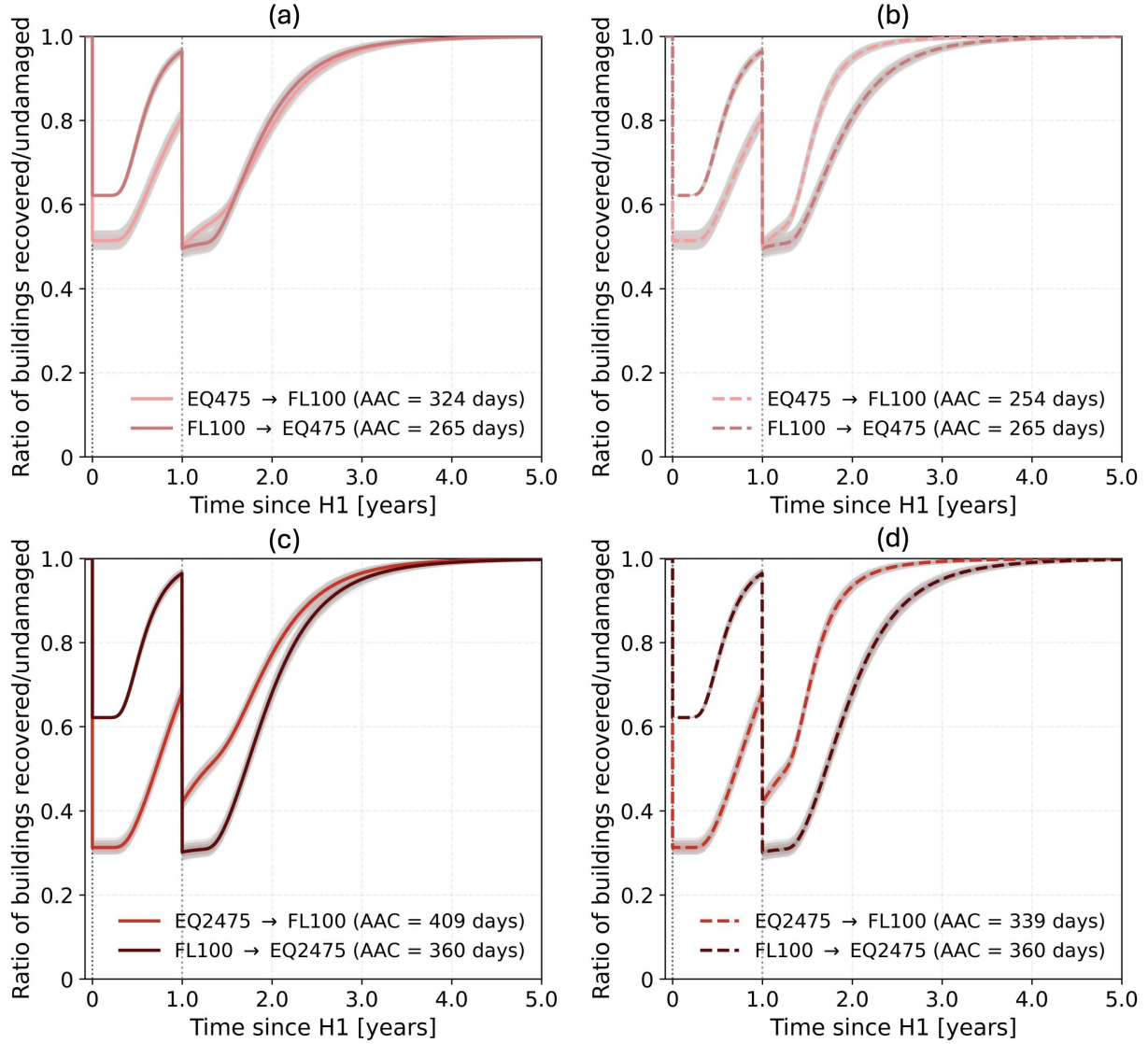


Figure 7: Recovery trajectories for the four multi-hazard scenarios with $\delta t = 1$ year—modelling case (1)—with (panels a and c) and without (panels b and d) the consideration of interaction heuristics.

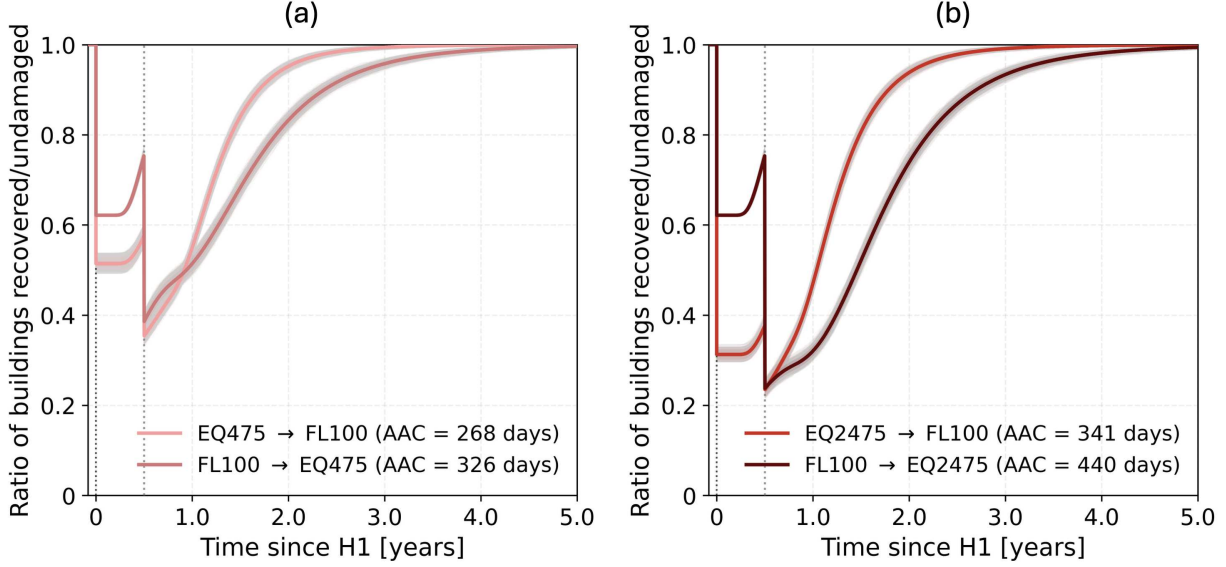


Figure 8: Recovery trajectories for the four multi-hazard scenarios with the consideration of $\delta t = 6$ months and interaction heuristics specified in the modelling case (2), representing moderate interactions compared to the baseline.

and $IF_{H2,con}$ is therefore unaffected by the interactions—which makes $IF_{H2,fin}$ the sole driver of IF delay.

In the alternative modelling case (3), the opposite trend is observed compared to the alternative modelling case (2). Relative to the results under the baseline interaction heuristics (Figure 5), the AAC increases from 304 to 318 days (4.6%) and 377 to 391 days (3.7%) for EQ475–FL100 and EQ2475–F100, respectively, and from 397 to 425 days (7.1%) and 538 to 577 days (7.2%) for FL100–EQ475 and FL100–EQ2475, respectively. These results show that even substantial acceleration in contractor mobilisation cannot compensate for a strong amplification of financing delays. Overall, the comparison between different interaction heuristics demonstrates that recovery outcomes are sensitive not only to the inclusion of interactions, but more importantly to how they are parameterised. In particular, financing delays emerge as the dominant driver of total recovery time. Small changes in the representation of financing interactions can therefore lead to disproportionately large changes in recovery trajectories, especially under short interarrival times where financing overlap is more pronounced. These findings highlight the need for improved empirical characterisation of IF delays and suggest the importance of carefully calibrating assumptions about interactions.

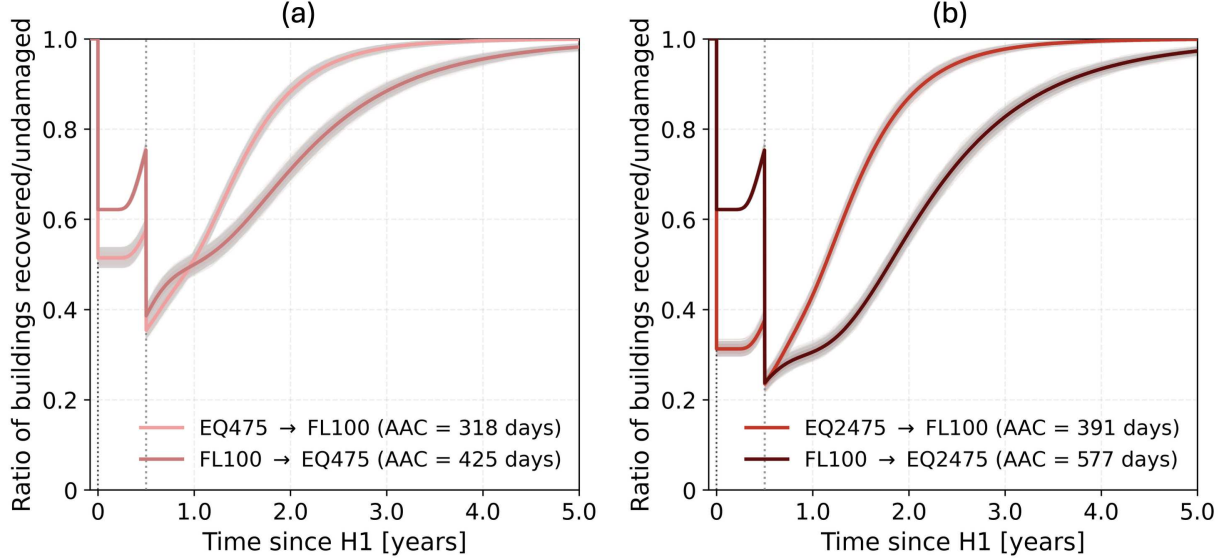


Figure 9: Recovery trajectories for the four multi-hazard scenarios with the consideration of $\delta t = 6$ months and interaction heuristics specified in the modelling case (3), representing severe interactions compared to the baseline.

Discussion

We introduced a simulation-based probabilistic framework for modelling multi-hazard recovery of building portfolios (e.g., across a city) that explicitly captures interactions among recovery activities—for example, financing and contractor mobilisation—associated with two physically independent hazards that occur in close temporal and spatial proximity. The methodology was demonstrated on 3,282 residential buildings (comprising reinforced-concrete and unreinforced-masonry structures classified into 20 typologies under an Italy-specific taxonomy) in Pompei, Italy, considering earthquake and flood scenarios occurring within a six-month interarrival interval. Case-study results showed that a simple superposition of single-hazard recovery outcomes cannot properly capture the compound impacts and recovery dynamics under sequential and coincident hazards. Neglecting IF interactions systematically underestimates total recovery time and overall resilience loss—by up to 50% in some cases—and alters the distributions of recovery trajectories. Sensitivity analyses further revealed that the interaction effects are strongly dependent on the interarrival time, hazard severity, and how interactions are modelled. In particular, financing-related delays emerge as the dominant driver of total recovery time, while contractor mobilisation—although benefiting from overlap effects—provides only partial reduction. Small changes in the modelling of financing interactions can lead to disproportionately large variations in recovery trajectories, especially when events occur in close succession. These findings highlight the importance of adequately representing interactions among impeding factors (for example, through more nuanced empirical calibration) in multi-hazard risk and recovery modelling.

The case study relies on assumptions informed by empirical evidence from Italian disasters and expert-based consultation with the (re)insurance industry, particularly for the adjustment and/or parameterisation of IF delays and their interactions, and is therefore subject to substantial epistemic uncertainty. In particular, the representation of interactions among

recovery processes is based on simplified assumptions regarding their triggering conditions and mechanisms, reflecting the current scarcity of empirical observations. Furthermore, the framework considers interactions primarily through IF delays and does not explicitly model interactions arising from cumulative physical damage, changes in repair times due to repeated hazard exposure, or other mechanisms that may affect recovery activities. The results therefore provide quantitative insights into the potential recovery trajectories of compound earthquake-flood events in Pompei under the adopted modelling assumptions, while primarily serving to demonstrate the usefulness of the proposed framework. The results should not be generalised to other urban contexts without context-specific investigations of local urban morphology, hazard characteristics, and recovery dynamics.

Future work can focus on evaluating additional multi-hazard scenarios, improving the empirical characterisation of impeding factors and their interactions through a systematic elicitation of expert judgement or data collection for past events, and assessing the framework’s sensitivity to key modelling assumptions, including the choice of fragility, vulnerability, and consequence models, and the representation of interactions among recovery processes.

Methods

Hazard scenario selection and modelling

We use openly available hazard maps to maximise reproducibility: flood depths from the Europe and Mediterranean Basin flood maps⁷² at 3 arc second (≈ 90 m) resolution and median peak ground acceleration (PGA) from the official Italian probabilistic seismic hazard maps⁷³ on a 5 km grid. The seismic maps report median PGA for specified return periods and include a within-site lognormal dispersion that captures epistemic uncertainty and is suitable for direct sampling. No map-level uncertainty was provided for flood depths, so we represent flood uncertainty with a lognormal distribution whose dispersion was matched to the seismic map’s within-site dispersion. We adopted this approach for three reasons: first, our study is an urban, parcel-scale case study in which unresolved local hydraulic processes (microtopography, drainage connectivity, and building scale conveyance) can introduce substantial uncertainty that the published 90 m product does not capture, so matching dispersions provides a conservative proxy for those unresolved epistemic effects; second, using a comparable dispersion preserves a consistent probabilistic treatment across hazards and avoids introducing artificial asymmetry in uncertainty propagation when comparing multi-hazard recovery outcomes; and third, we explicitly test this assumption in sensitivity analyses and find that varying the flood depths within plausible bounds does not alter repair times substantially (see Fig. 12). Grid intensity measures are assigned to building centroids using nearest neighbour mapping; sampling ignored spatial correlation. We note that 90 m flood cells and 5 km seismic cells are coarse for parcel-scale damage assessment (i.e., at individual building level): 90 m averages microtopography and local drainage features that control inundation at the building scale, and 5 km smooths local site amplification and shallow geology effects. Targeted seismic downscaling or site amplification corrections to sub kilometre resolution can better capture local variability, and higher resolution hydraulic modelling would reduce the need for a proxy dispersion for floods; where map-level or model-specific uncertainty estimates are available, they should replace the proxy used here. Consequently, our results are best interpreted as relative comparisons of recovery under alternative multi hazard scenarios rather than precise

absolute loss estimates, and the paper’s qualitative finding—that non additive urban recovery is driven by financing bottlenecks—remains robust across the tested assumptions on intensity measure dispersion and other modelling choices.

Figure 10 presents the median peak ground acceleration (PGA) and water depth values at the SEZ level across 1,000 realisations (i.e., $n_i = 1,000$) for these three individual events. We adopt the 100-year MRP flood event (corresponding to a 1% annual exceedance probability and approximately a 22% probability of occurring at least once within a 25-year period) as the most representative and commonly assessed flood scenario in this study, consistent with standard practice in flood risk assessment and management^{74,75}. This choice reflects the relatively small differences in flood impacts across MRP values in Pompei. Specifically, both the number of flooded buildings and the median flood depth vary only modestly between flood events with different MRPs (see Figure 11 for details). Furthermore, the adopted flood vulnerability (i.e., repair-time) model indicates that building repair times remain approximately 30 days for flood depths between 0.2 m and 1.2 m (Figure 12; details to follow), a range encompassing the majority of flood depths experienced by affected buildings across the scenarios considered. Consequently, increasing the flood MRP results in only limited changes in building repair times and the resulting recovery trajectories. The 100-year MRP flood therefore provides a representative basis for evaluating earthquake–flood recovery interactions while avoiding unnecessary complexity associated with analysing a wider range of flood events.

Four multi-hazard scenarios are constructed from the three individual events considered: (1) EQ475 followed six months later by FL100; (2) FL100 followed six months later by EQ475; (3) EQ2475 followed six months later by FL100; and (4) FL100 followed six months later by EQ2475. We adopt a storyline approach—i.e., focusing on physically plausible scenarios of events rather than fully probabilistic hazard occurrences⁷⁶—to assess multi-hazard interactions. Rather than attempting to quantify the highly uncertain joint probabilities of successive hazards and their interactions, the storyline approach enables a systematic exploration of how different hazard sequences and orders influence recovery trajectories under well-defined scenarios. It has therefore been widely adopted for investigating complex multi-hazard interactions^{77–79} and for communicating risk to both scientific and non-technical audiences to support decision-making⁸⁰. We adopt a time interval of $\delta t = 6$ months—typically corresponding to intermediate recovery phases⁸¹, when most IF delays remain ongoing³⁰—to examine how interactions between two physically independent events may influence recovery trajectories.

Damage and repair time analysis

For flood, $RT_{FL,b,i,j,k}$ values are sampled directly from the 1,000 realisations of the flood vulnerability model (see Figure 12) in Olmez & Deniz⁵⁶, with $n_d = 1$ and $n_r = 1,000$, for each $IM_{FL,b,i}$. Although the model developed by Olmez & Deniz was not specifically calibrated for the Italian building stock, the resulting 95th-percentile repair time of approximately 80 days is broadly consistent with post-flood recovery timescales reported in a European context—up to approximately 14 weeks⁸²—providing a general plausibility check for its application to the present case study. For earthquake-related consequences, the most likely DS ($n_d = 1$) is computed for each building, $DS_{EQ,b,i,j} \in \{0, 1, 2, 3, 4\}$, corresponding to no, slight, moderate, extensive, and complete damage, respectively, using the seismic fragility models developed

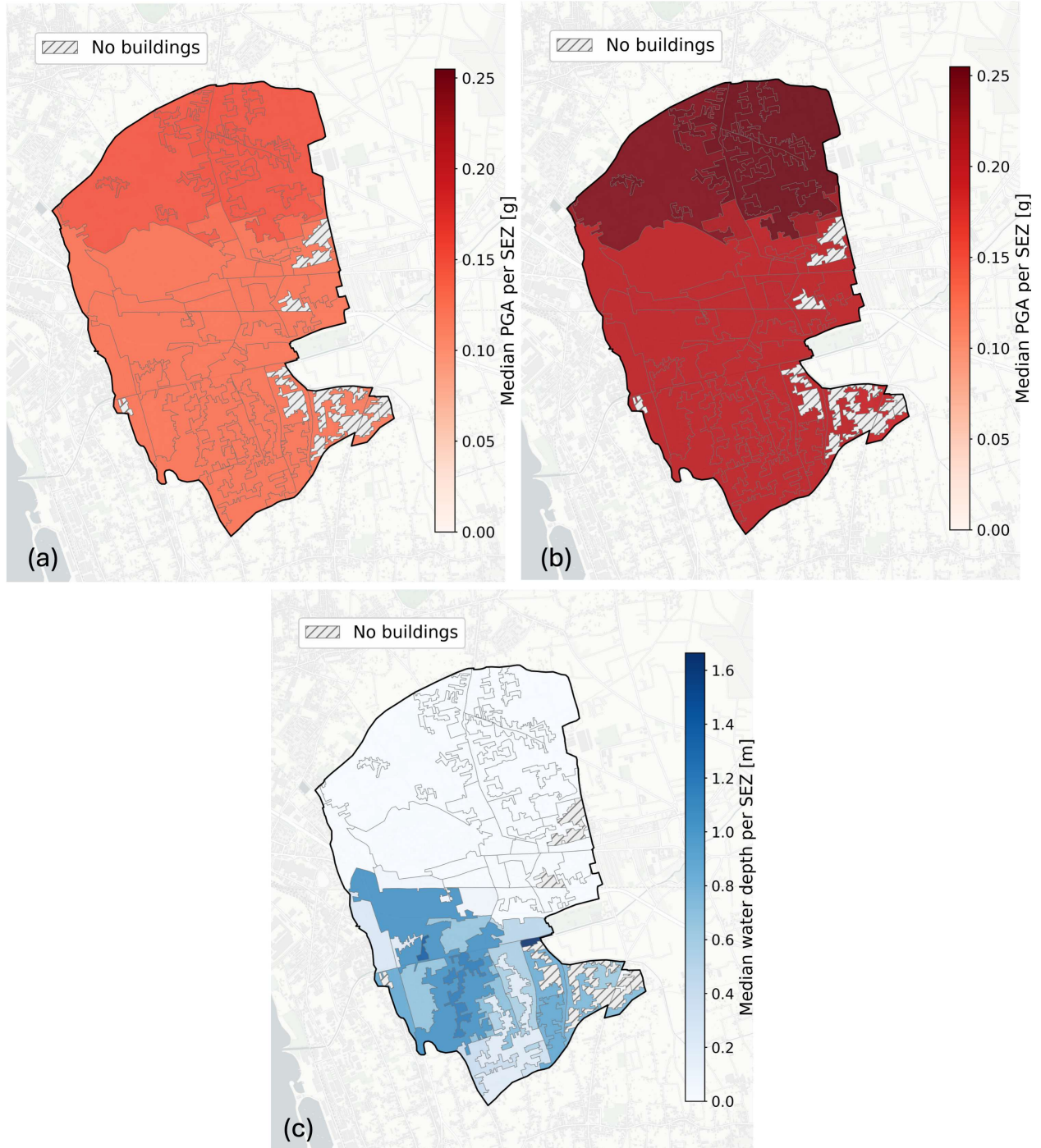


Figure 10: The median PGA [g] and water depth [m] at the SEZ level across the 1,000 realisations for the EQ475(a), EQ2475 (b), and FL100 (c) scenarios.

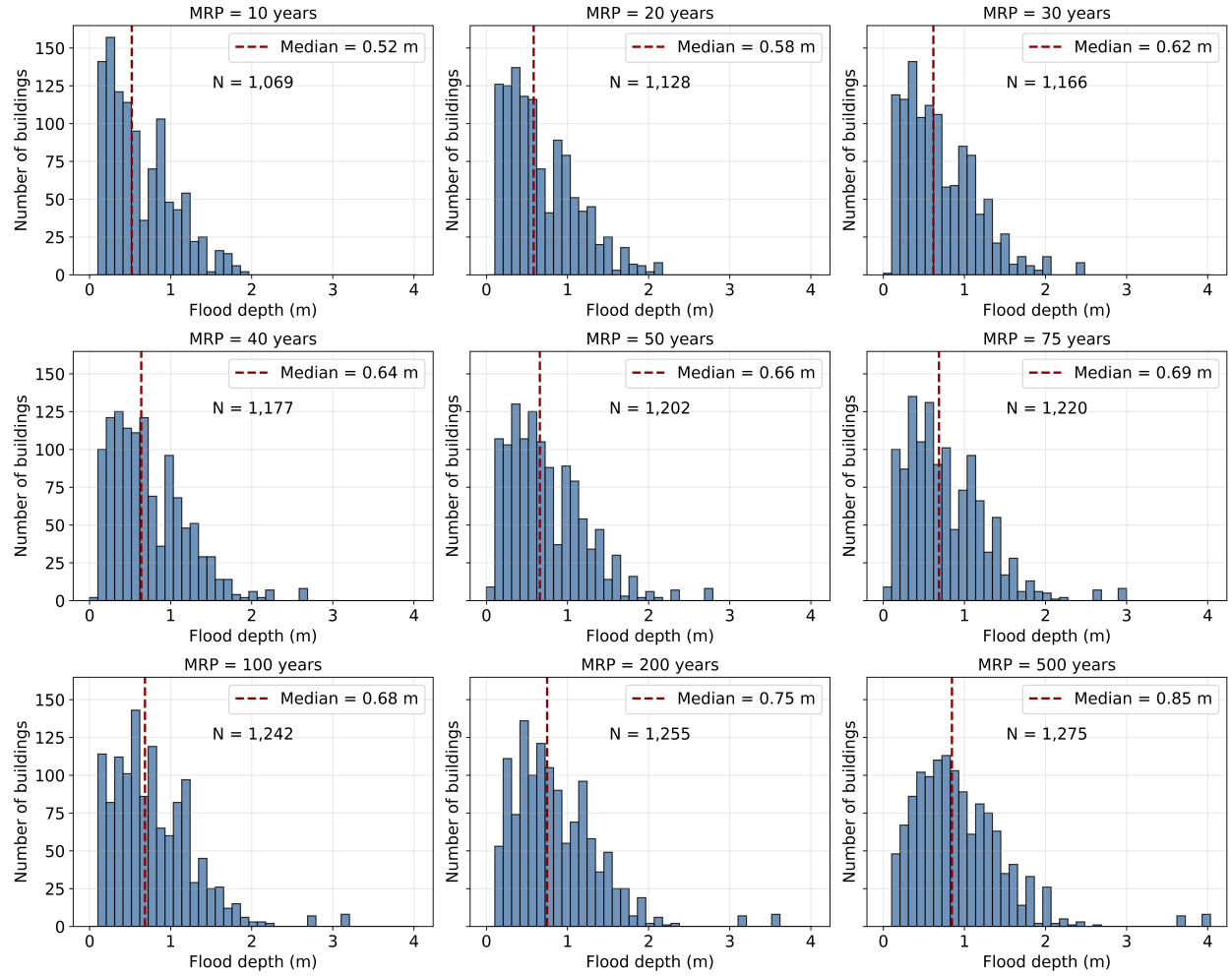


Figure 11: The distributions of water depth [m] across flooded buildings in Pompei under river flood events of MRPs ranging from 10 years to 500 years⁷².

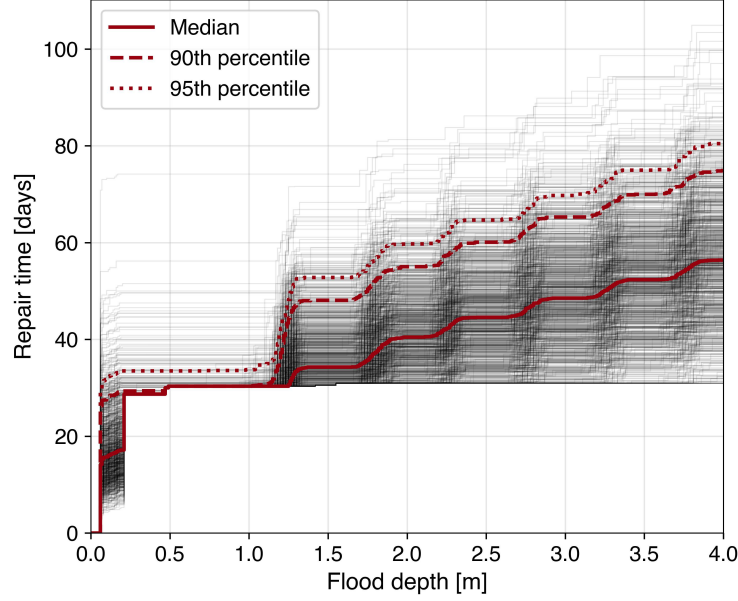


Figure 12: The flood repair-time models in Olmez & Deniz⁵⁶. The 90th and 95th percentiles indicate the repair times exceeded by 10% and 5% of the simulated realisations, respectively.

for Italian archetype RC frame and URM buildings by Rosti et al.^{49,50}; each typology corresponds to a unique set of seismic fragility models. Conditional on $DS_{EQ,b,i,j}$, 1,000 $RT_{EQ,b,i,j,k}$ realisations (i.e., $n_r = 1,000$) are generated using the seismic consequence models developed for Italian archetype RC frame buildings⁵⁵, resulting in $n_i \times n_d \times n_r = 1,000,000$ realisations per event. We adopt the seismic consequence models for three-storey low-code buildings (i.e., constructed prior to the introduction of modern seismic design codes in Italy). The corresponding repair-time distributions (medians and dispersions) are taken from Table 7 of Aljawhari et al.⁵⁵, with a replacement time of 198 days, consistent with empirical observations from contractors following the 2009 L'Aquila earthquake⁸³. This choice reflects the fact that the residential building stock in Pompei is predominantly low-rise, with an average height closer to three storeys rather than the 5- or 8-storey archetypes considered by Aljawhari et al.⁵⁵. The same seismic consequence models are adopted for both RC and URM buildings, because for Italian RC buildings, damage (and the resulting repair) is mostly incurred by the damage/collapse of infill walls^{84–86}, which exhibit behaviours similar to Italian URM construction.

IF delay quantification

We adopt a unified sequence of activities (i.e., individual IFs and repairs) following an earthquake or a flood proposed in Kourehpaz et al.³⁰, and focus on the most locally-relevant IFs for each hazard. We consider four main IFs for earthquake—inspection ($IF_{EQ,ins}$), permitting ($IF_{EQ,per}$), financing ($IF_{EQ,fin}$), and contractor mobilisation ($IF_{EQ,con}$)—in line with TREADS (Tool for Recovery Estimation And Downtime Simulation)⁵⁴, and five main IFs for flood—event duration ($IF_{FL,eve}$; i.e., the time it takes for floodwater to recede), restoration work and clean up ($IF_{FL,res}$), $IF_{FL,fin}$, $IF_{FL,con}$ and $IF_{FL,per}$ —in line with Resilience-Based Design Guidelines for Floods (REDi)⁵³. For $IF_{EQ,fin}$ and $IF_{FL,fin}$, we adopt from TREADS

and REDi the distributions associated with public financing as the baseline (and scale them based on empirical Italian disaster data; details to follow), reflecting the fact that post-disaster residential building recovery in Italy is largely driven by government-backed loans and grants, as observed following the 2009 L'Aquila earthquake^{87,88}. Specifically for earthquakes, $IF_{EQ,con}$ is represented in detail by six component-specific contractor mobilisation delays: structural (IF_{EQ,con_str}), interior (IF_{EQ,con_int}), exterior (IF_{EQ,con_ext}), mechanical (IF_{EQ,con_mec}), electrical (IF_{EQ,con_elc}), and staircase (IF_{EQ,con_sta}) in line with TREADS. These components correspond to delays in mobilising contractors for repairing structural damage, interior partitions, exterior building components (e.g., façade), mechanical systems, electrical systems, and the staircase, respectively. The overall $IF_{EQ,con}$ is then taken as the maximum of the six component-specific delays, reflecting that the mobilisation processes related to different types of contractors typically happen in parallel. In addition, for $IF_{EQ,per}$ and $IF_{EQ,con}$, two sets of lognormal distributions are adopted from TREADS depending on damage severity: one for $DS = 1$ and another for $DS > 1$. This is consistent with the distinction between repair class 1 and repair classes 2–5 in TREADS, in which repair classes classify damage according to the extent and severity of affected building components and their implications for achieving specific recovery states⁸⁹.

To capture the sequential and parallel nature (i.e., delay sequence) of various activities following Kourehpaz et al.³⁰, the earthquake-related total IF delay, $IF_{EQ,tot}$, is defined as:

$$IF_{EQ,tot} = IF_{EQ,ins} + \max(IF_{EQ,fin}, IF_{EQ,con}, IF_{EQ,per}) \quad (2)$$

Whereas the flood-related total IF delay, $IF_{FL,tot}$, is defined as:

$$IF_{FL,tot} = IF_{FL,eve} + \max(IF_{FL,res}, IF_{FL,fin}, IF_{FL,con}, IF_{FL,per}) \quad (3)$$

$IF_{EQ,tot,b,i,j,k}$ and $IF_{FL,tot,b,i,j,k}$ values are first sampled from the baseline lognormal distributions specified in TREADS and REDi, respectively. These sampled values are then scaled using scale factors—applied to medians only—such that (i) the median of sampled $IF_{EQ,tot,b,i,j,k}$ values, across buildings with $DS_{EQ,b,i,j} > 1$ and all realisations, equals 340 days—consistent with empirical observations from the 2009 L'Aquila earthquake (Italy)⁸³; and (ii) the 95th percentile of $IF_{FL,tot,b,i,j,k}$ values, across all flooded buildings and realisations, equals 390 days. The 95th percentile is adopted because post-event evidence from the 2023 Emilia-Romagna flood indicates that by 16 months after the event, most affected households had completed repairs well before this time, with only a small proportion still completing repair works⁹⁰. Assuming a 90-day repair time (corresponding to the maximum repair time under a 3.0 m flood depth in Olmez & Deniz⁵⁶), this suggests that an IF duration of approximately 390 days characterises the upper tail (rather than median) of the recovery distribution. Table 2 summarises the adjusted Italy-specific lognormal distributions of individual IF delays for earthquake and flood.

After this adjustment step, we account for interactions between the IF delays of successive events by modifying the scaled H2-related IF distributions. Following the expert-informed modelling assumptions introduced by Kourehpaz et al.³⁰, if financing delays from H1 remain substantial (i.e., over 20% of damaged buildings are still awaiting financing at time δt), the median of the scaled $IF_{H2,fin}$ distribution is doubled to reflect increased demand on financial resources. Conversely, if contractor mobilisation from H1 is still widely ongoing (i.e., over

Table 2: The adjusted Italy-specific lognormal distributions of individual impeding-factor (IF) delays for earthquake (EQ) and flood (FL) hazards. Values in parentheses (if applicable) correspond to DS = 1, while values outside parentheses correspond to DS > 1.

Hazard	Scale factor	IF	Median (days)	Dispersion	References
EQ	0.782	$IF_{EQ,ins}$	3.9	0.54	54,83
		$IF_{EQ,per}$	43.8 (5.5)	0.32 (0.86)	
		$IF_{EQ,fin}$	262.9	0.57	
		IF_{EQ,con_str}	117.8 (78.9)	0.33 (0.39)	
		IF_{EQ,con_int}	95.9 (39.4)	0.43 (0.35)	
		IF_{EQ,con_ext}	113.9 (71.8)	0.81 (0.53)	
		IF_{EQ,con_mec}	105.7 (66.8)	0.86 (0.47)	
		IF_{EQ,con_elc}	61.9 (47.1)	0.30 (0.43)	
		IF_{EQ,con_sta}	94.8 (44.9)	0.94 (0.39)	
FL	0.872	$IF_{FL,eve}$	1.7	0.50	53,90
		$IF_{FL,res}$	26.2	0.30	
		$IF_{FL,per}$	73.2	0.50	
		$IF_{FL,fin}$	170.0	0.50	
		$IF_{FL,con}$	64.5	0.50	

20% of damaged buildings are still mobilising contractors), the median of the scaled $IF_{H2,con}$ distribution is reduced by 75%—consistent with REDi⁵³—to reflect pre-existing contractor availability.

Author contributions

Chenbo Wang: Writing – original draft, Writing – review & editing, Methodology, Visualisation, Investigation, Data curation, Formal analysis, Conceptualisation. **Pouria Kourehpaz:** Writing – review & editing, Methodology, Investigation, Conceptualisation. **Marco Gaetani d’Aragona:** Writing – review & editing, Methodology, Investigation, Data curation. **Maria Polese:** Writing – review & editing, Methodology, Funding acquisition, Supervision. **Carmine Galasso:** Writing – review & editing, Methodology, Supervision, Funding acquisition, Conceptualisation.

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Data Availability Statement

All study data and codes are made available on GitHub at <https://github.com/wangc> b98, except data that have restricted access per the providers’ requirements.

Competing interests

The authors have no competing interests to declare.

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