

Article

Integral Seismic Risk Assessment through Fuzzy Models

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Abstract: The usage of indicators as constituent parts of composite indices is an extended practice in many fields of knowledge. Even if rigorous statistical analyses are implemented, many of the methodologies follow simple arithmetic assumptions to aggregate indicators to build an index. One of the consequences of such assumptions can be the concealment of the influence of some of the composite index's components. We developed a fuzzy method that aggregates indicators using non-linear methods and, in this paper, compare it to a well-known example in the field of risk assessment, called Moncho's equation, which combines physical and social components and uses a linear aggregation method to estimate a level of seismic risk. By comparing the spatial pattern of the risk level obtained from these two methodologies, we were able to evaluate to what extent a fuzzy approach allows a more realistic representation of how social vulnerability levels might shape the seismic risk panorama in an urban environment. We found that, in some cases, this approach can lead to risk level values that are up to 80% greater than those obtained using a linear aggregation method for the same areas.

Keywords: composite indices; fuzzy systems; fuzzy models; indicator aggregation; risk assessment; seismic vulnerability; social vulnerability; disaster risk reduction

1. Introduction

The primary objective of the use of indicators and composite indices is to obtain a scale of measurement to make comparisons among geographical areas. At the same time, a suitable index is expected to reflect a plausible encapsulation of all the different dimensions described by the set of indicators that integrates it. In the case of natural risk, these dimensions could be the social or structural components that are affected by a stressor agent from which a particular level of risk is generated.

Different types of indicator-based approaches are used in the assessment of natural hazard risks. A clear division exists between those approaches whose aim is to estimate each of the known risk components separately and those who look for an integrated risk assessment as the convolution of all of the potential risk sources as a single result. The UN World Risk Index [1], or the Disaster Risk Index [2], for example, fall into this last category. Multivariate methodologies to estimate social vulnerability, on the other hand, can be related to the first category [3,4]. A common point among all these methods can be found in the way they use linear weighted methods to aggregate their indicators to obtain a final index. Many researchers have proposed a variety of indicators to assess earthquake risk to represent the different and multiple components involved, such as the physical, economic, social, and environmental dimensions within an urban environment [5–7]. However, there is no clear consensus

on which are the most suitable proxies to be used in a composite index and, most importantly, to be comparable across borders [8–10].

In the field of seismic risk assessment, Moncho's equation [11] proposes that seismic risk is the result of physical risk aggravated by social conditions and lack of resilience capacities. This method has been implemented to produce an integrated seismic risk index by different agencies around the world, such as the probabilistic risk model CAPRA [12] or the Global Earthquake Model of the Eucentre in Italy [13].

Moncho's equation is developed as a composite index: after a selection of indicators, importance weights are related to each through a hierarchical process, and then a linear weighted aggregation method is implemented to obtain a final value.

The present work proposes a fuzzy modeling approach to represent an estimation of the complex interactions between the physical and social dimensions of seismic risk. This methodology is able to obtain non-linear models that allow a more robust and realistic measure of the influences that each risk component may produce to generate a particular risk level. Therefore, it concedes a clearer understanding of how the disproportional effects of a seismic hazard are distributed over a geographical area. A key area of urban planning is to reduce disaster damage and increase safety [8], a task that can be difficult in scenarios where uncontrolled urbanization trends take place. Combined with inadequate urban planning and structural inner deficiencies, these elements have emerged as obstacles to development and preparedness for complex phenomena such as earthquakes ([14–18]).

In order to emphasize the differences between the two methods of aggregation, we will refer to the fuzzy model as the "fuzzy method" and to the Moncho's equation implementation as the "index method".

The paper is distributed as follows: Section 2 discusses the common methodologies used to build composite indices, and some of their disadvantages are pointed out. The definition of Moncho's linear equation and its inner structure, the basis of the proposed research, is also presented. Section 3 gives a short introduction to fuzzy logic and the properties that make it a suitable method to deal with some of the disadvantages noted in Section 2. Section 4 describes the fuzzy risk model and selected configurations. Section 5 focuses on the solution surface properties of both methods and highlights some consequences regarding non-linearity and performance. It also describes the experiments made in two different urban environments, i.e., Barcelona and Bogotá, and discusses some consequences regarding risk management and reduction. Section 6 highlights some of the consequences of this study and future work.

2. Linear Methods When Used to Build Composite Indices

2.1. Two Fundamental Disadvantages of Linear Methods

The use of linear methods to form a composite index has different limitations, such as compensability, preference dependence and interpretation of associated weights. The assumption of preferential independence among indicators states that any contribution or influence made by an individual indicator to the overall composite is discernible at all times: a packaged and isolated capsule of information that can be propagated along with different information types, without any change of its nature. When this assumption is accomplished, simple additive methods of aggregation can be used [19]. Their use, however, may lead to a scheme of full compensability, where poor performance of some of the indicators can be compensated by high performances of other indicators. Geometric aggregation, even if less compensatory, still maintains a nonrestrictive use of weights as representations of importance or significance coefficients that can translate as diminishing or compensating for the influence of a particular dimension performing poorly with another dimension with higher performance [19,20]. The use of geometric aggregation is the method of preference when compensability needs to be avoided since a geometric aggregation, in addition to lowering

compensability, rewards more those indicators with higher scores, which can be used as a way to direct attention over those indicators with lower ranks, to increment the overall score [21].

Preferential independence should be assumed only for those indicators, among which no phenomena of conflict or synergy exist and where any possible trade-off ratio between indicators is independent of the values of the remaining indicators [22]. Therefore, an integral risk index must be dependent on the good performance or decline of all of its constituent dimensions, and therefore any risk level should reflect any bad performance of one or more of its components. Conversely, a good or satisfactory integral risk value should be the result of the solid performance of all of its dimensions, both structural and social [23].

Using non-compensatory logic and multi-criteria analysis is a suitable way to obtain satisfactory results when two or more performances are compared. Nonetheless, these methods largely rely on ranking schemes and do not try to explain the nature of the indicator’s interrelationships. One of the consequences is the way in which each indicator’s contribution is accounted for: regardless of the value of the difference between the contribution of two indicators, whether larger or smaller, the ranking between them remains the same.

2.2. The Moncho’s Equation

The so-called Moncho equation comprises a physical risk (R_{ph}), which represents the level of risk for structural elements, and an aggravation coefficient (F), in which socioeconomic fragilities and lack of resilience of the context are included. According to these, any final seismic risk level can be considered the result of the physical risk but aggravated by social conditions and lack of resilience capacities. A calculation of the total risk index is then obtained by a direct application of Equation (1).

$$R_T = R_{ph}(1 + F) \tag{1}$$

where R_T is the total risk, R_{ph} is the physical risk, and F is an aggravation coefficient.

Both the physical risk index R_{ph} and the aggravation coefficient F are estimated through an additive aggregation method, where an analytical hierarchical method is applied to assess weights of indicators. R_{ph} and F are then estimated by Equations (2) and (3), respectively.

$$R_{ph} = \sum_{i=1}^p W_{R_{ph}i} F_{R_{ph}i} \tag{2}$$

$$F = \sum_{i=1}^m W_{FSi} F_{FSi} + \sum_{j=1}^n W_{FRj} F_{FRj} \tag{3}$$

The term $FR_{ph}i$ represents physical (structural) characteristics, while $FFSi$ represents socioeconomic fragility characteristics and $FFRj$ the lack of resilience of the exposed context. The terms $WR_{ph}i$, $WFSi$, and $WFRj$ are the assessed weights for each indicator, respectively, and p , m , and n are the total number of indicators for physical risk, socioeconomic fragility, and lack of resilience, respectively. More detailed information can be found in [24,25].

3. A Fuzzy Approach for Integral Assessments

The objective of this study is to simulate the effects of an earthquake on an urban environment, with a more accurate estimation of how the social dimension may influence the final risk level, once the infrastructure damage has been taken into account.

Our pre-conception of accuracy regards two general aspects that may weaken the reliability of most of the assertions based on integral risk estimations through composite indices. The first, as we mentioned before, is the assumed preferential independence among indicators and the potential compensability sources coming from the use of weights as importance coefficients. The second aspect is related to the inherent uncertainty and impreciseness embedded in many of the facets that are used to describe a social risk-related feature, many of whom are not entirely reflected in the numerical value

associated with its quantitative representation. The treatment of such complexity and impreciseness can be very well handled by fuzzy logic, and this is why this methodology is gaining ground, as it allows the analysis of complex processes from a different perspective. By the use of linguistic variables, fuzzy logic produces results closer to common language, transforming the whole process of risk communication into a two-way bridge built on intuition.

Fuzzy logic [26] is a theory regarding the logic of imprecision and a mathematical tool capable of performing reasoning processes when available information is uncertain, incomplete, imprecise, vague, partially of truth, or even contradictory [27]. The introduction of the notion of multiple-valued membership degrees to a particular fuzzy set and a gradual transition scheme among system states are crucial elements that make fuzzy logic a suitable theory to handle complexity.

Fuzzy systems are approximators to algebraic functions since their main structure is based on a plausible (or empirical) relationship between antecedents and consequents. In this sense, the mapping between inputs and outputs represents an isomorphism among fuzzy logic, and abstract and linear algebra. However, one of the most evident advantages of fuzzy logic is that either inputs or outputs can be represented in the form of linguistic prepositions, enclosing in this manner the fuzziness contained in the information and describing a system behavior that could not be represented by analytical functions only.

The use of linguistic variables, as well as the use of a compositional rule of inference, allows the establishment of what is known as approximate reasoning. An inference rule can be expressed in natural language as: "IF premise (antecedent) THEN conclusion (consequent)"; if premises and conclusions are expressed by linguistic fuzzy variables, and fuzzy relations are used, these inference rules are then called fuzzy inference rules. Therefore, any system that infers its conclusion by means of fuzzy rules is called a fuzzy inference rule-based system (FIS).

4. An Integral Seismic Risk Fuzzy Model

The proposed model is composed of different modules: Aggravation Fuzzy Model, Physical Risk Fuzzy Model, and Total Seismic Risk Fuzzy Model. Figure 1 shows the structure of the whole model schematically. Each module is formed by different sub-modules that are the result of the aggregation of the set of indicators proposed by Carreño [24].

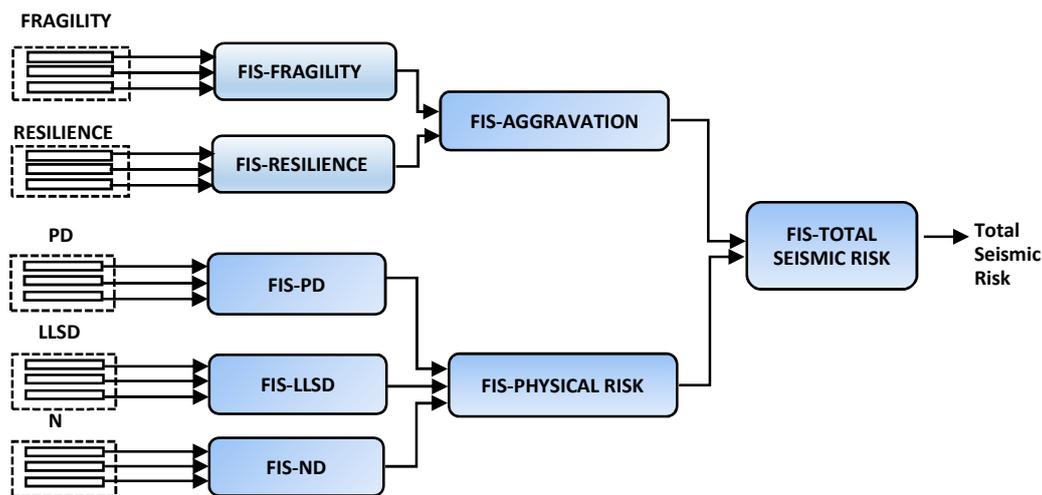


Figure 1. Conceptualization of the Seismic Risk Fuzzy Model. White rectangles represent indicators either describing social economic fragility or physical risk. Here: PD = Property Damage, LLSD=Life Line Sources Damage, ND = Network Damage, FIS = Fuzzy Inference System.

We designed the aggregation of indicators employing a Fuzzy Inference System (FIS) type based on Mamdani [27]. The aggravation fuzzy model (FIS-AGGRAVATION in Figure 1), includes two elements

representing the social fragility (FIS-FRAGILITY) and the resilience (FIS-RESILIENCE). Both elements are, in turn, fuzzy models that are based on their own indicators, represented by white rectangles in Figure 1. Each of these indicators are described in detail in the next sections. The outputs of each of these two models represent the fragility and resilience levels of a given region, respectively. These levels are used as inputs of the FIS-AGGRAVATION model to infer the aggravation level of that region. Likewise, the physical risk model (FIS-PHYSICAL RISK in Figure 1) receives the property damage (PD), lifeline sources damage (LLSD), and network damage (ND) levels as inputs to infer the physical risk level of the region under study. PD, LLSD, and ND are also fuzzy models based on their own indicators, introduced in the following sections and represented by white rectangles in Figure 1. Finally, the aggravation and physical risk levels inferred by the FIS-AGGRAVATION and FIS-FRAGILITY models are the inputs of the FIS-TOTAL SEISMIC RISK fuzzy model, which provides the total seismic risk level as an output.

Therefore, using the original indicator's raw values, each of the outputs of each sub-model also acts as inputs for the next inference layer in the model's structure. In this sense, we guarantee that all variables entered in the model remain as fuzzy sets, giving the chance to connect them through a new FIS without losing consistency, thereby allowing model completeness.

4.1. Physical Risk Fuzzy Model

The Physical Risk Fuzzy Model is based on previous work [28] and aims to describe the potential damages caused by an earthquake to different critical urban infrastructure and basic supply lines: Property, LifeLines and Network Supply lines. Three sub-models, each of which is a FIS, were used to represent each type of damage using indicators, as shown in Figure 1: Property Damage (PD), Life Line Sources Damage (LLSD) and Network Damage (ND). In this way, we can handle several indicators at the same time yet narrowing the complexity of the model as the number of fuzzy rules is limited to 2^n (with $n = 3$).

Table 1 shows a brief description of the indicators used in the Physical Risk model and the resources utilized for their estimation.

Table 1. Indicators used for the Physical Risk Fuzzy Model (References for ATC-13/ATC-21 and HAZUS area [29,30], respectively).

Property Damage (PD)
Damage Area (The percentage of constructed area that is destroyed, estimated by means of ATC-13 and HAZUS).
Dead People (Number of deaths per 1000 inhabitants as estimated by ATC-13 and HAZUS).
Injured People (Number of injured per 1000 inhabitants as estimated by ATC-13 and HAZUS).
LifeLine Sources Damage (LLSD)
Telephonic Substation Affected (number of telephonic stations with high seismic vulnerability according to ATC-21).
Electrical Substation Affected (number of electrical substations with high seismic vulnerability according to ATC-21).
Damage in Water Mains (number of breaks along the supply water network per kilometer as estimated by ATC-13 and HAZUS).
Network Damage (ND)
Damage in Gas Network (number of breaks along the gas network per kilometer as estimated by ATC-13 and HAZUS).
Fallen Length of Electrical Lines (fallen length of electrical lines per network kilometer as estimated by means of ATC-13 and HAZUS).
Damage in Mains Roads (Damage Index).

Each of these indicators was estimated using three FIS sub-models with their antecedent and consequent parts divided into three linguistic classes: Low, Medium, and High. For example, Table 2

shows the set of fuzzy rules that were used to estimate LifeLine Sources Damage levels (LLSD) using three indicators.

Table 2. Rules defined for the FIS sub-model used to estimate Life Lines Sources Damage (LLSD). TSA = Telephonic Substation Affected; ESBA = Electrical Substation Affected; DWM = Damage in Water Mains; Antecedent's and consequent's membership functions: H = high, M = medium, L = low.

-
1. If (TSA is L) and (ESBA is L) and (DWM is L) then (DLS is L)
 2. If (TSA is M) and (ESBA is M) and (DWM is M) then (DLS is M)
 3. If (TSA is H) and (ESBA is H) and (DWM is H) then (DLS is H)
 4. If (TSA is M) and (ESBA is L) and (DWM is L) then (DLS is L)
 5. If (TSA is H) and (ESBA is L) and (DWM is L) then (DLS is M)
 6. If (TSA is L) and (ESBA is M) and (DWM is L) then (DLS is L)
 7. If (TSA is M) and (ESBA is M) and (DWM is L) then (DLS is M)
 8. If (TSA is L) and (ESBA is M) and (DWM is L) then (DLS is M)
 9. If (TSA is L) and (ESBA is H) and (DWM is L) then (DLS is M)
 10. If (TSA is M) and (ESBA is H) and (DWM is L) then (DLS is M)
 11. If (TSA is H) and (ESBA is H) and (DWM is L) then (DLS is H)
 12. If (TSA is L) and (ESBA is L) and (DWM is M) then (DLS is L)
 13. If (TSA is M) and (ESBA is L) and (DWM is M) then (DLS is M)
 14. If (TSA is H) and (ESBA is L) and (DWM is M) then (DLS is M)
 15. If (TSA is L) and (ESBA is M) and (DWM is M) then (DLS is M)
 16. If (TSA is H) and (ESBA is M) and (DWM is M) then (DLS is H)
 17. If (TSA is L) and (ESBA is H) and (DWM is M) then (DLS is H)
 18. If (TSA is M) and (ESBA is H) and (DWM is M) then (DLS is H)
 19. If (TSA is H) and (ESBA is H) and (DWM is M) then (DLS is H)
 20. If (TSA is L) and (ESBA is L) and (DWM is H) then (DLS is M)
 21. If (TSA is M) and (ESBA is L) and (DWM is H) then (DLS is M)
 22. If (TSA is H) and (ESBA is L) and (DWM is H) then (DLS is H)
 23. If (TSA is L) and (ESBA is M) and (DWM is H) then (DLS is H)
 24. If (TSA is M) and (ESBA is M) and (DWM is H) then (DLS is H)
 25. If (TSA is H) and (ESBA is M) and (DWM is H) then (DLS is H)
 26. If (TSA is L) and (ESBA is H) and (DWM is H) then (DLS is H)
 27. If (TSA is M) and (ESBA is H) and (DWM is H) then (DLS is H)
-

To estimate a physical risk level, each sub-model acts as an independent inference system using as inputs their respective original set of indicators. In the subsequent steps, the Physical Risk model uses the estimated inferences obtained from the three FIS sub-models and performs the final estimation through the FIS called Physical Risk.

In the case of Physical Risk, its FIS has its antecedent part, divided into a universe of discourse of three linguistic classes: Low, Medium, and High. Each class is associated with a membership function type: Z-shaped, Pi-shaped, and S-shaped, respectively [31]. The FIS consequent part was characterized by five linguistic classes: Low, Medium-Low, Medium-High, High, and Very-High, each related to a membership function type: Z-shaped, Pi-shaped (the three middle ones), and S-shaped, respectively. Figure 2 shows a conceptualization of the membership functions used in the experiments.

All membership function shape parameters were chosen to suit both the numerical range and variability of available data. We used the center of gravity (COG) method for the defuzzification of each inference. Following a fuzzy modeling approach allowed us to implement simple fuzzy logic rules to relate each of the indicators (pertaining to a particular FIS) with a specific fuzzy outcome according to their empirical relationship. In this way, each FIS is composed of a set of fuzzy rules (if-then type), which relates the indicator's fuzzified values with an empirical fuzzy consequence.

The initial values of physical risk indicators were originated as outputs of a probabilistic risk scenario developed in the framework of the Risk-UE project of the European Commission [32].

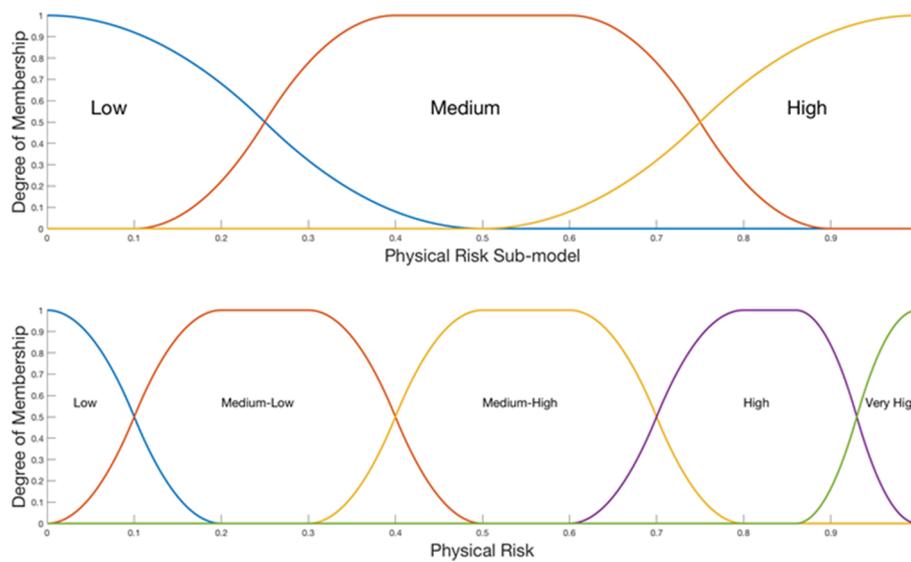


Figure 2. Simple conceptualization of the membership functions used for Physical Risk and Aggravation showing the input FIS (upper plot) and the output FIS (lower plot). The universe of discourse, and the exact parameters of the membership functions, are not shown in the figure since they depend on the variability and numerical range of each indicator’s numerical value.

4.2. Aggravation Fuzzy Model

The Aggravation Fuzzy Model is based on the seismic risk conceptualization provided by [33] and includes elements representing the social fragility and lack of resilience capacity of an urban area. The fragility dimension aims to enclose proxy elements describing the different life quality levels and social inequality space distribution. The resilience dimension describes a representative set of available city resources to respond to an emergency (some of the indicators included in this model were developed by city authorities and census open data). Table 3 shows a brief description of the indicators used in the Aggravation model.

Table 3. Indicators used for the Aggravation Fuzzy Model.

Fragility
Marginal Slums. Percentage of: Slum area/Locality area.
Social Disparity Index: Index from 0 to 1.
Population Density: Inhabitants / km2 of built area.
Resilience
Human Health Resources: Human resource in health per 1000 inhabitants.
Emergency Operability: Index given by City Authorities (from 0 to 2).
Development Level: Index given by City Authorities (from 1 to 4).

The inner structure of the Aggravation Fuzzy Model was developed following the same nature of the Physical Risk Fuzzy model, so each aggravation dimension constitutes an independent FIS. After Fragility and Resilience levels are estimated through their respective FIS, they are used as the primary input for a third FIS, where a final aggravation level is calculated (see Figure 1). In the same way as previously, inference fuzzy rules were defined among indicators to simulate empirical knowledge regarding fragility and resilience development and dynamics. An example of the fuzzy rules used for estimate aggravation can be seen in Table 4 describing the sub-model called Resilience, where three classes were defined for its antecedent part, while its consequent part was divided into five linguistic classes.

Table 4. Rules defined for the FIS sub-model used to estimate Resilience levels (R). HHR = Human Health Resources, EO = Emergency Operability, DL = Development Level. Antecedent’s membership functions: H = high, M = medium, L = low. Consequent’s membership functions: VH = Very High, H = High, MH = Medium-High, ML= Medium-low, L = Low.

1. If (HHR is L) and (DL is L) and (EO is L) then (R is VL)
2. If (HHR is M) and (DL is M) and (EO is M) then (R is M)
3. If (HHR is H) and (DL is H) and (EO is H) then (R is VH)
4. If (HHR is M) and (DL is L) and (EO is L) then (R is L)
5. If (HHR is H) and (DL is L) and (EO is L) then (R is H)
6. If (HHR is L) and (DL is M) and (EO is L) then (R is L)
7. If (HHR is M) and (DL is M) and (EO is L) then (R is M)
8. If (HHR is H) and (DL is M) and (EO is L) then (R is H)
9. If (HHR is L) and (DL is H) and (EO is L) then (R is M)
10. If (HHR is M) and (DL is H) and (EO is L) then (R is M)
11. If (HHR is H) and (DL is H) and (EO is L) then (R is H)
12. If (HHR is L) and (DL is L) and (EO is M) then (R is L)
13. If (HHR is M) and (DL is L) and (EO is M) then (R is M)
14. If (HHR is H) and (DL is L) and (EO is M) then (R is H)
15. If (HHR is L) and (DL is M) and (EO is M) then (R is M)
16. If (HHR is H) and (DL is M) and (EO is M) then (R is H)
17. If (HHR is L) and (DL is H) and (EO is M) then (R is M)
18. If (HHR is M) and (DL is H) and (EO is M) then (R is H)
19. If (HHR is H) and (DL is H) and (EO is M) then (R is H)
20. If (HHR is L) and (DL is L) and (EO is H) then (R is M)
21. If (HHR is M) and (DL is L) and (EO is H) then (R is H)
22. If (HHR is H) and (DL is L) and (EO is H) then (R is H)
23. If (HHR is L) and (DL is M) and (EO is H) then (R is H)
24. If (HHR is M) and (DL is M) and (EO is H) then (R is VH)
25. If (HHR is H) and (DL is M) and (EO is H) then ((R is VH)
26. If (HHR is L) and (DL is H) and (EO is H) then (R is H)
27. If (HHR is M) and (DL is H) and (EO is H) then (R is VH)

4.3. Total Risk Fuzzy Model

Once physical risk and aggravation levels have been estimated, they are used as inputs for the final FIS called Total Risk, which is used to determine a final integral seismic risk level as a result of the convolution of the aforementioned two dimensions. In this model, five linguistic classes characterize antecedents and consequents: Low, Medium-Low, Medium-High, High, and Very-High, as shown in the lower plot of Figure 2.

The FIS Total Risk is based on a set of 25 fuzzy rules interrelating empirical relationships between physical risk and social aggravation. Figure 1 shows a conceptualization of the flux of information and the main functioning of the whole Integral Seismic Risk Model. The fuzzy rules used to estimate Total Risk can be seen in Table 5.

Table 5. Rules defined for the FIS sub-model used to estimate Total Risk levels. TR = Total Risk, PhR = Physical Risk, AG = Aggravation, VH = very-high; H = high; MH = medium-high; ML = medium-low; L = low.

1. If (Ag is L) and (PhR is L) then (TR is L)
2. If (Ag is ML) and (PhR is L) then (TR is ML)
3. If (Ag is MH) and (PhR is L) then (TR is ML)
4. If (Ag is H) and (PhR is L) then (TR is ML)
5. If (Ag is L) and (PhR is L) then (TR is MH)
6. If (Ag is L) and (PhR is ML) then (TR is ML)
7. If (Ag is ML) and (PhR is ML) then (TR is ML)
8. If (Ag is MH) and (PhR is ML) then (TR is MH)
9. If (Ag is H) and (PhR is ML) then (TR is MH)

Table 5. Cont.

10. If (Ag is VH) and (PhR is L) then (TR is MH)
11. If (Ag is L) and (PhR is MH) then (TR is ML)
12. If (Ag is ML) and (PhR is MH) then (TR is MH)
13. If (Ag is MH) and (PhR is MH) then (TR is MH)
14. If (Ag is H) and (PhR is MH) then (TR is MH)
15. If (Ag is VH) and (PhR is MH) then (TR is H)
16. If (Ag is L) and (PhR is H) then (TR is MH)
17. If (Ag is ML) and (PhR is H) then (TR is VH)
18. If (Ag is MH) and (PhR is H) then (TR is VH)
19. If (Ag is H) and (PhR is H) then (TR is H)
20. If (Ag is VH) and (PhR is H) then (TR is VH)
21. If (Ag is L) and (PhR is VH) then (TR is VH)
22. If (Ag is L) and (PhR is VH) then (TR is VH)
23. If (Ag is MH) and (PhR is VH) then (TR is H)
24. If (Ag is H) and (PhR is VH) then (TR is H)
25. If (Ag is VH) and (PhR is VH) then (TR is VH)

5. Results and Discussion

In this section, the integral seismic risk fuzzy model described in the previous section and Moncho’s equation are used to estimate integral seismic risk levels for the cities of Barcelona, Spain, and Bogota, Colombia. We compare these results in terms of their spatial distribution patterns and their estimated quantitative risk values. Before going through the results obtained for these two cities, a comparison study of both approaches (fuzzy models and Moncho’s equation) in a synthetic problem is presented to clarify the different behavior of both types of models.

5.1. Comparison Surfaces of the Fuzzy Model and the Index Method in a Synthetic Dataset

An analysis of the differences between the solution surfaces of Moncho’s equation and the fuzzy model is performed. A synthetic database [33] is used to show how the linearity of Moncho’s equation generates a smooth surface, while a fuzzy model displays a rough surface more suitable to describe a non-linear response of the simultaneous influences of different indicators. These surfaces are shown in Figure 3.

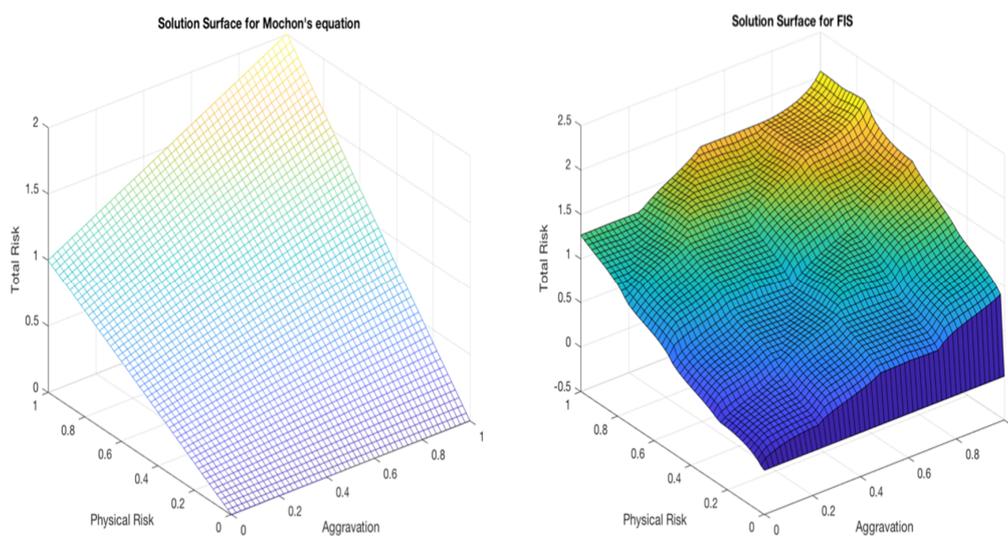


Figure 3. Moncho’s equation Surface (left) and Fuzzy Decision Surface (right) generated from a synthetic database of 100 numerical values ranging from 0 to 1 and taking finite steps of 0.02 units [23].

The lineal assumption made in Moncho's equation generates a non-balanced contribution between aggravation and physical risk to the overall composite, underestimating the influence of the aggravation, particularly in its lower part.

Let us first analyze the case in which the physical risk is zero. In this case, Moncho's equation always obtains a constant total risk of zero regardless of the aggravation value. The same happens not only with a value of zero but also for small values of physical risk, with the total risk remaining practically constant regardless of the aggravation taking large values. It is important to underline that both physical and aggravation are risk factors that must have an impact on total risk. The total risk should not be null just because there is no physical risk. The previous sentence is a fundamental point that we consider to be a strong limitation of the approaches that use Moncho's equation.

In the case of the fuzzy model, the apparent dependence on physical risk values and the inherent diminishing of the influence of aggravation is no longer observed on its solution surface. Hence, the way higher aggravation values combine with physical risk to generate total risk levels is consequent and more natural, with the main assumption made in an integral risk estimation in which both dimensions should be shaping any total risk level. As we will see later, these characteristics have a vital significance in terms of the final interpretation of the role that each indicator is playing to generate a particular total risk level.

Another interesting aspect to comment on is the shape of the surfaces. The surface obtained with Moncho's equation has a very pronounced profile due, on the one hand, to the fact that for low physical risk values, the total risk remains low regardless of the aggravation values. On the other hand, for high values of physical risk, the influence on the total risk of the aggravation is very high, e.g., the total risk is doubled when physical risk and aggravation have maximum values. Contrarily, the surface derived from the fuzzy model has a softer shape, with a moderate progression. This allows obtaining more balanced and sensible model responses for close values of physical risk and aggravation.

5.2. Results for Barcelona

The city of Barcelona is divided into 10 administrative districts and 73 neighborhoods. For statistical purposes, the city is also split into an arbitrary division of 273 small-sized areas called ZEP (small statistical areas, in Spanish; this division was recently replaced with a new group of 233 "basic statistical areas" but their statistical objectives remain the same). The left-hand side plots of Figure 4 show the spatial distribution of aggravation levels estimated for the 10 administrative districts of Barcelona according to the proposed fuzzy model (upper plot) and Moncho's equation (lower plot). Both estimations show that aggravation levels in Barcelona are divided into two main areas: the highest aggravation is spread mostly over the northeast part of the city, whilst lower aggravation levels are contained in the southwest.

It is interesting to note, however, how both models differ in representing the shift between the two extreme labels of these categories (from low to very high). The index method estimates the higher levels of aggravation for Districts (1), (8), (9), and (10), while the proposed method estimates the same districts, plus District (7), but with much larger aggravation magnitudes. These results, which effectively create a spatial frontier that indicates where significant aggravation levels start to grow, are important when the final risk level is estimated. Figure 5 shows the numerical aggravation levels per district obtained by the two models.

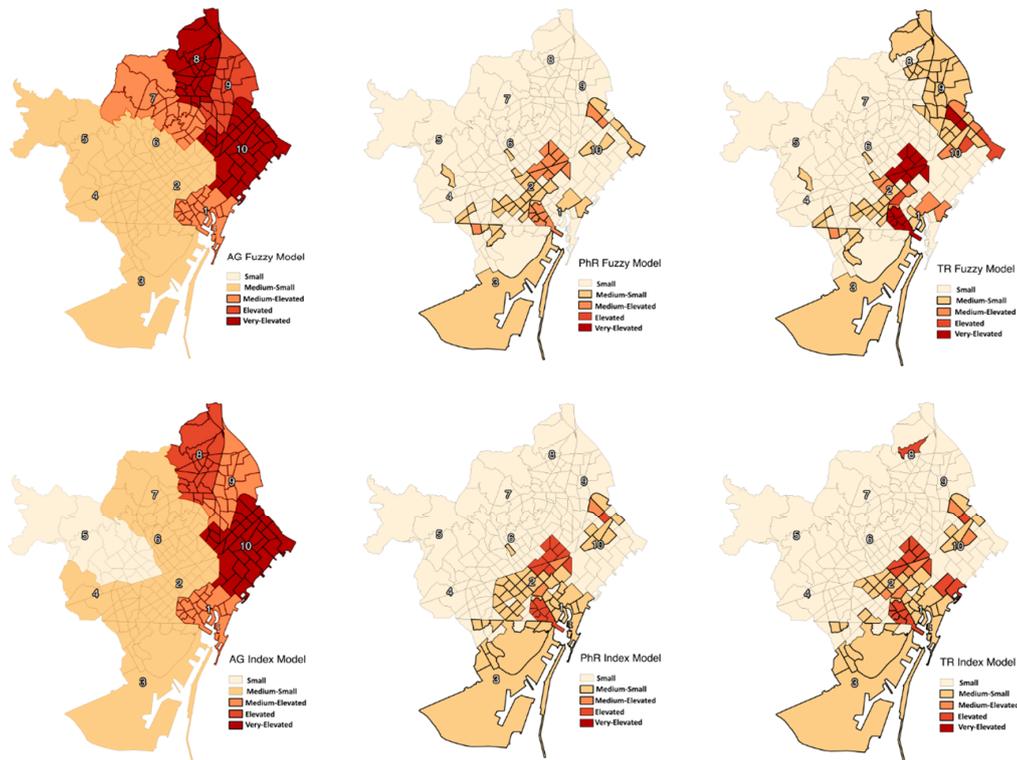


Figure 4. Risk components obtained for Barcelona city by the fuzzy model (upper row) and the index model (lower part). From left to right: social aggravation, physical risk, and total seismic risk. Significant values of each component have been highlighted to show a measure of how the assumption of compensability can lead towards different risk spatial patterns. Regardless of the resemblances between the spatial configurations estimated by the two models for social aggravation and physical risk levels, it is clear how a linear aggregation produces a different total risk pattern.

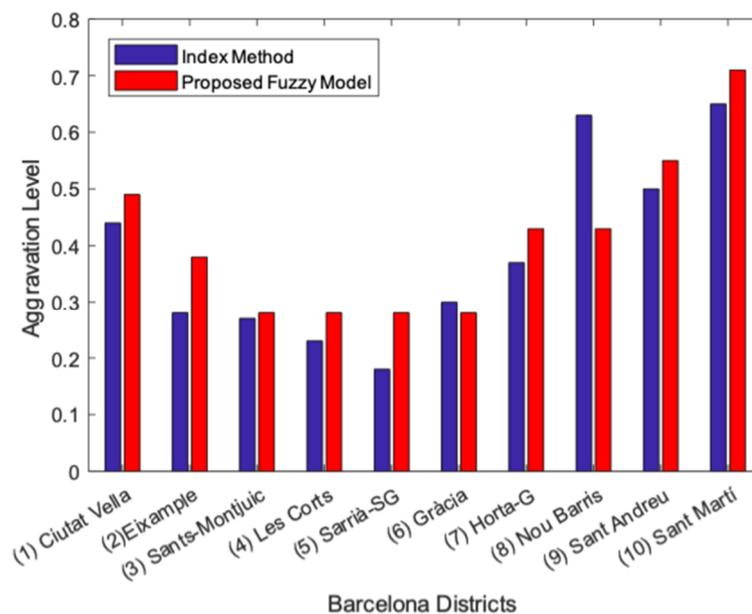


Figure 5. Aggravation values obtained for the 10 districts of Barcelona with the index method and the proposed fuzzy model.

The center plots of Figure 4 show the estimated spatial patterns of physical risk levels for the 248 administrative zones (ZEP) utilizing the fuzzy model and Moncho's equation, respectively. Both approaches show that the highest levels of physical risk are mostly contained in the central part of the city (districts: (1) Ciutat Vella and (2) Eixample). The most obvious difference is again in the magnitude of physical risk, as shown in Figure 6.

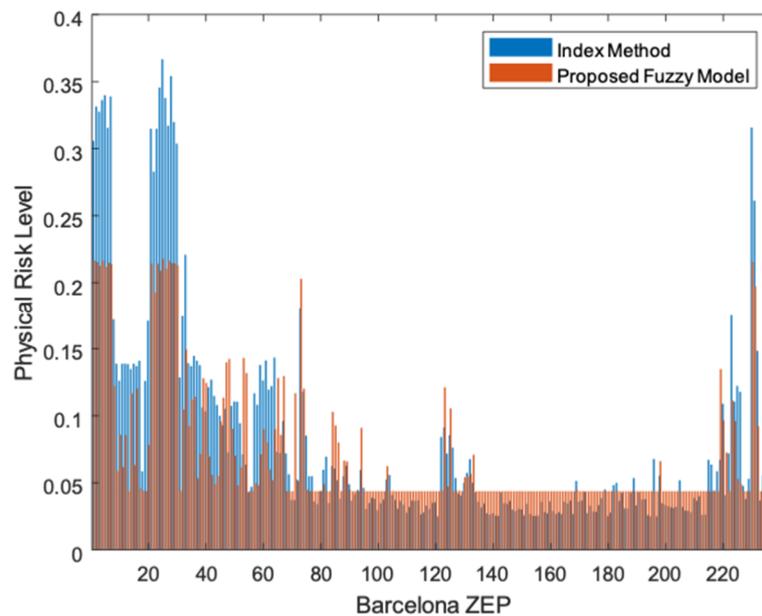


Figure 6. Physical Risk values for the 248 Barcelona small statistical areas (ZEP).

Moncho's equation estimates the highest magnitudes of physical risk at ZEPs contained in Districts (1) and (2). A magnitude of medium-low was estimated for a large extension of Districts (2) and (3), which seems to create a corridor of physical risk between these two districts. In contrast, the fuzzy model estimates that this same magnitude would be contained mainly towards the south and that the same corridor may exist but involves a reduced number of ZEPs.

The right-hand-side plots of Figure 4 show the total risk spatial distribution of the levels calculated from both approaches. Moncho's equation estimates spatial distribution of total risk with its highest values contained in the central area of the city, namely, over Districts (1) and (2). The fuzzy model also estimates higher levels in these areas but, additionally, another large area is estimated at the northeast of the city, having values labeled as medium-low. These spatial differences are worth examining more carefully since they are not just a matter of value difference but are related to how both methodologies, Moncho's and fuzzy, perform the aggregation of the two dimensions of risk. We will further discuss these implications in Sections 4 and 5.

Figure 7 shows total risk numerical values for the different ZEPs, where we can note the distribution of similar values between the fuzzy and Moncho methods. It is important to note, as we discussed before, that the physical risk levels estimated by the fuzzy model are lower than those calculated by Moncho's equation. However, this sort of underestimation related to Moncho's outputs is not reflected in the final total risk levels estimated by the fuzzy method, which are quite similar to those displayed by Moncho's equation. Therefore, we can see the crucial influence that aggravation values may have on the final total risk level.

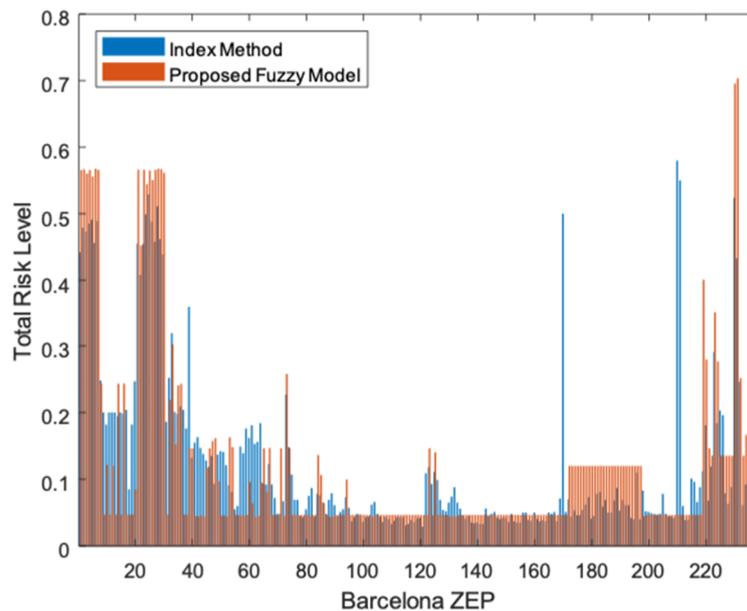


Figure 7. Total Risk values for the 248 Barcelona small statistical areas (ZEP).

5.3. Results for Bogota

Although Colombia's capital is divided into 20 administrative localities, in this study, we used only 19, since the 20th corresponds mainly to the rural area of the city. As before, to estimate social aggravation for each district, we used statistical and demographic data as reported in [24].

The left-hand-side plots of Figure 8 show aggravation levels obtained by means of the proposed fuzzy model (upper plot) and Moncho's equation (lower plot). In this case, the general aggravation level seems to be underestimated by the fuzzy model when compared with Moncho's equation, or index method. However, both models estimated that the highest values of aggravation are at the southwest part of the city, corresponding to Districts (4)–(8). The east part of the city remains with medium-low, while the northwest part of the city presents medium-high aggravation values.

The index method reaches a very-high value at the southwest part of the city while the northern part presents mostly a medium-low aggravation value. Figure 9 shows the numerical values of the aggravation levels for the 19 administrative districts of Bogota, obtained through the two methods. As in the Barcelona case, the trend is similar to that obtained by the index method, although there is a difference in the numerical values.

Physical risk levels were estimated using a probabilistic damage seismic scenario as a base, which considered an earthquake of close to 0.2g of rock acceleration, and which was studied by the Universidad de Los Andes in 1997 [34,35].

The center plots of Figure 8 show the physical risk spatial patterns of fuzzy and index methods, respectively. Both estimate the highest physical risk values in the northern part of the city (Districts: (1), (2), (11), (12), (13), and (17)). Figure 10 shows the physical risk numeric values over the 19 administrative districts of Bogota estimated by both methods. It is clear that Moncho's equation, or index method, present the lowest values for almost all city localities, while the fuzzy model estimates are as much as twice as high for the same locations.

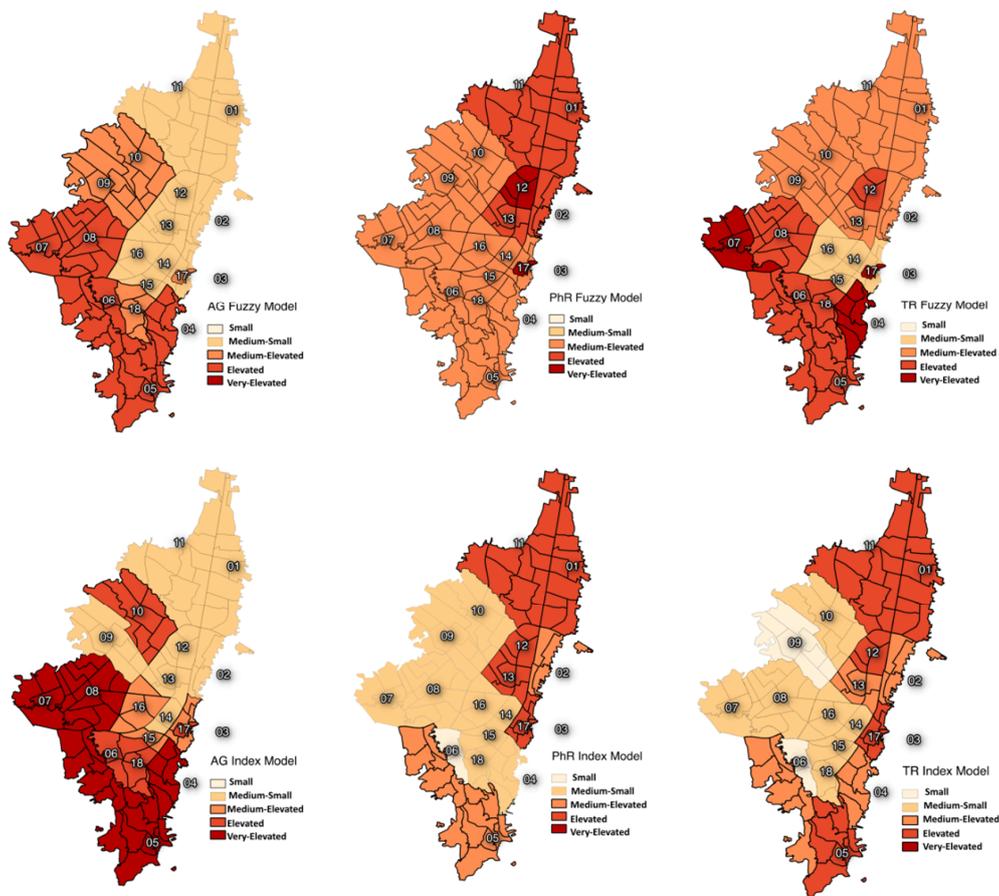


Figure 8. Risk components obtained for Bogotá city by: the fuzzy model (upper part) and the index model (lower part). From left to right: social aggravation, physical risk, and total seismic risk. Significant values of each component have been highlighted to show a measure of how the assumption of compensability can lead towards different risk spatial patterns.

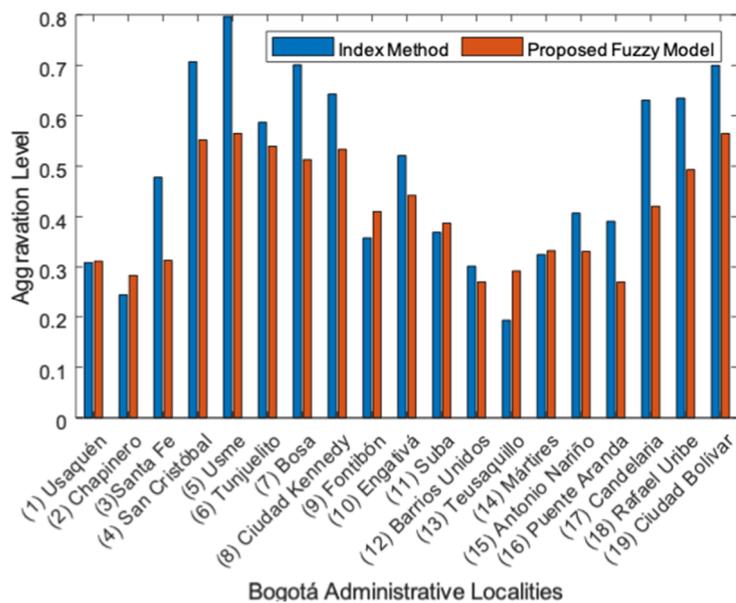


Figure 9. Aggravation values obtained for the 19 administrative localities of Bogotá with the index method and the proposed fuzzy model.

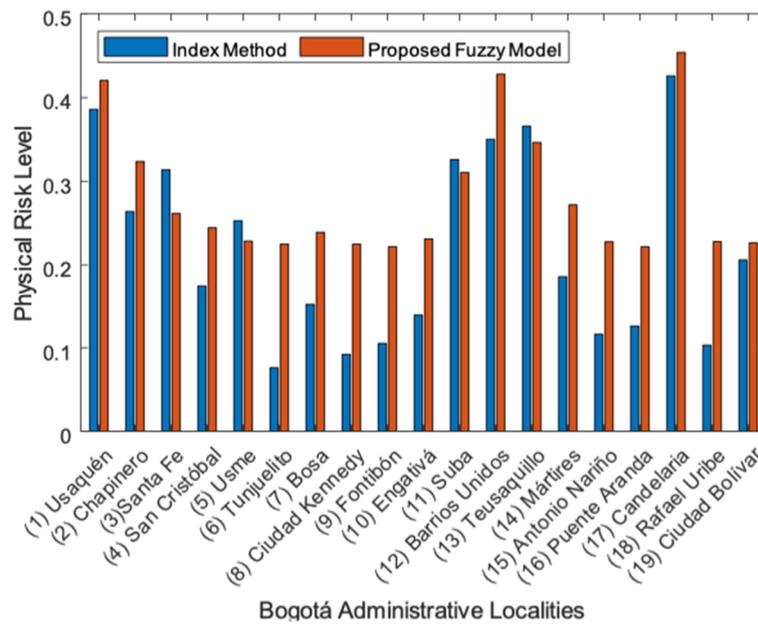


Figure 10. Physical Risk values obtained for the 19 administrative localities of Bogotá with the index method and the proposed fuzzy model.

The right-hand-side plots of Figure 8 show the estimated spatial patterns of total risk, according to the fuzzy model (upper plot) and the index method (lower plot), respectively. The fuzzy model estimates that the highest levels of risk are present mostly in the south and the center parts of the city. In contrast, the index method determines the highest risk levels for the northern part of the city and only a small region in the south.

Figure 11 shows the total risk numerical values over the 19 districts of Bogotá. The variability estimated by the fuzzy model is similar to that estimated by the index method, especially at the right-hand side of the plot.

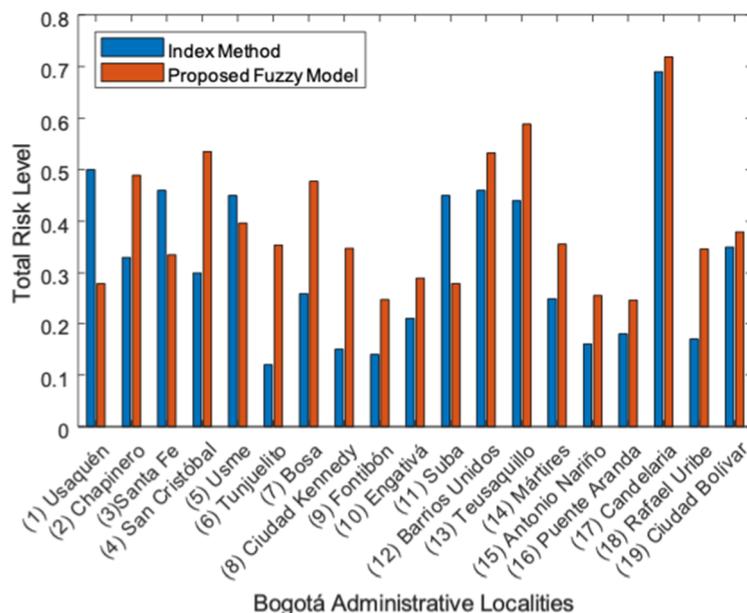


Figure 11. Total Risk values obtained for the 19 administrative localities of Bogotá with the index method and the proposed fuzzy model.

5.4. Comparison of Seismic Risk Spatial Distribution's Patterns of the Fuzzy Model and the Index Method in Barcelona and Bogotá

It is worth analyzing the differences carefully among total risk spatial patterns of both methodologies where the advantages in performing a non-linear aggregation of indicators through fuzzy methods can be seen. Such advantages are significantly important for any integral risk management scheme because a more explicit and transparent assessment of how the different dimensions of risk (either natural or anthropogenic) may be acting together to generate seismic risk is perceived.

Figure 4 highlights Barcelona's estimated values for aggravation, physical risk, and total risk levels achieved using the fuzzy model (upper row) and the index method (lower row). As we have discussed, both methodologies estimate the presence of a large area with significant aggravation levels located in the northeast part of the city. At the same time, both models assess that the highest physical risk levels are mostly contained in the central area (which corresponds to the oldest part of the city). However, it is noticeable that, according to the index method or Moncho's equation, the total risk spatial distribution seems to be limited or constrained by the nature of the original spatial configuration estimated for the physical risk.

This feature can be translated as an underestimation of the influence of the aggravation component, which could lead us to biased results or even to a contradiction scenario. For example, when calculating physical risk levels, only particular components pertaining to this dimension were considered, such as the number of lines of telephonic substations affected and the potential damage to the lifelines network. Although important, these components do not reflect the entire nature of risk which, by definition in Moncho's equation, must be integral in order to be realistic. This means social fragility and social vulnerability components (such as poverty, inequality, and number of slums) also play an important role, and must be taken into account in the final calculation of risk. Another way to interpret this is that the physical components of seismic risk are not the only ones that are driving seismic risk (and therefore its spatial distribution) and that the human element is also influencing risk redistribution. In any other case, all related activities of Disaster Risk Reduction, designed to reduce risk throughout communities' engagement and participation, would be unnecessary. Therefore, the assumption based on the hypothesis that physical risk is the main driver of the final distribution of seismic risk remains an open question and cannot be taken as an evenhanded reference.

This hypothesis is well reflected in the mathematical form of Moncho's equation, where the aggravation term is considered as a scalar/factor, increasing or decreasing the value of physical risk. We can see the consequences in Figure 4 for Barcelona, where only those geographical areas first estimated as having an amount and spatial pattern of physical risk, determine where total risk can appear later. The same also holds true in the case of Bogotá (Figure 8, lower row) where this same behavior can be seen even more clearly. In the maps, we can see how the large area in the southwest part of Bogotá with significant social aggravation levels does not have any influence on the distribution of total risk. One might conclude that according to the index method, bad performance of the areas with significant social aggravation levels could be compensated by good levels (low or medium) of physical risk, in such a way that the total risk level in those areas is estimated as being low.

In terms of risk management, assuming a physical risk-based approach can be critical. As is widely accepted, in an urban environment, the ex-ante social aggravation or vulnerability levels can be conditioners for future trends or potential paths that may define levels of preparedness and resilience [36–39]. Sometimes, such social processes may define particular dynamics that may amplify the effects of the hazard [38,40]. Consider, for example, the second-order effects (both in intensity and in duration time) over a panorama of high aggravation levels or the post-disaster recovery strategies that can be weakened by the presence of areas with significant levels of social fragility and inadequate resilience capacities [37,41–44]. All of this is translated as a coercive environment for pre- and post-disaster actions that could easily and rapidly transpire to be ineffective or insufficient.

This linear proportionality between total risk and the original spatial pattern of physical risk is not seen in the fuzzy model. On the contrary, as is shown in Barcelona (Figure 4, upper row), when the

final total risk level is estimated, it is influenced by the spatial pattern of physical risk (very similar to that estimated by the index method). Nevertheless, the effect of the social component is still present, merely in the area in the northern part of the city (with a total risk level of medium-low), which is consistent with the presence of the extensive area with high social aggravation levels estimated before.

The absence of compensability between total risk and physical risk can also be observed in the case of Bogota (Figure 8, upper row). As discussed previously, both methodologies estimated a considerable area with high aggravation levels over the southern part of the city, with the highest physical risk levels estimated in the northern part of the city. The influence of the social aggravation component on total risk distribution can be quantified as the large south area with high and very high total risk values, which is again consistent with the original aggravation estimated in that area.

Figures 12 and 13 show a quantification of the social aggravation component’s contribution to the total seismic risk level for Bogota’s administrative localities and Barcelona’s districts, respectively.

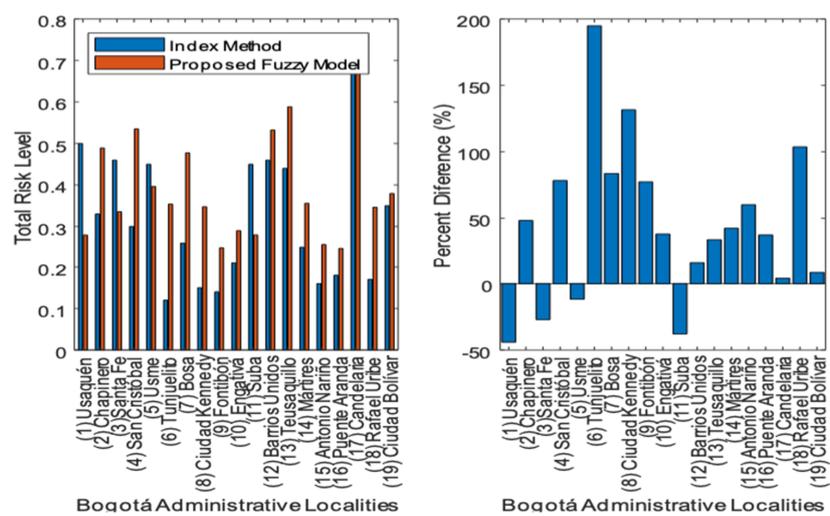


Figure 12. Percentage differences between the numeric value of the total risk estimations made by the index method and the fuzzy model for Bogota’s administrative localities. At left: values of total risk. At right: percentage difference.

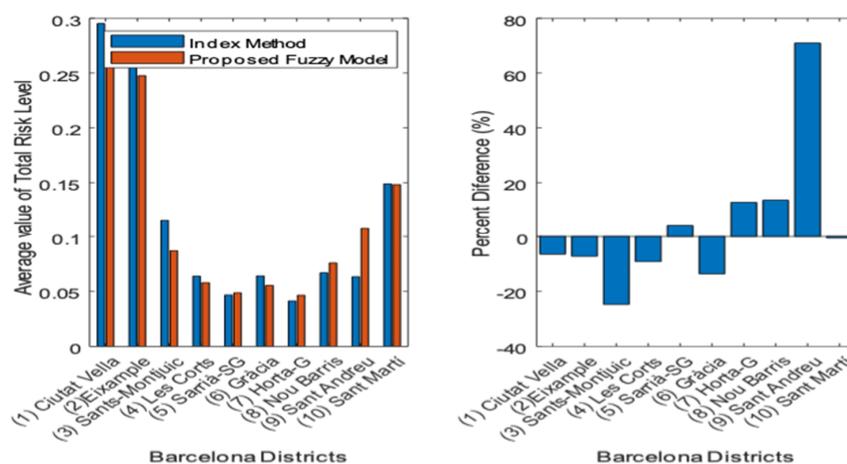


Figure 13. Percentage differences between the numeric value of the total risk estimations made by the index method and the fuzzy model for Barcelona’s districts. At left: values for each of Barcelona’s ZEPs, grouped and averaged per district. At right: percentage difference.

In the case of Barcelona, the percentage difference between the averaged total risk estimated by both models reaches values up to 70%. It is important to note that this difference corresponds to the

northeast area of District 9, with significant social aggravation levels. According to this result, the index method would underestimate the total risk level in this area by a factor of 10.

In the case of Bogota, the difference between the total risk estimated by both models is significantly more considerable (up to 200% for some areas); for example, in administrative localities 6, 7, 8, 9, 15, and 18, which are those that present the highest difference with respect to the values estimated by the index method, and also correspond to a high degree of social aggravation.

6. Conclusions and Future Work

Based on our results, we consider that a more realistic risk assessment (both in classification and distribution) can be achieved using fuzzy approaches. Using fuzzy inference, it is possible to analyze in more detail the influence of the social component considering a modeling framework in which social vulnerability is not exclusively dependent on the pre-existence of significant levels of physical risk. Avoiding the use of an unrestricted weighted linear aggregation scheme allowed us to represent a quantitative measure of how significant levels of social vulnerability are reflected in an integrated risk assessment, regardless of the good or bad performance of the physical/structural element. This fuzzy feature can lead towards a more formal quantification of how the presence of significant social fragilities or lack of resilience capacities might re-shape any seismic risk level.

The establishment of interrelated rules among indicators allows the assembly of compositional rules of inference that are based on the same elements that are assumed to generate urban seismic risk. Therefore, the inference process can be made following risk management knowledge allowing the model to represent, with a certain degree of freedom, the current understanding of how aggravation and physical risk merge. At the same time, it allows a real discussion of the fuzzy rule's structure strength, which can be improved through a deepest debate. Fuzzy logic potentialities can be exploited in a more suitable way because outputs from each FIS used in the seismic model are always fuzzy sets, giving the chance to connect them through a new FIS without losing consistency, and allowing model completeness. It is worth noting that modeling seismic risk through fuzzy methodologies allows a certain degree of flexibility over the model's structure. In this way, the inclusion of new variables is possible without significant technicalities. Economic and environmental variables could be added to the model to increase its feasibility. Finally, the fuzzy model can be adapted to make estimates of seismic risk at different space scales, whether at the urban, municipal, or national levels.

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