18TH WORLD CONFERENCE ON EARTHQUAKE ENGINEERING
WCEE2024
MILAN

MILAN, ITALY
30TH JUNE - 5TH JULY 2024

www.wcee2024.it

FRAGILITY CURVES SELECTION IN CENTRAL AMERICA: A NOVEL METHODOLOGY USING FUZZY ANALYSIS

M. Jiménez-Martínez[1], L. Navas-Sánchez[2], O. Hernández-Rubio[3], L. Hernández[4], B. González-Rodrigo[5], B. Orta-Rial[2]

[1] Escuela Técnica Superior de Ingenieros en Topografía, Geodesia y Cartografía, Universidad Politécnica de Madrid, Madrid, España, maribel.jimenez@upm.es

[2] Escuela Técnica Superior de Arquitectura, Universidad Politécnica de Madrid, Madrid, España

[3] GEOLYDER SL, Madrid, España

[4] Escuela Técnica Superior de Ingenieros Industriales, Universidad Politécnica de Madrid, Madrid, España

[5] Escuela Técnica Superior de Ingenieros de Montes, Forestal y medio natural, Universidad Politécnica de Madrid, Madrid, España

Abstract:

The utilization of a fragility curve (FC) can provide a more precise estimation of a structural system's performance level when exposed to seismic hazards. However, selecting an inappropriate FC can significantly affect the accuracy of loss and damage calculations in seismic risk assessments.
This article uses a new method to select fragility curves that are better suited to the most prevalent typologies in Central America (CA). To this end, a wide bibliographic search of different vulnerability and seismic risk studies for the Central American region has been conducted. A database was constructed with the parameters of the capacity and FCs available for diverse construction typologies. The novel methodology enables the classification of the FCs based on a multidimensional index that takes into account a collection of pertinent variables related to different characteristics of FCs. These variables are arranged into three major dimensions related to technical suitability of the FC, the suitability for the local system of the potential FCs candidates and the similarity between the building class of the candidate functions and the building class under study.
Additionally, a calibration and validation process on the variable scores of the multidimensional index proposed in the new methodology for evaluating and choosing FCs is conducted. The calibration process involves a survey of seismic vulnerability experts worldwide within the field of seismic risk studies. The fuzzy analytic hierarchy process (FAHP) method for multicriteria decision-making (MCDM) is employed to calculate the fuzzy scores or weights based on the experts' survey responses, leading to more objective and dependable scores compared to expert weights.
Consequently, the proposed ranking system derived from the new methodology has enabled the identification of the most suitable FCs for the primary construction types in CA. The suggested approach allows for the evaluation of the reliability level of FCs, which is contingent on the curve's class assignment and corresponding score. Additionally, the findings derived from the newly developed multidimensional index facilitate the assessment of the appropriateness of the selected FC, a crucial consideration for researchers investigating seismic vulnerability and risk.

1. Introduction

The reliability of a risk assessment procedure is strictly dependent on the adopted hazard, exposure, fragility, and consequence models (Graziotti et al., 2018). Therefore, when conducting seismic risk studies, there is a challenge in dealing with a multitude of uncertainties, especially in the methods used to assess them. For instance, one critical aspect is the choice of fragility curves (FC). FCs have evolved into a crucial instrument for seismic risk assessments and vulnerability analyses. They enable a connection between the seismic hazard present at a specific location and the impact of ground motion on constructed infrastructure. It is important to note that selecting the wrong FC can lead to highly unreliable estimates of damages and losses. Different types of buildings and structures can behave differently during an earthquake due to variations in construction materials, design, and level of maintenance of the building. Using an inadequately chosen FC may lead to inaccurate estimations of the vulnerability of these structures. This can result in an unreliable assessment of potential damages and losses. By accurately selecting FCs tailored to specific typologies, resources for mitigation efforts, such as retrofitting or reinforcement, can be allocated more efficiently. If the curves are not appropriately chosen, resources may be misallocated, leading to ineffective or inefficient risk reduction measures. Furthermore, different typologies of buildings may have varying levels of importance in terms of safety and economic impact. Adequate selection of FCs allows for the prioritization of structures that are more critical or have a higher risk. This ensures that efforts are directed towards mitigating the most significant risks first. Government authorities and policymakers often rely on seismic risk studies to develop and enforce building codes, zoning regulations, and disaster management plans. Therefore, accurate FC selection is essential for informing these decisions to enhance public safety and reduce potential losses in the event of an earthquake. Also, adequate FC selection is also critical for the insurance industry and financial institutions. It helps them assess and price earthquake insurance policies accurately, as well as estimate potential financial losses and liabilities. And, finally, understanding the vulnerabilities of different building typologies through appropriate fragility curve selection can aid in community preparedness and public awareness efforts, helping people understand the risks associated with their specific types of structures.

Unfortunately, many of the FCs commonly used in seismic risk studies for specific areas, such as Central America, were designed for regions with very different construction techniques and materials quality compared to the areas being studied, such as North America, Italy, or other countries with higher GDP and more research investment (Navas-Sánchez et al., 2023). Central America stands out as one of the world's regions facing the most significant seismic hazard. Additionally, this area is marked by substantial physical and social vulnerabilities. It is precisely the unfortunate combination of these two adverse factors that has resulted in a remarkably high number of casualties and economic losses in the past during seismic events.

Within this context, it is crucial to have some methodological approach for evaluating and selecting FC for seismic risk studies. Navas-Sánchez et al. (2023) propose an approach examining a catalog of existing proposals found in the literature that provides ranges and rankings to assess the suitability of a particular curve for a given area from a multidimensional index composed of a set of different variables. Whereas, on its part, the present paper calibrates and validates the scores assigned to the variables established in said previous methodology (Navas-Sánchez et al., 2023) for assessing and selecting fragility curves for seismic risk studies. Said calibration process is based on survey research to worldwide experts in seismic vulnerability within the context of seismic risk studies. Furthermore, the results are implemented in the “select.FC” methodology and validated using the fuzzy set methods application. In addition, a comprehensive database of FCs with the variables involved in the method already assessed is provided in order to render as easy as possible to researchers the selection of the most appropriate FC for a region.

Several studies have explored the impact of weights on composite indices, raising concerns about the reliability and credibility of the findings. Notable works by Permanyer (2012), B. Zheng and C. Zheng (2015), Becker et al. (2017), Seth and McGillivray (2018), and others have highlighted these issues. Consequently, numerous innovative approaches to address this weighting challenge were developed and used. One such approach involves combining expert opinions with the FAHP (Fuzzy Analytic Hierarchy Process) method, as exemplified by the work of Gopal and Akkar (2015), Kashani et al. (2020), Bisht et al. (2022), and similar studies. So, to overlook the uncertainty and inconsistency inherent in expert responses, and to assess their validity and reliability, and accommodate indices with a substantial number of proxies, we implement the FAHP method following the adaptation proposed by Al Fozaie and Wahid (2022) .

2. Methodology

2.1 The "select.FC" methodology to assess and select seismic fragility curves for seismic risk studies

The methodology to assess and select seismic fragility curves comprises the following procedural steps as proposed in a previous paper (Navas-Sánchez et al., 2023). To begin, it is essential to identify and characterize the typologies of buildings under examination. Next, an extensive search through available scientific literature is conducted, encompassing research projects, scientific articles, graduate and post-graduate theses, conference papers, and related sources. This search primarily focuses on sources that pertain to the characterization of buildings relevant to the specific area under analysis.

Subsequently, a rating index is derived from a proposed set of variables designed to assess pertinent aspects of the identified FCs considered as potential candidates for the studied typology. The Figure 1 from Navas-Sánchez et al. (2023) summarizes the conceptualization, dimensions and variables of the index proposed to evaluate FCs indicating in brackets the maximum scores of each one. Using this index, a classification is formulated to determine the suitability of the FCs for each identified building type. The Final Index, with a maximum score of 100 points, is computed based on a multidimensional index known as the Global Index. The Global Index is adjusted by a reduction coefficient that indicates how well the curve suits a particular building type within the region under study, referred as Building Class Similarity dimension. The quantity and nature of attributes between the two building types are taken into account to gauge the resemblance between the building classes of the candidate functions and the one for which its utilization is being assessed. In particular, the lateral load-resisting system, number of stories, ductility, year of construction, and compliance with seismic rules are the fundamental characteristics and those that might be seen as more significant in light of the analyzed typology's seismic susceptibility. The FC must match a typology of the same material as the one being investigated.

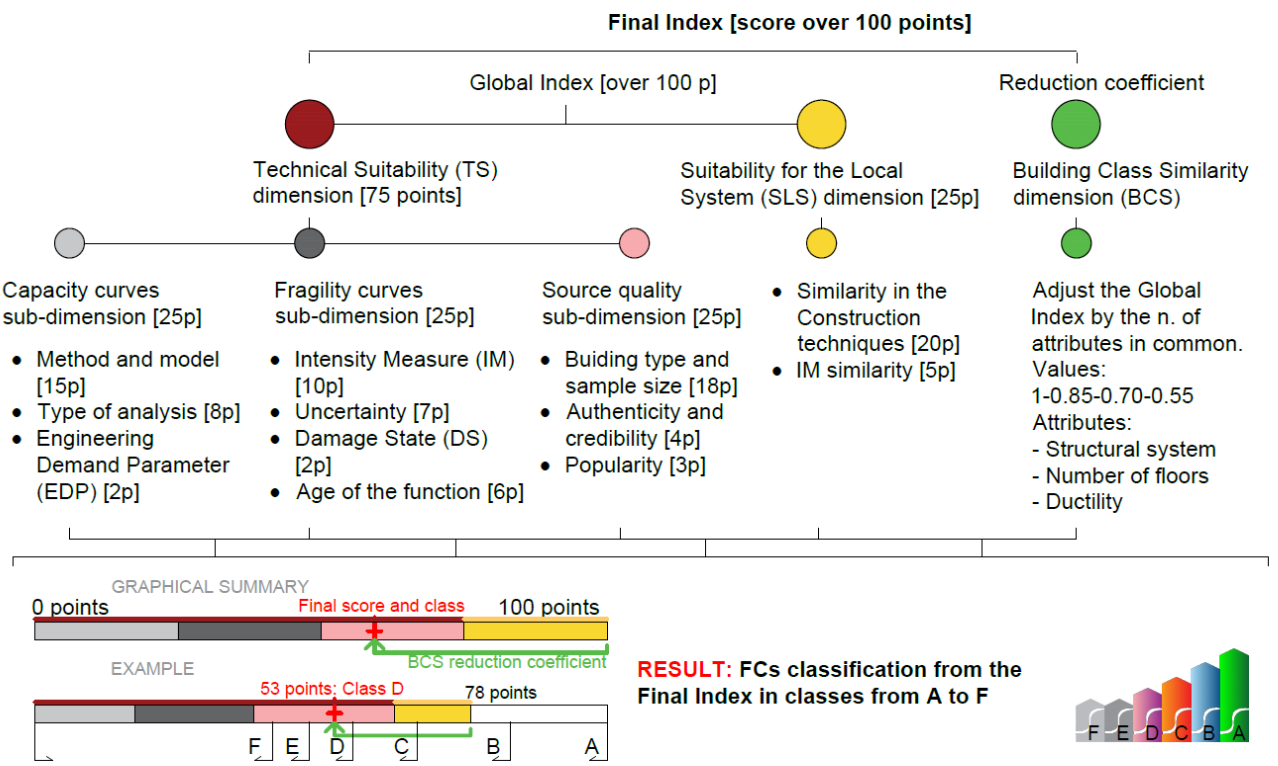

Figure 1. Dimensions and variables of the index proposed to evaluate FCs. Source: Navas-Sánchez et al. (2023).

The Global Index comprises two primary dimensions: the Technical Suitability of the FC, which encompasses three sub-dimensions (Capacity, Fragility, and Quality), and the Suitability for the Local System. Furthermore, each of these dimensions and sub-dimensions includes a set of variables that enable the evaluation of diverse aspects related to the FCs. These variables were selected following previous studies about the subject (Stone et al, 2017; Maio and Tsionis, 2015; Rossetto et al., 2014). The capacity curve's sub-dimension includes variables related with the method and model, analysis type and the engineering demand parameter (EDP) considered to build the curve. The fragility curve's sub-dimension refers to characteristics directly related to the FCs evaluated, such as the intensity measure (IM) used, the year of publication of the curve, the treatment given to the different sources of uncertainties associated with FCs and the damage threshold considered. The quality sub-dimension comprises a combined variable to assess whether the capacity and fragility curves originate from existing structures or building prototypes and considers the size of the building sample employed. This sub-dimension also includes variables related to the authenticity and credibility of the study, considering the type of publication where the examined FC is proposed (scientific article, doctoral thesis, conference paper, among others). The last variable in this block is the popularity of the FCs, that is, the level of diffusion and use measured from the number of citations in Google Scholar of the study that proposes the curve. Furthermore, according to the following variables: similarity in construction methods and IM similarity, the suitability for the local system dimension tries to evaluate the degree to which the FCs evaluated for the typologies analyzed are adequate for the study to be conducted.

2.2. Expert survey

From a survey online in Spanish and English, expert opinion was collected on the weights or relative importance of each variable, subdimensions, and dimensions included in the multidimensional index previously described to rate FCs. The survey has a total of 18 questions. The first block of questions asks the expert to assign a score on a scale of 1 to 9 to each of the twelve variables included in the global index (Figure 2). In another block of questions, the experts are required to compare pairs of different dimensions of the index to collect the relative importance that they assign to each one in comparison with the rest. Lastly, two more questions were also included that asked the experts to assign a value from 0 to 100 to the different dimensions and some relevant variables to evaluate the robustness and consistency of their responses to the first two blocks. In each question, the experts were given the option of adding comments.

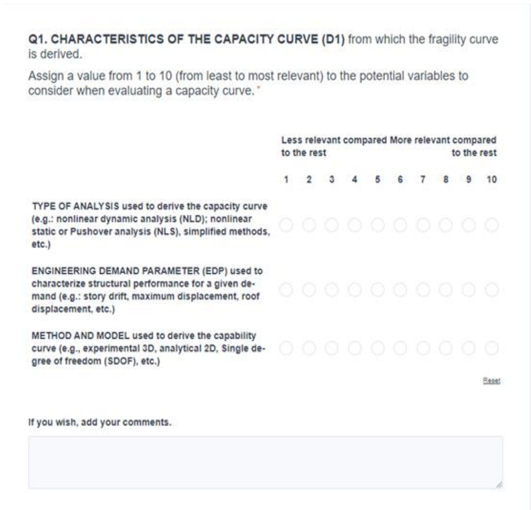

Figure 2. Survey scale and sample response

A total of 30 experts were identified based on their level of expertise on the subject. These experts have, in general, a high level of specialization reflecting in their research activity with high-quality scientific publications or in their professional activity. They were contacted via email and given a cover letter outlining the goal of the survey and the study it relates to. To date, 28 responses have been received, with a total of response rate of 93%. The experts who completed the survey are from different countries: Spain, Italy, Portugal, USA, Peru, Ecuador, Colombia, Guatemala, El Salvador, and Costa Rica.

2.3. Fuzzy hierarchical analysis

The multidimensional index proposed in Navas-Sánchez et al. (2023) is constructed from a set of scores assigned to each of the variables, sub-dimensions, and dimensions based on the criteria of the experts of the research group in which it was developed. However, the process of assigning weights to the different variables of a multidimensional index, such as the one proposed, is not trivial and is part of the most crucial step in the construction of a composite index, which is the aggregation of the different variables and dimensions into a single indicator. Therefore, as mentioned before, in the second stage of the research, it was considered appropriate to validate the weights assigned based on a survey carried out with a large panel of experts on the subject. However, the experts' responses are also limited, subject to significant subjectivity, uncertainty, and possible inconsistencies (Al Fozaie and Wahid, 2022). Hence, to address the limitations of the weighting system emerging from an expert survey, the fuzzy analytical hierarchy process (FAHP) method is implemented.

FAHP combines for one side, fuzzy set theory and, for another, analytic hierarchy process. Zadeh (1965) was the first to establish fuzzy set theory, which was focused on the rationality of uncertainty caused by imprecision or vagueness to address the vagueness of the human mind. The ability of fuzzy set theory to represent ambiguous data is one of its significant contributions. Additionally, the theory permits the application of mathematical operations and programming to the fuzzy domain. A class of objects with a range of membership grades is called a fuzzy set. A membership (characteristic) function that awards each object a membership grade ranging from zero to one defines such a set (Ataei et al., 2012). Fuzzy sets and fuzzy logic are effective mathematical tools for modeling uncertain systems. They also make making decisions easier when there is a need for more comprehensive and accurate information. Their role is essential when applied to complicated processes that are difficult to describe using conventional mathematical techniques, especially when the objective is to develop a good approximation. Fuzzy Set theory is a better method for simulating uncertainty resulting from mental events that are either random or chaotic. Instead of using purely objective probability measures, a logical approach to decision-making should consider human subjectivity, and for this, fuzzy numbers could be of great assistance. In this research we use triangular fuzzy numbers to deal with the uncertainty of expert responses to assign weights to each variable of the global index. A triangular fuzzy number is denoted simply as (l, m, u) or (l|m, m|u). The parameters l, m, and u, respectively, denote the smallest possible value, the most promising value and the largest possible value that describe a fuzzy event or object. The Figure 3 represents a triangular fuzzy number (Ataei et al., 2012).

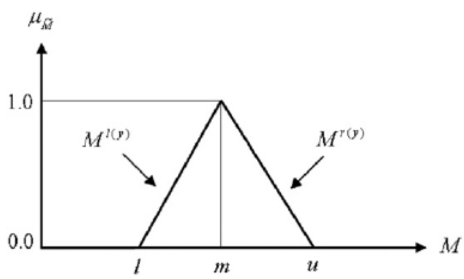

Figure 3. Triangular fuzzy number. Source: Ataei et al. (2012)

The analytical hierarchy process (AHP), initially developed by Saaty (1980), is a method that works well for dealing with complicated systems, including choosing among numerous options. It compares the options that have been taken into consideration. The AHP is based on a hierarchical split of the problem into its parts; the analysis then assists the decision-makers who, through pairwise comparisons, can understand the influence of the considered elements in the hierarchical structure. Among the different applications the AHP can have is weight criteria or variables according to paired comparisons.

In this research, the Fuzzy AHP method highlights the most prominent variables used in constructing the indices and assigns them the highest weight. By integrating expert responses and the FAHP method, it is possible to improve the objectivity of the weights and reduce the uncertainty of the expert responses (Al Fozaie et al., 2022). To be more specific, there is a great deal of uncertainty when combining expert opinion on a particular variable and turning it into a single value. This uncertainty may be due to a lack of understanding of the task, expert bias, the experts' disinterest in the survey, or just plain human error, all of which could produce unreliable results. Furthermore, FAHP is more appropriate in situations where there is a likelihood of ambiguity and fuzzy results, whereas AHP is more appropriate in judgments that are more easy or crisp. As a result, and because of the research gaps, the FAHP technique is more appropriate than the AHP method when gathering opinions from experts to create composite indexes (Al Fozaie et al., 2022). Furthermore, there are different variants of the FAHP method as those of van Laarhoven and Pedrycz (1983), Buckley (1985), and Chang (1996). Compared to others, the Buckley (1985)'s geomean method for calculating the fuzzy weights is easy to compute and guarantees a unique solution (Emrouznejad and Ho, 2017; Al Fozaie et al., 2012), then this is the FAHP method implemented in this research.

As previously mentioned, in this research, the FAHP method is implemented following the suggestions and adaptation proposed by Al Fozaie and Wahid (2022). The authors provide a guide on improving the expert weights by subjecting them to the FAHP method to compute fuzzy weights and interval weights, calculated by finding the midpoint between the expert weights and the fuzzy weight. The first step, once the expert responses are collected, is to analyze and normalize into weights the points assigned for the experts to the different variables of the Global Index. The second step is to categorize the expert weights into percentiles so that they can be transformed into triangular fuzzy numbers (see table 1). The third step of the FAHP method involves the fuzzification process developing the fuzzy pairwise comparison matrix (FPCM). For this, from the fuzzy values by percentil and the fuzzy scale for relative importance the distance the variable is from the ideal scale (9, 9, 9), that is, the steps to ideal (STI) scale is computed.

Table 1. Fuzzy values by percentile and fuzzy scale of relative importance

Percentile	**Fuzzy number**	**Relative importance**
0-20	(1, 1, 1)	Equal importance
21-40	(2, 3, 4)	Weak importance
41-60	(4, 5, 6)	Fair importance
61-80	(6, 7, 8)	Strong importance
80-100	(9, 9, 9)	Absolute importance

Then, the difference in the STI scale between each pair of variables facilitates the assignment of a triangular fuzzy scale to each pairwise comparison as shown in Table 2.

Table 2: Steps to ideal (STI) scale and the corresponding triangular fuzzy scale by cases

Cases	**STI**	**Fuzzy scale**
Variable is within 0 categories from the other	0	(1, 1, 1)
Variable is within 1 category from the other	1	(2, 3, 4)
Variable is within 2 categories from the other	2	(4, 5, 6)
Variable is within 3 categories from the other	3	(6, 7, 8)
Variable is within 4 categories from the other	4	(9, 9, 9)

The fourth step is to apply Bucley's geomean method to calculate the fuzzy weights. For this, the geometric mean of each value of the triangular fuzzy scale of each column is computed, that is, $r_i = (a_{i1} \times a_{i2} \times \ldots \times a_{in})^n$ where a_{ij} represents each one of the integers corresponding to the triangular fuzzy number of variable i and n is the number of variables. Then to calculate the fuzzy weights w_i, the sum of each one of the three column r_i and then multiply the inverse of this sum, i. e., with the corresponding value in column, i.e., $Fuzzy\, w_i = (\sum_j^n r_{ij})^{-1} \times r_{ij}$. This computation obtains three columns with the corresponding fuzzy weights of each variable's triangular fuzzy sets. The sixth step is to defuzzy or normalize the weights, calculating the average of the fuzzy weights for each variable, i. E., defuzzified $w_i = (w_1 + w_2 + w_3)$/n. The pairwise comparison has both advantages and disadvantages since, despite giving the most significant variables higher weights, it runs the risk of exaggerating their importance as well as diminishing the influence of lesser-weighted variables. Due to the severely imbalanced variable weights, this can consequently considerably affect the final index. So, Al

Fozaie and Wahid (2022) introduce interval weights—the midpoint between fuzzy and expert weights—to address this problem.

3. Results

3.1. Improved weights for the Global Index integrating expert opinion and fuzzy AHP

3.1.1 Average results before applying the fuzzy AHP

From the expert survey responses, the normalized weights (up to 100) assigned to each of the 12 variables that make up the global index by each of the 28 experts interviewed were computed. And, using the normalized weights it is possible to calculate what is called "expert weights" by Al Fozaie and Wahid (2022), that is, the weighting that would arise from averaging the experts' responses. With these first weights, it is possible to carry out a first validation exercise of the weights assigned with expert criteria to the first version of the index in Navas-Sánchez et al. (2023), called "Index weights" (Figure 4).

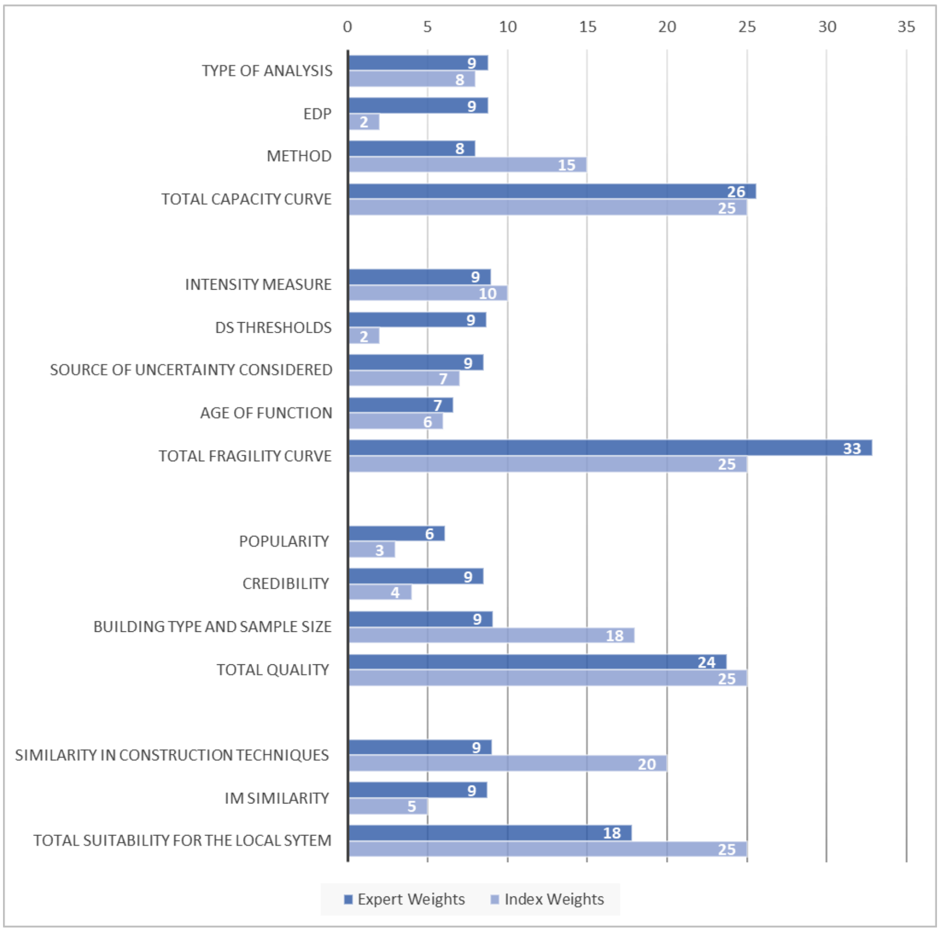

Figure 4. Expert weights and original weights of the Global Index (Index weights) by variable, sub-dimension and dimension

For half of the variables, the average weights from the experts' responses are similar to the "Index weights," with differences between the two of less than two percentage points. The most marked discrepancy between both sets of weights is observed for the variable "Similarity in construction techniques" of the dimension "Suitability for the local system." Indeed, Navas-Sánchez et al. (2023) considered a very relevant variable by assigning a weight of 20, while, on average, experts have assigned similar weights to the two variables of this dimension. Another dimension in which there is a significant discrepancy between both sets of weights refers to the fragility curve, mainly due to the greater weight assigned by the experts to the variable referring to the DS threshold compared to the "index weight." On the other hand, the final weights of the subdimensions referring to the capacity curve and the quality of the study are very similar. However, given the high degree of uncertainty and variability that arises from the different responses of the experts, it is crucial to implement the FAHP method to obtain more robust conclusions regarding the appropriateness of the index weights and the possible adjustments that would be advisable to introduce.

3.1.2. Implementation of the fuzzy AHP

The application of the FAHP requires first to calculate the ranking of the variables according to the expert weight previously computed, and the rank is then transformed into percentiles. Next, each variable is assigned the corresponding fuzzy value according to the percentile in which it was classified following the equivalence between percentiles and fuzzy values in Table 1. Table 3 shows these results and, in addition to the triangular fuzzy scale, indicates for each variable the intermediate scale based on the fuzzy number and the distance the variable is from the ideal scale, i.e., where the variables are “absolutely important.” The two variables with the highest weights and fuzzy scale are, on the one hand, the one related to building type and sample size of buildings used to construct the capacity and fragility curves and, on the other hand, the variable that attempts to capture the similarity in the construction techniques of the typology for which the curve was derived and the typology for which it is intended to be used. Next in importance is the intensity measure of the fragility curve evaluated and then, classified with a similar fuzzy scale, the type of analysis, the EDP and the similarity in the intensity measurements.

Table 3. Variables of Global Index according to the triangular fuzzy scale of relative importance

Variable	Weight	Rank	Percentile	F-scale	I-scale	STI scale
Building type and sample size	9.1	1	100	(9, 9, 9)	9	0
Similarity in construction techniques	9.1	2	90	(9, 9, 9)	9	0
Intensity measure	9.0	3	80	(6, 7, 8)	7	1
Type of analysis	8.8	4	60	(4, 5, 6)	5	2
EDP	8.8	4	60	(4, 5, 6)	5	2
IM similarity	8.8	6	60	(4, 5, 6)	5	2
DS thresholds	8.7	7	50	(4, 5, 6)	5	2
Credibility	8.5	8	30	(2, 3, 4)	3	3
Source of uncertainty considered	8.5	8	30	(2, 3, 4)	3	3
Method	8.0	10	20	(1, 1, 1)	1	4
Age of function	6.6	11	10	(1, 1, 1)	1	4
Popularity	6.1	12	10	(1, 1, 1)	1	4

The next step to obtain the fuzzy weights of each variable is to build the fuzzy pairwise comparison matrix shown in Table 4. For instance, the results from the expert survey indicate that the variable "Type of analysis" is "equally important" than "EDP," "DS thresholds," and "IM similarity," hence the fuzzy value observed in the cells corresponding to the comparison between the first variable and each of the remaining ones is equal to (1, 1, 1). Likewise, the variable "Type of analysis" is "fairly important" than the variable "Method," "Age of function," and "Popularity", so the fuzzy value in the FPCM is (4, 5, 6). On the other hand, the variables "Building type and sample" and "Similarity in construction techniques" are "fairly important" than "Type of analysis," with a fuzzy value in the corresponding celds of the FPCM equal to (¼, ⅕, ⅙). And "intensity measure" is "weakly important" than the first variable of the FPCM.

Once the FPCM is calculated, it is possible to apply Buckley (1985)’s geomean method to calculate the fuzzy weights. The result of this computation is shown in Table 5 along with the defuzzified weights, the “Expert weights”, the “Index weights”, and the “interval weights”. As observed, the two variables "Building type" and sample size" and "Similarity in construction techniques" that are classified first in the ranking and are located in the first percentiles of Table 3 present the highest weights. This result contrasts with that arising from calculating a simple average of the experts' normalized responses. For this, it would be more convenient to consider the interval weights assigned to the Global Index variables that emerge from the midpoint between the defuzzified weights and the "Expert weights."

Table 4. Fuzzy pairwise comparison matrix

Variables	Type of analysis	EDP	Method	Intensity measure	DS thresholds	Source of uncertainty considered	Age of function	Popularity	Credibility	Building type and sample size	Similarity in constr. techniques	IM similarity
Type of analysis	(1,1,1)	(1,1,1)	(4,5,6)	(1/2,1/3,1/4)	(1,1,1)	(2,3,4)	(4,5,6)	(4,5,6)	(2,3,4)	(1/4,1/5,1/6)	(1/4,1/5,1/6)	(1,1,1)
EDP	(1,1,1)	(1,1,1)	(1,1,1)	(1/2,1/3,1/4)	(1,1,1)	(1/2,1/3,1/4)	(4,5,6)	(4,5,6)	(2,3,4)	(1/4,1/5,1/6)	(1/4,1/5,1/6)	(1,1,1)
Method	(1/4,1/5,1/6)	(1/4,1/5,1/6)	(1,1,1)	(1/6,1/7,1/8)	(1/4,1/5,1/6)	(2,3,4)	(1,1,1)	(1,1,1)	(1/2,1/3,1/4)	(1/9,1/9,1/9)	(1/9,1/9,1/9)	(1/4,1/5,1/6)
Intensity measure	(2,3,4)	(2,3,4)	(6,7,8)	(1,1,1)	(2,3,4)	(4,5,6)	(6,7,8)	(6,7,8)	(4,5,6)	(1/2,1/3,1/4)	(1/2,1/3,1/4)	(2,3,4)
DS thresholds	(1,1,1)	(1,1,1)	(4,5,6)	(1/2,1/3,1/4)	(1,1,1)	(2,3,4)	(4,5,6)	(4,5,6)	(2,3,4)	(1/4,1/5,1/6)	(1/4,1/5,1/6)	(1,1,1)
Source of uncertainty considered	(1/2,1/3,1/4)	(1/2,1/3,1/4)	(2,3,4)	(1/4,1/5,1/6)	(1/2,1/3,1/4)	(1,1,1)	(2,3,4)	(2,3,4)	(1,1,1)	(1/6,1/7,1/8)	(1/4,1/5,1/6)	(1/2,1/3,1/4)
Age of function	(1/4,1/5,1/6)	(1/4,1/5,1/6)	(1,1,1)	(1/6,1/7,1/8)	(1/4,1/5,1/6)	(1/2,1/3,1/4)	(1,1,1)	(1,1,1)	(1/2,1/3,1/4)	(1/9,1/9,1/9)	(1/9,1/9,1/9)	(1/4,1/5,1/6)
Popularity	(1/4,1/5,1/6)	(1/4,1/5,1/6)	(1,1,1)	(1/6,1/7,1/8)	(1/4,1/5,1/6)	(1/2,1/3,1/4)	(1,1,1)	(1,1,1)	(1/2,1/3,1/4)	(1/9,1/9,1/9)	(1/9,1/9,1/9)	(1/4,1/5,1/6)
Credibility	(1/2,1/3,1/4)	(1/2,1/3,1/4)	(2,3,4)	(1/4,1/5,1/6)	(1/2,1/3,1/4)	(1,1,1)	(2,3,4)	(2,3,4)	(1,1,1)	(1/6,1/7,1/8)	(1/6,1/7,1/8)	(1/2,1/3,1/4)
Building type and sample size	(4,5,6)	(4,5,6)	(9,9,9)	(2,3,4)	(4,5,6)	(6,7,8)	(9,9,9)	(9,9,9)	(6,7,8)	(1,1,1)	(1,1,1)	(4,5,6)
Similarity in construction techniques	(4,5,6)	(4,5,6)	(9,9,9)	(2,3,4)	(4,5,6)	(6,7,8)	(9,9,9)	(9,9,9)	(6,7,8)	(1,1,1)	(1,1,1)	(4,5,6)
IM similarity	(1,1,1)	(1,1,1)	(4,5,6)	(1/2,1/3,1/4)	(1,1,1)	(2,3,4)	(4,5,6)	(4,5,6)	(2,3,4)	(1/4,1/5,1/6)	(1/4,1/5,1/6)	(1,1,1)

Table 5. Different weights by variable of the Global Index

Variables	Fuzzy weight 1	Fuzzy weight 2	Fuzzy weight 3	Defuzzified weight	Expert weights	Interval weights	Index weights
Capacity curves dimension							
Type of analysis	7.0%	6.8%	6.7%	6.8%	8.8%	7.8%	8.0%
EDP	7.0%	6.8%	6.7%	6.8%	8.8%	7.8%	2.0%
Method	2.0%	1.6%	1.4%	1.6%	8.0%	4.8%	15.0%
Subtotal	**15.9%**	**15.2%**	**14.7%**	**15.3%**	**25.6%**	**20.4%**	**25.0%**
Fragility curves dimension							
Intensity measure	13.0%	13.4%	13.8%	13.4%	9.0%	11.2%	10.0%
DS thresholds	7.0%	6.8%	6.7%	6.8%	8.7%	7.8%	2.0%
Source of uncert. considered	3.7%	3.2%	2.9%	3.3%	8.5%	5.9%	7.0%
Age of function	2.0%	1.6%	1.4%	1.6%	6.6%	4.1%	6.0%
Subtotal	**25.5%**	**25.1%**	**24.8%**	**25.1%**	**32.9%**	**29.0%**	**25.0%**
Quality dimension							
Popularity	2.0%	1.6%	1.4%	1.6%	6.1%	3.9%	3.0%
Credibility	3.7%	3.2%	2.9%	3.3%	8.5%	5.9%	4.0%
Building type and sample size	23.0%	24.0%	24.8%	23.9%	9.1%	16.5%	18.0%
Subtotal	**28.6%**	**28.8%**	**29.1%**	**28.8%**	**23.7%**	**26.3%**	**25.0%**
Suitability for the local system dimension							
Similarity in const. techniques	23.0%	24.0%	24.8%	23.9%	9.1%	16.5%	20.0%
IM similarity	7.0%	6.8%	6.7%	6.8%	8.8%	7.8%	5.0%
Subtotal	30.0%	30.8%	31.4%	30.7%	17.8%	24.3%	25.0%
Total	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**

3.2. Application to the most prevalent typologies in Central America

This section presents the results from applying the new, improved scores obtained for the global index from the expert weights and Fuzzy AHP method for some of the most prevalent typologies in Central America. The identification of the most common building classes in Central America was performed by Calderón et al. (2022) using existing studies and the judgment of local engineers. The GEM taxonomy (Silva et al., 2022) is used to characterize the typologies according to the attributes consider by Calderón et al. (2022) – construction material, lateral load resisting system (LLRS), ductility and stories. The objective of the exercise is twofold. Firstly, compare the classes in which a set of evaluated fragility curves is classified according to the original scores (the so-called weights index) and those that emerge from the new set of improved scores from the expert survey. This exercise allows the evaluation of the robustness of the classification initially proposed by Navas-Sánchez et al. (2023) to changes in the scores assigned to some index variables. On the other hand, it seeks to build a database with the most appropriate FCs for the different typologies of Central America, selected from an extensive search of fragility curves currently available in the literature.

Figure 5 presents, in the first bar, the scores of the sub-dimensions and dimensions of the multidimensional index obtained with the new Interval weights for the FCs selected from the set of curves available for some of the most prominent typologies in Central America. The third and fourth bars for each typology show the final index score according to the original weights by Navas-Sánchez et al. (2023) and the final index score according to the new interval weights for each of the selected FCs. The typologies included in Figure 5 are: (i) Reinforced masonry with wall LLRS, low ductility and 1 to 3 stories (MR\LWAL+DUH\HBET:3,1), (ii) Confined masonry with wall LLRS, high ductility and 1 to 3 stories (MCF\LWAL+DUH\HBET:3,1), (iii) Reinforced concrete with bare frame LRRS, low ductility and 2 stories (CR\LFM+DNO\HEX: 2), (iv) Reinforced concrete with bare frame LRRS, high ductility and 3 to 4 stories (CR\LFM+DUH\HBET:4,3), (v) Reinforced concrete with wall and frame, dual LLRS, high ductility and 6 to 12 stories (CR\LDUAL+DUH\HBET:12,6) and (vi) Wood and earth with panels LLRS, low ductility and 1 story (W+WWD\LWAL+DNO\HEX:1). The curves selected for each of them are the following: (i) FC1: MR/LWAL+DUC/HEX:1 by Calderón and Silva (2019), (ii) FC2: MCF/LWAL+DUC/HEX:1 by Villar-Vega (2017), (iii) CR\LFM+DNO\HEX:2 by Martins and Silva (2020), (iv) CR\LFM+DUC\HEX:3 by Martins and Silva (2020), (v) CR+CIP/LDUAL/HBET:11,6 by Esquivel (2020) based on Calderón (2018) and (vi) W+WWD\LWAL+DNO\HEX:1 by Martins and Silva (2020).

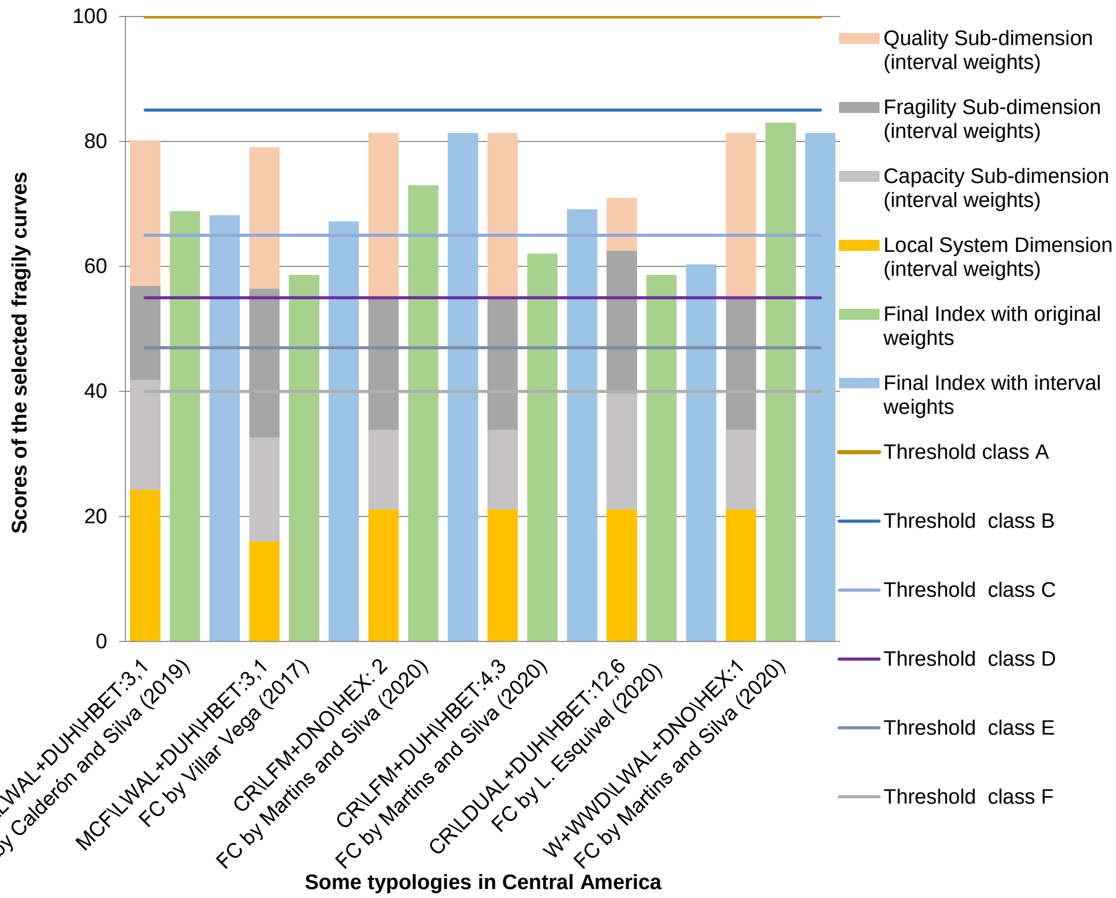

Figure 5. Scores of the selected fragility curves for some prominent typology of CA according to improved weights and original weights

The results show that most of the selected and evaluated FCs remain in the same class in which they were classified with the original weights, while the rest change to an immediately higher class. These results suggest that the selection and classification method in six classes proposed by Navas-Sánchez et al. (2023) is relatively robust to changes in scores. The disaggregation of the final index into the scores corresponding to each sub-dimension and dimension allows us to examine the variables in which the different CFs were better or worse evaluated. Thus, for example, it is observed that the CF with the lowest score in the dimension corresponding to the adaptation to the local system is Villar-Vega (2017) since it is a curve developed for a similar typology but from South America and, therefore, with some construction characteristics that may differ from those of the Central American region. Another striking result is that the extensive search carried out for FCs for the most prominent typologies in Central America has not allowed us to identify curves that were suitable enough to end up being classified in the highest class (A), and even for some of the typologies the best available curve was classified in class C. The relatively low class of some FCs selected for some typologies reflects the need to continue developing specific capacity and fragility curves for the typologies of this region that allow for more appropriate vulnerability and seismic risk studies with a lower level of uncertainty.

3. Conclusions and future lines of research

This paper aims to calibrate and validate the accuracy of the scores given to the variables of a multidimensional index developed in a previous methodology (Navas-Sánchez et al., 2023) designed for evaluating and choosing FCs for seismic risk analysis. This calibration process relies on surveying worldwide seismic vulnerability experts specializing in seismic risk studies. Furthermore, the outcomes of this calibration, carried out by applying the fuzzy AHP method, are integrated into the "select.FC" methodology. Additionally, an extensive database of FCs for some of the most prominent typologies for Central America, with their corresponding parameters, complete with their evaluation and classification according to the "select.FC" methodology, is built to facilitate the selection of the most suitable FC for a specific region to researchers or policymakers.

The results obtained from the expert survey and the implementation of the FAHP show some discrepancies in the scores assigned to certain variables by Navas-Sánchez et al. (2023) in their original "select.FC" methodology. The most significant differences in the weightings are observed in the variable referring to the method to derive the capacity curve, the definition of damage thresholds, the EDP, and the similarity in construction techniques. However, beyond these discrepancies in the aggregate, these discrepancies disappear. Therefore, the scores assigned to the two dimensions of the global index by Navas-Sánchez et al. (2023) and those that emerge with the FAHP from the expert survey are similar. Likewise, applying the new Interval weights to select the most suitable FCs for the most prominent typologies in Central America shows few changes in the final classes in which these curves are classified. Therefore, the "select.FC" method and its proposed classification of FCs into six categories based on the score obtained in the final multidimensional index seem relatively robust to important changes in the weights of some of the variables.

Future lines of research concerning the "select.FC" methodology consider several issues. First, evaluate the consistency of the experts' responses based on the additional questions included in the survey that were not used in this first exercise. This, in turn, will allow us to assess the robustness of the new scores obtained and recalibrate them if deemed appropriate. Secondly, the experts' responses and their level of expertise are heterogeneous. Therefore, it would also be advisable to adjust the experts' responses according to their degree of expertise, as suggested by Al Fozaie and Wahid (2022). In this way, greater weight could be given to the responses of experts with the highest levels of expertise in this area and obtain a final set of weights that reflects that adjustment. Another line of research consists of exploring ways to validate, against observed damage empirically, the curves selected as the best according to the “select.FC” methodology adjusted to the new weights that arise from the expert survey. Finally, an app is being developed that automates a CF's evaluation and classification process for a given typology. This new app will allow different interested users to have a comprehensive FC database and quickly select the most appropriate one for their vulnerability or seismic risk study with this improved methodology.

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