Deliverable

[Deliverable 4.7: Good-practice report on risk-cost-benefit in terms of socio-economic impact]

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Summary

This report summarises the work done in Task 4.6. The aim of this task as stated in the grant agreement is to build a risk-cost-benefit analysis framework for quantifying socio-economic impact of earthquake risk. Earthquakes are natural disasters that can have significant impacts on the socio-economic well-being of communities. Understanding the risks, costs, and benefits of earthquake mitigation strategies is critical for making informed decisions to reduce the impact of earthquakes. Risk-cost-benefit analysis is a valuable tool for decision-makers to evaluate the effectiveness of different mitigation strategies.

In this context, a user-ready risk-cost-benefit analysis framework can provide a comprehensive approach to quantify the socio-economic impact of earthquakes. This framework should incorporate the relevant factors that contribute to the costs and benefits of mitigation strategies, including the probability of earthquake occurrence, the severity of the earthquake, the vulnerability of the affected area, and the potential economic and social consequences.

The aim of such a framework is to enable stakeholders to assess the potential effectiveness of different mitigation strategies in a transparent and user-friendly manner. This can help decision-makers to identify the most effective measures for reducing the impact of earthquakes on communities, while balancing the costs and benefits of each strategy.

Overall, a user-ready risk-cost-benefit analysis framework has the potential to support evidence-based decision-making and promote the development of effective earthquake risk management strategies.

In this task we established a risk-cost-benefit analysis framework for the key dynamic products developed in other RISE tasks. The framework includes a comprehensive list of the various costs and benefits associated with each dynamic product, and we have found that not all of these products can be effectively evaluated using the classic cost-benefit analysis (CBA) methodology.

As a result, we have explored alternative frameworks that allow for the evaluation of cost-effectiveness for different tools, which can be used to support decision-making processes. This approach enables decision-makers to compare the relative effectiveness of different tools and make informed decisions based on the most cost-effective options available.

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Introduction

RISE takes an integrative and holistic approach to risk reduction, using a dynamic risk concept that incorporates all relevant information to assess risk at different stages of the earthquake cycle. RISE's developments advance the real-time seismic risk reduction capacities of European societies by transitioning to a new concept of dynamic risk. This concept includes several key elements, such as the development and validation of next-generation forecasting models to improve short-term and operational earthquake forecasting, enhancements to the rapid loss assessment methodology to account for the dynamics of exposure and vulnerability, the use of building sensor data to improve information on building damage after an earthquake, and improvements to the preparedness of societies, emergency managers, and long-term recovery management.

To achieve more resilient societies through real-time earthquake risk reduction, tangible advances must be made. However, this will require investment decisions from a variety of stakeholders, including national and regional governments, industry, building owners, infrastructure operators, and even individuals. It is up to societies to determine how much they are willing to invest in disaster-risk reduction and how to allocate limited resources effectively, considering multiple hazards. With multiple options for risk mitigation, it is crucial to balance requests from different hazard communities and make investments in the most effective measures. Ultimately, investments in earthquake safety are necessary for achieving resilient societies that can withstand the impacts of earthquakes.

Section 1 outlines the general risk cost benefit framework for decision making of the dynamic products developed in other RISE tasks. In Section 2, we examine the use of cost benefit analysis (CBA) in RISE and introduce an alternative framework, multi-criteria decision analysis (MCDA), for evaluating the cost effectiveness of key RISE dynamic products in a more holistic manner.
Section 3 presents the results of CBA for early earthquake warning (EEW), while Section 4 summarises the key dynamic products developed in other RISE tasks that require a more comprehensive approach to evaluating their cost effectiveness. In Section 5, we explain how the MCDA framework was applied to evaluate different RISE dynamic products in a case study developed in RISE task 6.1. Finally, Section 6 presents the results and discussion of our analysis.

Overall, this report provides a comprehensive overview of the risk cost benefit analysis framework for evaluating the socio-economic impact of earthquakes and highlights the importance of taking a holistic approach to decision-making in the field of earthquake risk reduction.

1. Risk Cost Benefit Analysis Framework for Decision Making

The earthquake risk cost-benefit framework is a tool used in decision-making to assess the benefits and costs of investing in earthquake risk reduction measures. The framework helps decision-makers to evaluate the potential consequences of earthquake events and to determine the most effective and efficient investments in risk reduction measures.

The framework involves several steps, including:

1. Identifying the potential risks of earthquakes in a given area, such as the likelihood and potential impact of earthquakes on buildings, infrastructure, and people.
2. Assessing the costs of potential damage from earthquakes, including the costs of repair or replacement of damaged infrastructure, and the costs of lost productivity.
3. Identifying potential earthquake risk reduction measures, such as seismic retrofitting of buildings, land-use planning, and emergency preparedness.
4. Evaluating the costs and benefits of these measures, taking into account the potential reduction in earthquake risks and the costs associated with implementing the measures.
5. Making a decision based on the cost-benefit analysis and implementing the chosen earthquake risk reduction measures.

The earthquake risk cost-benefit framework is a valuable tool for decision-making because it enables decision-makers to identify the most effective and efficient measures to reduce earthquake risks and to allocate resources accordingly. By using this framework, decision-makers can make informed decisions that balance the costs and benefits of investing in earthquake risk reduction measures, ultimately reducing the potential impact of earthquakes on society.

RISE encompasses a wide range of coordinated activities that contribute to a unified dynamic risk framework. Each module aims to advance the state-of-the-art in its respective domain, including earthquake early warning (EEW), operational earthquake forecasting (OEF), operational earthquake loss forecasting (OELF), structural health monitoring (SHM), rapid loss assessment (RLA), recovery and rebuilding efforts (RRE), and dynamic risk communication. These are collectively referred to as the "dynamic risk products of RISE".

In evaluating these dynamic risk products, we emphasise the innovation within RISE and their potential impact on risk mitigation. To secure substantial future investments from governments or industry to advance observational capabilities in EEW, OEF, or RLA, scientists and engineers must demonstrate a positive risk-cost-benefit balance. Our aim is to provide guidelines to aid stakeholders in their investment decision-making.

We have established a comprehensive framework, as presented in Table 1.1, which includes various key RISE products along with their costs, benefits, and possible mitigation actions. Our goal is not to favour one product over another, as some of the innovative solutions developed within RISE may provide cost-effective ways to complement each other in different ways. The framework in Table 1.1 contains both soft and hard resilience actions. Hard resilience refers to strengthening physical structures and components to withstand shocks from natural disasters such as earthquakes, storms, and floods, or more drastic changes such as changing the building codes. On the other hand, soft resilience involves less tangible and process-oriented measures and policies to cope with events as they occur and minimise adverse outcomes. RISE focuses on soft resilience measures and does not address building codes or methods of building strengthening. While it would be interesting to compare soft and hard resilience, this falls outside the scope of RISE. Therefore, Task 4.6 solely focuses on soft resilience.

Table 1.1 provides a comprehensive list of all potential benefits resulting from the implementation of a system, whether quantitative or qualitative, as well as whether the system being in the operational stage would result in any direct mitigation action. In addition, the table lists the possible costs of the system under different cost categories.

Table 1.1 Framework for Risk Cost Benefit Analysis of Dynamic RISE Products

Time	Dynamic risk products	Benefits	Costs	Mitigation Actions
Short term	EEW	- Reduced damage to equipment - Reduced BI - Reduced injuries & fatalities - Reduced losses in material batches	- Implementation costs - Instrumentation and hardware - Research & Development - software - Operational costs - personal - maintenance - false and missed alarms - evacuation costs	Shutdown critical systems (stop elevators, stop critical lifelines, business equipment, shut down computer systems)
				Dock-cover-hold-on (DCHO)
	OEF & OELF			Evacuate
				Protection of manufacturing processes
Short to Medium Term	RLA (classical way)	Financial and human loss estimates Estimate of displaced population	SHM: - building instrumentation - electricity to measure,	SHM can suggest: “evacuation” or issue

	RLA enhanced with SHM RLA enhanced with dynamic vulnerability	Assist civil protection authorities in the emergency action Time gain in emergency response Information gain in building damage state	stream and process data - false or missed alarms RLA: - PMs developing the methodology & tools	"safe for occupancy"
Medium to Long Term	RRE & Improving building codes & strengthening building stock	Reduced human losses Reduced Property damage Reduced BI	Retrofitting and rebuilding costs	

The table above illustrates a range of benefits associated with disaster risk reduction interventions. While some benefits can be quantified in monetary terms, others are qualitative measures. Traditional cost-benefit analysis (CBA) typically requires all benefits to be expressed in monetary terms, but for some benefits, such as reductions in human losses, there are methods to convert them to monetary values. However, benefits such as information gain or time gain cannot be monetized.

While CBA can be applied to some cases where benefits can be monetized, other key RISE dynamic products cannot be evaluated using this approach. As a result, we sought alternative methods that can account for all possible benefits in a more inclusive manner. Such methods need to be flexible enough to incorporate surveys and expert opinions in decision-making.

Section 2 discusses the use of CBA within the framework presented above, and discusses the alternatives to the classic CBA, namely multi-criteria decision-making analysis (MCDA).

2. Alternative Frameworks for Evaluating Costs and Benefits for decision making support

Ensuring that limited financial resources are used in a cost-effective way is crucial. However, achieving effective spending with high rates of return is often challenging in practice. To evaluate the cost-effectiveness of projects, various criteria are used, such as cost-benefit analysis (CBA), cost-effectiveness analysis (CEA), and multi-criteria decision analysis (MCDA).

Cost-benefit analysis (CBA): CBA is a method of evaluating the costs and benefits of disaster risk mitigation measures. It compares the total costs of an intervention against the total benefits it provides, both in monetary and non-monetary terms. The aim is to determine whether the benefits of implementing the mitigation measures outweigh the costs, and to what extent. For example, in the case of building retrofitting for earthquake resistance, CBA can be used to evaluate the costs and benefits of retrofitting existing buildings versus building new ones from scratch.

Cost-effectiveness analysis (CEA): CEA is another method of economic evaluation used to compare the costs of different interventions in disaster risk mitigation. Unlike CBA, CEA focuses on the relative costs of achieving a specific outcome. For example, in the case of flood management, CEA can be used to compare the costs of different flood management measures, such as building dams or implementing early warning systems, in terms of their ability to reduce flood damage. As CEA is only comparing the costs of different alternatives, regardless of the benefits they bring, it falls beyond the scope of our investigation.

Multi-criteria decision analysis (MCDA): MCDA is a decision-making tool used to evaluate and compare different options based on multiple criteria or objectives. MCDA can be used in disaster risk mitigation to consider multiple factors, such as cost, effectiveness, and community acceptance, and to weigh them against each other in order to select the best option. For example, in the case of selecting a location for a new emergency shelter, MCDA can be used to consider factors such as cost, proximity to at-risk communities, and availability of transportation.

Below we look into the use of CBA vs. MCDA for the framework set on Table 1.1.

Cost Benefit Analysis

CBA is a systematic approach to evaluating decisions that have a societal impact. It involves assigning a monetary value to the expected impacts of an option. In the context of earthquake risk mitigation, CBA can be used to quantify the socio-economic benefits of different risk reduction actions.

The starting point for a CBA analysis is the status quo, which represents the expected losses in the absence of any mitigation actions. Mitigation actions are then defined and their direct costs are estimated. The losses associated with and without the mitigation actions are also assessed. The benefits of the mitigation actions are then compared to their costs to determine which actions are the most cost-effective.

For earthquake early warning (EEW), CBA can be used to evaluate the effectiveness of direct mitigation actions such as evacuation or the activation of automatic shutdown systems. The benefits of these actions, such as reduced fatalities and injuries, can be quantified in monetary terms using established statistical methods. Our study on the application of CBA to EEW is discussed in detail in Section 3.

The applicability of cost-benefit analysis for assessing the efficiency of certain disaster risk reduction (DRR) interventions

CBA is a key analytical tool that can provide quantitative information regarding the prioritisation of risk reduction based on comparing benefits of an actual or planned intervention with its costs. In a CBA, costs and benefits are compared under a common economic efficiency criterion in order to derive a decision, for which in theory, all effects, costs and benefits, need to be monetized and aggregated.

While CBA can play a critical role in supporting decisions, its use and applicability are also constrained by important limitations. As stated above, in CBA the benefits need to be monetized. For cases benefits are not quantitative but rather qualitative, or for quantitative benefits that are not possible/reasonable to be monetized, CBA cannot be applied. Many of the costs and benefits from DRR can be of indirect and intangible nature, yet these can be difficult to identify and quantify for inclusion in a CBA. Quantitative disaster risk modelling has focussed on direct, tangible impacts, less so on the indirect and intangible effects. And ignoring the intangible effects would result in excluding many valuable benefits of DRR models.

Despite its limitations the CBA can be a powerful tool when deciding on and prioritising DRM measures. It is useful when the issues are complex and there are several competing proposals, and particularly so when comparing alternatives. Nevertheless, considering multiple variables and different objectives at the same time, its use has declined over the years (even at the World Bank). It is important to set clear rules about when, how, and on what CBA should be performed.

Multi Criteria Decision Analysis

In the context of scientific decision making, MCDA provides a framework for evaluating and selecting among different options. The framework is based on the identification of explicit objectives that have been set by the decision-making body, and the establishment of measurable criteria for assessing the attainment of these objectives. In straightforward cases, the mere process of defining objectives and criteria may be sufficient for decision-making purposes. However, in situations where a level of detail comparable to that of a CBA is required, MCA offers several methods for aggregating data on individual criteria to generate composite indicators of the overall performance of each option.

MCDA resembles a cost-benefit analysis, but with the notable advantage of not being solely limited to monetary units for its comparisons. Comparing conflicting sets of criteria, such as quality and costs, can sometimes lead to confusion and lack of clarity. When making comprehensive or important decisions, multiple criteria and levels of scale need to be accounted for.

MCDA is a technique that uses decision matrix to provide a systematic analytical approach for establishing criteria, such as risk levels, uncertainty and valuation, to evaluate and rank many ideas. It is most applicable to solving problems that are characterised as a choice among alternatives. It helps us focus on what is important, is logical and consistent, and is easy to use.

The use of a Multi-criteria analysis comes with various advantages when compared to a decision-making tool not based on specific criteria:

- It’s open and explicit
- The chosen criteria can be adjusted

- Many different actors can be compared with one another
- A Multiple Criteria Decision Analysis (MCDA) grants insight into different judgements of value
- Performance measurements can be left to experts
- Scores and weights can be used as reference
- It's an important means of communication between the different parties involved in the decision-making process

3. Effectiveness of Earthquake Early Warning in Reducing Earthquake Risk

We evaluate the effectiveness of an EEW in reducing earthquake casualty risk and optimise an existing seismic network in order to maximise earthquake early warning capabilities at minimum cost. A demonstration of the devised framework is carried out for Switzerland. With respect to the network optimization, we use a genetic algorithm to determine the optimal sensor distribution in a seismic network that maximises its EEW performance, as quantified via the maximum warning time for correct warnings in damaging earthquakes. The work is carried out in two parts:

Part 1: Risk-based EEW Performance Evaluation and Optimization (Böse et al., 2022)

The goal of EEW is to issue an alert before the damaging seismic waves of an earthquake hit, using waves that have already left the source but have not reached the location yet. We use warning time as a key performance indicator and assess the risk-based EEW performance using the example of Switzerland. We simulate 1k realisations of a 100 year long stochastic earthquake catalog with ~24k scenario earthquakes ($5.0 \leq M \leq 7.4$), which samples the earthquake rate forecast of the Swiss Hazard Model in space and time (Figure 3.1). We link the predicted ground-motions to the built environment and determine warning time statistics for different loss classes (here fatalities and injuries; Figure 3.2). Finally, we apply a genetic algorithm to optimise the Swiss Seismic Network by proposing sites for new stations in order to optimise its EEW performance for damaging earthquakes (Figure 3.3).

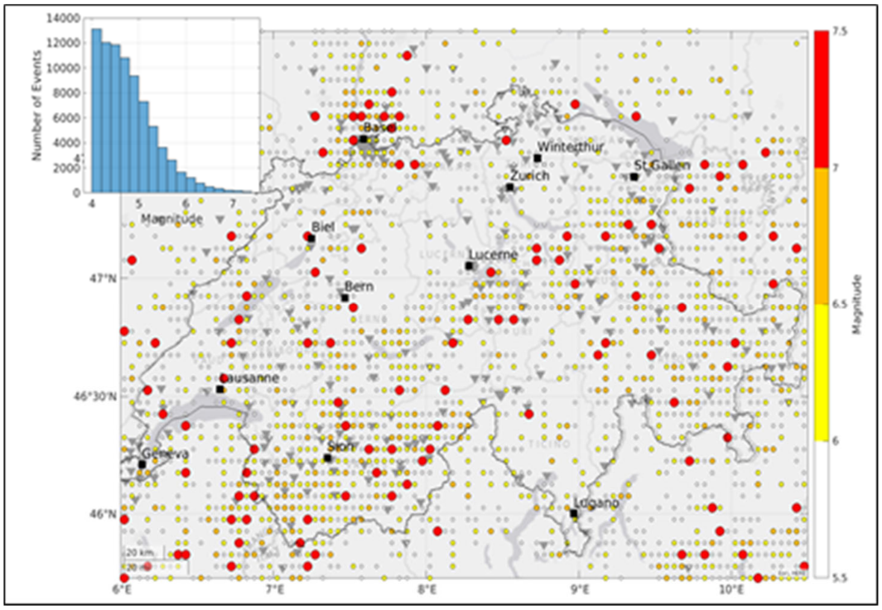


Figure 3.1. Stochastic earthquake catalog, including ~24k scenario earthquakes (5.0 ≤ M ≤ 7.4) in and around Switzerland.

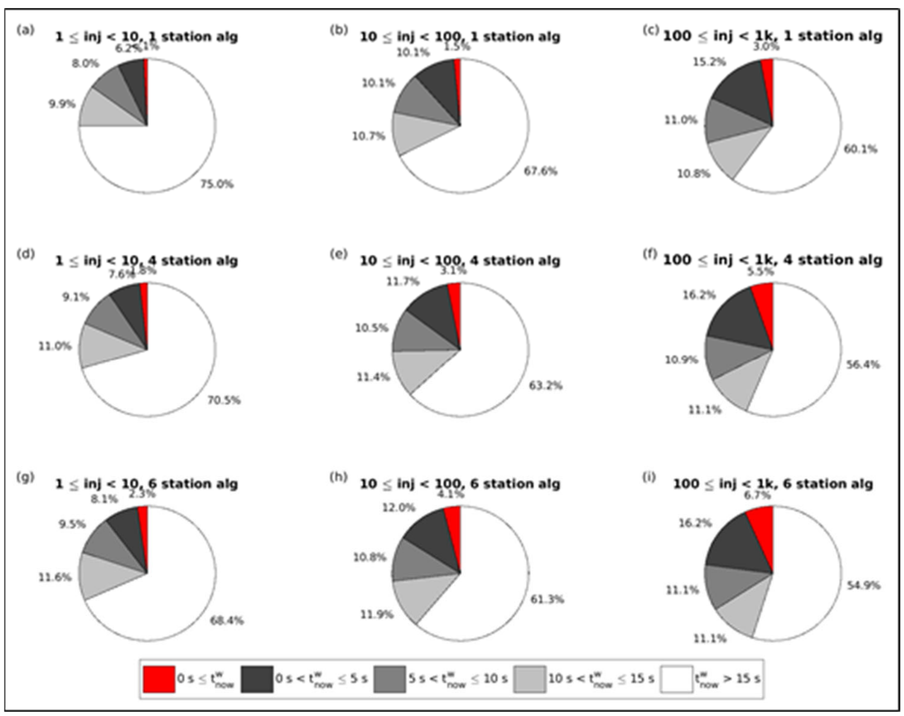


Figure 3.2. Warning time statistics (preliminary) for different loss classes (here injuries) and EEW algorithms. Warning times include 2 s data latency.

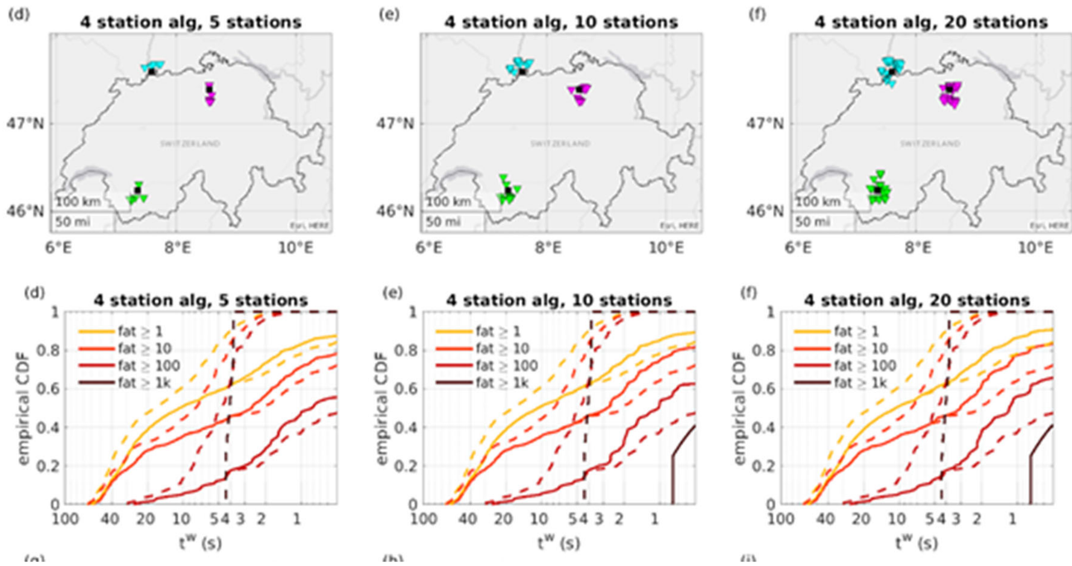


Figure 3.3. Proposed sensor locations (top) with the goal to optimise EEW performance for damaging earthquakes and their impact on warning time for different loss classes (here fatalities): lower dashed line: performance for current network; upper dashed line: maximum performance for an idealised network; solid line: performance for optimised network after deployment of 5, 10 or 20 new stations (from left to right). Warning time statistics include 2 s data latency.

Part 2: Effectiveness of EEW in mitigating seismic risk (Papadopoulos et al., 2023)

EEW systems aim to rapidly detect earthquakes and provide timely alerts, so that users can take protective actions prior to the onset of strong ground shaking. The promise and limitations of EEWS have both been widely debated. On the one hand, an operational EEWS could potentially mitigate earthquake risk by triggering potentially cost- and life-saving actions. On the other hand, the effectiveness of an EEWS hinges on the accuracy and timeliness of its alerts. EEWSs have substantially improved over the years, yet there are physical constraints as well as variability in the correlation between the early parts of the signal and earthquake source and ground-motion parameters that limit the alert speed and accuracy, even for an ideal system. Herein, we rely on regional event-based probabilistic seismic risk assessment, and devise a quantitative and fully customizable framework for evaluating the effectiveness of EEW in mitigating risk. We demonstrate this framework using Switzerland as a testbed.

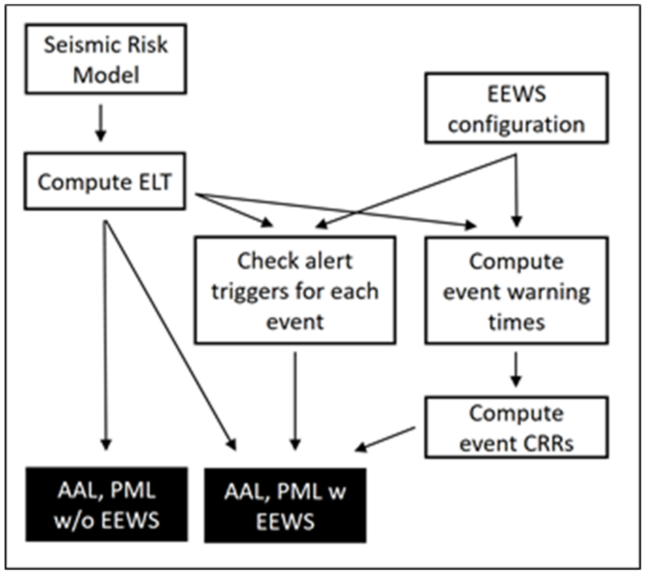


Figure 3.4. Workflow for assessing the effectiveness of an EEWS

The proposed framework is illustrated in Figure 3.4 and can be briefly summarised in the following steps:

1) A regional seismic risk model is used to generate a so-called event loss table (ELT). The latter comprises a catalogue of simulated earthquakes, generated from an underlying earthquake source model, together with associated losses (herein casualties, i.e., fatalities and injuries) computed using models of ground shaking intensity, exposure and vulnerability for the region of interest.

2) Given a seismic network configuration, the potential warning time at a site of interest is estimated for each earthquake in the ELT. Also, assessed is whether an alert is issued, given a set of predetermined alerting criteria.

3) For each earthquake for which an alert is issued, the warning time is used to determine the potential reduction of the event loss. To this end, a logical framework is devised using judgement informed by literature data from post-earthquake surveys. More precisely, the EEWS-adjusted loss for each event i can be computed as:

$$C_{EEWS}^{i}(t_i^w) = C_0^i * \left(1 - CRR(t_i^w) * F_{alert}^i * F_{day}^i\right)$$

where C_0^i is the event i loss without EEW, CRR denotes the casualty reduction ratio as a function of warning time t_i^w, F_{alert}^i is a binary flag that defines whether an alert is issued for event i or not, while F_{day}^i is a binary flag that is equal to one when the earthquake occurs during the day (we assume that alerts issued during the night will not have an effect on casualties). CRR is computed as:

$$CRR(t_i^w) = P_s * P_r * P(CA|t_i^w)$$

where P_s denotes the probability that an individual receives and notices the warning message, and P_r denotes the probability that the recipient responds to the warning. $P(CA|t_i^w)$ effectively represents the probability of casualty avoidance as a function of warning time available for earthquake i at the area of interest among individuals that receive and react to the warning. For the latter, we partition the sample space into recipients that will respond to the alert with the recommended duck cover and hold on (DCHO) protocol and those that will attempt to evacuate. The equation given below can then be used to estimate $P(CA|t_i^w)$. The description of the various parameters contained therein, along with values that were deemed reasonable, is given in Table 3.1. An investigation of the effect of some of these parameters on $P(CA|t_i^w)$ is also shown in Figure 3.5.

$$P(CA|t_i^w) = P(t_i^w) = P(t_i^w, SDCHO) \cdot P(t_i^w, ADCHO) \cdot P(ADCHO) \ \ + P(t_i^w, SE) \cdot P(t_i^w, AE) \cdot P(AE)$$

4) Using the EEWS-adjusted ELT, traditional risk metrics such as average annual losses (AAL) or probable maximum loss (PML) curves can be derived and contrasted with the original non-EEWS-adjusted estimates. This analysis can also serve as a stepping stone for a downstream cost-benefit analysis.

Table 3.1 Parameters for estimation of $P(CA|t_i^w)$

Probability terms	Description	Value for fatality avoidance	Value for injury avoidance
$P(CA \mid t_i^w, SDCHO)$	Probability of casualty avoidance given successful DCHO	25% (10%-40%)	65% (50%-80%)
$P(CA \mid t_i^w, SE)$	Probability of casualty avoidance given successful evacuation	99.9%	70% (40%-90%)
$P(SDCHO \mid t_i^w, ADCHO) = F_{SDCHO}(t_i^w \mid AE)$	Probability of successful DCHO given attempted DCHO and warning time	LN [$\tilde{t}^w_{DCHO} = 8.8$ s, $\sigma_{\ln t^w} = 0.4$] ($\tilde{t}^w_{DCHO} = 4-12$ s)	
$P(SE \mid t_i^w, AE) = F_{SE}(t_i^w \mid AE)$	Probability of successful evacuation given attempted evacuation and warning time	LN [$\tilde{t}^w_{evac} = 25$ s, $\sigma_{\ln t^w} = 0.8$] ($\tilde{t}^w_{evac}$ =15-45 s)	
P(ADCHO)	Probability of DCHO attempt	70% (20%-80%)	
P(AE)	Probability of evacuation attempt	30% (80%-20%)	
P_s	Probability that an individual receives the alert	0.8 (0.5-0.9)	
P_r	Probability that a recipient responds to the alert	0.65 (0.4-0.8)	

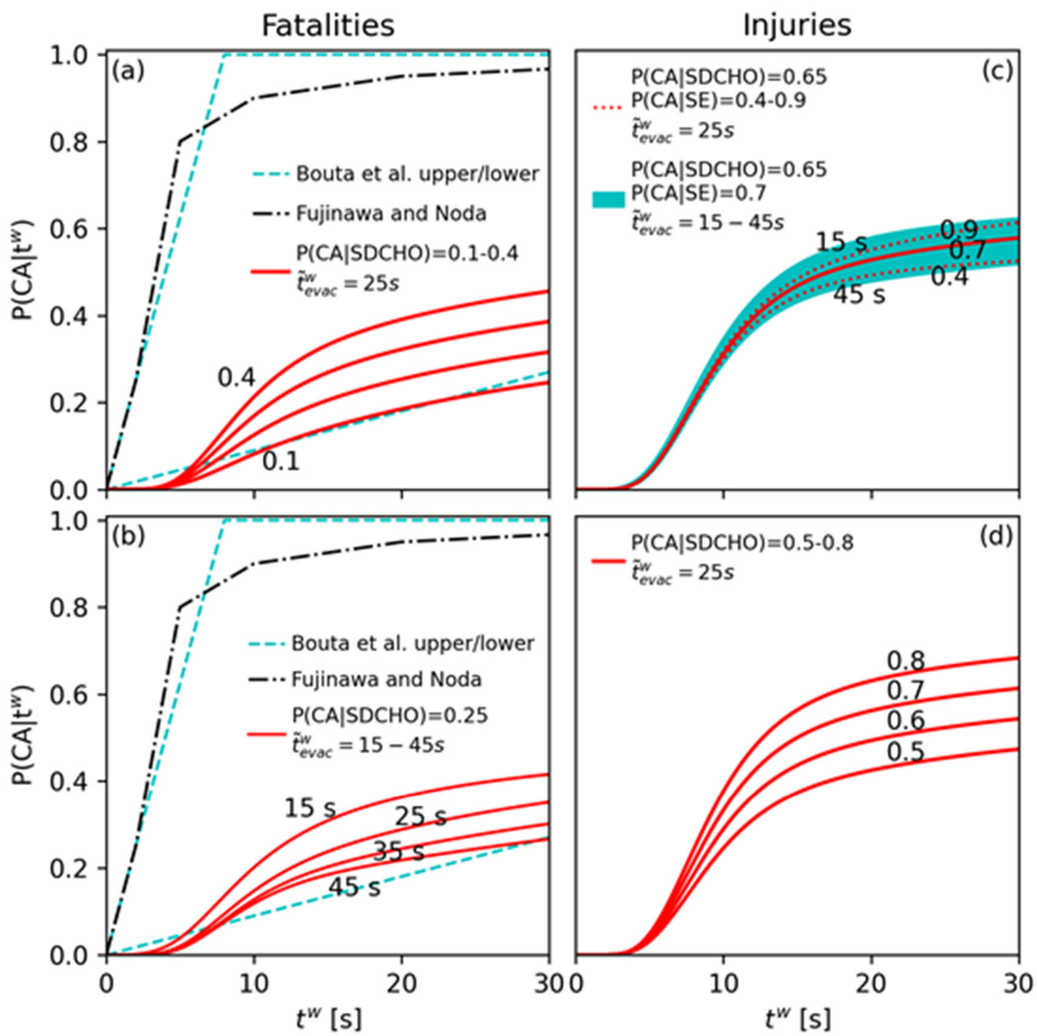


Figure 3.5 Effect of different parameters on P(CA|tw) for fatalities (a,b) and injuries (c,d) and comparison with other studies. Parameters not specified in the legends are taken as listed in Table 1.

The proposed methodology was tested via a case study for Switzerland. In Switzerland, the Swiss Seismological Service (SED) at ETH Zurich operates a non-public EEW demonstration system for Switzerland (Massin et al., 2021) that is based on a low-latency seismic network of 300 permanent stations and uses the Virtual Seismologist (Cua et al., 2009) and FinDer (Böse et al., 2018) EEW algorithms. For the case study, a simple risk model was put together using preliminary exposure and vulnerability datasets, being developed for the National Earthquake Risk Model of Switzerland. The seismic source model is obtained from the Swiss national seismic hazard model SUIhaz2015 (Wiemer et al., 2016), while an intensity prediction equation (IPE) developed for Switzerland (Fäh et al., 2011) was employed for the modelling of ground shaking. Lastly, local site conditions were modelled according to the amplification model currently in use for the ShakeMap system in Switzerland (Cauzzi et al., 2014). Following the steps described above, the casualty risk reduction was computed for major cities in Switzerland. Figure 3.6 shows such an example for injury reduction in the city of Zurich.

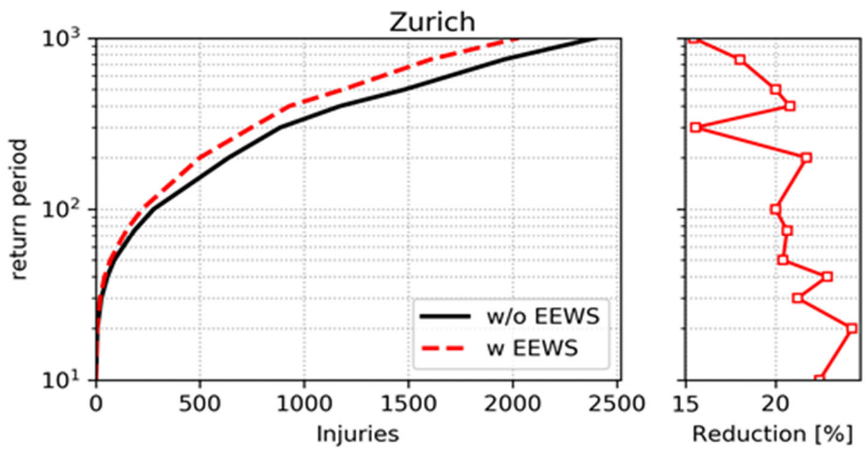


Figure 3.6 Injury PML curve for the city of Zurich with and without EEWS

While this kind of analysis involves numerous uncertainties, the proposed quantitative modelling of EEW benefits allows for exploring the impact of different factors and system design choices, and encourages data- and evidence-driven decision making. For instance, what-if analyses can be undertaken in a straightforward manner to provide support on decisions such the choice of alert triggering criteria, or the installation of new seismic stations (Böse et al., 2022). The estimated reduction in earthquake induced casualties, and possibly other losses, can also serve as the stepping stone for a downstream cost-benefit analysis. The latter would involve quantifying the costs for installing and operating an EEW system, contrasted against the possible projected benefits.

4. Dynamic Risk Products of RISE

In Task 4.6, we evaluate the cost effectiveness and benefits of various RISE dynamic risk products that have been developed in different RISE tasks. However, we exclude EEW from this evaluation as it is addressed separately in Section 3 using CBA. The focus is on RISE dynamic risk products that represent noteworthy improvements in methodology or procedure throughout the project.

i) Rapid Loss Assessment (Task 4.1) by Helen Crowley

Rapid (earthquake) Loss Assessment (RLA) after a severe earthquake can support civil protection agencies and emergency services to rapidly gain an overview of the expected building damages, number of fatalities, injured and displaced persons as well as economic losses. Such information allows coordinating and allocating the resources for the emergency response in an efficient manner. Of course, similar outputs can also be produced in advance, whereby these scenarios can be used to build up and support the awareness for damaging earthquakes among different stakeholders. More information on how RLA is provided in the Good Practice Report:

http://rise-eu.org/dissemination/good-practices/European-rapid-earthquake-loss-assessment/

Thanks to the developments in Task 4.1, the European ShakeMap system is now online (http://shakemapeu.ingv.it/) and exposure and vulnerability models for 44 European countries have been made available (https://gitlab.seismo.ethz.ch/efehr/esrm20).

A new prototype scientific service that allows the damage and losses to be assessed for any ShakeMap in the European ShakeMap system (the ESRM20 Rapid earthquake Loss Assessment code) has now been made available thanks to efforts in the RISE project: https://gitlab.seismo.ethz.ch/hcrowley/rapid_loss_eu. The service makes use of the Scenario from the ShakeMap calculator of the OpenQuake-engine (see Figure 4.1). An example output of the service (in terms of the loss distribution in a given country for a specific event) is shown in Figure 4.2.

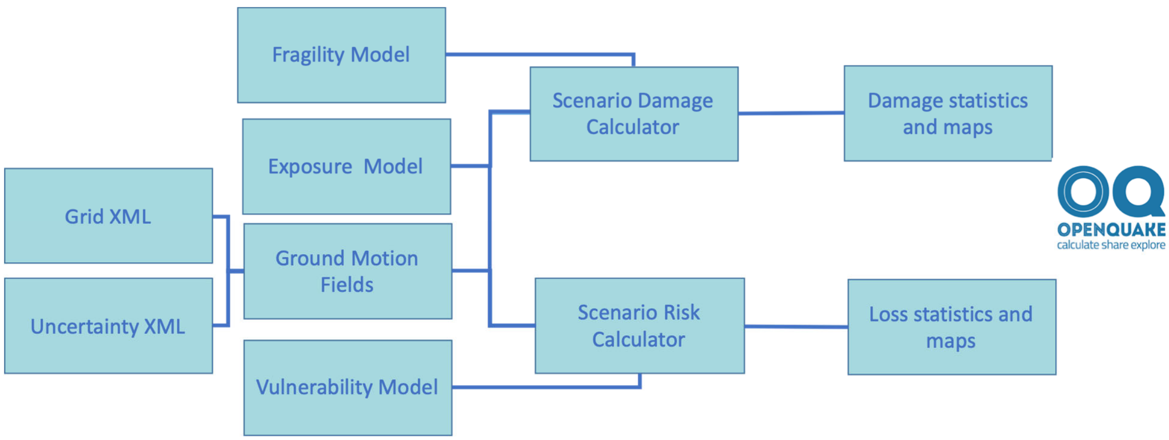


Figure 4.1 Scenario from ShakeMap Calculator (OpenQuake-engine https://github.com/gem/oq-engine/tree/master/openquake)

The ESRM20 Rapid Earthquake Loss Assessment (ReLA) code has been applied to all events in the European ShakeMap archive since it was launched in 2020 (a total of 1100 events with magnitude above 4). The results provided in terms of mean fatalities are compared with the observed losses reported in EM-DAT in Figure 4.3; the confusion matrix shows that the alert level would have been correctly estimated in 98.6% of the cases. More details on these services, and in particular the ShakeMap service, are provided in Deliverable D6.5.

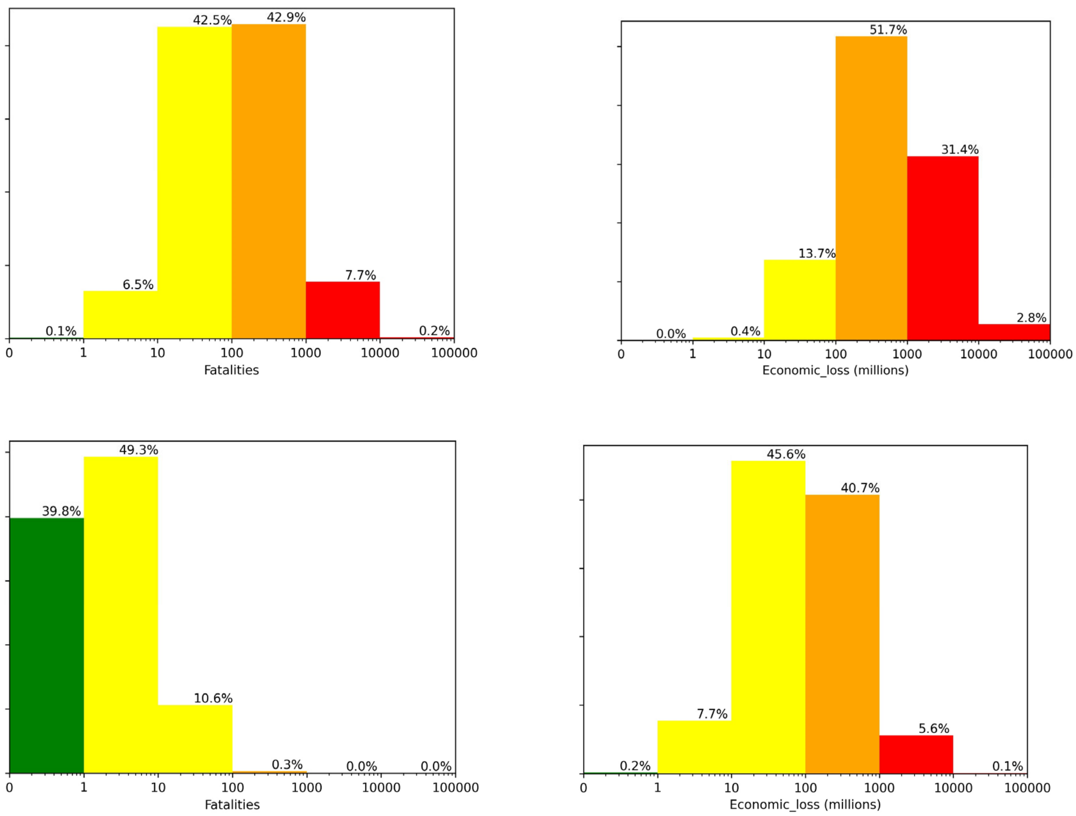
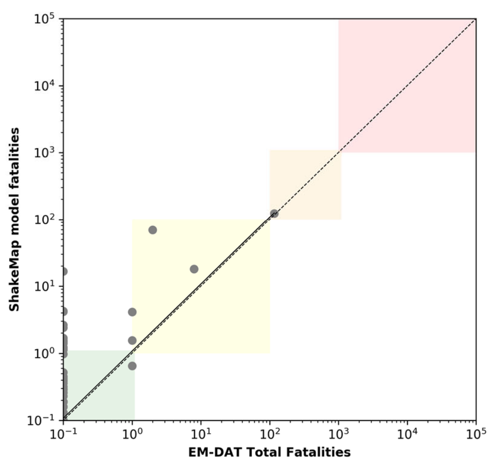


Figure 4.2 Example output for the 30th October 2020 Samos/Izmir earthquake. Distribution of the fatalities (left) and economic loss (right) for (top) Turkey and (bottom) Greece based on the PAGER impact scale (Wald et al., 2010)



		Actual Losses			
		Green	Yellow	Orange	Red
Predicted Losses	Red	0	0	0	0
	Orange	0	0	1	0
	Yellow	15	2	0	0
	Green	1082	0	0	0

Figure 4.3 (Left) Estimated mean fatalities using the ESRM20 Rapid earthquake Loss Assessment (ReLA) code (https://gitlab.seismo.ethz.ch/hcrowley/rapid_loss_eu) for all earthquakes in the European ShakeMap archive since 2020 (http://shakemapeu.ingv.it/archive.html) compared with the reported losses in EMDAT (www.emdat.be), (right) confusion matrix showing that the ESRM20 ReLA fatality-based alerts were correct (coloured cells) or over/under-estimated (grey cells) (following the comparison method presented in Wald et al., 2022).

ii) Operational Earthquake Loss Forecasting (Task 4.2)

In Italy, because of the work of the Istituto Nazionale di Geofisica e Vulcanologia, a system for operational earthquake forecasting, named OEF-Italy (Marzocchi et al., 2014), exists. It acquires information from the national monitoring network that continuously records the seismic activity in the country. Such information is used to probabilistically forecast the weekly expected number (i.e., rates) and locations of earthquakes with magnitude above a threshold occurring in the monitored area. The information provided by OEF-Italy are not measures of seismic risk because they only refer to the seismic source characterizations that, combined with ground motion propagation models, can be used to quantify the short-term seismic hazard. On the other hand, seismic risk requires additional information dealing with the vulnerability and the exposure of the existing building portfolio. Thus, to extend the results of OEF-Italy into the risk domain, profiting of the data provided by OEF-Italy, a system for operational earthquake loss forecasting (OELF), named MANTIS-K was developed (Iervolino et al., 2015). Such a system, named MANTIS-K, combines the weekly seismicity rates with vulnerability and inventory models for the Italian building stock to obtain weekly forecasts of seismic risk (consequences) metrics, that is, the expected number of collapsed buildings, fatalities, injuries, and displaced residents. The system, that is currently continuously working, was used to retrospectively analyse some significant seismic sequences (Chioccarelli et al. 2016).

However, MANTIS-K has some limitations that may affect the accuracy of the loss forecasting. The system adopts vulnerability and inventory models that do not change in time, that is, OEF rates are the only input that change among the loss forecasting computed at different times. This does not appear as an issue in peace conditions (i.e., when no earthquake has recently occurred in the area), but it may affect results right after the occurrence of a damaging earthquake (i.e., during a seismic crisis). Indeed, in such a case, MANTIS-K accounts for the fact that the estimated seismicity in the area increases (e.g., Marzocchi & Lombardi, 2009) but it is not able to model that the structures in the area may have already been damaged by previous seismic events. However, seismic crises are the cases in which the social relevance of the OELF results is the highest.

iii) State dependent fragility functions (Task 4.2)

To overcome the described limitations of MANTIS-K, an upgraded version of the system, named MANTIS v2.0, was developed in the context of RISE. The upgraded version of the OELF system is formulated to account for the evolution, over time, of the structural damage conditions. This implies that loss forecasting must account for the possible structural damage accumulation due to the occurrence of more than one earthquake in the forecasting period. Moreover, the upgraded system has to estimate the possible damage due to the occurred earthquakes and, consequently, forecast the performance level of buildings that, at the time of computation, are already at an intermediate performance level.

Despite discussing all the analytical formulation at the base of MANTIS v2.0 (provided in Chioccarelli et al. 2022), here the main modifications with respect to the original version of the OELF system are listed. In MANTIS-K the implemented large-scale vulnerability model was represented by the so-called Damage Probability matrices (DPM, Zuccaro and Cacace, 2009). The latter must be substituted by the so-called state-dependent fragility functions defined for each structural typology of the existing Italian building portfolio. To this aim, such state-dependent fragility functions were developed within the RISE project via an extended version of incremental dynamic analysis (e.g., Ryu et al., 2011; Baltzopoulos et al., 2019), referred to here as back-to-back or B2B-IDA. According to this method, the structural model is first subjected to a set of records, representing a first seismic event hitting the structure at its intact state and causing it to reach a first damage state (DSi). Each record of the set is scaled in amplitude to the lowest value of intensity measure that causes the structure to reach the damage state DSi. Thus, at the end of each record a different realisation of the damaged structural model is produced. Subsequently, each realisation of the structural model in DSi is subjected to another (or the same) set of accelerograms simulating an aftershock. Each record of the second set is scaled until the damaged structure reaches a more severe damage state, DSj with i>j. The state-dependent fragility can then be derived by collecting the scaled intensities of all records in the second set, possibly fitting a parametric model based on those results.

Moreover, updating the structural damage condition after the occurrence of each earthquake required the implementation of an automatic procedure that, before computing each loss forecasting, must (i) check the occurrence of significant earthquakes, (ii) if any, download the available shakemaps, (iii) combine the information of different shakemaps of the same earthquake to derive the distribution of the intensity measure adopted by the state-dependent fragility models, (iv) estimate the occurred damage combining information from shakempas and state-dependent fragility models.

The 2009 L'Aquila 2009 seismic swarm was retrospectively analysed by both the versions of the OELF system. The comparison of the results shows that by neglecting the possibility to have damage cumulation during a seismic swarm and the possibility to update the building portfolio according to the observed earthquake of the sequence leads to an underestimation of the forecasted losses, especially when the area of analysis is small and close to the epicentres of the sequence, i.e., it is supposed to be heavily damaged by the occurred shocks.

iv) Structural Health Monitoring in RLA (Task 4.5)

When a damaging earthquake occurs, the damage state of a wide range of buildings is unknown. Currently, post-earthquake building tagging into categories of safe or unsafe for occupancy relies on expert-conducted visual building inspection. As outlined in RISE report D4.4 (Reuland et al., 2022), the number of inspectors consists thus a key factor to accelerate the short-term recovery after an earthquake, due to the need to inspect slightly damaged buildings that kept their capacity to satisfy the function of providing safe shelter to occupants. While the use of machine-learning may reduce uncertainties by leveraging a small subset of inspected buildings (Bodenmann et al., 2023), regional damage and loss models do not provide the precision and accuracy required for building-specific damage tagging.

When the dynamic structural response of a building to a strong ground motion is recorded, for instance with accelerometers, structural health monitoring (SHM) techniques can be deployed to use building-specific monitoring data with the aim of providing near-real-time damage tagging, as described in RISE report D4.5 (Reuland et al., 2022). Therefore, damage-sensitive features (DSFs) are extracted from the recorded building behaviour to provide information regarding reversible nonlinearity and residual damage (Reuland et al., 2023) and thus, offer insights into the presence and severity of damage. The comparison of the DSFs, extracted during strong shaking of a structure, with predefined probabilistic distributions, that are for instance derived via suited structural models, allows for transforming the building performance into discrete damage grades (labels), for which alerts and warnings, in the form of building tags that follow a traffic-light logic, can be issued (see Figure 4.4). In addition, SHM of multiple buildings in a region may contribute to reducing the uncertainties stemming from (i) approximate buildings models before an earthquake strikes (Martakis et al., 2022) and (ii) shake maps, as fragility models can be formulated with respect to values that are independent of the ground-motion intensities (see Figure 4.4 and an application to two earthquake sequences in D6.1) or intensity measures for the building site can be extracted from measurements. Thereby, building monitoring contributes to reducing uncertainties pertaining to rapid loss assessment and damage accumulation in earthquake sequences as discussed in the previous sections.

While SHM does not improve the structural performance, providing information about building damage and reducing uncertainties contributes to (i) faster recovery, (ii) improved regional loss assessment, (iii) reduced uncertainties in damage accumulation during earthquake sequences, and (iv) targeted repair interventions and recovery planning. Still, some open challenges need to be addressed: appropriate modelling of structures, as equivalent single-degree-of-freedom models may carry too much model bias with respect to real structures; accelerating simulations with reduced-order models; and including other post-earthquake damage and loss components, such as localized failure modes (such as out-of-plane), damage to non-structural elements, and the risk related to adjacent buildings cannot be measured. As SHM provides various benefits, which cannot all be easily translated into monetary terms, considering a multi-criteria decision analysis, such as proposed in this deliverable, presents a valuable alternative.

SHM-based building tagging inevitably follows a probabilistic approach to damage tagging (Martakis et al., 2022) and thus, damage tags may not be attributed to all buildings with the certitude required for decision-making (see Figure 4.5). Still, following a data-based approach, the number of buildings requiring rapid visual inspection by human inspectors can be reduced, thus accelerating post-earthquake recovery and improving community resilience with respect to earthquakes.

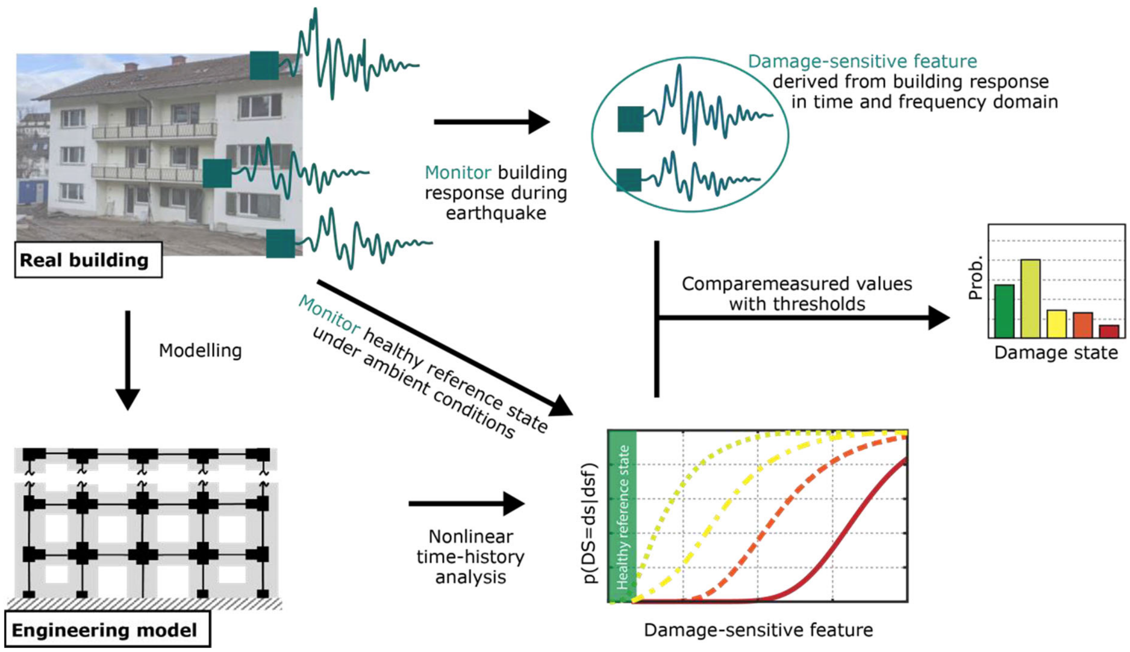


Figure 4.4. Use of dynamic SHM data for rapid post-earthquake damage assessment using pre-computed fragility models that are based on DSFs.

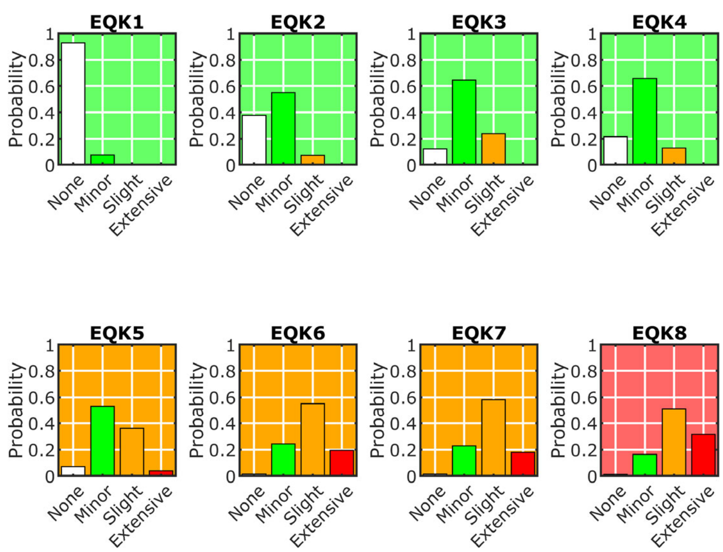


Figure 4.5. Prediction of building-specific post-earthquake damage tag probabilities for a large-scale specimen tested on a shake table to eight ground-motions (Reuland et al., 2022). While some data-driven building tags may be provided (green (no damage): EQK1, EQK2; red (unsafe building): EQK7, EQK8); more data or more refined models may be required for others.

5. Implementation of Multi Criteria Decision Analysis in a Case Study

Rapid Loss Assessment (RLA) is a quick and important method for assessing the impact of an earthquake on people, buildings, and infrastructure. It estimates the number of collapsed buildings, fatalities, homeless individuals, and direct economic losses, and these initial estimates are continually updated as more information becomes available. However, the full impact of an earthquake may take some time to be fully measured and reported. Accurate and timely assessments are crucial, as civil protection agencies need to know which areas have been most affected and the extent of the damage, to send appropriate teams and equipment for rescue efforts. Additionally, the number of homeless individuals must be determined to prepare emergency shelters. Governments may need to allocate funds for rescue and recovery operations, either domestically or as part of international aid. Insurers also need to plan for post-earthquake damage assessments to manage potential insurance claims. Therefore, RLA plays a critical role in post-disaster scenarios.

Task 6.1 developed the Real-Time Loss Tools, which are intended to demonstrate the dynamic assessment of seismic damage and losses by bringing together various developments of the RISE project. The Real-Time Loss Tools is focused on assembling a proof of concept that showcases the interaction and links between different components. It is designed to conduct rapid loss assessments (RLA) and operational earthquake loss forecasts (OELF) by incorporating probabilities of damage states based on structural health monitoring (SHM) methods. It calculates cumulative damage using state-dependent fragility models, estimating expected economic and human losses such as injuries and deaths, and updating the number of occupants in a building based on the time of the day of the earthquake, as well as whether people are allowed back into the buildings due to inspection and repair times, and are able to do so based on their own health status.

The output of this tool is the number of buildings in different damage states and/or probabilities of a building resulting in a damage state, estimated economic losses, injuries, and deaths after any earthquake in the sequence and after each seismicity forecast.

We use the results of 4 cases which model rapid loss assessment. Each case is forming an alternative in the MCDA. The four alternatives are explained below:

1) State-independent fragility models, without updating occupants (Alternative 1): State dependent fragility models are taken from task 4.1 that constitutes a set of Pan-European exposure and vulnerability models for the calculation of Rapid Earthquake Loss Assessment (RELA). During an earthquake sequence, the fragility models are not updated, meaning that even a building with some level of damage will be treated as undamaged, when an aftershock occurs. Although this is unrealistic, and implies that there is a magic healing of the building after an earthquake, before an aftershock, this is what has been traditionally done in previous studies. The occupants in the exposure model are not updated during the sequence, meaning that we assume the same amount of occupants remain in the buildings even after a mainshock.

2) State-dependent fragility models, without updating occupants (Alternative 2): In this case, we use the state dependent fragility models developed in Task 4.2, which updates the fragility models after an event, depending on the level of damage each building experiences. This can be called dynamic vulnerability, as the vulnerability of a building changes during a sequence because of the damage the building has after the mainshock. In this case, we do not update the occupants meaning that we assume the same number of occupants remain in the buildings during a sequence, even after a major event.

3) State-independent fragility models, with update of occupants (Alternative 3): In this case, we do not update the vulnerability component, however we update the number of occupants during the sequence. After the mainshock hits, it is expected that the people leave the buildings at least for a while during the immediate aftershock sequence. Therefore, it is not unrealistic to consider that the occupants leave the building. In this exercise, we update the number of occupants during the sequence, but we keep the vulnerability static, meaning that we do not use state-dependent fragility functions.

4) State-dependent fragility models, with update of occupants (Alternative 4): In this alternative we use state-dependent fragility functions and we update the number of occupants. In other words, we use dynamic vulnerability functions and dynamic occupancy in exposure in this exercise.

Below we explain a) the case study developed in Task 6.1, which provides the basis for b) MCDA developed in this task.

a) Case Study (Task 6.1)

As part of the demonstration activities of WP6, Task 6.1 has developed a proof of concept that brings together some of the main developments of the RISE project including advances in the fields of rapid loss assessment, operational earthquake loss forecasting and structural health monitoring. The open-source software named Real-Time Loss Tools[1] was developed for this purpose, and with the broader aim of creating a tool that the research community could use to explore all the aspects of this integration and develop strategies for future scalability and operationalisation. The Real-Time Loss Tools carry out rapid loss assessments (RLA) and operational earthquake loss forecasts (OELF) incorporating probabilities of damage states based on structural health monitoring (SHM) methods and taking into account the accumulation of damage during earthquake sequences. It does so by recursively calling OpenQuake (Pagani et al., 2014) and updating the exposure model (to reflect "current" damage states at each point in time) and other relevant input files. The number of occupants in buildings is updated as well by taking into account the time of the day of the earthquake as well as whether people are allowed back into the buildings (due to inspection and repair times) and are able to do so (due to their own health status).

[1] https://git.gfz-potsdam.de/real-time-loss-tools/real-time-loss-tools

As part of Task 4.6, the Real-Time Loss Tools were used to assess the benefits of using state-dependent fragility models (over state-independent ones) in rapid loss assessments during an earthquake sequence, as well as of updating the number of occupants in the buildings after each earthquake in the sequence or not. Operational earthquake loss forecasts and the incorporation of structural health monitoring results were not included in the analysis. Four alternative calculation workflows emerge from the combination of these two components with two options each:

- *Alternative 1: state-independent fragility models, no updating of occupants*
- *Alternative 2: state-dependent fragility models, no updating of occupants*
- *Alternative 3: state-independent fragility models, with updating of occupants*
- *Alternative 4: state-dependent fragility models, with updating of occupants*

Whether the human loss calculation includes or not the updating of occupants can be easily handled by the Real-Time Loss Tools in terms of the input files used to run the analyses. While the ability of a person to return to the building(s) they usually occupy depends on a complex series of factors associated with the specific conditions of post-earthquake recovery in the region where the earthquake occurs (as demonstrated within RISE Task 4.3; Reuland et al., 2022), the Real-Time Loss Tools focus on two main aspects. Firstly, it considers that different levels of injury require different degrees of treatment, and does so by requiring an input file that indicates the average number of days of a hospital stay of a person with each level of injury. In this work, the injury classification scale reported in HAZUS (FEMA, 2003) has been used:

- *Injury severity level 4: instantaneously killed or mortally injured.*
- *Injury severity level 3: injuries that pose an immediate life threatening condition.*
- *Injury severity level 2: injuries that require use of medical technology (e.g. x-rays, surgery), but are not expected to be life threatening.*
- *Injury severity level 1: injuries that require basic medical aid (in the field).*

For alternatives 3 and 4, which include the updating of occupants, the following number of days have been used (for details, see Nievas et al., 2023):

- Injury severity level 4: the inability to return is simulated using a very large number of days (36,500, i.e. around 100 years)
- Injury severity level 3: 8 days.
- Injury severity level 2: 3 days.
- Injury severity level 1: zero days.

For alternatives 1 and 2, all values have been set to zero days, which effectively results in all occupants being considered as present during all earthquakes in a sequence. The only factor that changes the number of occupants in this case is the factor that accounts for whether the earthquake occurs during the day, night or transit times (which is also used in alternatives 3 and 4).

The second aspect that the Real-Time Loss Tools consider for the updating of occupants is the time required to inspect and repair buildings as a function of their damage state, specified in an input file with structure similar to Table 5.1 below.

Table 5.1: Expected number of days needed for inspection and repair of buildings as a function of their damage state (values used in this analysis, see Nievas et al., 2023)

Damage State	Inspection	Repair
DS0	7	0
DS1	7	15
DS2	45	365
DS3	45	1,095
DS4	45	1,095

While the number of days specified in Table 5.1 were used for alternatives 3 and 4, all values were set to zero for alternatives 1 and 2. These and the number of days needed in hospital are used by the Real-Time Loss Tools to define timelines after each earthquake that indicate whether people are allowed to return to their buildings or not. When a new earthquake happens and a rapid loss assessment is run, the software looks at the timelines from the previous earthquakes to calculate the number of occupants by subtracting the number of people expected to not be allowed to return to their buildings from the total number of so-called "census" occupants, and multiplying it by zero or one, a factor that is determined from the number of days elapsed since the last earthquake and the values defined in Table 5.1 As the two columns in Table 5.1are added, no occupants are allowed back into the buildings in alternatives 3 and 4 when the previous earthquake has occurred less than 7 days before the current one being processed.

The option to use state-independent fragility models was added to the Real-Time Loss Tools prompted by the present study, as the software had been originally designed to work only with the state-dependent case. When using state-dependent models (which is indicated by the user in the configuration file), the damage and economic loss output of each rapid loss assessment is, by nature, cumulative, as the new probabilities of damage are conditional on the pre-existing damage status, which is embedded in the state-dependent fragility model itself. When using state-independent models, the software calculates the probability of non-exceedance of each damage state due to each earthquake (based on state-independent fragilities) and assumes that after N earthquakes a damage state is not exceeded only if it has not been exceeded in any of the previous events, which is calculated as the product of all previous probabilities of non-exceedance. The (cumulative) probability of exceedance and, consequently, the (cumulative) probability of occurrence, are calculated from the latter. The economic and human losses are calculated from the cumulative probability of occurrence, just like in the case when state-dependent fragility models are used.

This multi-criteria decision analysis was based on results from the seven case-studies defined within RISE Task 6.1, three of which stem from the 2009 L'Aquila earthquakes while the remaining four correspond to the 2016-2017 Central Italy earthquake sequence. Each of them represents a different location in which a fictitious building stock was placed and analysed, as shown in Figure F1. This fictitious building stock consists of an array of 3 x 3 tiles of around 100 m side each, containing an aggregated number of buildings each, and three individual buildings placed within the central tile. The use of a combination of tiles with aggregated buildings and individual building footprints to define building exposure follows the concept of the Dynamic Exposure Model developed by Schorlemmer et al. (2023) within RISE Task 2.7. The aggregated buildings in the tiles cover a range of classes of Italian masonry and reinforced concrete buildings defined in the European Seismic Risk Model 2020 (ESRM20; Crowley et al., 2021), for which Orlacchio (2022) developed state-dependent fragility models as part of RISE Task 4.2. The three individual buildings represent a theoretical typical Swiss residential unreinforced masonry building, a 15-storey reinforced concrete shear-wall hotel in Budva, Montenegro, and the 13-storey reinforced concrete shear-wall tower of the Grenoble City Hall, France, all of which have been studied within RISE. For more details on the exposure, fragility and consequence models used, as well as on the modelling of ground motions and general workflow, please refer to Nievas et al. (2023).

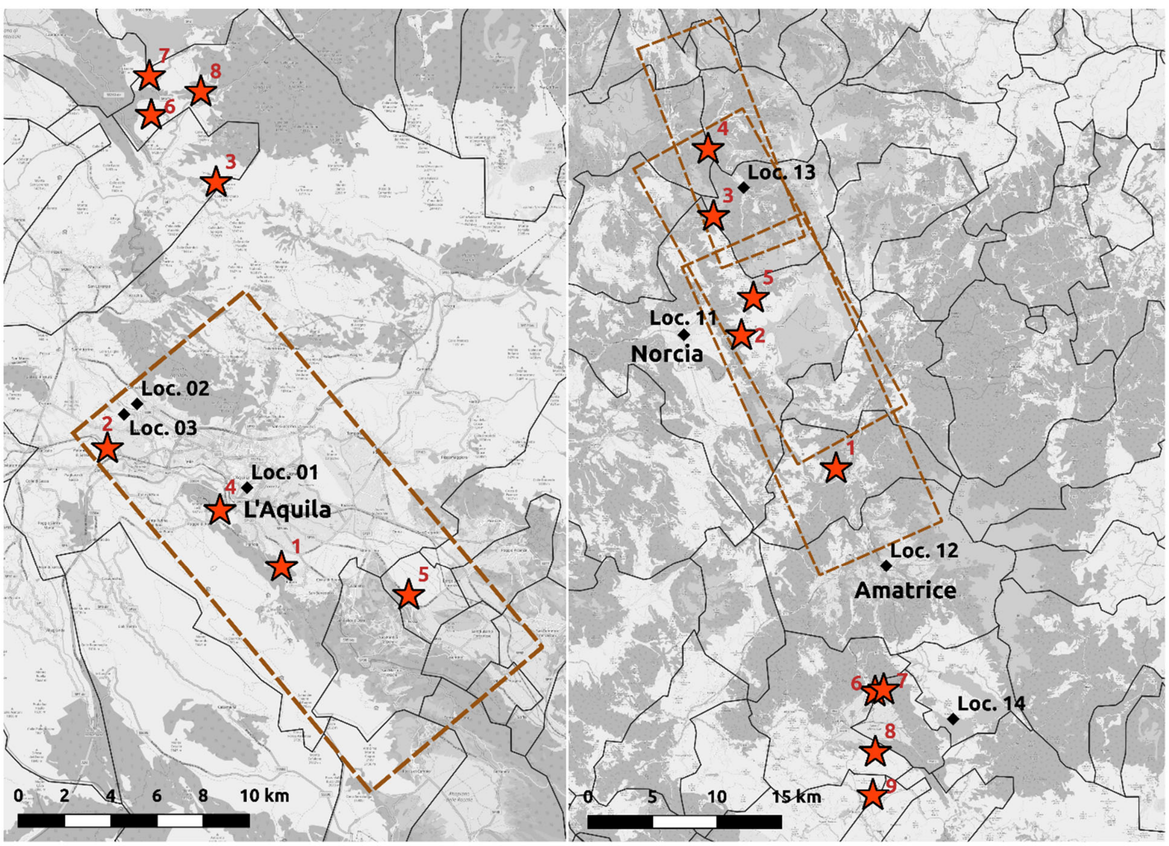


Figure 5.1 Earthquake epicentres (numbered stars) and exposure locations (rhombuses) used as case-studies for the 2009 L'Aquila (left) and 2016-2017 Central Italy (right) earthquake sequences. Rupture planes of larger shocks from the Italian Accelerometric Archive (ITACA; Russo et al., 2022) shown as dashed polygons. Background: OpenStreetMap.

The numbering of the epicentres depicted in Figure 5.1 refers to the chronological order in which earthquakes with moment magnitude Mw of 5.0 and above occurred during each of the two sequences, which are the earthquakes for which rapid loss assessments have been run for the present analysis (see Tables 5.2 and 5.3). It is noted that the focus on these magnitudes has been a choice for this study and does not imply that smaller magnitude earthquakes are not capable of causing damage (see, for example, Nievas et al., 2020).

Table 5.2: Earthquakes with Mw ≥ 5 of the 2009 L'Aquila sequence (according to ITACA)

EQ #	Date (UTC)	Time (UTC)	Lon.	Lat.	Depth (km)	Mw
1	6 April 2009	01:32:40	13.4193	42.3140	8.2	6.1
2	6 April 2009	02:37:04	13.3280	42.3600	8.7	5.1
3	6 April 2009	23:15:36	13.3850	42.4630	9.7	5.1
4	7 April 2009	09:26:28	13.3870	42.3360	9.6	5.1
5	7 April 2009	17:47:37	13.4860	42.3030	17.1	5.5
6	9 April 2009	00:52:59	13.3510	42.4890	11.0	5.4
7	9 April 2009	19:38:16	13.3500	42.5040	9.3	5.2
8	13 April 2009	21:14:24	13.3770	42.4980	9.0	5.0

Table 5.3: Earthquakes with Mw ≥ 5 of the 2016-2017 Central Italy sequence (according to ITACA).

EQ #	Date (UTC)	Time (UTC)	Lon.	Lat.	Depth (km)	Mw
1	24 Aug 2016	01:36:32	13.2400	42.7000	7.3	6.0
2	24 Aug 2016	02:33:29	13.1507	42.7922	8.0	5.3
3	26 Oct 2016	17:10:36	13.1243	42.8747	8.1	5.4
4	26 Oct 2016	19:18:06	13.1192	42.9211	5.7	5.9
5	30 Oct 2016	06:40:18	13.1620	42.8182	6.8	6.5
6	18 Jan 2017	09:25:42	13.2768	42.5450	10.0	5.1
7	18 Jan 2017	10:14:12	13.2849	42.5465	10.4	5.5
8	18 Jan 2017	10:25:26	13.2770	42.5033	9.4	5.4
9	18 Jan 2017	13:33:37	13.2747	42.4733	9.5	5.0

As the time in between shocks of the 2009 L'Aquila sequence is always smaller than 7 days, alternatives 3 and 4 do not present additional human losses other than for the Mw 6.1 mainshock. In the case of the 2016-2107 Central Italy sequence, occupants are allowed back in their buildings before the third and sixth earthquakes listed in Table 5.3 which leads to some additional (though limited) human losses.

b) Multi Criteria Decision Analysis

The Multi-Criteria Decision Analysis (MCDA) framework, established in Task 4.6, is designed to evaluate and compare the different dynamic risk products developed within the RISE project, considering a number of established criteria. Unlike Cost-Benefit Analysis, MCDA does not require benefits to be expressed in monetary terms or to have quantifiable values. This allows for the consideration of criteria such as time/information gain, model bias, uncertainty, and expert judgement, making it a valuable tool for informed decision-making.

This section will demonstrate how MCDA can be used to assess some of the RISE dynamic products, providing a more comprehensive analysis of the results obtained from Task 6.1, which integrates and showcases various RISE dynamic products through case studies. By incorporating MCDA into the evaluation process, we aim to determine which product better meets the criteria, rather than simply choosing which method performs "better". It is important to note that the work done in this task complements the analysis performed in Task 6.1. Our aim is to provide a thorough and comprehensive evaluation of the RISE dynamic products against a set of criteria, rather than a simplistic comparison. Below we list the typical steps taken in a typical MCDA, which we followed in our analysis:

1) Setting the objectives
2) Determining the decision alternatives
3) Identifying the criteria
4) Criteria weighting
5) Scoring
6) Building the decision matrix & ranking
7) Examining results, re-score, discuss

First, we will explain these steps in more detail. Then we will show its application to the case-studies defined in Task 6.1 and briefly described above.

1) Setting the Objectives

The initial step in implementing MCDA involves identifying the Decision Makers (DMs) involved in the decision-making process, determining their preferences, and specifying the objective or objectives they aim to achieve. For the purposes of this exercise, we will assume the objectives of the stakeholders. The overall objective of Task 4.6 is to develop "a user-ready risk-cost-benefit analysis framework for quantifying socio-economic impact". To accomplish this, we aim to incorporate key results and performance indicators from various RISE deliverables that quantify losses and socio-economic impact through RLA, SHM, and OELF.

For this particular exercise, our objective is to evaluate the newly developed dynamic RISE products and their use in RLA, based on a set of the criteria. We will evaluate: the traditional RLA (Task 4.1), the use of state-dependent fragility models developed in Task 4.2, and the method of updating the exposure by updating occupants during an earthquake sequence (Task 6.1).

While this exercise focuses on RLA, the framework we establish can be expanded to encompass a wider range of RISE products.

2) Determining the decision alternatives

The main objectives are decomposed into decision alternatives, Ai, and a hierarchy of evaluation criteria, Cj. Decision alternatives refer to alternative methods/approaches/projects that are being considered. For the exercise we perform in this task, the decision alternatives that will be ranked are:

- Alternative 1: state-independent fragility models, without updating occupants
- Alternative 2: state-dependent fragility models, without updating occupants
- Alternative 3: state-independent fragility models, with update of occupants
- Alternative 4: state-dependent fragility models, with update of occupants

3) Identifying the criteria

The preferences of the Decision Makers (DMs) are divided into multiple criteria, Cj, which encompass both costs and benefits. A list of the determined criteria will be provided. It is worth mentioning that not all analyses will utilise all of the criteria listed. We have conducted various analyses that consider some or all of these criteria, which are explained in the sensitivity analysis section. It is crucial to note that the evaluation criteria proposed in this framework are not considered to be the definitive and correct ones, but rather serve as a tool for scientific discussion of the problem and provide an example for the proposed framework.

Criteria1 - Model simplicity/model complexity (code development)

A simple model is one that uses only a few variables, assumptions, and equations to represent a system, while a complex model involves a larger number of variables, equations, and more sophisticated methods to represent the same system. A simple model is typically easier to understand, calibrate, and interpret, but may not capture all the important features of the system or produce accurate predictions. A complex model, on the other hand, can capture more details and nuances of the system, but can be more difficult to understand, calibrate, and interpret, and may require more computational resources to run. In this criteria we consider the effort spent in preparing the model (PMs) including code development. The model development refers to the state independent and state dependent fragility models as well as the exposure with and without updating the human occupancy.

Criteria 2 - Model run time

Model run time refers to the amount of time it takes for a computer model to complete a single simulation or a set of simulations. It typically includes the time required to initialise the model, input data, and parameters, and then execute the model code to generate outputs. The run time can vary depending on the complexity of the model, the amount and quality of the input data, and the computational resources available to run the model. Shorter run times are generally preferred, as they allow for quicker and more efficient model evaluations, but often it comes at the expense of accuracy or reliability.

Criteria 3 - Model uncertainty

This reflects the uncertainty in the considered models. An increase in model uncertainty occurs when there are more variables to determine and each variable has its own level of uncertainty.

Criteria 4 - Realistic estimation of human losses (model bias in human loss estimation)

Human loss estimates cover fatalities and injuries categorised in 4 severity levels according to HAZUS classification.

Criteria 5 - Realistic estimation of economic losses (model bias in financial loss estimation)

Economic losses mean, in our context, the total direct financial losses in terms of replacement costs of structural and non-structural components of buildings, as well as their contents. This analysis does not include indirect losses (e.g. downtime), but the framework would be equally applicable.

Model Bias for Criteria 4 & Criteria 5

Model bias refers to a systematic error in a model's predictions that arises from incorrect assumptions. For example, state-independent fragility models are biased towards representing buildings as less vulnerable than they actually are, assuming that they can return to an undamaged state after each earthquake, which is clearly not accurate. Similarly, failing to update occupancy estimates after a major earthquake that is followed by aftershocks would also result in biased predictions that overestimate the human losses, as people who would not really be occupying the buildings after a certain earthquake shock (due to their own health status or the damage status of the buildings) would still be modelled as present.

Model uncertainty vs. Model Bias

Updating the number of occupants in buildings during an earthquake sequence is a complex process that involves dealing with significant uncertainties. These uncertainties arise from various sources, including the human loss model used to calculate the number of injured or deceased people, the time required for building inspections and repairs, the duration of hospital stays for those injured, and the number of days needed to inspect buildings after an earthquake occurs. Additionally, there are other factors we have not considered, such as disruptions to critical infrastructure like electricity and water, which could prevent people from returning to their homes. Given the multitude of factors at play, the uncertainty associated with updating occupancy estimates after an earthquake is generally significant. Ignoring the uncertainty in the number of occupants of buildings irrespective of earthquakes occurring or not, the lower and upper bounds of number of occupants after a first earthquake of relevance is given by assuming zero occupants and 100% of occupants, respectively. The latter is the assumption made herein for alternatives 1 and 2, as it is aligned with what has been usually done in rapid loss assessments, i.e., treating each earthquake independently. However, the human loss model used for alternatives 3 and 4 is more accurate compared to assuming 100% occupancy for all earthquakes, as we know from past events such as the 2009 L'Aquila and 2016-2017 Central Italy sequences that this is not what happens in reality. Therefore, the models that update the occupancy during a sequence have larger uncertainty but are less biased models.

4) Criteria weighting

This is the criteria weighting step based on stakeholder priorities. Just choosing the right criteria will not be sufficient to combine and analyse the different scales of choice. One preference unit is not necessarily the same as another. The criteria usually have different importance and the alternatives in turn differ in our preference for them on each criterion. Importance weights are used to measure the relative importance when considering the qualitative and quantitative criteria. The importance weights are key factors in the process of multi-criteria decision making, as are the ones reflecting the decision maker's experience, judgement and preference in the framework of the MCDA approach. Each DM can assign their own weights to each interest. To make such trade-offs and choices we need a way to measure. We use Analytical Hierarchy Process (AHP) for weighting the criteria. AHP is an effective management tool that can handle many alternatives at one time and so permits comparisons to be made. Other popular techniques, such as the Relative Merit Method or Dimensional Analysis, can only handle two alternatives at a time.

Analytical Hierarchy Process (AHP)

AHP is one of the several methods for making decisions with multiple criteria, originally developed by Saaty (1977). The AHP method breaks down decision-making problems into a hierarchy, and makes pairwise comparisons to establish priorities among the elements in the hierarchy. It also provides measures of judgement consistency, which are evaluated to ensure the validity of the decision-making process. AHP is an extremely useful tool for making valid decisions when there are a variety of qualitative and quantitative criteria, and multiple actors or decision makers (DMs) involved.

To compare the elements in each level, AHP uses pairwise comparisons with respect to their importance to an element in the next higher level. This starts at the top of the hierarchy and works down, resulting in the creation of a number of square matrices called preference matrices. These matrices compare elements at a given level based on judgments of preference, using what Saaty defines as "the fundamental scale of AHP" (Saaty 1996), which is reproduced in Table 1. The fundamental scale used in AHP allows decision makers to incorporate their experience and knowledge in an intuitive and natural way. This scale is also insensitive to small changes in a decision maker's preferences, which helps to minimise the effect of uncertainty in evaluations. AHP uses an absolute scale in which people use numbers to express how much one element dominates another with respect to a common criterion. The scale derived from these absolute numbers is a ratio scale.

DMs responses to the set of questions "How important is criterion A relative to criterion B?" are gathered in verbal form and subsequently codified according to the nine-point scale (Table 5.4) and finally organised in terms of a pairwise comparison matrix (Table 5.5).

Table 5.4. The fundamental scale of absolute numbers

Intensity of Importance	Definition	Explanation
1	Equal Importance	Two activities contribute equally to the objective
2	Weak or slight	
3	Moderate importance	Experience and judgment slightly favor one activity over another
4	Moderate plus	
5	Strong importance	Experience and judgment strongly favor one activity over another
6	Strong plus	
7	Very strong or demonstrated importance	An activity is favored very strongly over another; its dominance demonstrated in practice
8	Very, very strong	
9	Extreme importance	The evidence favoring one activity over another is of the highest possible order of affirmation
Reciprocals of above	If activity i has one of the above nonzero numbers assigned to it when compared with activity j, then j has the reciprocal value when compared with i	A reasonable assumption
Rationals	Ratios arising from the scale	If consistency were to be forced by obtaining n numerical values to span the matrix

Table 5.5. Rating scale assumed for the hierarchy process AHP pairwise comparison.

Less important									Equally		More important							
Extremely		Very Strongly		Strongly		Moderately			Important		Moderately		Strongly		Very Strongly		Extremely	
..	1/9	1/8	1/7	1/6	1/5	1/4	1/3	1/2	1	2	3	4	5	6	7	8	9	..

Consistency Measure

AHP provides decision makers with a useful way of checking and improving consistency. A by-product of solving the eigenvalue problem to measure priorities we obtain the principal eigenvalue, λ max, from which we can derive the consistency index (C.I.) as follows: C.I. = (λ max - n)/ (n-1), where n is the order of the comparison matrix. The measurement of consistency reflects whether the decision maker understands and captures the interactions among different factors of the problem or his decision is a matter of random hitting the target. However, perfect consistency is hard to achieve in real life problem solving. Saaty states "inconsistency must be precisely one order of magnitude less important than consistency, or simply 10% of the total concern with consistent measurement. If it were larger it would disrupt consistent measurement and if it were smaller it would make insignificant contribution to change in measurement" (Saaty 1996 & 2004, p: 9). CI is calculated for each of the analyses, and weights are reassessed if CI exceeds the 0.1 threshold.

5) Scoring

This step involves scoring the alternative options. The performance of each alternative is scored against each criterion. This may be completed by all stakeholders (individually), a subset of participants or by researchers. This may involve the use of empirical data, expert opinion, scenarios and modelling.

Common rating scales that can be used in MCDA for different criteria are a relative scale and an ordinal scale. With a relative scale each alternative is rated relative to the others in satisfying a particular interest. For example, among the 4 alternative criteria, assign each a 1, 2, 3, or 4 depending on which satisfies the interest: the best = 4; second best = 3; third best = 2; and the worst at satisfying the interest = 1.

With an ordinal scale you use a scale of your choosing (for example, a 5-point scale, or a 10-point scale) and assign each alternative a rating for how well it satisfies a particular interest. An example of a five-point scale might be: 5 = excellent; 4 = good; 3 = satisfactory; 2 = below average; 1 = poor. In the analysis performed in this task, we used a 5-point ordinal scale, where 5 = excellent; 4 = good; 3 = satisfactory; 2 = below average; 1 = poor.

6) Building the decision matrix & ranking

A decision matrix is a commonly used tool in multiple criteria decision analysis (MCDA) to organise and evaluate the performance of different alternatives on multiple criteria. It is a table (Table 5.6), that compares each alternative against each criterion as shown in Figure 5.2, and assigns scores or weighted scores to each cell in the table. A typical decision matrix consists of a set of alternatives (rows) and a set of criteria (columns). The alternatives can be any options that are being considered for a decision, such as different products, projects, or policies. The criteria are the factors or attributes that are relevant to the decision, and can be qualitative or quantitative in nature.

To evaluate each alternative on each criterion, decision makers assign scores or weights to the corresponding cells in the matrix. Scores are used in a simple additive model, while weights are used in a more complex weighted additive model. The scores or weights can be assigned based on different methods, such as pairwise comparisons, rating scales, or expert judgments. Once the scores or weights are assigned, decision makers can calculate the overall performance of each alternative by aggregating the scores or weighted scores across all criteria. They can also compare the alternatives based on different performance measures, such as total score, weighted score, or overall rank.

The decision matrix (Table 5.6) used in the analyses evaluates and compares different alternatives set in step 2, based on a set of criteria established in steps 3 and 4. We use the result of the analysis performed in Task 6.1 as the basis for the scoring. Figure 5.2 illustrates how every alternative is evaluated against each criterion.

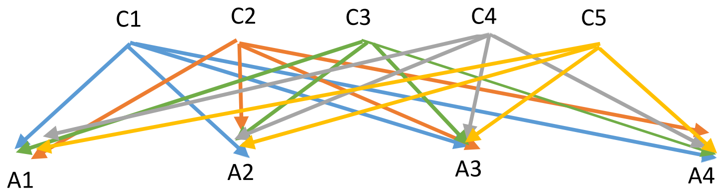


Figure 5.2. Schematic representation of the Alternative and the set Criteria.

Table 5.6 Decision Matrix

	C1	C2	C3	C4	C5
A1	5	5	5	1	1
A2	4	3	3	1	5
A3	3	4	4	5	1
A4	2	2	2	5	5

7) Examine Results, Re-Score, Discuss

Once the board members have scored each alternative, they can compare their results. If a single alternative is preferred by everyone, the decision is made. However, if no clear winner emerges, the board has several options:

- If an alternative is consistently rated as the lowest or second lowest by all board members, it is deemed a "dominated alternative" and can be removed from consideration.
- Even if no site can be eliminated as a dominated alternative, the board can examine the scores and weights, focusing on alternatives with similar scores for further discussion. Board members can compare and discuss their interest weights, experimenting with assigning higher or lower weights to different sub-interests. This approach can yield insights and help the board reach an agreement.

This step involves conducting sensitivity analysis to explore the effect of different weighting strategies on the ranking of alternatives. The board can also revisit the criteria and consider changing them. In the case study presented below, we examined different weighting approaches and criteria sets, and analysed their impact on the ranking of alternatives. Finally, we discuss the results of our analysis.

IMPLEMENTATION OF MCDA TO A CASE STUDY

In order to apply the steps outlined above, we have taken the four alternative case studies developed in Task 6.1 that were described earlier and conducted three separate multi-criteria decision analyses (MCDAs). Each analysis represents a different set of stakeholder preferences for ranking the alternatives.

It's important to note that comparing the four alternatives is not meant to suggest that they are all equally valid options. Rather, our aim is to demonstrate how to apply multi-criteria decision analysis to this particular context and provide a framework for decision-making based on the stakeholders' preferences.

Figures 5.3 and 5.4 presents the output of the analysis conducted in Task 6.1 in terms of percentage of census occupants that are injured with severities 1 through 3, for location 11 under the 2016-2017 Central Italy sequence and the four alternatives considered. Alternatives 3 and 4 update the number of occupants in buildings after the first earthquake in the sequence, which results in an almost flat line in the human loss figure. This is because the model assumes that people leave the buildings after the first earthquake and only return before the third and sixth earthquakes with Mw 5+ of the sequence. For Alternatives 1 and 2, the model does not update the occupancy in the buildings, and assumes that everyone is back in the buildings during the entire sequence. The figures show a significant increase in the percentage of human losses for both alternatives, with Alternative 2 estimating higher losses than Alternative 1. This is primarily due to the fact that Alternative 2 uses a state-dependent fragility model, which treats already damaged buildings as damaged when a second earthquake hits. This leads to further damage and, consequently, human losses if people are in the buildings.

While the figures shown in Figure 1 depict only one case for the Central Italy sequence, we analysed various other cases for both Central Italy and L'Aquila, the details of which can be found in Appendix A. The results for these cases were consistent with our analysis in MCDA. Therefore, we only present one case here.

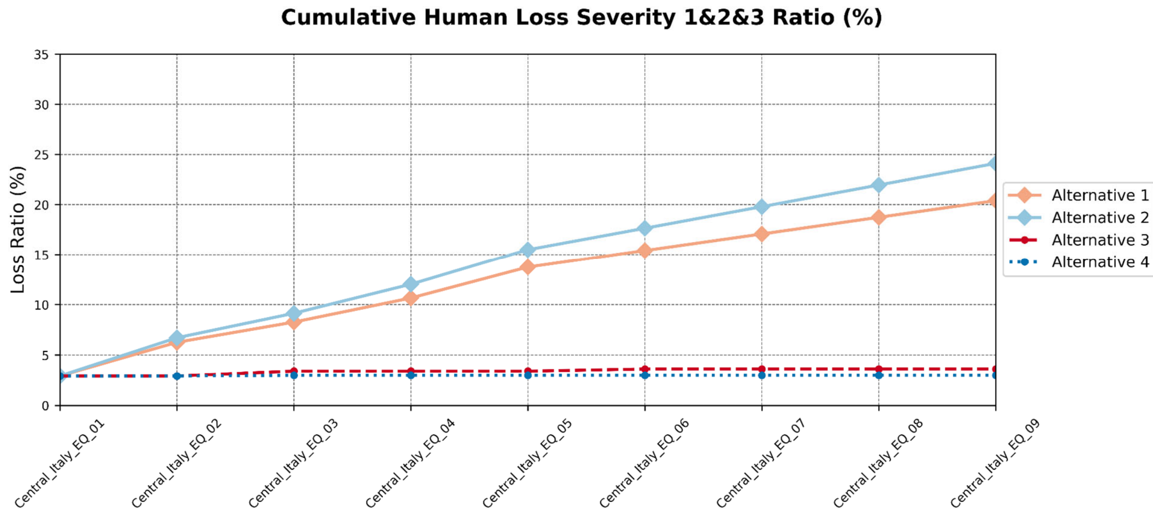


Figure 5.3. Cumulative human loss severity ratio, considering the three severity levels (1+2+3)

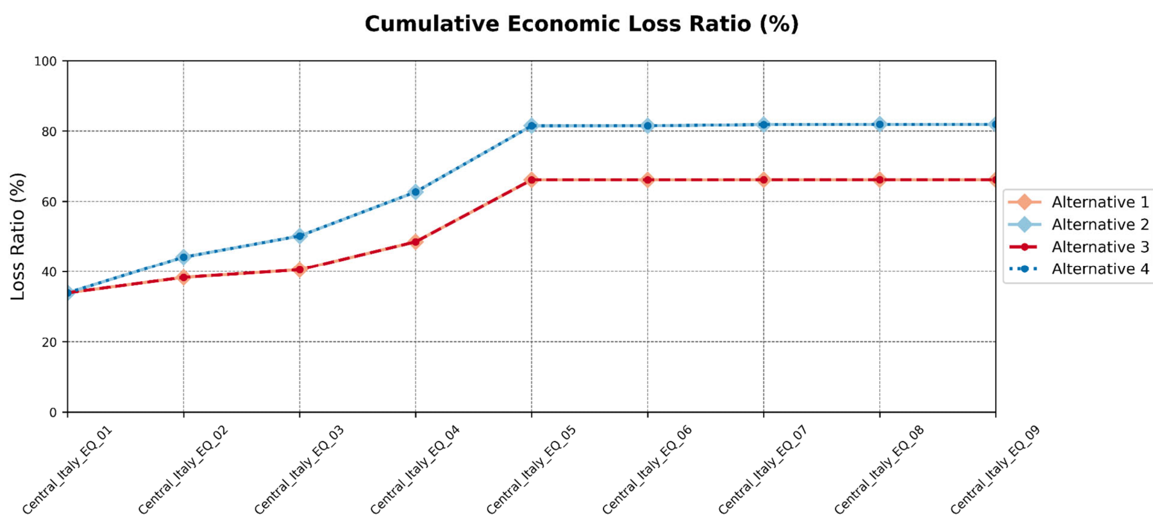


Figure 5.4. Cumulative economic loss ratio

The evaluation of the four alternatives is based on the findings of Task 6.1, which were applied to both the Central Italy and L'Aquila sequences. To assess the alternatives, a 5-point ordinal scale was used, with scores ranging from 1 (poor) to 5 (excellent). Three distinct analyses were conducted, each using a different method to assign weights to the criteria.

Analysis 1:

We will be using the Analytic Hierarchy Process (AHP) to evaluate our model's performance based on four criteria. Our analysis will take into account the preferences of stakeholders who prioritise realistic and unbiased models, even if they result in higher costs. Model run time will also be given moderate importance. To facilitate our assessment, we will create a Pairwise Comparison Matrix

(Table 5.7) using the AHP method, which will enable us to compare the relative importance of the four criteria being evaluated. These criteria are as follows:

C1= Model simplicity (code development)
C2= Model run time
C3= Model bias for Estimating human losses
C4= Model bias for Estimating economic losses

Pairwise Comparison:

Pairwise comparison is a key step in AHP that involves comparing two elements at a time with respect to a given criterion. The pairwise comparison involves constructing a decision matrix that lists all the pairwise comparisons between the elements being evaluated for a specific criterion. Each element is compared to every other element, and the comparisons are made on a numerical scale. In this matrix, the diagonal elements are all 1, because we are comparing each criterion to itself. The off-diagonal elements represent the relative importance of each criterion compared to the others. For example, the element in row A and column B is 3, which means that criterion A is considered three times more important than criterion B. Table 5.7 shows the pairwise comparison matrix for Analysis 1.

Table 5.7. Pairwise Comparison Matrix

	C1	C2	C3	C4
C1	1	3	1/5	1/5
C2	1/3	1	1/7	1/7
C3	5	7	1	1
C4	5	7	1	1

Normalisation:

The next step is normalisation. The normalisation step in AHP involves transforming the original pairwise comparison matrix into a new matrix that reflects the relative importance of the criteria or alternatives being compared. The table 5.8 represents the normalisation stage, where the priority vectors are the main eigenvectors derived from the pairwise comparison matrices. These priority vectors are presented in distributive form, meaning they have been normalised by dividing each element by the sum of all elements in the vector to ensure they add up to 1.

Table 5.8. Normalisation

	C1	C2	C3	C4	SUM	AV	Consistency Measure	AV=criteria weights

C1	0.09	0.17	0.09	0.09	0.43	0.11	4.04	0.11
C2	0.03	0.06	0.06	0.06	0.21	0.05	4.01	0.05
C3	0.44	0.39	0.43	0.43	1.68	0.42	4.12	0.42
C4	0.44	0.39	0.43	0.43	1.68	0.42	4.12	0.42

Consistency Index:

Once the matrix is normalised, we need to check the Consistency Index. The consistency index (CI) is a measure of how consistent the pairwise comparison matrix is. The consistency index is defined as: CI = (λ_max - n) / (n - 1);

where λ_max is the largest eigenvalue of the pairwise comparison matrix, and n is the number of criteria or alternatives being compared. The eigenvalue is used to characterise certain properties of a matrix, such as its stability and consistency. In the case of AHP, the eigenvalue of the pairwise comparison matrix is used to assess the consistency of the matrix. The larger the eigenvalue, the more consistent the matrix is. The consistency index compares the largest eigenvalue of the pairwise comparison matrix to the number of criteria or alternatives being compared, and gives a measure of how much the matrix deviates from perfect consistency. The consistency index ranges from 0 to 1, with a value of 0 indicating perfect consistency and a value of 1 indicating complete inconsistency. If the consistency index is greater than 0.1, it indicates that the pairwise comparison matrix may not be consistent, and further analysis is required to resolve any inconsistencies. One way to resolve inconsistencies is to adjust the pairwise comparison matrix by making small changes to the values in the matrix until the consistency index is below 0.1.

Consistency Index (C.I.) is calculated following Saaty (1980, 1994) and found as C.I. = 0.025. As C.I. is below the suggested 0.1 threshold, the above comparison matrix is consistent. The criteria weights on Table 5.9 are used to weight the scores on table5.10.

Scoring:

In AHP, scoring is the process of assigning numerical values to each alternative based on its performance or effectiveness with respect to a particular criterion. To do this, pairwise comparisons are made between each alternative and a reference alternative, and the results are recorded in a pairwise comparison matrix. Each element in the matrix represents the relative importance or preference of one alternative over another. These values are typically assigned on a scale (we used 5-point ordinal scale). Once the pairwise comparison matrix is completed, the scores for each alternative are calculated by taking the geometric mean of the values in each row of the matrix. This process ensures that the scores reflect the overall performance or effectiveness of each alternative relative to the others with respect to the criterion being evaluated. Finally, the scores for each alternative are combined across all criteria to generate a final ranking or prioritisation of the alternatives. The alternative with the highest final score is considered the most desirable or preferred option.

We use a 5-point ordinal scale (: 5 = excellent; 4 = good; 3 = satisfactory; 2 = below average; 1 = poor), and our scaling is based on Task 6.1 results. Table 5.9 shows the scores for the four alternative cases for each criteria. Once the initial scores are assigned, then the weights are applied to the scores. The table 5.10 shows the weighted scores assigned to each alternative, which are used to determine their ranking.

Table 5.9. Scoring

DECISION MATRIX WEIGHTS & SCORES				
	C1	C2	C3	C4
Weights:	0.106	0.052	0.421	0.421
A1	5	5	1	1
A2	4	3	1	5
A3	3	4	5	1
A4	2	2	5	5

Table 5.10. Weighted scores and ranking

DECISION MATRIX WEIGHTED SCORING & RANKING						
	C1	C2	C3	C4	SUM	RANKING
A1	0.53	0.26	0.42	0.42	1.63	4
A2	0.43	0.16	0.42	2.10	3.11	2
A3	0.32	0.21	2.10	0.42	3.05	3
A4	0.21	0.10	2.10	2.10	4.53	1

According to this analysis and the selected criteria, alternative 4 is ranked as the top choice due to its higher priority score, followed by alternative 2, in close succession by alternative 3, with alternative 1 left for last.

Analysis 2:

In this analysis, we evaluated our model's performance using five distinct criteria. Along with the four factors used in analysis 1, uncertainty is added as a fifth criterion. We assume that stakeholders would prefer models that are more realistic and less biased, even if they come with higher costs. While model run time was considered moderately important, we gave less priority to model uncertainty compared to the other criteria. With these assumptions in mind, we utilised the AHP method to create a Pairwise Comparison Matrix (Table 5.11). The selected criteria for this analysis are:
C1= Model simplicity (code development)
C2= Model run time
C3= Model Uncertainty
C4= Estimating human losses
C5= Estimating economic losses

Table 5.11. Pairwise Comparison Matrix

	C1	C2	C3	C4	C5
C1	1	3	5	1/3	1/3
C2	1/3	1	3	1/5	1/5
C3	1/5	1/3	1	1/7	1/7
C4	3	5	7	1	1
C5	3	5	7	1	1

Table 5.12 shows the normalisation stage.

Table 5.12. Normalisation

	C1	C2	C3	C4	C5	SUM	Average	Consistency Measure	AV=criteria weights
C1	0.13	0.21	0.22	0.12	0.12	0.81	0.16	5.18	0.16
C2	0.04	0.07	0.13	0.07	0.07	0.39	0.08	5.03	0.08

C3	0.03	0.02	0.04	0.05	0.05	0.20	0.04	5.03	0.04
C4	0.40	0.35	0.30	0.37	0.37	1.80	0.36	5.22	0.36
C5	0.40	0.35	0.30	0.37	0.37	1.80	0.36	5.22	0.36

Consistency Index (C.I.) is calculated as C.I. = 0.031. As C.I. is below the suggested 0.1 threshold, the above comparison matrix is consistent. The criteria weights on Table 12 are used to weight the scores on table13. The scoring system remains consistent with Analysis 1, which is based on the results of Task 6.1, on a 5-point ordinal scale. Weighted scores are shown on Table 5.13.

Table 5.13. Weighted scores and ranking

DECISION MATRIX WEIGHTED SCORING							
	C1	C2	C3	C4	C5	SUM	RANKING
A1	0.81	0.39	0.20	0.36	0.36	2.12	4
A2	0.65	0.24	0.12	0.36	1.80	3.16	2
A3	0.49	0.32	0.16	1.80	0.36	3.12	3
A4	0.32	0.16	0.08	1.80	1.80	4.16	1

This analysis gave similar results as the previous analysis 1. Based on the five selected criteria, alternative 4 is ranked as the top choice due to its higher priority score, followed by alternative 2, 3 (in very close succession) and 1 respectively.

Analysis 3:

In this analysis, we are utilising the same five criteria as in Analysis 2. However, this time, we are assuming that the stakeholders prioritise the realistic estimation of human losses and model simplicity over the other criteria. To reflect this, we have prepared a Pairwise Comparison Matrix (Table 5.14) using the AHP method. Table 5.15 shows the normalisation stage.

Table 5.14. Pairwise Comparison Matrix

	C1	C2	C3	C4	C5
C1	1	3	7	1/3	5
C2	1/3	1	5	1/5	3

C3	1/7	1/5	1	1/9	1/3
C4	3	5	9	1	7
C5	1/5	1/3	3	1/7	1

Table 5.15. Normalization

	C1	C2	C3	C4	C5	SUM	Average	Consistency Measure	Criteria weights
C1	0.21	0.31	0.28	0.19	0.31	1.30	0.26	5.43	0.26
C2	0.07	0.10	0.20	0.11	0.18	0.67	0.13	5.20	0.13
C3	0.03	0.02	0.04	0.06	0.02	0.17	0.03	5.09	0.03
C4	0.64	0.52	0.36	0.56	0.43	2.51	0.50	5.46	0.50
C5	0.04	0.03	0.12	0.08	0.06	0.34	0.07	5.03	0.07

Consistency Index (C.I.) is calculated following Saaty (1994) and found as C.I. = 0.054. As C.I. is below the suggested 0.1 threshold, the above comparison matrix is consistent. The criteria weights on Table 5.15 are used to weight the scores on table 5.16.

Scoring is kept the same as in Analysis 1, based on Task 6.1 results. Weighted scores are shown on Table 5.16

Table 5.16. Weighted scores and ranking

DECISION MATRIX WEIGHTED SCORING							
	C1	C2	C3	C4	C5	SUM	RANKING
A1	1.30	0.67	0.17	0.50	0.07	2.72	3
A2	1.04	0.40	0.10	0.50	0.34	2.39	4
A3	0.78	0.54	0.14	2.51	0.07	4.04	1

A4	0.52	0.27	0.07	2.51	0.34	3.71	2

Examining results, re-score, discuss

The three analyses above represent a sensitivity analysis. Sensitivity analysis involves evaluating the impact of changing the criteria weights on the overall ranking of the alternatives. This step is important because the weights assigned to the criteria influence the final ranking of the alternatives. After performing a sensitivity analysis, the decision maker can change the weights assigned to each criterion to reflect their relative importance. This step involves considering the trade-offs between the different criteria and deciding how much weight to assign to each one. Once the criteria weights have been adjusted, the alternatives are re-scored based on the revised weights. This step is important because it allows the decision maker to see how the changes in weights affect the overall ranking of the alternatives. Finally, the decision maker should discuss the results of the MCDA analysis with stakeholders and other decision makers. This step involves considering the robustness and validity of the analysis, identifying any limitations or uncertainties, and determining whether additional information or analysis is needed to make a final decision.

Overall, the sensitivity analysis, changing the criteria weights, re-scoring, and discussing the results are important final steps in the MCDA process that help to ensure that the decision-making process is transparent, robust, and reliable.

6. Results and Discussions

Quantifying losses through RLA, SHM, performance-based earthquake engineering and OELF are critical inputs needed for a risk-cost-benefit analysis framework for quantifying socio-economic impact. To allow for rational policy making decisions, investment decisions and risk reduction measures must be underpinned by a transparent, reproducible, and socially accepted process of rational decision making. In this task we investigated the classic and widely used cost benefit analysis (CBA) as envisioned in the proposal. We began by developing a framework for integrating various RISE dynamic products, analysing their costs and benefits, and assessing their suitability in a dynamic risk concept. We initially explored the use of CBA as a decision support tool and then focused on applying CBA to these products to identify which ones were suitable for such analysis. Our results show that CBA can be effectively applied to early earthquake warning (EEW) systems. As we encountered challenges in applying CBA to certain risk products, we explored alternative approaches for decision support. Our search for such approaches led us to consider the potential of Multi-Criteria Decision Analysis (MCDA) for a variety of products. We highlight the benefits of using MCDA to assist decision-makers in selecting appropriate methodologies and/or tools.

Both CBA and MCDA are methods used in decision-making processes. Both methods involve the assessment of alternatives against a set of criteria, but they differ in how they approach the process. CBA is a method that compares the costs and benefits of different alternatives to determine the most efficient and effective option. It involves measuring the costs of implementing an alternative against the benefits that will be gained from that alternative. The goal is to determine if the benefits outweigh the costs, and if the alternative is economically feasible. In the context of CBA, we can only evaluate the benefits in monetary terms, whereas a lot of the methods provide benefits that are not in monetary terms. MCDA, on the other hand, is a method that takes into consideration multiple criteria to evaluate different alternatives. It involves the identification of a set of criteria that are relevant to the decision being made, and then assessing each alternative against those criteria. The goal is to identify the alternative that performs the best against the criteria that have been identified.

The main difference between CBA and MCDA is that CBA focuses primarily on the economic costs and benefits of different alternatives, whereas MCDA takes into consideration a broader range of criteria beyond just economic factors. MCDA allows decision-makers to consider non-economic factors, such as social and environmental impacts, which are not necessarily captured in a traditional CBA.

We have shown that CBA has its application and can provide valuable insight for the decision makers for the economical suitability of the selected methodologies. Once the benefits of the methods that need to be evaluated are not limited to financial benefits, MCDA can be utilised. We have shown the flexibility of MCDA and the capability of its transparency in decision support. The results of both CBA and MCDA support a dialogue with end-users such as decision makers and the public.

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8. Appendix A

This appendix summarises results obtained for the seven locations used as case-studies for the Multi-Criteria Decision Analysis presented in Chapter 6 (three locations for L'Aquila, four locations for Central Italy. For the sake of simplicity, the four alternatives considered are summarised herein:

- Alternative 1: state-independent fragility models, no updating of occupants
- Alternative 2: state-dependent fragility models, no updating of occupants
- Alternative 3: state-independent fragility models, with updating of occupants
- Alternative 4: state-dependent fragility models, with updating of occupants

Cumulative Ratio of Economic Losses

The following plots show the evolution of economic losses during the earthquake sequences in terms of ratio of building replacement costs to total replacement costs of the whole building stock. Results from alternatives 1 and 3 are the same, and so are results from alternatives 2 and 4, as economic losses are only influenced by the use of state-dependent or state-independent fragility models, but are not influenced by whether the occupants are updated or not. As can be seen and would be expected, the use of state-independent fragility models leads to systematically lower damage and, thus, economic losses than state-dependent fragility models.

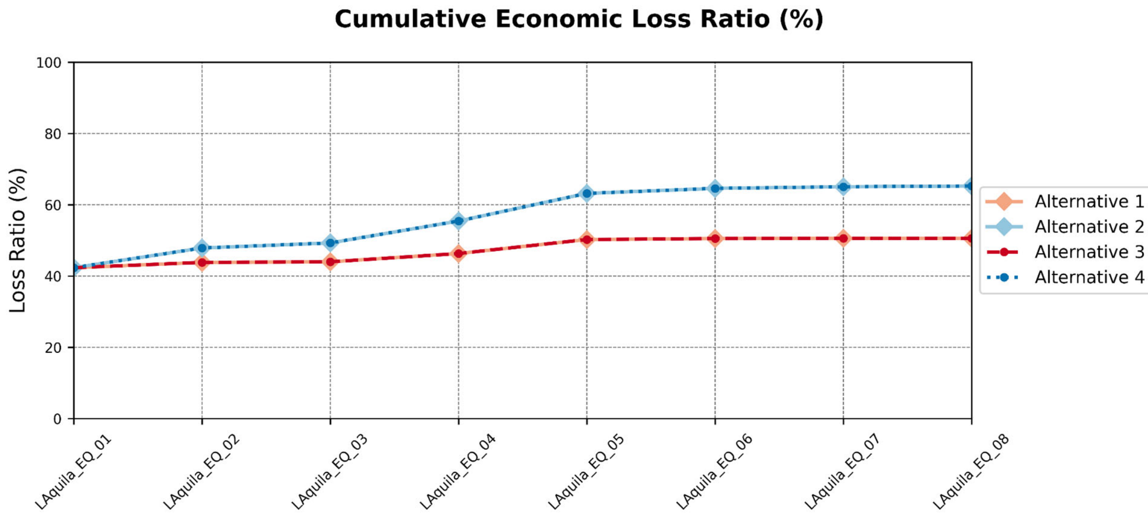

Figure A1. Cumulative economic loss ratios for the four alternatives for location 01 of L'Aquila.

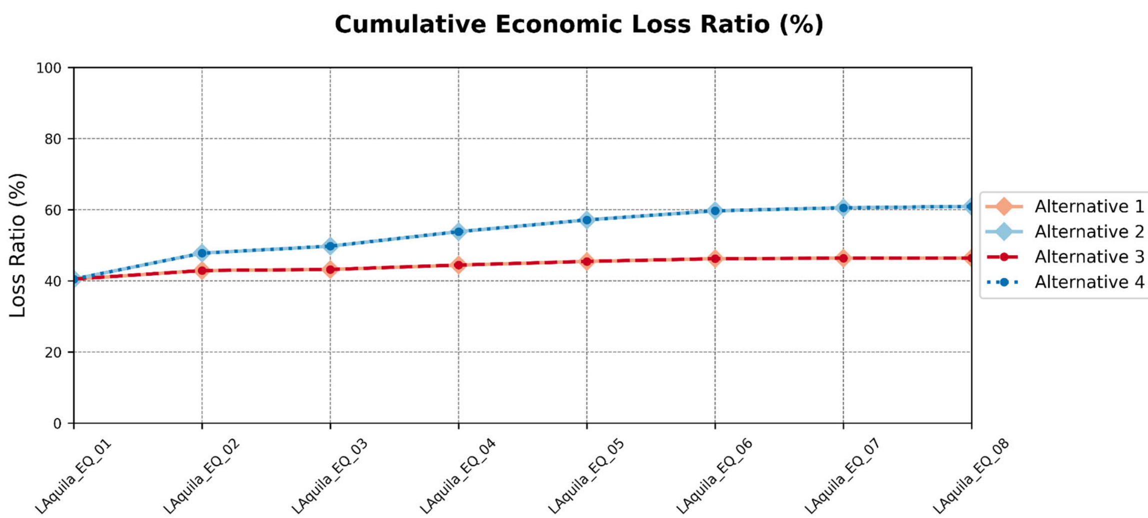

Figure A2. Cumulative economic loss ratios for the four alternatives for location 02 of L'Aquila.

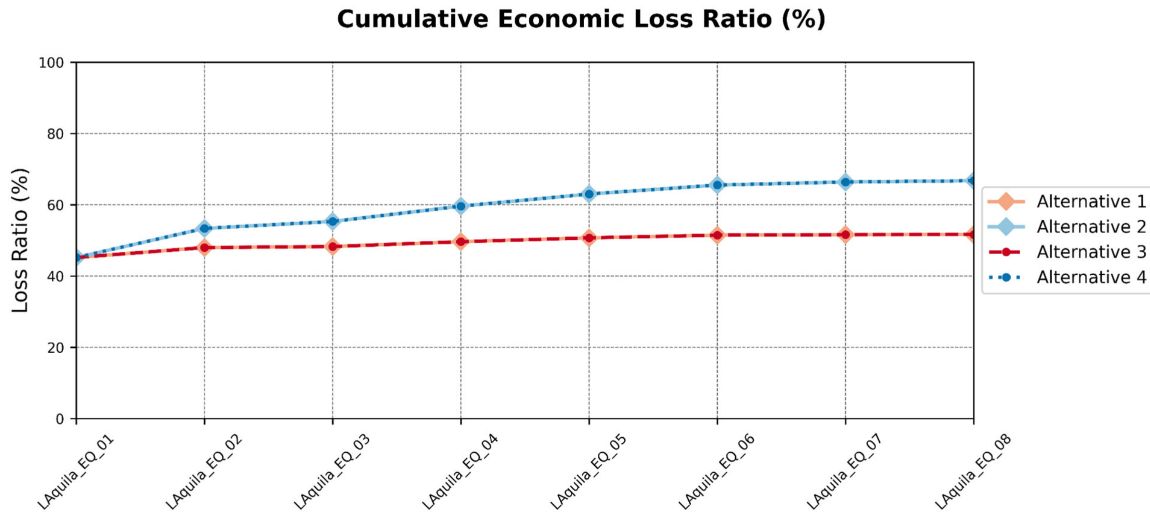

Figure A3. Cumulative economic loss ratios for the four alternatives for location 03 of L'Aquila.

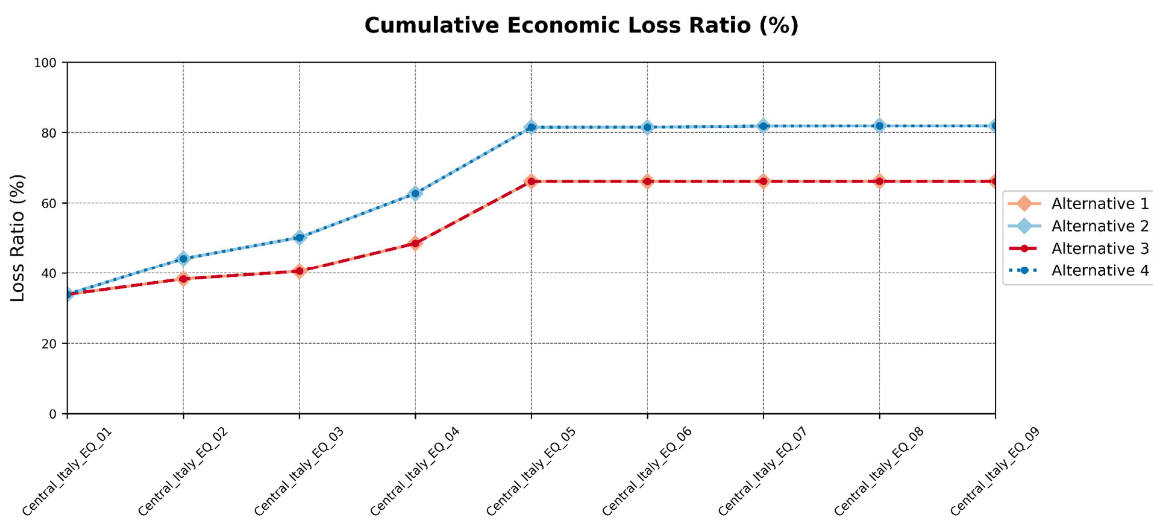

Figure A4. Cumulative economic loss ratios for the four alternatives for location 11 of Central Italy.

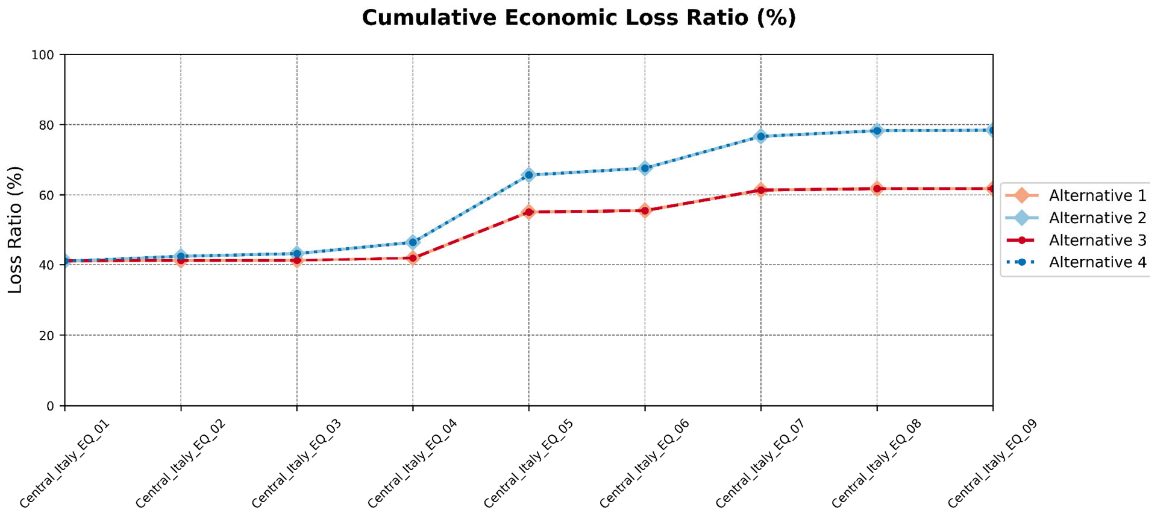

Figure A5. Cumulative economic loss ratios for the four alternatives for location 12 of Central Italy.

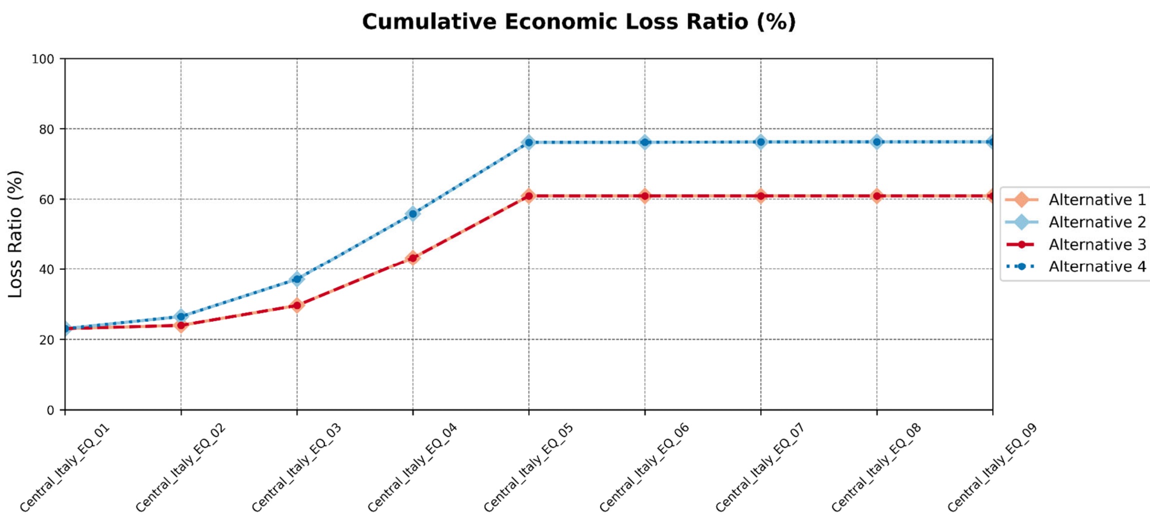

Figure A6. Cumulative economic loss ratios for the four alternatives for location 13 of Central Italy.

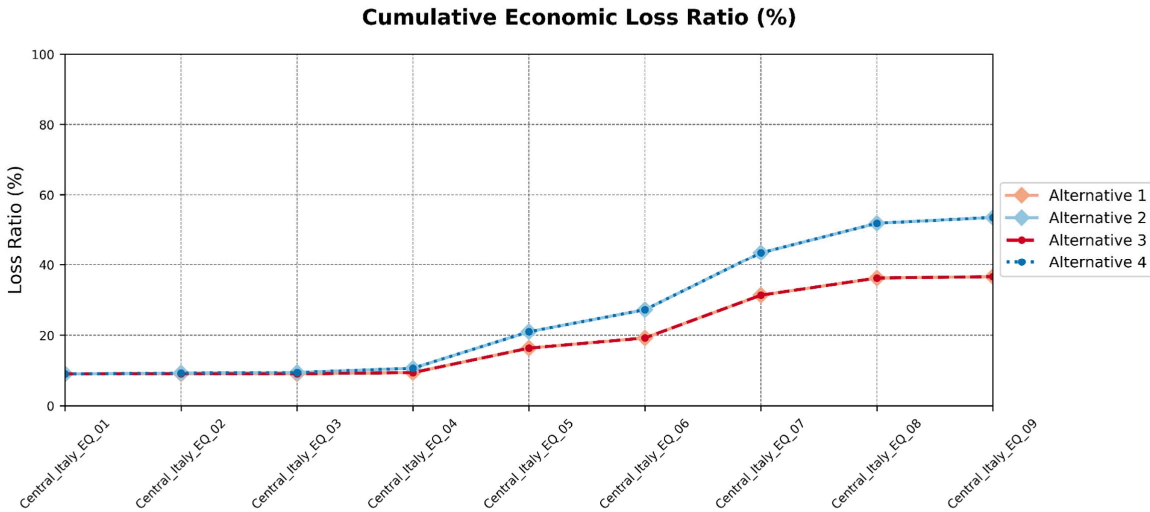

Figure A7. Cumulative economic loss ratios for the four alternatives for location 14 of Central Italy.

Cumulative Ratio of Injuries

The following plots show the evolution of injuries during the sequences in terms of ratio of people who sustain injuries of severity 1, 2 or 3 with respect to the total number of census occupants of the building stock as a whole. A first outcome that strikes the eye is the fact that not updating the occupants (alternatives 1 and 2) leads to significantly larger numbers of injuries being calculated than when occupants are updated (alternatives 3 and 4). In the case of the 2009 L'Aquila sequence updating the occupants leads to horizontal lines in the plot, due to the fact that occupants are present in the buildings only during the first earthquake. In the case of the 2016-2017 Central Italy sequence, some occupants are able to return to buildings in our model right before the third and the sixth earthquakes, and thus lines are not horizontal for alternatives 3 and 4, although the additional injuries that occur during the third and sixth earthquakes are very few in comparison to those that occur during the first earthquake.

When not updating occupants (alternatives 1 and 2), using state-independent fragility models (alternative 1) leads to fewer injuries than using state-dependent ones (alternative 2), because in both cases 100% of the occupants are considered as present during each earthquake, irrespective of previous injuries, and alternative 1 predicts lower damage than 2, and lower damage leads to fewer injuries being predicted.

The fact that the opposite seems to occur when comparing alternatives 3 and 4 for the four Central Italy locations appears as counter-intuitive. As alternative 4 has (by the time the third earthquake hits) already accumulated more damage than alternative 3 because of the use of state-dependent fragilities, there are more people who cannot return to their buildings in alternative 4 than in alternative 3 (due to the damage status of the buildings, and therefore fewer occupants and fewer injuries in alternative 4 than in alternative 3. This might be influenced by the way in which the

Real-Time Loss Tools are carrying out the updating of occupants, which is by calculating at each step the expected number of injured people who cannot return to their buildings for a building based on all its possible damage states and associated probabilities and then distributing them to each damage grade proportionally to the number of census people allocated to each damage grade, which is proportional to the probability of the damage grade itself. Ideally, one would like to keep track of every possible path of damage (which propagates into all possibilities with each earthquake) and the associated numbers of injuries instead, as discussed in Nievas et al. (2023), but the feasibility in terms of computational demand still needs to be evaluated.

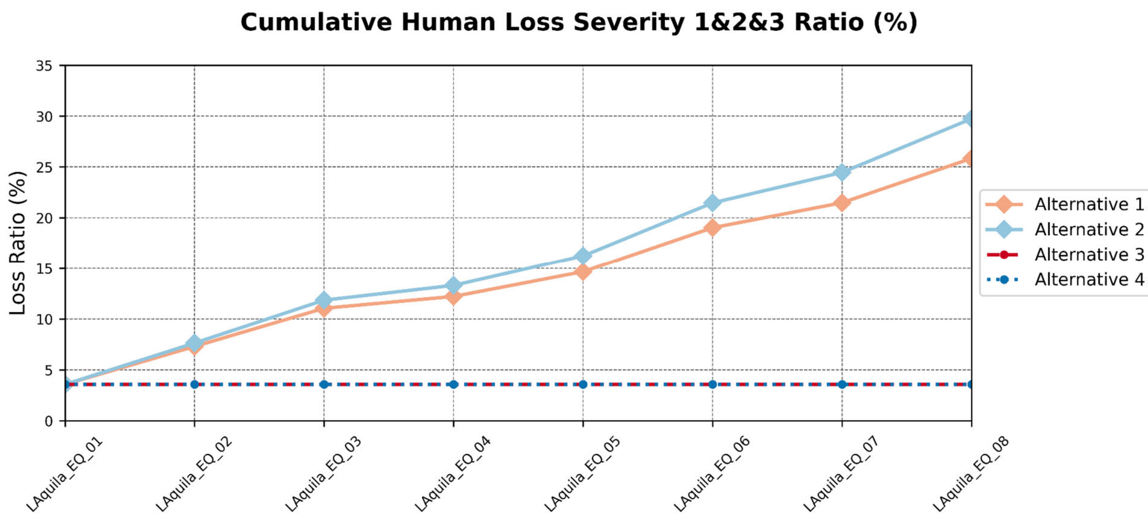

Figure A8. Cumulative ratios of injuries (severity 1, 2, 3) to total number of census occupants for the four alternatives for location 01 of L'Aquila.

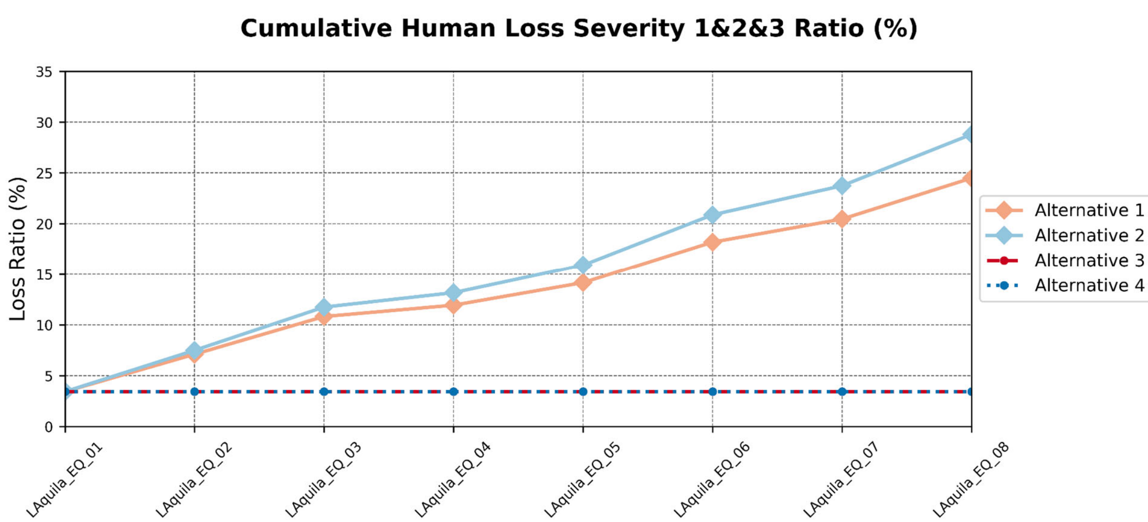

Figure A9. Cumulative ratios of injuries (severity 1, 2, 3) to total number of census occupants for the four alternatives for location 02 of L'Aquila.

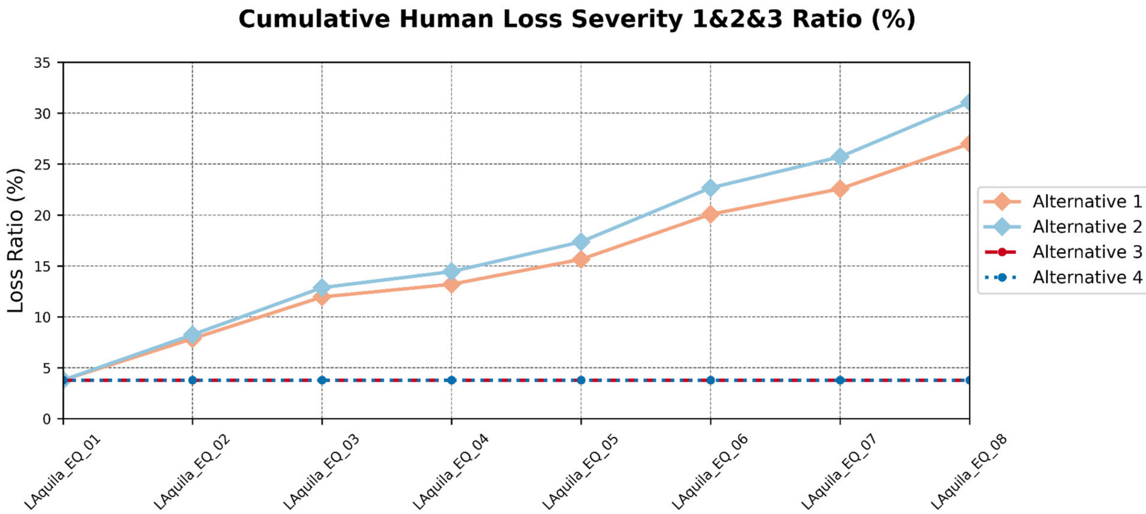

Figure A10. Cumulative ratios of injuries (severity 1, 2, 3) to total number of census occupants for the four alternatives for location 03 of L'Aquila.

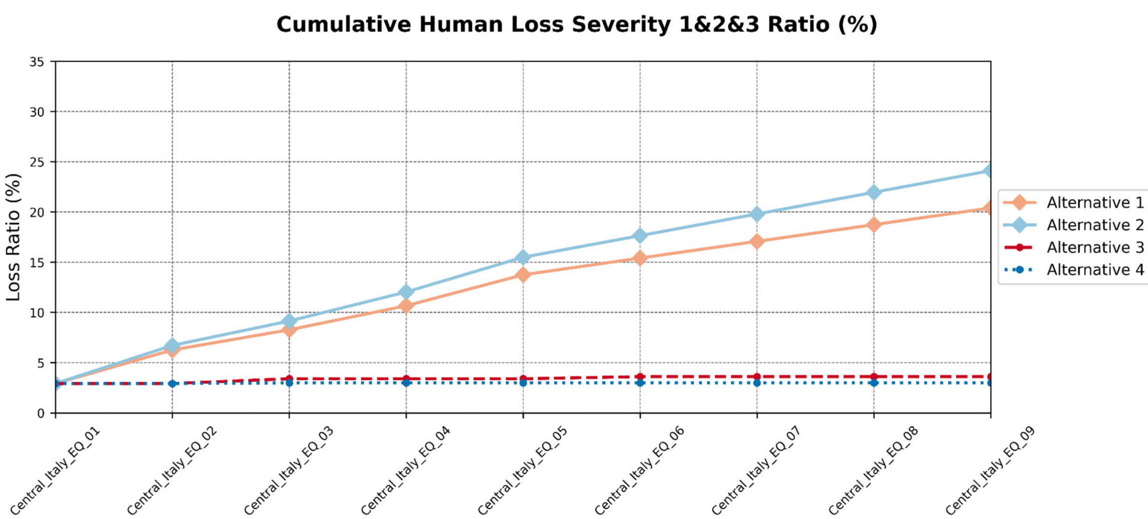

Figure A11. Cumulative ratios of injuries (severity 1, 2, 3) to total number of census occupants for the four alternatives for location 11 of Central Italy.

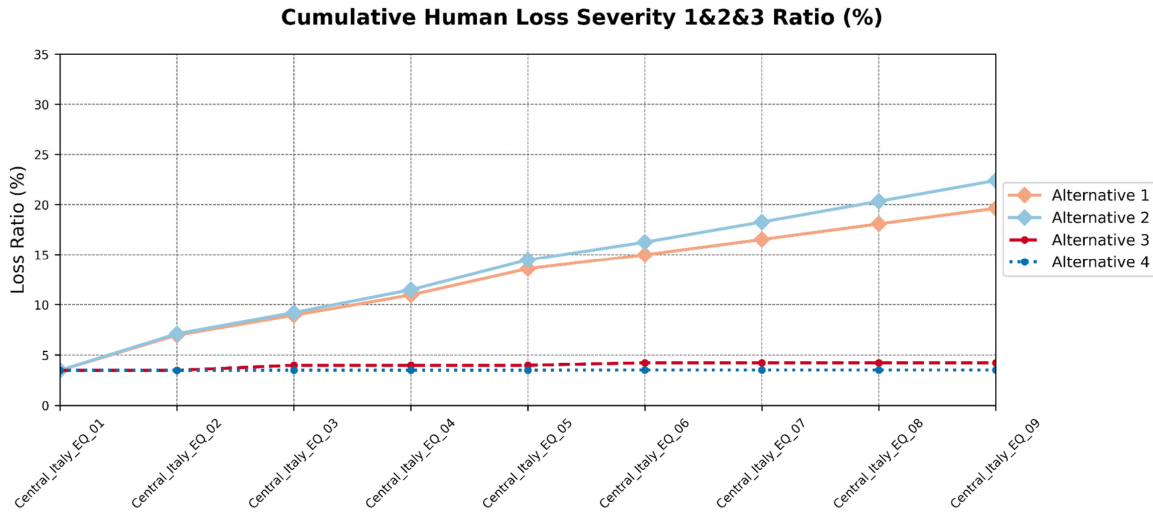

Figure A12. Cumulative ratios of injuries (severity 1, 2, 3) to total number of census occupants for the four alternatives for location 12 of Central Italy.

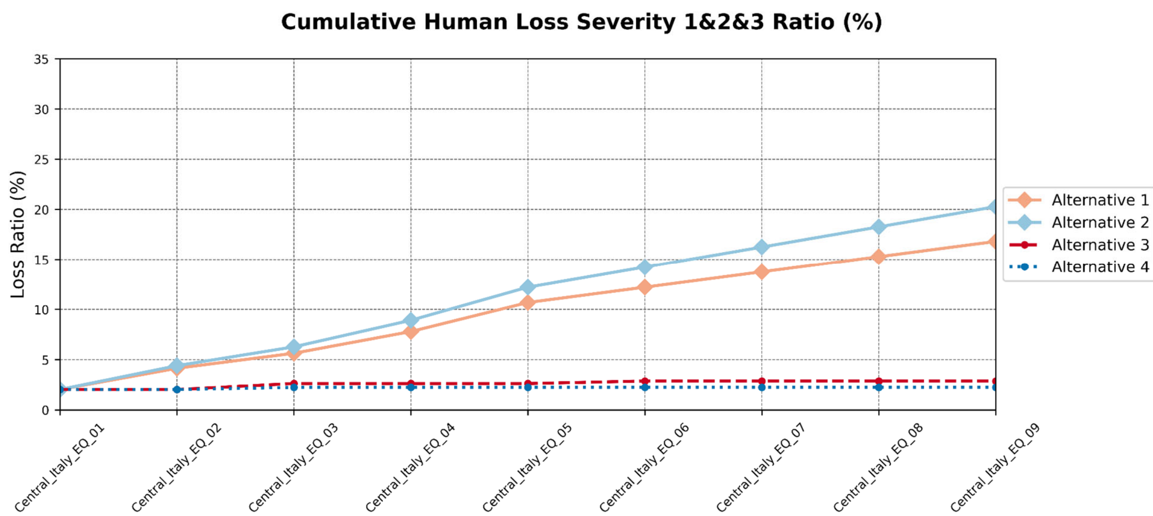

Figure A13. Cumulative ratios of injuries (severity 1, 2, 3) to total number of census occupants for the four alternatives for location 13 of Central Italy.

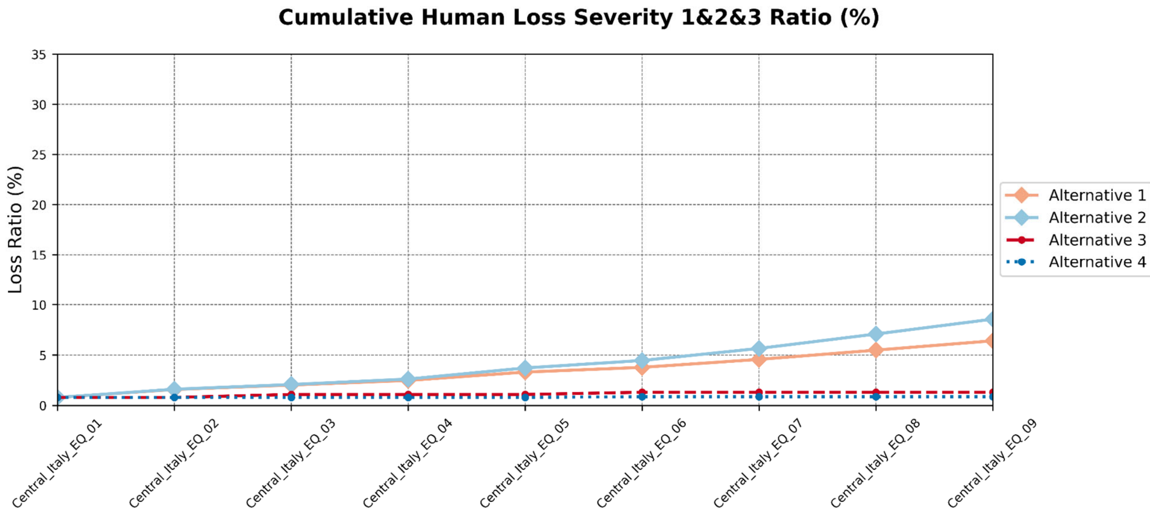

Figure A14. Cumulative ratios of injuries (severity 1, 2, 3) to total number of census occupants for the four alternatives for location 14 of Central Italy.

Cumulative Ratio of Deaths

The following plots show the evolution of deaths (injuries of severity 4) during the sequences in terms of ratio of deaths to the total number of census occupants of the building stock as a whole. The same comments and observations as for the case of injuries of severity 1 through 3 apply.

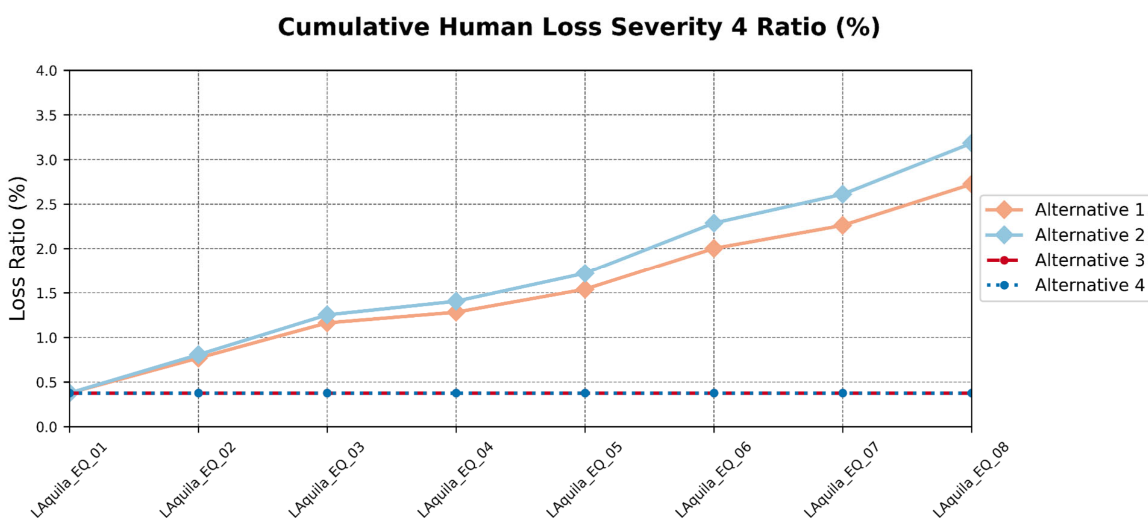

Figure A15. Cumulative ratios of deaths (injuries of severity 4) to total number of census occupants for the four alternatives for location 01 of L'Aquila.

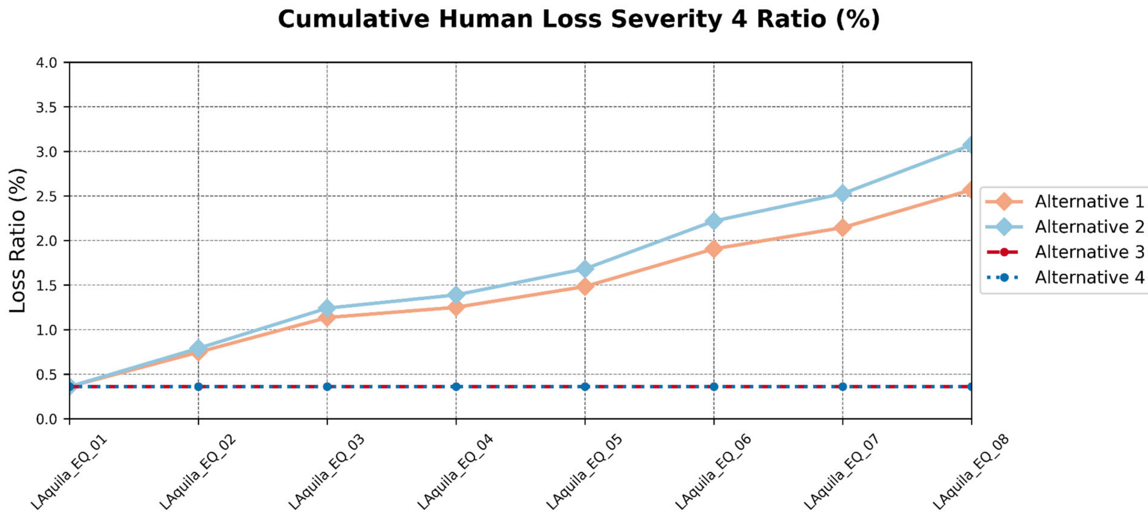

Figure A16. Cumulative ratios of deaths (injuries of severity 4) to total number of census occupants for the four alternatives for location 02 of L'Aquila.

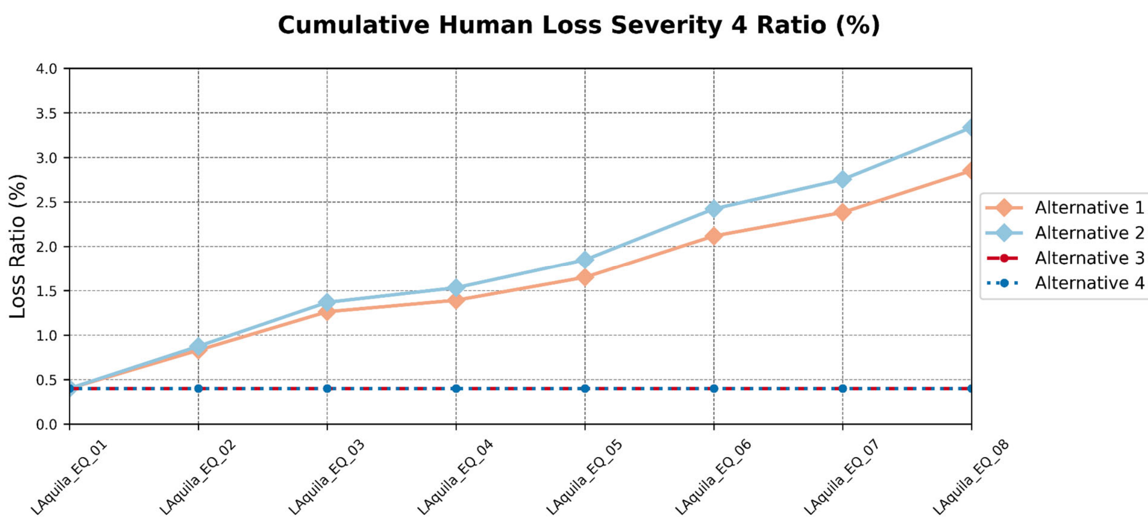

Figure A17. Cumulative ratios of deaths (injuries of severity 4) to total number of census occupants for the four alternatives for location 03 of L'Aquila.

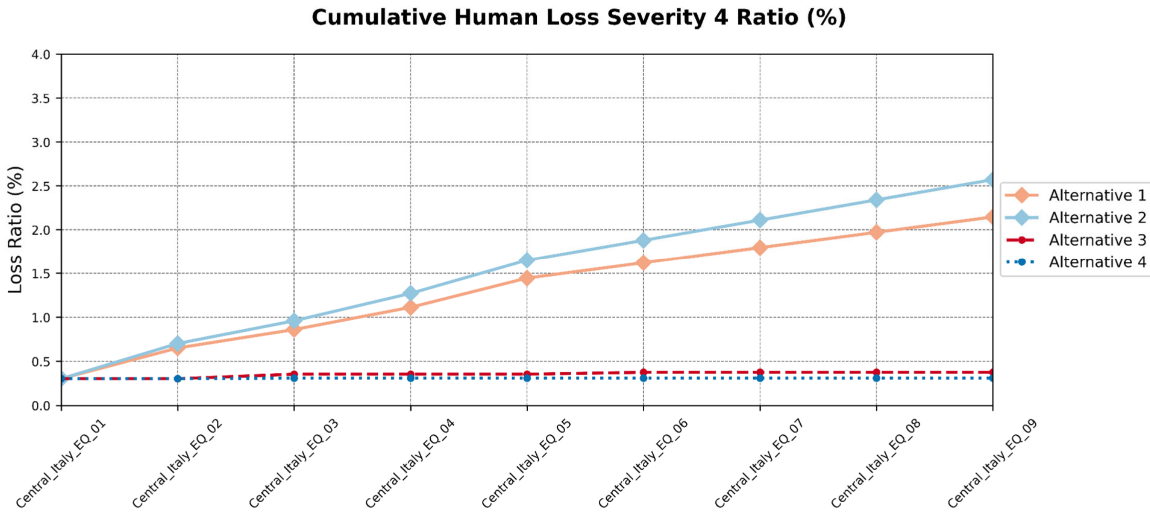

Figure A18. Cumulative ratios of deaths (injuries of severity 4) to total number of census occupants for the four alternatives for location 11 of Central Italy.

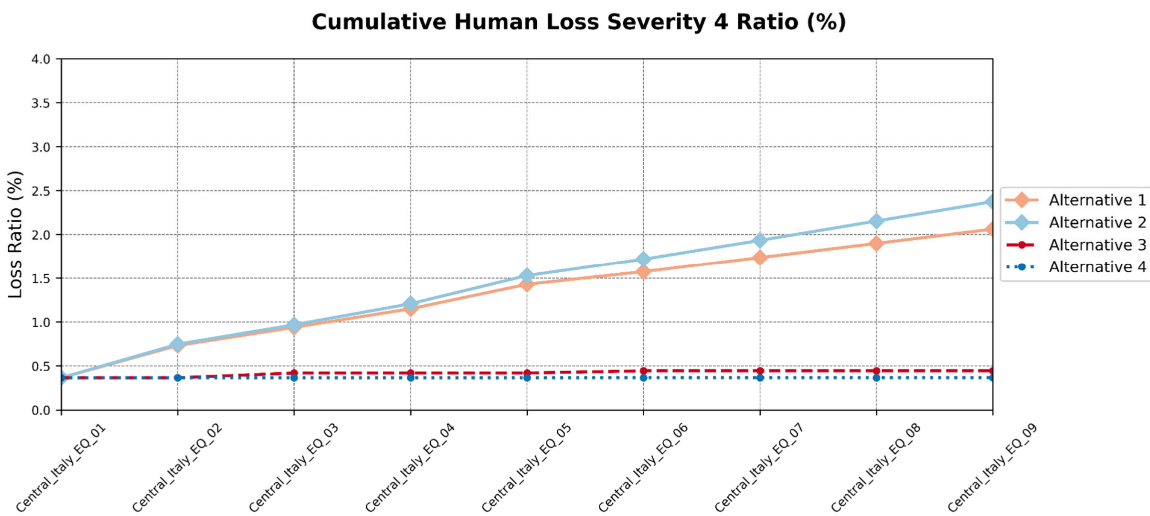

Figure A19. Cumulative ratios of deaths (injuries of severity 4) to total number of census occupants for the four alternatives for location 12 of Central Italy.

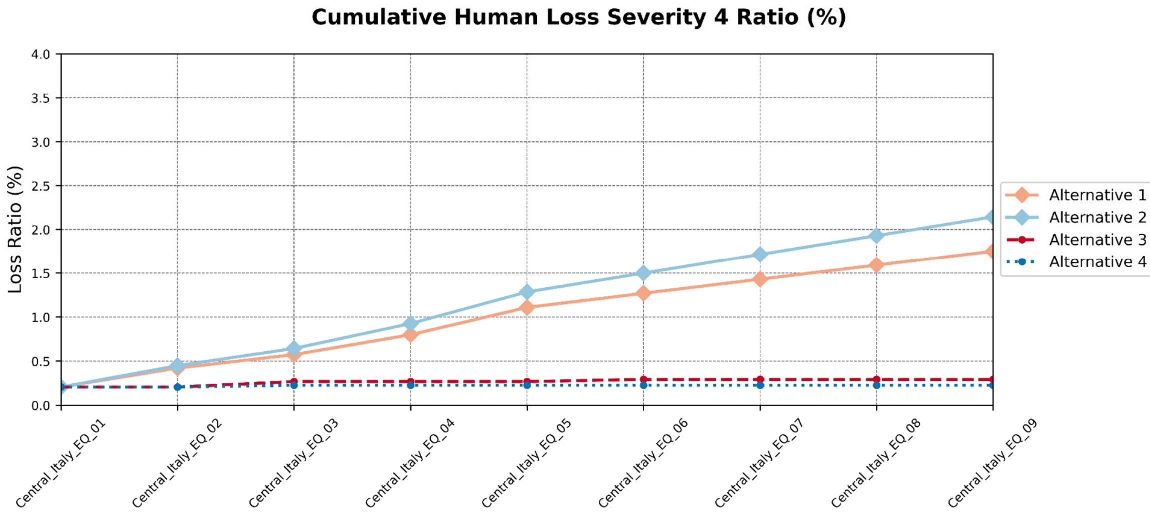

Figure A20. Cumulative ratios of deaths (injuries of severity 4) to total number of census occupants for the four alternatives for location 13 of Central Italy.

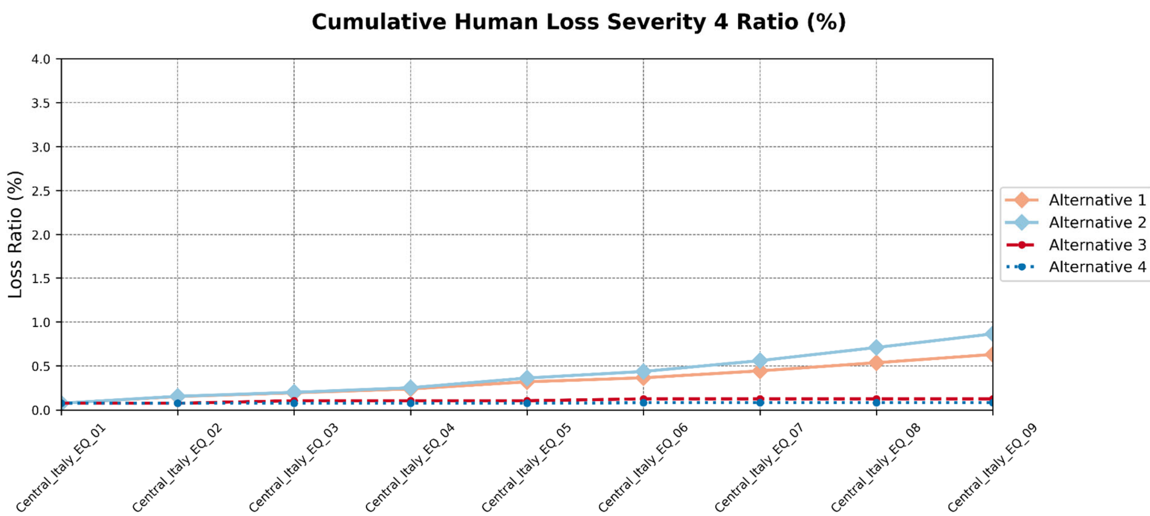

Figure A21. Cumulative ratios of deaths (injuries of severity 4) to total number of census occupants for the four alternatives for location 14 of Central Italy.