

Seismic vulnerability analysis of existent buildings. Loss estimation and uncertainty analysis for deterministic earthquake scenarios.

Ismaël Riedel

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THÈSE

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préparée au sein de l'**Institut des Sciences de la Terre** dans **l'École Doctorale Terre, Univers, Environnement**

Analyse de la vulnérabilité du bâti existant. Estimation et réduction des incertitudes dans l'estimation des dommages et des pertes pour un scénario sismique donné

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Chapter 1

General introduction

Among the natural hazards and major catastrophes, earthquakes are one of the most damaging, deadliest and unpredictable of all. Indeed, in only a very short fraction of time entire regions can be completely destroyed and, even with the large existing worldwide surveillance network, they cannot be predicted. With increasing impacts on countries' economies, modern earthquakes cost in average tens of billons of dollars and kill 35,000 people per year worldwide (USGS).

In the ranking of the world's costliest natural disasters since 1900 (Munich Re, IMF, World Bank, EM-DAT disaster database), the 2011 Tohoku earthquake and tsunami (Japan) takes the lead with a provisional estimated economic loss of \$210 billion (2010 US dollars), around 4% of the country Gross Domestic Product in that year (GDP). Another Japanese earthquake appears in the second place. The 1995 Kobe earthquake cost \$110 billon, around 1.9% of GDP. Depending on the sources, the hurricane Katrina of 2005 (United States) comes third with an estimated loss of \$100 billon (0.8% GDP). Three earthquakes follow on the list. The 2008 Sichuan earthquake (China), the 1994 Northridge earthquake (United States) and the 2010 Chile earthquake with estimated losses of \$85 billion, \$57 billion and \$30 billon, respectively. In the European context, one of the costliest earthquakes was the 1980 Irpinia earthquake (Italy), causing \$20 billion economic loss. Only exceptional riverine floods or tropical cyclones can match this destructive potential.

In developing countries, even if the total economic loss may be far lower, the impact of earthquakes on the national economy might be greater due to losses being a larger proportion of the GDP. At the top of the list we can name the 2010 Port-au-Prince (Haiti) earthquake with losses of more than 73% of the national GDP. The recent 2015 Nepal earthquake produced losses of almost 50% of GDP and the 1972 Managua (Nicaragua) earthquake losses reaching 40% of GDP (Coburn and Spence, 2002).

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In terms of natural disasters by death toll since 1900 (USGS, UN, EM-DAT disaster database), the 2010 Haiti earthquake takes the third place with 316,000 casualties preceded by the big China floods of 1931 that killed around 2 million people and the Bangladesh tropical cyclone of 1970 responsible of 320,000 deaths. The Tangshan earthquake (China) of 1976 killed 242,000 while the 2004 Sumatra earthquake and tsunami 227,000. In Europe, the 1908 Messina earthquake (Italy) remains the deadliest, accounting for 75,000 people killed.

It is becoming evident, as the International Monetary Fund (IMF) (www.imf.org) diagnoses through its working paper (WP/12/245), that natural disasters are affecting more people and they are becoming costlier in time. This trend is particularly true for earthquakes, for which their related fatalities reached unprecedented values in the beginning of the 21st century. Approximately 699,000 people died in earthquakes during the century's first decade (Holzer and Savage, 2013).

Although it may seem that the world is undergoing more tremors, the rate has remained fairly constant in time. We can expect in average 1300 moderate earthquakes (Magnitude Mw = 5 to 5.9) every year worldwide, around 130 between Mw = 6 to 6.9, 15 between Mw = 7 to 7.9 and 1 great event per year with Mw = 8 or higher (USGS).

In fact, this upward trend is a result (expected to continue) of the population growth and the rising concentration of people living in urban areas more exposed to seismic hazards (e.g., Coburn and Spence, 2002; Oliveira *et al.*, 2006). According to UN databases (www.un.org) the population of seismically hazardous areas, as a proportion of world population has remained approximately constant in time. **Figure 1** shows the global hazard map and the presence of important population concentrations (megacities) in regions of very high or high seismic hazard (Global Seismic Hazard Assessment Program GSHAP, UN Population Division). According to Bilham (2009), 65% of the world's larger cities today may be subjected to significant seismic shaking.

Holzer and Savage, (2013) showed the direct link between the exponential population growth and the modern increase in the number of earthquakes with large death tolls. **Figure 2** represents the individual earthquakes from the year 800 with a death toll larger than 50,000. In the same plot, the total world population in indicated. Even if deadly earthquakes have occurred in the past, the increase in their frequency is clearly a consequence of the large urban population growth in the 19th and 20th centuries.



Figure 1 - Global seismic hazard map and world population concentrations (GSHAP, 2011)



Figure 2 - Individual earthquakes from 800 to 2011 with more than 50,000 fatalities from USGS catalog and the link with the exponential population growth (from Holzer and Savage, 2013).

At the scale of France, the situation is not categorically different. Even if the seismic hazard is lower compared with other parts of the world, the population and the industrial and economic assets exposed to it has also exponentially increased during the last centuries. **Figure 3** shows the hazard map for France with the most important population concentrations and the location of nuclear power plants.

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In metropolitan France, large cities are located in regions with a significant seismic hazard. Oversimplifying the situation, these regions (in red) have a 10% probability of suffering severe destructive shaking from earthquakes in the next 50 years (i.e., ground accelerations with 475 years return period). Almost 4.0 million people (5.9% of total population) currently live on important hazard regions of France. These habitants have therefore in average 16% probability of experiencing at least one destructive earthquake during their lives (80 years life expectancy).

In addition, France is ranked first in the world in terms of nuclear power plants per habitant for any country. Fifty-nine nuclear reactors distributed between nineteen active power plants generate approximately 75% of France's electricity, many of them reaching their designed operational lifetime and located on hazardous regions. The potential catastrophic consequences of damage to such a facility and especially the observed effects on Fukushima nuclear power plant after the 2011 Tohoku earthquake, have risen awareness among public agents and emphasized the importance of seismic risk assessments in France.



Figure 3 - French seismic hazard map, population concentrations, total population by hazard region and nuclear power plants locations.

With the extensive damage observed after worldwide moderate-to-strong earthquakes of the last decades, awareness of natural catastrophes has considerably increased, and the evaluation and reduction of this risk has become a priority for local authorities in order to ensure the well-being and safety of populations as well as for economic and social security. There is a growing demand for detailed seismic risk analysis to strengthen disaster risk mitigation and response. These studies allow (1) identifying the probability and the expected impacts of earthquakes to integrate these risks explicitly into economic planning frameworks, (2) improving coordination and readiness of emergency assistance after the event and (3) furnishing adequate information for the insurance and reinsurance companies to work with. However, risk analysis are embedded with uncertainties, and dealing with these uncertainties is a key component for any decision-making (Spence *et al.*, 2008).

Seismic risk can be seen as the probability that humans will incur harm, loss or damage to their built environment if they are exposed to a seismic hazard with a given probability of occurrence. In general, it can be expressed qualitatively as: **Seismic Risk = Seismic Hazard x Vulnerability x Exposure.**

Seismic hazard and seismic risk are fundamentally different. Seismic hazard is a natural phenomenon such as ground shaking generated by an earthquake, whereas seismic risk is the probability of harm or losses if someone or something is exposed to that hazard (i.e. an interaction between seismic hazard and seismic vulnerability). High seismic hazard does not necessarily mean high seismic risk and vice versa.

Exposure is the totality of persons, goods, equipment, or activities susceptible to the forces of a natural hazard. They are characterized by their vulnerability, defined as the loss susceptibility – from 0% to 100% - resulting from the occurrence of an event of a given severity. For constructions, a seismic vulnerability function is a relationship that defines the expected damage (for a building or a class of building) as a function of a given ground motion parameter representing the seismic hazard.

Some regions, generally located relatively far from zones with high tectonic activity, have a lower (but not negligible) level of seismic activity and are therefore named low-tomoderate seismic hazard regions. Countries like France, Spain, Portugal, Germany and Switzerland form part of this category. Even though these regions are considered to be of moderate hazard, they are not free of seismic risk, and particularly not if the exposure and the vulnerability of their cities is high.

For example, France is fairly considered as a low-to-moderate seismic hazard country. However, a major historic earthquake hit France in the twentieth century (1909) with an estimated magnitude of more than 6 and major effects in the (at that time rural) region of Aixen-Provence (south-eastern France), causing 42 fatalities, many more injuries, and severe economic losses. Other important events are part of the seismic history of metropolitan France (M_w : 6.5 Bâle earthquake in 1356, I: VIII-IX Chandeleur earthquake in 1428, M_w : 6.3 Ligure earthquake in 1887). More recently, Ossau-Arudy 1980 (M_L : 5.1) and Annecy 1996 (M_L : 4.8) earthquakes caused estimated losses of €4 million (Environment ministry - MEDD 1982) and €50 million, respectively (AFPS, French Paraseismic Association, 1996), even at these low magnitudes.

At present time, earthquake engineers can design and construct new structures capable of resisting the strongest ground motions produced by earthquakes. However, even if earthquakes codes can be improved, the low-rate renovation of building stocks in cities, estimated around 1% a year (Coburn and Spence, 2002), makes existing buildings the dominant source of physical vulnerability. Indeed, if we consider the case of most European cities, the majority of existing buildings have been designed before the application of earthquake design rules.

In France for example, the first recommendations appeared in 1955 (called Recommendations AS 55) after the Orléansville, Algeria earthquake (French territory at that time). These recommendations were updated in 1969 to give the Recommendations PS 69 forged between the agreement of engineers and the public state. Some authors state that this recommendation was really applied only after 1979. New earthquakes allowed the improvement of it, like in 1982, until the elaboration of the norm called PS 92, in 1992. In addition, a simplification of this norm (PS-MI 89/92) has been created for individual houses. Finally, after the long work of norm homogenization throughout Europe, the Eurocode was created. Eurocodes are a set of harmonized technical rules developed by the European Committee for Standardization for the structural design of construction works in the European Union. In particular the EN 1998, also known as "Eurocode 8: Design of structures for earthquake resistance", is the European Standard for the design of structures in seismic

zone, using the limit state design philosophy. It was approved on 23 April 2004. By March 2010 the Eurocodes are mandatory for European public works and the *de facto* standard for the private sector. The Eurocodes replace the existing national building codes published by national standard bodies, although many countries had a period of co-existence. Additionally, each country issued a National Annex to the Eurocodes. In France, the new rules were accompanied by new seismic zone delimitation applicable from 2011 (the old one dated from 1991). According to the author's studies (Riedel *et al.*, 2014a and 2014b) approximately 70% of buildings in France were constructed without any seismic conception while more than 90% were designed using earthquake design norms considered now obsolete.

While nothing can be done to prevent earthquakes from happening, it is on reducing their effects that we must place our efforts. One of the areas contributing to the reduction in earthquake fatalities and losses, besides the improvement of technical norms and the reinforcement of existing buildings, is the anticipation and simulation of earthquake effects for crisis management and the development of appropriate risk mitigation actions. Another possible solution is to privatise the risk by offering insurance to homeowners and then to export large parts of the risk to the world's reinsurance markets (Bommer *et al.*, 2002). In order to design such mitigation plans or insurance and reinsurance schemes, a reliable earthquake loss model for the region under consideration needs to be compiled such that the future losses due to earthquakes can be determined with relative accuracy.

This risk assessment requires not only the estimation of the seismic hazard, but also the representation of the quality of existent buildings and the structures' capacity to withstand the seismic ground motion: this is the objective of large scale seismic vulnerability assessments. Such assessments should allow: (1) the estimation of probable damage due to an earthquake scenario or the annual probability of damage at a large overall scale, (2) the spatial representation of effects for crisis management, (3) the identification of most vulnerable building categories that must benefit from priority reinforcement, and finally (5) inform local authorities on the level of risk to which the population is exposed compared with other natural or domestic hazards (Dunand and Gueguen, 2012; Lestuzzi *et al.*, 2009). Coupled with real-time seismic ground motion estimates (e.g., Wald *et al.*, 1999; Worden *et al.*, 2010), macroscale vulnerability data are crucial for the early assessment of damage.

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Over the last two decades, many methods have been published to assess the seismic vulnerability of buildings at a large scale, most of them calibrated using post-event damage information or by expert judgement. They estimate the probability of reaching a certain level of damage for a given class of buildings and a given seismic demand. Some challenges and difficulties these methods have to face are (1) the large number and the variability of the response of existing buildings to seismic loads, (2) the lack of understanding of the seismic behaviour of old structures as well as inadequate information concerning the quality of construction materials, and (3) the lack of observations to adjust empirical methods to the highest damage grade. These issues introduce significant uncertainty into seismic vulnerability assessment and therefore into seismic risk analysis. These difficulties are even more critical in moderate-to-low seismic hazard regions, where historical and documented earthquake damage statistics are scarce and where the mobilization of resources for seismic evaluation is rather limited.

Few vulnerability assessment studies have been conducted in France, focused on large exposed cities and applying traditional empirical methods. However, the application of these methods requires so much information that the evaluation struggles to find sufficient political motivation and financial resources to complete the seismic inventory of buildings. Consequently, the structural characteristics required for the seismic vulnerability assessment of existing buildings are not available for all exposed urban areas of the country.

In low-to-moderate seismic hazard regions we are placed at a crossroad. Historical and current measured seismicity prove the presence of a non-negligible hazard. However, this threat is associated to long return periods and it may be lower than other natural hazards, reducing public concern and political motivation. We still need to assess the seismic vulnerability of the exposed elements but the resources for such evaluation are limited. We must therefore find a solution economically convenient, practicable, readily applicable but pertinent to complete the assessment.

Thesis outline

Due to the inherent complexity of estimating hazard, exposure, vulnerabilities and their interaction in space and time, seismic risk quantification is a very daunting task. Estimating

realistic impacts due to large earthquakes may only be done approximately. This work tries to deal in part with this problem and is divided in three main chapters.

Chapter 2 presents a global introduction to earthquake loss modelling. The different components involved in these evaluations are presented and detailed: seismic hazard assessments, exposure assessment, and the seismic vulnerability of structures. A special attention is given to the prevailing empirical methods of large-scale vulnerability assessment. Finally, several state-of-the-art earthquake loss models are presented with their main characteristics, advantages and drawbacks.

Chapter 3 propose a way to perform an efficient estimation of the seismic vulnerability of buildings at an urban scale using convenient, reliable building data that are readily available regionally instead of the information usually required by traditional methods. Using a dataset of existing buildings in Grenoble (France) with an EMS98 vulnerability classification and by means of two different data mining techniques -association rule learning and support vector machine- seismic vulnerability proxies are developed. These proxies are applied to all of France using basic information from national databases (census information) and data derived from the processing of satellite images and aerial photographs to produce a nationwide vulnerability map. This macroscale method to assess vulnerability is easily applicable in case of a paucity of information regarding the structural characteristics and constructional details of the building stock. The approach is validated with data acquired for the city of Nice, by comparison with the Risk-UE method. Finally, damage estimates are compared with historic and recent earthquakes that caused moderate-to-strong damage in France. Due to the increasing vulnerability of cities, the number of seriously damaged buildings can be expected to double or triple if these historic earthquakes were to occur today.

Chapter 4 is advocated to the calculation of earthquake losses and to the analysis and reduction of uncertainties. In the first part, three ground motion prediction equations (GMPE) are presented and tested against instrumental data from France. A comparison between predicted and observed ground motion is done, and the prediction with smaller residuals is highlighted. In the same way, observed and predicted intensities calculated using a combination of ground motion prediction equations and ground motion to intensity conversion equations (GMICE) and directly using intensity conversion equations (IPE) are compared for fifteen French earthquakes. The full estimation from earthquakes scenarios to

probable number of damaged buildings in a typical European city is presented in the second part. A comprehensive analysis of uncertainties is carried on at every step, and the final combined uncertainty is calculated. The major sources of variability are depicted and recommendations on how to efficiently reduce them are proposed. In the last part, the evolution of damage and risk when structural improvements are performed to buildings is reviewed. Economic loss assessments are performed for France using regulatory hazard maps for different time horizons. In particular, for five French cities the proposed loss model is used to design retrofitting schemes by carrying out cost-benefit studies for different types of structural intervention plans. Optimal investment scenarios are calculated, which may support strategic decisions regarding the risk mitigation in France.

A summary of results, the general conclusion and perspectives for improvements and future work are presented in Chapter 5.

Chapter 2

A state of the art review on earthquake loss estimation models

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2.1. Introduction to earthquake loss modeling

2.1.1 Introduction

A loss estimation model is a tool used to assess potential losses due to the occurrence of a risk (natural or man-made). In terms of natural hazard, models have been created for floods, storms or seismic risk. It was only following several costly disasters in Europe, but especially after hurricane Andrew of 1992 which was, at the time of its occurrence, the costliest hurricane in United States history (\$26.5 billion) and after the Northridge earthquake in 1994 (\$20.0 billion loss) which caused catastrophic losses for insurers and reinsurers, that the usefulness of such models has been recognized. These tools allow a better quantification of the risks they cover and thus, a better knowledge of the exposure. Based on mathematical algorithms linking the parameters characterizing the natural phenomenon itself and the information regarding the exposed elements, risk models provide a priori estimates of the potential damage.

The formulation of an earthquake loss model for a given region is not only of interest for predicting the economic impact of future earthquakes, but can also be of importance for risk mitigation. For example, the model can be used to mitigate risk through the calibration of seismic codes for the design of new buildings. Theoretically, the additional cost in providing seismic resistance can be quantitatively compared with the potential losses that are subsequently avoided. Furthermore, the loss model can be used to design retrofitting schemes by carrying out cost/benefit studies for different types of structural interventions (Calvi *et al.*, 2006). It is now generally accepted that developing these kind of financial tools for risk management, as well as improving building earthquake codes and rising awareness, is costeffective.

Loss computations typically use one of the three general approaches: empirical, analytical or hybrid (semi-empirical). The regression-based empirical approach in general consists of performing statistical analysis on historical loss data using a chosen hazard-specific parameter (e.g., magnitude, intensity) and deriving regression parameters that can be used for future loss estimation (Jaiswal and Wald, 2010). The analytical approach involves a multi-step process consisting of seismic hazard analysis (estimating ground shaking in terms of peak ground motions or spectral response or intensities, and their uncertainty), exposure analysis

(estimating human and economic exposure of the building stock), structural analysis (assessing structural response given the shaking hazard), damage analysis (estimating damage given the structural response), and loss analysis (estimating social and economic losses due to structural and nonstructural damage) (FEMA, 2006). The hybrid (or semiempirical) approach is generally a simplified analytical/empirical approach in which both structural response and damage analyses are combined by directly correlating structural damage or losses with macroseismic shaking intensity.

As shown in **Figure 2. 1**, the simplified flow chart of an analytical earthquake loss model presents the main parameters and modules involved in this type of approaches: the definition of the hazard, the definition of the exposure and its vulnerability, the calculation of physical damage and the assessment of economic and human losses.



Figure 2. 1 – Simplified general flow chart of an earthquake loss model. Hazard estimations are combined with exposure and vulnerabilities to estimate direct physical damage. Direct damage is often used as an input to estimate direct and indirect economic loss and human harm (i.e., casualties).

In practice, different levels of analysis can be performed, gradually increasing accuracy and details but also the information required, from a simpler, general evaluation (first level) to more sophisticated models. This offers the user the choice of the level of assessment in terms of his objectives and/or his means. Analytical and semi-empirical loss models have been developed in preference for more comprehensive analysis since they are adaptable to worldwide and regionals estimations, they allow a better handling of uncertainties and they circumvent the need of historical data, making them applicable in regions of moderate-to-low seismicity.

2.1.2 An economic concern

To obtain a consistent measure, the actual damage state is usually linked to the dollar losses of the capital stock and the indirect losses, as well as to the number of human fatalities. Estimating realistic earthquake economic impacts can be a really complicated task, and due to the large number of uncertainties involved in the process, it can only be done approximately.

The results produced from the physical damage module, are often used as inputs into the economic model to estimate potential losses. These costs are divided in direct and indirect economic losses.

Direct economic losses are relatively simple to model and are essentially measured by the repair or replacement costs of damaged components or building contents (Brookshire *et al.*, 1997). Estimation of probable physical damage is usually given on different damage states (e.g., slight, moderate, extensive, collapse). These damage states can be translated into financial losses based on the repair (or replacement) cost linked to each damage grade. Loss-to-damage ratios, often called consequence models, were empirically created in regions of high seismic activity. They provide the ratio between the costs to repair a damaged building to the cost of rebuilding it (the entire cost of the building) and are used to estimate direct economic losses.

Indirect economic losses are harder to define since they entail estimating losses that go beyond those relating to repair cost of damage. Nonetheless, these losses cannot be ignored since they can be quite substantial, an example of which is the 1994 Northridge earthquake, which resulted in an estimated \$7.74 billion of indirect losses, i.e. 39% of total losses (Gordon *et al.*, 1996). Definitions of this type of loss include: losses that extend beyond the direct physical impact such as income and business inventory losses; losses that result in the reduction of economic output due to business disruption (Brookshire *et al.*, 1997), and losses that result from the multiplier, or ripple effect throughout the entire economy that result in supply bottleneck and a reduction in demand (Boisvert, 1992). Estimating the ripple effect associated with a natural hazard involves collecting extensive data, which might not be available or may be difficult to gather. Moreover, it involves understanding not only the economy of the region, but also social and cultural aspects that play an important role in influencing post disaster response. For example, experience from natural and man-made disasters indicates that the economy has a great deal of resilience. Resilience refers to the ability to dampen the maximum potential impacts at any given point in time after the event and the ability to recover as quickly as possible (Adger, 2000; Rose, 2004, 2007). One of the most prominent sources of resilience is the ability of businesses to reschedule, or recapture, lost production after the event (Park *et al.*, 2011).

There are two main approaches that can be used to analyse the indirect impact: Computable General Equilibrium (CGE) modelling and Input-Output (IO) model. CGE modelling simultaneously optimizes the behaviour and demands of consumers and firms, taking into account economic balances and resource constraints (Shoven and Whalley, 1992). Since all goods in the model are assumed to be inter-related, a change in one will create changes in all others, and thus the system will constantly have to adjust itself to remain in equilibrium. Accordingly, in order to estimate the demand and price of one good, the demands and prices of all goods need to be estimated. Since this is impractical, constraints are used that enable the evaluation of a single good. For example, CGE approach has been used in measuring the indirect economic impact of the power disruption caused by the earthquake in Los Angeles (Rose and Guha, 2004) and the indirect economic impact caused by water supply disruption in Poland (Rose and Liao, 2005).

IO modelling has been used more extensively in studying natural hazard loss. Developed by Leontief in 1966, the model illustrates the inherent interdependency between the different sectors in the economy. Due to this interdependency, changes in one sector of the economy will lead to changes in the others (Rose, 1995; Bourque and Conway, 1977). A known drawback of IO modelling is that the model is rigid, thus preventing one from taking into account the dynamic resiliency that exists in the economy. The IO model has been employed in assessing the economic impact of power disruptions due an hypothetical repetition of the Memphis earthquake in 1811 (Rose *et al.*, 1997); the indirect economic impact of the blackout in northeast USA in 2003 (Anderson *et al.*, 2004); and the indirect economic impact of the power and transportation disruptions caused by the 2008 snowstorms in southern China (Hu *et al.*, 2014).

2.1.3 Loss prediction approaches

Earthquake consequences can be explored essentially at two different times scales. Loss models can generate loss values for probable future events (i.e., before the even occurs), or rapidly after an event strikes (near real-time estimates / while an event is evolving).

The estimation of possible losses due to future earthquakes is vital for urban development managers, emergency planners, for the insurance and reinsurance industries, and potentially also for seismic code drafting committees (Bommer and Crowley, 2006). In the aftermath of a damaging earthquake, there are also immediate demands for rapid assessment of direct capital impacts and human casualties (post-earthquake loss models). The sources of these demands are diverse. On one hand, the news media will ask for this information for public dissemination, as quickly as speculative data are available. Most important for recovery and crisis management, on the other hand, are the officials estimates demanded by state agencies. After the events, relief efforts can be significantly benefitted by the availability of rapid estimation and mapping of expected damage and casualties (So and Spence, 2012). These estimates must be submitted generally starting only a few hours after the occurrence, and they are adjusted with incoming new information.

Depending on the desired assessment and on the information available, "pre-event" loss models can be grouped in two main categories: deterministic or probabilistic. They differentiate in the way the input hazard is treated.

The first category is the analysis of a particular earthquake scenario and the evaluation of its potential to generate losses. Deterministic evaluations of seismic hazard are based on the treatment of past events (usually the biggest known earthquake in the region is one option for a scenario) or on distinguished physical parameters conditioning the occurrence of an event (e.g. a close seismic fault of a given size, related to possible magnitudes).

Historical earthquakes in the studied region can be introduced as a base scenario in order to estimate its effects on the actual exposure. Even if not comprehensively representing the risk, these analyses raise awareness among the local authorities, decision makers and the community about the potential losses their regions could incur for a repetition of an even they know or they have already heard of. The results of this type of analysis can be used to develop contingency plans for crisis management, as well as to assess the security of a particular critical facility (e.g. nuclear power plant, chemical industry, hospitals). A probable earthquake scenario can be analysed to identify the most exposed areas, as well as the most vulnerable structures that would benefit from priority retrofitting. Cost-benefits assessments regarding these reinforcements may also be based on these results. Estimates of damage (physical and/or economic) obtained by this approach are usually associated with the concept of "Probable Maximum Loss" (PML).

The second type of analysis corresponds to the development of probabilistic seismic hazard assessments (PSHA). These scenarios are based on the statistical processing of historical information, using one or more parameters characterizing the event. The evaluation accounts for seismicity rates of the region, information regarding the faults, the tectonic context, probable magnitudes, etc. It is common to use models determining seismicity rate or the frequency of occurrence of earthquakes of different magnitudes, where the number of events is usually expressed following a Poisson distribution (see Section 2.2).

The results of this approach are loss exceedance probability curves (**Figure 2. 2**), defining different levels of expected loss associated with several return periods. For example, these results can be expressed as "there is a 20% probability of exceeding \$50 million loss over a period of 50 years for the studied region". It is usual to express this curve for a one-year period, defining the expected Average Annual Loss (AAL).





For example, as a major stakeholder, insurers need realistic PML values to foresee the possible losses they would face after a major earthquake and also AAL, to calculate optimal insurance premiums. Assessment of potential losses allows considering budget allocation for structural retrofitting in order to reduce damages and also implementing an effective financial protection strategy meant to provide loss coverage of public infrastructures and private buildings (Marulanda *et al.*, 2013).

Loss estimations are however subjected to many large uncertainties associated with the input parameters at every step of the calculation. Identification, characterisation and appropriate treatment of the uncertainties are amongst the major challenges associated with the development of earthquake loss models (Bommer & Crowley, 2006; Tyagunov *et al.*, 2014).

The following sections study in more detail the three fundamental parameters that intervene in the structure of an analytical loss model; The information related to ground motions (hazard), the information related to the exposed elements, and the damage estimation algorithms (vulnerability).

2.2. Seismic hazard assessments

Seismic hazard is a characteristic of an earthquake that can cause damage and loss. Examples are ground motion amplitudes or fault displacements. The assessment of seismic hazard can be treated by a deterministic or a probabilistic approach. The first approach usually gives the probable hazard (e.g., ground-motion) related to a single defined event, which is used for deterministic loss evaluations. On the other hand, a probabilistic seismic hazard assessment (PSHA) for a specific site consists of determining the frequency with which an earthquake characteristic takes on a defined range of values during some fixed time in the future (Mc Guire, 2004). A very short review on PSHA analysis is given in what follows.

Let the earthquake characteristic be quantified by the variable C, and the range of values is typically defined as an exceedance of a specific value c. Traditionally, peak acceleration (PGA) has been used to quantify ground motion at the site. However, characteristic C may as well be a level of intensity, the duration of seismic shaking or the fault displacement. Recently, the preferred parameter is response spectral accelerations (SA), which gives the maximum acceleration experienced by a damped, single-degree-of-freedom oscillator of several fundamental periods (a crude representation of building response).

The mathematical basis for seismic hazard calculations is derived so that all inherent assumptions can be stated explicitly. **Figure 2. 3** (modified from Mc Guire, 2004) shows the procedure and different parts for conducting a PSHA. Step (A) divides the earthquake threat into sources, which might be identified faults or geographical areas that produce earthquakes characteristics. In step (B) the possible magnitudes and the rate of occurrence, as well as the distribution of distances from earthquakes to the site of interest is modelled. In step (C) models are used to estimate site intensity, peak motion characteristics or spectral characteristics as a function of earthquake characteristics. The last step (D) corresponds to the final probability calculations.



Figure 2.3 – The steps in performing a probabilistic seismic hazard assessment (PSHA). Modified from Mc Guire, 2004.

In the following sections the three main phases involved in a PSHA are studied in more detail: the specification of the seismic-hazard source model(s), the specification of the ground motion model(s), and the probability estimations.

2.2.1 Seismic-hazard source model

Defining the seismic-hazard source model has as objectives to identify all earthquake sources capable of producing damaging earthquakes characteristics (e.g., ground-motions), characterize the distribution of earthquake magnitudes (i.e., the rates at which earthquakes of various magnitudes are expected to occur) and characterize the distribution of source-to-site distances associated with potential events. These elements are included in steps (A) and (B) of **Figure 2. 3**.

The first step in analysing historical seismicity and making projections about future seismicity is to define seismic sources. There are two general types. These sources could be faults, for which the tectonic features causing earthquakes have been identified with for example, observations of past earthquake locations and geological evidence. If individual faults are not identifiable (e.g., in low-to-moderate seismicity regions), earthquake sources may be described by areal regions in which earthquakes may occur anywhere.

It is usually assumed that earthquakes act independently (i.e., the occurrence of an event at one source does not affect the occurrence of events at other sources). As aforementioned, this assumption while common, can be enhanced by the inclusion of earthquake triggering and fault interaction theories.

To predict ground shaking at a site, it is also necessary to model the distribution of distances from earthquakes to the site of interest. For a given earthquake source, it is generally assumed that earthquakes will occur with equal probability at any location on the fault. Given that locations are uniformly distributed, it is generally simple to identify the distribution of source-to-site distances using only the geometry of the source.

The second step in modelling seismicity is estimating the size of future earthquakes. The single most commonly used descriptor of earthquake's size is its magnitude. The final goal is to develop a distribution of earthquake magnitudes. Most applications of seismic hazard analysis use the exponential probability distribution to represent the relative frequency of different earthquake magnitudes in each of the defined faults. This is because magnitude-frequency statistics of historical earthquakes can often be represented by a truncated exponential distribution. In addition, this function is analytically convenient in the hazard calculations.

The Gutenberg-Richter model expresses the relationship between the magnitude M and the total number of earthquakes having a magnitude of at least M in any given region and time period:

$$log_{10}N = a - b * M \quad or \quad N = 10^{a - b * M}$$
 (3)

where M is the magnitude, N is the number of events having a magnitude \geq M and a and b are constants depending on the studied zone.

When the information allows it, it is possible to apply probabilistic models with "memory", which include the time spent since the last event. Due to the accumulation of strain energy, the probability of occurrence of a future earthquake increases with the time elapsed since the last event.

2.2.2 Seismic hazard ground-motion models

Earthquakes can produce damage, injury and loss of life in different ways. However, ground shaking is the major cause of damage and loss after an event. Empirical and semiempirical methods are used to estimate site intensity, peak motion characteristics or spectral values as a function of earthquake characteristics. These prediction models, usually called Ground Motion Prediction Equations (GMPEs), can predict the probability distribution of ground motion intensity, as a function of many predictor variables such as the earthquake's magnitude, distance, faulting mechanism, the near-surface site conditions, the potential presence of directivity effects, and stress-drop.

Empirically based estimates of ground motion characteristics are generally developed using statistical regression on observations from large libraries of observed ground motion intensities (or to synthetic data where observations are lacking). Different relationships have also been developed for different tectonic regimes. Given the large number of earthquakes and sites considered in hazard analysis, prediction relationships must be simple and easy to compute, typically having the following type of forms:

$$\ln A = c_0 + f(m) + f(r) + f(soil) + \varepsilon$$
(4)

$$I_s = c_0 + f(I_e, m) + f(r) + f(soil) + \varepsilon$$
(5)

where A is ground motion amplitude (i.e., peak motion parameters or spectral amplitude); I_s is macroseismic intensity; f(m), f(r) and f(soil) are terms function of magnitude, distance and soil type respectively; c_0 is a constant; and ε is a random variable taking on a specific value for each observation. The first types (equation 4) are called Ground Motion Prediction Equations (GMPEs) while the second types (equation 5) are named Intensity Prediction Equations (IPE). Models to convert ground motion parameters to intensities have also been developed and they are referred to as Ground Motion to Intensity Conversion Equations (GMICE).

An example of the relationship developed by Boore, Joyner and Fumal (1997) is shown in Figure 2. 4.



Figure 2. 4 – Median value (solid lines) and 95% confidence region (dashed lines) predicted by the Boore, Joyner and Fumal (1997) prediction equation for strike slip earthquakes and soil site conditions. The analytical expression for this particular case is: $\log PGA = 0.53 (M - 6) - 0.39 \ln(D^2 + 31) + 0.25$. Where D is the distance. The circles are southern California observations for events within 0.2 magnitude units of that computed. The black normal curve represents the distribution of predicted values at 1 km distance. (Modified from Field, 1999)

Over the past several years, many prediction equations have been developed worldwide. At a relatively fast rate, old equations are improved and new equations are created using larger and enriched earthquakes datasets, enhanced site-effects evaluations, detailed fault representations, or simply better regression techniques.

It is apparent from **Figure 2. 4** that there is significant scatter in observed ground motion intensities. Thus, these predictive models must provide a probability distribution, rather than just a single value. These uncertainties, both aleatory and epistemic, are usually represented with a lognormal distribution (i.e., the natural logarithm of predictions has a normal distribution).

2.2.3 Probability calculations

The seismic hazard at the site for earthquake characteristic C is defined as the frequency Υ with which a specific value c is exceeded during time t. This total frequency Υ is made up of contributions from each independent source j, where the frequency of exceedance of a specified value of c from each source is calculated as:

$$Y_j(C \text{ exceeds } c) = Y_j(C > c) = v_j \iint P_j[C > c \parallel \bar{s} \text{ at } l] P[\bar{s} \text{ at } l] d\bar{s} dl$$
(6)

where Υ_j is the frequency with which c is exceeded from earthquakes at source j. \bar{s} is a vector of source properties. v_j is the rate of occurrence of earthquakes of interest at source j. $P_j[C > c \parallel \bar{s} at l]$ is the probability that c is exceeded at the site, conditional on an earthquake at source j, with properties \bar{s} at location 1 (\parallel means "given that"). $P[\bar{s} at l]$ is the probability that an earthquake with source properties \bar{s} occurs at location 1.

In the example shown in **Figure 2. 3**, $P[\bar{s} \ at \ l]$ is evaluated as $P[l \parallel \bar{s}] P[\bar{s}]$. $P[l \parallel \bar{s}]$ is show in step (A) as a probability density function $f(l \parallel m)$ that is conditional on magnitude (a source property) and uses distance from the rupture to the site to quantify earthquake location. $P[\bar{s}]$ is shown in step (B) as the probability density function $f_M(m)$, which uses magnitude to parameterize the earthquake source. Thus $P[\bar{s} \ at \ l]$ in equation 6 is evaluated as $f(l \parallel m)$ $m) f_M(m)$ (in other words pdf functions for distance and magnitude terms respectively)

A GMPE (or its equivalent – Section 2.2.2) is used to calculate $P_j[C > c \parallel \overline{s} at l]$ in step (C). Given the earthquake location l, parameterized with the distance r between the site and the source, and given the source properties \overline{s} , the distribution of ground motions, fault displacements, or other characteristic C can be calculated.

The rate of earthquake occurrence v_j requires a careful definition of the events that will be considered. For many analyses, v_j is just the rate of earthquake occurrence above some minimum magnitude. Finally, the total seismic hazard at the site is calculated as:

$$\Upsilon[C > c] = \sum_{j} \Upsilon_{j}[C > c]$$
(7)

Y is the total frequency with which C exceeds c, and it equals the sum of contributions from all sources. The results of a PSHA are usually expressed by means of hazard curves (step (D) in **Figure 2. 3**). These curves represent the frequency with which selected values of a seismic hazard such as ground motion amplitude are expected to be exceeded (Mc Guire, 2004).

There are generally two categories of uncertainties that need to be handled differently. Aleatory: the probabilistic uncertainty that is inherent in a random phenomenon and cannot be reduced by acquiring additional data or information. Epistemic: the uncertainty that results from lack of knowledge about some model or parameter. This type of uncertainty can in principle be reduced, by additional data or improved information.

The seismic hazard analysis integrates over these uncertainties, and they are represented by the vertical axis of a seismic hazard curve (step (D) - Figure 2.3).

Epistemic uncertainties are treated e.g. by "logic-tree" analyses, i.e., by representing the inputs to the assessment (steps A to C) using alternative values with assigned weights, calculating an alternative value of Υ , and deriving an alternative hazard curve (dashed lines in step D). Often, the mean seismic hazard result (with respect to epistemic uncertainties) is used as a single measure of seismic hazard for decision-making. The treatment of uncertainties is now generally considered to be a key element, if not the single most important factor, in performing probabilistic seismic hazard analysis (Spence *et al.*, 2003; Tyagunov *et al.*, 2014).

The probabilistic calculation is conceptually simple (equation 6 and 7). In practice however, the calculation is not so obvious. Besides the non-triviality of defining the spatial distribution of small earthquakes on large faults, there is also the problem that different prediction relationships use different definitions of their input parameters (e.g., different definitions of distance) but also give different results (e.g., geometric mean of horizontal PGA components, or the maximum horizontal value).

2.3. Exposure and seismic vulnerability of structures

The creation of a viable earthquake risk model depends crucially on the quality of the exposure data contained in it (Spence *et al.*, 2012). This exposure data is represented by information related to all assets types susceptible of produce damage or loss when subjected to earthquakes characteristics: e.g., population, dwelling buildings, transport and energy infrastructures, lifelines, hospitals, schools, cultural heritage, etc.

The building stock, being usually a vast majority of the total man-made structures in a region, contributes a large proportion of the financial and economic risk, and is also responsible for much of the human losses. Therefore, global and regional databases of building inventories for use in near-real-time post-earthquake loss estimation and pre-earthquake risk analysis (Jaiswal *et al.*, 2010; Spence *et al.*, 2012), as well as catalogues of human population exposure for casualties' estimations (Allen *et al.*, 2009; Jaiswal *et al.*, 2009) have been developed. However, the creation of these datasets is a really daunting task, and they are usually far from being complete. Some reasons are the complications of merging data from several regions with different level of detail, the different typologies of structures to account for, the lack of information especially in developing countries and the ever-evolving vulnerability of urban environments.

A significant component of a loss model as aforementioned, is a methodology to assess the vulnerability of these exposed elements. The seismic vulnerability represents the intrinsic predisposition of the building to be affected and suffer damage as a result of the occurrence of an event of a given severity. The aim of a vulnerability assessment is to estimate the probability (average and uncertainty) of a given level of damage to a given building type from a given hazard (Calvi *et al.*, 2006). Damage can be expressed according to a damage scale (GNDT, 1986; Risk-UE, 2003), monetary units (FEMA, 1999) or even converted to loss of human life.

For large-scale studies (city, region), the approach is generally statistical because knowledge of existing buildings is often partial. At the scale of a single structure, studies are more often deterministic and involve computer modelling. In this later case, additional information regarding the building (e.g., plans, materials) as well as larger resources (e.g. laboratory tests, numerical modelling) are usually required. These approaches are however time-consuming and onerous and cannot be easily applied for large-scale assessments.

A vulnerability assessment needs to be made for a particular characterisation of the seismic hazard, which will represent the seismic demand and correlate the ground motion with the damage to the buildings. Traditionally, macroseismic intensity and peak ground acceleration (PGA) have been used, whilst more recently spectral response values (SA) are preferred.

The concept of damage also differs according to the methods. In empirical vulnerability procedures, damage is usually discretised in a scale. This damage scale is also used in reconnaissance efforts to produce post-earthquake damage statistics. In analytical procedures, the damage is generally described in terms of a parameter, for which several limits are set to define multiple levels of damage. This is related to limit-state mechanical properties of the buildings, such as inter-storey drift capacity.

Overall, the various methods for vulnerability assessment that have been proposed in the past for use in loss estimation can be divided into two main categories: empirical (based on observed post-earthquake damage distributions) or analytical (based on the behaviour of structures obtained by numerical modelling or reduced-scale laboratory tests), both of which can be used in hybrid methods. They combine post-earthquake damage statistics with simulated, analytical damage statistics derived from mathematical models usually to complete the lack of empirical observation for the highest damage levels, especially in moderate-to-low seismicity regions. Since this study will be focused on the vulnerability and loss assessments at the large scale, we study in more detail the empirical methods in the following sections.

2.3.1 Empirical methods of vulnerability assessment

The seismic vulnerability assessment of buildings at large geographical scales founded on empirical methods were first developed in high seismicity countries in the early 70's and 80's. In United States by the Federal Emergency Management Agency (FEMA, 1999, 2001, 2003) and in Italy by the Gruppo Nazionale per la Difesa dai Terremoti (GNDT) (Benedetti et Petrini, 1984; GNDT, 1993). These models are calibrated from damage assessment data, collected after earthquakes in areas that suffered different intensities. Many other countries has used and adapted these methodologies to estimate the vulnerability in their highest seismic regions. In the context of the European project RISK-UE (2003) (Spence and Lebrun 2006; Mouroux and Le Brun, 2006) a method adapted to the European context was developed and applied to seven cities, including the French city of Nice. Lagomarsino and Giovinazzi, (2006) have also proposed a method directly derived from a macroseismic intensity scale. Experimental methods (Michel *et al.*, 2012; Gueguen, 2013) for example by the use of ambient vibration measurements have also been proposed as a complement of empirical methods.

In most large-scale vulnerability assessment methods, buildings are classified into a relevant typology from a seismic vulnerability point of view. The typology should describe as simply as possible the building stock of the study area. Depending on the extent of this zone and on the homogeneity of the building stock, the typology may be more or less precise or detailed. The usual minimum elements that allow discriminating the different types are: the type of structure (e.g., frames, walls); the material of the structural system (e.g., reinforced concrete, masonry, wood, steel); and the level of earthquake design or the quality of the construction (e.g., respect of earthquake code rules, usually linked to the age of the building). Other characteristics allow refining this classification.

Since in the past hazard maps were in general defined in terms of macroseismic intensities, the first empirical methods were calibrated as a function of these discrete damage scales. With time and need, as aforementioned, peak ground motion values (e.g., PGA) or spectral values were favored.

There are three main types of empirical methods for the seismic vulnerability assessment of buildings that are based on the damage observed after earthquakes. Damage Probability Matrices (DPM) express in a discrete form the conditional probability of obtaining a damage level j, due to a ground motion of intensity i, $P(D = j \parallel i)$. Vulnerability Index methods (Iv) based on observed structural characteristics of buildings attribute a vulnerability index to structures. A formulation developed from post-earthquake damage experience links this index with the probable damage. Finally, Vulnerability Functions are continuous functions expressing the probability of exceeding a damage state, given a function of the earthquake intensity.
2.3.1.1 Damage probability matrices

The basic concept of a damage probability matrix (DPM) is that a given typology of building will have the same probability of being in a given damage state for a given earthquake intensity. That probability is estimated statistically from historical earthquake damage distributions or in some cases, by expert judgment.

An example of the format of the firsts DPMs (Whitman *et al.*, 1973) is presented in **Table 2.1** for a particular building typology, where proportions of buildings with a given level of structural and non-structural damage are provided as a function of intensity.

Table 2. 1 - Format of a Damage Probability Matrix (DPM) for a building typology proposed by Whitman et al., (1973) (from Calvi *et al.*, 2006). Proportion of buildings with a given damage state as a function of earthquake intensity. Damage ratio: ratio of cost of repair to cost of replacement.

Damage State	Structural Non-structural Damage Damage	Non-structural	Damage	Percentage of buildings as a function of intensity of earthquake				
		Ratio (%)	V	VI	VII	VII	IX	
0	None	None	0-0.05	10.4	-	-	-	-
1	None	Minor	0.05-0.30	16.4	0.5	-	-	-
2	None	Localised	0.30-1.25	40.0	22.4	-	-	-
3	Not noticeable	Widespread	1.25-3.50	20.0	30.0	2.7	-	-
4	Minor	Substantial	3.50-4.50	13.2	46.9	92.3	58.8	14.7
5	Substantial	Extensive	7.50-20.00	-	0.2	5.0	41.2	83.0
6	Major	Nearly total	20.00-65.00	-	-	-	-	2.3
7	Building condemned		100.00	-	-	-	-	-
8	Collapse		100.00	-	-	-	-	-

The use of DPM is still current in many countries and old versions of DPM have been updated to include changes in intensity scales, the type of new buildings and the information provided by the latest damaging earthquakes (Di Pasquale *et al.*, 2005; Dolce *et al.*, 2003). DPM methods, while advantageously simple, have however several problems. One of the most important lies obviously, in the discrete definition of its components.

- The lack of damage information for all damage grades and for all building typologies for a given level of intensity leads to "incompleteness" of the matrices. The statistics from multiple earthquake events need to be combined, and damage distribution for large magnitude earthquakes are often missing. - A macroseismic intensity scale is defined by considering the observed damage of the building stock and thus in a loss model both the ground motion input and the vulnerability are based on the observed damage due to earthquakes.

- Seismic hazard maps are now usually defined in terms of peak ground motions (e.g., PGA) or spectral ordinates, making DPM correlated with intensity less useful. This problem can be overcome by converting ground-motions to intensity, but the uncertainty is this conversion needs to be accounted for.

- The use of empirical vulnerability definitions in evaluating retrofit options or in accounting for construction changes cannot be explicitly modelled; however simplifications are possible, such as upgrading the building stock to a lower vulnerability class.

2.3.1.2 Vulnerability Index methods

These methods are based on the observation of structural characteristics of buildings to assign them a vulnerability index (Iv). They propose afterwards, a relation to link this vulnerability index to a damage scale for a given earthquake characteristic. The Italian method (GNDT) but also the Risk-UE used and adapted version of this method for their risk assessments.

A field survey is needed to define the building typology as well as to collect information on the parameters of the building, which could influence its vulnerability. The methods usually have several levels of detail according to the quality of the information collected. The parameters usually gathered are: the number of floors, the position of the structure (regarding the ground floor (flat or slope) and the position within other buildings), plan and elevation configuration (regularity), type of foundation, state of conservation, type and quality of materials, distance between walls, structural and non-structural elements, existence of heavy elements, short columns or soft story effects.

The scores given to each parameter and the weights assigned to them (to account for their relative importance) are determined empirically based on post-seismic damage information. The global score given to each building is often normalized by the maximum possible score so as to stagger the Iv from 0 (less vulnerable building) to 1 (very vulnerable building) or between 0 and 100 depending the method.

The data from past earthquakes is used to calibrate vulnerability functions to relate the vulnerability index Iv to a global damage factor d of buildings with the same typology, for the same macroseismic intensity or ground motion predictor. The damage d is considered as a continuous variable raging from 0 (no damage) to 1 (collapse), however this damage has to be also translated in a qualitatively way, in order to be used during post-earthquake surveys.

For example **Figure 2. 5**, shows linear vulnerability functions to relate damage factor d and peak ground acceleration (PGA) for different values of vulnerability index Iv. The damage factor is assumed negligible for PGA values less than a given threshold and it increases linearly up until a collapse PGA, from where it takes a value of 1.



Figure 2. 5 – Example of vulnerability functions to relate damage factor and ground motion parameter (PGA) for different values of vulnerability index. In this example, possible lv ranges from 5 (less vulnerable) to 80 (very vulnerable) (Modified from Calvi *et al.*, 2006)

It is worth mentioning that these methods manipulate variables like Iv and d both in a discrete and continuous manner. The transition from one to the other is, for example, possible by applying Fuzzy Set Theory.

The main advantage of vulnerability index methods is that they allow a better determination of the vulnerability characteristics of the studied building stock (not based on the building typology alone). Moreover, the earthquake characteristic to estimate damage includes ground motion parameters rather than intensities. However, the methodology shares some of the inconveniences of DPM methods. In addition, the coefficients and weights applied in the calculation of the index have a degree of uncertainty that is not generally accounted for.

For large-scale vulnerability assessments, the large number of parameters required in a detailed analysis will imply large human and financial efforts. In a country where such data is not already available, the calculation of the vulnerability index for a large building stock would be extremely time consuming.

2.3.1.3 Vulnerability functions

Continuous vulnerability functions (also called "fragility curves") were introduced slightly later than DPMs. These mathematical models estimate the probability that a given structure suffers damage as a function of the seismic demand. Different damage levels can thus be studied. It is worth mentioning that these relations are essentially based on extrapolations from post-earthquake observed damaged distribution, but also from expert judgment, laboratory tests and more recently on numerical modeling (see Section 2.3.2).

These functions introduce the concept of variability (or uncertainty) (**Figure 2. 6**). In a completely deterministic system, we would know exactly the opening seismic demand value for which damage will appear, and fragility curves would show a sudden step at that point. The presence of variability implies uncertainties in the definition of that value. The increasing slope of the relations represents these uncertainties, and their inclusion is essential for risk analysis.



Figure 2. 6 - General description of a fragility curve and the concept of variability (uncertainty).

The first fragility curves provided damage levels for different types of buildings according to intensity scales. To overcome the issue of the discrete definition of macroseismic intensities, Spence, (1992) included a Parameterless Scale of Intensity (PSI). Similarly, in order to pass from discrete to continuous vulnerability evaluation, Giovinazzi and Lagomarsino (2004) introduced fragility curves to correlate intensity to the mean damage grade, which is a continuous variable (from 0 to 5), and a histogram of damage grades is evaluated by a proper discrete probabilistic distribution (binomial). The fragility curve is defined by two parameters, the vulnerability index and a ductility index, which should be evaluated from information about the building.

Since 1997 (NIBS, 1997; Sabetta *et al.*, 1998), empirical fragility curves with a binomial distribution were derived as a function of characteristics directly linked to the ground motions (e.g., PGA) and no longer to macroseismic intensity. More recently, alternative empirical vulnerability functions have also been proposed, generally with normal or lognormal distributions, which do not use macroseismic intensity or PGA to characterise the ground motion but are related to the spectral acceleration or spectral displacement at the fundamental elastic period of vibration.

Examples of fragility curves for a given building type and for different damage levels are shown in **Figure 2.7**. (from FEMA, 2003).



Figure 2. 7 – Example of fragility curves for a given type of building and four damage levels: Slight, moderate, extensive and collapse. (From FEMA, 2003)

2.3.2 Analytical / mechanical methods of vulnerability assessment

Analytical methods of vulnerability assessments are more often used to study the behavior of a single particular building. Since they are costlier and more time consuming than empirical methods they are usually not applied to study buildings at a large scale. Their use is appealing for example, to study critical structures for which a better understanding of the response is essential (e.g., nuclear power plants). These methods feature a more detailed and transparent vulnerability assessment, with direct physical meaning. They allow detailed sensitivity studies and furnish direct calibration to various characteristics of building stock and seismic hazard.

Analytically derived vulnerability curves (and DPM) have been proposed to overcome some of the problems of empirical methods highlighted in the previous sections.

These methods make use of computational analysis instead of observed damage data. They require the selection of a computational model of the structure (with definition of relevant structural parameters), the selection of the earthquake intensity indicator (and the selection of a representative set of earthquakes to be included), the selection of the damage model (with the definition of the criteria for identification of damage states) and of course, the selection of a methodology for dynamic nonlinear analysis. Finally, damage is calculated following a given probabilistic distribution.

Since the derivation of analytical vulnerability curves is computationally intense and time consuming, these curves cannot usually be developed for all buildings typologies of different regions. Therefore, analytical methods are more often used to "complete" empirical fragility curves where observational data is not available to constrain them. **Hybrid methods** combine post-earthquake damage statistics with simulated, analytical damage statistics derived from mathematical models of the building typology under consideration. For example Kappos *et al.*, (2006) have empirically derived DPM and proposed to complete the lack of empirical observations for the highest damage level based on results from non-linear dynamic analysis.

Capacity spectrum-based methods (mechanical models) (ATC, 1996) were generalized after the development of HAZUS (Hazard US) (Whitman *et al.*, 1997; FEMA, 1999, 2003) (see Section 2.4.2). The notion of Level of Performance came to substitute the notion of Limit States (serviceability and ultimate limit state). Performance-based seismic analysis technique can be used for a variety of purposes such as a rapid evaluation of a large inventory of buildings, evaluation of an existing structure to identify damage states and correlation of damage states of buildings to various amplitudes of ground motion (Freeman, 2004).

Different levels of performance are defined each of which can be related to a damage state. For example FEMA define four performance levels: Immediate Occupancy (Slight damage), Damage Control (Moderate damage), Safety to Life (Severe damage), Collapse Prevention (Collapse). The method to estimate the performance level reached for a given seismic demand is relatively standard in earthquake engineering. The method consists in drawing in the space of spectral acceleration as a function of spectral displacements (Sa; Sd) the curve representing the behavior of the structure (capacity curve) and the curve representing the seismic demand (response spectrum in an acceleration-displacement format) (**Figure 2. 8**).

The structural response is modelled by means of a force-displacement curve (acceleration-displacement) so-called "capacity curve". This curve provides essential information in terms of stiffness, overall strength and ultimate displacement capacity. They can be seen as the classic materials Stress-Strain curves. This capacity curve can be obtained by an equivalent static calculation called Pushover analysis. It simulates the response which could be achievable by subjecting the structure, simulated by and adequate numerical model, to a static horizontal load pattern of increasing amplitude, aimed at describing the equivalent seismic forces. It establishes therefore, a relationship between the demand and the structural capacity. Laboratory measurements over shaking tables are in the same way represented under this form and can be used to validate numerically obtained capacity curves. Each point of this curve can be associated with an exact pattern and level of damage. In the case of vulnerability assessments at a large scale, this curve aims to idealize the response of an entire stock of structures with homogeneous behaviour.

The demand curves can be regulatory response spectrum, the envelope of spectrums of several earthquakes or the response spectra of a particular earthquake (scenario). In order to account for non-linear inelastic behaviour of the structural system, effective viscous damping values are applied to the linear-elastic response spectrum similar to an inelastic response spectrum.



Figure 2. 8 – Determination of the performance point for different seismic demands and for two types of structures. The performance point is found where the capacity curve (acceleration-displacement) intersects the demand curve (response spectrum). Modified from FEMA (2003)

The expected damage assessment is provided by comparing the capacity curve with the seismic demand. The graphical intersection of the two curves gives the "performance point" and it approximates the response of the structure. By determining the point, where this capacity spectrum "breaks through" the earthquake demand, an estimate of the spectral acceleration, displacement, and damage (performance) that may occur for a specific structure responding to a given earthquake can be developed. For example, if the performance point falls in the linear part of the capacity curve, the structure responds in an elastic way to that particular seismic demand.

Once the performance point is evaluated and the proper damage states are defined, it is possible to proceed to the assessment of vulnerability and fragility curves. In HAZUS (see Section 2.4.2), the performance point obtained from an average building provides the displacement input into the limit state vulnerability curves to give the probability of being in a given damage band. The vulnerability curves are lognormal functions with a total logarithmic standard deviation, which combines all sources of uncertainties. In particular, the conditional probability $P[D_k \parallel d_{PP}]$ of being in, or exceeding, a particular damage state D_k , given the spectral displacement at the performance point d_{PP} is defined by the following expression:

$$P[D_k \parallel d_{PP}] = \phi \left[\frac{1}{\beta} \ln \left(\frac{d_{PP}}{d_k} \right) \right]$$
(8)

where ϕ is the standard normal cumulative distribution function and β is the normalized standard deviation of the natural logarithm of the displacement threshold d_k .

Collapse Mechanism-Based Methods have been proposed for analytical vulnerability assessment. These methods use collapse multipliers calculated from mechanical theories to ascertain whether a mechanism will form and thus damage will occur (Calvi *et al.,* 2006). These procedures have been predominantly applied to masonry buildings.

Other methods, both analytical and empirical, exist in the literature and were not included in this chapter.

Overall, the benefits obtained by the use of more detailed analytical methods needs to be compared with the increased amount of information, time and resources required to construct them. Their detail and transparency allows comprehensive sensitivity studies and for example the possibility to include the influence of retrofitting on the response of existing structures. However, other than the compilation of databases of building stock inventory (required for any loss model), information on many structural characteristics is needed to calibrate the analytical models. In addition, complete hazard assessment needs to be carried out in terms of spectral ordinates.

The application of mechanical models to the large scale requires that capacity models are based on a limited number of geometrical and mechanical parameters. This need implies that they have to be somehow "simplified". In most cases the definition of these curves refers to numerical analysis provided on prototype buildings, which will require extrapolation to an entire building stock. In addition and unlike macroseismic (empirical) methods, the validation of mechanical models is much more complex, since the direct comparison is not available.

2.4. State-of-the-art

Many models are now available from the private international market of catastrophe loss and risk modeling. These models cover not only seismic risk, but also any other type of natural or man-made hazard, offering specific models for each country. Due to the proprietary nature of these data, the parameters used are generally confidential, not available to the public. In addition, large private reinsurance companies (such as Swiss Re and Munich Re) have also developed their own models for quantifying risk, but their parameters are still unrevealed, as well as the rest of the private models. There are also open and public loss estimation models (e.g., HAZUS, Risk-UE, GEM, CAPRA) and various models developed and implemented at a local level, at a given site.

We present in this section a very brief and non-exhaustive summary of the state-of-theart most used and recognized public earthquake loss estimation models, as well as concepts and definitions that will be useful for the ensuing of this work.

2.4.1 The European Macroseismic Scale (EMS98)

The European Macroseismic Scale (EMS98) (Grunthal, 2001) is an improved intensity scale which classes the severity of a ground motion according to the observed or felt effects at a particular site. It has twelve intensity degrees, from I (not felt) to XII (completely devastating). They are defined, like any other intensity scale, based on felt or observed effects on humans, elements and constructions.

Many of these scales have existed for a long time (e.g. Mercalli Scale with its many modifications, MSK scale, etc.) but the EMS98 was the first one to incorporate the concept of building vulnerability in its definition quantitatively. Using MMI scale, for example, the collapse of any building will imply immediately very high intensity values in that place. However, EMS98 will consider the collapsed building's tendency (vulnerability) to suffer damage. If the building was an adobe (earth-brick) construction, built following no earthquake standards or norms, the intensity will come out to be lower than if a code-conform share-wall reinforced concrete building has collapsed. This intensity scale refines thus the intensity assignment.

The EMS98 defines six vulnerability classes, from A (highest vulnerability) to F (lower vulnerability), and five degrees of damage from Grade 1 (negligible to slight damage) to Grade 5 (destruction). It divides structures in four main groups according to their type namely; masonry, reinforced concrete (RC), steel or wood buildings. **Table 2. 2** shows the differentiation of structures into vulnerability classes. **Table 2. 3** presents the classification of damage to masonry and reinforced concrete buildings. Evidently, the vulnerability of a building not only depends on its structure type. Many other parameters play a role in the response of buildings to a seismic solicitation. Therefore, EMS98 scale gives for a given building typology,

the most likely vulnerability class, a probable range and a range of less probable, exceptional cases.

Type of Structure		Vulnerability Class					
		Α	В	С	D	E	F
	rubble stone, fieldstone	0					
	adobe (earth brick)	O	H				
NRY	simple stone		0				
ASO	massive stone		-	О			
W	unreinforced, with manufactured stone units	 	0	1			
	unreinforced, with RC floors		∣⊢	0			
	reinforced or confined			ŀ	0	Η	
FORCED CONCRETE (RC)	frame without earthquake-resistant design (ERD)	ŀ		0	1		
	frame with moderate level of ERD		╎┝		ю	Η	
	frame with high level of ERD			┝		Ю	-1
	walls without ERD			O	Η		
	walls with moderate level of ERD			┢┅	0	Η	
REIN	walls with high level of ERD				ŀ	0	H
STEEL	steel structures			ŀ		0	-1
WOOD	timber structures		ŀ		0	-1	

Table 2. 2 – Building typologies and the classification into vulnerability classes in EMS98 (From Grunthal, 2001)

Omost likely vulnerability class; — probable range; ----range of less probable, exceptional cases

The definition of intensity scales includes (for damaging levels of intensity) a somehow qualitative representation of the percentage of buildings of each vulnerability class and the degree of damage they have suffered. As an example the definition of intensity degree VII reads:

« VII. Damaging. Most people are frightened and try to run outdoors. Many find it difficult to stand, especially on upper floors. Furniture is shifted and top-heavy furniture may be overturned. Objects fall from shelves in large numbers. Water splashes from containers, tanks and pools. Many buildings of vulnerability class A suffer damage of grade 3; a few of grade 4. Many buildings of vulnerability class B suffer damage of grade 2; a few of grade 3. A few buildings of vulnerability class C sustain damage of grade 2. A few buildings of vulnerability class D sustain damage of grade 1 »





A macroseismic method has been proposed by Giovinazzi and Lagomarsino (2004), and futher improved in Lagomarsino and Giovinazzi (2006) that leads to the definition of damage probability functions based on the EMS98 macroseismic scale. The qualitative descriptions of "Few", "Many" and "Most" for all damage grades and for the levels of intensity ranging from V to XII, allowed the confection of damage probability matrices for all vulnerability classes. As an example, a matrix for vulnerability class C is presented in **Table 2. 4**.

EMS98 Intensity	D1	D2	D3	D4	D5
V	-	-	-	-	-
VI	Few	-	-	-	-
VII	-	Few	-	-	-
VIII	-	Many	Few	-	-
IX	-	-	Many	Few	-
Х	-	-	-	Many	Few
XI	-	-	-	-	Many
XII	-	-	-	-	Most

Table 2. 4 - Example of a damage model for vulnerability class C as presented in EMS98.

Numerical values were proposed for these qualitative terms such as: "some" (5%), "many" (35%), and "most" (80%). On this basis, damage matrices are established giving the occurrence probability distribution P(D = Dk) for each intensity as a function of building vulnerability. The problems related to the "incompleteness" of the matrices (i.e., the lack of information for all damage grades for a given level of intensity) have been tackled by assuming a beta damage distribution and by applying Fuzzy Set Theory. The damage probability matrices produced for each vulnerability class have been related to the building stock through the use of an empirical vulnerability index which depends on the building type, the characteristics of the building stock (e.g., number of floors, irregularity, etc.) and the regional construction practices.

2.4.2 HAZUSTM Model

Hazus-MH (Hazard U.S. – Multy Hazard) is a software tool developed for the U.S. Federal Emergency Management Agency (FEMA) by the National Institute of Building Sciences (NIBS) that contains models for estimating potential losses from earthquakes, floods and hurricanes (www.fema.gov/hazus - last accessed, April 2015). It uses Geographic Information Systems (GIS) technology to estimate physical, economic and social impacts of disasters. Hazus-MH loss estimates are widely used in disaster mitigation planning and emergency response planning in the United States and can be used for cost-benefit analysis for a wide range of disaster or mitigation related projects (Kircher *et al.* 2006; Ploeger *et al.* 2010; Price *et al.* 2010).

The software is organized into several interdependent modules, allowing the insertion of particular additional data and giving the user the possibility to limit the analysis to their level of interest. The main modules can be divided into: the analysis of the hazard; the inventory of the exposure; the direct physical damage estimation; the indirect damage estimation; and the assessment of direct and indirect economic losses.

Three types of analysis can be performed depending on the level of complexity of the study. The first level of analysis (Level 1) is based on default settings and provides raw general results. Increasingly detailed user-supplied data allows improving the level of detail and accuracy of loss estimates (Level 2 or Level 3 analysis). Level 2 analysis allows for additional user-specified improvements such as National Earthquake Hazard Reduction Program (NEHRP) soils maps for improved soil amplification factors, liquefaction susceptibility, building and infrastructure inventory improvements, and improved fragility relationships.

Level 3 analysis requires in addition technical information of the building stock as well as economic values, which generally requires time, resources, and efforts.

The study of the hazard includes, in addition to the determination of the ground motion, an analysis of the potential for liquefaction, landslides and surface fault rupture. Ground movement is characterized by the spectral response, PGA and PGV. Ground motion is defined using either a deterministic or a probabilistic analysis. Deterministic earthquake analysis in Hazus-MH is done using either an "historical epicentre event" that lies on the selection from a large catalogue of earthquakes with magnitude larger than 5; a "source event" based on the choice of a seismic source from a comprehensive inventory; or using an "arbitrary earthquake scenario" (FEMA/HAZUS also uses ShakeMap for real events and scenarios). For the arbitrary earthquake scenario, the user specifies the hazard by selecting an attenuation function, event parameters (i.e., location and magnitude), and soils data, which are used to apply the necessary amplification factors. The second way to define a deterministic earthquake scenario in Hazus-MH is using a "user-supplied hazard" using ground-motion maps.

Alternatively, probabilistic scenario analysis in Hazus-MH is based on ground shaking data derived from USGS probabilistic hazard map data (Petersen *et al.*, 2008). Different hazard maps are available corresponding to different return periods.

For both deterministic or probabilistic hazard assessments Hasus-MH has different attenuation functions and combination attenuation relationships. For example, some functions are (appropriate for the central and eastern USA), Atkinson and Boore (1995); Frankel *et al.*, (1996); Somerville *et al.*, (2001); Cambell (2003); Toro *et al.*, (1997); and Kaka and Atkinson (2005).

Exposure data within Hazus-MH consists of population and infrastructure inventories. Population data include demographics such as age, income, and gender. Infrastructure data include general building stock, essential facilities, high-potential loss facilities, transportation networks, and utility lines. Each type is divided in sub-classes. For the general building for example, 36 typologies are considered. They are defined according to the structural system materials and the number of floors. Overall, 16 structural systems are defined: W1 and W2 for wood buildings, S1 to S5 for steel, C1 to C3 for concrete, PC1 and PC2 for constructions with pre-casted concrete elements, RM1 and RM2 for reinforced

masonry, URM for unreinforced masonry and MH for the particular "mobil-homes" class. In addition, Hazus-MH considers their level of earthquake design, usually linked to the age of construction (Pre code, Low code, Moderate code, High Code).

Hazus-MH supplies default data for users that do not have the resources to develop detailed local inventories; these default data are compiled from existing national data sets. In the case of the building inventory (general building stock) for the central and eastern USA, default data were derived from census and employment data. The mapping schemes for the building inventory are based on proprietary insurance data, opinions from experts, and from tax records (FEMA 2011). Improving Hazus-MH's default inventory is recommended for improving loss estimations. Updating the general building stock, however, is particularly challenging.

Direct physical damage is estimated according to four categories (slight, moderate, extensive and complete) with damage level dependent on structure type (FEMA, 2011). The approach to estimate damage is based on the Capacity Spectrum-Based method described on Section 2.3.2. Capacity curves were obtained on the base of detailed analytical calculations for all types of structures, and averaged to the standard types by empirical evaluations. The curves are simplified to bilinear models. Fragility curves are then used to calculate the probability of exceedance of a given damage level, for a structure with a displacement given by the performance point. In Hazus-MH, many of the default fragility relationships are based on empirical methods, with fragility relationships primarily developed based on California earthquakes, but also based on expert judgement and laboratory tests.

Indirect physical damage can also be assessed. Floods produced by damage to dams, spill of hazardous materials and fires. The first two are estimated on the basis of physical damage to related structures in the inventory. For fires, a relation between PGA and the start of fires has been developed empirically using thirty North American earthquake statistics.

The output of the physical damage modules serves as input to **estimate fatalities and economic loss**. Hazus-MH uses a combination of empirically derived relationships between the percentage of expected fatalities and the level of damage of the building. These relations have a regional dependency and can take into account the time of the day of the earthquake. Direct and indirect economic losses are calculated on the basis of economic models, taking into account the repair and replacement price of physical damage as well as business interruption and ripple effects.

As aforementioned in this chapter, uncertainties in earthquake-loss models are present at every step of the assessment. They fall into two main categories: hazard assessment uncertainties and uncertainties in the vulnerability assessment. On top of that, there are uncertainties in the conversion of physical damage to economic units and fatalities.

An independent validation of Hazus (NIBS 2001) for five Californian earthquakes found that estimated building losses were typically within ± 50 % of the observed losses. However, in some cases, difference in predicted versus documented building losses ranged from an under-prediction of 60 % to an over prediction of 340 %. The number of estimated deaths was over predicted by up to 200 % (NIBS 2001).

Kircher *et al.*, (2006) compared Hazus-MH damage, loss, and casualty estimates for the 1994 Northridge M6.7 earthquake to actual damages, losses, and casualties. This comparison revealed that Hazus-MH both under- and over predicted structural damages by -46 to +11 %. Comparison of modelled and actual economic losses revealed a range of under- and over prediction by -11 to +26 % (\pm billions of dollars). For Hazus-MH casualty estimates, deaths were over predicted up to +250 %.

Price *et al.*, (2010) quantified the range of uncertainty in Hazus-MH earthquake-loss estimation for three earthquake scenarios in Nevada. The sensitivity analysis was only focused on earthquake characteristics (epicentre location, depth, magnitude). They found that uncertainties related to these parameters were within \pm a factor of five of the actual values.

Finally, Remo and Pinter (2012), conducted sensitivity anaylysis of the Hazus-MH earthquake loss model for assessments in the central USA. They used earthquake damage surveys from the 2008 M 5.2 Carmel, Illinois earthquake. These sensitivity analyses revealed that earthquake damage, loss, and casualty estimates are most sensitive to the seismic hazard data and selection of the attenuation function. The selection of the seismic hazard data and attenuation function varied earthquake damages and capital-stock losses by ± 68 % and casualty estimates by ± 84 %. The validation assessment revealed that Hazus-MH over predicted observed damages by 68 - 221 % depending on the model parameters employed (Remo and Pinter, 2012).

2.4.3 Risk-UE Model

The European Risk-UE project (Spence and Lebrun, 2006; Mouroux and Le Brun, 2006) (www.risk-ue.net - last accessed April 2015), "An advanced approach to earthquake risk scenarios with applications to different European towns" (2001 - 2004) was created as a method for the assessment of potential effects of earthquakes at the city scale within an European context. The main goals of the project were: to inform decision makers and alert city planners about the level of seismic risk they were dealing with; to demonstrate the benefit deriving from inside knowledge of this risk; and eventually rise preparedness and help in the implementation of risk management plans to effectively reduce the risk.

Many common points can be found between Risk-UE and other products (e.g., Hazus, GNDT), therefore only a brief presentation of the project with its main characteristics is done.

Within the Risk-UE project a modular methodology has been developed. Possible earthquake scenarios were created focusing on the distinctive features of European cities in order to identify weak points of the urban system. The approach has been applied to seven European cities: Barcelona (Spain), Bitola (Macedonia), Catania (Italy), Bucharest (Romania), Nice (France), Sofia (Bulgaria) and Thessaloniki (Greece), for which the results of several disaster simulations in terms of damage, casualties, direct and indirect costs and social impacts have risen the awareness of public and private sectors. The cities have been chosen for their combination of high seismic hazard (at each country level), the high vulnerability of their building stock or the high agglomeration of resources and economic activities.

Some of the strategic objectives were: i) For earthquakes scenario that have a reasonable chance of occurring (considering the seismotectonic context) and taking into account the vulnerability of European cities, asses the direct consequences in terms of cost and victims. ii) Participate in developing urban building stock datasets within a GIS environment. iii) Communicate results and developments to all interested companies and public. iv) Develop a methodology adapted to European vulnerability context (response of historical centers, monuments and buildings with cultural heritage).

The project was divided in seven work packages (WP) (Mouroux and Le Brun, 2006):

WP01: European distinctive features, Geographic Information System (GIS) inventory, database and building typology; WP02: Seismic hazard assessment, both at regional and local level; WP03: Urban system analysis. Aimed at highlighting weak points under normal conditions, during crisis and recovery periods; WP04: Vulnerability assessment of current buildings; WP05: Vulnerability assessment of old town centers, historical monuments and buildings; WP06: Vulnerability assessment of lifeline facilities and essential structures; WP07: Seismic risk scenarios.

As the name describes it, the aim of WP01 was to provide a methodology for collecting and classifying building and earthquake data for urban seismic risk assessment in Europe. To assess vulnerability (WP04), Risk-UE has established a building type matrix of present building stock, which was based on the typologies of EMS98 macroseismic scale (Section 2.4.1) expanded to further detail the buildings typology.

Two approaches to vulnerability analysis have been adopted. The first approach (hereafter referred to as LM1), suitable for assessments in urban environments with lack of detailed site-specific hazard estimates, is based on the empirical method of EMS98. The second approach (LM2), suitable for urban environments possessing detailed local seismicity studies (in terms of spectral quantities, or displacements), is based on analytical and mechanical methods (like in Hazus-MH).

Regarding hazard, the selection of the approach is made according to the seismicity level of the region, the documented earthquake history and the required level of accuracy. In medium and high seismicity regions, priority will be given to a deterministic approach; in zones with more complex or uncertain seismicity patterns, a constant hazard ground-shaking scenario will also be evaluated and compared with the previous one. In this way, hazard is also assessed at two levels. Level 1 entails the construction of a macroseismic scenario, in terms of EMS98 intensity (used as an input to LM1 approach to computing damage). Level 2 is obtained by assuming a "reference" event of a specified magnitude at a specified location (seismic source). The ground-motion distribution in the city is calculated by the use of GMPEs.

In overall, the project had a positive impact on local communities, raised awareness and communicated the seismic risk European cities are facing effectively to decision-makers and risk-management responsible. Databases of dwellings, historical buildings and lifelines, and their vulnerability were created for the seven test cities. However, for a detailed analysis of this seismic vulnerability, the method requires extensive field surveys to recover several building parameters and an exhaustive building typology. As a result, no other city in France has ever been studied using this methodology since.

2.4.4 Global Earthquake Model (GEM)

The GEM foundation is a public-private partnership that drives a global collaborative effort to develop resources for transparent assessment of earthquake risk and to facilitate their application for risk management around the globe (GEM site – www.globalquakemodel.org - last accessed, April 2015). GEM developed (starting in 2009) an open-source software named OpenQuake (www.openquake.org - last accessed, April 2015), for estimating seismic hazard and losses.

OpenQuake-engine includes four main modules or calculators (Silva et al., 2014):

M1. A scenario risk and a scenario damage calculators, capable of calculating losses due to a single deterministic event, using a set of ground-motion fields, an exposure model and a vulnerability model. Uncertainties in the vulnerability functions are included as well as the aleatory variability of the hazard (using a large number of ground-motion fields). The mean and standard deviation in the loss ratio distribution are calculated, and converted into absolute loss metrics by multiplying these statistics by the respective cost.

M2. A probabilistic event-based risk calculator, uses stochastic event sets and the associated ground motion fields to compute loss exceedance curves within a given time span for each asset contained in an exposure model.

M3. A Classical PSHA-based risk calculator, that allows the computation of probability of losses and loss statistics for single assets. It uses a classical PSHA approach (Field *et al.*, 2003) to compute hazard curves at each site. Logic trees are implemented to account for the epistemic uncertainty from the parameters in the source model, as well as different GMPE for each tectonic region. These hazard curves can be combined with a vulnerability and exposure model to derive asset-specific loss exceedance curves.

M.4. A retrofitting benefit-cost ratio calculator, that can support users in understanding whether employing retrofitting interventions or choosing a better seismic design might be profitable from an economic point of view. It uses the results of loss exceedance from the previous calculators, (either probabilistic even-based risk or the classical PSHA-based calculators). Loss exceedance curves are calculated with the original and the retrofitted vulnerability configurations, and the economic savings can be depicted (in terms of average annual expected losses). The benefit is divided by the retrofitting cost to obtain the benefit-cost ratio. However, OpenQuake only considers losses due to structural damage, with no consideration of damage to non-structural components, contents and any indirect losses (e.g., business interruptions).

Exposure data is stored in what is called the Global Exposure Database (GED) (Vinay *et al.*, 2013), which provides a spatial inventory of exposed assets for the purposes of catastrophe modelling and loss estimation. The GED provides information about two main assets at risk: residential population and residential buildings. The data included in the GED is a result of a global effort (GEM partners) in: analysing existing data sets; selecting those that were most suited to the GED; implementing population strategies to extrapolate the necessary attributes in format suitable for characterizing building and population exposure and; homogenizing the data from various sources into a consistent format. The GED is divided in different levels according to the scale and completeness of the analysis: from a first level (level 0) where buildings are represented on a 1 by 1 km grid with statistical information about the building to a representation. Database are filled with global population census and worldwide available building statistics for the lowest levels, and from statistics created from surveys, census, local studies and/or expert opinions for more detailed representations.

Buildings are divided in the "GEM taxonomy" which the principal objective is to describe and to classify the buildings structural systems that exist in the world in a consistent manner, mainly using their key engineering characteristics so that such classification can ultimately led to assessing their potential risk from underlying hazards.

Criteria for development of the GEM Building Taxonomy were that the taxonomy be relevant to seismic performance of different construction types; be comprehensive yet simple; be collapsible; adhere to principles that are familiar to the range of users (general public, experts); and ultimately be extensible to non-buildings and other hazards (Brzev *et al.*, 2013). Extensive research on available taxonomic schemes were conducted, and as many features as

possible were included. The base typologies were defined according to characteristics referenced by the World Housing Encyclopaedia (http://www.worldhousing.net, last accessed April 2015) (Porter *et al.*, 2001).

The methodology for the calculation of replacement costs for buildings with a global focus (Wehner and Edwards, 2013), proposes a computational process for determining the rate (measured in currency per unit floor area) to reconstruct a building with given characteristics. The reconstruction cost is determined by multiplying the rate by the floor area.

Since GEM is a global collaborative project developing open-source tools to evaluate seismic risk, the correct information used in the calculations highly depends on the users participation. Users have the possibility to upload user-defined hazard, fragility, vulnerability, site conditions and exposure models. This allows a constant update and correction of datasets, but the level of detail is highly unequal depending on the region of the world studied.

Particularly in moderate to low seismic prone regions the model is still incomplete, and the application of globally determined exposure or vulnerability models generalise the calculations. A tool like OpenQuake might benefit from a method to evaluate the seismic vulnerability of the building stock, where only little information in term of buildings characteristics is available.

2.5. Summary

The catastrophic effects of the last earthquakes on modern societies have shown the importance and the need of earthquake loss models. They allow an estimation of the risk these societies are facing, rising awareness and motivating preparedness. Public and privates organizations around the globe are now convinced that they should not make programming decisions and investments without truly understanding the risk of the areas in which they work. To understand how to manage seismic risk, they need to know where the risk is highest and what options exist to mitigate it (Crowley *et al.*, 2004).

Loss modeling involves calculations of a series of interconnected components. The estimation of probable hazard, a modeling of the exposed elements, the analysis of their vulnerability and expected response to hazard, the calculation of damage and the conversion of it to economic and human losses. Uncertainties appear in each of these components, and its

handling and understanding is a key factor to apprehend and analyze the results. This work is in part advocated to the analysis of these uncertainties (Chapter 4). The understanding of the main sources of variability would help to target efforts to reduce them more efficiently.

Many loss estimations models have been created, at the regional or a global scale. Some of them have been presented in this chapter but the list was evidently not comprehensive. PAGER (Prompt Assessment of Global Earthquakes for Response) is an automated system that produces content concerning the impact of significant earthquakes around the world, informing emergency responders, government and aid agencies, and the media of the scope of the potential disaster. PAGER rapidly assesses earthquake impacts by comparing the population exposed to each level of shaking intensity with models of economic and fatality losses based on past earthquakes in each country or region of the world. Earthquake alerts, which were formerly sent based only on event magnitude and location, or population exposure to shaking, are generated based on the estimated range of fatalities and economic losses (Wald et al., 2010). It is worth noting the very wide uncertainty bands associated with PAGER estimates of economic losses and casualties.

PAGER uses tools like ShakeMap in the rapid estimation of hazard. ShakeMap is a product of the U.S. Geological Survey (USGS) earthquake hazards program in conjunction with regional seismic network operators (Wald *et al.*, 1999). It provides near-real-time maps of ground motion and shaking intensity following significant earthquakes based on observed and predicted data.

Jaiswal and Wald (2013) have also proposed an empirical methodology to rapidly estimate first orders economic losses after significant earthquakes worldwide. The model requires as inputs the shaking intensity estimates (from shakemaps), the spatial distribution of population from LandScan database, modern and historic country population and Gross Domestic Product (GDP) data, and finally economic loss data from Munich Re's historical earthquake catalogue.

In the same way, many methods have been proposed for the assessment of the vulnerability component of loss models, especially for high seismicity regions. While many methodologies were proposed at regional scales, one can site for example the GEVES project (Spence *et al.*, 2008) as a global earthquake vulnerability estimation system.

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In low-to-moderate seismic hazard regions however, vulnerability and loss models are difficult to apply because the level of information (regarding both hazard and exposure) is often limited. Since the seismic risk is less significant than other natural or man-made hazards (especially related to the larger return periods), it is extremely hard to find the economical and political motivation to develop full exposure models for the seismic vulnerability assessment. The risk is nonetheless present and non-negligible.

For these regions, other methodologies need to be developed, they have to be simple, transparent, flexible and applicable whether detailed information is available or not.

Chapter 3

Seismic vulnerability assessment of urban environments in moderate-to-low seismic prone regions using association rule learning and support vector machine methods

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3.1. Introduction

The extensive damage observed after the latest moderate-to-strong earthquakes together with population growth and the urbanization of megacities has considerably increased awareness regarding natural disasters over recent decades (Jackson, 2006). There is also an increasing demand for detailed seismic risk analysis, to furnish adequate information for the insurance and reinsurance companies (Spence *et al.*, 2008). Even though some regions are considered to be of moderate hazard, they are not free of seismic risk, and particularly not if the vulnerability of their cities is high (Dunand and Guéguen, 2012). Major earthquakes on the scale of France, for example, have caused real catastrophes during the last centuries.

A complete seismic risk assessment requires not only the estimation of the seismic hazard, but also the representation of the quality of existent buildings and their expected response based on the definition of their vulnerability. Coupled with real-time seismic ground motion estimates (e.g. Wald *et al.*, 1999; Worden *et al.*, 2010), macro-scale vulnerability data are crucial for the early assessment of damage.

Old structures, designed before the application of earthquake design rules and present everywhere, are certainly a critical element affecting the extent of loss and fatalities. Many empirical methods for vulnerability assessment have been published, most of them calibrated on post-earthquake observations or by expert judgement (e.g. Gruppo Nazionale per la Difesa dai Terremoti [GNDT], 1993; Hazus, 1997; Spence and Lebrun, 2006) or directly derived from a macroseismic intensity scale (Lagomarsino and Giovinazzi, 2006). Hybrid methods (e.g. Kappos *et al.*, 2006) or experimental methods (Michel *et al.*, 2012) have also been proposed as a complement of empirical methods. They estimate the probability of reaching a certain level of damage for a given class of buildings and a given seismic demand. Recent initiatives as part of the Global Earthquake Model project (http://www.globalquakemodel.org, last accessed April 2015) also attempt to provide worldwide vulnerability assessment. This large-scale model aims to propose and develop global procedures for deriving vulnerability functions for a wide variety of building types defined according to their structural characteristics referenced by the World Housing Encyclopaedia (http://www.worldhousing.net, last accessed April 2015) as the building taxonomy (Porter *et al.*, 2001).

These methods and initiatives have to deal with a significant amount of uncertainty, as stated in Chapter 2, Section 2.3. In addition, in moderate-to-low seismic hazard regions the application of conventional empirical methods requires so much information that the evaluation struggles to find sufficient political motivation and financial resources for accomplishing the seismic inventory of buildings. For example, the Risk-UE project (Spence and Lebrun, 2006) aimed to propose a seismic vulnerability assessment method for Europe, but due to its relatively complexity, only one city in France has been studied using this method (the city of Nice, which was a test site for the Risk-UE project). Consequently, the structural characteristics required for the seismic-vulnerability assessment of existing buildings are not available for all exposed urban areas of the country, even though seismic exposure is higher than in the past and a repetition of historic earthquakes may provide more casualties and economic losses as suggested by Jackson (2006) for the worldwide situation.

To overcome the lack of building information at the macroscale, we propose in this chapter to assess vulnerability not considering the information required for a conventional analysis, but the sole information already available in a region or country (**Figure 3. 1**). Two different data mining methods, association rule learning (ARL) (Agrawal *et al.*, 1993) and support vector machine (SVM) (Boser *et al.*, 1992; Cortes and Vapnik, 1995) are applied to define vulnerability proxies between the elementary characteristics of buildings and the vulnerability classes of the European Macroseismic Scale EMS98 (Grunthal and Levret, 2001). This is a two-step procedure: the first step (the learning phase) consists in defining the proxy using a sample of buildings for which elementary structural characteristics (or attributes) and vulnerability classes are available. The second step (the application phase) is to apply the proxy to a target region for which vulnerability classes are not available, but elementary attributes are.

In the initial part of this chapter, the dataset used in the first step is presented: the test bed of the city of Grenoble, one of the cities in France most exposed to seismic hazard, for which an extensive vulnerability analysis has been performed (Guéguen *et al.*, 2007). The ARL and SVM methods are then presented and applied to the Grenoble target site, deriving two vulnerability proxies for a Grenoble city-like environment. In the third part of this study, the derived vulnerability proxies are applied to the entire country and validated by comparison with the Risk-UE method applied in Nice. Finally, the probable damage produced by historic earthquakes was computed, considering (equivalent) earthquake-era and present-day urbanization to simulate the evolution of vulnerability and thus, probable damage over time.



Figure 3. 1 - Two-step process. During the learning phase, a vulnerability proxy is deduced from a test area for which a full seismic vulnerability evaluation is available. In the second step, this proxy is applied to a large region where only some attributes are available in order to estimate vulnerabilities. A final step combines the estimated vulnerability with hazard information to deduce probable damage

3.2. Grenoble test-bed area

During the VULNERALP project (Guéguen *et al.*, 2007), a simplified empirical method based on the Italian GNDT was proposed and tested in Grenoble, one of France's most exposed cities to earthquakes. By sending experts into the field, basic information was collected to assign elementary structural characteristics to existing buildings. The main pieces of information were date of construction ranked by period, number of floors ranked by category, roof shape (flat or slope), construction material, some qualitative description of plan and elevation irregularities, and building position in the block (corner, in-between, stand-alone, etc.). In addition to basic information, experts associated a type of building according to the EMS98 typology with the most likely vulnerability class (Grunthal and Levret, 2001). The EMS98 scale was originally defined for macroseismic intensity assessment after an earthquake, but since buildings vulnerability is taken into account for defining intensity, vulnerability classification can be used to represent the seismic damage in a target region for a given intensity. Building vulnerability is established as belonging to a category of buildings (EMS98 typology) with six classes from A (most vulnerable) to F (least vulnerable). At the end of the process, the expert survey compiled the Grenoble building vulnerability database, in which 5,000 buildings were characterized according to their EMS98 vulnerability class and some essential attributes. These attributes are elementary since they are considered as reliable (no uncertainty in their definition) and can be obtained relatively easily on a large scale. For example, the information about the number of storeys and period of construction is available in the INSEE database (French national statistic institute, www.insee.fr, last accessed April 2015), grouped by geo-localized cells called IRIS2000.

These units were defined in 1999 for the population census. The name "IRIS2000" (IRIS in the rest of this document) alludes both to the year of establishment and the size, corresponding to 2000 inhabitants. They represent the national standard for geographical data distribution and must therefore meet geographic and demographic criteria. They also have contours that are stable over time and easily identifiable. Municipalities of at least 10,000 inhabitants and most municipalities of between 5,000 and 10,000 inhabitants are divided into IRIS. By extension, municipalities with less than 2,000 inhabitants are considered as an IRIS unit. France has 50,100 IRIS units plus 700 in the overseas regions. Only residential dwellings are included in the INSEE database; which is a significant limitation to the study. Buildings per IRIS are described by attributes and grouped into categories. The number of floors divided into three categories (<4, [4–8], and >8 floors) and the period of construction, according to social and urban evolutions in France (<1915, [1915–1948], [1949–1967], [1967–1974], [1975–1982], [1983–1989], and >1990).

In Grenoble, the INSEE database contains 9098 buildings: 5,359 buildings with fewer than four floors; 2,958 buildings with between four and eight floors; and 781 buildings with more than nine floors. The distribution per period of construction is as follows: 2,264 buildings constructed before 1915; 1,729 buildings between 1915 and 1948; 2,978 buildings between 1949 and 1967; 768 buildings between 1968 and 1974; 384 buildings between 1975 and 1982; 489 buildings between 1983 and 1989; and 486 buildings after 1990. **Figure 3. 2a** shows the division of Grenoble and neighbouring towns into IRIS units.

At the beginning of the VULNERALP project, "period of construction" attribute ranks were defined according to the historical evolution of the urbanization and development of the construction code, whereas the "number of floors" attribute was defined according to the traditional interval given by the GNDT method. These categories and ranges do not match with the ones present in the INSEE database. Therefore, we considered the ground truth (i.e., the VULNERALP database) as the reference model. We then redefined the building distribution in each INSEE interval according to the VULNERALP intervals and considering a constant annual rate of urbanization in each INSEE period together with a uniform distribution of buildings per number of floors.



Figure 3. 2 - a) IRIS units in Grenoble, France from INSEE database. b) NERA study area in Grenoble. Building footprint layer superimposed on a VHR orthoimage. 560 buildings are characterized and classified according to EMS98 vulnerability classes

Additionally, during the NERA project (Network of European Research Infrastructures for Earthquake Risk Assessment and Mitigation - www.nera-eu.org, last accessed April 2015), a building-by-building field survey was carried out in a small area of Grenoble (about 950 x 700 m) including all buildings within the surveyed area (**Figure 3. 2b**) (Spence *et al.*, 2012). 560 residential buildings were characterized and classified according to EMS98. This subarea test was chosen because it shows a mix of building typologies representative of the Grenoble metropolitan area. Finally, remote sensing data are available in Grenoble, including a very high-resolution (VHR) orthorectified panchromatic image (airborne data, 25 cm resolution), a digital elevation model (DEM) (airborne acquisition, 1 m resolution in three dimensions), and building footprints from cadastral data. With this information, the Urbasis project (ANR-09-RISK-009) characterized the urban area based on building footprints and the surrounding open spaces within the NERA zone. Fifteen morphological indicators were computed according to Hamaina *et al.* (2012) for the characterization of urban fabric:

length, width (W), elevation (H), area and volume of the building units, circularity according to Miller (ratio of footprint area to the area of circle having the same perimeter as the footprint), open space morphometry (proportion of the area occupied by open spaces), shared wall ratio (ratio between the length of perimeter walls shared with other buildings and the whole perimeter), average distance to nearest buildings (average distance between building footprints of neighbouring cells), generalized ratio W/H, mean ratio of isovist area (area of space visible from a given point in space) divided by area of the enclosing circle, ground space index (ratio of a building's footprint area to the piece of land upon which it is built), floor space index (ratio between the building's volume and the area upon which it is built), among others. However, only a few were used for the vulnerability classification, as described in Section 3.4.2.

Many authors have recently introduced the potential of remote sensing data as a complement for the seismic vulnerability assessment of urban areas (Geiss and Taubenbök, 2012). For example, Wieland *et al.*, (2012) proposed an approach for rapid evaluation of structural vulnerability-related building features based on satellite remote sensing and ground-based omnidirectional imaging. Borsi *et al.*, (2010) also illustrated how suitable processing of satellite images can contribute to the vulnerability evaluation of industrial areas, especially when no other sources of information are available.

3.3. Association Rule Learning

Data mining, a process at the intersection of computer science and statistics, attempts to identify patterns and establish relationships in large datasets. These techniques are used in many areas of research, including mathematics, cybernetics, genetics, and marketing. There are a number of different types of learning algorithms that can be used for the (exploratory) data analysis: decision trees, decision rules, association rules, neural networks, Support Vector Machines (SVM), Bayesian classifiers among others (Teukolsky *et al.*, 2007). The overall goal of data-mining techniques is to extract information from a data set and transform it into an understandable structure for further use.

Association Rule Learning (ARL) is a popular and well-documented method for discovering relationships between variables in large databases. Agrawal *et al.*, (1993) introduced association rules as *if/then* statements to help reveal relationships between seemingly unrelated data in a relational database or other information repository.

By "an association rule," we mean an implication of the form $Y \rightarrow Xi$, in which Y is a set of items that belongs to a database of attributes and Xi is a single item in the database and not present in Y. Each relationship between Y and Xi is represented as a binary vector, equal to 0 if Y and Xi are not related and to 1 otherwise. The ARL method defines the relationships (or proxy) between Y and Xi once a learning phase has been completed on the database.

In this work, we develop a vulnerability proxy, using the simplified ARL method using Grenoble's database of buildings. Structural information (attributes Y) and EMS98 vulnerability class (item Xi) allow definition of a conditional matrix between them (the learning phase). The conditional probability of having class $Xi=\{A, B, C, D, E\}$ knowing that an event Y has a non-zero probability (i.e. the probability of Xi, given Y) is the number denoted by P(X | Y) and defined by:

$$P(X|Y) = \frac{P(X \cap Y)}{P(Y)}$$
(1)

X and Y are not totally independent because, according to almost all empirical methods, vulnerability also depends on elementary structural characteristics. Knowing that we randomly select one building in the city for the variable "a building experiencing an attribute Y," the probability P(X | Y) of belonging to class X can be calculated:

$$P(X|Y) = \frac{N_{xy}}{N_y} \tag{2}$$

in which Nxy is the number of buildings belonging to class X with attribute Y, and Ny the total number of buildings with attribute Y. In Grenoble, the data set used for the learning sample does not include EMS98 class F. Moreover, no information is available on the quality of the expert survey. Therefore, the most likely class of vulnerability was considered herein.

As is often the case in practice, the number of buildings is not enough to define the most efficient ARL possible. To ensure that our training sample was adequate, we compared the INSEE database and the distribution of the structural parameters used for the learning phase and given by the Vulneralp expert survey. We focused on the two attributes available in INSEE, with the objective of extending the association to the whole French territory.

Table 3. 1 shows that buildings randomly surveyed in the city of Grenoble (the dataset for this study) are representative of the area's urbanization as a whole, their distributions being quite similar (maximum difference observed 9%).

Using equation 2, the vulnerability class Xi according to EMS98 is then associated with attributes and used as a vulnerability proxy. **Table 3. 2** summarizes the Grenoble Vulnerability Matrix (GVM) of each conditional probability of being in EMS98 class X, knowing information related to Y.

Attributes	VULNERALP	INSEE
Number of floors		
≤ 2 floors	64.48%	55.57%
[3-5] floors	20.60%	21.80%
≥ 6 floors	14.91%	22.63%
Construction period		
< 1945	46.94%	45.66%
[1945-1970]	29.03%	32.46%
[1970-2000]	22.43%	18.70%
> 2000	1.59%	3.18%

 Table 3. 1 - Percentage of buildings in Grenoble per attribute (number of floors and construction period) included in the Vulneralp and INSEE database

Table 3. 2 – Grenoble Vulnerability Matrix (GVM) proxy. Conditional probabilities for each EMS98 vulnerability class according to building attributes. Obtained by the learning phase applied to the Vulneralp database

INSEE attributes	(A)	(B)	(C)	(D)	(E)
<1945 and ≤2 floors	0.390	0.483	0.086	0.039	0.002
[1945-1970] and ≤2 floors	0.008	0.818	0.131	0.036	0.008
[1970-2000] and ≤2 floors	0.000	0.245	0.105	0.210	0.441
>2000 and ≤2 floors	0.000	0.200	0.000	0.000	0.800
<1945 and [3-5] floors	0.113	0.556	0.289	0.042	0.000
[1945-1970] and [3-5] floors	0.000	0.008	0.803	0.174	0.015
[1970-2000] and [3-5] floors	0.000	0.000	0.016	0.100	0.884
>2000 and [3-5] floors	0.000	0.000	0.000	0.050	0.950
<1945 and ≥6 floors	0.000	0.029	0.912	0.059	0.000
[1945-1970] and ≥6 floors	0.000	0.000	0.396	0.604	0.000
[1970-2000] and ≥6 floors	0.000	0.000	0.017	0.521	0.462
>2000 and ≥6 floors	0.000	0.000	0.100	0.250	0.650

After the learning phase giving the GVM proxy, the second phase is implemented to obtain a geo-localised distribution of classes Xi in each IRIS, knowing Y for the whole French territory and using the formula:

$$P_{j}(X) = \frac{\sum_{1}^{12} N_{ji} P(X|Y_{i})}{N}$$
(3)

where Pj(X) is the probability of having vulnerability class X = (A, B, C, D, E) in each j IRIS cell, Nji the number of buildings with attribute Yi in j, N the total number of buildings in IRIS j and P (X|Yi) the value of the probability given by the GVM proxy for the X \rightarrow Yi association (**Table 3. 2**). Figure 3. 3 shows the vulnerability classes in Grenoble computed using the GVM proxy, considering [number of floors] and [construction period].



Figure 3. 3 - Distribution of the EMS98 vulnerability class in Grenoble computed using the GVM proxy (ARL) considering INSEE attributes, i.e. Construction period and number of floors.

The same main trends as those reported by Guéguen *et al.*, (2007) and Michel *et al.*, (2012) are also observed in **Figure 3. 3**: highest vulnerability in the historic downtown area, lowest vulnerability around the periphery and heterogeneous intermediate districts covering all periods of urbanisation and mixing masonry and reinforced concrete buildings. Application of

the proxy to the entire country assumes an urbanisation nation-wide similar than the one present in Grenoble, and this assumption will be tested in Sections 3.5 and 3.6.

3.4. Support Vector Machine

The SVM is a state-of-the-art classification method (Boser et al., 1992; Cortes and Vapnik, 1995). It is a supervised learning model with associated learning algorithms that analyze data and recognize patterns; it is used for classification and regression analysis (Teukolsky et al., 2007). A supervised classification task usually involves dividing data into training and testing sets. Each instance in the training set has one "target value" (i.e. the class label) and several "attributes" (i.e. the features or observed variables). The goal of SVM is to produce a model (based on the training data) that predicts target values for the test data (a set of patterns with a known label not considered in the training but used to evaluate the accuracy of the classification). A SVM model represents the samples as points in the space of the features. In an ideal case, after mapping, the separate categories can be divided by a hyperplane. Unlabeled samples are then mapped into that same space and expected to belong to a category based on the side of the hyperplane into which they fall. SVMs are primarily designed for 2-class classification problems; therefore, in its most basic form, it is a binary and linear classifier, i.e. resulting in classification using a linear hyperplane function (see Section 3.4.1). It often happens that the sets to be classified cannot be separated linearly in that space. In such cases, the original finite-dimensional space can be mapped into a higher-dimensional space using the kernel trick, which is likely to make separation easier in that space (Cortes and Vapnik, 1995). The multiclass problem (i.e. more than two classes) is often resolved by dividing the problem into smaller, simpler binary cases. The formal definition of the method and its principal aspects are presented in Section 3.4.1.

The effectiveness of SVM depends on the selection of the parameters controlling classification, i.e. the hyperplane parameters, the degree of misclassification, as well as the kernel parameters. The best parameter combination is selected by a grid search (Cortes and Vapnik, 1995). The entire dataset is divided into smaller sets (n-folds). For each subset, one training set and one testing set are created, and the input variables are correlated in a grid search. The parameters with the best cross-validation accuracy in each n-fold are picked, and usually an average is then used for the classification. This work uses an adapted version of the PRTools toolbox for MATLAB (Duin *et al.*, 2007).

Within a supervised classification framework, a SVM statistical learning algorithm is used on the Grenoble test-bed dataset to label the buildings according to the desired EMS98 standard for seismic vulnerability classes. Solving the optimization problem (Section 3.4.1) gives the parameters of the maximum-margin hyperplane needed for the classification. Having found the best hyperplane (using only the training set), accuracy is estimated automatically using the remaining data (the test set), i.e. by comparing the new estimated vulnerability class with the "real" one. Accuracy is thus measured by creating a confusion matrix and calculating the ratio between the sum of the diagonal values (correct classification) over the sum of all the elements in the matrix.

3.4.1 SVM Definitions

For the sake of simplicity, a formal definition of the linear binary case is first presented. The nonlinear case (still binary) is then studied. At last, the multiclass case is considered (nclass classification problem). Definitions are built following Teukolsky *et al.*, (2007) and Cortes and Vapnik (1995).

Linear classification

Before entering into the mathematical definitions, a qualitative graphical description will help understanding the basic foundation of the method. Given some data points belonging to one of two classes (binary problem), viewed as p-dimensional vectors (a list of p numbers) for SVM, many planes might exist that classify the data (**Figure 3. 4**). Intuitively, a good separation is achieved by the plane that has the largest distance to the nearest training data point of any class (so-called functional margin), since in general the larger the margin the lower the generalization error of the classifier.



Figure 3. 4 - Different splitting hyperplanes. "A" does not separate the classes. "B" does, but only with a small margin. "C" separates them with the maximum margin

Therefore, the basic idea is to choose the plane so that the distance from it to the nearest data point on each side is maximized. Given some training data D, a set of points of the form

$$D = \{(\mathbf{x}_i, y_i) \mid \mathbf{x}_i \in \mathbb{R}^p, y_i \in \{-1, 1\}\}_{i=1}^n$$

where the y_i is either 1 or -1, indicating the class to which the point x_i belongs. Each x_i is a pdimensional real vector. We want to find the maximum-margin hyperplane that divides the points having $y_i = 1$ from those having $y_i = -1$. Any hyperplane can be written as the set of points x satisfying

$\boldsymbol{w} \cdot \boldsymbol{x} + \boldsymbol{b} = \boldsymbol{0}$

where . denotes the dot product and w the normal vector to the hyperplane. The parameter $\frac{b}{||w||}$ determines the offset of the hyperplane from the origin along the normal vector w (**Figure 3.5**). If the training data are linearly separable, we can select two hyperplanes in a way that they separate the data and there are no points between them, and then try to maximize their distance. The region bounded by them is called "the margin". These hyperplanes can be described by the equations (**Figure 3.5**)

w.x + b = 1 and w.x + b = -1

By using geometry, we find the distance between these two hyperplanes is $\frac{2}{||w||}$, so we need to minimize ||w||. As we also have to prevent data points from falling into the margin, we add the following constraint: for each i either

 $w \,.\, x_i \,+\, b \,\geq 1$ for x_i of the first class, or

 $w.x_i + b \le -1$ for x_i of the second class

This can be rewritten as

 $y_i (w \cdot x_i + b) \ge 1$ for all $1 \le i \le n$


Figure 3. 5 - Maximum-margin hyperplane and margins for an SVM classification after training with samples from two classes. Samples on the margin are called the support vectors

The optimization problem is then posed as:

Minimize (in w, b) ||w||; subjected to (for any i = 1, ..., n) $y_i (w \cdot x_i - b) \ge 1$

To simplify the problem it is possible to alter the equation by substituting ||w||, the norm of w, with $\frac{1}{2}||w||^2$ without changing the solution (the minimum of the original and the modified equation have the same w and b). This is a quadratic programming optimization problem.

 $\label{eq:minimize} \text{Minimize (in w, b) } \frac{1}{2}||w||^2 \ \text{; subjected to (for any $i=1,\ldots,n$) y_i (w.x_i + b) ≥ 1}$

In mathematical optimization, the method of Lagrange multipliers is a strategy for finding the local maxima and minima of a function subject to equality constraints. By introducing Lagrange multipliers α , the previous constrained problem can be expressed as

$$\min_{w,b} \max_{\alpha \ge 0} \ \{\frac{1}{2} ||w||^2 - \sum_{i=1}^{n} \alpha_i \left[y_i \left(w \, . \, x_i + b \right) - 1 \right] \}$$

This problem can now be solved by standard quadratic programming techniques and programs. The "stationary" Karush–Kuhn–Tucker condition implies that the solution can be expressed as a linear combination of the training vectors

$$w = \sum_{i=1}^n \alpha_i \, y_i x_i$$

only a few α_i will be greater than zero. The corresponding x_i are exactly the "support vectors", which lie on the margin and satisfy

$$y_i (w \cdot x_i + b) = 1$$

from this, we can derive that the support vectors also satisfy

$$w.x_i + b = \frac{1}{y_i} = y_i \Leftrightarrow b = w.x_i - y_i$$

which allows defining the offset **b**. In practice it is more robust to average over all support vectors N_{sv}

$$b = \frac{1}{N_{sv}} \sum_{i=1}^{N_{sv}} (w \cdot x_i - y_i)$$

A modified maximum margin idea was proposed, allowing for mislabeled examples. If there exists no hyperplane that can split the examples (some points may fall within the margins), the "Soft Margin" method will choose a hyperplane that splits the examples as cleanly as possible, while still maximizing the distance to the nearest cleanly split examples. The method introduces slack variables ζ_i , which measure the degree of misclassification of the data x_i .

$$y_i (w \cdot x_i + b) \ge 1 - \zeta_i \qquad 1 \le i \le n$$

The optimization becomes a trade off between a large margin and a small error penalty. The final equation leads to a quadratic programming solution. The membership decision rule is based on the sign function and the classification is done by $y_{new} = sgn(w.x_{new} + b)$ where (w, b) are the hyperplane parameters found during the training process and x_{new} is an unseen sample.

Non-linear classification

In addition to performing linear classification, SVM can efficiently perform non-linear classification using what is called the kernel trick, implicitly mapping their inputs into highdimensional feature spaces. For machine learning algorithms, the kernel trick is a way of mapping observations from a general set S into an inner product space V, in the hope that the observations will gain meaningful linear structure in V. Linear classifications in V are equivalent to generic classifications in S. The trick to avoid the explicit mapping is to use learning algorithms that only require dot products between the vectors in V, and choose the mapping such that these high-dimensional dot products can be computed within the original space, by means of a kernel function. The resulting algorithm is formally similar, and the maximum-margin hyperplane can be fitted in the transformed feature space.



Figure 3. 6 - Kernel Machine. The separation surface (H) can become linear when feature vectors are mapped in a highdimensional space (here 3D - *right plot*) while it may be nonlinear in the original input space (here 2D - *left plot*)

The transformation may be nonlinear and the transformed space high dimensional, therefore even if the classifier is a hyperplane in the high-dimensional feature space, it may be nonlinear in the original input space (**Figure 3. 6**).

There exist several choices of kernel function k. The Kernel is related to the transform $\phi(x_i)$ by the equation $k(x_i, x_j) = \phi(x_i) \cdot \phi(x_j)$. Generally the Gaussian kernel is a common good choice $k(x_i, x_j) = \exp(-\frac{1}{2}|x_i - x_j|^2/\sigma^2)$, and it proved to give the best results in our study. Therefore, the classifications in this work are done using this kernel.

Multi-Class SVM

Even if SVM are intrinsically binary classifiers, in practice several-classes classifications are usually of interest. Different multiclass classification strategies can be adopted, based on binary analysis or the less used "all-together" method. The former is the dominant approach, which reduces the single multiclass problem into multiple binary classification problems and can be of the form:

One-Versus-All: Involves training N different binary classifiers, each one trained to distinguish the data in a single class from the data in all remaining classes. Classification of new instances is done by a winner-takes-all strategy, in which the classifier with the highest output function assigns the class.

One-Versus-One: Builds binary classifiers that distinguish between every pair of classes. Classification is done by a max-wins voting strategy, in which every classifier assigns the instance to one of the two classes, then the vote for the assigned class is increased by one vote, and finally the class with the most votes determines the instance classification. The One-Versus-One classification proved to be more robust in the majority of cases, and showing the best results, is the one selected in our study.

3.4.2 First phase: Learning

In the first phase, the entire dataset is divided into two. The elements that form the training set are selected randomly each time the classifier runs, but respecting the distribution of vulnerability classes. This introduces variability that has a slight effect on accuracy. To take this variability into account, 2,000 calculations were run (2,000 random training and testing divisions) and an accuracy histogram was created. The histogram shows a Gaussian-like distribution (**Figure 3. 7a**). The median and the 16 and 84 percentiles (\pm one standard deviation σ) can be estimated as a measurement of deviation. **Figure 3. 7a** shows the histogram of accuracy for a training set of 30% of Grenoble dataset and considering three attributes (i.e. construction period, number of floors, and shape of the roof).

Furthermore, accuracy will depend on the size of the training set (as a percentage of the total set). **Figure 3. 7b** shows the evolution of median accuracy for growing sizes of training sets including dispersion (16 and 84 percentiles). The evolution shown in **Figure 3. 7b**

is independent of the attributes included in the classification, and the same trend - regarding training set size - is found regardless of the dataset studied. Above 20 and 30% of training set size, maximum attainable accuracy is reached, and the influence of increasing size is lessened. A training size of 30% is therefore used for the calculations hereafter. It is worth noticing that even with 100% of the dataset used as training set (training and testing sets are the same), the accuracy stays stable around the maximum accuracy (in this case $\approx 65\%$).



Figure 3. 7 - a) Histogram of accuracy for 30% training set and 2,000 runs. b) Overall accuracy and dispersion evolution on growing training set sizes. Accuracy increases and dispersion decreases as training size increases up to approximately 25%, then it stabilizes at the final value. The lower-limit is the accuracy obtained if all classes are simply assigned to the most probable class (*bottom green line*). The maximum possible accuracy is obtained using 100% of data for training and testing on the same set (*upper-limit red line*).

Finally, mean accuracy will depend on the building information (attributes) incorporated to train the machine. Keeping this idea in mind, the method is run on the Grenoble NERA subset, for which several building features are available including those obtained by the processing of remote sensing data. Each test involves different attributes, different numbers of attributes, and their combinations. In order to capture only the individual influence of these attributes on the accuracy of the estimation, exactly the same NERA building dataset and training set size (30%) are used throughout the analysis.

The characteristics obtained by the NERA survey (i.e. construction period and number of floors) proved to be the basis of a relatively good classification and should always be included to achieve acceptable accuracy of 62.4% in the estimation of EMS98 vulnerability class (buildings correctly classified) (**Figure 3. 8a**). By adding roof shape, a parameter obtained by processing aerial images, accuracy is improved slightly to 63.5 %.

The shape of the roof is indirectly related to construction material. Accuracy is not enhanced drastically, since indirect construction material information might be also included in the other two attributes. In other words, the added information is not completely independent (**Figure 3. 8b**).

Note that many features can be extracted from remotely sensed data, but not all are independent and therefore add no new information for the classifier to work with. Out of the fifteen image-processing attributes available in NERA subset, only three produce a significant improvement of accuracy: width of the mean area-enclosing rectangle of the building footprint, shared wall ratio, and finally, average distance to nearest buildings. These three features represent the shape of urbanization. For example, average distance to nearest building is as sort of measurement of building density, a low-average distance indicates a cluster of buildings close to each other. By adding these pieces of information to the process, mean accuracy reaches 71.2 % of correctly classified buildings (**Figure 3.8c**).



Figure 3. 8 - Effects of different attributes on the accuracy. a) Only two attributes; construction period and number of floors. b) Three attributes, after adding shape of the roof. c) Six attributes, after adding three parameters obtained from cadastral data processing: width of buildings, shared-wall ratio (ratio between shared walls and the whole perimeter) and distance to nearest building (an indication of urban environment density). d) Six attributes, but merging vulnerability classes into only 3 classes (A-B); (C-D); (E-F). Note change of x-axis range in Fig. 3.8 d).

Figure 3. 8 shows a general trend: the addition of more (independent) information on buildings improves the accuracy of the method. In all cases, the dispersion regarding the random selection of the training set elements is small. Furthermore, 80 % of the misclassified buildings are labelled with a vulnerability class neighbouring the correct one. The confusion matrix shows most values immediately bordering the diagonal and zero elsewhere (**Table 3. 3**).

Since the classifier struggles to "differentiate" nearby classes clearly, the effect of merging them was studied by reducing the multiclass problem from six to only three classes. Classes A and B were joined to make class 1, C and D class 2, and E and F class 3. Classifier accuracy increased drastically, reaching 94 % of correctly assigned buildings (**Figure 3. 8d**). For this last example, it is worth noticing that even if accuracy in classification increases drastically, this does not mean that accuracy in vulnerability evaluation increases too, since we have a rougher vulnerability classification. For the rest of this study, a six-class classification is used.

Table 3. 3 - Example of confusion matrix obtained by SVM on the NERA subset, considering a 30% training set (median case). Six classes (A to E) and six attributes (construction period, number of floors, roof shape, width, shared-wall ratio, average distance to nearest building). Columns correspond to the "real" vulnerability class and rows to the estimated vulnerability class (e.g. from the 169 class "B" buildings, 24 were assigned as "A", 142 as "B" and 3 as "C"). The values on the diagonal (in bold) are the correctly assigned building classes.

	А	В	С	D	Е	F	
А	52	24	2	0	0	0	
В	45	142	7	0	0	0	
С	0	3	45	22	0	0	
D	0	0	6	10	2	0	
E	0	0	0	0	28	0	
F	0	0	0	0	0	0	
	97	169	60	32	30	0	388

Accuracy 0.71

3.4.3 Second phase: Application to the Grenoble dataset

The second phase is then implemented to obtain the geo-localized distribution of vulnerability classes in each IRIS, knowing some attributes for the whole French territory. Since INSEE data only give information on two building features (per IRIS unit), the SVM

was trained only with the [number of storeys] and [construction period] attributes for the Grenoble dataset, and then used at the scale of an IRIS unit.

As seen previously, the SVM assigns a class according to the side of the classification function (hyperplane) on which the point falls. However, classification is not always clear, even after the hyperplane has been defined in the first phase. For example, if a point falls into a clearly divided region of the space, confidence in the classification will be near to one (or 100%). But in some cases, confidence is lower for points falling near the hyperplane. In any case, SVM assigns the value with the highest confidence percentage. The method allows viewing of the "confidence" at each decision it makes.

Once the machine has been trained and to take this confidence into account, twelve points representing all the possible combinations of the two attributes (i.e., four categories of construction period and three ranges of number of floors) were added to the classification. A Grenoble Vulnerability Matrix (GVM) was created with the confidence distribution provided by the SVM considering each combination (**Table 3. 4**).

INSEE attributes	(A)	(B)	(C)	(D)	(E)
<1945 and ≤2 floors	0.221	0.636	0.103	0.031	0.009
[1945-1970] and ≤2 floors	0.074	0.672	0.184	0.054	0.016
[1970-2000] and ≤2 floors	0.019	0.105	0.143	0.341	0.391
>2000 and ≤2 floors	0.013	0.107	0.121	0.114	0.646
<1945 and [3-5] floors	0.119	0.660	0.175	0.037	0.009
[1945-1970] and [3-5] floors	0.011	0.022	0.779	0.163	0.025
[1970-2000] and [3-5] floors	0.010	0.055	0.069	0.175	0.693
>2000 and [3-5] floors	0.009	0.065	0.026	0.030	0.871
<1945 and ≥6 floors	0.043	0.058	0.802	0.084	0.013
[1945-1970] and ≥6 floors	0.013	0.020	0.245	0.685	0.038
[1970-2000] and ≥6 floors	0.010	0.026	0.096	0.606	0.261
>2000 and ≥6 floors	0.025	0.068	0.101	0.281	0.526

 Table 3. 4 - GVM proxy (SVM). "Confidence" values for the classification of each combination of attributes in EMS98 vulnerability classes. Obtained by SVM applied to the Grenoble (Vulneralp) database with a 30% training set.

Seeing the values of **Table 3. 4** as conditional probabilities to be in an EMS98 class knowing the building attributes, we calculate:

$$N_j(X) = \sum_{1}^{12} N_{ji} P(X|Y_i)$$
 (4)

where Nj(X) is the number of buildings of vulnerability class Xi = {A, B, C, D, E} in each j IRIS cell, Nji the number of buildings with attributes Yi in j, and P(X|Yi) the value of the probability given by the GVM proxy for the $X \rightarrow Yi$ association (**Table 3.4**).

Since IRIS cells are geo-localised throughout France, a vulnerability map of the whole country can be produced, based on the GVM proxy (SVM). Figure 3. 9 shows the computed vulnerability classes in Grenoble. Similar results are found, and the general trends of urbanisation can also be observed.



Figure 3. 9 - Distribution of the EMS98 vulnerability class in Grenoble computed using the GVM proxy (SVM) on INSEE attributes, i.e. construction period and number of floors.

For each IRIS unit in Grenoble, the ratio between the number of buildings in each vulnerability class obtained using the ARL proxy and the number obtained using the SVM proxy is shown in **Figure 3. 10**. The average ratio for the city, while close to unity, is higher than 1 for the most vulnerable classes and lower for the least vulnerable classes. This suggests that, compared with SVM, ARL predicts more buildings of the more vulnerable classes and

fewer of the less vulnerable classes. For a particular earthquake scenario, and on the broader scale, greater estimated damage would be expected if vulnerability is estimated using ARL rather than SVM, as will be shown in Section 3.6.



Figure 3. 10 - Comparison between estimated vulnerability classes using ARL and SVM proxies in Grenoble. For each IRIS unit and for each vulnerability class, the ratio between the number of buildings estimated by ARL and the number estimated by SVM is shown (grey dots). The average ratio for the city is shown as blue dots

3.5. Validation and testing

The derived vulnerability proxies are applied to the entire country, defining the vulnerability EMS98 class distributions nation-wide. In order to corroborate the application of these methods a comparison with the Risk-UE method applied in Nice, (a test site for the project) is presented in this section. In addition, the influence of the reliability of attributes used in the SVM method is tested with a different dataset of buildings.

3.5.1 Validation in the city of Nice

The city of Nice, one of France's cities most exposed to seismic hazard, has undergone numerous vulnerability evaluations (e.g., Bard *et al.*, 2005; Spence and Lebrun, 2006). In order to validate the GVM proxies, seismic damage in Nice was predicted using both GVM proxies applied to INSEE data (obtained by SVM and ARL) and with the vulnerability indexes obtained by the Risk-UE method. Validation was achieved by comparing the damage rate computed at the macroscale for different seismic scenarios.

For the Risk-UE analysis (LM1), vulnerability is measured in terms of a vulnerability index (Iv), which is defined taking into account the structural characteristics of buildings and

adjusted according to damage observed during earthquakes in Italy. The hazard is described in terms of macroseismic intensity, according to the European Macroseismic Scale EMS98. The correlation between seismic input and expected damage, as a function of the assessed vulnerability, is described by the analytical function:

$$\mu_D = 2.5 \left(1 + tanh \frac{I_{EMS98} + 6.25 I_v - 13.1}{2.3}\right) \quad (5)$$

where μ_D is the average observed damage in buildings of the given vulnerability index Iv and subjected to a given macroseismic intensity. EMS98 characterises damage according to 6 levels (Dk with k = 0,1,2,3,4,5), ranging from D0 (no damage) to D5 (complete destruction). To take into account the variability of the damage level k in a set of buildings, Lagomarsino and Giovinazzi (2006) assume a binomial distribution.

Therefore, the probability P(Dk) of observing each damage level Dk (k = 0 to 5) for a given mean damage μ_D is evaluated according to the probability function of the binomial distribution, namely:

$$P(D_k) = \frac{5!}{k! (5-k)!} \left(\frac{\mu_D}{5}\right)^k \left(1 - \frac{\mu_D}{5}\right)^{5-k}$$
(6)

In Nice, the Risk-UE project identified 27 zones (Z_{RISKUE}) considered homogeneous for vulnerability assessment (**Figure 3. 11** top-left). A random sample of buildings was selected to assess the vulnerability of each zone, with Iv between 0.365 and 0.849. Each zone was then geo-localised and characterised by a surface area, an average vulnerability Iv and a probable range Ivmax - Ivmin. The spatial distribution of the EMS98 vulnerability classes deduced from the GVM proxy (SVM) is given in **Figure 3. 11**.

The traditional trends observed in European urban centres are also observed in Nice, namely the more vulnerable historic downtown area with a preponderance of classes B and C, and more modern and less vulnerable suburb areas (mostly class D and E). These distributions of vulnerabilities can be portrayed by both methods (i.e. Risk-UE and GVM proxy). However, as INSEE and Risk-UE zoning rules are not the same, data was fused by reducing the information to a common reference to enable comparison (i.e. data alignment process).



Figure 3. 11 - Application of the GVM proxy to the city of Nice. Distribution of the seismic vulnerability index computed by the RiskUE method (top left). Distribution of the EMS98 vulnerability classes in Nice computed by the GVM (SVM) proxy.

The city was thus divided into elementary zones Zi as small as possible, so that $Z_i = Z_{RISKUE} \cap Z_{IRIS}$ ultimately corresponding to 457 elementary zones. For each Zi, Risk-UE vulnerabilities (Iv) and GVM estimated vulnerability distributions were assigned assuming a homogeneous distribution for each sub-area. The data alignment process resulted in some vulnerability information being different between Risk-UE and the GVM proxy. This is the case of Z_{RISKUE} number 9, for example, which is characterized by low vulnerability because it

covers recent urbanization, whereas the Z_{IRIS} crossing this zone covers more or less all of the historic downtown area with high vulnerability. For this reason, the comparison between Risk-UE and the GVM proxies must be made at a macroscale rather than zone by zone.

For the EMS98 scale, the frequency of expected damage is defined by linguistic terms ("few," "many," "most" buildings). The definitions provided by EMS98 can be regarded as damage matrices (e.g. for vulnerability class A in **Table 3. 5**, top). Lagomarsino and Giovinazzi (2006) proposed a numerical translation for these qualitative terms such as: "some" (5%), "many" (35%), and "most" (80%). On this basis, damage matrices are established giving the occurrence probability distribution P(D = Dk) for each intensity as a function of building vulnerability (e.g. for vulnerability class A in **Table 3. 5**, bottom).

 Table 3. 5 - EMS98 macroseismic scale. Implicit Damage Probability Matrix for vulnerability class A (top). Damage occurrence probability from EMS98 for vulnerability class A and macroseismic intensity from IV to XII (bottom)

EMS98 Intensity	D1	D2		D3	D4	D5
IV	-	-		-	-	-
V	Few	-		-	-	-
VI	Many	Few		-	-	-
VII	-	-	Ν	lany	Few	-
VIII	-	-		-	Many	Few
IX	-	-		-	-	Many
Х	-	-		-	-	Most
XI	-	-		-	-	-
XII	-	-		-	-	-
IS98 Intensity	D0	D1	D2	D3	D4	D5
	1.00	0.00	0.00	0.00	0.00	0.00
	0.95	0.05	0.00	0.00	0.00	0.00
	0.60	0.35	0.05	0.00	0.00	0.00
	0.05	0.20	0.35	0.35	0.05	0.00
l	0.00	0.05	0.20	0.35	0.35	0.05
	0.00	0.00	0.05	0.25	0.35	0.35
	0.00	0.00	0.00	0.00	0.20	0.80
	0.00	0.00	0.00	0.00	0.00	1.00
	0.00	0.00	0.00	0.00	0.00	1.00

Damage to buildings occurs from intensity V, with D1 damage grade affecting some buildings of classes A and B (Grunthal and Levret, 2001). These matrices have to be completed for the damage range for which there is no definition, since the sum of the different damage grades must be equal to one for each intensity. According to EMS98, we assume (1) a monotonically decreasing function at a high damage level Dk; (2) a normal distribution of probabilities around the mean damage grade for an intermediate level of damage; and (3) a monotonically increasing function at a low damage level Dk. For example, for buildings in class A and intensity VII, EMS98 says that "many (35 %) buildings in vulnerability class A suffer grade 3 damage and a few (5 %) suffer grade 4 damage." The remaining 60 % are distributed over the lower levels of damage to propose a continuous, smoothed probability function of damage. **Figure 3. 12** shows the translation of the EMS98 damage classification (D0 - D5) according to vulnerability class and macroseismic intensity.



Figure 3. 12 – Translation of the EMS-98 damage classification (D0 - D5) according to vulnerability class and macroseismic intensity (IV – XII). Different color lines represent the different damages states.

The probability of occurrence of damage Dk for intensities V - XII, computed using Risk-UE and the GVM proxies (i.e., ARL and SVM), averaged at the scale of the city, is shown in **Figure 3. 13**. The median Iv is used for RiskUE while the probabilities estimated using the range Ivmax and Ivmin are shown as dotted black lines (uncertainty range). For GVM methods, the proxy giving the median accuracy is used, while the estimations using the proxy giving 16 and 84-percentile accuracy are plotted as dotted lines. Note that the values change so little that the curves overlap. Overall, slight differences are observed between the methods. Nevertheless, at the macroscale and for the intensities causing damage, the orders of

magnitude of damage occurrence probability are quite similar. Although the GVM proxy was defined for a Grenoble-like environment, the damage prediction provides reliable information at the first order. Moreover, the simplified approach of computing the distribution of vulnerability class per IRIS based on just two very simple attributes allows generalization to the whole of the French territory, ultimately producing a geo-localized assessment of vulnerability.



Figure 3. 13 – Prediction of damage in Nice, France using Risk-UE (black continuous line) with its uncertainty rage (black hidden line) and using GVM proxy methods, i.e. ARL (red continuous line) and SVM (blue continuous line) for intensity scenarios ranging from V to XII

3.5.2 Testing SVM method on different datasets

The size, the representation, the accuracy and the reliability of the datasets used for any datamining technique, has an influence in the precision of the results. The minimum required size, to achieve a desired level of accuracy, depends on the variability of the elements forming the dataset. In any case, the bigger the dataset, the better. Since the training set used by SVM is formed by a random selection of elements, large datasets assure results that are stable (i.e. same

mean accuracy and small variability in the distribution of final accuracy). In section 3.4.2 the distribution of accuracy in the estimations of EMS98 vulnerability classes by SVM (30% training size - 2,000 runs) on Grenoble database (5,000 buildings) using three attributes (number of floors, construction period and shape of the roof) had approximately a mean of 63.5% with $\pm 1.2 \sigma$. This same distribution is found if we run the classifier n-times.

In order to study the influence of the original dataset size on the final distribution of accuracy, we remove step-by-step 10% of buildings to create smaller initial datasets (i.e. 90%, 80%, 70% ... 10% of total Grenoble dataset). Each reduced dataset is created 10 times differently, removing n*10% of buildings randomly from the original set. On each of these reduced sets, SVM is applied (30% training set – 2,000 runs). Using datasets sizes of 40% of Grenoble dataset (2,000 buildings) or larger, no significant changes on accuracy distribution is noted. For the 10 datasets created with 30% (1,500 buildings) mean accuracies varies from 61 to 63% ($\approx \sigma \pm 1.3$); for 20% (1,000 buildings) from 60 to 64% ($\approx \sigma \pm 1.2$). Finally using datasets created randomly with only 10% of the original dataset (500 buildings) mean accuracies range from 55 to 65 % ($\approx \sigma \pm 1.3$).

When the initial dataset grows smaller, particularities have a higher influence in the classification and add thus a larger variability. The mean accuracy can be larger or smaller that the mean using the entire dataset, but it is not stable. It is worth noticing that the variability in accuracy regarding the selection of training and testing set inside each reduced dataset remains small and invariable (σ value). In our study, we recommend to use datasets of at least 1,000 buildings to apply SVM methods. Even if the results are already stable with smaller datasets given the representation of buildings is trustworthy.

The use of basic information of buildings characteristics, which are easily or already available at a large scale, is one of the benefits of using SVM methods to estimate vulnerabilities. The definition of proxies requires a dataset containing in addition a vulnerability description of structures. In this study the Grenoble dataset presented in Section 3.2 was used, which was then extrapolated to the entire country using INSEE dataset, and assuming a Grenoble-like building environment.

Keeping this idea in mind, many datasets would seem appropriate to define a proxy between building parameters and vulnerability. The BCSF (*Bureau Central Sismologique Français*)

undertook in 2011 a search for relevant datasets to assess seismic vulnerability classes under EMS98 for all existing buildings (Schlupp *et al.*, 2011). Datasets created from post-seismic surveys in France (since 2004) remain inaccurate and available on a limited number of municipalities. Postal questionnaires sent to the municipalities or directly to inhabitants lay on the basis of voluntarism (usually less than 10% usable replies) and the accuracy of the collected information cannot be verified.

A third option was to use data from tax declaration of landowners. Being mandatory, they form an extensive dataset at the national level including all residential buildings. Indeed, for estimating property taxes the DGI (*Direction Générale des Impôts* – Central Tax Office) provides a form to be filled by property-owners including information among others on materials, location, number of floors (approximately), total area, and year of construction of the building. These declarations are grouped in a numeric database called MAJIC II (*Mise A Jour des Informations Cadastrales*).

This dataset does not contain any information on buildings' seismic vulnerabilities, and cannot therefore be used by itself to define a proxy by means of SVM method. However, since the information is joined to cadastral areas under a GIS (Geographic Information System), buildings from Grenoble, NERA and INSEE databases (Section 3.2) can be retrieved. This is a challenging task, and many buildings have to be depicted manually while many others could not be located in all databases. In all, after the merging process, we included to the Grenoble and NERA datasets, the structures materials and the total area as well as the number of floors and year of construction from MAJIC II dataset.

Having construction materials of every residential building nation-wide would seem a promising information to estimate seismic vulnerability more precisely. Nonetheless, after including this parameter in SVM (like in Section 3.4.2) the mean accuracy does not get improved, rather, it is slightly smaller than without including construction material as an attribute.

In order to study the influence of MAJIC II material attributes in detail, we perform the analysis on NERA dataset, where construction materials are also available (being masonry or reinforced concrete). **Figure 3. 14** shows the effect of including construction material from NERA and from MAJIC II on the overall accuracy of the vulnerability estimation. Number of floors and construction period were left as base attributes.



Figure 3. 14 - Influence of material attribute as described in NERA and MAJIC II datasets on the overall accuracy of vulnerability class EMS98 estimation

The construction material as described in NERA dataset slightly increases the accuracy, whereas the material type from MAJIC II has no positive effect and actually faintly reduces the mean accuracy. Material is not independent with the others; in fact, including the number of floors and the age of the construction (two parameters easy to obtain) the construction material is statistically almost defined. To prove this, we run a SVM classification on NERA dataset using the material as the target value. Including number of floors and construction period, the construction material is correctly classified for 94.8% of the buildings. This accuracy rises to 97.2% if we also include the shape of the roof. This explains the only "slight" improvement of accuracy when this attribute is included.

Materials in NERA database are considered to be correct since expert assigned them during a field trip. Comparing in a building-by-building basis the construction materials from NERA and MAJIC II databases it can be seen that in the later, 17% of buildings have been incorrectly assigned.

Indeed, citizens filled this database, and the construction material is sometimes not evident for an inexperienced eye. Moreover, since it is not a relevant parameter to evaluate property taxes, it is usually not verified nor corrected. One of the strength of SVM (and datamining techniques) is to use simple and reliable information on buildings. If the base information carries incertitude and errors, the method decreases its precision.

3.6. A new look at France's historic earthquakes. Their consequences in 2015

Once the exposure and the seismic vulnerability of a region is estimated, probable damage to buildings can be assessed for any given seismic demand. In this section, damage is modelled for a few historic earthquakes in France to enable (1) the estimation of damage if the same (or similar) earthquake were to strike today, using the present-day vulnerability; (2) validation of the model on the basis of damage estimations, using vulnerability at the time of the earthquake.

France is characterized by moderate seismicity, and destructive earthquakes are rare. Comparing modelled and real damage is challenging since the information concerning observed damage is old, sparse, and often imprecise. Nonetheless, for some historic earthquakes, quantitative information on observed damage can be retrieved (SisFrance, http://www.sisfrance.fr , last accesed April 2015; Scotti *et al.*, 2004), albeit the type of damage is not well detailed. Three of the best-documented historic French earthquakes are modelled in this section, using the macroseismic intensities observed as the seismic demand. For this evaluation, it is assumed that MSK reported intensities coincide with EMS98 scale intensities. According to Musson *et al.*, (2009), no empirical conversion is necessary between the EMS-98 (used here) and the MM, MCS or MSK intensity scales. This analysis, carried out as an example focused on the seismic vulnerability evaluation, eliminates the difficulties of simulating ground motion using prediction equations, including at the same time site and source effects. Evaluation of the consequences of an historic event occurring at the present time allows representation of the effects the evolution of vulnerability has over time.

3.6.1 Lambesc earthquake (1909)

The historic Lambesc earthquake, which hit south-eastern France in June 1909, is probably the strongest earthquake in the recent history of France. This earthquake produced macroseismic intensities MSK between VIII and IX in the epicentral area (**Figure 3. 15**), 30 km from Marseille, France's second largest city in terms of population and economic activity. Its magnitude was recently re-appraised and estimated at around 6.0 (Baroux *et al.*, 2003). It was a shallow depth earthquake (less than 10 km), and it was felt more than 300 km from the epicenter. 46 casualties and about 250 injured were reported after the event and referenced in

the SisFrance database (Scotti *et al.*, 2004). In terms of losses, Lambert (1997) compiled serious damage to buildings in different cities within the region affected. This earthquake is all the more important since it served as a scenario in 1982 to forecast seismic losses and casualties, taking into account urbanization evolutions between 1909 and 1982. The results provided information that increased the awareness of the authorities, an element (among others) that led to the establishment of the modern national earthquake rules for construction design, published about 15 years later.



Figure 3. 15 - Isoseists contour lines and intensity domains (on MSK scale) for the historic 1909 Lambesc earthquake (SisFrance catalogue, BRGM, EDF, IRSN).

In our analysis, we consider an area including all sectors with a macroseismic intensity above IV. In total, the studied area represents 4,162 IRIS cells, covering a large part of southeastern France. Using the GVM proxies calculated using the two data mining methods, ARL and SVM, the vulnerability class distribution was computed from INSEE data. Since the INSEE database gives the distribution of buildings present in 2008 according to the period of construction, and no information on the inventory of past - and now non-existent - buildings, we assume that the number of buildings per IRIS corresponds to the buildings that were present in each period. We thus accept a slow rate of replacement and are able to provide an approximate simulation of the damage produced by the 1909 Lambesc earthquake, assuming that the buildings present in 1915 and still existing in 2008 were those present in 1909. We did not take into account the possible retrofitting or modifications of existing structures, as well as some special structural characteristics (e.g., short column, soft story, and irregularities). These characteristics certainly affect the seismic vulnerability of buildings, but for a macroscale evaluation, they are not available in national census and they cannot be obtained through the processing of aerial/satellite images.

The temporal evolution of seismic vulnerability as estimated (SVM) can be assessed for different periods of construction (before 1915, before 1945, before 1970, before 2000 and before 2008) in order to visualize the effects of the rate of urbanization on seismic vulnerability (**Figure 3. 16**). In general, probabilities for high vulnerability classes (classes A and B) are reduced with time, and probabilities for the less vulnerable classes increase, reflecting the construction of new buildings that are more resistant to ground shaking. However, in terms of numbers, vulnerable buildings (classes A and B) still represent a large portion of the total (almost 40% of all buildings in 2008). Furthermore, the evolution of the total number of buildings for the considered IRIS cells is significant, with more than 160,000 new constructions between 1945 and 2008, which is also coherent with the urbanisation rate observed in Grenoble and reflecting the post-World War II needs for housing. New buildings are, in general, less vulnerable, thanks to the use of reinforced concrete rather than masonry and the application of new building codes, introduced after the 1970s.



Figure 3. 16 - Time evolution of the proportion of buildings' EMS98 vulnerability class in the area affected by the Lambesc earthquake. Vulnerability classes estimated with GVM proxy from SVM applied to INSEE dataset.

The number of buildings for each EMS98 damage grade D0 to D5 (or damage probability) is computed by crossing the GVM proxy applied to the INSEE attributes and using the 1909 macroseismic intensity curves as seismic demand, as follows:

$$N_{j,I_{EMS98}}^{D_k} = \sum_{i=A}^{i=F} N_{ji} P(D_k | i, I_{EMS98})$$
(7)

where $N_{j,I_{EMS98}}^{D_k}$ is the number of buildings with damage grade Dk (k=0 to 5) for each j IRIS cell and intensity I_{EMS98} ; Nji the number of buildings of vulnerability class i (i = A to F) for IRIS j; and P(D_k|i, I_{EMS98}) the probability of damage grade Dk of a vulnerability class i building for a given macroseismic intensity EMS98 (e.g. values of **Table 3. 5** bottom for class A). IRIS units not entirely within an iso-value (i.e., intersected by an isoseismal line) are divided following the isoseismal line and thus have two intensity values. The number of buildings is distributed in proportion to the area of each sub-unit and respecting the vulnerability class distribution inside the original IRIS.

The number of damaged buildings predicted according to the ARL proxy is displayed on **Figure 3. 17** and according to the SVM proxy on **Figure 3. 18**. For representation, they are grouped into three damage grades according to the EMS98 scale: slight damage (D1), moderate damage (D2+D3) and strong damage (D4+D5). To compare the results with historical description available in villages or cities, damage might be regrouped differently. **Figure 3. 17a** and **Figure 3. 18a** represent the number of damaged buildings for the 1909 earthquake affecting dwellings built before 1915. The highest damage computed is localised close to the epicentre, which is where the highest intensities are found. In overall results by both methods, between 170 and 240 buildings suffer heavy damage, while between 2,600 and 2,700 are estimated as suffering moderate damage, the rest being distributed over the studied area. The historic information from 1909 concerning cities close to the epicentre enables a reliable comparison city-by-city of estimated and observed damage (**Table 3. 6**). In this regard, our method allows the estimation of probable damage for each IRIS unit, therefore for each city or town.

In 1982, the results of a simulation of the Lambesc earthquake performed by the ministry in charge of natural hazard indicated 1.8% of buildings collapsed (D5), 85.8% of buildings damaged (D1 - D4) and 12.4% with no damage (D0) in the epicentral region. Keeping the same assumptions as for the 1909 estimate (i.e., 2008 inventory of buildings

before 1982 and 1909 iso-intensities), the GVM proxy (SVM) applied to buildings built before 1982 gives the same order of magnitude for the damage distribution; that is, 0.8, 81.5, and 17.7% of buildings collapsed, damaged, and with no damage, respectively.



Figure 3. 17 - Evaluation of the level of damage for the Lambesc earthquake scenario considering a) 1909 urbanization (*left column*) and b) 2008 urbanization (*right column*), using the GVM proxy obtained from ARL. Damage is grouped by slight D1 (*top row*), moderate D2+D3 (middle row) and severe D4+D5 (*bottom row*) according to the EMS98 damage scale. Color scale gives the number of buildings per damage levels. Total numbers of predicted damaged buildings for the entire region are indicated



Figure 3. 18 - Evaluation of the level of damage for the Lambesc earthquake scenario considering a) 1909 urbanization (*left column*) and b) 2008 urbanization (*right column*), using the GVM proxy obtained from SVM. Damage is grouped by slight D1 (*top row*), moderate D2+D3 (middle row) and severe D4+D5 (*bottom row*) according to the EMS98 damage scale. Color scale gives the number of buildings per damage levels. Total numbers of predicted damaged buildings for the entire region are indicated (mean and standard deviation)

Table 3. 6 compares the number of buildings damaged according to historic information (from SisFrance archives) and the predicted using GVM proxies from ARL and SVM methods using the 1915 catalogue of buildings. Slight differences exist, which may reflect especially the differences between the 2008 inventory of buildings built before 1915 and the actual state of urbanization in 1909. Nevertheless, the damage obtained is appropriate in terms of estimation at the macroscale. The lack of more accurate descriptions of historic damage and

information on urbanization at the time prevents better comparison. Estimations using the GVM proxy obtained with SVM seem to be closer to the damage observed, while estimations with the ARL proxy are more conservative, giving a larger number of damaged buildings.

Table 3. 6 - Comparison between damage observed during the 1909 Lambesc earthquake (historic records SisFrance) and simulated using the GVM proxy obtained by ARL and SVM methods. D_{1+2+3} total number of buildings with damage grade D1; D2 or D3

City or town	Observed	Simulated (ARL)	Simulated (SVM)
Lambesc (R _{epic} = 5 km)	600 damaged	361 D ₁₊₂₊₃	376 D ₁₊₂₊₃
	50 destroyed	77 D ₄₊₅	58 D ₄₊₅
Rognes (R _{epic} = 3 km)	250 damaged	172 D ₁₊₂₊₃	173 D ₁₊₂₊₃
		18 D ₄₊₅	14 D ₄₊₅
Saint-Canat (R _{epic} = 4 km)	310 damaged	148 D ₁₊₂₊₃	152 D ₁₊₂₊₃
	50 heavily damaged	28 D ₄₊₅	21 D ₄₊₅
La Roque d'Anthéon (R _{epic} = 7 km)	110 heavily damaged	127 D ₁₊₂₊₃	124 D ₁₊₂₊₃
		3 D ₄₊₅	2 D ₄₊₅
Aix-en-Provence (R _{epic} : 20 km)	1,500 damaged	1409 D ₁₊₂₊₃	1433 D ₁₊₂₊₃
		25 D ₄₊₅	18 D ₄₊₅

Compared to ARL, SVM allows an assessment of the variability in the estimation of damage, related to the uncertainty in the estimate of vulnerability. For this later evaluation, the mean accuracy of the method using two attributes (i.e. number of floors and construction period) is approximately 63%, and the vast majority of mislabelled buildings are in a neighbouring vulnerability class (Section 3.4.2). To include this uncertainty in the final estimation of damage, 1,000 possible distributions of vulnerability classes are randomly created at each involved IRIS unit. These distributions take into account the precision of the SVM method (i.e. 63% of classes are correctly assigned, and 37% might be on an immediately lower or upper vulnerability class). Damage is then assessed at each IRIS unit with Lambesc isoseist as input hazard and for the 1,000 possible distributions of estimated vulnerability. The total mean number of damaged buildings for the region and for each damage grade is calculated doing the sum of the means of each j IRIS:

$$Mean_{Lambesc}^{SVM} = \sum_{j=1}^{j=4162} Mean_j$$
(8)

while the total standard deviation is calculated as:

$$STD_{Lambesc}^{SVM} = \sqrt{\sum_{j=1}^{j=4162} STD_j^2}$$
(9)

It is worth noticing that the variability in the estimation of damage as indicated in **Figure 3. 18**, only considers the uncertainty in the estimation of vulnerability. A full analysis including the uncertainties in the estimation of hazard is reviewed in Chapter 4.

Finally, the simulation can be continued by forecasting the impact of a future earthquake with the same characteristics as the 1909 Lambesc earthquake (i.e., same location and same macroseismic intensity) on the state of urbanization in 2008 (Figure 3. 17b and Figure 3. 18b). In 2008, the region suffering macroseismic intensity V or higher during the 1909 earthquake have more than 1.10 million buildings and a population of more than 5 million. 37% of buildings are vulnerability class A or B, 41% class C and classes D and E represent 22%. If the 1909 earthquake re-occurred in 2008, about 50,000 buildings would be affected with different levels of severity, i.e., approximately 5 % of the total number of buildings. The small epicentral area (intensities VII and VIII) includes more than 14,000 damaged buildings, representing 44 % of the buildings. All the buildings suffering heavy damage and 81 % of those suffering moderate damage are within this area.

Overall, if the same earthquake occurred again, it would cause more damage in terms of number of buildings for any damage type, closely linked to the urbanization growth between 1909 and 2008 (increased number of buildings with a high percentage of vulnerable classes before 1970). The percentage of damaged buildings is smaller compared to 1909, but the number is nonetheless higher. As shown in **Figure 3. 17b** and **Figure 3. 18b**, the probable number of heavily damaged buildings doubles, reaching around 430 constructions (only a few buildings are completely destroyed (D5)), and the number suffering moderate damage triples, with 9,400 buildings affected for the entire region. Approximately 40,000 buildings are expected to suffer slight damage, characterized by hairline cracks in very few walls, falling chimneys or small pieces of plaster, according to the EMS98 damage description.

A comparison between ARL and SVM damage estimations for the Lambesc earthquake scenario in 2008 is shown in **Figure 3. 19**. The difference between the percentages of buildings damaged in each IRIS unit estimated using ARL and the percentage estimated

using SVM is represented in a histogram for each damage level. The ARL method gives slightly higher percentages (or number of damaged buildings) especially for the lower damages grades.



Figure 3. 19 - Difference between the percentages of buildings damaged at each IRIS unit for the Lambesc earthquake scenario in 2008 estimated using ARL and SVM methods. Slight damage D1 (left), moderate damage D2+D3 (middle), strong damage D4+D5 (right). Note change in axis between figures

3.6.2 Arette earthquake (1967)

Another of the most violent event experienced in France during the twentieth century occurred on August 1967 in Arette, in the western Pyrenees near the French–Spanish border. With a magnitude estimated at 5.8 M_L (Rothé and Vitart, 1969), this earthquake produced a macroseismic intensity MSK of VIII in the epicentral region (**Figure 3. 20**). It was felt in an area with a radius of 220 km from the epicenter and caused 1 death, 15 injured, and major damage to buildings. This analysis considers the area including all sectors with a macroseismic intensity above IV on the French side of the border (1,092 IRIS units).

As before, the number of damaged buildings for each damage grade is computed by crossing the GVM proxies applied to the INSEE attributes to estimate vulnerability, and with the 1967 intensity curves as seismic demand. We provide an approximate simulation of the damage caused by the Arette earthquake in 1967, considering buildings built before 1970 and existing in 2008 as those present in 1967.

The number of predicted damaged buildings for the Arette region according to the ARL proxy are displayed on **Figure 3. 21** and according to the SVM proxy on **Figure 3. 22**.



Figure 3. 20 - Isoseists contour lines and intensity domains (on MSK scale) for the historic 1967 Arette earthquake (SisFrance catalogue, BRGM, EDF, IRSN)

Figure 3. 21a and **Figure 3. 22a** show the number of buildings in each damage grade for the 1967 earthquake affecting dwellings built before 1970. As for the previously modelled earthquake, the information from 1967 concerning cities close to the epicentre enables a reliable comparison of the predicted and observed damage.

Table 3. 7 compares the number of buildings damaged according to historic observations (Rothé and Vitart 1969 - SisFrance) and the number estimated by GVM proxy simulations. The historical description of damage gives incomplete and imprecise quantitative information and some rough percentages of damaged buildings, making comparison difficult. Even though the disparities (reflecting the differences between the 2008 inventory of buildings built before 1970 and the real state of urbanization in 1967) the damage obtained by simulation is appropriate in terms of estimation at the macro scale.

Figure 3. 21b and **Figure 3. 22b** forecast the impact of a future earthquake having the same characteristics as the 1967 Arette earthquake on the state of urbanization in 2008. The region that experienced macroseismic intensity V or higher during the earthquake (damage to constructions expected) counts in 2008 about 91,000 buildings and a population of more than 376,000. If the 1967 earthquake re-occurred in 2008, nearly 6,800 buildings would probably have been affected with different levels of severity, i.e., approximately 7% of the total.

The epicentral area (intensities VII and VIII) includes more than 1,080 damaged buildings, representing 60% of the buildings in the area. Every building with heavy damage and 58% of those suffering moderate damage are inside this area.



Figure 3. 21 - Evaluation of the level of damage for the Arette earthquake scenario considering a) 1967 urbanization (*left column*) and b) 2008 urbanization (*right column*), using the GVM proxy obtained from ARL. Damage is grouped by slight D1 (*top row*), moderate D2+D3 (*middle row*) and severe D4+D5 (*bottom row*) according to the EMS98 damage scale. Color scale gives the number of buildings per damage levels. Total numbers of predicted damaged buildings for the entire region are indicated



Figure 3. 22 - Evaluation of the level of damage for the Arette earthquake scenario considering a) 1967 urbanization (left column) and b) 2008 urbanization (right column), using the GVM proxy obtained from SVM. Damage is grouped by slight D1 (top row), moderate D2+D3 (middle row) and severe D4+D5 (bottom row) according to the EMS98 damage scale. Color scale gives the number of buildings per damage levels. Total numbers of predicted damaged buildings for the entire region are indicated (mean and standard deviation)

Table 3. 7 - Comparison between damage observed during the 1967 Arette earthquake (historic records SisFrance) and simulated using the GVM proxy obtained by ARL and SVM methods. D3+4+5 total number of buildings with damage grade D3; D4 or D5

City or town	Observed	Simulated (ARL)	Simulated (SVM)
Basses Pyrénées (global)	2,283 damaged	5,319 D ₁₊₂	5,229 D ₁₊₂
	340 heavily damaged	189 D ₃	160 D ₃
	or destroyed	38 D ₄₊₅	29 D ₄₊₅
Arette, Lanne and Montory	40% heavily damaged	270 D ₁₊₂	269 D ₁₊₂
(epicentral area)	or destroyed	104 D ₃₊₄₊₅ (22%)	95 D ₃₊₄₊₅ (20%)
Arette (R _{epic} = 6 km)	Many heavily damaged	150 D ₁₊₂	146 D ₁₊₂
	some destroyed	30 D ₃ (11%)	28 D ₃ (10%)
		6 D ₄₊₅ (2%)	6 D ₄₊₅ (2%)
Montory (R _{epic} = 2 km)	All slight damaged	51 D ₁₊₂	53 D ₁₊₂
	40 heavily damaged	35 D ₃₊₄₊₅	32 D ₃₊₄₊₅
		(total 87%)	(total 86%)
Lanne (R _{epic} : 0.5 km)	Many damaged	94 D ₁₊₂₊₃ (75%)	93 D ₁₊₂₊₃ (74%)
	some destroyed	8 D ₄₊₅ (6%)	6 D ₄₊₅ (5%)

Even if, as for the previous earthquake, the same seismic event striking at present time would cause more damage (in terms of number of buildings for any damage type), the increase is smaller. As shown in **Figure 3. 21** and **Figure 3. 22**, the probable number of heavily damaged buildings remains almost the same; the number of buildings suffering moderate and slight damage increases by 10 and 15 % respectively. Compared with the Lambesc simulation, the evolution of urbanization over this period of 41 years (1967–2008) is obviously less radical than over almost a century (1909–2008).

Figure 3. 23 shows the comparison between ARL and SVM estimated damage for the Arette earthquake scenario in 2008. As in the previous case, the ARL method gives a slightly higher number of damaged buildings for any damage grade.



Comparison bewtween ARL and SVM estimated damage for Arette Earthquake in 2008

Figure 3. 23 - Difference between the percentages of buildings damaged at each IRIS unit for the Arette earthquake scenario in 2008 estimated using ARL and SVM methods. Slight damage D1 (left), moderate damage D2+D3 (middle), strong damage D4+D5 (right). Note change in axis between figures

3.6.3 Corrençon earthquake (1962)

In april 1962 the Corrençon earthquake, southeast France (close to the Italian border), produced hundreds of chimneys falls up to Grenoble 30 Km from the epicentre. With an estimated magnitude of 5.3 M_L and an epicentral intensity of VII this earthquake produced mainly slight damage, with some moderate damage buildings in the epicentral region, **Figure 3**. **24** (Rothé, 1972 - SisFrance). No human were killed.



Figure 3. 24 - Isoseists contour lines and intensity domains (on MSK scale) for Corrençon 1962 historical earthquake (SisFrance, BRGM, EDF, IRSN)

The area affected during Corrençon 1962 is relatively smaller compared with the previous studied historical earthquakes. The region with macroseismic intensity larger than IV includes in our study 490 IRIS units. Following the same procedure as with the previous modelled earthquakes, the vulnerability class distribution is computed using ARL and SVM proxies on INSEE data. The number of damaged buildings for each damage grade EMS98 is then calculated using the 1962 macroseismic intensity curves as seismic demand. The simulation of the damage produced by the Corrençon earthquake in 1962, is prepared considering buildings before 1970 and existing in 2008 as those present in 1962. The number of buildings in each damage grade is displayed on **Figure 3. 25** using ARL proxy and on **Figure 3. 26** using SVM proxy. **Figure 3. 25a** and **Figure 3. 26a** represent the predicted probable number of damaged buildings for the 1962 earthquake affecting dwellings built before 1970.

Table 3. 8 compares de number of buildings damaged according to historical information (Rothé 1972 - SisFrance archives) and the number simulated using GVM proxies for different cities or towns. The account of damage observed for this earthquake is entirely qualitative, and only rough quantities are given. The comparison between observed and modelled damage does not allows estimating any errors or accuracy. However, once again the assessments seem to fall in the range of what the descriptions of observed damage define.

Figure 3. 25b and **Figure 3. 26b** forecast the impact of a future earthquake having the same characteristics as the 1962 Corrençon earthquake on the state of urbanisation in 2008. The region that felt macroseismic intensity V or larger during the earthquake; have in 2008 more than 53,000 buildings and a population of more than 450,000. If the 1962 earthquake reoccurred in 2008, nearly 2,700 buildings would probably be affected with different levels of severity, i.e. 5% of the total number of buildings. The epicentral region (intensity VI and VII) includes more than 1,500 damaged buildings, representing 30% of the buildings present in that area. Every building having high or moderate damage is inside this small area. Collapsed or destroyed buildings are not to be expected, i.e. no buildings with damage grade D5. Once again, the same earthquake at present time would produce larger damage (in term of number of buildings for any damage type). As shown in **Figure 3. 25** and **Figure 3. 26** the probable number of heavily damaged buildings remains almost the same, the ones with moderate damage and light damage have an number increase of 27% and 25% respectively.



Figure 3. 25 - Evaluation of the level of damage for the Corrençon earthquake scenario considering a) 1962 urbanization (*left column*) and b) 2008 urbanization (*right column*), using the GVM proxy obtained from ARL. Damage is grouped by slight D1 (*top row*), moderate D2+D3 (*middle row*) and severe D4+D5 (*bottom row*) according to the EMS98 damage scale. Color scale gives the number of buildings per damage levels. Total numbers of predicted damaged buildings for the entire region are indicated



Figure 3. 26 - Evaluation of the level of damage for the Corrençon earthquake scenario considering a) 1962 urbanization (*left column*) and b) 2008 urbanization (*right column*), using the GVM proxy obtained from SVM. Damage is grouped by slight D1 (*top row*), moderate D2+D3 (*middle row*) and severe D4+D5 (*bottom row*) according to the EMS98 damage scale. Color scale gives the number of buildings per damage levels. Total numbers of predicted damaged buildings for the entire region are indicated (mean and standard deviation)

City or town	Observed	Simulated (ARL)	Simulated (SVM)	
Château-Bernard (R _{epic} = 2 km)	Important damage to buildings, chimney and tile falls	14 D ₁ (30%) 13 D ₂₊₃ (28%)	14 D ₁ (30%) 12 D ₂₊₃ (26%)	
Gua (R _{epic} = 4 km)	Important damage to some buildings, slight damage, chimney falls	102 D1 (29%) 90 D ₂₊₃ (26%) 3 D4	103 D ₁ (30%) 84 D ₂₊₃ (24%) 2 D ₄	
Rencurel (R _{epic} = 15 km)	Slight damage	14 D ₁ (16%) 4 D ₂₊₃ (4%)	14 D ₁ (16%) 4 D ₂₊₃ (4%)	
Saint Paul de Varces (R_{epic} = 9 km)	Slight damage, many chimney falls	48 D1 (30%) 49 D2+3 (30%) 1 D4	49 D ₁ (30%) 46 D ₂₊₃ (29%) 1 D ₄	
Grenoble (R _{epic} : 25-30 km)	Hundreds of chimney falls	160 D ₁	165 D1	

 Table 3. 8 - Comparison between damage observed during the 1962 Corrençon earthquake (Rothé, 1972) and simulated using the GVM proxy obtained by ARL and SVM methods. D2+3 total number of buildings with damage grade D2 or D3

Being this event of relatively low damaging potential, no significant differences are found on the damage expectations using vulnerabilities calculated with ARL and SVM proxies.

3.7. Summary and conclusions

The main aim of this chapter was to validate a macroscale methodology for seismic vulnerability assessment, in a situation where only poor descriptions of construction characteristics (with respect to those necessary for an *ad hoc* analysis) are available for a large number of buildings. In a moderate seismic-prone region, where it is often difficult to mobilize resources for the reduction of seismic risk, the idea of using readily available data to expand the assessment to any given region is obviously of interest.

Using the information available in Grenoble, we proposed two vulnerability proxies (GVM proxy) defined using the ARL and SVM methods. These proxies create a relationship between two building characteristics (present in the French national census database) and their most probable EMS98 vulnerability class. Since INSEE data are available for the whole of the French territory, it is possible to apply the GVM proxy to simulate the impact of historic earthquakes on present-day urbanization and/or to forecast global damage levels in the impacted zone a few minutes after the occurrence of an earthquake. Even though the proxies were created for France city-like environments, their application to other European cities should be tested. Furthermore, the INSEE dataset provides information on residential
buildings only. No commercial buildings or public infrastructures were included in our damage estimations.

The flexibility and adaptability of the method is one of its main advantages. If the information available is at the scale of a building, the estimation of vulnerability and damage can obviously be carried out at this same scale. This routine can easily be applied anywhere to create specific proxies, provided basic information on the buildings and a definition of their vulnerability are available. These proxies can then be exported to other target regions where seismic vulnerability needs to be assessed. We proved the adaptability of the method regarding the information available. Having more (or more detailed) independent attributes during the training phase increases the accuracy of the vulnerability class estimation.

National census information, satellite or airborne photographs and cadastral data are relatively cheap sources of information available over a large scale, which could eventually allow a reliable definition of vulnerability proxies. Further exploration of the impact of urban parameters on vulnerability could be tested in more detail in the future.

In Nice, a more sophisticated method (Risk-UE – LM1) based on a relatively detailed description of structural features and using macroseismic intensity as the ground motion parameter, predicted similar levels of damage across the city compared to the datamining techniques.

After being validated in Nice the technique was tested for three historic earthquakes that caused damage in France. Although the attributes describing the buildings are very basic, the analyses confirmed the suitability of the solution, providing reliable estimates of damage for earthquake scenarios. According to our analysis, SVM provides a better estimate of damage compared with historic data. Unfortunately, historic descriptions of losses are sparse and imprecise, and the effectiveness of SVM compared with the ARL method needs to be confirmed. Because of this lack of elements of comparison and the shortage of details about historic damage, it is difficult to quantify the assessment errors that might be obtained for a given earthquake.

Using datamining techniques to evaluate seismic vulnerability we were able to highlight and quantify certain obvious trends, such as the reduction in the proportion of vulnerable buildings with the development of urbanization. We also confirmed and quantified the increasing effects of earthquakes in terms of damage, mainly due to the explosion of urbanization and urban concentrations in certain areas prone to seismic hazard. These elements are essential to enable the evaluation of economic and human losses. Once the distribution of vulnerability classes is known, the consequences in terms of damage can be simulated rapidly after an earthquake, providing an additional element to the simulation of ground motion via ShakemapTM for a seismic warning system.

For example, in the Lambesc region, if the 1909 earthquake had occurred in 2008, there would have been serious consequences in terms of casualties and economic losses: approximately 430 buildings would have suffered severe levels of damage (D4 and D5), a dozen buildings would have been completely destroyed (D5), and more than 9,400 buildings would have been affected by moderate damage (D2 and D3). Even over a period of 40 years, urbanization development increases the seismic risk of a region (Arette and Corrençon earthquakes simulation). We observed a strong increase in damage, even for earthquakes of moderate magnitudes, with levels of damage comparable to those observed during earthquakes of similar characteristics (magnitudes) in L'Aquila, Italy or Christchurch, New Zealand.

As a final validation of the macroscale method to assess vulnerability, we predict loss for a recent earthquake for which precise description of damage is available.

On April the 7th 2014, an earthquake occurred in the French Alps, with epicentre 6 km southwest of Saint-Paul-sur-Ubaye and 11 km north of Barcelonnette, France. Its magnitude (Mw) was estimated between 4.7 and 4.9 according to different sources and the epicentral intensity felt was VI on the EMS98 scale (**Figure 3. 27**). Acceleration measured at the closest station (few kilometres) was 50 cm/s² (0.05g), a value approximately three times lower than the one to be consider by norm for the design of new structures in that region (Zone IV - 160 cm/s²) according to the new French seismic zoning of 2011. No particular site effects were reported but observed intensities and measured accelerations led to acknowledge some directivity effects, already experienced in past events of the region.

Habitants close to the epicentre left their houses and moments of anxiety were reported. Damage to structures was spread, with 272 buildings concerned; most with slight some with moderate damage.



Figure 3. 27 – Macroseismic map of Barcelonette earthquake April the 7th 2014. Modified from report BCSF (BCSF201-R1)

Vulnerability class distributions are calculated for the region with the GVM proxy obtained from SVM only. Damage to structures is predicted using the observed intensities as the seismic demand. **Figure 3. 28** shows the number of buildings damaged, resulting from the evaluation. In overall, as a mean value, 255 buildings are expected to suffer damage (8% of the total in the region of intensity V and VI). 233 slight (D1) and 22 would suffer moderate damage (D2). No severe damage to buildings is to be expected (D4 or D5). The prediction corresponds closely to the observed number of buildings that suffered the consequences of the ground shaking (272 buildings total). The suitability of the method is thus validated with a modern earthquake.

In this study, validations of the method were performed with historic and a modern earthquake and based on reported macroseismic intensities as ground motion. Forecasted intensities as produced by ShakemapTM might be available minutes after an earthquake, which combined with vulnerability estimations would allow additionally a prediction of damage in almost real-time. This information is of outermost importance for the first actions of a crisis management campaign.



Figure 3. 28 - Evaluation of the level of damage for the Barcelonette earthquake scenario considering 2008 urbanization and using the GVM proxy obtained from SVM. Damage is grouped by slight D1 (*left*) and moderate D2+D3 (*right*) according to the EMS98 damage scale. Color scale gives the number of buildings per damage levels. Total numbers of predicted damaged buildings for the entire region are indicated (mean and standard deviation)

Data mining methods, which were used to define the best relationship between attributes and vulnerability class during the learning phase, appear to be well suited to the large-scale assessment of seismic vulnerability and thus to the simulation of seismic damage.

However, a rapid estimation of the hazard (accelerations and intensities) is a complicated task, which requires the combination of real ground shaking measurements (i.e. seismic stations network), application of predictive equations, consideration of site effects, and prompt collection of in-situ data from concerned habitants. These estimations deal large amount of uncertainties, and even more if the information to constrain ground motions is scarce. In France, a work group within RAP (Accelerometric Permanent Network) developed the firsts shakemapsTM with application for French events. The tool follow the methodology of USGS Shakemap (Wald *et al.*, 1999). Ground-motions and intensities are estimated from predictions with soil amplifications, corrected with observed ground motions and reported intensities.

The observatory system of ISTerrre (Grenoble, France) provided shakemaps of PGA and intensities 5 minutes after the earthquake. For this particular event, only few stations measured accelerations near the epicentral region, and rapid prediction of hazard were based almost entirely on the application of prediction equations. In addition, site effects due to soil conditions were not included because of the lack of detailed soil maps. As a result, estimations gave almost circular isoseists with an epicentral intensity of V (**Figure 3. 29**). Damage distribution calculated with this input hazard predicted in average only 6 buildings with slight damage.



Figure 3. 29 - Evaluation of the level of damage for the Barcelonette earthquake scenario considering 2008 urbanization and using the GVM proxy obtained from SVM and intensities estimated in almost real time by Shakemap (RAP).

This shows that the estimation of the hazard would play an important role for damage modelling using this intensity-based methodology. These almost real-time estimations are being perfection in countries like US, and the rapid and massive incoming of information from Did You Feel It (DYFI) population-filled questionnaires (Atkinson and Wald, 2007) is of great importance to constrain intensity predicted values. Results are promising.

At the same time, if the estimation of the hazard is appropriate, the vulnerability estimations obtained from datamining methods are both pertinent and sufficient for a global loss analysis. In the following chapter, a sensitivity test on damage results is done for the hazard and the vulnerability models.

Chapter 4

Loss estimations. From earthquake scenarios to building damage, a comprehensive uncertainty analysis

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4.1. Introduction

Earthquakes generate a variety of economic and human impacts. These effects can be divided in direct economic losses, typically measured in terms of property damage, building contents loss, business inventory loss, injuries and deaths; and indirect economic losses such as business interruption, relocation expenses, earthquake-induced supply shortages, demand reductions and income losses. In addition, there may be ripple effects throughout the economy. Indirect losses may occur in economic sectors not sustaining direct damages (Brookshire *et al.*, 1997). More recently, awareness of sociological and psychological indirect effects as well as potential environmental impacts has been articulated, but to this date there has been little measurement (Whitehead and Rose, 2009).

To obtain a consistent measure, the actual damage state is usually linked to monetary unit (dollars) losses of the capital stock and the indirect losses, as well as to the number of human fatalities. Estimating realistic earthquake economic impacts can be a really complicated task, and due to the large number of uncertainties involved in the process, it can only be done approximately. In addition, these estimates can fluctuate months or years following large earthquakes.

The estimation of possible losses due to future earthquakes is vital for emergency planners and for the insurance and reinsurance industries, and potentially also for seismic code drafting committees (Bommer and Crowley, 2006). But also after the events, relief efforts can be significantly benefitted by the availability of rapid estimation and mapping of expected damage and casualties (So and Spence, 2012). One of the key strategic activities of disaster risk management is the catastrophe risk assessment, which requires the use of reliable methodologies that allow an adequate calculation of probabilistic future losses of all exposed elements. These earthquake loss models can be classified as probabilistic, producing probable loss using a stochastic event catalogue which represents a sample of possible future earthquakes, or as deterministic, estimating probable losses caused by an specific (usually critical) single event. They are based on limited data, speculation and increasingly on analytical models.

Earthquake loss computations typically use one of three general approaches: empirical, analytical or hybrid (semi-empirical) (see Chapter 2). The lack of historical loss data in

moderate-to-low seismic prone regions (especially to the high damage state) encourages the use of analytical and semi-empirical approaches. These models involve a multi-step process where seismic hazard, exposure, vulnerability, and damage/loss must be estimated and combined. Loss estimations are thus subjected to many large uncertainties associated with the input parameters at every step. Identification, characterisation and appropriate treatment of the uncertainties are amongst the major challenges associated with the development of earthquake loss models (Bommer and Crowley, 2006).

Many earthquake loss models are now available, which propose a complete analytical/semi-empirical estimation of damage, loss or more generally risk before or after the event occurred (e.g. HAZUS, GEM, CAPRA, PAGER). However, the treatment of uncertainties is usually not clearly known or not handled in a fully comprehensive way.

At present, uncertainty is usually studied through sensitivity analysis. Many studies have been published in which the sensitivity of probabilistic seismic hazard estimates (PSHA) to various input parameters has been systematically explored. However, the uncertainty in an earthquake loss model is obviously much greater than that in a seismic hazard model since it is compounded by the uncertainties associated with each step of the calculation, including not only hazard uncertainties (including site effects), but also exposure and vulnerability. Losses expressed in financial units are also subjected to the uncertainty in assigning costs to physical damage. Only a handful of sensitivity studies for earthquake risk models have been published (e.g., Spence *et al.*, 2003; Bommer and Crowley 2006; Remo and Pinter, 2012; Tyagunov et al., 2014), systematic and comprehensive explorations of uncertainties in earthquake loss models have yet to be presented in the literature.

This chapter presents a comprehensive uncertainty analysis for a semi-empirical deterministic earthquake loss model, which is oriented generally to an European, and more particularly to a French seismicity and vulnerability context. In the first part, three ground motion prediction equations (GMPE) are presented and tested against instrumental data from France. A comparison between predicted and observed ground motion is done, and the prediction with smaller residuals is highlighted. In the same way, observed and predicted intensities calculated using a combination of ground motion prediction equations and ground motion to intensity conversion equations (GMPE-GMICE) and directly using intensity conversion equations (IPE) are compared for fifteen French earthquakes.

The full estimation from a deterministic set of earthquake scenarios, to probable number of damaged buildings in a typical European city is presented in the second part. A detailed analysis of uncertainties is carried on at every step, and the final combined uncertainty is calculated. The last part is dedicated to study particular cases, like the evolution of damage and risk when structural improvements are performed to buildings. Cost-Benefit curves are created, which could guide stakeholders through investment decisions or risk acceptance.

4.2. Testing GMPE estimates against observations in France

Over the last years, many ground motion prediction equations (GMPE) have been developed worldwide. At a relatively fast rate, old equations are improved and new equations are created using larger and enriched earthquakes datasets, enhanced site-effects evaluations, detailed fault representations, or simply better regression techniques. These studies provide to engineers, the probable ground motions new designed structures will have to withstand and are an important part of any earthquake loss estimations.

The French Accelerometric Network (RAP) web service provides accelerometric data recorded on the French territory by the regional networks (www-rap.obs.ujf-grenoble.fr - last accessed April 2015). It has been operating since 1995 with an increasing number of stations installed with time (Péquegnat et al., 2008). The dataset of this study consists of 1566 recorded pairs of ground motion parameters, in particular peak ground accelerations (PGA) obtained from the maximum absolute value of the acceleration time-history in both horizontal directions (the geometric mean was derived). It contains earthquakes felt in metropolitan France with Mw larger than 3.0 and hypocentral distances up to 800 km between 1995 and 2007. The dataset was prepared during the NERA research and development project (Péquegnat et al., 2011; Roca et al., 2011). In order to only consider recordings of engineering interest, we filter the dataset only including mean PGA values higher than 1 cm/s^2 . The final ground-motion dataset contains 242 records from events with Mw ranging between 3.0 and 5.5, and hypocentral distances up to 350 km (86% of data recorded within 100 km). The earthquakes mainly belong to the seismically active part of France (i.e., Alps, Pyrenees and Lower Rhine Embayment), which can be classified as shallow crustal regions (Delavaud et al. 2012). Regarding site conditions, only some stations have confident Vs_{30} estimations. The majority are classified according to the four ground categories defined in Eurocode 8: A, B, C and D corresponding to a mean Vs₃₀ of 800, 550, 250 and 100 m/s respectively. Magnitudes

have all been converted to Mw and both epicentral and hypocentral distances are available. Since magnitudes are small, the size of fault planes or the styles of faulting have negligible influence in the final ground motion.

Previous works of Beauval *et al.*, (2012) and Tasan *et al.*, (2014) have identified two models as best fitting French accelerometric data: Cauzzi and Faccioli (2008) and Akkar and Boomer (2010). However, the dataset used in those studies were smaller the one used here. We have chosen three recent models for testing the accelerometric dataset:

- Akkar *et al.* (2014) (AK14) - an improvement of Akkar and Bommer, (2010) - presents the latest generation of ground-motion models for the prediction of the geometrical mean of horizontal elastic response (pseudo-) spectral accelerations, as well as peak ground acceleration and velocity, derived using pan-European databases, for magnitudes ranging Mw 4 to 7.6, at distances up to 200 km (epicentral, hypocentral and Joyner and Boore distance metrics). The spectral period range is 0.01s - 4s. The model has been developed from data recorded in Europe and Middle East. This improved version includes a nonlinear site amplification function that is a function of Vs₃₀ and reference peak ground acceleration on rock.

- Cauzzi and Faccioli (2008) (CF08) model predicts geometrical mean of accelerations for magnitudes ranging from 5 to 7.2, at distances up to 150 km (hypocentral distance). The spectral period range is 0.05s - 20 s. The equation is based on a worldwide crustal earthquake dataset. 80% of this dataset comes from the Japanese K-NET strong-motion network, and 5% comes from Europe and Turkey. Site conditions are included either directly using Vs30 as the predictor variable or using the Eurocode 8 ground categories.

- Ameri *et al.* (2013) (AM13) a new equation developed during SIGMA project (SIGMA-2013-D2-92) predicts geometric mean of the horizontal components for accelerations over the spectral period range 0.01s-3s. The database is composed by strong-motion recorded in the broader European and Middle Eastern area, and enriched with a large number of data from small-to-moderate magnitude earthquakes, mainly from France and Switzerland. The magnitude and distance range of validity are Mw: 3 to 7.6 and epicentral or Joyner-Boore distance from 0 to 200 km. Site-effect models based on Vs₃₀ and on EC8 site classes are included. A regional stress-drop model for French events is proposed which allows

explaining part of the between-event variability observed at short spectral periods for small magnitude events.

These three models have been selected from an extensive list of GMPES available in literature. They are modern models that fulfil basic selection criteria (Cotton *et al.*, 2006). The equations have been developed for active shallow crustal regions while CF08 and AK14 (an improved version of Akkar and Boomer 2010, extended to lower magnitude levels) have been selected within the SHARE project (Delavaud *et al.*, 2012). AM13 has been developed to be particularly applicable in France, since it includes French events in the lower magnitude level and it was strongly recommended for this study (Cotton personal communication).

The equations are tested against the dataset previously described. It is worth noticing that two of the GMPEs are applied below their magnitude validity limits. We refer to Beauval *et al.*, (2012) for a detailed discussion on the regional dependence of prediction equations, and on the use of them outside their validity limits.

We perform residuals analysis, which enables to evaluate the fit between models and observations. Residuals are defined as the difference of PGA between the observation and the prediction in terms of the logarithm, normalized by the standard deviation of the model. **Figure 4. 1a** shows the histograms of the residuals with the fitted Gaussian distribution for each GMPE tested (black line). The mean and the standard deviation are indicated. The standard normal distributions representing each model (red curve) are also superimposed. With a mean of the residuals close to 0 and a standard deviation close to 1, CF08 is the model that fits the data the best. AK14 comes in second place with also a suitable fit regarding the mean of residuals but with a higher variability (**Figure 4. 1a** – second row).

Finally, AM13 generate residuals with a mean shifted towards higher values (positive residuals means that the model under predicts the values), although providing a rather good variability. It is worth noticing that for this later model and due to the lack of information, we could not include the French-specific stress-drop term in the calculations. We cannot therefore, fully judge the pertinence of this model in this study. The stress-drop term is unluckily to be precisely known minutes after an event, which would make this model not practical for a situation where almost-real-time estimations of earthquake effects are envisioned. Therefore, there is a trade-off between time and accuracy that need to be analysed depending on the objectives and/or the means of the assessment. Results including additional



terms in prediction equations may lead to better ground-motion estimations, but will require more time and efforts to supply the results.

Figure 4. 1 - Testing three ground-motion prediction models against accelerometric French data. Column (a): histogram of residuals superimposed on the standard normal distribution representing the model (*red curve*), a residual corresponds to $[Log(observation) - Log(prediction)]/\sigma$. Column (b): distribution of residuals versus magnitude (0.1 magnitude binning). Column (c) and (d): distribution of the residuals with respect to source-site distance (5 km and 10 km distance binning respectively). Squares: mean of residuals, error bars correspond to ±1 standard deviation of model (normalized residuals). (Mean: mean normalized residuals, Std: standard deviation of normalized residuals). Note changes in y-axes in columns b, c and d

In order to highlight potential trends, residuals are plotted against magnitude (Figure 4. 1b) and versus source to site distances in the near field (Figure 4. 1c) and the far field (Figure 4. 1d).

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For CF08 the mean of residuals have no specific trend regarding magnitude, and they are contained within one standard deviation (dashed red lines). They are rather stable also with source-to-site distance with a slight under estimation at the far field (positive residuals). For the near field, where damage would be expected, the model is appropriate and has no particular trend. It is important to emphasize that in the far field, the small number of recordings (with significant PGA) gives only few points to perfectly constrain the results. Similar remarks can be done for AK14, except that residuals show a larger dispersion. Regarding source-to-site distances, a stronger trend is observed with an over prediction in the near field and an under prediction for the far field. This suggests that the attenuation with distance as modelled in AK14 does not reproduce observed attenuation of ground motions in France. In AM13 no trend is depicted, regarding magnitude or source-to-site distance. Mean residuals are stable, however the model clearly underestimates the observed values of acceleration (points over one positive standard deviation).

Founded on these results, and as in Tasan *et al.*, (2014), CF08 is established as the model best fitting French accelerometric data and is then selected for this study. The model has a large σ value, which fits well the rather large dispersion observed in the French data set.

4.3. Testing intensity estimates against observations in France

The current use and convenience of macroseismic intensity data in modern seismology has in part been driven by the development of tools like ShakeMap (Wald *et al.*, 1999) and its derivative products. The public easily perceives and understand intensity values, which make communication of earthquake hazard and risk more rapid and effective in comparison with standard seismological or engineering metrics (Allen *et al.*, 2012). In addition, in moderate-tolow seismic prone regions, damage functions derived from physical properties of structures and experimental data are seldom available for all structure types.

Therefore, intensity observations are the only mean to relate ground motion to damage and to afterwards evaluate the vulnerability of different structures types. It is also commonly accepted that adapting damages estimation methodologies from foreign regions to suit local structure types would eventually add more uncertainties that would otherwise be achieved from simple, intensity-based approaches. Consequently, the use of macroseismic intensity continues to have much relevance today. This present-day use of intensity scales (Lagomarsino and Giovinazzi, 2006; Faenza and Michelini, 2010, Silva *et al*, 2013) has driven the development and enhancement of many ground motion intensity conversion equations (GMICE) but also directly intensity prediction equations (IPE).

Using a set of eighty-seven intensity values from fifteen modern French earthquakes (**Table 4. 1**) we perform a residual analysis. Intensity values were taken from BCSF (*Bureau Central Sismologique Français*) reports and intensity maps at the locations of stations where ground motion was also recorded (PGA geometric mean). These intensities are thus average values corresponding to the isoseist region where the station is found.

Location (Region) (Year)	Lat Long. (°)	Magnitude	Distance range to stations (km)	Observed Intensity range	
Nice (Provence-Alpes-Côte d'Azur) (2001)	43.51 N – 7.48 E	4.5	26 - 122	3 - 5	
Rambervillers (Lorraine) (2003)	48.37 N – 6.64 E	5.4	34 - 272	2 - 4.5	
Aucun (Midi-Pyrénées) (2002)	42.93 N – 0.19 W	4.8	15 - 48	4 - 5	
Arudy (Aquitaine) (2002)	43.05 N – 0.32 W	4,4	10 - 32	3 - 5	
Arudy (Aquitaine) (2002)	43.24 N – 0.24 W	4.6	12 - 35	3 - 5	
Arudy (Aquitaine) (2003)	43.10 N – 0.34 W	4.4	8 - 29	3 - 5	
Roulans (Franche-Compté) (2004)	47.30 N – 6.28 E	5.1	25 - 181	3 - 5	
Saintes (Guadeloupe) (2004)	15.77 N – 61.46 W	6.3	33 - 82	4.5 - 6	
Vallorcine (Rhône-Alpes) (2005)	46.03 N – 6.89 E	4.9	10 - 87	2 - 5	
Argelès-Gazost (Midi-Pyrénées) (2006)	42.99 N – 0.05 W	4.9	5 - 65	2 - 5.5	
Argelès-Gazost (Midi-Pyrénées) (2008)	43.04 N – 0.13 W	4.2	9 - 28	2 - 3.5	
Bagnères-de-Bigorre (Midi Pyrénées) (2010)	43.02 N – 0.29 E	4.3	11 - 40	3 - 4.5	
Barcelonnette (Prov-Alpes-C d'Azur) (2012)	44.51 N – 6.69 E	4.5	12	5.5	
Vannes (Bretagne) (2013)	47.73 N – 2.79 W	4.6	15	3	
Barcelonnette (Prov-Alpes-C d'Azur) (2014)	44.51 N – 6.71 E	5.2	9 - 110	3 - 5.5	

Table 4.1 – Catalogue of the fifteen French earthquakes used for the residual analysis.

The dataset contains information from earthquakes with Mw between 4.2 and 6.3 and hypocentral distances up to 270 km. It is worth noticing that in this study we consider M_L (values from BCSF) equivalent to Mw for these magnitudes ranges and therefore no conversion is applied. Observed intensity values range from 2 to 6. Saintes (Guadeloupe) event is included in this study even though it is not a metropolitan France earthquake. First, because it is a shallow crustal earthquake (not subduction), which shares the same tectonic regime as the rest of French tremors; second, to include a larger intensity event on the list.

Residuals are defined as [Observed Intensity – Predicted Intensity]. Intensities are predicted either directly using IPE equations or using a combination of GMPE to estimate PGA, and GMICE to convert it to instrumental intensity. Only mean PGA predicted values and mean predicted intensities are used for this analysis, the variability is included and studied in Section 4.4 and Section 4.5.

For the sake of simplicity CF08 is the only GMPE applied. Moreover, only PGA is used to estimate intensities with GMICEs. Even if many authors demonstrate that PGV is a most appropriate ground motion parameter correlated to damage (Wald *et al.*, 1999a, Boatwright *et al.*, 2001, Kaka and Atkinson, 2004) this is particularly true for the higher damage states, whereas both PGA and PGV perform similarly for the lower damage or intensity levels. In addition, PGA is a parameter commonly available and used worldwide (e.g., Shakemap). Not all GMPEs include PGV in their equations, and not all GMICE have a conversion from PGV to intensities. Finally, in Section 4.2, CF08 was chosen as the best-fitting model for France PGA data, while the fitting between observed and estimated PGV using CF08 (not shown in this work), produced larger residuals.

Two GMICE are used to convert estimated PGA into intensities:

- Atkinson and Kaka (2007) (AK07) developed empirical relationships between instrumental ground-motion parameters (PGA and PGV) and Modified Mercalli Intensity (MMI) using data from felt moderate earthquakes in central United States completed at higher intensities based on observations in California. The predictive relationships include magnitude and distance dependencies.

- Faenza and Michelini (2010) (FM10) used an extensive Italian database to determine new relations between Mercalli-Cancani-Sieberg (MCS) intensity scale and PGA and PGV.

Two IPE are used to derive intensity directly from magnitude and distance pairs:

- Allen et al. (2012) (AL12) developed globally applicable macroseismic intensity prediction equations for earthquakes of moment magnitude Mw 5.0 - 7.9 and intensities (MMI) of degree II and greater for distances less than 300 km for active crustal regions. The IPEs are developed for two distance metrics: closest distance to rupture and hypocentral distance.

- Bakun and Scotti (2006) (BS06) used intensity assignments for French earthquakes of Mw 3.6 - 5.4 and hypocentral distances up to 250 km to develop intensity attenuation models for the Alps, Armorican, Provence, Pyrenees and Rhine regions of France using Medvedev-Sponheuer-Karnik intensity scale (MSK). Each equation is used according to the region of the earthquake (**Table 4. 1**). Saintes (Guadeloupe) earthquake was modelled with the Alps attenuation equation.

Note that different macroseismic scales are used throughout the world (i.e. MMI for USA, MSK, MCS and EMS98 for Europe and JMA in Japan), however according to Musson *et al.*, (2009), no empirical conversion is necessary between the EMS98 (used here) and the MMI, MCS or MSK intensity scales.

It is instructive to assess how well the predictive relations match the observed data for different magnitudes and distances. Figure 4. 2 plots intensity residuals for predictions from the four different models and as a function of magnitude (Figure 4. 2a) and hypocentral distance (Figure 4. 2b).

While a similar rather good assessment is obtained with all four models, AL12 produce the smallest overall residuals (mean residuals -0.08 intensity units, standard deviation 0.79). Only CF08-AK07 has a small global tendency to under predict intensity values (positive mean residual) while the other three models slightly over predict them.

No particular trend is found as a function of magnitude, especially for AL12 with all median residuals falling within the ± 1 intensity residual values. At short distances, where damage is probably expected, all four models produce similar appropriate residuals (distance smaller than 50 km). CF08-FM10 and BS06 tend to under predict intensity values at distances larger than 100 km, while CF08-AK07 is the one closest to zero residuals (dashed red line) at the far field.

In conclusion, the choice of the better intensity model for France is not obvious, especially if we are interested in small to moderate magnitude events at short distances. AL12 is the model giving less overall residuals, without any significant trend as a function of magnitude or distance. In addition, being an IPE, it does not require the calculation of ground motions (PGA) prior to the calculation of intensity.



Figure 4. 2 - Testing four intensity prediction models against observed French data. A residual corresponds to [Intensity Observed – Intensity Predicted]. Column (a): distribution of residuals versus magnitude (0.1 magnitude binning). Column (b) distribution of residuals with respect to hypocentral distance (20 km distance binning). Grey points indicate individual intensity residuals, squares: mean of residuals and error bars: residual standard deviation for the given magnitude or distance bin. (m: mean residuals, sd: standard deviation of residuals)

It is worth noticing that the quality of the dataset could be judged, since the values of observed intensity correspond only to an averaged isoseist value at the location of the stations. Likewise, more records would be preferred to better constrain the results, especially at larger magnitudes and source-to-site distances.

4.4. From earthquakes to damage. Uncertainty Analysis

We position ourselves in this section in a situation where earthquake risk is to be assessed for a city or region before the upcoming of a given event. We perform a semiempirical deterministic approach to predict probable damage to buildings for different earthquake scenarios including a comprehensive analysis of the uncertainties. This physical damage will be translated into loss in the succeeding sections. Following the same methodology presented in Chapter 3 the input information of the hazard is the estimated macroseismic intensity level, while the expected response of buildings is managed through the vulnerability classification of EMS98 scale (vulnerability class A to F) and its damage grades (D0 to D5) (Grunthal and Levret, 2001). **Figure 4. 3** presents the different paths followed in this section. Four intensity distributions are calculated using the prediction equations presented in Section 4.3, in order to study their influence in the final distribution of expected damage.



Figure 4. 3 - Schema describing the different paths taken in this work to estimate damage from earthquake magnitudedistance pairs. The approach presented in Chapter 3 is applied to estimate damage from four macroseismic intensity distributions in a 1000-building synthetic city with different vulnerability distributions.

4.4.1 Estimation of intensity

Nine earthquake scenarios (magnitude-distance pairs) are selected: Mw: 5, 6 and 7 at distances of 10, 50 and 100 km. We rely on a ground-motion prediction equation (Cauzzi and Faccioli, 2008) (CF08) which estimate peak ground acceleration for these deterministic events. Once the shaking distribution is estimated, we convert to instrumental intensity through the use of ground motion to intensity conversion equations. In this process, added to the uncertainty in the prediction of instrumental ground motion (PGA), we need to also account for the uncertainty of the conversion between ground-motion and intensity.

To combine this variability, we do a Monte Carlo sampling of 1,000 points of the calculated PGA distribution with the GMPE. Each of these ground motion values are converted to intensity using the GMICE proposed, which gives 1,000 distributions of intensities (mean and σ). Once again a Monte Carlo sampling of 1,000 intensity values is done for each estimated distribution. All the sample points are merged to give the final intensity distribution (1,000,000 points) for which a normal distribution can be fitted. This final distribution with total variability σ^{total} includes the uncertainty in the estimation of PGA using a GMPE σ_{GMPE}^{PGA} , and the uncertainties in the conversion of PGA to intensity using a GMICE σ_{GMICE}^{I}

Intensities are also calculated using intensity prediction equations. These IPE usually specify standard deviations of approximately one intensity unit. For these cases the uncertainty is directly calculated from the IPE. $\sigma^{total} = \sigma^{I}_{IPE}$

Figure 4. 4 presents the distributions of estimated intensities using the four different paths for all nine magnitude-distance pairs. For BS06 only the Alps regional equation is used. The mean and the standard deviation of the fitted normal distribution (black curve) are indicated for each case.

For any particular earthquake scenario, differences in the estimated mean value appear between the prediction equations, especially for the higher intensities (larger magnitudes, shorter distances), in some cases differences as high as two intensity levels. For example, for a Mw 5 at 10 km, CF08-AK07 predicts mean intensities of 5, while CF08-FM10 and BS06 mean intensities of 7. Note that macroseismic intensity is not linear. One intensity level difference for low intensity values in not the same for the high ones. Indeed, as established in Section 4.3 and for probable French events (Mw \leq 6), CF08-AK07 predicts smaller mean intensities (under prediction), while CF08-FM10 and BS06 calculate the larger mean intensities (over prediction). For a Mw 7 at 10 km, AL12 estimate mean intensities of 8 and CF08-AK07 of 10. For lower predicted mean intensities (I_{EMS98} \leq V), all equations give similar results.

Regarding the standard deviation, it seems clear that using a combination of GMPE and GMICE (top row of each magnitude-distance pair) the variability is larger than using directly an IPE (bottom rows). This trend is particularly clear for scenarios with mean intensities larger than V.



Figure 4. 4 – Estimated intensity distributions for nine earthquake scenarios (*magnitudes in columns, distances in rows*). Intensities are calculated by means of two approaches which use a combination of GMPE and GMICE namely, Cauzzi&Faccioli 2008 – Atkinson&Kaka 2007 (CF08-AK07) and Cauzzi&Faccioli 2008-Faenza&Michelini 2010 (CF08-FM10) and two directly using IPE; Allen et al 2012 (AL12) and Bakun&Scotti 2006 (BS06). The mean (rounded to the unity) and the standard deviation (rounded to one decimal) of the fitting normal distribution (*black curve*) are indicated.

Undoubtedly, these methods combine the uncertainty in the estimation of PGA to the uncertainty in the conversion to intensity, increasing the overall standard deviation in the estimation. For all the scenarios AL12 and BS06 have a standard deviation of approximately one intensity unit ($\sigma \approx \pm 1$), while they can get as large as 1.7 or 1.8 for CF08-AK07 and CF08-FM10 respectively for an earthquake of Mw 7 at 10 km.

In conclusion, the results show the dependence of estimates with the equations selected for the calculations, especially for the intensity levels of engineering interest. Mean differences of two intensity levels will have a large impact in the estimation of probable damage, as will be shown later. However, the direct use of IPEs would lead to a reduction in overall uncertainties when compared with methods which use a GMPE-GMICE combination. In addition, Allen and Wald, (2009) demonstrated clear dependencies on the combination of some GMPEs and GMICEs for the aggregated global ground-motion data over all magnitude and distance ranges, not studied in this work.

IPEs can easily be used in near real-time earthquake response systems, where the only information required in the aftermath of the event is the magnitude and the location. However, the estimations can only be adjusted by field surveys or by the population response of macroseismic questionnaires (e.g. "Did you feel it?) (Atkinson and Wald, 2007). Using PGA and transforming it to intensity on the other hand, indirectly includes part of the sites effects, making adjustments easier and automatic. The downfall is the need of numerous stations to be able to correctly constrain the prediction results.

We do not intend to do a complete estimation of the probable hazard in this work (probabilistic seismic hazard assessment). We propose only nine earthquake scenarios for which we estimate accelerations and intensities, i.e. a deterministic approach. We do not include the probability of occurrence of these scenarios.

4.4.2 Estimation of vulnerability

In order to capture all sources of uncertainties in the estimation of damage, we create a synthetic 1,000-building city with a building typology distribution average of a classical European city (**Table 4. 2**) (Spence *et al.*, 2012). In the EMS98 scale, the correspondence of each building typology to a particular vulnerability class is defined by linguistic terms for which we propose a numerical translation. "Most likely vulnerability class" (more than 70%),

"Probable range" (less than 30%) and "Range of less probable, exceptional cases" (less than 5%). As in Chapter 3, Section 3.6.1, we also consider the uncertainty in the estimation of the most probable vulnerability classes EMS98 given by Support Vector Machine using two attributes (i.e., 63% of correct assignment).

From this city, we created 1,000 possible vulnerably distributions corresponding to the building typology distribution. This was achieved through an automatic random selection process similar to a multi-agent system. Each typology has a most likely, a probable and a less probable range of vulnerability class according to EMS98 scale (**Table 4. 2**). I addition, each building has more than 63% probability of being in the correct vulnerability class, and less than 37% of being in the immediately lower or upper vulnerability class.

Note that this city is a synthetic average of Europeans cities, used as an example only and which turned out to be less vulnerable than the average French cities.

Table 4. 2 – Distribution of EMS98 building typologies of a typical European city created for this study. ERD: Earthqu	ake
resistant design. Ranges of vulnerability classes according to building typology.	

	Building typology EMS-98	Percentage	(A)	(B)	(C)	(D)	(E)	(F)		
Masonry	Simple stone	5 %	I	-0						
	Massive stone	15 %	0							
	Unreinforced, with manufactured stone units	15 %	I	0	1					
	Unreinforced, with reinforced concrete floors	20 %		l-	0	I				
	Reinforced or confined	5 %			I-	0	1			
Reinforced concrete	Frame without ERD	10 %	ŀ		-0	-1				
	Frame with moderate level of ERD	7 %		ŀ		-0	-1			
	Frame with high level of ERD	3 %	IIOI							
	Walls without ERD	10 %		I	0	1				
	Walls with moderate level of ERD	7 %			I-	0	1			
	Walls with high level of ERF	3 %				I	0	1		

• most likely vulnerability class; I---- probable range; I---- range of less probable, exceptional cases

4.4.3 Estimation of probable damage

We calculate probable damage following the approach based on EMS98 scale (as in Chapter 3). For one particular earthquake scenario, we incorporate the intensities distributions calculated by four methods in Section 4.4.1 as the input hazard. Note that the Gaussian

distributions should be sampled within meaningful limits.

A large level of truncation (e.g., $\pm 3 \sigma$) allows a higher variability of intensities having a direct impact on the predicted damage distributions. In order to include only the most probable values, we truncate the intensities distribution to one standard deviation ($\pm 1 \sigma$) thus including 68% of values. As a result, the total combined standard deviation for the predicted damage distribution will be reduced. Calculated intensities are considered uniform throughout the city (no spatial distribution of intensities), which is equivalent as seeing the city as a point in space. From the building response side, we incorporate one typical European city with 1,000 possible distributions of vulnerability class according to EMS98 (Section 4.4.2).

To reduce the number of results, and to consider only some earthquake scenarios capable of producing damage in a typical European city, we estimate damage for earthquakes of Mw: 5, 6 and 7 at 10 km only. Earthquakes of the two smaller magnitudes have occurred several times in metropolitan France (Lambert, 1997) and considering the constant population growth seen in European cities (UN Population Division. http://www.un.org), there is consequently a non-negligible probability of occurrence of these damaging earthquakes near cities or towns in the future.

Figure 4. 5, Figure 4. 6 and **Figure 4. 7** show, as a probability of exceedence, the expected number of damaged building for three different levels of damage corresponding to D1 (Slight), D2+D3 (Moderate) and D4+D5 (Severe) as defined by the EMS98 macroseismic scale and for earthquakes of Mw 5, 6 and 7 at a distance of 10 km respectively. Since the total number of buildings in the synthetic city is 1,000, the results can be easily converted from number of damaged buildings to percentage of damaged buildings. Y-axes represent the probability to exceed a particular number of damaged buildings. As additional information, the mean and the standard deviation of the predicted damaged distribution are indicated for each damage type.

Due to the combination of all uncertainties, standard deviations are large. The most probable value (MPV) (i.e. number of damaged buildings, by range of fifty, with the highest probability of occurrence) is perhaps a most representative value to describe the expected damage. The MPV is also given for each damage type, together with the probability attached to it. To be able to compare results from one method to the other, the exceedance curves, the mean, the standard deviation and the MPV have to be analysed together.



Figure 4. 5 – Number of damaged buildings (Probability of exceedance) for a Mw: 5 at 10 km earthquake scenario. Damage is estimated for a 1,000-buildings city with 1,000 different probable vulnerability distributions and using four distributions of intensities (truncated to $\pm 1\sigma$). Intensities are calculated with a) CF08-AK07. b) CF08-FM10 c) AL12. d) BS06. Slight Damage (*yellow line*) corresponds to D1 (EMS98 damage grade). Moderate Damage (*orange line*) to D2+D3. Severe Damage (*red line*) to D4+D5. Mean and standard deviation of the expected damage distribution are indicated, as well as the most probable value (MPV) (50 buildings range) with its probability.



Figure 4. 6 – Number of damaged buildings (Probability of exceedance) for a Mw: 6 at 10 km earthquake scenario. Damage is estimated for a 1,000-buildings city with 1,000 different probable vulnerability distributions and using four distributions of intensities (truncated to $\pm 1\sigma$). Intensities are calculated with a) CF08-AK07. b) CF08-FM10 c) AL12. d) BS06. Slight Damage (yellow line) corresponds to D1 (EMS98 damage grade). Moderate Damage (orange line) to D2+D3. Severe Damage (red line) to D4+D5. Mean and standard deviation of the expected damage distribution are indicated, as well as the most probable value (MPV) (50 buildings range) with its probability.



Figure 4. 7 – Number of damaged buildings (Probability of exceedance) for a Mw: 7 at 10 km earthquake scenario. Damage is estimated for a 1,000-buildings city with 1,000 different probable vulnerability distributions and using four distributions of intensities (truncated to $\pm 1\sigma$). Intensities are calculated with a) CF08-AK07. b) CF08-FM10 c) AL12. d) BS06. Slight Damage (yellow line) corresponds to D1 (EMS98 damage grade). Moderate Damage (orange line) to D2+D3. Severe Damage (red line) to D4+D5. Mean and standard deviation of the expected damage distribution are indicated, as well as the most probable value (MPV) (50 buildings range) with its probability.

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Expected damage differs depending on the equations used to estimate intensities, especially for the most destructive scenarios. As it is expected, the methods predicting higher mean intensities produce larger or more severe expected damage. The uncertainty in damage distributions seems smaller for methods depicting intensities directly from IPE (plots c and d from **Figure 4. 5**, **Figure 4. 6** and **Figure 4. 7**). However, the influence of the variability in the intensity distribution on the variability of expected damaged cannot be analysed with these plots since mean intensities differ from one method to another. This analysis will be performed in section 4.5, as well as the comparative evaluation on the influence of the intensity and the vulnerability variability.

Uncertainties can be graphically linked with the slope of curves - the flatter the curves the larger the uncertainties - (a prediction with no uncertainties would have an abrupt vertical step at a particular number of damaged buildings). They can also be depicted from the standard deviation compared to the mean value, and finally, with the probability of occurrence of the most probable value (a higher value would indicate less variability). As it can be seen, uncertainties are rather large independently of the method used.

The choice of the hazards models selected in any risk evaluation has a strong influence on the predicted damage. However, there is a closer agreement for earthquakes scenarios with less destructive potential. For example, in **Figure 4. 5** (Mw: 5 at 10 km) all four methods predict no severe damaged buildings as the MPV with a relative high probability.

The final uncertainty σ^{total} combines the uncertainty at each level of the hazard estimation σ_{GMPE}^{PGA} ; σ_{GMICE}^{I} ; σ_{IPE}^{I} as well as the uncertainty in the vulnerability classification for a given building typology σ_{EMS98}^{Vul} . (note that only the uncertainty in the GMPE is accounted for).

This variability combined makes the final uncertainty exceedingly large. Developers and decision makers should be aware of it when doing damage estimations. In many cases the standard deviation of the estimated damage distribution is as big as the mean value. The most probable expected number of damaged buildings (MPV by a range of 50) has confidence values as low as 30%.

Even though estimations are uncertain and they differ depending on the method used, some general trends can still be identified with relative high confidence.

For an earthquake of Mw 5 at 10 km of a typical European city or town (**Figure 4. 5**), no severely damaged or collapsed buildings are to be expected. According to AL12 between 10 and 15 % of buildings (mean 12%) are predicted to suffer slight damage, while 4% would experience moderate damage (**Figure 4. 5c**). In the most favourable case (**Figure 4. 5a**), 5% of buildings might suffer slight damage and 1% moderate damage. Other estimations predict between 18-22% and 10-13% damaged buildings respectively.

An earthquake of Mw: 6 at 10 km (**Figure 4. 6**) would probably lead to exceptional building destruction, which is the main cause of human casualties. Events with these characteristics are part of metropolitan French history (e.g. Lambesc earthquake 1909). Between 0 and 5% of the buildings would suffer severe damage, between 20-35% would experience moderate and 22-26% slight damage. In overall 50% of the buildings would be affected all damage grade included. There is a fairly good agreement between all methods on the MPV for all damage levels. Note that uncertainties are large and expected number of damage buildings can be depicted with a decreasing confidence.

For a Mw: 7 at 10 km (Figure 4. 7), collapsed buildings are most probably expected. Due to the lack of intensity information at these high magnitude levels, it is senseless to compare which of the hazard methods is most adapted (see Section 4.3). However, all approaches predict severely damaged and collapsed buildings, approximately 5% using AL12 intensities (Figure 4. 7c), and reaching between 25-35% for the other estimations. Larger uncertainties can be seen for the methods of Figure 4. 7a and Figure 4. 7b, compared with methods using IPE to calculate intensities (Figure 4. 7c and Figure 4. 7d). In the formers, and considering severe damage estimations, curves are increasingly flat, standard deviations are huge and MPV have only 30% confidence value. Slight and moderate damage are obviously extensive, 13-25% and 37-52% respectively. According to three of the methods, around 90% of the buildings will suffer any kind of damage (67% according to Allen *et al.*, 2012) which makes this scenario a genuine catastrophe for any European environment.

Overall, uncertainties grow larger for event with important destructive potential. For smaller or farther events, all methods for calculating hazard, and therefore loss, are comparable. Probable damage exceedance curves like the ones presented in this section for a few earthquake scenarios are key elements for any risk assessment, catastrophe preparedness and economic investments decisions. They allow informing on the risk the community is facing, especially if the hazard is also studied in a probabilistic way. Physical damage estimations like these are the base to calculate monetary loss (direct and indirect costs) as well as human casualties, adding another source of uncertainty (correlation costs/damage and casualties/damage) to an already uncertain estimation. We are nowadays capable of doing only broad damage and loss estimation before an earthquake strike near a city.

4.5. Isolating sources of uncertainties

In this section the main sources of uncertainties in the estimation of damage using the proposed intensity-based methodology are discriminated. We analyse the influence of individual variability on the final results, and we highlight the elements having larger impact on the final cumulated uncertainty. These elements should be confronted in priority if we seek to effectively reduce uncertainties in damage estimates.

4.5.1 Hazard variability

In order to study only the sensitivity of intensity variability on the variability of damage, we create four artificial intensity distributions with the same fixed mean value (i.e., VII) and gradually larger standard deviations (i.e. 0.5, 1.0, 1.5 and 2.0) (**Figure 4. 8**). We truncate the distributions to the $\pm 1 \sigma$ range as done in Section 4.4.3 and we perform a Montecarlo sampling of 1,000 points. We also consider a synthetic 1,000-building city (Section 4.4.2 - **Table 4. 2**) but with a fixed vulnerability distribution corresponding to the most probable value of each building typology according to EMS98 scale (no uncertainty included).

Figure 4. 9 presents estimated damage (probability of exceedance) using the four distributions of intensity and for a 1,000-building city with a single vulnerability distribution. The representation and colour-scale is the same as in previous figures.

As expected, damage uncertainties rapidly increase for intensity distributions with larger variability. On the other hand, if intensity estimates are constrained to ± 0.5 intensity units, uncertainties have very small values (**Figure 4.9a**).



Figure 4. 8 – Four intensity distributions with the same mean value and progressively larger standard deviation. These distributions are used to estimate damage following EMS98 scale and to analyze the influence of their variability on the estimated damage distribution.

When the standard deviation of intensities distributions grows higher than one intensity level, damage estimations rapidly lose confidence (**Figure 4. 9c** and **Figure 4. 9d**). The mean value of damaged buildings (even if slightly different for each case) remains comparable. However, standard deviations drastically increase.

Note that the MPV is the same for all cases and all damage level. Nonetheless, with a promptly decreasing probability of occurrence ascribed to it. For the first case (**Figure 4. 9a**) between 250-300 buildings are expected to suffer slight damage with a 100% confidence value. In **Figure 4. 9d**, the same number of buildings are expected as the MPV but confidence level drops down to 54%. For moderate and severe damage estimates, confidences in the MPV drop from 99% to 29% and 65% respectively when standard deviations in the intensity distributions grows from ± 0.5 to ± 2 .

Graphically, it can be seen how the curves grow flatter when the variability in intensity distributions increase. In **Figure 4. 9a** a sudden vertical step is clearly detected at a particular number of damaged buildings, indicating low uncertainties. This step is progressively disappearing for the estimations with larger intensities variability, while the curves flatten.



Figure 4. 9 – Number of damaged buildings (Probability of exceedance) for different intensity distributions. Damage is estimated for a 1,000-buildings synthetic city with a given vulnerability distribution. Distributions of intensities are truncated to $\pm 1\sigma$. Slight Damage (*yellow line*) corresponds to D1 (EMS98 damage grade). Moderate Damage (*orange line*) to D2+D3. Severe Damage (*red line*) to D4+D5. Mean and standard deviation of the expected damage distribution are indicated, as well as the most probable value (MPV) (50 buildings range) with its probability.

4.5.2 Hazard versus vulnerability variability

We analyse in this sub-section the influence of hazard (intensity) variability, compared to variability in the estimation of vulnerability. Two damage estimations are made. In the first case we propose a 1,000-building city with a unique vulnerability class distribution and an intensity distribution with mean VIII and ± 1 standard deviation (**Figure 4. 10a**). In the second example we add 1,000 probable vulnerability distributions for the given building typology distribution (EMS98) while intensity distribution has no uncertainties (mean: VIII $\pm 0 \sigma$) (**Figure 4. 10b**). As it can be seen in **Figure 4. 10**, uncertainties in the estimation of intensities (hazard) have a much larger influence in the total damage variability when compared to the impact of the uncertainties in the vulnerability estimation (using this method to estimate damage). An accurate definition of the hazard term would be more efficient in reducing uncertainties, rather than perfectly defining the vulnerability class. Note that we study the effects on final damage variability and not the exactitude in the estimation. In **Figure 4. 10** the mean values, and the MPV of number of damaged buildings are the same, while the confidence in each evaluation is significantly different.

This outcome is only validated here when damage is estimated with an intensity-based method. Other studies and sensitivity analysis have found however similar results regarding the elements having more influence on the final damage or loss variability, using other loss methodologies. Remo and Pinter (2012) evaluated the sensitivity of the Hazus-MH (v 2.0) earthquake model to the selection of seismic hazard data, attenuation functions, soils data, liquefaction data, and structural fragility curves. These sensitivity analyses revealed that earthquake damage, loss, and casualty estimates are most sensitive to the seismic hazard data and selection of the attenuation functions. Tyagunov et al., (2014) presented a study that analyses different uncertainties associated with the hazard, vulnerability and loss components by the use of logic tree. The study performed loss analysis for the city of Cologne, Germany. For the considered set of input parameters, the greatest contribution to the total uncertainty comes from the hazard part (mainly from the assigned maximum magnitudes and selected intensity prediction equations). Bommer and Crowley (2006) studied the influence of groundmotion variability in earthquake loss modelling for building stock in urban areas. They concluded that the variability in ground-motion predictions, being so large, cannot be neglected in the calculation of seismic hazard and consequently in the estimation of seismic risk. Spence et al., 2003 explored the sensitivity of the main inputs to the loss model by

exploring discrepancies between the model predictions and field observations from the 1999 Kocaeli earthquake. The conclusion of this sensitivity study was in overall, that the differences between the observed losses and the losses predicted by the spectral displacement model can be explained by a combination of the uncertainties in the model parameters for both the ground motion and the vulnerability.

In conclusion, according to the results of Sections 4.5.1 and 4.5.2, a reduction of the variability related to the hazard would efficiently decrease the overall uncertainty in damage estimations when using intensity-based loss models. On the other hand, simplified methods to evaluate vulnerability at a large scale (e.g. methods based on datamining techniques) would be adequate or sufficient for a global loss analysis. These vulnerability evaluations, combined with correct and precise hazard estimates (e.g. in the aftermath of an earthquake) would give damage assessments with relatively low variability.



Figure 4. 10 – Number of damaged buildings (Probability of exceedance) for different intensity and vulnerability distributions. Damage is estimated for a 1,000-buildings synthetic city. a) No vulnerability uncertainty. Intensity distribution with mean: 8 and standard deviation: 1. b) No intensity uncertainty. Intensity distribution with mean: 8 and standard deviation: 0 in a city with 1,000 probable vulnerability distributions. Distributions of intensities are truncated to $\pm 1\sigma$.

4.6. On the effects of improving existing building stock

Since nothing can be done to avoid earthquakes from happening, it is on the reduction of their effects that we must place our efforts. Humans need to do as much as possible to act earlier, improve disaster preparedness, mitigate risk, improve building earthquakes codes and increase community resilience to seismic events. Enhancing existing structures response to ground motions is one direct way to get a plausible reduction of that risk.

In recent years, the increased occurrence of induced seismicity has also heightened public concern. Tremors can now occur in regions where little or no natural seismicity was expected. In those regions, the building stock is usually more vulnerable, since no earthquake design rules were to be applied. This seismicity, due to a wide range of anthropogenic activities such as fluid injection and extraction, hydraulic fracturing and mining, can have an important impact on the built environment.

Even for induced seismicity cases, Bommer *et al.* (2015) propose to apply the same risk quantification and mitigation measures that are applied to the hazard from natural seismicity. The consequent risk can be addressed by appropriate financial compensation to property-owners, or by the application of strengthening measures in the built environment, rather than attempting to ensure a threshold on tremors magnitude or ground-shaking amplitude, which has failed so far.

The probable expected reduction of risk when actions are taken to improve the constructions in a community is a crucial piece of information for decision makers and for the insurance industry to work with. Such estimations would help them compare where to target theirs efforts and to quantify the labours they need to mobilize to get a particular desired development in the general building response and therefore a reduction of damage and risk.

Before doing a monetary conversion of physical damage, we perform a quantitative estimation of the probable reduction in the number of damaged buildings for a particular earthquake scenario when different structural improvements take place. This example will be the foundation for the more detailed costs assessments of the following sections.

The study is performed for the same 1,000-building synthetic city presented in **Table 4**. **2** and for an earthquake scenario of Mw: 6 with epicentre at 10 km. As before, the hazard is considered uniform for the entire city (same intensity distribution for all city surface). In order to involve all sources of uncertainties we include in the computations a distribution of calculated intensities, and 1,000 possible distributions of vulnerability for the building typology as in EMS98. For the sake of simplicity, intensities are calculated only with the equation by AL12, since it proved to be one of the best correlated with French data for this magnitude level (see Section 4.3) while having at the same time, a reduced variability.

We represent the physical strengthening of buildings as a change in their vulnerability class, from a most vulnerable to a less vulnerable. A building originally characterized with a given vulnerability class, would improve its seismic performance after the upgrading, and it will behave as a building with a different (lower) vulnerability class. We do not however, detail the exact work needed to achieve these improvements, nor the feasibility or suitability of them in this section. The results have a statistical meaning at the scale of the entire building stock and they are not envisioned as a detailed diagnosis of each building or building class. A most detailed analysis of the reinforcements, as well as their average costs will be studied in the next section.

The mean vulnerability distribution of the city is composed of: 0.9% of vulnerability class A, 25.7% of class B, 46.9% of class C, 18.4% of class D, 7.3% of class E, and 0.8% of class F.

We propose in this exercise three levels of building stock enhancement for the city: Figure 4. 11a -All vulnerability class A buildings to class B, and 50% of class B into class C. Figure 4. 11b - All vulnerability class A and B buildings to class C. Figure 4. 11c - All vulnerability class A and B buildings to class C, and 50% of class C into class D. The damage distribution estimated for the original city (no modification to buildings) can be retrieved in previous Figure 4. 6c. The curves are also plotted in a grey scale in Figure 4. 11 for comparison.

These are only three reinforcements scenarios. Many other possibilities of improvement can be considered. We have deliberately chosen to enhance in priority the most vulnerable classes, with the idea of reducing the number of severely damaged or collapsed buildings first.



Figure 4. 11 – Effects of the improvement of building's resistance in the reduction of damage. Damage probability of exceedance for a Mw: 6 at 10 km earthquake scenario for different vulnerability enhancements. Damage is estimated for a typical European 1,000-building city. Intensity distributions assessed using IPE of Allen et al., 2012. Distributions of intensities are truncated to $\pm 1\sigma$. Idem color code as previous figures, grey curves, estimated damage distribution for the original city.

The reduction in the expected number of buildings can be recognized by a shift to the left (and down) of the curves. In addition, the mean values and the MPV are indicated. Note that the variability (standard deviations) is still important.

At the first level of improvement (Figure 4. 11a) a reduction of expected damaged can be observed for moderate and severe damage, with lowered means values of 13% and 50%
respectively and the MPV decreased of one range level (compare to **Figure 4. 6c**). As it would be expected the mean number of slight damaged buildings vaguely increases, since some buildings that would have moderate or severe damage will have after the reinforcement merely slight damage. The same trend can be found for all levels of improvements.

In **Figure 4. 11b**, all buildings that were class A or B has been reinforced being converted to class C. Severe damage to buildings is no longer to be expected, reducing drastically the probability of humans' life loss. At the same time, the mean number of moderate damaged buildings is reduced a 32% compared to the original city expected damage.

Finally, the third level of enhancement (**Figure 4. 11c**), which will additionally modify 50% of class C buildings into class D, would reduce the mean number of moderate damaged buildings 62% while in this case also reducing the number of slight damaged buildings approximately 16%.

It is worth noticing that, as before, uncertainties are large, and the values of the reduction of probable mean damages should be taken only as an order of magnitude.

This analysis allows only viewing the reduction in the number of damaged buildings for some reinforcements scenarios. However, a comprehensive assessment of the benefits of the improvements cannot be really depicted from these results, since efforts (costs) to enhance structures were not included. At the same time costs for replacement and repair highly depend on the damage state of the construction. Cost-benefits analysis with investments and losses expressed in financial units enables such analysis.

4.7. Loss estimates and cost-benefit analysis

Recent low magnitude events in France like the M 5.1 Ossau-Arudy 1980, M 4.8 Annecy Earthquake (1996) and M.5.2 Barcelonnette (2014) earthquakes have produced substantial damage and economic loss in cities close to the epicenter. Stronger shaking is to be expected for a repetition of historical earthquakes with characteristics comparable to the event that stroke the Italian city of L'Aquila in 2009. These factors have raised the awareness of political and private responsible to understand the risk their cities might incur. Retrofitting existing buildings is an option to substantially reduce the expected losses from an earthquake.

Benefits of mitigation actions

The design of a mitigation program depends on the benefits and cost of different loss reduction measures to the relevant interested parties. Cost-benefit analyses are a system of procedures for evaluating decisions that have an impact on society. In an earthquake loss model, these analyses compare the cost of mitigation measures (e.g. to strengthen buildings) with the cost induced by the effects of an earthquake or a set of probable earthquakes (e.g. cost of repair and replacement of damaged buildings).

After the specification of the problem, the identification of the interest parties and the definition of the alternative options, a cost-benefit analysis determines the expected losses to systems with and without the mitigation alternatives and the direct cost of the improvement actions. It then calculates the attractiveness of the mitigation options and chose the best alternative by maximizing the economic benefit or savings.

These assessments require therefore three principal elements. i) An estimation of the number of damaged buildings and their damage grade for all reinforcement options and for an earthquake scenario, or more generally for a probable set of ground-motions parameters (using a probabilistic seismic hazard assessment). ii) A conversion between physical damage and direct cost of repair and replacement (and eventually indirect costs), and iii) An evaluation of the cost of the mitigation actions, for example, to reinforce buildings.

These elements add to the final analysis a great part of their own uncertainty. The repair and replacement cost related to the damage state of a structure, and the cost of reinforcements highly depends on the structure type. These economic analyses are thus, simply broad estimations, with sense only at a large scale and eventually regionally dependent. They should be used with consciousness of the large level of uncertainties involved.

For the current analyses, the reference alternative is the current vulnerability of the structures without a mitigation measure in place. This reference point allows evaluating how well other alternatives perform. In general, if there is sufficient political dissatisfaction with the proposed mitigation options and/or the perceived benefits (i.e., reduction of losses) are less than the expected cots to mitigate the risk, then the reference alternative is maintained (no reinforcements to the structures).

Economic loss

The estimation of number (or percentage) of damaged buildings is done in this section for three earthquake scenarios; Mw 5, 6 and 7 at 10 km and for the 1,000 building city of **Table 4. 2**. We follow the same intensity-based approach presented in previous sections. We use a combination of the results by the four methods (CF08-AK07; CF08-FM10; AL12; BS06) with equal weighting factor. For each of the four estimated damage distributions (and each damage grade) a Monte Carlo sampling of 5,000 points is done. All values are merged into a new dataset where the mean and standard deviation is re-calculated (20,000 points). For each reinforcement scenario, the vulnerability of the synthetic city is respectively changed, and the damage calculations are restarted.

The cost of repair and replacement depends mainly on the damage state of the structure, but also on the structure type. These relations are usually named "consequence models" or simply loss-to-damage functions. Their models provide the ratio of cost of repair to cost of replacement for a set of damage states. They are commonly derived empirically based on information regarding the repair costs claimed by householders after the occurrence of earthquakes. Consequence models have been developed for regions where earthquake damages to property are frequent (Italy, Greece, United States of America, Turkey).

We have selected three of them in this section to develop an European model with particular application to France. A pondered average of the cost ratios of the damage states equivalent to the ones considered in this work is estimated (D0 to D5). Note that some models use different damage scales, and adjustments need to be done. **Table 4. 3** shows the models with their main loss-ratio values. For this work, the structures types in the model for Greece (Kappos *et al.*, 2006), are merged in one general model using a 60% for URM-buildings loss ratios and 40% of RC-buildings. For the general average model the same weight is given for each of the three models in **Table 4. 3**.

The resulting consequence model is shown in **Table 4. 4**, and is the one used in this work to calculate economic losses from physical damage. Note that these values are ratios between the costs of repair to the cost of replacement (i.e. reconstruction of the building). These ratios can be seen as the percentage of the value of the building that need to be invested to repair it, or likewise, the percentage of the value of the building that was lost.

_	Kappos et al., (2006) – Model for Greece. Structure type specific					
	Damage state label	Range of loss index (%)	Central index (%)			
es	None	0	0.0			
	Slight	[0 – 1]	0.5			
uctur	Moderate	[1 – 10]	5.0			
c Str	Substantial to heavy	[10 – 30]	20.0			
R	Very heavy	[30 – 60]	45.0			
	Collapse	[60 – 100]	80.0			
	None	0	0.0			
res	Slight	[0 – 4]	2.0			
ructu	Moderate	[4 – 20]	12.0			
M St	Substantial to heavy	[20 – 50]	35.0			
UR	Very heavy	[50 – 100]	75.0			
	Collapse	[50 – 100]	75.0			
Di Pasquale and Goretti (2001) – Model for Italy. All building types						
	DI Pasquale and Gore	etti (2001) – Model for Italy. Ali	building types			
	Di Pasquale and Gore Damage state label	Range of loss index (%)	Central index (%)			
	Di Pasquale and Gore Damage state label None	Range of loss index (%)	Central index (%) 0.3			
bes	Damage state label None Slight	Range of loss index (%) -	Central index (%) 0.3 4.1			
ng types	Di Pasquale and Gore Damage state label None Slight Moderate	Range of loss index (%) - - -	Central index (%) 0.3 4.1 21.8			
ouilding types	Di Pasquale and Gore Damage state label None Slight Moderate Heavy	Range of loss index (%) - - - - -	Central index (%) 0.3 4.1 21.8 41.0			
All building types	Di Pasquale and Gore Damage state label None Slight Moderate Heavy Very heavy	Range of loss index (%)	Central index (%) 0.3 4.1 21.8 41.0 78.1			
All building types	Di Pasquale and Gore Damage state label None Slight Moderate Heavy Very heavy Collapse	Range of loss index (%)	Central index (%) 0.3 4.1 21.8 41.0 78.1 81.4			
All building types	Di Pasquale and Gore Damage state label None Slight Moderate Heavy Very heavy Collapse -443 (2003) – Model for C	Range of loss index (%) California (US). All building type	Central index (%) 0.3 4.1 21.8 41.0 78.1 81.4			
All building types	Di Pasquale and Gore Damage state label None Slight Moderate Heavy Very heavy Collapse -443 (2003) – Model for C Damage state label	Range of loss index (%) California (US). All building typ Range of loss index (%)	Central index (%) 0.3 4.1 21.8 41.0 78.1 81.4 Des Central index (%)			
All building types	Di Pasquale and Gore Damage state label None Slight Moderate Heavy Very heavy Collapse -443 (2003) – Model for C Damage state label Slight	Range of loss index (%) California (US). All building typ Range of loss index (%) -	Central index (%) 0.3 4.1 21.8 41.0 78.1 81.4 pes Central index (%) 2.0			
pes All building types	Di Pasquale and Gore Damage state label None Slight Moderate Heavy Very heavy Collapse -443 (2003) – Model for C Damage state label Slight Moderate	Range of loss index (%) California (US). All building type Range of loss index (%)	Central index (%) 0.3 4.1 21.8 41.0 78.1 81.4 pes Central index (%) 2.0 10.0			
All types All building types	Di Pasquale and Gore Damage state label None Slight Moderate Heavy Very heavy Collapse -443 (2003) – Model for O Damage state label Slight Moderate Extensive	Range of loss index (%) California (US). All building typ Range of loss index (%)	Central index (%) 0.3 4.1 21.8 41.0 78.1 81.4 Des Central index (%) 2.0 10.0 50.0			

Table 4.3 – Damage states and loss indices for three consequence models.

It is worth mentioning that the final consequence model is described by deterministic values (no uncertainty), since the only loss-to-damage model with a probabilistic distribution is Kappos *et al.*, (2006). Therefore, we are not able to propagate the uncertainty related to consequence models in the final loss estimation.

These elements allow estimating the loss due to "direct losses" (i.e., losses related to physical damage). In addition to reducing the physical damage, there are additional significant benefits of mitigation in the form of fewer fatalities and injuries from an earthquake.

Table 4. 4 – Damage states and loss indices for an average European city (France). Calculated as an average of three consequence models, for Italy, Greece and California (US).

Model for Europe (France). All structure types						
	Damage state label	Range of loss index (%)	Central index (%)			
/pes	D0 - None	-	0.0			
	D1 - Slight	-	3.0			
res t	D2 - Moderate	-	14.0			
All structu	D3 - Substantial to heavy	-	34.0			
	D4 - Very heavy	-	65.0			
	D5 - Destruction	-	90.0			

Indirect losses will also arise in the aftermath of the event and will continue to grow with time. The estimation of indirect costs as seen in Chapter 2, is extremely complex. Business interruptions, relocation expenses, supply shortages, demand reductions and income losses, together with ripple effects throughout the economy require detailed studies that strongly depend on the economical level of the region affected. This analysis is out of the scope of this work.

However, global indirect losses can be roughly estimated as a fraction of direct losses when no other information is available (Brookshire *et al.*, 1997). We propose in **Table 4. 5**, deterministic values (no uncertainty) for indirect losses with respect to direct losses for each damage grade. Indeed, indirect losses depend on the level of damage. Slight damage generate no or very small indirect costs, while a collapsed building will trigger business interruptions, relocations expenses and probably human casualties. There might also be intangible factors such as psychological trauma and stress, which might also have a place in evaluating alternative risk reduction strategies (Smyth *et al.*, 2004). The values of **Table 4. 5** are given as an average example. They should be adjusted regionally and with detailed economic surveys.

Table 4.5 – Indirect loss as a fraction of direct loss for different damage grades.

Damage state label	Indirect Loss (% of direct loss)		
D0 - None	0.0		
D1 - Slight	5.0		
D2 - Moderate	10.0		
D3 - Substantial to heavy	30.0		
D4 - Very heavy	60.0		
D5 - Destruction	80.0		

Cost of mitigation actions

The direct cost of mitigation alternatives (investment to reinforce buildings) is an extremely sensible component in a cost-benefit analysis. For a particular building, the owners, whether they live or not on the premises, will have to incur these expenses unless the government partially subsidizes a program of retrofitting residential property, which could lead to an increase of public taxes. Seismic reinforcements can also be completed from particulars while other renovation works are done in a construction (e.g., isolation, refurbishing, general renovation). Experience in high seismicity regions showed the inability of residents, specially when the structure is shared between several owners, to agree on an appropriate mitigation measure, which is one of the reasons nothing is done to reduce the seismic risk of the structure (Fisek *et al.*, 2003). The case of buildings in moderate-to-low seismic prone region is even more complex. We do not intend to go through this problem in this work and we focus on the economical values regardless the sources of investments.

The retrofitting cost depends on many factors such as, the type of structure, the feasibility or convenience to intervene, the actual condition of the building and the desired final state of the construction. As aforementioned, the strengthening of buildings is represented in this study as an enhancement to their vulnerability class. Since loss-to-damage ratios are in percentage of the building cost, we decide to evaluate the cost of reinforcements also as a percentage of the value of the building. This allows at the same time generalization and avoiding direct monetary prices. These values are simply seen as "how much will cost to reinforce a building from his actual vulnerability class, to the desired less vulnerable class, as a percentage of the building total value".

Prices to seismically reinforce buildings can usually be found per building type and per surface area. They are average costs for standard reinforcements solutions. However, they are most of the times costs to strengthen a building to become code-conformed, or to incorporate special seismic resistant solutions like dynamic damped foundations. Even this information is really hard to find, since contractor and insurance companies keep them secret for their budget speculations. The investment we plan in our study is to improve the response of buildings to seismic loadings, even if the construction remains below the code requirements.

Average reinforcements costs in this study (for a French building environment), are mainly assessed from FEMA 156 and FEMA 157 which gives typical costs for the seismic rehabilitation of existing buildings in US. The values where corrected with a study of seismic vulnerability and reinforcements relevance of buildings in the city of Lourdes, France, developed by the group GEOTER and HAUSS in 2011 (GEO-HAU) (Rapport GTR/DDT65/0511-855). We complete the information with other cost-benefit analysis in different European countries (Smyth *et al.*, 2004; Valcarcel *et al.*, 2013; Bostenaru Dan, 2014) and with personal and expert knowledge on building economy

GEO-HAU report, gives the complete cost of the works needed to modify existing structures (if technically possible) so that they respect the minimum French codes requirements in that region (Seismicity Zone 4). The values are given for different vulnerable buildings.

These standards values take into account information of real projects of reinforcements and new constructions. They are analyzed by the exploration of large private databases. They establish a correlation between the costs per square meter and the main input parameters of the building (vulnerability indexes, structure type, year of construction, number of floors, surface to be treated). The strengthening solutions considered are standard, operational, relatively cheap and they are mastered in current building practice. It remains true that operational studies may offer different solutions for a given building, without anyway significantly changing average costs.

The analysis of reinforcement projects showed that the solutions are often recurrent. It is often convenient to (GEO-HAU) (Rapport GTR/DDT65/0511-855):

- Improve longitudinal bracing: rather on facades than in the interior (due to operation and functional constrains) by adding longitudinal bracers or stability elements. This can be done without loss of functionality on one or two sides, depending on actual and desired vulnerability factors. In some cases, bracers can be added to walkways. For small levels of improvements (and investments costs) connections between facades and walls can be improved at the floors and roof levels as well as increase the stiffness of wooden floors with a thin reinforced concrete layer. These works would eventually need a verification of foundations.

- Improve transversal bracing: by replacing partition masonry or stud walls by reinforced concrete walls or stability elements.

- Particularly for masonry buildings: replacement of masonry panels by concrete walls. Girdling of the building to confine the masonry. Eventually add pre-stressed cables and chains to masonry.

- Remove transparencies: by adding bracing walls taking care to the optimal load transmission to foundations.

- Reduce torsion effects: by increasing the stiffness partially to allow compensating dissymmetry and irregularities. By removing elements if they are not indispensable (e.g. non structural decorations). By detaching or isolating heavy exterior stairs or replacing them by lighter structures.

- Improve load paths and transmission: by disposing vertical load-bearing elements to ensure a direct descent of weights.

- Eliminate the risk of short-column effects and weak angles. Remove the risk of clashing (elements bumping into each other): by adding or repairing appropriate joints.

- Create diaphragms at the roof: by reinforcing wood structures of roofs and ensure a good connection with beams or walls.

Finally, other measures can be implemented either as accompanying works for heavy reinforcements, or independently to minimize the impact of lower intensity earthquakes.

- Maintenances due to dilapidation of materials. Reinforcements of chimneys and the bindings of handrails. Replace heavy handrails in concrete or masonry by steel handrails. Eliminate gateways effects between buildings. Demolish non-structural elements poorly attached to the structure, especially at higher levels. Perform anticorrosion treatments to metallic structures.

The final calculated average costs of reinforcements to modify a building from the actual vulnerability class to another (less vulnerable) are shown in **Table 4. 6.** As aforementioned, they are estimated using reference reinforcement values from buildings in the city of Lourdes (GEO-HAU - Rapport GTR/DDT65/0511-855), completed with expert judgment and validated with values from other cost-benefit analyses.

They are calculated as a percentage of the building cost (reconstruction to new). Note that reinforcing buildings of low vulnerability classes (e.g. vulnerability class A to B) cost in average less than reinforcing a building with better-expected dynamic response (e.g. vulnerability C to D). In the same way, there is a limit in the possible upgrading. Buildings of very low vulnerability classes cannot be reinforced to become of very high vulnerability classes.

It is worth mentioning that we consider that the reinforcements can always be completed and that they succeed in the effective reduction of vulnerability. We do not analyze the convenience of reinforcing a building to only change one vulnerability class at a particular case. We do not take into account the possible effect of a wide-spread demand for retrofitting nor the impact of the disruption of normal activities of the residents in the building while the structure is being retrofitted. The values have a statistical meaning and are not meant to represent the case of any building in particular. The costs are indicative, targeted to French cities and deterministic, they do not allow the propagation of uncertainties in the loss analysis.

Table 4. 6 – Reinforcements cost for different vulnerability and strengthening scenarios as a percentage of the total building value.

Actual vulnerability class	Final vulnerability class	Cost (%)
А	В	5.0
А	С	14.0
А	D	22.0
В	С	10.0
В	D	20.0
С	D	25.0
С	E	30.0

For example, Smyth *et al.*, (2004) uses in their cost-benefit analysis for a single structure in Istanbul, building replacement values and cost of reinforcements obtained from a construction contractor specializing in earthquake retrofitting in Turkey (unknown), which is believed to be a reliable estimate. In their case, the building is a typical five-story building, built in 1968, with a plan footprint of 28 by 11 meters, and an elevation of 13.5 m. The structure is a moment-resisting reinforced concrete frame without shear walls. The cost of the building replacement is \$250,000 (US Dollars). The structure was studied for three levels of retrofitting with a supposed increased level of improvement. A braced retrofitted version, a partial shear wall retrofitted version and a full shear wall retrofitted version. The associated mitigation costs were respectively \$65,000 (26%), \$80,000 (32%) and \$135,000 (54%). If we consider the original vulnerability class C, and the three retrofitting levels as changes to vulnerability cases D, E and F respectively, the costs are in accordance with those of **Table 4. 6**.

Retrofitting schemes

Many reinforcements scenarios could be envisaged depending on the final goal or concern. Reinforcements could be planed to minimize human life risk, i.e. reduce de number of victims (casualties and injuries) for a probable or deterministic earthquake scenario. On the other hand, they could be planed to minimize cost or in simpler words, to save money. For this later case an iterative process of all possible reinforcements scenarios would be needed, until the optimal investment-loss combination is found. In addition the optimal solution depends on the actual vulnerability distribution of the region and the probable earthquake scenarios that can be experienced. In this work only one solution globally satisfying both approaches is proposed. However, it might not be the most economically convenient.

The number of earthquake shaking-related deaths depend on the ground shaking intensity, the numbers of buildings affected at a particular intensity, their occupancy and the fatality rate among occupants (Coburn and Spence, 2002). It is now widely recognized that the number of earthquake shaking-related deaths is closely related to the number of buildings that fully or partially collapse (So and Spence, 2012). For a given shaking intensity, most vulnerable buildings will experience more damage. On the other hand, repair costs (direct loss) as well as indirect loss are larger for buildings with a more severe level of damage. For these reasons, we propose to reinforce most vulnerable classes in priority.

Total direct and indirect loss values and total investments values are calculated as a percentage of the entire city building stock value as:

$$C^{direct} = \sum_{i=1}^{i=5} P_{Di} * C_{Di}$$
(1)

$$C^{indirect} = \sum_{i=1}^{i=5} P_{Di} * C_{Di} * C_{Di}^{ind}$$
 (2)

$$C^{total} = C^{direct} + C^{indirect}$$
(3)

where C^{total} , C^{direct} and $C^{indirect}$ are the total loss cost, the total direct loss and the total indirect loss respectively, as a fraction of the total building stock worth. P_{Di} is the estimated percentage of damaged buildings of grade i (D1 to D5), C_{Di} is the loss-to-damage ratio of **Table 4. 4** corresponding to damage grade i, and C_{Di}^{ind} is the indirect loss ratio as a fraction of direct loss from **Table 4. 5** for different damage grades i.

The investment equation in its more general form reads:

$$I^{total} = \sum P_{X \to Y} * Q_{X \to Y}$$
(4)

where I^{total} is the total cost of investment as a fraction of the total building stock value. $P_{X \rightarrow Y}$ is the percentage of buildings of vulnerability class X that are reinforced to class Y, and $Q_{X \rightarrow Y}$ is the cost to reinforce a building of class X to class Y as a percentage of the building worth from **Table 4.6**.

The distribution of increasing investments among vulnerability classes is done in the following order:

- A percentage of buildings of class A are strengthen to class B.
- A percentage of class A are strengthen to class C, and the rest to class B (100% of buildings class A are reinforced).
- A percentage of class A are strengthen to class C, and the rest to class D (100% of building class A reinforced).
- All buildings of class A are strengthen to class D and a percentage of class B are improved to class C.
- All buildings of class A are strengthen to class D. A percentage of class B are improved to class C and the rest to class D (100% of class A and B reinforced).
- All buildings of class A and B are strengthen to class D. A percentage of class C are improved to class D.
- All buildings of class A, B and C are strengthen to class D.

Beyond those limits of improvements the costs of investments rapidly grow, and as it will be proved later, there are not average economic benefits (e.g. strengthening buildings class C and D to behave like class E is very costly). However, it could be envisioned for regions of important seismic hazard where the probability of human casualties is to be reduced to the minimum. Obviously, the percentage of buildings of each vulnerability class to reinforce depends on the distribution of vulnerability of the region of interest. At the same time, the reduction of losses also depends on the hazard considered. **Table 4. 7** presents the scenario of reinforcements for the 1,000-buildings city of **Table 4. 2**. Note that due to the small percentage of vulnerability class A buildings, the first level of investment (i.e. 0.5%) is already enough for strengthening all of them to class D, plus a small percentage of class B to C.

Investment (%) A→D (%) B→C (%) B→D (%) C→D (%) 0.0 (none) 0.0 0.0 0.0 0.0 0.5 100.0 3.1 0.0 0.0 1.0 100.0 0.0 21.8 0.0 1.5 100.0 40.5 0.0 0.0 0.0 0.0 2.0 100.0 59.3 0.0 2.5 100.0 78.0 0.0 3.0 100.0 96.8 0.0 0.0 3.5 100.0 84.6 15.4 0.0 0.0 4.0 100.0 65.8 34.2 4.5 47.1 0.0 100.0 52.9 5.0 100.0 28.3 71.7 0.0 5.5 100.0 90.4 0.0 9.6 6.0 100.0 0.0 100.0 2.1 6.5 100.0 0.0 100.0 6.5 7.0 100.0 10.8 100.0 0.0 7.5 15.2 100.0 0.0 100.0 8.0 100.0 0.0 100.0 19.5 23.9 8.5 100.0 0.0 100.0 100.0 28.2 9.0 0.0 100.0 9.5 100.0 0.0 100.0 32.6 10.0 100.0 0.0 100.0 36.9 10.5 100.0 0.0 100.0 41.3 45.6 11.0 100.0 0.0 100.0 0.0 100.0 50.0 11.5 100.0

Table 4. 7 – Scenarios of increasing reinforcement investments for a synthetic city. The mean vulnerability distribution of the city is: A-1.9%; B-26.7%; C-46.0%; D-18.4%; E-6.2%; F-0.8%

For each of these investments scenarios, the mean vulnerability distribution of the city is changed and the mean (and ± 1 standard deviation) probable losses are recalculated. The first point (no investments) corresponds to the expected loss of the city for the actual distribution of vulnerabilities.

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Figure 4. 12 explains on an example illustration (with arbitrary values), how results are represented in this work together with some key features that can be depicted from them. The plot on the left part represent the expected economical loss as a percentage of the total city building stock for a particular hazard scenario and as function of the retrofitting costs. The mean and one standard deviation are included. The value at the origin (0.0% investment) corresponds to the expected loss in the original city. The expected loss for any investment can be depicted from this plot. Vertical dotted orange lines indicate the level of investments for which no buildings with damage grade D4 or D5 (as denoted) are in average to be expected number of victims, even if they might not be convenient investments on the pure economic point of view. It is worth mentioning that these later values are taken from calculation results and are added to the plots for a visual representation. The smallest retrofitting costs that reduce the percentage of damage buildings (D4 or D5) to a value equal to 0.0 % are found and selected. Obviously, they are illustrated but they cannot be depicted directly from the plots.



Figure 4. 12 – Explanatory figure. Expected economical loss as a percentage of the entire city building stock value and as a function of the investment for a given hazard scenario (left). Corresponding cost-benefit curve (right).

To be able to compare and decide if an investment is convenient (or not) from a solely economical point of view, the investment cost is added to the mean loss that is expected for that particular reinforcement scenario and plotted as a function of investment in **Figure 4. 12** right part. If the decrease on mean expected losses are larger that the cost invested to reach that reduction, this added value will be smaller that the expected losses for the original city set-up.

In those cases, it can be said that the investment is beneficial from an economic point of view. These investments points can be found with smaller ordinate values than the one at the origin corresponding to 0.0% investment (original city). The range of "cost-effective" investment values is indicated in the explanatory **Figure 4. 12** (right). In addition, the investment point that minimizes the added value (investment + corresponding loss) is the economically optimal value, which is found as a global minimum on the figures. This investment value is called the optimal value because it maximizes savings among all the retrofitting scenarios. The savings for each cost-effective retrofitting scenario can be found as the difference between the added value at the origin (expected loss with no investments) and the added value of the investment point. Indeed, savings are calculated as:

$$Savings = L_0 - (I + L_I) \tag{5}$$

where L_0 is the expected mean loss for the original city, I is a particular investment, and L_I is the expected mean loss for the investment I.

On the contrary, if the investment is too large compared to the reduction it yields in the mean loss, their sum will be bigger than the original loss and it would not be economically convenient to reinforce the buildings (negative savings). In those cases it is preferred to let the earthquake occur, and repair or replace the damaged buildings afterwards.

It is important to recall that the analyses of cost-effective and optimal investment values are based purely on an economic point of view. In addition to reducing the physical damage, there are further significant benefits of mitigation in the form of fewer fatalities and injuries from an earthquake that are not accounted for in this study. One solution could be to add a value to human life and add it as an economical parameter. For the rest of this work, cost-effectiveness as well as savings and optimal investment values are calculated from an economic point of view, without consideration of the social aspects.

Results on a typical European city

Coming back to our synthetic city of 1000 buildings, **Figure 4. 13** (left column) shows the expected loss as a percentage of the total city buildings value for three earthquake scenarios and as a function of the investment cost. Average direct loss is represented as a continuous blue line with the $\pm 1 \sigma$ range (dashed blue lines). This uncertainty corresponds only to the uncertainty in the estimation of the number (or percentage) of damaged buildings for each damage grade, and does not include uncertainties in loss-to-damage ratios nor in investments cost ratios. Total probable loss (direct + indirect loss) is represented as red lines.

For all three earthquakes scenarios and as expected, a reduction of the direct and total loss is seen for increasing investments costs (**Figure 4. 13** – left column). However, the reduction of expected losses is "faster" with investments for earthquake scenarios of larger destructive potential (note the change of Y-axis scales between plots). The shape (slope) of the curves indicates that for all hazard scenarios the losses are reduced more significantly at the first levels of investments. After a given threshold, which depends of the earthquake scenario, curves are flatter (an increase of investments cost, only reduce the losses a small amount).

In **Figure 4. 13a** (left column) an earthquake of Mw 5 at 10 km of the city would create expected mean direct losses of approximately 1.8% of the total building value of the city. In this case indirect losses are expected to be negligible and therefore, the total damage curve overlaps the direct losses. This scenario can be compared with Barcelonnette earthquake (France) of 2014. Economic losses linked to that earthquake in towns near the epicenter are not public. However, fast calculations using the observed damage to building gives the same order of magnitude (between 0 and 3% loss) (Report Barcelonnete BCSF). For this scenario, no D5 buildings are in average to be expected, and an investment of 0.5% would also reduce the mean number of D4 damaged buildings to zero.

For a Mw 6 at 10 km (**Figure 4. 13b** – left column) expected mean direct losses are of approximately 9.2% while mean total losses of 12.0%. This earthquake scenario can be compared to Lambesc (France) earthquake of 1909, or to the most recent L'Aquila (Italy) earthquake of 2009 where 308 humans lost their lives and total damage estimates are around 16 billons dollars (Global Risk Miyamoto). Note the faster reduction of total losses with increasing investments, compared to direct losses. An investment of 2.5% would reduce mean probable D5 damaged buildings to zero, whereas an investment of 10.5% would be needed to prevent in average damages grade D4.

An event of Mw 7 at 10 km (**Figure 4. 13c** – left column) would be a genuine catastrophe for a city of this vulnerability set-up. Damage and loss values reach impressive proportions. We can expect in average 28.5% of the city worth as direct losses and total losses of 42.0%.



Figure 4. 13 – Expected loss as a percentage of the entire city buildings value and as a function of the investment (left column) for three earthquake scenarios. a) Mw 5 at 10 km. b) Mw 6 at 10 km. c) Mw 7 at 10 km. Mean direct loss (*blue continuous lines*). Mean total loss (*red continuous lines*). Uncertainty range ($\pm 1 \sigma$) (*dashed lines*). Orange points and vertical dotted lines correspond to the value of minimum investments for which mean expected number of buildings with damage grade D4 or D5 are zero. Cost-benefit curves (right column). Blue and red points correspond to the optimal investment values for direct and total loss respectively. Note changes in Y-axis.

Direct and especially indirect losses are however rapidly reduced for increasing retrofitting investments. For an investment of 11.5% (last point of our reinforcement scenario) the expected direct and total loss are reduced to 15.2% and 20.8% respectively. Even at these investments levels, D5 and D4 buildings are to be expected, and reduce their probabilities of occurrence require much larger funds.

In **Figure 4. 13a** (right column) all the added values are over the initial loss value for all investments level. For this earthquake scenario (Mw 5 - 10 km), the cost of reinforcements are too high compared to the obtained reduction of the loss. According to these results no reinforcements to buildings would be recommended, from an economic point of view.

For an earthquake scenario of Mw 6 at 10 km (Figure 4. 13b – right column) investments up to 4.0% would be economically convenient regarding direct losses and up to 7.0% for total losses. All the investments points within those ranges will result in a saving of money if the earthquake occurs. However, as it can be seen on the figure, the optimal points are 2.5% for direct losses and 3.0% for total losses. A reinforcement scenario with 2.5% of investment cost would produce for this event mean direct losses of 6.2% (Figure 4. 13b – left column). These two values sum to 8.7% cost compared to the expected 9.2% loss if nothing is done to reinforce the structures (0.5% savings). Even more significant, 3.0% of investment cost would reduce total losses to 7.0%, which would sum 10.0% total cost, compared to 12.0% expected loss with no reinforcements (2.0% savings).

All the investments levels included in this study are appealing from an economic point of view for an earthquake scenario of Mw 7 at 10 km (**Figure 4. 13c** – right column). 5.5% investment is the optimal to reduce direct losses. This reinforcement scenario will result in 18.7% mean direct loss for this event, producing 4.3% savings. Regarding total losses, the optimal value of 8.0% investments would generate average savings of 10.6%.

In overall, seismically upgrading buildings allow reducing the expected loss for any earthquake scenario. However it might not always be cost-effective. The reduction of the risk as well as the cost-benefits analysis depends on the actual vulnerability distribution of the existing building stock and also on the destructive potential of the probable seismic event. For this example, spending funds to reinforce buildings is not cost-effective for low magnitude events, while it becomes progressively more convenient for earthquakes of larger magnitudes (larger savings). Optimal investments values are also more important for these larger events (lower investments still are cost-effective).

Direct loss (blue lines in figures) would interest house owners and insurance companies since it accounts only for repair and replacements costs. City planners, state and safety agencies would be more interested in the total costs (red lines in figures) since it also include probable indirect costs related for example to business interruptions. Optimal investments cost are not necessarily the same for these two losses estimations. Moreover, if it is desired to minimize human death and harm, recommended investments can also be different to optimal economic values.

Finally, these results correspond to three earthquake scenarios, but the probability of occurrence of the events is not considered. A fully complete loss assessment will require the knowledge of the hazard probability of occurrence (PSHA analysis), which is out of the scope of this work. Cost benefit analyses are done here on the basis of scenario events affecting the particular building stock of a city, comparing the cost of the upgrading for that city with the benefit in terms of reduced loss in that scenario event. Such an analysis will always overstate the benefits because it ignores the costs of upgrading which would have been involved in other places which were not affected by that event. Only a probabilistic risk assessment can properly estimate and compare costs and benefits. As seen in previous sections, uncertainties are large at this level. In this case, the uncertainties related to consequence models, in the definition of investments costs or the inter-event variability of damage are not included. However, final loss estimations have variability within a \pm factor of almost two of the mean values.

The loss and investments values are percentage of the actual building stock worth. These values can be translated into economic units (dollars, euros) by multiplying them by the actual price of the structures in the city. In the next section, examples on real cities will be given.

4.8. Loss estimates and cost-benefits analysis for France

We perform in this section loss estimates for France, and in particular, reinforcements cost-benefit analysis for several French cities. The probable hazard given by French standards is considered while the vulnerability of structures is computed using the proxy calculated by Support Vector Machine (SVM) method in the city of Grenoble in Chapter 3.

4.8.1 Regulatory French hazard

France has since 2010 new seismic regulations related to the prevention of seismic risk, earthquake design rules for buildings and seismic zoning for the entire territory. The seismic requirements to apply in each particular case depend on the importance category of the building and the seismicity zone in which it is located. The new seismic zoning divides the country in five regions of growing seismicity (Zones 1 to 5) (**Figure 4. 14**). For seismic zone 1 (very week) there is no particular seismic prescription for buildings called "at normal risk" (e.g., excluding nuclear power plants, chemical industries, hospitals, etc.). For zones 2 to 5 seismic rules have to be applied for all buildings categories.



Figure 4. 14 – French seismic zoning applicable since May the 1st 2011. (From article D.563-8-1 of the Environment Code).

The updating of the seismic zoning was necessary after the creation of the European seismic building code (Eurocdode 8) and possible by the development of seismic knowledge. This new seismic zoning was defined as the result of scientific studies to assess the seismic hazard based on a probabilistic method, with reference return period of 475 years (according to EC8 standards), and taking into account the improved knowledge of the historical seismicity and active faults, as well as new instrumental seismicity data on French territory. For the design of buildings, the seismic ground-motion is represented on the codes by standards response spectra, which depend on the seismic zone (ground accelerations), the category of the building (importance coefficient) and the soil class on which it is built (soil class coefficient). The seismic zones allow defining the acceleration at the rock to take into account in the definition of those spectra. As aforementioned, these accelerations are given for a return period (R_T) scenario of 475 years. This return period correspond to an exceedance probability of 10% in 50 years. For a given period T, the exceedance probability of a natural phenomenon of return period R_T is defined by a Poisson model as:

$$P_R = 1 - e^{-\frac{T}{R_T}}$$
(6)

We can also construct the response spectra for different return periods according to clause 2.1 (4) of EN 1998-1 (CEN, 2005a). When looking at the peak ground accelerations, it is generally accepted that the annual rate of exceedance $H(a_{gR})$ of an acceleration level a_{gR} is proportional to a_{gR} , i.e.,:

$$H(a_{gR}) \approx k_0 * a_{gR}^{-k} \tag{7}$$

The value of k can vary between 2 and 3.5 depending on the seismicity zone, and a value of k = 3 is generally accepted. Therefore for two acceleration levels a_{gR1} and a_{gR2} , the ratio of the two associated exceedance probabilities P_1 and P_2 is approximately:

$$\frac{P_2}{P_1} \approx \left(\frac{a_{gR2}}{a_{gR1}}\right)^{-k} \tag{8}$$

Therefore, from the accelerations defined in the codes corresponding to 475 years return period (and an exceedance probability P in 50 years), we can estimate ground accelerations for others return periods, and another associated exceedance probability P_R over the same 50 years, applying the coefficient:

$$\gamma \approx \left(\frac{P}{P_R}\right)^{-1/k} \tag{9}$$

Using equations 6 and 9, we calculate ratio coefficients for return periods of 95 and 47 years. These return periods correspond to an exceedance probability of 10% in 10 and 5 years respectively. **Table 4. 8** presents the regulatory accelerations for each seismic zone as well as the calculated accelerations for different return periods with their associated probability of exceedance.

Table 4. 8 – Regulatory accelerations for French seismic zones and a return period R_T = 475 years. Calculated accelerations for R_T = 95 years and R_T = 47 years

	l evel of	Accelerations (rock site) [cm/s ²]				
Seismic Zone	hazard	R T 475 years (10% in 50 years)	R _T 95 years (10% in 10 years)	R T 47 years (10% in 5 years)		
1	Very weak	40.0	25.0	21.4		
2	Weak	70.0	43.8	37.5		
3	Moderate	110.0	68.8	58.9		
4	Important	160.0	100.00	85.7		
5	Strong	300.0	187.51	160.7		

In order to estimate loss for these hazard levels, the accelerations of **Table 4. 8** are converted to intensities using ground-motion to intensity conversion equations (Atkinson and Kaka (2007) and Faenza and Michelini (2010)). The mean value of the two models rounded to the closest intensity unit is selected while no uncertainties were included for this part of the study. Note that metropolitan France only has seismic zones 1 to 4. Calculated intensity values are shown in **Table 4. 9**.

Table 4. 9 – Calculated intensities from regulatory accelerations for French seismic zones and a return period R_T = 475 years, R_T = 95 years and R_T = 47 years. Intensities are calculated with AK07 and FM10.

Seismic	Level of hazard	Calculated Intensities for different accelerations levels				
Zone		R_T 475 years (10% in 50 years)	R T 95 years (10% in 10 years)	R_T 47 years (10% in 5 years)		
1	Very weak	V	V	IV		
2	Weak	VI	V	V		
3	Moderate	VII	VI	VI		
4	Important	VIII	VII	VI		

Since intensities are described by a discrete variable (one intensity level precision), same values can be calculated from different acceleration levels. It is also worth mentioning that these values are the intensities calculated from accelerations with given return periods, and they are not exactly the intensities with the same exceedance probability. In order to get those values, a hazard map on intensity should be developed, following every step of a full PSHA process. **Figure 4. 15** shows the intensity maps for France according to the seismic zoning for accelerations with three different return periods.



Figure 4. 15 – Intensity maps for France calculated from regulatory accelerations using a combination of ground-motion to intensity conversion equations (AK07 and FM10) (rounded to one intensity unit). a) Intensities calculated for accelerations with a probability of exceedance of 10% in 50 years (475 years return period). b) Intensities calculated for accelerations with a probability of exceedance of 10% in 10 years (95 years return period). c) Intensities calculated for accelerations with a probability of exceedance of 10% in 5 years (47 years return period). c) Intensities calculated for accelerations with a probability of exceedance of 10% in 5 years (47 years return period).

For return periods of 475 years (10% exceedance probability in 50 years), maximum intensity of VIII (in zone 4) would be expected. These levels of intensity occurred during several French historic earthquakes, e.g., Lambesc 1909 or Arette 1967. On the other hand, maximum intensity of VI would be expected for return periods of 47 years (10% exceedance probability in 5 years). These levels of intensity are more frequently experienced for smaller events like the recent Barcelonnette earthquake of 2014.

4.8.2 Loss estimates for France

With these calculated intensities and with vulnerability class distributions estimated by SVM methods, expected loss is calculated for the entire French territory following the process of Section 4.7.

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In addition, expected loss as a function of reinforcements costs, and cost-benefit analysis are performed for five French cities. As aforementioned, no uncertainties are included in the definition of the hazard (accelerations / intensities) and the mean vulnerability distribution calculated from SVM is adopted at each IRIS unit. The results are thus, average loss ratios. Moreover, we only present the results for direct losses.

Figure 4. 16, Figure 4. 17 and Figure 4. 18 show estimated mean direct economic loss for regulatory accelerations with 475, 95 and 47 years return period respectively.



Figure 4. 16 – Expected direct loss for regulatory accelerations with 475 years return period. Loss is given as a percentage of the total buildings worth for each IRIS unit in metropolitan France. The mean direct loss for five French cities is indicated. The scales of city-maps are not necessarily the same among each other.

Obviously, expected loss depends on the level of hazard (seismic zones) but also on the capability of buildings to resist ground-motions, i.e., their seismic vulnerability. Mean expected loss is larger for cities located in zones with important seismic hazard (Zone 4), but this expected loss is not uniform among the IRIS units (or neighborhoods) within a city limit. The most vulnerable units have larger expected loss ratios. Expected loss is smaller for hazard levels with reduced return periods. Since France is a low-to-moderate hazard country, these estimations can be very roughly seen as the minimum expected loss with 10% probability of exceedance in 50, 10 and 5 years, corresponding to 475, 95 and 47 years return periods.



Figure 4. 17 – Expected direct loss for regulatory accelerations with 95 years return period. Loss is given as a percentage of the total buildings worth for each IRIS unit in metropolitan France. The mean direct loss for five French cities is indicated. The scales of city-maps are not necessarily the same among each other.



Figure 4. 18 – Expected direct loss for regulatory accelerations with 47 years return period. Loss is given as a percentage of the total buildings worth for each IRIS unit in metropolitan France. The mean direct loss for five French cities is indicated. The scales of city-maps are not necessarily the same among each other.

The direct mean expected loss for the probable hazard in 5 years is of course smaller that the expected loss for the probable level of hazard in 10 or 50 years. The loss for hazard levels with 475 years return period (**Figure 4. 16**) can be as large as 20-25% for seismic zone 4 and highly vulnerable IRIS units. For hazard levels with 95 and 47 years return period, maximum expected loss is approximately 5-10% and 1-5% respectively (**Figure 4. 17** and **Figure 4. 18**).

Five French cities are selected for a more detailed analysis. Grenoble and Nice (Zone 4) are located in the Alps region with a large concentration of industrial, touristic and economic activity. Lourdes (Zone 4) on the Pyrenees region has an essential historical value. Nantes and Strasbourg (Zone 3), located at Armorican and Rhine regions respectively, are two large cities of France with a high concentration of habitants and economic activities.

Mean expected direct loss for the three cities located in seismic zone 4 is between 12 - 15% for regulatory accelerations corresponding to 475 years return period, whereas this value is between 5 - 6% for the cities located in seismic zone 3. For 95 years return period, losses are estimated between 4 - 6% for cities in zone 4 and around 1% for cities in zone 3. Finally, for 47 years return period, estimated losses are less than 1% for cities in zones 3 and 4. Note that since intensities calculated for seismic zone 3 are the same for return periods of 95 and 47 years (i.e., VI), losses estimations for Nantes and Strasbourg for these two return periods are also the same.

We perform cost-benefits analysis of reinforcements for these five cities following the methodology of Section 4.7.

4.8.2.1 Grenoble

The average vulnerability distribution for Grenoble (from SVM proxy) is composed by approximately: 8.0% of vulnerability class A; 33.0% class B; 22.9% class C; 19.9% class D and 16.2% class E. The exact investment scenario is indicated in **Table 4. 10**.

Expected loss as a percentage of the total city building value for Grenoble and as a function of the investment cost, as well as cost-benefit curves are show in **Figure 4. 19**. Mean direct and mean total loss are estimated for three levels of regulatory hazards, 475, 95 and 47 years return period.

For hazard levels with 475 years return period, direct and indirect losses are rapidly decreased with growing reinforcements investments. For direct losses, investments up to 9.5% are cost-effective with 5.0% as the optimal value. For this later level of investments, expected mean direct loss is reduced from 12.3% to 4.8% therefore, with a mean total economic saving of 2.5%. A retrofitting investment of 0.5% would reduce the mean expected number of collapsed (D5) buildings to zero (0%), while a 5.5% investment would be needed to reduce D4 damaged buildings to 0%. These later values are taken from calculations and they are not shown in these figures (see Section 4.7 and explanatory **Figure 4. 12**).

Table 4. 10 – Scenarios of increasing reinforcement investments for Grenoble.	The mean vulnerability	distribution of the
city is: A-8.0%; B-33.0%; C-22.9%; D-19.9%; E-16.2%; F-0.0%		

Investment (%)	A → B (%)	A → C (%)	A → D (%)	B → C (%)	B → D (%)	C → D (%)
0.0 (none)	0.0	0.0	0.0	0.0	0.0	0.0
0.5	86.5	13.5	0.0	0.0	0.0	0.0
1.0	17.4	82.6	0.0	0.0	0.0	0.0
1.5	0.0	41.8	58.2	0.0	0.0	0.0
2.0	0.0	0.0	100.0	7.0	0.0	0.0
2.5	0.0	0.0	100.0	22.2	0.0	0.0
3.0	0.0	0.0	100.0	37.3	0.0	0.0
3.5	0.0	0.0	100.0	52.5	0.0	0.0
4.0	0.0	0.0	100.0	67.6	0.0	0.0
4.5	0.0	0.0	100.0	82.7	0.0	0.0
5.0	0.0	0.0	100.0	97.9	0.0	0.0
5.5	0.0	0.0	100.0	87.0	13.0	0.0
6.0	0.0	0.0	100.0	71.8	28.2	0.0
6.5	0.0	0.0	100.0	56.7	43.3	0.0
7.0	0.0	0.0	100.0	41.5	58.5	0.0
7.5	0.0	0.0	100.0	26.4	73.6	0.0
8.0	0.0	0.0	100.0	11.3	88.7	0.0
8.5	0.0	0.0	100.0	0.0	100.0	2.3
9.0	0.0	0.0	100.0	0.0	100.0	11.0
9.5	0.0	0.0	100.0	0.0	100.0	19.8
10.0	0.0	0.0	100.0	0.0	100.0	28.5
10.5	0.0	0.0	100.0	0.0	100.0	37.3
11.0	0.0	0.0	100.0	0.0	100.0	46.0
11.5	0.0	0.0	100.0	0.0	100.0	54.7

For regulatory accelerations with 95 years return period, investments up to 1.5% are economically cost-effective. The optimal investment value of 0.5% reduces mean direct losses from 4.6% to 3.5% (0.6% mean savings). No collapsed buildings (D5) are expected for this hazard level, and an investment of 1.0% would also reduce expected D4 damaged buildings to zero.

For hazard levels with 10% exceedance probability in 5 years (47 years return period), all investments are not cost-effective. The already low expected loss value (less than 0.8%) is only slowly reduced with increasing investments. Investments of approximately 7.5% would bring expected loss ratio to almost 0.0%.



Figure 4. 19 – Mean expected direct and total loss for the city of Grenoble. Loss as a function of reinforcement investments (left). Cost-benefits curve (right). Direct loss (*continuous lines*). Total loss (*hidden lines*). Estimations are given for hazard levels with 475 years return period (*red lines*), 95 years return period (*blue lines*) and 47 years return period (*black line*). Optimal investment for 475, 95 and 47 years return period are indicated as red, blue and black points respectively on the x-axis.

The analysis of these results indicate that for Grenoble, even considering only direct losses, and from a pure economical point of view (no human life protection nor social aspects included), the retrofitting of building is convenient and suitable for the longest time spans (return period).

These losses and investments ratios correspond to a percentage of the total building stock value. Prices for buildings per square meters can be found on the market. These prices will depend on the location, the type of construction and the quality of the asset among others. However, average prices for the city can be deduced. On the other hand, INSEE datasets give the number of residential buildings, their approximate surface and the number of floors for every IRIS unit in France and therefore for each town or city.

Grenoble counts approximately 9,100 residential buildings, with an average surface per floor of 110 square meters. 59% of the buildings have less than 4 stories, 33% between 4 and 8 and 8% more than 8 floors. The average price of existing buildings is €2,620 (Euros) per square meter (calculated from real-state and property agencies, April 2015). In overall, the city of Grenoble has approximately €10.2 billons worth in residential building stock only.

Calculated loss and investment ratios can now be translated to approximate monetary value (€). Every step of 0.5% corresponds roughly to €51 million investment. A hazard level with 475 years return period would generate direct losses of €1.3 billion in Grenoble, while the optimal reinforcement investment (€510 million) would produce savings of €295 million.

For hazards with 10% exceedance probability in 10 years (95 years return period), initial direct losses would reach of €470 million. An investment of €51 million would produce mean optimal savings of €62 million. Hazard levels with 47 years return period would produce mean direct losses of €77 million. **Table 4. 11** summarizes the economic results for the city of Grenoble.

Investment	475 years return period		95 years r	95 years return period		47 years return period	
investment	Mean loss	Mean savings	Mean loss	Mean savings	Mean loss	Mean savings	
0 (none)	1.3 billion	0	470 million	0	77 million	0	
51 million	1.1 billion	149 million	357 million	62 million	75 million	-	
102 million	990 million	208 million	324 million	44 million	66 million	-	
153 million	944 million	203 million	308 million	9 million	63 million	-	
204 million	893 million	203 million	289 million	-	58 million	-	
255 million	826 million	219 million	259 million	-	50 million	-	
306 million	760 million	234 million	229 million	-	42 million	-	
357 million	694 million	249 million	198 million	-	34 million	-	
408 million	628 million	264 million	168 million	-	26 million	-	
459 million	562 million	279 million	138 million	-	14 million	-	
510 million	495 million	295 million	108 million	-	10 million	-	
561 million	460 million	279 million	97 million	-	9 million	-	
612 million	430 million	258 million	89 million	-	9 million	-	
663 million	400 million	237 million	81 million	-	8 million	-	
714 million	370 million	216 million	73 million	-	7 million	-	
765 million	340 million	195 million	64 million	-	6 million	-	
816 million	310 million	174 million	56 million	-	5 million	-	
867 million	284 million	149 million	49 million	-	5 million	-	
918 million	272 million	110 million	46 million	-	4 million	-	
969 million	260 million	71 million	43 million	-	4 million	-	
1.02 billion	248 million	32 million	40 million	-	3 million	-	
1.07 billion	236 million	-	36 million	-	3 million	-	
1.12 billion	224 million	-	33 million	-	3 million	-	
1.17 billion	212 million	-	30 million	-	2 million	-	

Table 4. 11 – Summary of economic results (in €) for the city of Grenoble, for direct losses only.

4.8.2.2 Nice

For the following cities and for sake of simplicity, the tables of retrofitting scenarios as well as economic summaries are given in Annexe (Section 4.10) at the end of this chapter. The investment scenario for the city of Nice is detailed on Table A. 1. Expected loss as a function of investment costs as well as cost-benefit curves are shown in **Figure 4. 20**.

Nice counts approximately 29,800 residential buildings. The average price of existing buildings is €3,250 per square meter, which gives overall €41.4 billons worth in residential building stock.



Figure 4. 20 – Mean expected direct and total loss for the city of Nice. Loss as a function of reinforcement investments (left). Cost-benefits curve (right). Direct loss (*continuous lines*). Total loss (*hidden lines*). Estimations are given for hazard levels with 475 years return period (*red lines*), 95 years return period (*blue lines*) and 47 years return period (*black line*). Optimal investment for 475, 95 and 47 years return period are indicated as red, blue and black points respectively on the x-axis.

As in the previous case, direct and indirect losses are rapidly decreased with growing retrofitting investments for hazard levels with 475 years return period. Regarding direct losses, investments up to 10.5% are cost-effective with 5.5% as the optimal value (€2.3 billion). For this latter level of investments, expected mean direct loss is reduced from 13.3% (€5.5 billion) to 5.1% (€2.1 billion) therefore, with a mean total economic saving of 2.7% (€1.1 billion). A reinforce investment of 0.5% (€207 million) would reduce the mean expected number of collapsed (D5) buildings to zero, while a 6.0% investment (€2.5 billion) would be needed to reduce D4 damaged buildings to 0% (these values are not shown in figures).

For regulatory accelerations with 95 years return period, investments up to 1.5% are economically cost-effective. The optimal investment value of 0.5% (€207 million) reduces mean direct losses from 5.1% to 3.9% (0.7% mean savings, €290 million). No collapsed buildings (D5) are expected for this hazard level, and an investment of 0.5% would also reduce expected D4 damaged buildings to zero (values taken from calculations, not seen on figures).

For hazard levels with 10% exceedance probability in 5 years (47 years return period), and as the previous case, all investments are not cost-effective. The expected loss value without any reinforcement in the city of Nice is 0.82 %, thus approximately €340 million loss. Once again, no investment is recommended for this hazard level, without accounting for social and human safety aspects.

Economic results, for direct losses are summarized in Table A. 2 (Annexe section).

4.8.2.3 Lourdes

Lourdes is smaller compared to the rest of the studied cities. The principal economic activity is linked to tourism and many buildings have a strong historical value. The city has 3,700 residential buildings, with a total building stock value of approximately \notin 1.4 billion (\notin 1,200 per square meters in average). Table A. 3 shows the detail investment scenario, and **Figure 4. 21** direct and total loss as a function of reinforcement investments.

Expected mean direct loss for hazard levels with 10% exceedance probability in 50 years (475 years return period) is 14.8 % (€207 million). The optimal investment of 6.5% (€91 million) would generate benefits (savings) of 3.0% (€42 million). 0.5% reinforcement investment (€7 million) would reduce the expected mean percentage of collapsed buildings (D5) to 0.0% and 6.5% (€42 million) would reduce the percentage of D4 damaged buildings to zero.

For hazard levels of 95 years return period, expected direct loss of 5.7% (€80 million) can be in average optimally reduced to 4.5% with 0.5% investment (0.7% savings, €10 million). No collapsed buildings are to be expected in average for this hazard level, and investments of 0.5% (€7 million) would reduce the mean percentage of D4 damage buildings to zero.

Once again investments are not cost-effective for Lourdes to reduce direct losses for hazard levels with 47 years return period. Expected direct loss of 1.0% corresponds to approximately €14 million.



Figure 4. 21 – Mean expected direct and total loss for the city of Lourdes. Loss as a function of reinforcement investments (left). Cost-benefits curve (right). Direct loss (*continuous lines*). Total loss (*hidden lines*). Estimations are given for hazard levels with 475 years return period (*red lines*), 95 years return period (*blue lines*) and 47 years return period (*black line*). Optimal investment for 475, 95 and 47 years return period are indicated as red, blue and black points respectively on the x-axis.

4.8.2.4 Nantes

Nantes is an important city located in a lower seismicity zone of France (zone 3). The city counts 43,800 residential buildings. With an average of \notin 2,680 cost per square meter the total residential building stock value is approximately \notin 50 billion. Table A. 5 shows the detail investment scenario, and **Figure 4. 22** direct and total loss as a function of reinforcement investments for the city of Nantes.

Expected mean direct loss for hazard levels with 475 years return period is 5.8 % (≤ 2.9 billion). Investments up to 2.0% are cost-effective. The optimal investment of 0.5% (≤ 250 million) would reduce expected loss to 4.5% generating savings of 0.8% (≤ 400 million). No collapsed buildings are to be expected in average for this hazard level, and investments of 0.5% would reduce the mean percentage of D4 damage buildings to zero.

Since Nantes is located in a region where the seismicity is lower, loss estimates for hazard levels with 95 and 47 years return period are small compared to the reinforcement costs. Investments are therefore not cost-effective for these return periods. Note that as mentioned earlier, predicted intensities (from regulatory accelerations) are identical for this zone and these return periods. Therefore, losses estimations coincide.

Even if direct losses of 0.98% are expected (€490 million), it is recommended, from a pure economic point of view, to repair damaged buildings after the event (in case of occurrence) rather than try to retrofit the actual building stock.



Figure 4. 22 – Mean expected direct and total loss for the city of Nantes. Loss as a function of reinforcement investments (left). Cost-benefits curve (right). Direct loss (*continuous lines*). Total loss (*hidden lines*). Estimations are given for hazard levels with 475 years return period (*red lines*) and 95 years return period (*blue lines*). Optimal investment for 475 and 95 years return period are indicated as red and blue points respectively on the x-axis.

4.8.2.5 Strasbourg

Strasbourg is another large city located in seismicity zone 3. It counts 23,600 residential buildings. With an average of €2,960 cost per square meter, the total residential building stock value is approximately €30 billion. Table A. 7 shows the detail investment scenario, and **Figure 4.23** direct and total loss as a function of reinforcement investments.



Figure 4. 23 – Mean expected direct and total loss for the city of Strasbourg. Loss as a function of reinforcement investments (left). Cost-benefits curve (right). Direct loss (*continuous lines*). Total loss (*hidden lines*). Estimations are given for hazard levels with 475 years return period (*red lines*) and 95 years return period (*blue lines*). Optimal investment for 475 and 95 years return period are indicated as red and blue points respectively on the x-axis.

Expected mean direct loss for hazard levels with 10% exceedance probability in 50 years (475 years return period) is 5.7 % (\leq 1.7 billion). Investments up to 2.0% are cost-effective. The optimal investment of 0.5% (\leq 150 million) would reduce expected loss to 4.4% generating savings of 0.8% (\leq 240 million). No collapsed buildings are to be expected in average for this hazard level, and investments of 1.0% (\leq 300 million) would reduce the mean percentage of D4 damage buildings to zero.

Strasbourg is also located in seismic zone 3 where hazard levels with 95 and 47 years return period generate in average smaller expected direct losses compared to the reinforcements costs. Investments are therefore not cost-effective for these return periods. Mean direct losses are estimated at 0.94% for these return periods, which corresponds approximately to €280 millions.

4.9. Summary and conclusions

We presented in the first part of this chapter a complete analysis of buildings expected damage for different earthquake scenarios, considering uncertainties in semi-comprehensive way. We concluded that for our intensity-based method, final damage estimations are more sensitive to hazard-related variability than to seismic vulnerability variability. Estimated hazard variability has to be decreased in priority in order to reduce the final damage uncertainty more effectively. Different authors that performed sensibility analyses on earthquake loss models have reach to similar conclusions. Remo and Pinter (2012) evaluated the sensitivity of Hazus-MH and revealed that earthquake damage, loss, and casualty estimates are most sensitive to the seismic hazard data and selection of the attenuation functions. Bommer and Crowley (2006) concluded that the variability in ground-motion predictions, being so large, cannot be neglected in the calculation of seismic hazard and consequently in the estimation of seismic risk. Tyagunov *et al.*, (2014) concluded that for the considered set of input parameters, including hazard, vulnerability and loss models, the greatest contribution to the total uncertainty comes from the hazard part.

This conclusion justifies a suitable use of big-data methods like SVM to estimate the building stock vulnerability at a large scale, especially for regions of moderate hazard. Vulnerability estimations using these methods proved to deliver appropriate results (Chapter 3).

We evaluated that we can reduce the uncertainty in estimated ground shaking by using direct prediction methods, i.e., Intensity Prediction Equations (IPE) instead of a combination of Ground Motion Prediction Equations (GMPE) and Ground Motion to Intensity Conversion Equations (GMICE) as presently used in real-time earthquake impact assessment systems such as ShakeMapTM and PAGER.

In this regard, Cauzzi and Faccioli (2008) was the model giving the smallest residuals when compared to French accelerometric data, and was chosen as the reference ground motion prediction equation to estimate PGA in this work. For intensities predictions, Allen et al., (2012) was the model giving less overall residuals when compared with observed intensities for fifteen modern French earthquakes. However, a combination of different equations (logic tree) was implemented since the accuracy of each model depends on the magnitude and distance of interest.

The estimation of hazard in this work was not comprehensive. A full probabilistic seismic hazard assessment (PSHA) is needed in that situation, which was out of the scope of the present study. We proposed several earthquakes magnitude-distance pairs without any consideration of the probability of occurrence of those events. Results can also be improved by addition of the site effects. Indeed, all calculations in this study did not account for any modification of hazard due to sites conditions.

In any case, uncertainties in the process to estimate the number of damaged buildings combine together to an exceedingly large value using the tools we have at present-day. This is especially true for larger events, producing higher levels of damage. For smaller earthquakes (like non-exceptional French events), standard deviations are manageable, even though the final results have still a strong dependency on the equations selected to estimate ground motions or intensities.

We performed economic loss estimations and simplified cost-benefit analyses for France and in particular, for five French cities. Only dwelling buildings were included. The exposure model was taken from INSEE datasets and the seismic vulnerability distribution of buildings was calculated using SVM methods (Chapter 3). Several hypothetical retrofitting scenarios were proposed with increasing investments costs. An upgrading of a building was represented by a shift in its vulnerability class. We then subjected these cities in each of the reinforced states to a suite of hazard scenarios. Input intensities were calculated from regulatory accelerations from French codes. This hazard allowed a first rough estimation of expected mean direct (and indirect) losses for different time horizons (return periods of 475, 95 and 47 years). The analyses were, however, deterministic since the use of hazard curves, representing the probability of exceeding several intensities levels (calculated from a complete PSHA analysis) were not available. Due to this lack of a full probabilistic analysis of the hazard, and to the oversimplification needed to calculate average annual loss (AAL), we did not include these calculations in this work. Finally, the benefits in terms of avoided damage or collapse were compared with the costs of each retrofitting measure. This work should be regarded as a first step that can be refined and expanded so it becomes more realistic.

Loss estimations showed important expected repair and replacement costs of buildings in French cities for different time spans.

For regulatory hazard levels with 475 years return period, mean direct loss of $\notin 1.3$ billion and total loss of approximately $\notin 2.1$ billion were predicted in Grenoble. The same levels of hazard forecasted in Nice $\notin 5.5$ billion and $\notin 7.5$ billion mean direct and total loss respectively. In Lourdes $\notin 207$ million and $\notin 280$ million. In Nantes $\notin 2.9$ billion and $\notin 3.5$ billion. Finally in Strasbourg, $\notin 1.7$ billion and $\notin 2.1$ billion.

These values are calculated taking into account only expected physical damage to residential buildings and total loss are only roughly estimated. It is worth noticing that in the
occurrence of an event, damage and losses would not be confined within city limits. For example, an earthquake near Grenoble will produce damage to neighboring communes and towns.

As a comparison example, the total cost of the Mw 6.3 L'Aquila (Italy) earthquake (2009) that had maximum epicentral intensity of VIII (intensity predicted for Zone 4 and 475 years return period in France), including financial losses and reconstruction efforts, is estimated to exceed US\$ 16 billion (American Dollars. 1 US\$ = 0.93 Euros, April 2015). Earthquake damage was not limited to buildings, however; roadways and bridges were also affected. In addition, industrial and commercial structures sustained damage, leading to business interruption and other financial losses (Global Risk Miyamoto).

For regulatory hazard levels with 95 years return period, mean direct loss of €470 million and mean total loss of approximately €560 million were predicted in Grenoble. This level of hazard created in Nice €2.1 billion and €2.5 billion mean direct and total loss respectively. In Lourdes €80 million and €95 million. In Nantes €490 million and €530 million. Finally in Strasbourg, €280 million and €305 million.

For hazard levels with 10% exceedance probability in 5 years (47 years return period), mean total losses of €77 millions are expected in the city of Grenoble, €340 million for the city of Nice; €14 million for Lourdes; €490 million for Nantes and €280 million for Strasbourg.

The Mw 4.8 Annecy (France) earthquake (1996), which had maximum epicentral intensities of VI - VII (intensity predicted for Zone 4 with 47 and 95 years return period in France respectively), caused estimated losses of €50 million (AFPS, French Paraseismic Association 1996).

We include an estimation of loss expected for a repetition of the M 6.0 Lambesc historical earthquake (1909). Using the damage data obtained in Chapter 3, Section 3.6.1 and buildings values for the average region of \notin 2600 per square meter; we calculate economical losses following the methodology of Section 4.7. If the exact same event happened on today's urbanization, mean direct expected losses would be approximately \notin 5.1 billion and total mean losses of approximately \notin 6.2 billion. This estimation includes all damage regions affected with intensities higher than V. Once again, these loss values correspond to damage to dwelling buildings alone.

General trends of the quantitative reduction of risk for different earthquakes scenarios and for regulatory accelerations with different return periods, showed a rapid decline of probable mean direct and total loss after the strengthening of structures, in particular for the higher hazard levels. The results of this study suggest that retrofitting are desirable (costeffective) in France for all but the very shortest time horizons (i.e., return periods larger than 95 years for cities in zone 4 and for return periods larger than 475 years in zone 3).

Relatively small reinforcement investments reduced the probability of collapsed buildings (D5) for all hazard levels by upgrading the most vulnerable constructions present in the city (vulnerability class A and B). By avoiding the collapse of buildings we rapidly decrease at the same time the expected number of fatalities. This benefit was not included in the decision of the convenience of a solution and only the economic aspect was considered. However, this information might encourage the responsible authorities to invest in the retrofitting of existing buildings in order to increase human safety.

It is worth recalling that uncertainties have cumulated during the estimation process to very large final values. The estimation of number of damaged buildings for a probable event or in the aftermath of an earthquake carries uncertainties linked to the estimation of the hazard as well as in the estimation of vulnerabilities. The conversion of physical damage to loss and finally to monetary units depends on consequence models (loss-to-ratio models) and economic models that include even more uncertainties. Note that this uncertainties were not included in the calculations. According to our results, final loss estimations using our methodology have variability within a \pm factor of two of the mean values (standard deviation in the order of the mean value). These factors are of the same order of magnitude (or smaller) than the ones found on loss models like Hazus (Kircher *et al.*, 2006; Price *et al.*, 2010; Remo and Pinter, 2012).

Retrofitting scenarios only have a statistical meaning at a large scale. They are not intended to study the best reinforcement to apply to a particular building. In addition, many retrofitting scenarios can be proposed. An iterative process can be developed to find the most convenient solution depending on the chosen goal. Indeed, the analysis should be expanded by considering the differential impact of these measures on tenants in the buildings, their neighbors, owners, city, provincial and central administrators, each of whom have different stakes in the resistance of buildings to earthquake damage. To initiate a cost-benefit analysis, the options that are being considered and the interested parties in the process should be normally specified, in other words, determine whose benefits and costs ought to be counted. Depending on the decided politic, the mitigation measures can be for example voluntary or optional for residents or forced by regulations.

Cost-benefits analyses are very sensitive to average reinforcements costs. These values were estimated from reinforcements studies for buildings in the city of Lourdes and carry themselves a large uncertainty. These values can be better defined for each particular case with information on similar real reinforcements projects. This information, usually known to assurance and construction companies, would certainly improve the results.

The author acknowledges that the results of the cost-benefit analysis as stated here are surely not detailed and comprehensive enough to be able to support some strategic decisions regarding the reduction of earthquake risk in France. They may only serve as a benchmark for more realistic and targeted cost-benefit analysis.

4.10. Annexe

Table A. 1 – Scenarios of increasing reinforcement investments for Nice. The mean vulnerability distribution of the city is:A-9.1%; B-36.3%; C-22.5%; D-16.6%; E-15.5%; F-0.0%

				D		0.20
Investment (%)	а у в (%)	A₩C (%)	A y D (%)	B y € (%)	B y D (%)	(%)
0.0 (none)	0.0	0.0	0.0	0.0	0.0	0.0
0.5	94.4	5.6	0.0	0.0	0.0	0.0
1.0	33.3	66.7	0.0	0.0	0.0	0.0
1.5	0.0	68.7	31.3	0.0	0.0	0.0
2.0	0.0	0.0	100.0	0.0	0.0	0.0
2.5	0.0	0.0	100.0	13.8	0.0	0.0
3.0	0.0	0.0	100.0	27.6	0.0	0.0
3.5	0.0	0.0	100.0	41.3	0.0	0.0
4.0	0.0	0.0	100.0	55.1	0.0	0.0
4.5	0.0	0.0	100.0	68.8	0.0	0.0
5.0	0.0	0.0	100.0	82.6	0.0	0.0
5.5	0.0	0.0	100.0	96.4	0.0	0.0
6.0	0.0	0.0	100.0	89.9	10.1	0.0
6.5	0.0	0.0	100.0	76.1	23.9	0.0
7.0	0.0	0.0	100.0	62.4	37.6	0.0
7.5	0.0	0.0	100.0	48.6	51.4	0.0
8.0	0.0	0.0	100.0	34.9	65.1	0.0
8.5	0.0	0.0	100.0	21.1	78.9	0.0
9.0	0.0	0.0	100.0	7.3	92.7	0.0
9.5	0.0	0.0	100.0	0.0	100.0	4.2
10.0	0.0	0.0	100.0	0.0	100.0	13.1
10.5	0.0	0.0	100.0	0.0	100.0	22.0
11.0	0.0	0.0	100.0	0.0	100.0	30.9
11.5	0.0	0.0	100.0	0.0	100.0	39.8

Investment	475 years return period		95 years r	eturn period	47 years return period	
investment -	Mean loss	Mean savings	Mean loss	Mean savings	Mean loss	Mean savings
0 (none)	5.52 billion	0	2.10 billion	0	343 million	0
207 million	4.69 billion	623 million	1.60 billion	293 million	339 million	-
414 million	4.39 billion	716 million	1.46 billion	226 million	303 million	-
621 million	4.16 billion	739 million	1.37 billion	109 million	281 million	-
828 million	3.95 billion	742 million	1.32 billion	-	277 million	-
1.03 billion	3.73 billion	750 million	1.20 billion	-	244 million	-
1.24 billion	3.46 billion	813 million	1.08 billion	-	210 million	-
1.45 billion	3.20 billion	874 million	963 million	-	178 million	-
1.66 billion	2.93 billion	937 million	841 million	-	145 million	-
1.86 billion	2.66 billion	998 million	719 million	-	112 million	-
2.07 billion	2.39 billion	1.06 billion	597 million	-	78 million	-
2.28 billion	2.12 billion	1.12 billion	474 million	-	45 million	-
2.48 billion	1.96 billion	1.07 billion	417 million	-	34 million	-
2.69 billion	1.84 billion	992 million	385 million	-	31 million	-
2.90 billion	1.71 billion	907 million	351 million	-	28 million	-
3.10 billion	1.59 billion	823 million	318 million	-	25 million	-
3.31 billion	1.47 billion	737 million	285 million	-	22 million	-
3.52 billion	1.35 billion	653 million	252 million	-	19 million	-
3.73 billion	1.23 billion	568 million	219 million	-	16 million	-
3.93 billion	1.14 billion	449 million	195 million	-	13 million	-
4.14 billion	1.09 billion	291 million	182 million	-	12 million	-
4.35 billion	1.04 billion	133 million	168 million	-	10 million	-
4.55 billion	991 million	-	155 million	-	9 million	-
4.76 billion	943 million	-	142 million	-	8 million	-

Table A. 2 – Summary of economic results (in \in) for the city of Nice, for direct losses only.

Investment (%)	A → B (%)	A→C (%)	A → D (%)	B → C (%)	B → D (%)	C → D (%)
0.0 (none)	0.0	0.0	0.0	0.0	0.0	0.0
0.5	93.5	6.5	0.0	0.0	0.0	0.0
1.0	31.5	68.5	0.0	0.0	0.0	0.0
1.5	0.0	65.7	34.3	0.0	0.0	0.0
2.0	0.0	0.0	100.0	0.7	0.0	0.0
2.5	0.0	0.0	100.0	11.4	0.0	0.0
3.0	0.0	0.0	100.0	22.1	0.0	0.0
3.5	0.0	0.0	100.0	32.8	0.0	0.0
4.0	0.0	0.0	100.0	43.5	0.0	0.0
4.5	0.0	0.0	100.0	54.2	0.0	0.0
5.0	0.0	0.0	100.0	64.9	0.0	0.0
5.5	0.0	0.0	100.0	75.6	0.0	0.0
6.0	0.0	0.0	100.0	86.3	0.0	0.0
6.5	0.0	0.0	100.0	97.1	0.0	0.0
7.0	0.0	0.0	100.0	92.2	7.8	0.0
7.5	0.0	0.0	100.0	81.5	18.5	0.0
8.0	0.0	0.0	100.0	70.8	29.2	0.0
8.5	0.0	0.0	100.0	60.1	39.9	0.0
9.0	0.0	0.0	100.0	49.4	50.6	0.0
9.5	0.0	0.0	100.0	38.7	61.3	0.0
10.0	0.0	0.0	100.0	28.0	72.0	0.0
10.5	0.0	0.0	100.0	17.3	82.7	0.0
11.0	0.0	0.0	100.0	6.5	93.5	0.0
11.5	0.0	0.0	100.0	0.0	100.0	5.0

Table A. 3 – Scenarios of increasing reinforcement investments for Lourdes. The mean vulnerability distribution of the cityis: A-9.0%; B-46.7%; C-15.7%; D-13.8%; E-14.8%; F-0.0%

Investment	475 years return period		95 years r	eturn period	47 years return period	
investment	Mean loss	Mean savings	Mean loss	Mean savings	Mean loss	Mean savings
0 (none)	207 million	0	80 million	0	14 million	0
7 million	179 million	21 million	63 million	10 million	14 million	-
14 million	169 million	24 million	59 million	7 million	13 million	-
21 million	161 million	25 million	56 million	3 million	12 million	-
28 million	156 million	23 million	54 million	-	12 million	-
35 million	147 million	25 million	50 million	-	11 million	-
42 million	138 million	27 million	46 million	-	9 million	-
49 million	128 million	29 million	42 million	-	8 million	-
56 million	119 million	32 million	37 million	-	7 million	-
63 million	110 million	34 million	33 million	-	6 million	-
70 million	101 million	36 million	29 million	-	5 million	-
77 million	92 million	38 million	25 million	-	4 million	-
84 million	83 million	40 million	21 million	-	3 million	-
91 million	73 million	42 million	17 million	-	2 million	-
98 million	68 million	41 million	15 million	-	1 million	-
105 million	64 million	38 million	14 million	-	1 million	-
112 million	60 million	35 million	13 million	-	1 million	-
119 million	56 million	32 million	12 million	-	0.9 million	-
126 million	52 million	29 million	10 million	-	0.8 million	-
133 million	48 million	26 million	9 million	-	0.7 million	-
140 million	44 million	23 million	8 million	-	0.6 million	-
147 million	39 million	20 million	7 million	-	0.5 million	-
154 million	35 million	18 million	6 million	-	0.4 million	-
161 million	32 million	14 million	5 million	-	0.3 million	-

Table A. 4 – Summary of economic results (in €) for the city of Lourdes, for direct losses only.

Investment (%)	A → B (%)	A→C (%)	A → D (%)	B → C (%)	B → D (%)	C → D (%)
0.0 (none)	0.0	0.0	0.0	0.0	0.0	0.0
0.5	100.0	0.0	0.0	0.0	0.0	0.0
1.0	44.7	55.3	0.0	0.0	0.0	0.0
1.5	0.0	87.9	12.1	0.0	0.0	0.0
2.0	0.0	25.5	74.5	0.7	0.0	0.0
2.5	0.0	0.0	100.0	6.6	0.0	0.0
3.0	0.0	0.0	100.0	17.8	0.0	0.0
3.5	0.0	0.0	100.0	28.9	0.0	0.0
4.0	0.0	0.0	100.0	40.1	0.0	0.0
4.5	0.0	0.0	100.0	51.2	0.0	0.0
5.0	0.0	0.0	100.0	62.4	0.0	0.0
5.5	0.0	0.0	100.0	73.5	0.0	0.0
6.0	0.0	0.0	100.0	84.6	0.0	0.0
6.5	0.0	0.0	100.0	95.8	0.0	0.0
7.0	0.0	0.0	100.0	93.1	6.9	0.0
7.5	0.0	0.0	100.0	81.9	18.1	0.0
8.0	0.0	0.0	100.0	70.8	29.2	0.0
8.5	0.0	0.0	100.0	59.6	40.4	0.0
9.0	0.0	0.0	100.0	48.5	51.5	0.0
9.5	0.0	0.0	100.0	37.3	62.7	0.0
10.0	0.0	0.0	100.0	26.2	73.8	0.0
10.5	0.0	0.0	100.0	15.0	85.0	0.0
11.0	0.0	0.0	100.0	3.9	96.1	0.0
11.5	0.0	0.0	100.0	0.0	100.0	8.6

Table A. 5 – Scenarios of increasing reinforcement investments for Nantes. The mean vulnerability distribution of the cityis: A-10.0%; B-44.8%; C-15.1%; D-10.5%; E-19.6%; F-0.0%

Investment	475 years return period		95 years r	eturn period	47 years return period	
investment	Mean loss	Mean savings	Mean loss	Mean savings	Mean loss	Mean savings
0 (none)	2.89 billion	0	492 million	0	492 million	0
250 million	2.24 billion	401 million	490 million	-	490 million	-
500 million	2.07 billion	315 million	447 million	-	447 million	-
1.00 billion	1.93 billion	207 million	410 million	-	410 million	-
1.25 billion	1.88 billion	7 million	406 million	-	406 million	-
1.50 billion	1.77 billion	-	380 million	-	380 million	-
1.75 billion	1.63 billion	-	340 million	-	340 million	-
1.00 billion	1.48 billion	-	300 million	-	300 million	-
2.00 billion	1.33 billion	-	260 million	-	260 million	-
2.25 billion	1.18 billion	-	220 million	-	220 million	-
2.50 billion	1.04 billion	-	180 million	-	180 million	-
2.75 billion	888 million	-	140 million	-	140 million	-
3.00 billion	742 million	-	100 million	-	100 million	-
3.25 billion	593 million	-	60 million	-	60 million	-
3.50 billion	513 million	-	43 million	-	43 million	-
3.75 billion	473 million	-	39 million	-	39 million	-
4.00 billion	433 million	-	35 million	-	35 million	-
4.25 billion	393 million	-	31 million	-	31 million	-
4.50 billion	353 million	-	28 million	-	28 million	-
4.75 billion	313 million	-	24 million	-	24 million	-
5.00 billion	272 million	-	20 million	-	20 million	-
5.25 billion	233 million	-	16 million	-	16 million	-
5.50 billion	193 million	-	13 million	-	13 million	-
5.75 billion	168 million	-	10 million	-	10 million	-

Table A. 6 – Summary of economic results (in €) for the city of Nantes, for direct losses only.

Investment (%)	A → B (%)	A → C (%)	A → D (%)	B → C (%)	B → D (%)	C → D (%)
0.0 (none)	0.0	0.0	0.0	0.0	0.0	0.0
0.5	99.0	0.0	0.0	0.0	0.0	0.0
1.0	45.5	54.5	0.0	0.0	0.0	0.0
1.5	0.0	89.4	10.6	0.0	0.0	0.0
2.0	0.0	27.5	72.5	0.0	0.0	0.0
2.5	0.0	0.0	100.0	6.6	0.0	0.0
3.0	0.0	0.0	100.0	18.5	0.0	0.0
3.5	0.0	0.0	100.0	30.4	0.0	0.0
4.0	0.0	0.0	100.0	42.3	0.0	0.0
4.5	0.0	0.0	100.0	54.2	0.0	0.0
5.0	0.0	0.0	100.0	66.1	0.0	0.0
5.5	0.0	0.0	100.0	78.0	0.0	0.0
6.0	0.0	0.0	100.0	89.8	0.0	0.0
6.5	0.0	0.0	100.0	98.3	1.7	0.0
7.0	0.0	0.0	100.0	86.4	13.6	0.0
7.5	0.0	0.0	100.0	74.5	25.5	0.0
8.0	0.0	0.0	100.0	62.6	37.4	0.0
8.5	0.0	0.0	100.0	50.7	49.3	0.0
9.0	0.0	0.0	100.0	38.8	61.2	0.0
9.5	0.0	0.0	100.0	27.0	73.0	0.0
10.0	0.0	0.0	100.0	15.1	84.9	0.0
10.5	0.0	0.0	100.0	3.2	96.8	0.0
11.0	0.0	0.0	100.0	0.0	100.0	7.2
11.5	0.0	0.0	100.0	0.0	100.0	17.0

Table A. 7 – Scenarios of increasing reinforcement investments for Strasbourg. The mean vulnerability distribution of thecity is: A-10.1%; B-42.1%; C-20.4%; D-15.4%; E-12.0%; F-0.0%

Investment	475 years return period		95 years r	eturn period	47 years return period	
investment	Mean loss	Mean savings	Mean loss	Mean savings	Mean loss	Mean savings
0 (none)	1.70 billion	0	283 million	0	283 million	0
150 million	1.31 billion	240 million	282 million	-	282 million	-
300 million	1.21 billion	191 million	257 million	-	257 million	-
450 million	1.13 billion	127 million	234 million	-	234 million	-
600 million	1.09 billion	7 million	231 million	-	231 million	-
750 million	1.03 billion	-	217 million	-	217 million	-
900 million	945 million	-	193 million	-	193 million	-
1.05 billion	856 million	-	169 million	-	169 million	-
1.20 billion	768 million	-	145 million	-	145 million	-
1.35 billion	679 million	-	121 million	-	121 million	-
1.50 billion	590 million	-	97 million	-	97 million	-
1.65 billion	502 million	-	73 million	-	73 million	-
1.80 billion	414 million	-	49 million	-	49 million	-
1.95 billion	334 million	-	28 million	-	28 million	-
2.10 billion	310 million	-	26 million	-	26 million	-
2.25 billion	286 million	-	23 million	-	23 million	-
2.40 billion	262 million	-	21 million	-	21 million	-
2.55 billion	238 million	-	19 million	-	19 million	-
2.70 billion	214 million	-	17 million	-	17 million	-
2.85 billion	190 million	-	14 million	-	14 million	-
3.00 billion	166 million	-	12 million	-	12 million	-
3.15 billion	142 million	-	10 million	-	10 million	-
3.30 billion	129 million	-	9 million	-	9 million	-
3.45 billion	119 million	-	8 million	-	8 million	-

Table A. 8 – Summary of economic results (in €) for the city of Strasbourg, for direct losses only.

Chapter 5

General conclusions and perspectives

During the last decade hundred of thousands of people have died in earthquakes. The human tragedy is inestimable, and the overall economic loss is of impressive proportions. In the first months following Haiti earthquake of 2010, where more than 242,000 people lost their lives and 2.3 million were left homeless, the international response swamped a weakened government unable to take charge of the coordination of relief efforts (UN report).

The same scenario was found after many natural disasters worldwide: we were not ready.

We need to understand earthquake behavior and consequences better, mitigate risk, improve disaster readiness, increase society resilience to seismic events and especially, act earlier. On that regard, the situation is relatively better and encouraging than that of a couple decades ago. Loss models are now being developed worldwide and particularly on high-risk regions around the globe. These models are tools used to assess potential losses due to the occurrence of a hazardous event, and their development is of key importance for societies at risk.

These societies at risk are not only located in regions of very high seismic hazard. Many countries of central Europe are situated in what is called moderate-to-low seismic hazard regions. In these countries, the building stock is predominantly old, and it was built mainly at times when no earthquake design rules were established, or with rules now considered obsolete. Moreover, the earthquake in L'Aquila (Italy) in 2009, showed that ancient buildings could suffer significant losses under shaking levels lower that those given by current seismic regulations. Some newer buildings, supposedly designed to withstand these levels of shaking, were not free from damage.

Unfortunately, every step in damage or loss estimation processes presents uncertainties related to: the definition of the hazard, the definition of the exposure, the definition of damage relations or vulnerabilities, as well as in the definition of economical losses. Final loss estimates are only an approximate order of magnitude of what can really be expected (Jaiswal and Wald, 2013).

In the first main part of this work, as an important component of earthquake loss models, we have developed a methodology to estimate seismic vulnerability of buildings at a large scale using datamining techniques. This macroscale method creates a proxy, which establishes a relationship between building characteristics and their probable vulnerability class. It is easily applicable and adaptable to the readily regional available building data and is particularly useful where traditional methods cannot be easily applied or for first level evaluations. Even if it was conceived for basic assessments, several validations by comparison with more detailed methods have shown its relevance and applicability.

To be developed, the method requires a "test" area (e.g., city, region) with a full and trustworthy vulnerability assessment. All buildings types should be represented in the sample set and the number of studied buildings (if not all) should be large enough to minimize the influence of "especial cases". Proxies are developed for this particular test region. The application of it to extrapolate buildings vulnerability to other areas hypothesizes similar construction type and techniques between the source and the target region.

We have combined proxies developed with information for the city of Grenoble (France) with census information from INSEE datasets to calculate vulnerability distributions for the entire country. Validation in the city of Nice, and simulations of three French historical earthquakes confirmed the appropriateness in the application of this proxy to southern regions of the territory. It remains however not entirely proven that this proxy can be applied to represent other regions' vulnerability successfully.

It would be interesting and instructive to develop proxies with datasets for different regions or countries, compare them and, for example, create global national proxies by a thoughtful combination. To achieve this, we have already requested vulnerability data from European organizations. In addition, the World Bank would be interested in seeing the application and results of this methodology in South American and Caribbean countries, where the resources are certainly limited to carry out full building stock repertories. The adaptability and accuracy of the method can be further explored with newer and enriched datasets. In the same way, other datamining techniques like Random Forests, or Neural Networks can be further explored. We can also supplementary validate and generalize the method by modeling damage for recent large European earthquakes for which detailed damage assessments are available.

Data mining methods appear to be well suited to a first level large-scale assessment of seismic vulnerability and thus to the simulation of seismic damage. The flexibility and adaptability of the method is one of its main advantages. In global loss models like GEM or PAGER, the methodology would be a good candidate to complete global exposure and vulnerability models for regions where the information regarding the building stock is scarce.

Besides the validation of the method by comparison with Risk-UE calculations in the city of Nice and by comparison with observed damage for three historical French earthquakes, the vulnerability evaluation of present-day urbanization allowed the assessment of the probable effects that these regions would incur if these events were to strike again. Damage is expected to double or triple compared with observed statistics at that time. Economic loss assessments for a repetition of the M6.0 Lambesc earthquake (1909) predicted mean total losses in the order of €6.2 billion for the entire affected region. This estimate only considers damage to dwelling buildings. This value is expected to be much higher since all other infrastructure (roadways, bridges, industries, utility lines, etc.) is also susceptible to damage and could contribute a large proportion of the total economic losses.

In the second main part of this work we have presented a complete assessment of damage in a typical European city, for a deterministic set of earthquake scenarios. The vulnerability of buildings was characterized with the classes of EMS98 scale calculated using Support Vector Machine methods. We have considered uncertainties in a comprehensive way, and final damage variability had factors of the order of \pm two of the mean value. Final combined uncertainties are therefore very large, and results should be used with caution. Decisions can be eventually taken from mean damage values, but uncertainties have to be explicitly indicated and fully understood.

The final uncertainty of our intensity-based method is comparable with the one of models like Hazus-MH (first levels of assessment). For our method, final damage estimates are attributed more to hazard-related variability than to seismic vulnerability variability.

Several sensitivity analyses on Hazus-MH attained the same conclusion. This justifies once more the use of a simplified, fast, inexpensive and readily available method of vulnerability estimations for first level earthquake loss model in moderate-to-low seismic hazard regions.

Vulnerability models have nonetheless a critical importance for the estimation of damage, and exhaustive methods should be applied when detailed probable loss data is required.

In general, when estimating hazard characteristics, the most direct method of estimating the final desired parameter is the most preferable. It is better for example, to go from magnitude directly to intensities than to use peak motion parameters as an intermediate step. The reason is that any intermediate variable introduces variability, complications and possible biases in the analysis.

In any case, Cauzzi and Faccioli (2008) was found to be the best ground motion prediction equation to estimate peak ground accelerations in France. Even if not prominently superior, the model of Allen *et al.*, (2012) is recommended for the direct estimation of intensities in France.

Economic loss estimations showed important expected repair and replacement costs of buildings in French cities for hazards with different time horizons. Input hazard was calculated from regulatory accelerations in French codes, and vulnerability distributions with SVM proxy applied to INSEE data. For large cities located in the highest hazard regions of metropolitan France (seismicity zone 4) like Grenoble or Nice, expected economic losses for events with 475 years return period, can be comparable or larger than the one observed during the earthquake in L'Aquila, Italy in 2009 ($\approx \text{€15}$ billion). By simple extrapolation, and due to the expected number of collapsed buildings, it is sad to anticipate a probable death toll larger than in Italy where more than 300 people lost their lives, and a much longer recovery phase if such an even happened in France. For hazard with shorter return periods, losses are still significant.

Other than global loss estimates at the scale of a region or city, our method allowed a graphical representation of expected losses at a lower scale: the IRIS unit. For important urban-environments, this unit represents a neighborhood or even a group of buildings within a certain location. We have portrayed in maps, the zones that are expected to suffer more the

effects of an event, either because they are seismically more vulnerable or because the hazard demand is higher in that place (or both).

We have proposed several hypothetical retrofitting scenarios with increasing investment costs for a typical synthetic European city and for five "real" cities in France. The benefits in terms of the reduction of expected damage to buildings were compared with the costs of each retrofitting measure. The results of this cost-benefit analysis suggested that, even when considering only direct losses and from a purely economic point of view, reinforcements actions are desirable for the longest time horizons (i.e., hazards with larger destructive potential). In France, retrofitting of buildings is cost-effective for hazards with return period larger than 95 years (10% exceedance probability in 10 years) for regions in zone 4, and for hazard with return periods larger than 475 years (10% exceedance probability in 50 years) for regions in zone 3. Optimal investments values, which maximize the savings in case of the occurrence of the event, were calculated for each city.

Public institutions might be pleased to find out that relatively small investments reduced the probability of collapsed building for all hazard levels in France. This was achieved through investment scenarios targeting the retrofitting of the most vulnerable structures in priority (Vulnerability class A). This information can guide decision-makers in mitigation frameworks aiming at the reduction of human casualties.

The results of this work have only statistical meaning and they are not intended to study the case of particular structures. As has been acknowledged, the study has been conducted using certain simplifying assumptions. Some of them are due to lack of better information, and others for sake of simplicity, to keep the analyses manageable. This work should be regarded as a first step that can be improved and expanded so it becomes more realistic. Throughout the work, practicability was favored over fundamental theoretical analysis or explanations.

On that regard, there are several prospects for future research to refine the loss assessments and the cost-benefits analyses using this methodology.

The estimation of hazard throughout this work was not comprehensive and purely deterministic, and that is the first point that can be enhanced. For better-targeted evaluations of potential losses, hazard curves ensuing from complete probabilistic seismic hazard assessments should be used. These hazard curves (e.g., in terms of intensities) represent the (annual) exceedance probability of various intensities associated with future earthquakes that can have effects on the studied region. This is a much comprehensive way of calculating losses. The methodology undertaken in this work can easily incorporate these curves with no significant modification or efforts. The results would be more accurate, since regulatory values used so far are only a disaggregated part of the total hazard, and can be used for a broad first estimation only. Moreover, average annual loss for the target city could be correctly developed. The results of cost-benefit analysis will depend on this improved version of expected losses.

Several authors assert the importance of time dependency in the estimation of hazard. The use of time-dependent hazard curves defined relative to the time of occurrence of previous events on the region could be important on high seismicity regions. In low seismicity regions like central Europe, the increase in the likelihood of an event in the region as a function of time will not be significantly large. Hazard models "without memory" are still appropriate for our case. Furthermore, in terms of reinforcement investments, if a mitigation plan is convenient at present time, it should be even more attractive in the following years (before the events actually happen).

Results can also be improved by addition of site effects. For example, predicted values of hazard (intensities) can be adjusted depending on the site soil or topographic condition to take into account possible modifications due to site effects. Regulatory accelerations used in this work are for rock sites; no site effects were thus included in the calculations.

On the building response side, more detailed retrofitting schemes could be proposed. However, we are limited by the drawbacks of a discrete intensity-based method. The use of detailed fragility functions would allow the modeling and calibration of retrofitting behaviors (like it is done in models like GEM or Hazus), but once again there is the trade-off between desired accuracy and available resources.

For future loss and cost-benefit analyses we need to explore the representativeness of the input parameters better. For example, the cost to reinforce buildings is a sensible input value for these assessments. Variations of this parameter can rapidly change the convenience or not of an investment. Efforts to precise these values regionally are highly recommended. In the same way, since damaging earthquakes are rare in France, alternative methods to derive more precise consequence models should be found. In this work, we have developed one from a pondered average of different European models.

Finally, other than including all the structures and infrastructures susceptible of producing damage and loss in the calculations, we need to include and specify explicitly all the benefits and the cost associated with the different alternatives. Indeed, indirect costs were only considered in an extremely simplified manner and no consideration of "second-order" effects were measured. These second-order effects could be represented by the example of a collapsed building that produced damage to a nearby construction that have not suffered any damage from the ground shaking itself. Indirect costs need to analyze business interruptions, demand reductions, supply shortages, relocation expenses (when a building is not long habitable) among others. Number of fatalities and their economic impact have to be also included for loss estimations.

All these elements complicate loss estimations and were out of the scope of this work. However, they could be included in future more detailed versions.

The results of this work, in terms of global loss estimations might not be detailed enough to support some strategic decision regarding the reduction of earthquake risk in France. They are only hoped to serve as a benchmark for more realistic and targeted analyses.

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