EXPOSURE AND VULNERABILITY ASSESSMENT VIA THE INTEGRATION OF REMOTE AND IN SITU INFORMATION: CASE STUDY OF KYRGYZSTAN

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Abstract

The exposure and vulnerability of society and its various elements to natural hazards are the parameters that potentially display the most temporal dynamism. Therefore, there is a need for cost efficient and rapid means to obtain robust estimates of these factors. This is especially important for those societies and communities that lack both the financial and technical resources to undertake detailed surveys, while building-by-building assessments are, in any case, not feasible for even the richest economies.

The work presented here outlines a procedure combining top-down and bottom-up approaches to develop models of physical exposure and vulnerability for seismic risk assessment purposes. The proposed procedure integrates information automatically extracted from remote sensing sources with other already available ancillary sources in order to optimize the collection of in-situ data. The use of mobile mapping systems, along with modern web-based technologies and geostatistical analysis allows for a very prompt and reliable characterization of the built-up environment, paramount to the subsequent quantitative risk estimation stage.

The resulting model of the residential building stock is then associated to a suitable set of vulnerability curves describing the expected propensity of the considered building types to be damaged (or to collapse) when exposed to different levels of ground motion. An empirical approach has been followed, which is originally derived from the formulation of EMS-98 macroseismic intensity.

Results from the use of these data source types and tools are presented for the case of the urban environment of Kyrgyzstan, which in recent decades has undergone rapid and, in many cases, unplanned growth. The tools and systems presented here have been successfully employed in a World Bank-supported project aimed at Measuring Seismic Risk in the Kyrgyz Republic.

Keywords: Seismic Risk Assessment; Seismic Exposure; Seismic Vulnerability; Remote Sensing; Mobile Mapping

1. Introduction

Central Asia, covering the countries of Kazakhstan, Kyrgyzstan, Tajikistan, Turkmenistan and Uzbekistan (Fig. 1) with a combined population of about 60 million people is one of the most seismically hazardous regions of the world. A high level of seismic hazard [1,2] coupled with a potentially high physical vulnerability of the building stock results in a high seismic risk for the region.

Risk is generally estimated as a function of three components: hazard, i. e. the likelihood to exceed specific levels of ground motion; exposure and vulnerability. Exposure refers to the compilation of all the elements (people, property, systems, societal functions, the economy, traditional and cultural heritage and the environment) present in hazard zones that are potentially subject to losses (e.g., [3]), where a given element may be exposed to one or more hazards. Vulnerability describes how susceptible a population, asset or structure is to the loading imposed upon it by the earthquake-generated ground motion. Hereinafter we will refer to exposure as the set of residential buildings and the related inhabitants, since this is usually the main cause of fatalities.

As a heritage of the common Soviet history of Central Asia, Kyrgyzstan shares with most of the neighbouring countries a largely similar set of building types and construction practices. After the collapse of the Soviet Union, however, the building stock developed independently in the countries, resulting in different building typologies and manifested in the respective national building codes. Where there seems to be a good knowledge about the composition of governmental buildings that were constructed during the Soviet-era, information about the building stock of the private sector that mainly developed after 1990 is largely missing in exposure and vulnerability models [4]. Moreover, due to a general lack of resources to keep track of the increasingly high spatio-temporal evolution of urban areas, only sparse data are available about exposed assets. The available data are, moreover, often outdated, spatially fragmented or highly aggregated and their characterization appears to be strongly heterogeneous across national borders.

It is therefore important to devise efficient and scalable approaches for developing reliable models of exposure and vulnerability, in order to further improve the assessment of seismic risk. This is in turn allowing Civil Protection authorities and decision makers to undertake better decision for the mitigation of the negative consequences of earthquakes.

In this paper we describe and discuss the approach followed for estimating the physical exposure and physical vulnerability within a project, supported by World Bank, aimed at the assessment of seismic risk in Kyrgyzstan. The methodologies employed for the collection and integration of exposure data have been developed within the Earthquake Model Central Asia (EMCA, see e. g. [5]) project, as regional contribution to the Global Earthquake Model Project1.

2. Methodology - exposure

The approach followed for the assessment of exposed assets combines different information sources and data collection techniques in the framework of an integrated sampling scheme, where each source and technique is used to infer specific scale-dependent information about the exposed building stock and its population [6]. Top-down are combined with bottom-up assessments and three analysis levels with respective spatial scales are distinguished, which will be referred to as regional scale, neighbourhood scale and per-building scale.

1 www.globalquakemodel.org

At regional scale different geospatial datasets are combined with local expert knowledge to identify and locate exposed settlements, to develop a unified building taxonomy for the region and to derive composite models of building types for urban and rural areas. This scale represents a first level approximation of exposure over large areas, both at district and regional (respectively *rayon* and *oblast*, in Kyrgyzstan) aggregation level.

At regional scale, a set of medium-resolution multi-spectral satellite images (LANDSAT) are used to extract the settlements extent and to delineate selected urban areas into zones that appear relatively homogeneous in terms of their predominant building types and approximate construction date period. The processing is based on an automatic segmentation of the images, followed by a supervised classification of each of the extracted segments, according to the methodology proposed in [7].The resulting labelled segmentation provides a meaningful spatial support for the aggregation of the exposed building stock information based on the observed different urbanization patters.

The labelled segmentation of urban areas is used as input for a sampling procedure to identify areas to be analysed at per-building scale using the in-situ visual screening technique described by [8]. At this scale, any information is defined at the most detailed level of individual building. The sampling strategy employs the estimated spatial distribution of urban patterns with the available information on the roads network of the same area (provided by the freely-available OpenStreetMap platform). An optimized driving route is thus selected, such that the areas showing different characteristics in the satellite imagery are adequately sampled for in-situ observation.

In order to promptly collect the in-situ visual data, a mobile mapping system based on omnidirectional imaging has been deployed to capture images of the buildings [8]. The system is driven along the pre-calculated sample routes, automatically capturing a dense stream of geo-referenced, high resolution panoramic images of the surrounding area. A set of buildings that are most likely visible from the street along the predefined route are then sampled, and their omnidirectional images are remotely analysed using a Remote Rapid Visual Screening (RRVS) tool that combines a GIS interface with an omnidirectional image viewer [8]. Additionally the direct observation tools from the GEM Inventory Data Capture Tools (IDCT, see [9]) project were used to integrate the remote visual screening with a smaller set of in-depth, direct inspections.

Every inspected building is associated to a set of structural and non-structural features according to the GEM taxonomy [10]. A set of building typologies has been selected as representative for the observed residential building stock in Kyrgyzstan, and will form the base of the resulting exposure model.

The estimation of this model in a sound statistical framework requires that the expected probability of the different buildings typologies is modelled based on their observed frequencies, but also accounting for the uncertainty resulting from insufficient or spatially-biased sampling.

In order to account for such uncertainty, a Bayesian updating approach including prior distribution on the typologies´ distribution is considered. Different priors could be chosen, but in the case of multivariate data the natural choice is a Dirichlet distribution of building types. When direct observation are available, as the ones derived from the RRVS activity, this information is integrated with the prior following the Bayes approach [11].

The posteriori estimate of the different building typologies can be described as:

(1)

Where represents the vector of probabilities of the specific building types {1,...,K}, is the likelihood of the observations given the model, and is modeled by a multinomial distribution, while is the prior described by a Dirichlet distribution. represents the vector of hyper parameters which govern the distribution, and -in fact- encodes the information available on the expected frequency of the building types. The resulting posterior distribution is of the following form:

(2)

where the term B is a normalizing factor, and are the actual counts, that is the observed frequencies of the building types.

The above described updating mechanism can be used not only to consider a prior on the distribution, which drives the expected distribution where insufficient empirical observations are available, but also to continually update the statistical model as soon as new information is made available.

The uncertainty on the building frequency associated to the prior can then be estimated by sampling a suitable number of instances from the related Dirichlet distribution, and considering the confidence bounds of the resulting empirical distribution.

The statistical model describing the distribution of building types, along with the observed distribution of the buildings parameters (number of storeys, for instance) allows for the estimation of the total number of buildings per category. This is obtained by a suitable disaggregation of the population at district level, provided by the National Statistical Office as part of the Census, also considering the distinction between urban and rural.

In order to provide reasonable quantitative estimates of the expected seismic loss, also the total number of buildings has to be estimated, for each of the selected aggregation area (in our case, the district). The total number of buildings NB can thus be computed as:

(3)

Where NP is the total number of inhabitants of the district, and is extracted from the census data. The building frequencies for each building typology *t* are sampled from the corresponding Dirichlet distribution. The average occupancy (I. e. the expected number of people living in a building of type *t*) is defined by:

(4)

Where, is the probability mass function (PMF) of the number of storeys *s*, is the PMF of the number of building bs, is the average number of households per storey and building section, and is the average size of an household in the buildings of type t.

Since the frequencies themselves are described by statistical distributions, the Equation 4 has to be evaluated through numerical methods. Thus, a bootstrapping procedure has been carried out by simulating a suitable number of realization of a stochastic process involving the distributions, and considering the 5%, 50% and 95% percentiles to represent the confidence interval of the underlying distribution. This procedure has been carried out for each district taking into account the results of the RRVS observations. Distribution of number of storeys, when available, has been extracted from the observation. Where no suitable data were available, a prior derived from expert judgement has been used. This resulted in a sound estimation of the expected number of buildings for each considered category.

3. Methodology – vulnerability

Vulnerability functions express the likelihood that assets at risk (in our case, residential buildings) will sustain varying degrees of loss over a range of earthquake ground motion intensities. Whereas fragility functions describe the probability of exceeding different limit states (such as damage or injury levels) given a certain level of ground shaking. Despite the fundamental differences, both relations follow similar methodologies for development, which can either be empirical, analytical, or based on expert knowledge and judgement.

Empirical methods are the most widespread. They are based on past earthquake surveys, where the level of observed damage is plotted against the recorded seismic intensity of a certain measure. Empirical methods are found to be site-specific, since construction quality, building standards and codes of practices usually differ from one place to another.

Macroseismic modelling is a widely used approach that is based empirical observations and on expert judgement, where elements that follow common characteristics (typologies) can be assigned to a different vulnerability class, and a vulnerability index ( ) is defined. The index has a value between 0 and 1, based on the observed characteristics of the buildings, where the most vulnerable structures have a value closer to 1. Vulnerability functions are then defined in a closed-form relation as a function of the vulnerability index . Giovinazzi and Lagormarsino [12, 13] suggested an empirical relation that expresses the mean damage grade as a function of and the macroseismic intensity I, where the mean damage grade ranges from 0 to 5.

From the mean damage grade, fragility can be expressed as the damage distribution with the following beta probability density function

Where a, b, t and q are the distribution parameters. The cumulative density of the beta law can thus be used to compute the probability that a building with vulnerability index reaches or exceeds a given damage state:

The vulnerability index is a measure of the propensity of a certain building, or a class of similar structures, to be damaged by different levels of ground motion. In earthquake risk assessment practice, buildings or infrastructure elements at risk are often divided into different typologies that represents its vulnerability class. Constructing typologies involves the grouping of structures that have similar structural characteristics, and are expected to perform in the same way for a given seismic loading.

Typology is thus a high level descriptor of a system. Main construction material, structural system, seismic design level, are among usual typology parameters that are used to assign an initial value of , which is referred to as . A lower level taxonomy can then be utilised in order to derive specific behavioural modification factors according to locally observed characteristics, which is added to the initial value to achieve the vulnerability index . Furthermore, a regional modification factor can be added in the case where region specific data is not available:

(5)

Values for and can be constrained by available statistical data, yet analytical methods or expert judgement can be utilised to assign initial values for the broad typology, and behavioural factors for different characteristics. [13, 14] provided ranges for of for different building typologies according to EMS-98 classification. Values for can also be found in literature [14], where increments are assigned accounting also for the level of earthquake resistant design level (ERD). This allows extending the empirical study for regions outside Europe, where the initial study was conducted.

The probability distribution of each damage state within a specific building type and earthquake intensity is established. This can be regarded as the probability of a single building in the class to reach a specific damage state, or the percentage of buildings in a typology that exceed a damage state.

The presented fragility relation relies on the beta law for the probability distribution, while many seismic risk assessment platforms require inputs in terms of normal (or lognormal) distribution parameters. Due to the limited skewness of the functions and the consistent interval between mean values, reliable normal (or lognormal) distribution approximations can be achieved using basic fitting methods.

Since hazard assessments is often carried out in terms of instrumental intensity as for instance peak ground acceleration (PGA) or velocity (PGV), a suitable conversion is required, using an intensity-ground motion conversion equation (IGMCE). The global IGMCE proposed by [15] is used here, as is one of the few available relationships that does not require inversion.

This conversion also introduces uncertainty which must be propagated. For a given risk assessment, it is reasonable to assume that this uncertainty is fully correlated (i.e. if the PGA prediction for a given macroseismic intensity is higher than expected at one location, it is likely to be higher at other locations). Therefore, it is appropriate to consider this uncertainty to contribute to the lower and upper bound fragility functions to be included in a logic tree approach (in which uncertainty is taken as fully correlated), rather than adjusting the β value (standard deviation) of the fragility function.

4. Results

The methodologies described in Section 2 for the development of an exposure model has been applied to the territory of Kyrgystan. A set of 16 building typologies representative for the residential building stock have been selected (see Table 1) on the base of past studies [5]. For each building typology, a prior relative frequency has been also assigned (not shown).

L1	Obs Freq	acronym	Description	L2	Description	Kyrgyz building code
c1	53%	M	Masonry, unreinforced and reinforced	c1.1	Masonry unreinforced, wood floors	1.4
				c1.2	Masonry unreinforced, RC floors	1.5 - 1.6
				c1.3	Masonry, reinforced or confined	1.1 - 1.2
				c1.4	Masonry, with seismic provisions	1.3
c2	1%	RCM	Reinforced Concrete, Monolithic	c2.1	Monolithic, concrete moment frame	2.1
				c2.2	Monolithic, concrete frame and shear walls	2.2
				c2.3	Monolithic, concrete frame and brick infills	2.3
				c2.4	Monolithic, RC walls	4
c3	3%	RCPC	Reinforced Concrete, Pre-cast	c3.1	Precast, large panel, serie 105	3.1
				c3.2	Precast, large panel, serie 464	3.2
				c3.3	Precast, flat slab, sere KUB	2.8
				c3.4	Pre-fabricated, RC frame	
c4	42%	ADO	Adobe and Earthen	c4	Adobe or earthen walls	9.5

c5	0.3%	W	Wood, Timber	c5.1	Load-bearing, braced wood frame	9.7
				c5.2	Wooden frame and adobe infills	9.6
c6	0.1%	S	Steel	c6	Steel	8

Table 1: Description of the considered building typologies at L1 (coarse) and L2 (detailed) level and the aggregated observed frequencies. The righmost column lists the correspondent types in the buildings code SNIP 2.07.01-89.

In order to preliminary characterize the overall territory a semi-automatic analysis of LANDSAT 8 imagery has been carried out following [7], and the outcome of the analysis have been combined with two further raster layers encoding respectively the spatial density of population provided by Landscan™ (2012 vintage), and the spatial density of roads intersections computed from the information freely available from the OpenStreetMap platform. The layers have been combined with equal weights following the approach proposed by [16]. The resulting map, shown in Figure 1, describes the expected level of urbanization (or the likelihood of a cell of containing an urban area) with a spatial resolution of 0.008 degrees (roughly 0.6 km^2). Values greater than 0.2 indicate inhabited areas, both urban and rural, with the urban areas being described by an index value greater than 0.6. These thresholds have been simply chosen by visual inspection. According to the obtained results, the inhabited areas sum up to ~5800km^2 (2.9% of the country´s total extension), and the urban areas account for 7.7% of the inhabited areas (0.2% of the country area).

Based on this preliminary characterization, several Remote Rapid Visual Surveys (RRVS, see [5,6,8]) have been conducted in order to collect and integrate building-by-building information. Around 7'000 buildings have been inspected across the country, and their structural features recorded according to the GEM Taxonomy (v2.0, see [10]). Each inspected building has been labelled according to the typologies listed in Table 1, and the distribution of the observed typologies has been updated according to the Bayes rule as described in Section 2. In Figure 2 the resulting confidence intervals derived from the related Dirichlet distributions describing the probability of the frequencies themselves, aggregated at country scale.

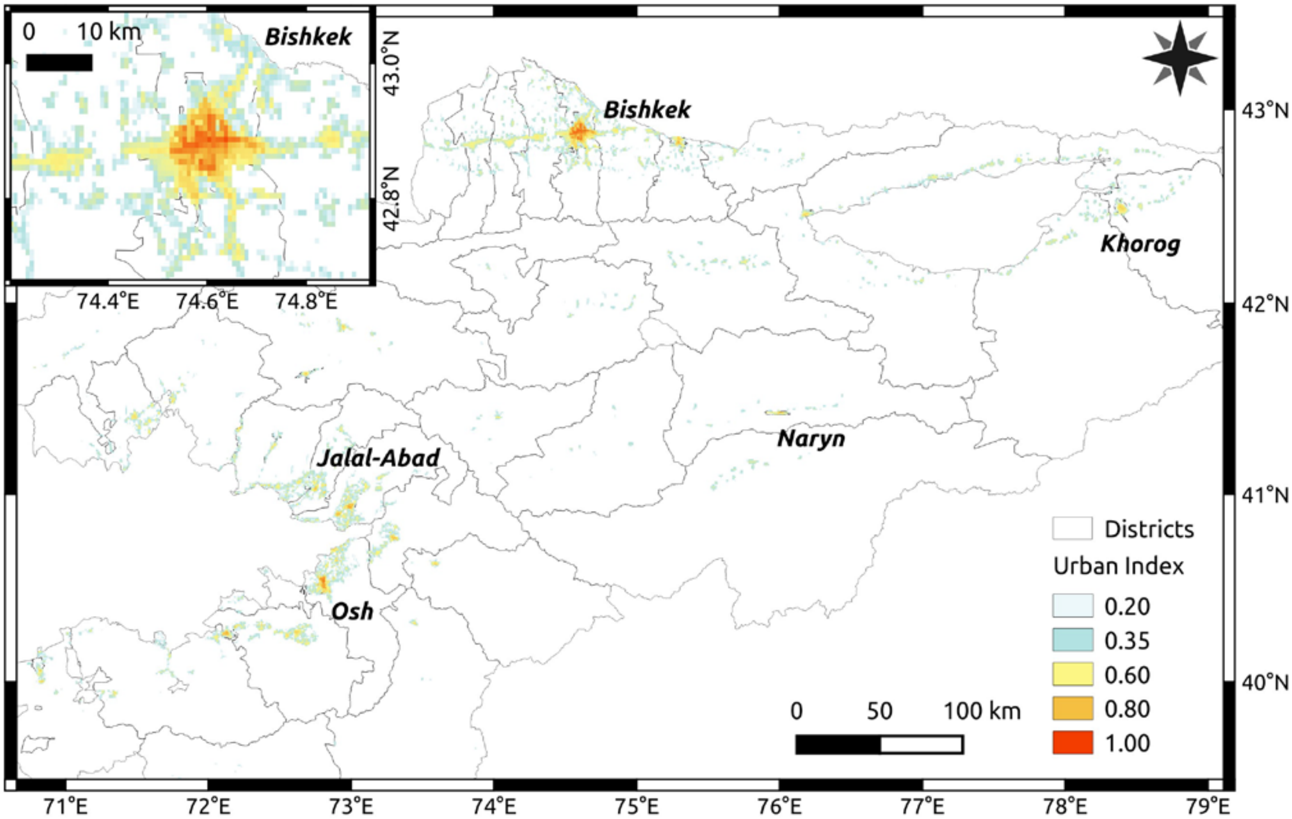

Figure 1: Spatial distribution of the built-up areas in Kyrgyzstan, classified according to the expected urbanization level. An urbanization index close to zero indicates a mostly inhabited area, while a value close to one refers to densely-inhabited urban environments. The inset shows a close-up of the Bishkek area. Four of the most populous Kyrgyz settlements are also displayed, along with the outline of the country regions (oblasts).

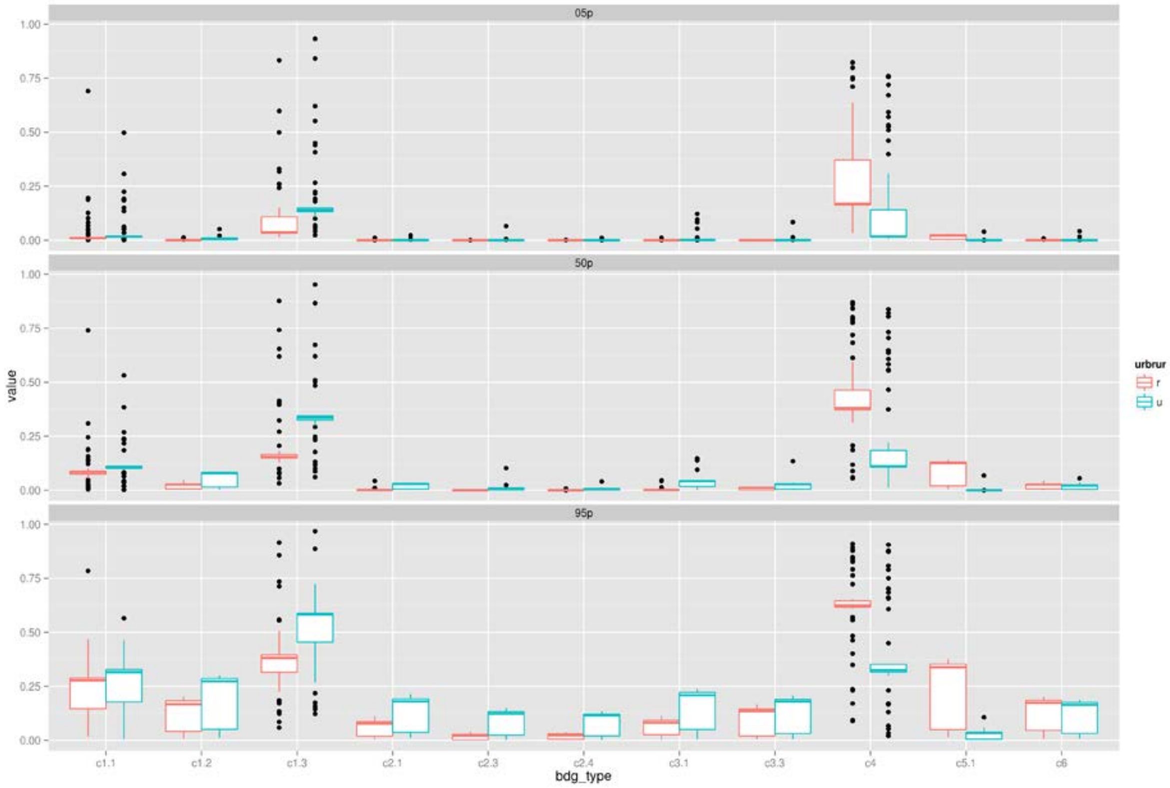

Figure 2: Confidence intervals (5% and 95%) and median values of the estimated building type (L2 detail level) frequencies at country scale, obtained by bootstrap-sampling the corresponding Dirichlet distributions. Black dots represent outliers.Red interquantile ranges refer to rural areas, cyan ones refer to urbaan areas (i. e. with urban index greater than 0.6).

By considering the confidence intervals of all districts, at country level we obtain the estimates listed in Table 2. As we can note, the overall number of buildings, based on a purely residential occupancy model, is estimated to lie in the range between 240'000 and 590'000 units with 90% probability, with a median value of about 342'000 buildings.

	5% percentile	**Median (50% percentile)**	**95% percentile**
Urban	55'360	66'643	85'998
Rural	182'613	275'638	505'183
Total	237'973	342'281	591'180

Table 2: Total (median) number of residential buildings expected in Kyrgyzstan, with 90% confidence bounds.

The estimated total number of residential buildings is reasonable considering the observed composition of the building stock, and the underlying uncertainties.

The SYNER-G approach described in the previous section was applied to Kyrgyz building typologies using the EMCA typologies. Assignment of V_i* and V_m indices to EMCA typologies is described in the following subsections. For many of the V_m adjustments, a weighted average was used, since buildings within a specific typology are not homogeneous. These weightings were assigned on the basis of judgement. For each typology, where available, summary descriptions from the World Housing Encyclopedia reports for the Kyrgyz Republic are given, and are used to motivate selections of V_m values where possible. Otherwise, typology description and V_m values are assigned according to observations captured during the exposure assessment stage.

The fragility functions associated with vulnerability indices from V_i^{--} to V_i^{++} were calculated, and a distribution of weights for each of these relationships was assumed. The error from the IGMCE was then combined with the variability associated with the uncertainty on the vulnerability index to give a distribution of mean values of the fragility function (the standard deviation was taken as the value associated with the best estimate vulnerability index, V_i). The 10^{th} and 90^{th} percentiles were then taken as lower bound and upper bound, respectively.

Damage state	**DS3**			**DS4**			**DS5**		
Typology ID	Lower Bound μ	Upper Bound μ	β	Lower Bound μ	Upper Bound μ	β	Lower Bound μ	Upper Bound μ	β
c1.1	0.11	0.22	0.21	0.15	0.30	0.21	0.24	0.47	0.21
c1.2	0.13	0.28	0.23	0.18	0.40	0.23	0.28	0.61	0.23
c1.3, c1.4	0.24	0.59	0.25	0.35	0.86	0.25	0.54	1.33	0.25
c2.1	0.15	0.75	0.25	0.22	1.08	0.25	0.35	1.67	0.25
c2.2	0.20	0.80	0.25	0.29	1.17	0.25	0.45	1.81	0.25
c2.3	0.12	0.52	0.24	0.18	0.74	0.24	0.27	1.14	0.24
c2.4	0.22	0.92	0.26	0.32	1.34	0.26	0.51	2.09	0.26
c3.1	0.31	0.77	0.26	0.45	1.13	0.26	0.70	1.76	0.26
c3.2	0.35	0.89	0.26	0.52	1.30	0.26	0.81	2.04	0.26
c3.3	0.14	0.31	0.23	0.20	0.45	0.23	0.31	0.70	0.23
c3.4	0.17	0.84	0.25	0.24	1.22	0.25	0.38	1.89	0.25
c4.1	0.09	0.16	0.19	0.12	0.21	0.19	0.19	0.32	0.19
c5.1, c5.2	0.15	0.42	0.24	0.21	0.61	0.24	0.33	0.94	0.24
c6	0.44	1.35	0.26	0.66	2.00	0.26	1.05	3.21	0.26

Table 3: Lognormal distribution means for lower and upper bound fragility functions in terms of PGA (units of g), damage states DS3 to DS5 (standard deviation taken as for best estimate).

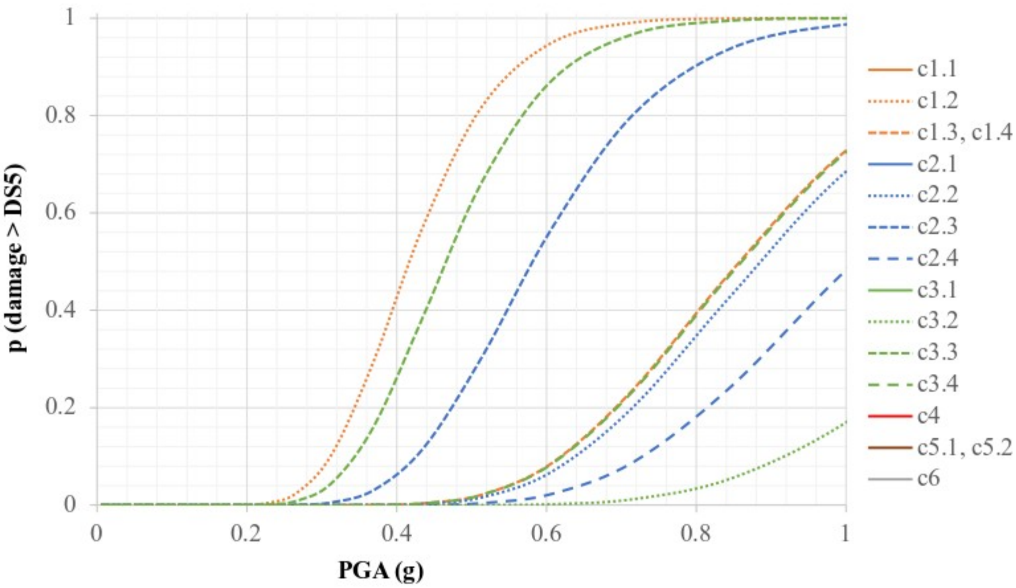

Figure 3: Damage state DS5 - fragility functions in PGA for EMCA building typologies (median estimates of the lognormal parameters have been considered).

4. Conclusions

We have presented an original methodology that contributes to the prompt, reliable and scalable assessment of seismic risk in urban environments. The proposed approach focuses on the efficient development of exposure and vulnerability models at large scale, usually a critical and underrated stage of seismic risk assessment, by exploiting a combination of processing of geo-information and visual data capturing by mobile mapping. This example moreover shows how a statistical model for exposure can accommodate both the information already available, in form of a suitable prior, and the new information which can be made available by specific surveying activities. In the latter case, the overall model will evolve adapting its uncertainty to the amount and distribution of the available information. At the same time, a sound description of the underlying uncertainty allows the practitioners to have a better understanding of the expected performance of the model in the framework of seismic risk estimation.

An empirical approach to the modelling of the seismic vulnerability has been followed, which combines a macroseismic methodology based on the widely used EMS-98 European Macroseismic Scale, with a refined weighting index approach able to better tune the vulnerability assessment to the specific features of the building inventory.

The proposed approaches are scalable and provide a consistent consideration of the uncertainties throughout the whole process, from data collection to model estimation. The implementation of a sound base for exposure and vulnerability should be considered as a critical step in the assessment of seismic risk for mitigation and prevention purposes. The resulting models might be further improved by intensifying the data collection activities and/or by carefully applying more sophisticated methodologies, in an iterative schema which will be less prone to obsolescence and thus will prove more useful to civil protection authorities and risk practitioners.

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