Advances in Intelligent Systems and Computing 402

Mohammad S. Obaidat
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Joaquim Filipe *Editors*

Simulation and Modeling Methodologies, Technologies and Applications

International Conference, SIMULTECH 2014
Vienna, Austria, August 28–30, 2014
Revised Selected Papers

Springer

Advances in Intelligent Systems and Computing

Volume 402

Series editor

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ISSN 2194-5357 ISSN 2194-5365 (electronic)
Advances in Intelligent Systems and Computing
ISBN 978-3-319-26469-1 ISBN 978-3-319-26470-7 (eBook)
DOI 10.1007/978-3-319-26470-7

Library of Congress Control Number: 2015955364

Springer Cham Heidelberg New York Dordrecht London

Printed on acid-free paper

Springer International Publishing AG Switzerland is part of Springer Science+Business Media (www.springer.com)

Contents

Social Aggravation Estimation to Seismic Hazard Using Classical Fuzzy Methods

J. Rubén G. Cárdenas, Àngela Nebot, Francisco Mugica, Martha-Liliana Carreño and Alex H. Barbat

Abstract In the last years, from a disasters perspective, risk has been dimensioned to allow a better management. However, this conceptualization turns out to be limited or constrained, by the generalized use of a fragmented risk scheme, which always consider first, the approach and applicability of each discipline involved. To be congruent with risk definition, it is necessary to consider an integral frame, and social factors must be included. Even those indicators that could tell something about the organizational and institutional capacity to withstand natural hazards, should be invited to the table. In this article, we analyze one of the most important elements in risk formation: the social aggravation, which can be regarded as the convolution of the resilience capacity and social fragility of an urban center. We performed a social aggravation estimation over Barcelona, Spain and Bogota, Colombia considering a particular hazard in the form of seismic activity. The Aggravation coefficient was achieved through a Mamdami fuzzy approach, supported by well-established fuzzy theory, which is characterized by a high expressive power and an intuitive human-like manner.

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M.S. Obaidat et al. (eds.), *Simulation and Modeling Methodologies, Technologies and Applications*, Advances in Intelligent Systems and Computing 402, DOI 10.1007/978-3-319-26470-7_14

Keywords Fuzzy sets · Risk management · Natural hazards · Vulnerability index · Social vulnerability · Seismic vulnerability · Fuzzy inference system

1 Introduction

Social vulnerability is one of the key factors to assembly risk in space and time, however, such important element is largely ignored over ex-ante, ex-post, and cost/lost estimation reports, in part because the measurement of social vulnerability is not quite understood, and in part because the presence of epistemology oriented-based discrepancies along vulnerability definition, which binds a particular methodology with the orientation where such definition has been used, i.e., ecology, human, physical, etc. Therefore, there is a concept discrepancy when a social vulnerability model is about to be built. Diverse models have been used to obtain social vulnerability estimations. For example, Cutter et al. [1] used a hazard-of-place model to examine the components of social vulnerability to natural hazards among US counties through the development of a vulnerability index based on the reduction of variables by a factor analysis plus an additive model. Kumpulainen [9] using ESPON Hazards integrative model, created a vulnerability index map for all Europe regions based on an aggregated model, considering that regional vulnerability is measured as a combination of damage potential (anything concrete that can be damage) and the coping capacity. The principal difference between these models rely on one basic definition: while in Cutter's model the hazard potential is dependent on risk and mitigation, in ESPON model risk is a combination of the same hazard potential and the regional vulnerability.

Carreño et al. [6] proposed an seismic aggravation risk model based on Cardona's conceptual framework of a risk model analysis for a city considering a holistic perspective, thus describing seismic risk by means of indices [2] and assessing risk with the expression known as Mocho's equation in the field of in the field of disaster risk indicators. They propose that seismic risk is the result of physical risk (those elements susceptible to be damage or destroyed) and an aggravation coefficient that includes both: the resilience and the fragility of a society.

In this article, we propose a complete Mamdani fuzzy social aggravation model starting from the aggravation descriptors described in Carreño et al. [6]. The aggravation model synthesizes the social aggravation characteristics of a city struck by an earthquake that could conduct to social vulnerability enhancement or moderation. A main advantage of the proposed model is its white box nature that results in a high level understandability model. Moreover, the fuzzy approximation used in this paper is well established and with a solid background.

2 Previous Models

Cardona [2] proposed a holistic model of seismic risk at urban level which considers a structuralist and figurative vision by using representations of the interaction between human settlements and their surroundings. One of the main points in Cardona's risk model is the assumption that vulnerability has identifiable components, whom can be regarded as a reflection of two main components: fragility or physical susceptibility (exposition) and social fragility and lack of resilience. By means of an index characterization, the model branches among different indicators running through these two previous risk components, where each indicator is a representative value of a defined descriptors set.

Carreño et al. [6] made a slight modification of the Cardona original model, following the consideration that holistic risk could be regarded as it were hazard-function (considering the hazard intensities) and social and physical vulnerability on a period of time, but considering that risk might be viewed as a function of the potential damage on asset plus the socioeconomic aggravation onto the urban system produced by the lack of resilience and fragility reported at site. Therefore in Carreño model, for seismic risk modeling, the formulation of the index is based, in one hand; on seismic damage scenarios (or the hazard and physical vulnerability convolution) and in the other, on the estimation using a set of descriptors of social vulnerability based on fragility and resilience indicators, but grouped into a single module called: aggravation.

A conceptualization of Cardona's modified seismic risk model can be seen in the Fig. 1.

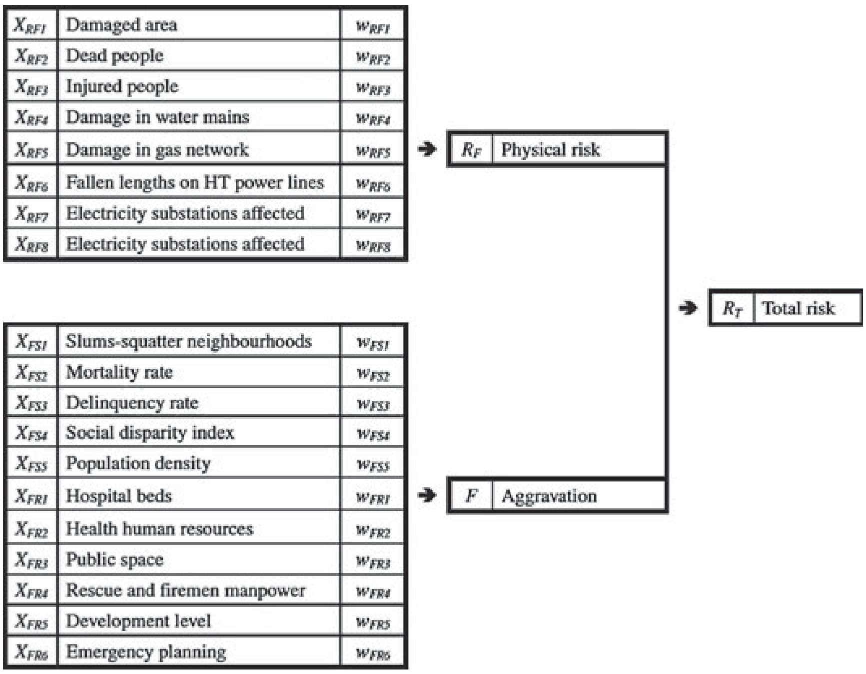

Fig. 1 Carreño et al. [5, 6] Holistic seismic risk model

Table 1 Descriptors used for aggravation estimation [6]

Aggravation descriptors
Marginal slums
Population density
Mortality rate
Delinquency rate
Social disparity
Hospital beds
Human health resources
Emergency and rescue personnel
Development level
Emergency operability

Many times the strength of a vulnerability model becomes weakened not because the type or resolution of the models themselves but because the lack of information and accurate data, in such a way that the results achieved are misleading in many ways.[1] Furthermore, the lack on understanding about how accurately measure vulnerability is one of the major uncertainty sources among social models. In most of the cases, social vulnerability is described using the individual characteristics of people (age, race, health, income, type of dwelling unit, employment, gross domestic product (GDP), income, etc.) Just in recent time, vulnerability models started to include place inequalities, such as level of urbanization, growth rates, and economic vitality [6].

Although there is a general consensus about some of the major factors that influence social vulnerability, disagreement arise in the selection of specific variables to represent these boarder concepts [1].

The descriptors used by [6] for aggravation estimation can be seen in the Table 1.

2.1 Index Method

Carreño et al. [6] obtained a seismic risk evaluation at urban level by means of indicators that leads to the calculation of a total risk index. This is obtained by direct application of Moncho's equation described in 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 a aggravation coefficient.

[1]Sometimes redirecting toward a definition staying that vulnerability is a characteristic and not a condition, leading toward the assumption that without damage, or a specific hazard, vulnerability places could stand forever.

Thus, considering seismic risk as produced for physical and an aggravation coefficient; the risk index provides an approximate vision of the state of the social capital infrastructure.

The physical risk is evaluated by using the Eq. 2

$$R_{Ph} = \sum_{i=1}^{p} w_{R_{Ph}k} F_{R_{Ph}k} \tag{2}$$

where $F_{R_{Ph}k}$ are the physical risk descriptors, and $w_{R_{Ph}k}$ are their weights and p the total number of considered descriptors in the estimation. As we have said, the physical risk descriptors values can be obtained from previous physical risk evaluation (damage scenarios) already made at the studied location.

The F coefficient depends on a weighted sum of an aggravation factors set associated to socioeconomic fragility of the community $\left(F_{SFi}\right)$ and lack of resilience of exposed context $\left(F_{LRj}\right)$, according to Eq. 2.

$$F = \sum_{i=1}^{m} w_{SFi} F_{SFi} + \sum_{i=1}^{n} w_{LRj} F_{LRj} \tag{3}$$

where w_{SFi} and w_{LRj} are the assessed weights on each factors calculated by an analytic hierarchy process [6, 10], and m and n the total number of descriptors, of fragility and lack of resilience, respectively. The descriptors of the socioeconomic fragility and lack of resilience of exposed context are obtained from existent databases and statistical data for the studied area.

When using Moncho's equation for estimate total risk, came to arise the consideration that F can be up to much twice the value of P_R, which is not always accomplished, because some times the indirect effects are much larger than the direct effects, leading a mislead in risk estimation.

2.2 *Carreño's Fuzzy Method*

Taking the objective to build a more flexible risk management tool when information is incomplete or is not available, Carreño et al. proposed the use of fuzzy logic tools and expert opinion to replace indexes by fuzzy sets. The same descriptors are used and the sequences of calculations are similar to those made in the conventional index method, however, the aggravation's descriptors values which were originally obtained by demographic data bases are replaced by local expert opinions. Using linguistic qualifiers, instead of using numerical values, the aggravation value can be evaluated. Distinct linguistic descriptors qualifiers where proposed, which range in five levels of aggravation description: *very low, low, medium, high, very high*. Using local expert opinion, a membership function was defined for each linguistic level used to link the reported demographic or expert opinion value to one level of aggravation.

With the positive link between a reported data and its suitable linguistic level, the level is then grouped into another set of membership functions, (based on expert opinion or strictly arbitrary) which plays as a homogenizer since it blends the original qualifier level into a new single fuzzy set.

They calculated the fuzzy union between social fragility and lack of resilience descriptors, $\mu_f\left(x_{SF}, x_{LR}\right)$, and applied on each of these new membership functions, μ, the weights, w, corresponding to the level of aggravation, L_F, of each descriptor x_{SFi} and x_{LRj}, as defined in Eq. 3.

$$\mu_f\left(x_{SF}, x_{LR}\right) = max\left(w_{SF1}\mu_{FL1}\ \left(L_{F1}\right)...w_{LR1I}\mu_{FL\,I}\ \left(L_{F1}\right)\right) \tag{4}$$

The proposed weighted and union methods between social fragility and lack of resilience descriptors can be seen in Fig. 1.

In the same way of index's method, weights are assigned to each fuzzy set by using an analytic hierarchy process. The aggravation coefficient F is calculated as the centroid abscise of the area beneath the curve obtained with Eq. 3.

However, we think that the Carreño's fuzzy model is not entirely appropriate because it is a nonconventional fuzzy approach, which may be questionable due to the fact that fuzzy mathematical raised in the inference process is not well established and accurately validated.

3 Classical Fuzzy Method

Behind the holistic risk proposal is the consideration of an urban center as it behaves as a complex dynamic system; in which a collection of various structural and non-structural elements are connected and organized in such a way as to achieve some specific objective through the control and distribution of material resources, energy, and information, [2]. The hypothesis considers then, that there are some system elements (or a collection of them) not necessarily structural or geological (but social) that can be identified in terms of their true affectation or affectation predisposition of the complex system state. In this way, the complex dynamic systems theory considers that risk is in fact, a state characterization of the complex system which is, at all time, in a *potentially at crisis situation* or, in a instability state. Methodologically, this can be seen as:

$$P_C = T_a I_c \tag{5}$$

where P_C is potential crisis, T_a is a trigger agent capable to produce such crisis, and I_c the instability conditions of the system [3, 4].

The system elements identify as related with the creation of the instability conditions when considering seismic risk, are assumed to be the social fragility and the resilience capacity of a urban center, along with the physical infrastructures that could be damaged. At the other hand, the trigger event, in this particular case, is the earthquake itself. In this way, an urban center which is meant to last, must find the ways to decrease the reachable factors that leads toward the crisis state. This is obviously done trough risk management processes and, at the end, with a sustainability development scheme.

The model proposed in this research pretend to build an aggravation coefficient by re-defining Carreño et al. descriptors into three different Fuzzy Inference Systems (FIS), called: resilience, fragility, and aggravation. Each subsystem is defined by a set of rules directly over the aggravation descriptors. A conceptualization of the different steps along the proposed model can be seen in Fig. 3. The variables involved in each subsystem are presented in the left-hand side of Fig. 2. FIS #1, corresponds to the Social fragility model and has as input variables the Marginal Slums (MS), the social disparity index (SDI) and the population density (PD). The output of FIS #1 is the level of Fragility. On the other hand, FIS #2 corresponds to the Resilience model and has as input variables the human health resources (HHR),the emergency operability (EO), and the development level (DL). The output of FIS #2 is the resilience level. The aggravation model (FIS #3) takes as inputs the fragility and resilience

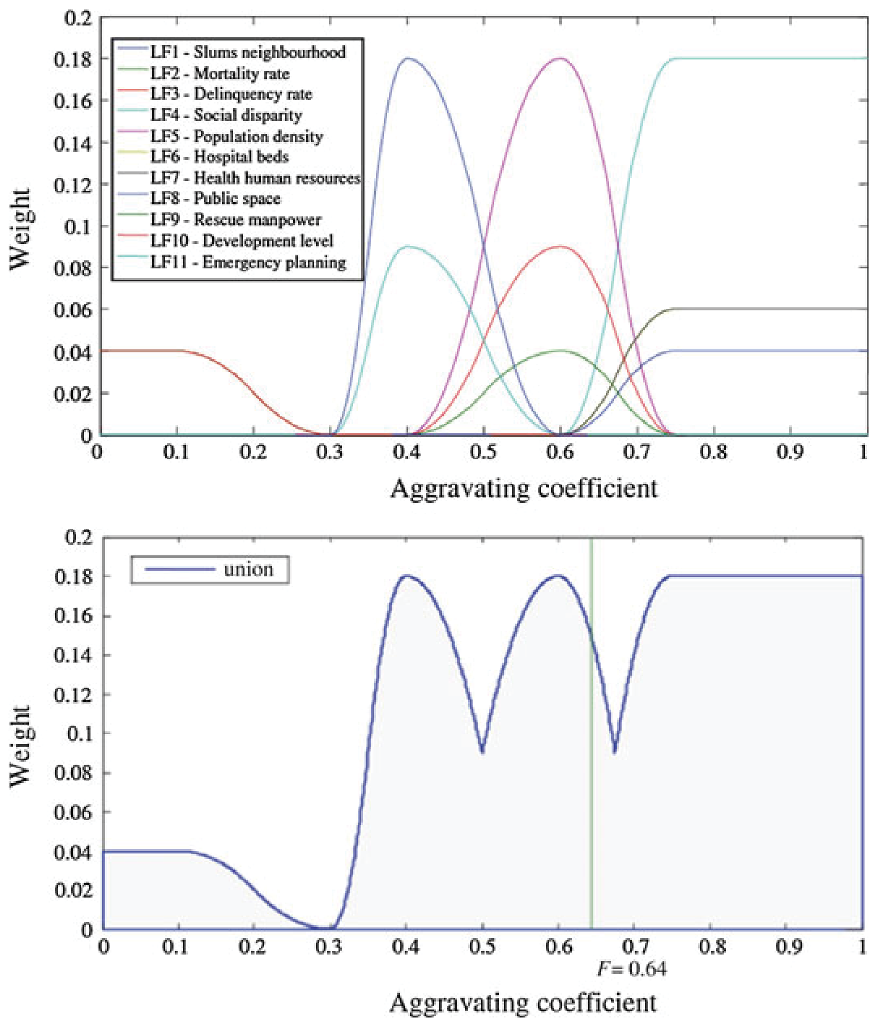

Fig. 2 Carreño weighting (*up*) and union method (*low*) for San Martí District, Barcelona Spain (taken from Carreño et al. [6])

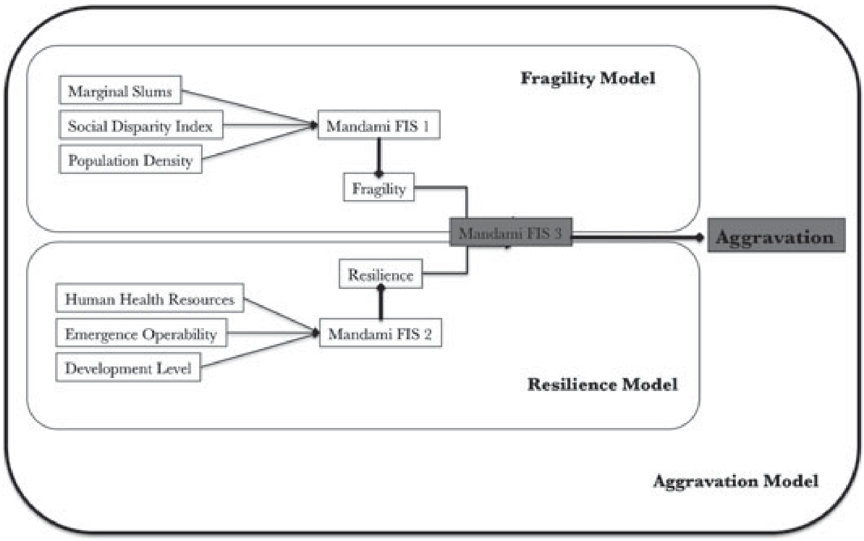

Fig. 3 Conceptualization of fuzzy classical model to estimate aggravation coefficient

levels that are the output of FIS #1 and #2, respectively, and infers the aggravation coefficient. All the fuzzy inference systems proposed in this research are based on the Mamdani approach [7], since it is the one that better represents the uncertainty associated to the inputs (antecedents) and the outputs (consequents) and allows to describe the expertise in an intuitive and human-like manner. Our main objective is to develop a fuzzy aggravation model as much interpretable as possible and with high expressive power. In our approach, the original 10 variables presented in Table 1 are reduced to six variables. Population density, slum area or marginal slums, human health resources, and development level remain the same, and social disparity index and Emergence operability are redefined in such a way that subsume the other variables.

The reduction or simplification of the original variables was made by taking advantage of certain descriptors that are linked and could englobe various descriptors in one single class considering its social nature, for example: the descriptors called: mortality rate and delinquency rate, are related between them and are reflecting social consequences produced by a social structure failure (could be lack of access) to certain social advantages, such as having an efficient public health program, or no marginalization dynamics, or access to education and effective justice and law policies. Therefore, we consider these descriptors could be enclosed within the descriptor called social disparity index, which is a fragility descriptor as well. In the case of resilience descriptor, we merge descriptors called: public space, hospital beds, and emergency Personnel, into the descriptor called emergence operability, because the former descriptors acts when the emergency is being or has recently occurred, and therefore are related with the capacity of the city to face an emergence situation, and the assets that a city has to confront it. We modify fuzzy classes by reducing the number of linguistic levels defined for each descriptor up to 3 (*low, medium, high*) along their respective universe of discourse, but we kept the same five levels for the final output (resilience, fragility, and aggravation). We think that three classes are enough to represent accurately the input variables of the resilience and fragility models. Moreover, a reduction of the number of classes implies also a more compacted and reduced set of fuzzy rules. In the same way, to improve model's sensibility, we adjust membership functions forcing them to be more *data-based* kind of type, and thus considering the reported aggravation data as embedded along membership functions limits definition. With these new membership functions we build a set of fuzzy logic rules that could infer the behavior of the aggravation coefficient components using the three Mamdani Fuzzy Inferences Systems mentioned before (see Fig. 3).

The developing of the fuzzy rules was established for consider all possible combinations between the input descriptor's linguistic levels, giving a total of 27 rules for calculating fragility and resilience values, respectively. The rules were intended to follow risk management literature which could suggest possible outcomes when three of these elements interact to form resilience or fragility. The Mamdani aggravation model, that has as input variables the resilience and the fragility, discretized into five classes each, is composed of 25 fuzzy rules.

In Table 2 the rules of the Mamdani resilience model are presented as an example. As mentioned before, the use of classical fuzzy systems, with well established fuzzy inference theory, allow a high level understandability model and easily manageable by experts which in turn leads toward a deepest discussion in the topic of social vulnerability description and casual interrelation.

Let's describe the inference process by following the example of the proposed Resilience FIS. The fuzzy inference engine combines the fuzzy *if-then* rules (see Table 2) into a mapping from fuzzy sets in the input space $U \subset R^n$ to fuzzy sets in the output space $V \subset R$, based on fuzzy logic principles. Let's $U = U_1\ x\ U_2\ x\ U_3 \subset R^n$ and $V \subset R$, where U_1, U_2 and U_3 represents the universes of discurse of human health resources, development level, and emergency operability input variables, respectively, and V the universe of discourse of Resilience. In our case each input variable contains three fuzzy sets and the output variable is discretized into five fuzzy sets. Then, the fuzzy rule-based shown in Table 2 can be expressed in a canonical form as shown in Eq. 6.

$$R^{(l)}\ :\ IFx_1isA_1^l and...andx_nisA_n^l THENyisB^l \tag{6}$$

where A_1^l and B^l are fuzzy sets in U_i and V, respectively, $x = (x_1,\ x_2,\ x_3) \in U$ are human health resources, development level, and emergency operability linguistic variables, $y \in V$ is the resilience linguistic variable and $l = 1, 2, ..., 27$ is the rule number. Consider now the fuzzy facts: x_1 is A'_1, x_2 is A'_2, x_3 is A'_3, being A'_1, A'_2 and A'_3 fuzzy sets.

The generalized modus ponens allows the deduction of the fuzzy fact y is B' by using the compositional rule of inference (CRI), defined trough the fuzzy relation between x and y, as defined in Eq. 7.

$$B' = A' \circ R \tag{7}$$

Table 2 Logic rules used for resilience estimation

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 H) and (EO is L) then (R is M)
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 L) 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)

HHR Human health resources, *DL* Development level, *EO* Emergency operability, *R* Resilience, *VH* Very high, *H* High, *M* Medium, *L* Low, *VL* Very low

where $A' = (A'_1, A'_2, A'_3)$. The simplest expression of the compositional rule of inference can be written as Eq. 8.

$$\mu_{B'^i}(y) = I\left(\mu_{A^i}(x_0), \mu_{B^i}(y)\right) \tag{8}$$

when applied to the ith rule; where:

$$\mu_{A^i}(x_o) = T\left(\mu_{A^i_1}(x_1), \mu_{A^i_2}(x_2), \mu_{A^i_3}(x_3)\right)$$

where $x_0 = (x_1, x_2, x_3)$. Here, T is a fuzzy conjuctive operator and I is a fuzzy implicator operator.

Once the inference is performed by means of the compositional rule of inference scheme, the resulting individual (one for each rule) output fuzzy sets are aggregated into an overall fuzzy set by means of a fuzzy aggregation operator and then a defuzzification method is employed to transform the fuzzy set into a crisp output value, i.e., the resilience level following the example.

The defuzzification method used in this work is the center of gravity (COG), which slices the overall fuzzy set obtained in the inference process into two equal masses. The center of gravity can be expressed as Eq. 9.

$$COG = \frac{\int_a^b x\mu_B(x)dx}{\int_a^b \mu_B(x)dx} \tag{9}$$

where B is fuzzy set on the interval $[a, b]$.

4 Results and Comparison

To obtain a final social aggravation inference value, we used the aggravations linguistic levels that can be viewed in Fig. 4. In the case of index method, we used the levels of aggravation that can been seen in Table 3. Both: linguistic classes and levels of aggravation were reported by Carreño et al. [6].

4.1 Barcelona

Figure 5a shows the estimated spatial distribution of the aggravation coefficient and its correspondent level for the 10 administrative districts, of the city of Barcelona,

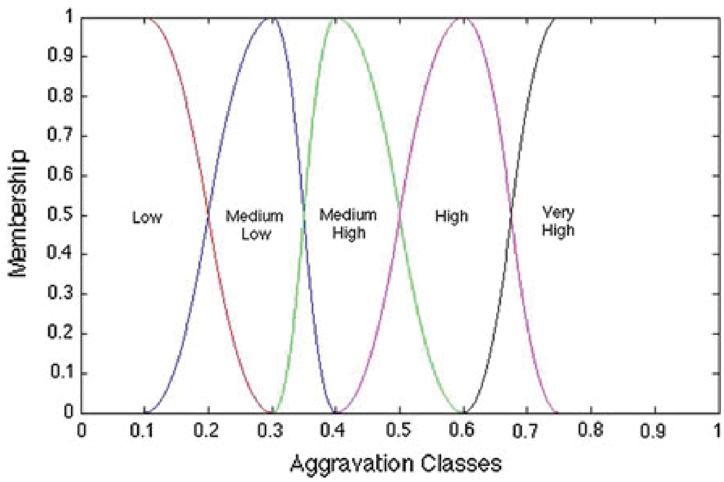

Fig. 4 Membership functions for levels of aggravation. Carreño et al. [6]

Table 3 Levels of aggravation used in index method, Carreño et al. [6]

Level	Aggravation
Low	[0–0.19]
Medium low	[0.20–0.39]
Medium high	[0.40–0.54]
High	[0.55–0.64]
Very high	[0.65–1.00]

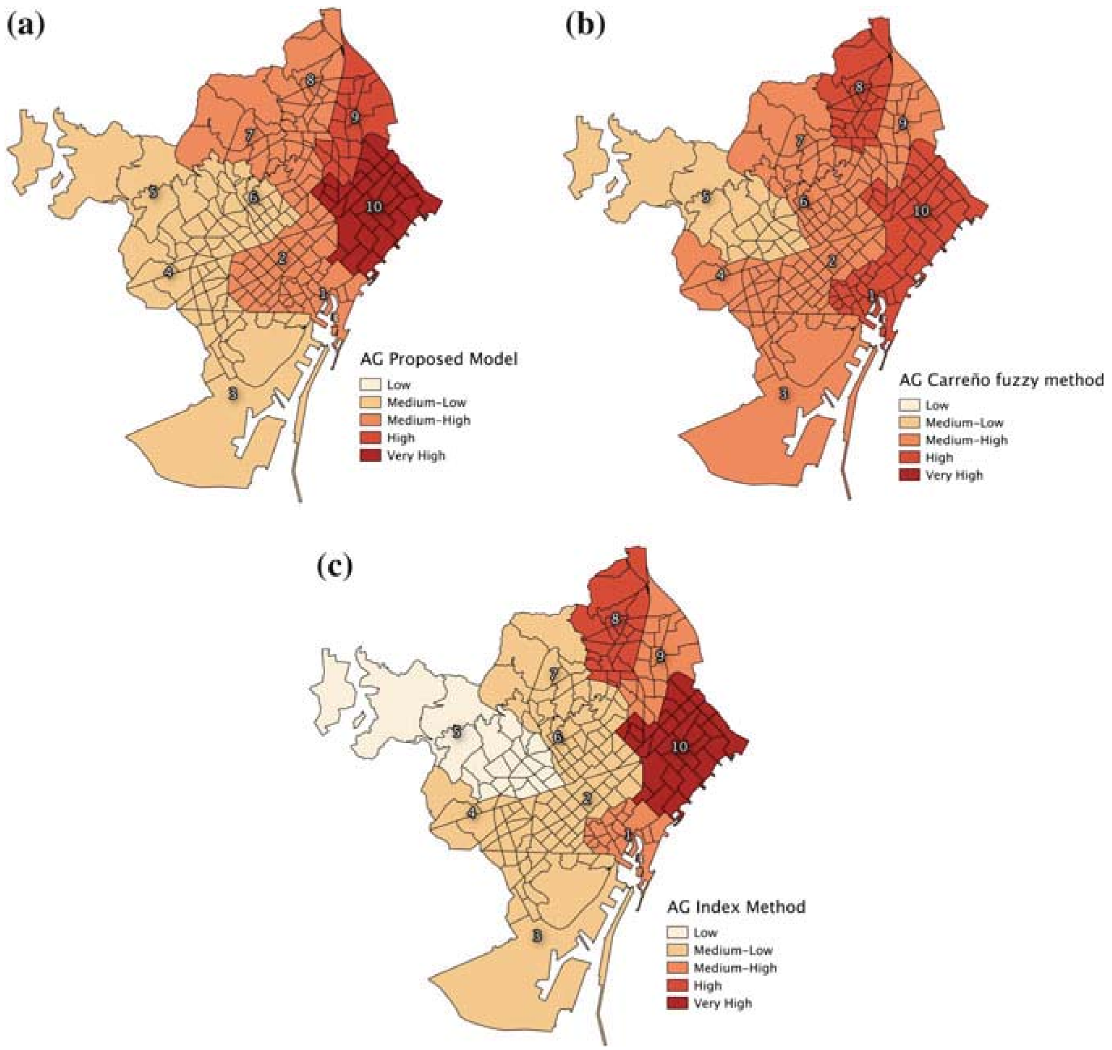

Fig. 5 Aggravation coefficient: **a** Proposed fuzzy model. **b** Carreño fuzzy method. **c** Index method. Districts: (1) Ciutat Vella, (2) Eixample, (3) Sants-Montjuic, (4) Les Corts, (5) Sarrià-Sant Gervasi, (6) Gràcia, (7) Horta-Guinardó, (8) Nou Barris, (9) Sant Andreu, (10) Sant Martí

achieved through the proposed model, (b) and (c) shows the aggravation coefficient calculated by Carreño et al. using fuzzy methods, and the aggravation coefficient estimated using index method respectively.

The proposed model, as well as the other two alternative methods, estimates that highest aggravation is spread mostly over the northeast part of the city. But only in the proposed model and index method levels of *very high* are reached over Sant Martí district. In our model, the level of *high* is reached over San Andreu, while in the index and Carreño method is for Nou Barris. *Medium-high* values for L'Eixample, Horta Guinardo, and Ciutat Vella are estimated by the proposed model while the rest of the city presents values of *medium-low* aggravation level. The index method estimate that only Ciutat Vella have a *Medium-high* value and the rest of the city ranges between *low* and *medium-low* aggravation values, while Carreño method gives a level of aggravation of *medium-high* for almost all the city, except in Sarria-Saint Gervasi, where it gives a value of *medium-low*. The first thing that we noted is that the proposed fuzzy model resembles more the index method rather than Carreño's method. Even if the spatial distribution is not the same (which was not the aim of our model), we observe that the aggravation classes distribution in both models has a similar spread. As expected, the actual distribution of the level of aggravation is not the same, thus index method could be regarded as if giving lowest aggravation values, but it is necessary to remember that the limit levels to define the aggravation classes are not the same, making the two models (FIS and Index) impossible to coincide in this part. Although, we do observe a under and overestimation on the actual aggravation values estimated by our proposed model, as we will discuss next.

Figure 6a–c shows the aggravation coefficient numerical value obtained by the proposed fuzzy model, Carreño fuzzy method, and index method, respectively. Districts are ordered from lower to highest aggravation level. In these figures, we can see that even there is no correct total match among the two methods, all of them preserve quite the same order in terms on higher and lower aggravation levels.

When comparing the numerical aggravation value obtained from the proposed model to a robust method like index models [8], it suffer by a slight under and overestimation of the aggravation values by district. In the proposed method this issue could be addressed with the inclusion of weights to each descriptor, as the other methods do. Nevertheless, we consider that even with these small numerical dissimilarities, the proposed fuzzy model limits the different aggravation levels in a suitable way, allowing the identification of more potentially problematic zones with a good resolution and reduced computation time.

Figure 6d shows the same as (a), (b), and (c) but without ordering the districts by aggravation value, showing how the aggravation values behaves along the different districts. As it can bee seen, even if the explicit aggravation coefficient value is not the same for each district, a similar trend shape come to appears (with the inherent over and underestimation aggravation level), which leads to the conclusion that the general behavior of the proposed model is coherent with the result achieved by Index Method.

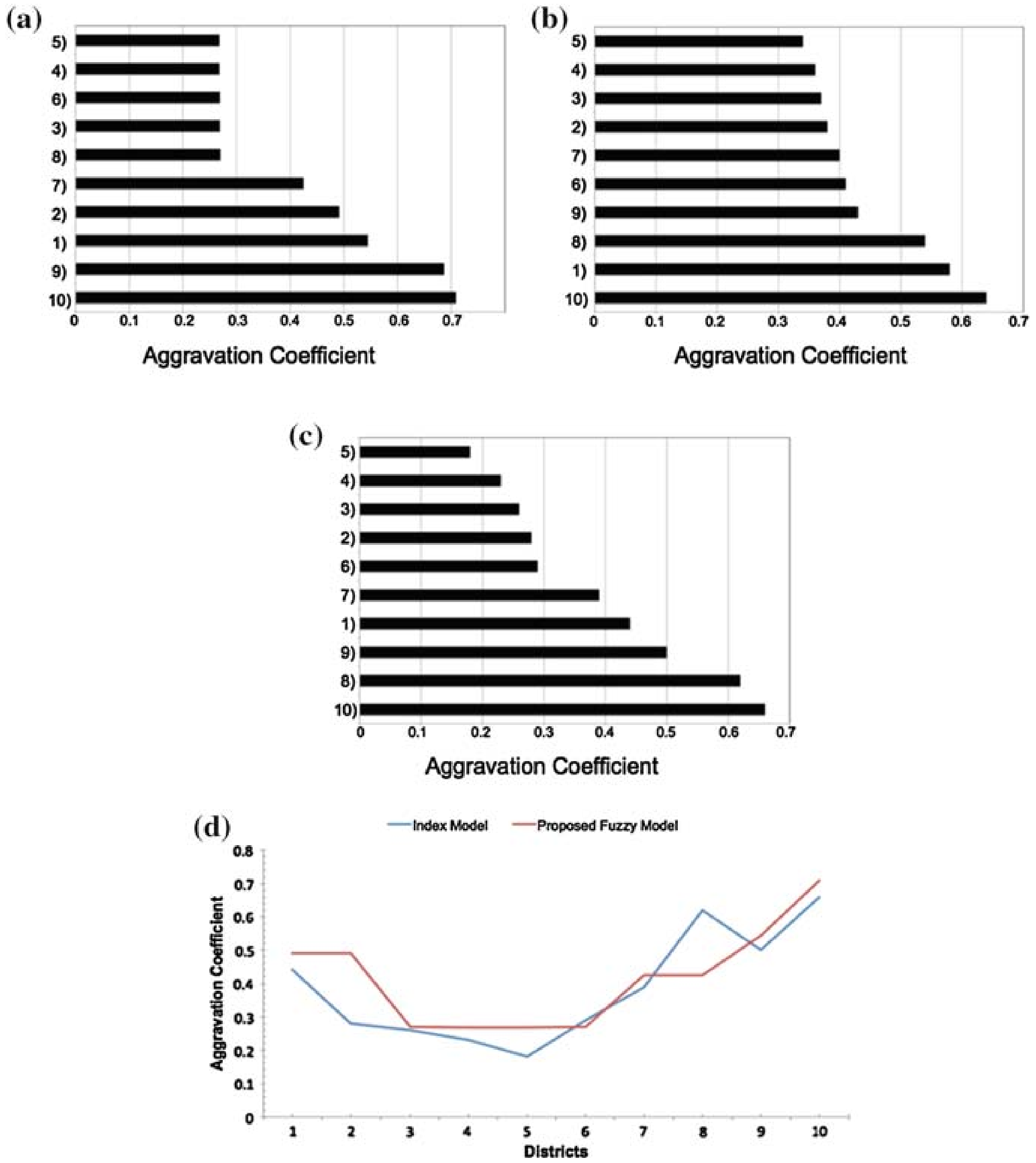

Fig. 6 Aggravation coefficient values by district, sorted from lower to higher: **a** Proposed fuzzy model. **b** Carreño fuzzy method. **c** Index method. **d** Aggravation coefficient comparison over the 10 Barcelona Districts (numeration as Fig. 5)

4.2 Bogota, Colombia

Colombia's Capital is divided since 1992 into 20 administrative districts. However in our study, we took into account only 19 on these because the district called Sumapaz correspond basically to the rural area of the city. For the Social Aggravation Coefficient estimation on each district we used statistical and demographic data from 2001 [6].

In Fig. 7a–c we can see the Aggravation coefficient value obtained by the fuzzy proposed model, Carreño fuzzy method and Index method respectively. The general

Aggravation level seems to be underestimated by the FIS model, however, the FIS spatial pattern distribute the highest values of aggravation at the South West part of the city as reported by index method, this corresponding to the districts of: Ciudad Bolivar, Bosa, Usme, and San Cristobal. The East part of the city remains with *medium low*, and the North West part of the city presents *medium-high* aggravation value. The index method reach a *very high* value at South West part of the city

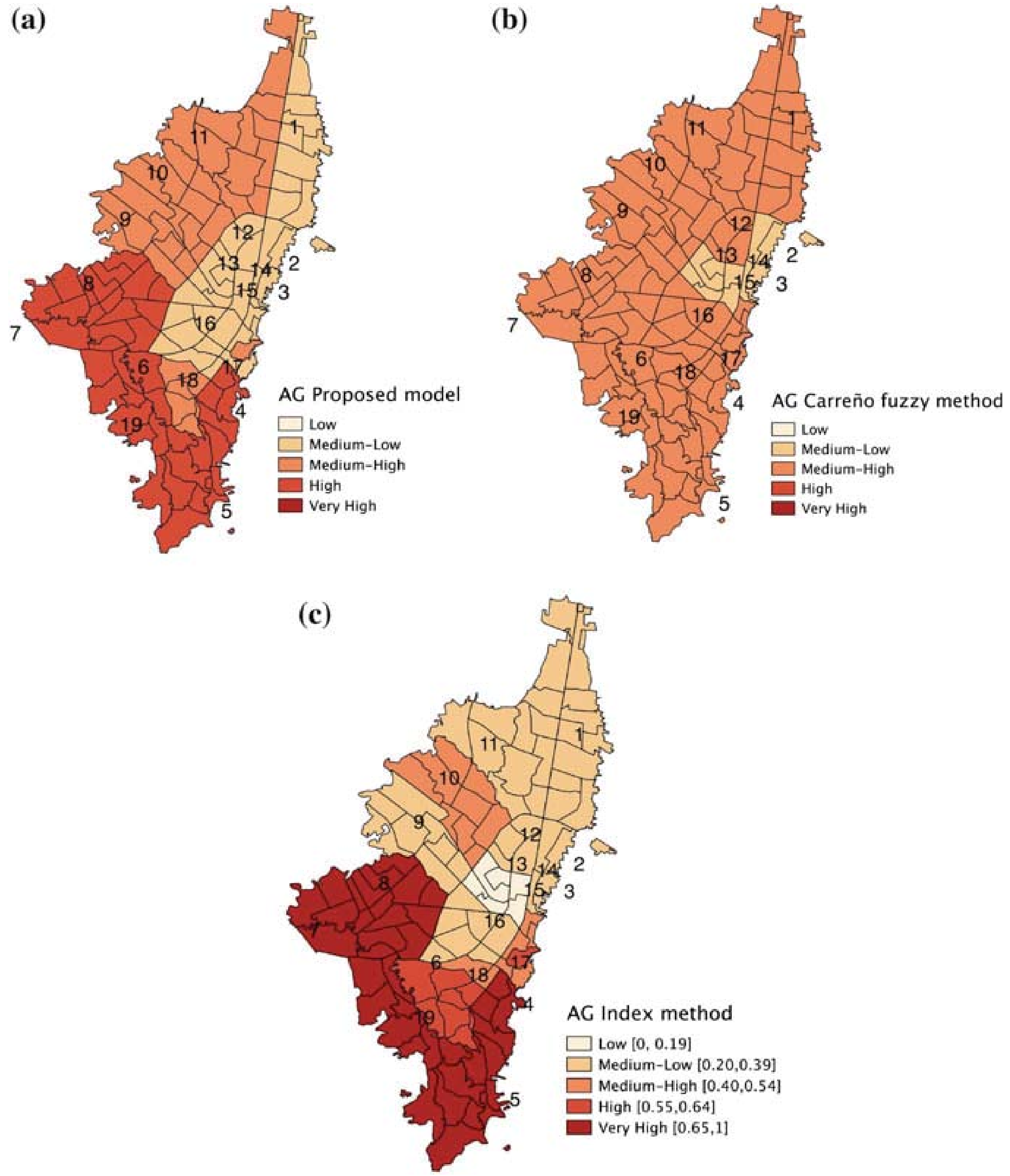

Fig. 7 Aggravation coefficient: **a** Proposed fuzzy model. **b** Carreño fuzzy method. **c** Index method. Localities: (1) Usaquén, (2) Chapinero, (3) Santa Fe, (4) San Cristóbal, (5) Usme, (6) Tunjuelito, (7) Bosa, (8) Ciudad Kennedy, (9) Fontibón, (10) Engativá, (11) Suba, (12) Barrios Unidos, (13) Teusaquillo, (14) Mártires, (15) Antonio Nariño, (16) Puente Aranda, (17) Candelaria, (18) Rafael Uribe, (19) Ciudad Bolvar

while the northern part presents mostly a *medium-low* aggravation value. Carreño fuzzy method presents an almost homogeneous level of aggravation, with values of *medium low* for Teusaquillo and Chapierno districts.

Figure 8a–c show the Aggravation Coefficient numerical value using the fuzzy proposed model, the Carreño fuzzy method and index method, respectively. Districts are ordered from lower to highest aggravation level. As in the case of Barcelona, we can note that even there is no correct total match among the three methods, all of them preserve quite the same order in terms on higher and lower aggravation levels.

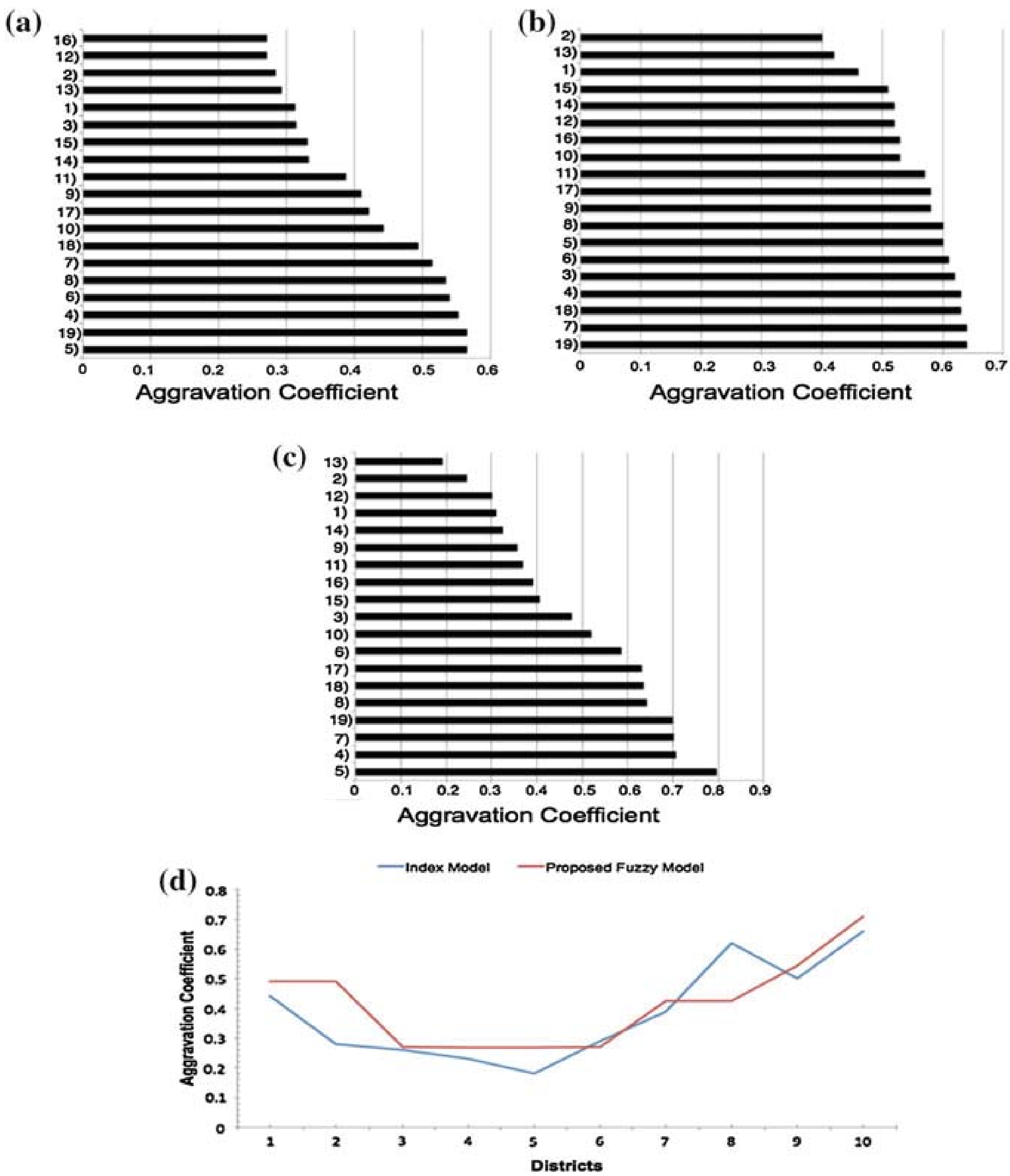

Fig. 8 Aggravation coefficient values by district, sorted from lower to higher: **a** Proposed fuzzy model. **b** Carreño fuzzy method. **c** Index method. **d** Aggravation coefficient comparison over the 10 Barcelona Districts (numeration as Fig. 5)

Figure 8d shows the trend line of the Aggravation Coefficient over the 19 administrative districts of Bogota Colombia, obtained by the three methods announced previously; where it is noted that the underestimation referred on previous lines. Similar to Barcelona case, the trend is quite alike with the one estimated using index Method.

4.3 Discussion

According to the previous analysis, with the use of classical fuzzy inference system methodology it is plausible to reproduce the results obtained from a more analytical method such as indexes, for example: in terms of district aggravation classification, or in reproducing similar spatial pattern of aggravation. In first term, the proposed inference model allows a useful simplification for the large quantity of variables required for social aggravation analysis, in the spirit of reduce the subjectivity associated with aggravation descriptors suitability designation by using a more flexible and small descriptors set in which the underlying links between them can be more easily observed, enabling a more understandable analysis scheme for social aggravation inference estimation. Building rules directly over the aggravation descriptors allows to assemble a compositional rule of inference over the very same descriptors that are assumed to create aggravation itself, and therefore, the inference process can be made using rules designed to follow risk management knowledge, allowing the model to represent, with a certain degree of freedom, the actual understanding of aggravation formation, and at the same time, it allows a real discussion of the rule's structure strength; which can be absolutely improved with a deepest debate.

Fuzzy logic inference capabilities can be exploited in a more suitable way because the outputs from each FIS used in the model are always fuzzy sets, giving the chance to connect them trough a new FIS without loosing consistency, allowing model completeness.

At the other hand, the proposed model slightly over and underestimated aggravation values for some districts when comparing with index model, as it is also de case of Carrenõ's fuzzy model. However, if necessary, the proposed fuzzy model can be further tuned if descriptors are weighted.

4.4 Future Work

The flexibility of the model enables its adaptation to several conditions which could be used in more general studies of social vulnerability and that can also help to fill some gaps among analytic methods. For example, the same procedure can be applied to a more general social vulnerability model that considers not only physical, and aggravation inputs, but environmental, economic, and even completely subjective descriptors can be add as well, such as solidarity or brotherhood.[2] All of these can then be embedded into one single inference model. One of the main problems of risk ex-ante and ex-post models is that they do not necessarily consider the interconnectivity of social characters (sectors) in a real scenario, for example, the lack of hospitals in one geographic area does not necessarily mean that human health resources is zero at that place. It will be like assuming that the fire department can only help those who are in close proximity. Assuming interconnectivity, the potential damage to the social network-connections in case of disaster is the real issue that must be addressed, and we consider it plausible to be approach using fuzzy methods. Although the proposed model was intended to be applied to assess the risk over an urban environment when it's strike by an earthquake, the structure of the social vulnerability module of the model, (the one who deals with resilience and fragility), can easily be transformed in a non-disaster dependent analytic framework. Therefore adapting itself to other types of disasters, or even to the study and analysis of social vulnerability by itself.

5 Conclusions

We obtain a inference fuzzy model to make an estimation of social aggravation over the cities of Barcelona and Colombia using the descriptors proposed in [6]. Building inference compositional rules over the selected descriptors, we were able to obtain a robust method that resembles the identification of relevant aspects and characteristics of seismic risk at urban level already achieved by two other consolidated methods. The proposed model displays more simplicity, flexibility, and resolution capacities and can be rapidly transformed into a non-disaster event model type with the inclusion of new type of variables, englobing a more detailed social vulnerability scheme and interconnectivity issues.

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