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Measuring and improving community resilience: A fuzzy logic approach

Melissa De Iuliis [a], Omar Kammouh [b,*], Gian Paolo Cimellaro [a]

[a] Dept. of Structural, Geotechnical and Building Engineering, Politecnico di Torino, Corso Duca Degli Abruzzi, 24, Torino, Italy
[b] Dept. of Multi-Actor Systems, Faculty of Technology, Policy, and Management, Delft University of Technology, Netherlands

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ABSTRACT

Due to the increasing frequency of natural and man-made disasters, the scientific community has paid considerable attention to the concept of resilience engineering. On the other hand, authorities and decision-makers have been focusing their efforts on developing strategies that can help increase community resilience to different types of extreme events. Since it is often impossible to prevent every risk, the focus is on adapting and managing risks in ways that minimize impacts to communities (e.g., humans and other systems). Several resilience strategies have been proposed in the literature to reduce disaster risk and improve community resilience. Generally, resilience assessment is challenging due to uncertainty and the unavailability of data necessary for the estimation process. This paper proposes a Fuzzy Logic method for quantifying community resilience. The methodology is based on the PEOPLES framework, an indicator-based hierarchical framework that defines all aspects of a community. A fuzzy-based approach is implemented to quantify the PEOPLES indicators using descriptive knowledge instead of complex data, accounting for the uncertainties involved in the analysis. To demonstrate the applicability of the methodology, three cases with different levels of data availability are performed to obtain a resilience curve and resilience index of two out of seven dimensions of the PEOPLES framework. When numerical data does not exist, descriptive data based on expert knowledge is used as input. Results show that the proposed methodology can cope with both numerical and descriptive input data with different uncertainty levels providing good estimates of resilience. The methodology can be used as a decision-support tool to assist decision-makers and stakeholders in assessing and improving their communities' resilience for future events, focusing on specific indicators that suffer from resilience deficiencies and need improvements.

1. Introduction

Past global disaster events have shown an upward trend over the years, suggesting that modern communities are often not resilient enough to natural and man-made disasters. In recent decades, an increase in the intensity and frequency of extreme weather events (e.g., rainfall, temperature, and wind) has ultimately led to climate change-related hazards, such as increased flooding, heatwaves, and sea-level rises [1]. Previous events, such as the intense flooding in Thailand (2011) and Hurricane Sandy (2012), have indicated that extreme events can have far-sighted impacts upon communities [2]. Therefore, research on disaster resilience has gained increased attention. Since resilience is a multidisciplinary concept and encompasses different research areas, several definitions of resilience can

* Corresponding author.
E-mail addresses: melissa.deiuliis@polito.it (M. De Iuliis), o.kammouh@tudelft.nl (O. Kammouh), gianpaolo.cimellaro@polito.it (G.P. Cimellaro).

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be found in the literature. The term resilience was introduced by Allenby and Fink [3] as “the ability of a system to remain in a practical state and to degrade gracefully in the face of internal and external changes”. Bruneau et al. [4], and later Cimellaro et al. [5], defined resilience as “the ability of social units to mitigate hazards, contain the effects of disasters when they occur, and carry out recovery activities to minimize social disruption and mitigate the effects of future earthquakes”.

Disaster resilience is often classified into *technological units* and *social systems* [6]. The literature offers state-of-the-art approaches to quantify community resilience [7–13], mostly indicator-based approaches. Resilience indicators provide a way to cope with the complexity of community systems while computing their resilience. Among the available indicator-based resilience frameworks, there is the Hyogo Framework for Action (HFA) [14,15], which is an internationally agreed top-down framework to increase the resilience of nations and communities through the implementation of detailed measures at the government and policy levels. Based on the Hyogo Framework, Kammouh et al. [16] have introduced a quantitative method to quantify resilience at the country level. Another top-down resilience framework is the Baseline Resilience Indicator for Communities (BRIC) [17], a quantitative framework that focuses on the inherent resilience of communities. A qualitative framework that measures resilience along with the ability to recover from seismic events is the San Francisco Planning and Urban Research Association framework (SPUR) [18]. It considers the recovery of buildings, infrastructures, and services to determine the resilience of physical infrastructure. Another hierarchical framework for evaluating community-level resilience was proposed by Kwasinski et al. [19]. The model consists of community dimensions and their relationships with community services, systems, and resources.

Similarly, Cimellaro et al. [20] presented the PEOPLES framework, a top-down theoretical framework that addresses all aspects of a community. These aspects are classified under seven community dimensions: Population; Environment; Organized government services; Physical infrastructure; Lifestyle; Economic; and Social capital. Later, the PEOPLES framework was upgraded into a quantitative framework for measuring community resilience [21–24]. Alshehri et al. [25] proposed a quantitative and qualitative assessment tool to measure community resilience to disasters. The dimensions of the framework were developed using the census-based Delphi techniques. Another resilience-based risk assessment approach at the community level was developed by Marasco et al. [26]. The PEOPLES framework was adopted as the community resilience blueprint for determining resilience through its comprehensive indicators and structure. Joerin and Shaw [27] developed the Climate Disaster Resilience Index (CDRI), focusing on physical, social, economic, institutional, and natural dimensions of a community to quantitatively assess the resilience of communities against climate-related disasters such as floods, landslides, etc. Shammin et al. [28] adopted a holistic approach to designing community-based adaptation programs against climate change impacts.

Recently, several data-driven frameworks have been investigated to assess community resilience. For instance, Hong et al. [29] proposed a generalizable method using large-scale smartphone geolocation data to evaluate community resilience. Abdel-Mooty et al. [30] developed a data-driven community flood resilience categorizations framework that can be used to develop realistic disaster managements strategies and risk mitigation measures.

Despite this robust literature on community resilience quantification, there is still considerable disagreement about the indicators that define resilience and the most useful frameworks for measuring it. The scientific community is aware that data availability is one of the main issues. The modeling approaches presented require accurate data inputs to be incorporated into the models to be functional, time, and technical expertise. Access to this data is limited, and often, data collection comprises uncertainties and a lack of knowledge, and the accuracy is insufficient. An important aspect missing from different existing resilience assessments is the inclusion of uncertainty. Assessing uncertainty will help understand the studied system and reduce critical areas of uncertainty [31–34]. The engineering community’s typology and definition of uncertainty are extensive and often discordant [35]. Klir and Yuan [36] categorized uncertainty into two basic types: vagueness and ambiguity (see Ref. [37] for an extensive list of the uncertainty types).

The difficulty in the data and indicators acquisition process, as well as in defining the interaction between them, makes resilience assessment so complex that decision-makers and industry cannot use it. Stakeholders and practitioners often lack the resources to use the available data-intensive methods. To respond to this challenge, many studies have focused on developing methods for quantifying community resilience and assessing the impacts of recovery strategies through probabilistic approaches, such as Bayesian Networks [38]. For example, Abdelhady et al. [39] proposed a novel framework that integrates damage estimated after a hurricane through vulnerability models with a probabilistic community recovery model. Schultz and Smith [40] developed a Bayesian network-based approach to evaluate the resilience of infrastructure networks and buildings in Jamaica Bay, New York. Kammouh et al. [41] introduced a novel approach to assess the time-dependent resilience of engineering systems using resilience indicators through the Dynamic Bayesian Network (DBN). Another Bayesian network-based approach for seismic resilience quantification was proposed by Ref. [42]. Cai et al. [43] employed a Bayesian network to investigate interdependencies of resilience components and improve disaster resilience. Furthermore, Kameshwar et al. [44] developed a probabilistic decision support framework for community resilience planning under multiple hazards using Bayesian Network. Despite the advantages of the Bayesian network, such as updating the system to which it is applied when new data and information become available, the main concern is its application in case of epistemic uncertainties and the computational effort in determining conditional probabilities [45]. When dealing with uncertainty, choosing an appropriate model depends on the characteristic of the uncertainty presented in the problem description. Generally, probabilistic models are used to characterize random variables and treat their uncertainties through statistical information. Statistical information is required for comparing probability distribution functions (PDFs) with data. If this information is insufficient (e.g., no numerical data are available), an alternative uncertainty model must be utilized. When few data are available with significant uncertainty, expert knowledge with linguistic assessment is most frequently required. The Fuzzy set theory provides the basis for modeling a non-probabilistic uncertainty model that considers fuzzy sets, subjective information, and human knowledge to represent the uncertainty in the parameters. Moreover, in fuzzy systems, the uncertainties contained in both inputs and output of the system are used to formulate the system structure itself, unlike conventional systems that formulate a model based on assumptions and then consider uncertainties.

The primary goal of this paper is to cover the previously mentioned shortcomings of existing scientific literature by introducing a Fuzzy Logic-based method within the context of the PEOPLES framework. The proposed method utilizes the resilience indicators presented in Ref. [22] to develop an extensive resilience model that accounts for all aspects of a community. Since some indicators may be challenging to quantify in specific scenarios, the fuzzy logic technique is used for inference to account for the data-related uncertainties. The methodology here derived does not require precise and deterministic data but rather expert knowledge and experience for its implementation to determine the different parameters involved in the resilience evaluation of urban communities and provide consistent resilience values.

The contributions of this work are summarized as follows:

1. Developing a comprehensive hierarchical framework that captures casual and logical relationships among the PEOPLES dimensions belonging to a specific component.
2. Implementing the weighting technique developed in Ref. [22] to rank the indicators according to their importance.
3. Employing the fuzzy logic inference technique to account for data uncertainties of the analyzed indicators.
4. Presenting three cases with different levels of uncertainty to demonstrate the applicability of the introduced resilience estimation methodology.
5. Verifying the methodology by comparing the model output with the output obtained from Ref. [22].

The resilience quantification methodology presented in this paper can be used as a decision-support tool by decision-makers to (i) determine the state of their communities after a hazardous event and (ii) prioritize planning and management strategies, assign appropriate resources for enhancing the individual indicators that suffer from resilience deficiencies, and improving the resilience of their communities to future hazardous events. The remainder of the paper is organized as follows. Section 2 reviews the PEOPLES framework along with its seven dimensions. Section 3 is dedicated to reviewing the basic knowledge of the Fuzzy Logic and its implementation within the PEOPLES framework. Section 4 describes the proposed methodology for estimating community resilience. Section 5 presents three cases with different levels of uncertainty to demonstrate the applicability of the methodology and verify the proposed resilience estimation model by comparing the model output with the output of the benchmark system. Sensitivity analysis for membership functions and defuzzification methods is presented in Section 6 to reduce the subjectivity of the fuzzy system. Finally, conclusions are drawn in Section 7 together with the proposed future work.

2. PEOPLES framework

PEOPLES is a multi-layered framework developed at the Multidisciplinary Center of Earthquake Engineering Research (MCEER, State University of New York) that aims to identify different resilience characteristics of a community at different scales (spatial and temporal) and assess possible responses of a community by taking into account the interdependence between community levels [7]. The PEOPLES framework consists of seven dimensions of a community divided into a set of components, each of which is subdivided into several indicators. The seven dimensions are summarized by the acronyms PEOPLES as follows [6,46] (see Fig. 1): Population and demographics, Environment and ecosystem, Organized government services, Physical infrastructure, Lifestyle and community competence, Economic development, and Social-cultural capital.

Every dimension of the PEOPLES framework is divided into a set of components and every component is further broken down into a

Fig. 1. Peoples resilience framework – dimensions (adapted from Ref. [46]).

set of indicators. Regarding the indicators, a list of 115 resilience indicators found in the literature was collected and allocated to the proper components of PEOPLES [22]. Each indicator has a numerical value assigned to it to enable an analytical examination of the indicator's performance and make all indicators computable. Furthermore, each value is normalized to the target value (*TV*). The target value provides the baseline for measuring the resilience of a system and represents the quantity at which the analyzed value is considered fully resilient [47]. For instance, considering the measure "Number of beds per 100,000 population" (Indicator 4.2.1 in Appendix), the output of this measure would be an absolute number of beds that cannot be incorporated into other measures unless it is normalized; thus, the result is divided by TV, which in this scenario represents the "optimum" number of beds per 100,000 people (e.g., TV = 1000 beds/100,000 people). If the ratio of the value of the measure and the TV is less than one, this means that the indicator could still be improved; while if the ratio is greater than one, a value of 1 is assigned to the measure [22]. Furthermore, the measures are classified into "static measures (S)" and "dynamic measures (D)". A static measure is a measure that is not impacted by a hazardous event, while a dynamic measure is a measure that is event-sensitive (i.e., the value of the measure changes following a hazard event). The variables (i.e., dimensions, components, and indicators) included in the PEOPLES framework do not contribute equally to the resilience output. Therefore, they are classified according to their importance. Each variable in the same group is assigned an importance factor (I) which is normalized using a min-max rescaling technique. The min-max rescaling technique is used to scale the importance score of each variable between 0 and 1, where 0 corresponds to the worst rank and 1 represents the best rank. To represent the functionality of each variable (i.e., dimensions, components, and indicators) within the PEOPLES framework, a set of parameters obtained from past events or by performing hazard analysis is used: un-normalized initial functionality q_{0u}, normalized initial functionality before the event q_0, post-disaster functionality q_1, the functionality after recovery q_r, and the restoration time T_r required to complete the recovery process [22].

3. Background on fuzzy logic

Zadeh [48] introduced the concept of fuzzy set theory and fuzzy logic to address the subjectivity of human judgment in the use of linguistic terms in the decision-making process [49,50]. The purpose of fuzzy logic is to solve high degree uncertainty problems and to represent vague, ambiguous, and chaotic information [51,52]. Over the years, Fuzzy Logic has become a key factor in many fields due to its effectiveness and reliability.

In the existing literature, fuzzy set theory and fuzzy logic have been applied in Machine Intelligence Quotient (MIQ) to simulate human ability, in earthquake engineering for seismic damage evaluation [37,53,54], in fragility curve analysis [55], and natural disaster risk management [56].

Fuzzy logic assigns different membership grades (μ) ranging between 0 and 1 to a variable x to indicate the membership of the variable to several classes (fuzzy sets). The strength of the fuzzy logic inference system relies on the following two main features: (i) fuzzy inference system can handle both descriptive (linguistic) knowledge and numerical data; (ii) fuzzy inference system uses approximate reasoning algorithm to determine relationships between inputs by which uncertainties can be propagated throughout the process [57]. In this work, the Mamdani Fuzzy Logic inference method, known as the Max-Min method, is implemented as it is the most suitable when the fuzzy system relies on expert knowledge and experience [58]. Implementing fuzzy logic as an inference system to quantify the resilience requires three main steps: 1) fuzzification and membership functions (MFs); 2) Fuzzy Inference System (FIS) to aggregate the indicators, and 3) defuzzification (Fig. 2). Theoretical information and detailed applications of fuzzy logic can be found in Refs. [36,59].

4. Fuzzy-based methodology to estimate community resilience

The methodology proposed in this work enhances the previous work introduced by Ref. [22] by incorporating fuzzy logic in the computation process. The methodology can be divided into the following (see Fig. 3):

- Resilience modeling and indicator grouping: a hierarchical rule base model is built based on the structure of the PEOPLES framework. According to predefined criteria, indicators belonging to a specific component are further divided into subgroups. This step is necessary to have a manageable and straightforward hierarchical structure for each dimension to simplify the subsequent implementation of Fuzzy Logic and reduce its computation requirements.
- Interdependency analysis and importance factor: weighting factors and importance factors are allocated to each PEOPLES variable (i.e., indicators, components, and dimensions) as they do not contribute equally to the overall resilience output.

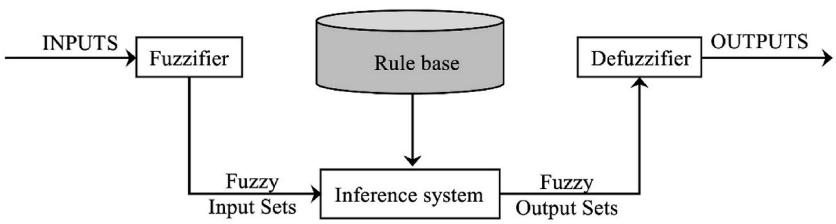

Fig. 2. Fuzzy inference system (FIS).

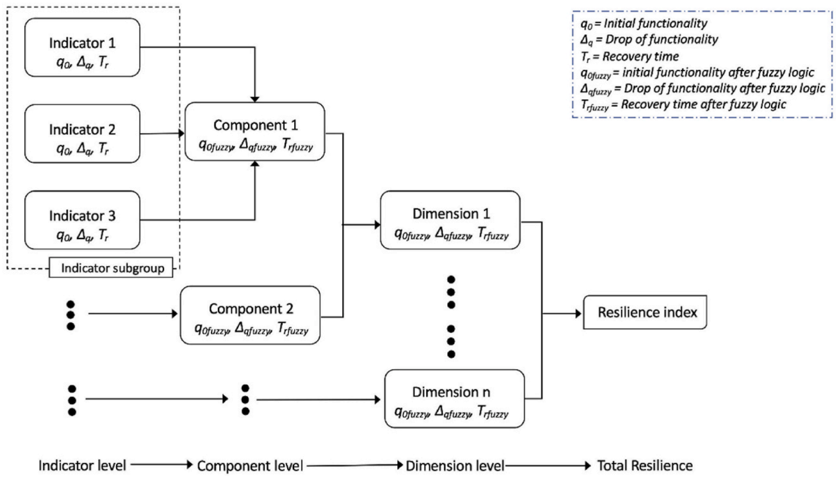

Fig. 3. Hierarchical rule base model applied to PEOPLES framework.

- Inference: the last step of the methodology is to combine the indicators through a Fuzzy Logic (FL) inference system and obtain the final output of the framework.

4.1. Step 1: resilience modeling and indicators grouping

The first step of the methodology is the definition of a hierarchical scheme for the seven dimensions of the PEOPLES framework. A total of eight flowcharts are presented (Fig. 4-Fig. 11); i.e., seven flowcharts for the seven dimensions and an additional flowchart for the final resilience output. Indicators within each component are further clustered into subgroups with no more than three indicators each to simplify the implementation of fuzzy logic. That is, in a fuzzy-based model, a high number of inputs results in an exponential increase in the number of fuzzy rules as well as membership functions. This paper adopts a decomposition technique at the level of indicators proposed in Ref. [60] to reduce the computational complexity. Further details are provided in Section 5.

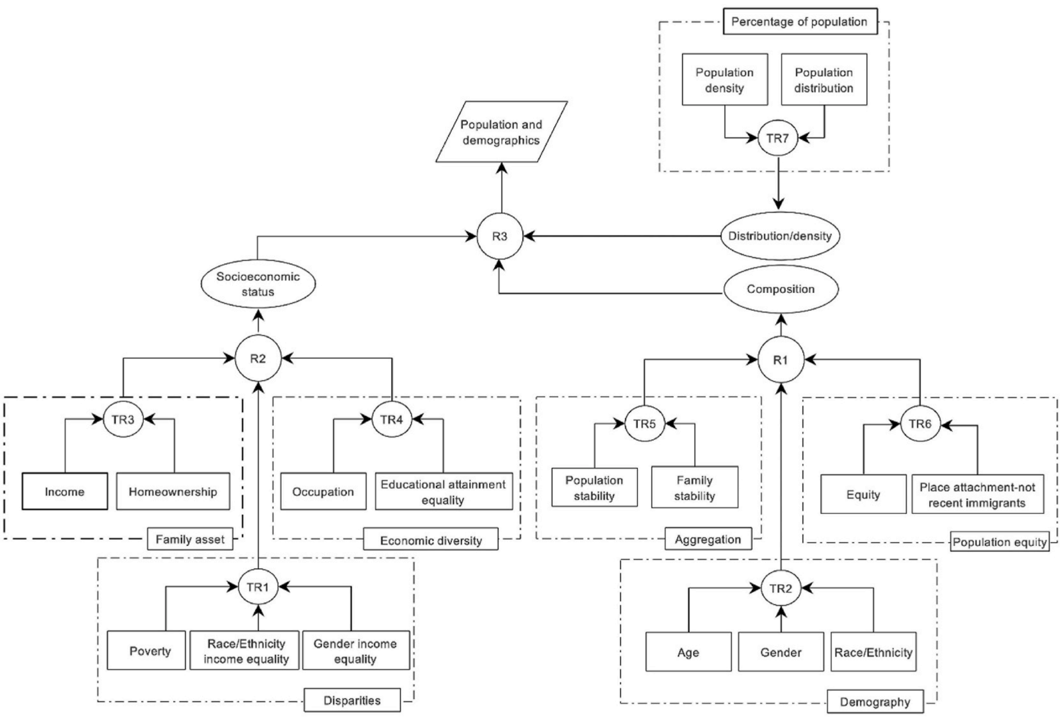

Fig. 4. *Population and demographics* dimension hierarchical scheme.

4.1.1. Population and demographics

This dimension contains indicators that describe the population and demographics in a given community. It considers the socio-economic composition of the community and measures social vulnerabilities that could affect the emergency response and recovery systems (e.g., minority and socioeconomic status, age distribution, population density). For instance, *median income* and *age distribution* information is essential to measure the community's economic health. The *Population and demographics* dimension comprises three components, *Distribution/density, Composition*, and *Socioeconomic status*, with nine indicators. Indicators within this dimension are clustered into six subgroups: Percentage of population, Family asset, Economic diversity, Aggregation, Population equity, Disparities, and Demography. The hierarchical scheme designed for the *Population and demographics* dimension is shown in Fig. 4.

4.1.2. Environment and ecosystem

The *Environment and ecosystem* dimension serves as indicators for measuring the ability of the ecological system to return to or near its pre-event state. Environmental degradation has strongly contributed to increasing risks from natural hazards by altering the frequency and intensity of climate-related hazards and decreasing ecosystems' physical buffering capacity [61].

One such indicator is the Normalized Difference Vegetation Index (NDVI) that can be applied to quantify ecosystem structure following disturbances caused by climate change impact, such as fire, flooding, and hurricanes [46]. For instance, the main soil changes resulting from climate change would be soil temperature regimes and soil hydrology. The community response to climate change risks would be determined by considering the resource users and their access to new technologies [62].

The *Environment and ecosystem* dimension contains six components: *Water, Air, Soil, Biodiversity, Biomass (Vegetation)*, and *Sustainability*, with 13 indicators. Indicators within this dimension are classified into five subgroups: Environment quality, Percentage of land, Land type, Land use, and Vegetation index (see Fig. 5). Note that components with a single indicator are processed as a single component. In other words, the indicators of those components are clustered within the same subgroup.

4.1.3. Organized governmental services

The *Organized governmental services* dimension includes information about traditional legal and security services such as police, emergency, and fire departments as well as services provided by public health, hygiene departments, and cultural heritage departments. The indicators within this dimension are also related to disaster emergency plans, training, and other operations that might help ensure proper disciplined responses. The *Organized governmental services* dimension comprises 5 components: *Executive/administrative*, *Judicial*, *Legal/security*, *Mitigation/preparedness*, and *Recovery/response*, with 26 indicators. As the *Judicial* component presents one indicator, it has been linked to the *Executive/administrative* component indicators. As shown in Fig. 6, the hierarchical scheme consists of 10 subgroups where indicators are aggregated to get the result of the *Organized governmental services* dimension.

4.1.4. Physical infrastructure

The *Physical infrastructure* dimension emphasizes the built environment of a community. It incorporates both *Facilities* and *Lifelines* components with 21 indicators, as illustrated in Fig. 7. Indicators included within the *Facilities* component refer to housing, commercial and cultural facilities. Indicators under the *Lifelines* component consider food supply, health care, utilities, transportation, and communication networks. The hierarchical scheme is structured in 7 subgroups: Communication, Evacuation, Healthcare, Services,

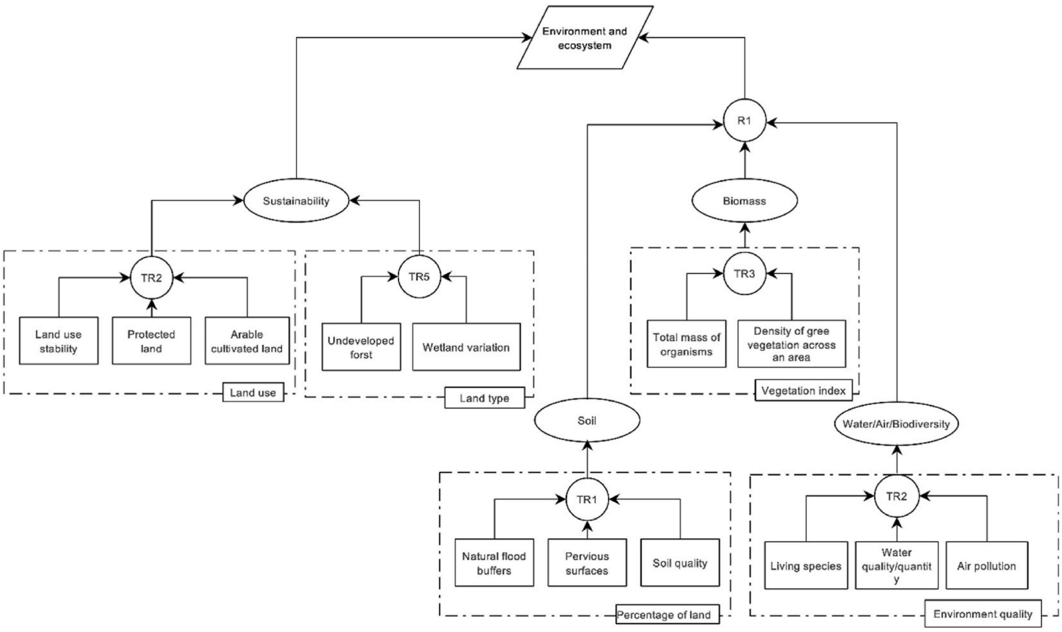

Fig. 5. Environment and ecosystem dimension hierarchical scheme.

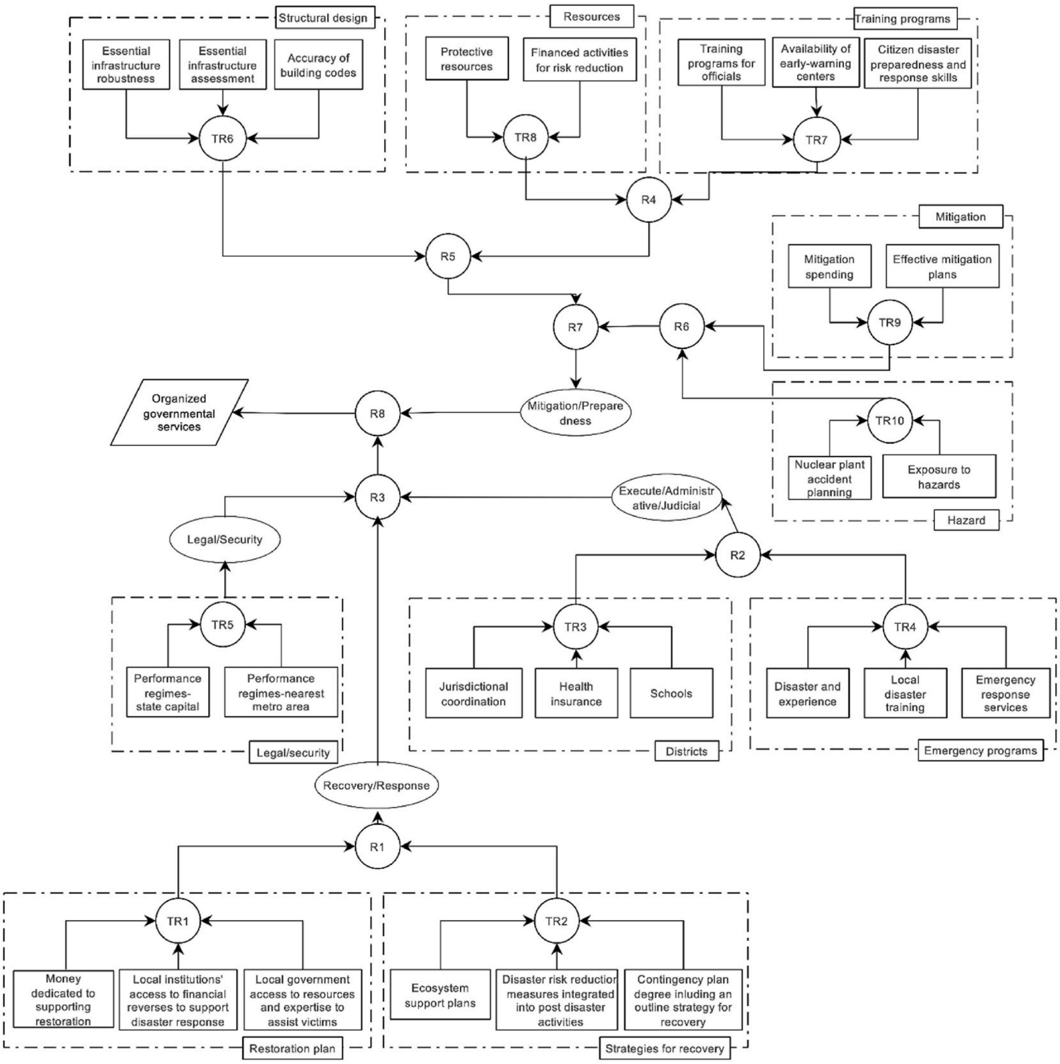

Fig. 6. Organized governmental service dimension hierarchical scheme.

Commercial activities, Housing, and Supply.

Among PEOPLES dimensions, *Physical infrastructure* is often the dimension that needs urgent attention after a hazardous event. Authorities and government services work to restore the utilities' functionality to allow critical facilities to perform their functions.

4.1.5. Lifestyle and community competence

This dimension deals with the ability of a community to develop solutions to complex problems, including warning plans, procedures, and disaster training programs. Also, the participation of community members in the activities required to sustain the community is a crucial indicator to measure community resilience. It is believed that communities that collectively believe that they can stand complex problems are more likely resilient against environmental and governmental obstacles.

Lifestyle and community competence is divided into two components: *Quality of life* and *Collective actions and efficacy*, with seven indicators. The hierarchical framework of the *Lifestyle and community competence* dimension is organized into three subgroups: Abilities, Security, and Neighborhood (see Fig. 8).

4.1.6. Economic development

The *Economic development* dimension includes the static evaluation of a community's current economy (economic activity) and the dynamic evaluation of a community's economic growth (economic development). The former accounts for the provision of labor to produce economic goods and services, while the latter measures a community's productive capacities in terms of technologies, technical cultures, and the capacities and skills of those engaged in production. Key indicators of the *Economic development* dimension also focus on life expectancy and poverty level. Thus, it is evident that this dimension is closely connected with the *Population and Demographics* dimension. Other vital indicators cover the availability of evacuation plans and drills for structures, adequacy plans for

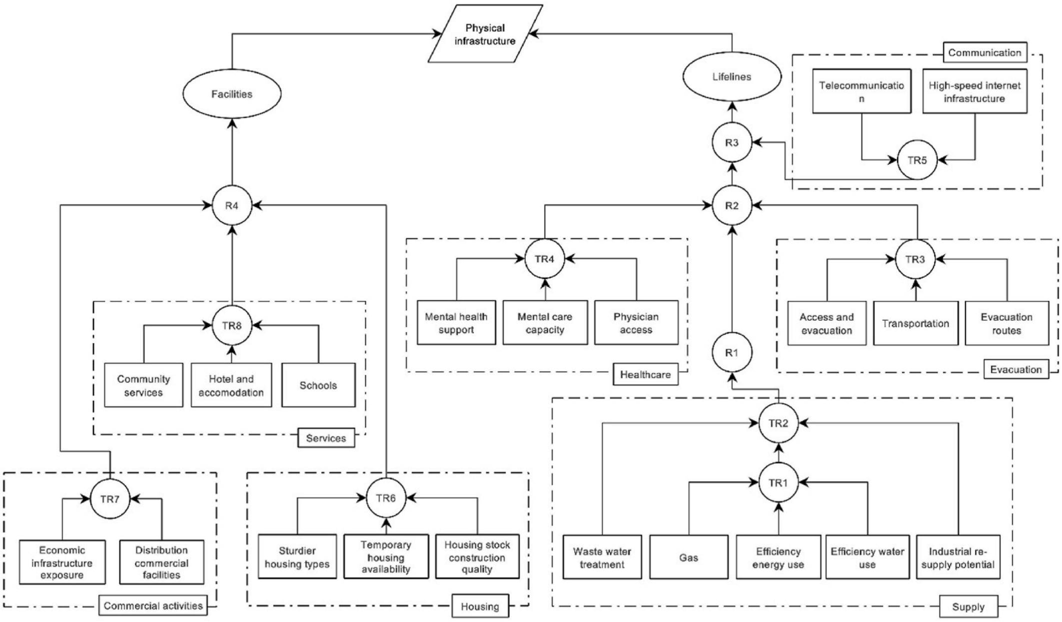

Fig. 7. Physical Infrastructure dimension hierarchical scheme.

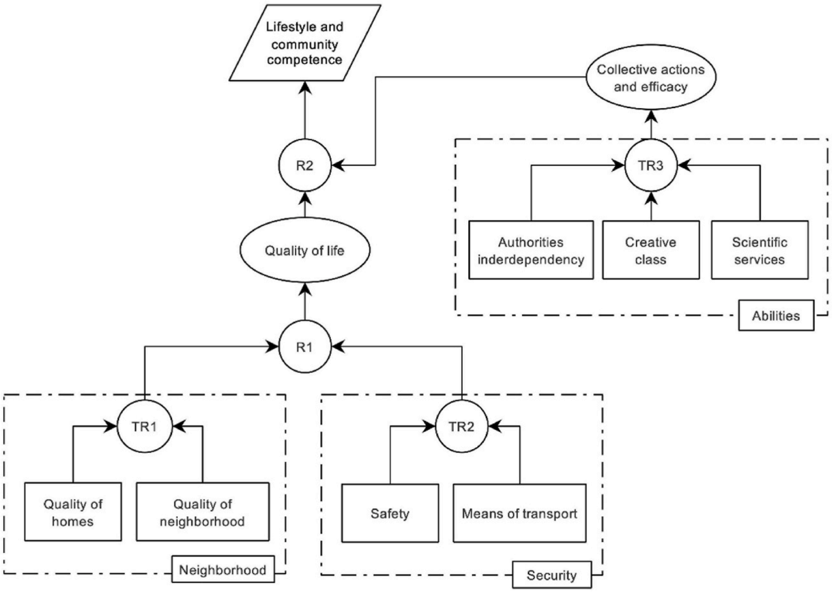

Fig. 8. Lifestyle and community competence dimension hierarchical scheme.

damaged buildings, and commercial reconstruction following a disaster. The *Economic development* dimension consists of 3 components: *Financial services*, *Industry production*, and *Industry employment services*, with 16 indicators. Seven subgroups are used to group indicators in the hierarchical framework, as illustrated in Fig. 9.

4.1.7. Social-cultural capital

The last dimension of the PEOPLES framework, namely *Social-cultural capital,* incorporates education, social, and cultural services, child and elderly services, and community participation in formal organizations such as religious congregations, schools, and resident associations. The *Social and cultural capital* dimension is measured through the acquisition of surveys concerning the number of members of civil and community organizations, and the quality of life. Furthermore, key indicators include adequacy plans and management plans following a hazard.

The *Social-cultural capital* dimension is split into seven components: *Community participation*, *Nonprofit organization*, *Place*

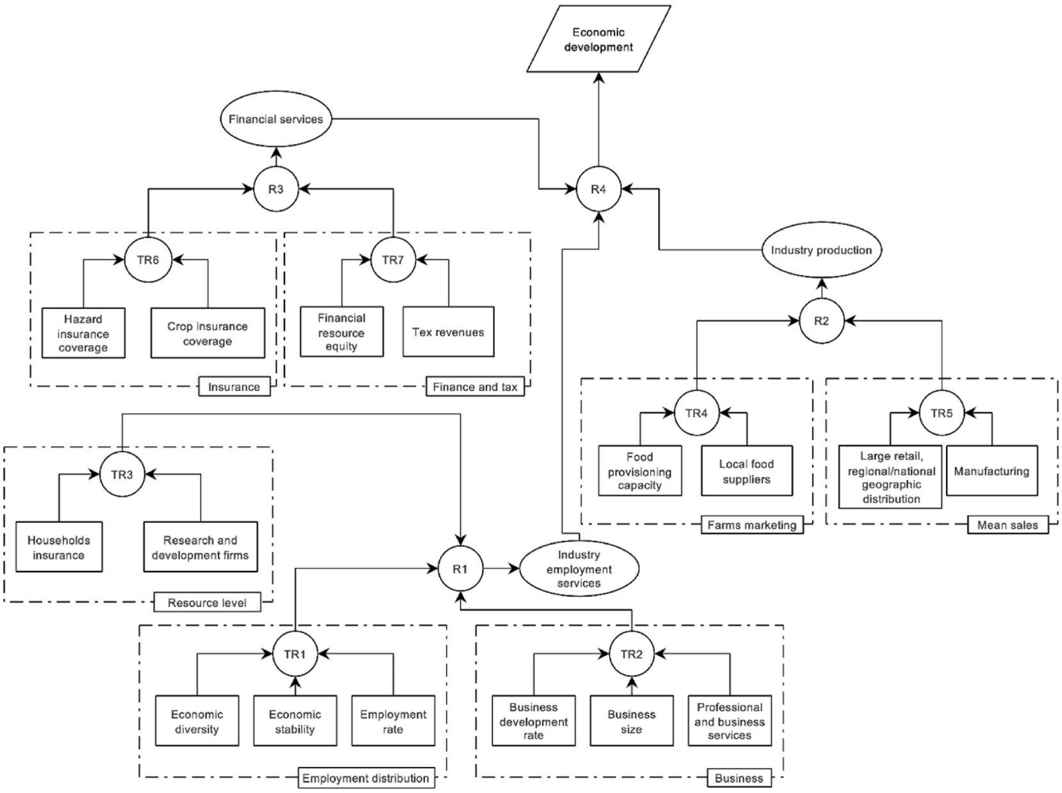

Fig. 9. Economic development dimension hierarchical scheme.

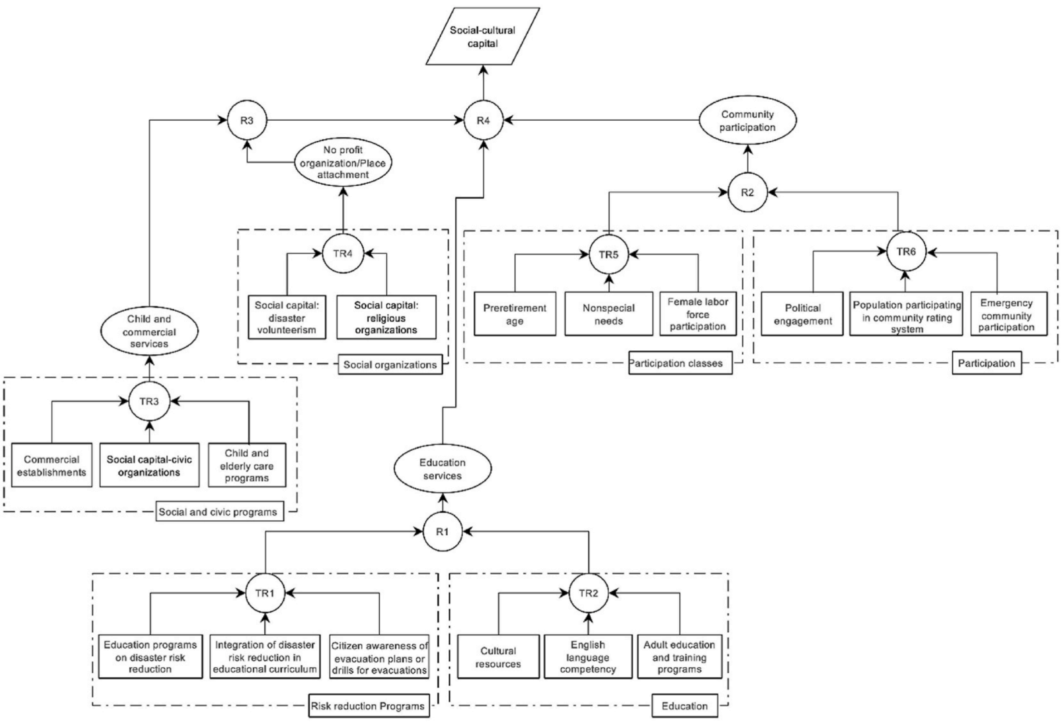

Fig. 10. *Social-cultural capital* dimension hierarchical scheme.

attachment, *Child and elderly activities*, *Commercial centers*, *Cultural and heritage services*, and *Education services*, with a total of 17 indicators (see Fig. 10). Indicators within this dimension are classified into six subgroups: Social organizations, Participation classes, Participation, Social and civic programs, Risk reduction programs, and Education.

4.1.8. The final resilience output

The final hierarchical scheme that combines the seven dimensions is shown in Fig. 11. The *Population and demographics* dimension is closely related to the *Economic development* dimension as the latter involves the life expectancy and poverty rates of the population, and therefore they are grouped. The *Physical infrastructure* dimension is related mainly to the *Organized governmental services* dimension, which considers the infrastructure robustness and assessment, and the availability of resources for recovery programs. The *Environment and ecosystem* dimension depends on the *Organized governmental services* dimension, which verifies the availability of local government plans to support the restoration, protection, and sustainable management of ecosystem services [63]. Finally, the *Social-cultural capital* dimension is considered a prerequisite to *Lifestyle and community competence* as the *Social-cultural capital* dimension incorporates different services that a community has provided for itself [64].

4.2. Step 2: interdependency analysis and importance factor

PEOPLES indicators do not contribute equally to the overall resilience outcome; hence, their interdependencies can affect the final result [22]. To include interdependencies in this work, weighting factors are assigned to each variable through an interdependency analysis. In the analysis, variables of the PEOPLES framework are classified into three main groups [22]:

1. Indicators within a component are considered as a group (29 groups in total).
2. Components that fall within a dimension are taken as a group (7 groups in total).
3. The seven dimensions of PEOPLES make up a group (1 group).

The interdependency analysis assumes that the importance of a variable is related to the number of other variables in the same group that depends on it. Variables in the same groups are given importance factors using the [$n \times n$] adjacency matrix in Fig. 12, where n is the number of variables in the analyzed group. Each cell (a_{ij}) in the matrix represents the degree of dependence between two variables and can take the values 0 or 1. A value of 0 indicates that the variable in the row does not depend on the variable in the column, while 1 indicates that the variable in the row depends entirely on the variable in the column. The importance factor is carried out by summing up the values in each matrix column.

An interdependency matrix is built for each group of variables. A single interdependency matrix is constructed for the seven dimensions of PEOPLES, for each group of components under the dimensions, and finally for every group of indicators under the components. This results in 37 matrices to perform the interdependency analysis for the different variables of the PEOPLES framework.

The level of interdependency between two variables can be identified using descriptive knowledge in the form of a walk-down survey filled by a team of experts. For instance, "low" and "high" dependence between two variables can be translated into 0 and 1, respectively. Importance factors for different variables are collected through walk-down surveys filled by experts to reduce subjectivity and possible uncertainty. More than one person (e.g., approximately a group of 10 experts) defines the interdependency between any two variables. Experts employ their knowledge to provide information in a yes/no or 1/0 format. Due to the comprehensive structure of the PEOPLES framework, the expert can quickly fill out the survey without making arbitrary guesses. Then, the average of all responses is considered as the final importance factor that is used for further analysis.

Finally, a weighting factor for each variable (w_i) is obtained by dividing the importance factor by the maximum importance factor, as indicated in Equation (1) [22]:

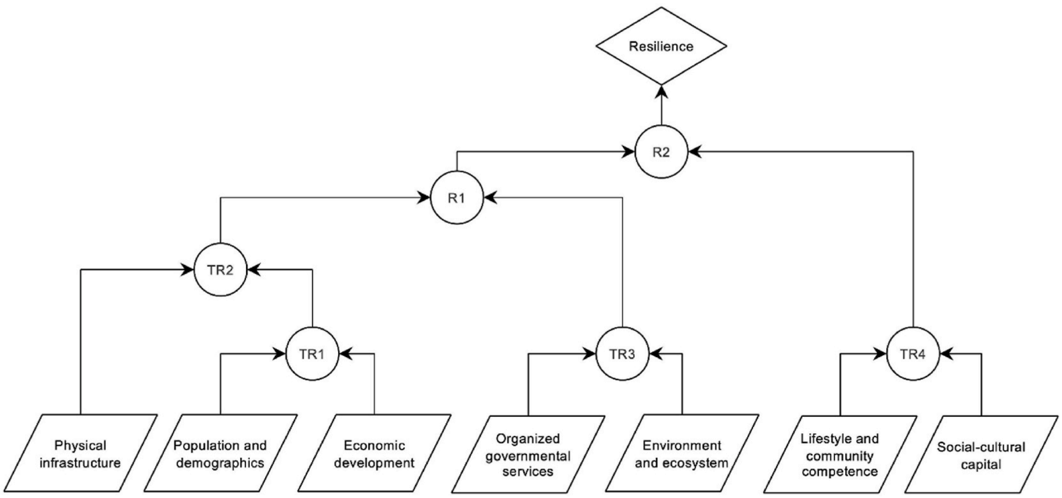

Fig. 11. Resilience hierarchical scheme.

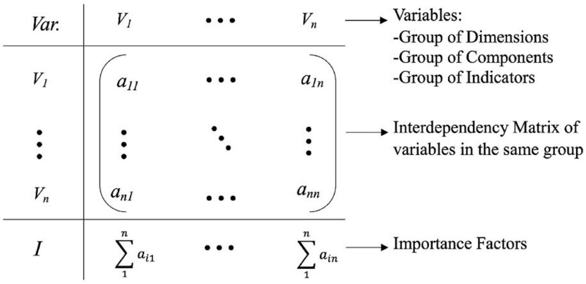

Fig. 12. Interdependency matrix between variables in a same group (adapted from Ref. [22]).

$$w_i = \frac{\sum_{j=1}^{n} a_{ji}}{\sum_{i=1}^{n} \sum_{j=1}^{n} a_{ji}} \tag{1}$$

4.3. Step 3: inference system

The last step of the methodology is implementing the fuzzy logic inference system for combining the PEOPLES variables to get the resilience index. In the following, the fuzzy logic process is described.

Fuzzification process – Membership functions: The fuzzification process is helpful when it comes to uncertainties in the estimation of system inputs as it can cope with both numerical and descriptive variables. In the case of numerical input, the fuzzification process is straightforward and depends on the shape of the MFs. MFs can have different forms, such as triangular, trapezoidal, and Gaussian shapes. The simplest MFs are formed using straight lines. Both triangular and trapezoidal fuzzy MFs have been widely used due to their simple formulas and computational efficiency in representing linguistic variables [65,66]. Descriptive inputs, instead, must be converted in fuzzy terms by assigning different membership degrees to the different granularities. For example, within the PEOPLES framework, if the average number of internet connections, television, radio, and telephone per household in a community is classified as “poor”, the indicator *Telecommunication* can be converted in fuzzy terms by assigning the membership degrees to the granularities [L, M, and H] as follows: [μ_L, μ_M, μ_H] = [0.9, 0.1, 0]. The chosen membership degrees show a low level of functionality for the *Telecommunication* indicator. If the average number of internet connections, television, radio, and telephone per household in a community is classified as “good”, the membership degrees assigned to the granularities [L, M, and H] would be: [μ_L, μ_M, μ_H] = [0.2, 0.8, 0.2], showing a medium level of functionality. Finally, if the average number is classified as “rich”, the indicator *Telecommunication* can be converted in fuzzy terms by assigning the membership degrees to the granularities [L, M, and H] as follows: [μ_L, μ_M, μ_H] = [0 0.1, 0.9]. The chosen membership degrees show a high level of functionality for the *Telecommunication* indicator.

Fuzzy Inference System (FIS) – fuzzy rules: a Fuzzy Inference System (FIS) aims to map the input information into an output space exploiting the previously defined fuzzy sets. The relationships between inputs and outputs are defined through the *fuzzy rule base* (FRB) that comes from the heuristic knowledge of experts or historical data. As mentioned above, in this work, the Mamdani Fuzzy Logic inference system, known as the Max-Min method, is adopted Mamdani system consists of if-then statements (rules) that link the input (antecedent) to a consequent (output). Each rule delivers a partial conclusion, which is aggregated to the other rules to provide a conclusion (aggregation). In a complex system with many input indicators, the number of rules must cover all the possible combinations.

Defuzzification process – crisp number: the defuzzification step is carried out to obtain a crisp number from the fuzzy output set resulting from the inference process. The defuzzification is performed according to the MF of the output variable and represents the inverse of the fuzzification process. Several defuzzification techniques have been developed, such as the center of gravity, the center of area, and the mean of maximum method [67].

5. Demonstrative example and verification

To demonstrate the applicability of the proposed fuzzy logic-based methodology, three different cases for evaluating the resilience of San Francisco city have been applied.

1. Case 1: *Physical Infrastructure* dimension with complete data.
2. Case 2: *Physical Infrastructure* dimension with partial data.
3. Case 3: *Lifestyle and Community competence* with no data available.

In Case 1, the hazard event considered in the analyses is the 1989 Loma Prieta earthquake, characterized by a moment magnitude of 6.9 M_w. The introduced methodology has been implemented focusing only on the *Physical Infrastructure* and *Lifestyle and Community competence* dimensions. In the first case, the list of indicators and components within the *Physical Infrastructure* and the corresponding functionality and repair time parameters required to quantify the resilience (see Appendix A) is considered as input data. For this study, open database sources were investigated to determine the parameters of the San Francisco community [68]. In Appendix A, q_{0u} is the un-normalized initial functionality that must be normalized to be combined with the other parameters. The normalization of the initial functionality q_0 is done by dividing the un-normalized functionality q_{0u} over the Target Value *TV* described before. According to their nature (i.e., static, or dynamic), the classification of indicators is indicated in Appendix A as *Nat.* Furthermore, the recovery time

Table 1
Interdependency matrix between indicators under the Lifelines component.

Indicator	Telecommunication	Mental health support	Physician access	Medical care capacity	Evacuation routes	Industrial resupply potential	Internet infrastructure	Efficient energy use	Water use	Gas	Access and evacuation	Transport	Wastewater treatment
Telecommunication	1	0	0	0	0		1	1	0	0	1	1	0
Mental health support	0	1	0	1	0	0	0	0	0	0	0	0	0
Physician access	0	0	1	1	0	0	0	0	0	0	0	0	0
Medical care capacity	1	0	1	1	0	0	0	1	1	1	0	1	1
Evacuation routes	0	0	0	0	1	0	0	1	1	1	0	1	1
Industrial resupply potential	0	0	0	0	1	1	0	1	0	0	1	1	0
Internet infrastructure	1	0	0	0	0	1	1	1	0	0	0	0	0
Efficient energy use	0	0	0	0	0	0	0	1	1	0	1	0	0
Water use	1	0	0	0	0	0	0	1	1	0	1	1	1
Gas	1	0	0	0	0	0	0	1	1	0	1	1	1
Access and evacuation	1	0	0	0	1	0	0	1	1	1	1	1	1
Transport	1	0	0	0	1	0	0	1	1	1	1	1	1
Wastewater treatment	1	0	0	0	0	1	0	1	1	0	1	1	1
Importance factor	8	1	2	3	4	3	2	11	7	5	8	9	6

Table 2
Interdependency matrix between indicators under the Facility component.

Indicator	Sturdy housing type	Temporary housing0	Housing stock quality	Economic infr. exposure	Commercial facilities	Community services	Hotels and accommodation	Schools
Sturdy housing type	1	0	0	0	0	0	1	1
Temporary housing0	1	0	0	0	0	1	0	
Housing stock quality	0	0	1	1	0	0	0	0
Economic infr. exposure	1	0	1	1	0	1	0	1
Commercial facilities	0	0	0	0	1	0	0	1
Community services	0	0	0	0	1	1	0	1
Hotels and accommodation	1	0	0	0	0	1	1	1
Schools	0	0	0	0	0	1	0	1
Importance factor	2	2	3	3	2	4	2	2

parameter T_r is normalized based on a 3-year time span, which is usually the time reference for civil applications.

Case 2 is equivalent to Case 1 with an additional assumption that some of the data are not available. This case is introduced to study the effect of partial unavailability of data. Case 3 is an application of the methodology to another dimension of the PEOPLEs framework, assuming no availability of data. For this case, a group of experts was asked to evaluate the missing indicators and components by providing information in linguistic terms.

In the following sections, the three cases are described.

5.1. Case with available numerical data

Step 1: Resilience modeling and indicators grouping.

The first step of the proposed methodology is defining a hierarchical framework for the analyzed dimension. As illustrated in Fig. 7, indicators together with the corresponding parameters belonging to *Facilities* and *Lifelines* components are divided into subgroups with no more than three indicators each. The indicators are clustered in 7 subgroups following the PEOPLES structure: Housing, Commercial Activities, Services, Healthcare, Evacuation, Supplies, and Communication. In every subgroup, indicators (e.g., *telecommunication*, *high-speed internet infrastructure*, etc.) are combined through fuzzy rules to obtain *Facilities* and *Lifelines* components. Finally, the components in turn, are combined to get the resilience output.

Step 2: Interdependency analysis and importance factor.

Once the hierarchical framework for the studied dimension is built, the second step of the methodology starts. The weighting factors of the different variables under the *Physical infrastructure* dimension are determined using the interdependency matrix technique. The interdependency matrix of the indicators within the *Lifelines* and *Facility* components is shown in Table 1 and Table 2 [22]. The report by the National Institute of Standards and Technology [69] and the Lifelines Council [70] were used to fill the interdependency matrix.

Once the importance factors have been extracted from the interdependency matrix, weighting factors for indicators and components under the Physical infrastructure dimension are obtained through Eq. (1).

Table 3 lists the weighting factors of the different variables under the *Physical infrastructure* dimension.

Step 3: Inference – Fuzzy logic.

The design of the hierarchical framework and the calculation of the weighting factors of the variables within the analyzed dimension allow implementing fuzzy logic as an inference system. Weighting factors are used to determine fuzzy rules for aggregating indicators and components. Assuming to mapping the three granularities [L, M, H] into the numerical values $[F_L, F_M, F_H] = [1–3]$, which indicate an increase of functionality (F) of the system, and considering two inputs x_1 and x_2 with $w_1 = 0.75$ and $w_2 = 0.5$ respectively, where w_1 signifies a higher impact of the input towards the output, Eq. (2) is used to evaluate rules:

Table 3
Weighting factors of variables within *Physical infrastructure* dimension for city of San Francisco.

Component/Indicator	*W*
4.1 Facility	0.5
Housing	
4.1.1 Sturdy housing types	0.5
4.1.2 Temporary housing availability	0.5
4.1.3 Housing stock construction quality	0.75
Commercial activities	
4.1.4 Economic infrastructure exposure	0.75
4.1.5 Distribution commercial facilities	0.5
Services	
4.1.6 Community services	1
4.1.7 Hotels and accommodations	0.75
4.1.7 Schools	0.5
4.2 Lifelines	1
Healthcare	
4.2.1 Mental health support	0.09
4.2.2 Medical care capacity	0.27
4.2.3 Physician access	0.18
Evacuation	
4.2.4. Access and evacuation	0.73
4.2.5 Transportation	0.82
4.2.6 Evacuation routes	0.36
Supplies	
4.2.7 Efficient energy use	1
4.2.8 Efficient water use	0.64
4.2.9 Gas	0.45
4.2.10 Industrial resupply potential	0.27
4.2.11 Wastewater treatment	0.55
Communication	
4.2.12 Telecommunication	0.73
4.2.13 High-speed Internet infrastructure	0.18

$$F_{out} = \frac{\sum_{i=1}^{n} F_{inp,i} \cdot w_{inp,i}}{\sum_{i=1}^{n} w_{inp,i}} \tag{2}$$

where F_{out} is the granularitiy of the output, F_{inp} is the numerical value corresponding to the belonging granularity of the input *i*, w_i is the weighting factor for indicator *i*, and *n* is the total number of indicators in the subgroups. Consider the following example of a fuzzy rule: IF x_1 is *Low* AND x_2 is *High*, THEN the output is $F_{out} = 1.8$, which can be rounded to 2. Therefore, the level of the output is *Medium*.

The aggregation is done by following the relationships between the variables provided by the hierarchical model.

The following steps to implement the fuzzy logic inference system are performed:

Step 3.1: Fuzzification process – membership functions.

As mentioned before, a set of parameters is used to define the functionality of PEOPLES indicators. The proposed methodology adopts three of the four functionality parameters: initial functionality q_0, functionality drop (robustness), defined as $\Delta q = q_0 - q_1$, where q_1 is the functionality after the event, and the restoration time T_r. These parameters could have different states called linguistic quantifiers or fuzzy sets. To implement the fuzzy inference system in the PEOPLES framework easily, the number of states is set to three states for all indicators' parameters: *low, medium*, and *high* for the functionality parameters*, short, long,* and *very long* for the recovery time parameter, and *resilient*, *intermediate*, and *not resilient* for the resilience index. Considering more than three states leads to a more complicated fuzzy process. That is, if more states are considered (e.g., five states), more MFs would then be necessary, and a high number of fuzzy rules would be required to cover all the possible permutations of the states. A higher number of states can make the results more specific; however, this comes at the cost of input demand: the expert would then need to provide more detailed MFs and more fuzzy rules, which could be not practical. Therefore, choosing three states would provide the best balance between input demand and output clarity. The MFs considered in the methodology are based on trapezoidal fuzzy numbers and they are expressed by four vertices (a, b, c, and d) as:

$$\mu_{\tilde{n}}(x) \begin{cases} 0, & x < n_1, \\ \dfrac{x - n_1}{n_2 - n_1}, & n_1 \le x \le n_2, \\ 1, & n_2 \le x \le n_3, \\ \dfrac{x - n_4}{n_3 - n_4}, & n_3 \le x \le n_4, \\ 0, & x > n_4 \end{cases} \tag{3}$$

where $\tilde{n}$ is a trapezoidal fuzzy number and can be defined as (n_1, n_2, n_3, n_4), $\mu_{\tilde{n}}(x)$ is the membership function.

The MFs have been first designed relying on the intuition method, which relied on the authors' opinion and understanding [59]. That is, membership functions have been generated to be as symmetric as possible to get the simplest trapezoidal membership functions as depicted in Fig. 13.

For instance, in the figure, the linguistic variable "Low" of the initial functionality q_0 of *Telecommunication* indicator can be represented as (0, 0, 0.1, 0.2), the membership function of which is:

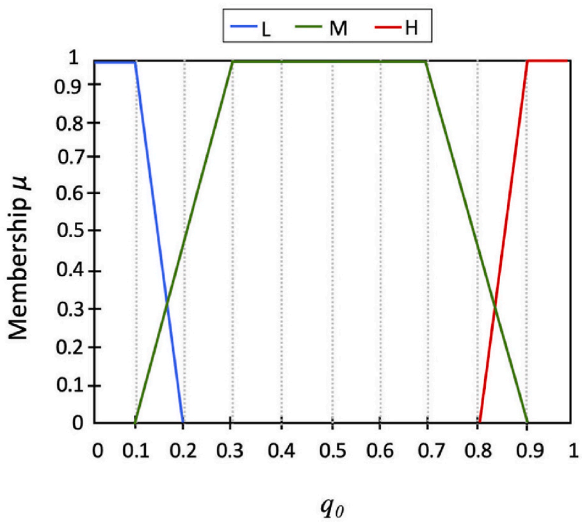

Fig. 13. Membership function and granulation for the initial functionality q_0 of Telecommunication indicator.

$$\mu_{Low}(x)\begin{cases}0, & x<0,\\ \dfrac{x-0}{0-0}, & 0\le x\le 0,\\ 1, & 0\le x\le 0.1,\\ \dfrac{x-0.2}{0.1-0.2}, & 0.1\le x\le 0.2,\\ 0, & x>0.2\end{cases} \tag{4}$$

Later, membership functions have been calibrated so that the resilience outcome predicted by the model is equal (or nearly equal) to the resilience outcome obtained in the benchmark case study [22]. Calibration is a fundamental operation and consists of gradually modifying the shapes of the MFs such that the final output approximately matches that of the benchmark case study. An example of granulation assigned to the initial functionality q_0 of the *Telecommunication* indicator and *Resilience* indicator is illustrated in Fig. 14.

The functionality and recovery time parameters for each indicator and component listed in Appendix A are used as numerical inputs in the fuzzification process. That is, one can enter the corresponding membership graph using directly the numerical values listed in Appendix A and obtain the membership degree.

The MFs used in the methodology associated with the *Physical Infrastructure* dimension along with its components and indicators are based on trapezoidal fuzzy numbers (see Fig. 14) and they are listed in Table 4.

The membership degrees obtained through the fuzzification process for the components under the *Physical Infrastructure* dimension are listed in Table 5.

Step 3.2: Aggregation through Fuzzy rules.

The most common type of FRB, known as the Mamdani type is adopted herein.

As shown in Fig. 7, many indicators with their corresponding parameters are considered in the physical infrastructure framework, and consequently, several fuzzy rules are necessary to combine them. As mentioned before, a decomposition technique at the level of indicators is adopted to have no more than three indicators in each subgroup aggregated through intermediate rules (temporary rules), for example TR_1, TR_2, TR_3, etc. By implementing the decomposition technique, a maximum of $3^3 = 27$ rules per subgroup must be determined. The output of the intermediate inference is combined through fuzzy rule based R_1 and R_2. For instance, indicators within the subgroup *Services* are aggregated through TR_1, indicators under the subgroup *Commercial Activities* are combined through TR_2, and finally, the indicators under the subgroup *Housing* are aggregated through TR_3. The outputs of these components are then aggregated through R_1 to obtain the *Facilities* component. At each level of the hierarchical scheme, the three-tuple fuzzy set output is defuzzified to obtain a single crisp value. In turn, this value is fuzzified into the next level.

An example of the fuzzy rules assigned for combining the recovery time parameter of the *Commercial Activities* indicators is given in Table 6.

Table 6 shows that the output is mainly driven by the *Economic infrastructure exposure* indicator (w = 0.75), in agreement with the fact that it is more important than the *Distribution commercial facilities* indicator (w = 0.5).

Using the fuzzy rule table (Table 6), the recovery time T_R parameter of the *Commercial Activities* indicator is computed as follows:

$$\begin{aligned}\mu_S^{CA} &= \max(\min(1,0.95),\min(1,0),\ \min(0,0.95)) = 0.95\\ \mu_L^{CA} &= \max(\min(1,0),\min(0,0),\min(0,0.95)) = 0\\ \mu_{VL}^{CA} &= \max(\min(0,0),\min(0,0),\ \min(0,0)) = 0\end{aligned} \tag{5}$$

Step 3.3: Defuzzification process – crisp output.

The last step of the fuzzy-based methodology is the defuzzification process. The center of gravity (also called the center of area) method is used here. Generally, the center of gravity method yields superior results and is the most commonly chosen [71]. The advantage of this method is that it is easy to compute for triangular and trapezoidal functions [72]. Furthermore, one of the advantages of the center of gravity defuzzification method is that in case of symmetrical membership functions in the output linguistic categories,

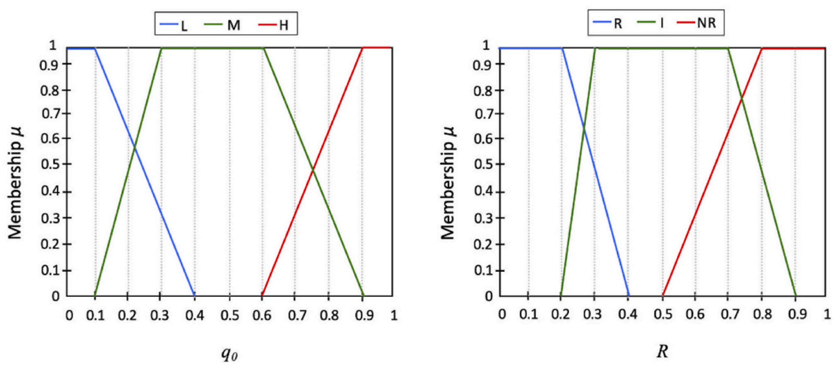

Fig. 14. Membership function and granulation for the initial functionality q_0 of Telecommunication indicator and Resilience indicator.

Table 4
Membership functions for Physical Infrastructure dimension, components, and indicators.

Dimension/component/subgroups/ indicators	Initial functionality q_0 (μ_L, μ_M, μ_H)	Drop of functionality Δ_q (μ_L, μ_M, μ_H)	Repair time T_r (μ_S, μ_L, μ_{VL})
4 - *Physical infrastructure*	(0, 0, 0.1, 0.3), (0.2, 0.3, 0.6, 0.8), (0.5, 0.9, 1, 1)	(0, 0, 0.3, 0.5), (0.2, 0.5, 0.7, 0.8), (0.7, 0.9, 1, 1)	(0, 0, 0.1, 0.2), (0.1, 0.3, 0.7, 0.8), (0.7, 0.9, 1, 1)
4-1 - *Facilities*	(0, 0, 0.1, 0.4), (0.1, 0.3, 0.6, 0.9), (0.6, 0.9, 1, 1)	(0, 0, 0.3, 0.5), (0.2, 0.5, 0.7, 0.8), (0.7, 0.9, 1, 1)	(0, 0, 0.1, 0.4), (0.2, 0.3, 0.7, 0.8), (0.7, 0.9, 1, 1)
Housing	(0, 0, 0.1, 0.4), (0.1, 0.3, 0.6, 0.9), (0.6, 0.9, 1, 1)	(0, 0, 0.3, 0.5), (0.2, 0.5, 0.7, 0.8), (0.7, 0.9, 1, 1)	(0, 0, 0.1, 0.2), (0.1, 0.3, 0.7, 0.8), (0.7, 0.9, 1, 1)
4-1-1 - Sturdier housing types	(0, 0, 0.1, 0.4), (0.1, 0.3, 0.6, 0.9), (0.6, 0.9, 1, 1)	(0, 0, 0.3, 0.5), (0.3, 0.5, 0.7, 0.8), (0.7, 0.9, 1, 1)	[0, 0, 0.1, 0.2], [0.1, 0.3, 0.7, 0.8], [0.7, 0.9, 1, 1]
4-1-2 - Temporary housing availability	(0, 0, 0.1, 0.4), (0.1, 0.3, 0.6, 0.9), (0.6, 0.9, 1, 1)	(0, 0, 0.3, 0.5), (0.3, 0.5, 0.7, 0.8), (0.7, 0.9, 1, 1)	[0, 0, 0.1, 0.2], [0.1, 0.3, 0.7, 0.8], [0.7, 0.9, 1, 1]
4-1-3 - Housing stock construction quality	(0, 0, 0.1, 0.4), (0.1, 0.3, 0.6, 0.9), (0.6, 0.9, 1, 1)	(0, 0, 0.3, 0.5), (0.3, 0.5, 0.7, 0.8), (0.7, 0.9, 1, 1)	[0, 0, 0.1, 0.2], [0.1, 0.3, 0.7, 0.8], [0.7, 0.9, 1, 1]
Commercial Activities	(0, 0, 0.1, 0.4), (0.1, 0.3, 0.6, 0.9), (0.6, 0.9, 1, 1)	(0, 0, 0.3, 0.5), (0.3, 0.5, 0.7, 0.8), (0.7, 0.9, 1, 1)	[0, 0, 0.1, 0.2], [0.1, 0.3, 0.7, 0.8], [0.7, 0.9, 1, 1]
4-1-4 - Economic infrastructure exposure	(0, 0, 0.1, 0.4), (0.1, 0.3, 0.6, 0.9), (0.6, 0.9, 1, 1)	(0, 0, 0.3, 0.5), (0.3, 0.5, 0.7, 0.8), (0.7, 0.9, 1, 1)	[0, 0, 0.1, 0.2], [0.1, 0.3, 0.7, 0.8], [0.7, 0.9, 1, 1]
4-1-5 - Distribution commercial facilities	(0, 0, 0.1, 0.4), (0.1, 0.3, 0.6, 0.9), (0.6, 0.9, 1, 1)	(0, 0, 0.3, 0.5), (0.3, 0.5, 0.7, 0.8), (0.7, 0.9, 1, 1)	[0, 0, 0.1, 0.2], [0.1, 0.3, 0.7, 0.8], [0.7, 0.9, 1, 1]
Services	(0, 0, 0.1, 0.4), (0.1, 0.3, 0.6, 0.9), (0.6, 0.9, 1, 1)	(0, 0, 0.3, 0.5), (0.3, 0.5, 0.7, 0.8), (0.7, 0.9, 1, 1)	[0, 0, 0, 0.3], [0.1, 0.3, 0.7, 0.8], [0.7, 0.9, 1, 1]
4-1-6 - Community services	(0, 0, 0.1, 0.4), (0.1, 0.3, 0.6, 0.9), (0.6, 0.9, 1, 1)	(0, 0, 0.3, 0.5), (0.3, 0.5, 0.7, 0.8), (0.7, 0.9, 1, 1)	[0, 0, 0.1, 0.2], [0.1, 0.3, 0.7, 0.8], [0.7, 0.9, 1, 1]
4-1-7 - Hotels and accommodations	(0, 0, 0.1, 0.4), (0.1, 0.3, 0.6, 0.9), (0.6, 0.9, 1, 1)	(0, 0, 0.3, 0.5), (0.3, 0.5, 0.7, 0.8), (0.7, 0.9, 1, 1)	[0, 0, 0, 0.3], [0.1, 0.3, 0.7, 0.8], [0.7, 0.9, 1, 1]
4-1-8 - Schools	(0, 0, 0.1, 0.4), (0.1, 0.3, 0.6, 0.9), (0.6, 0.9, 1, 1)	(0, 0, 0.3, 0.5), (0.3, 0.5, 0.7, 0.8), (0.7, 0.9, 1, 1)	[0, 0, 0, 0.3], [0.1, 0.3, 0.7, 0.8], [0.7, 0.9, 1, 1]
4-2 - *Lifelines*	(0, 0, 0.1, 0.3), (0.2, 0.4, 0.6, 0.8), (0.6, 0.9, 1, 1)	(0, 0, 0.3, 0.5), (0.2, 0.5, 0.7, 0.8), (0.7, 0.9, 1, 1)	[0, 0, 0.1, 0.3], [0.1, 0.3, 0.7, 0.8], [0.7, 0.9, 1, 1]
Healthcare	(0, 0, 0.1, 0.4), (0.1, 0.3, 0.6, 0.9), (0.6, 0.9, 1, 1)	(0, 0, 0.3, 0.5), (0.3, 0.5, 0.7, 0.8), (0.7, 0.9, 1, 1)	[0, 0, 0.1, 0.2], [0.1, 0.2, 0.7, 0.8], [0.7, 0.9, 1, 1]
4-2-1 - Mental health support	(0, 0, 0.1, 0.4), (0.1, 0.3, 0.6, 0.9), (0.6, 0.9, 1, 1)	(0, 0, 0.3, 0.5), (0.3, 0.5, 0.7, 0.8), (0.7, 0.9, 1, 1)	[0, 0, 0.1, 0.2], [0.1, 0.2, 0.7, 0.8], [0.7, 0.9, 1, 1]
4-2-2 - Medical care capacity	(0, 0, 0.1, 0.4), (0.1, 0.3, 0.6, 0.9), (0.6, 0.9, 1, 1)	(0, 0, 0.3, 0.5), (0.3, 0.5, 0.7, 0.8), (0.7, 0.9, 1, 1)	[0, 0, 0.1, 0.2], [0.1, 0.2, 0.7, 0.8], [0.7, 0.9, 1, 1]
4-2-3 - Physician access	(0, 0, 0.1, 0.4), (0.1, 0.3, 0.6, 0.9), (0.6, 0.9, 1, 1)	(0, 0, 0.3, 0.5), (0.3, 0.5, 0.7, 0.8), (0.7, 0.9, 1, 1)	[0, 0, 0.1, 0.2], [0.1, 0.2, 0.7, 0.8], [0.7, 0.9, 1, 1]
Evacuation	(0, 0, 0.1, 0.4), (0.1, 0.3, 0.6, 0.9), (0.6, 0.9, 1, 1)	(0, 0, 0.3, 0.5), (0.3, 0.5, 0.7, 0.8), (0.7, 0.9, 1, 1)	[0, 0, 0.1, 0.2], [0.1, 0.2, 0.7, 0.8], [0.7, 0.9, 1, 1]
4-2-4 - Access and evacuation	(0, 0, 0.1, 0.4), (0.1, 0.3, 0.6, 0.9), (0.6, 0.9, 1, 1)	(0, 0, 0.3, 0.5), (0.3, 0.5, 0.7, 0.8), (0.7, 0.9, 1, 1)	(0, 0, 0.1, 0.2], [0.1, 0.2, 0.7, 0.8], [0.7, 0.9, 1, 1]
4-2-5 - Transportation	(0, 0, 0.1, 0.4), (0.1, 0.3, 0.6, 0.9), (0.6, 0.9, 1, 1)	(0, 0, 0.3, 0.5), (0.3, 0.5, 0.7, 0.8), (0.7, 0.9, 1, 1)	[0, 0, 0.1, 0.2], [0.1, 0.2, 0.7, 0.8], [0.7, 0.9, 1, 1]
4-2-6 - Evacuation routes	(0, 0, 0.1, 0.4), (0.1, 0.3, 0.6, 0.9), (0.6, 0.9, 1, 1)	(0, 0, 0.3, 0.5), (0.3, 0.5, 0.7, 0.8), (0.7, 0.9, 1, 1)	[0, 0, 0.1, 0.2], [0.1, 0.2, 0.7, 0.8], [0.7, 0.9, 1, 1]
Supplies	(0, 0, 0.1, 0.4), (0.1, 0.3, 0.6, 0.9), (0.6, 0.9, 1, 1)	[0, 0, 0.3, 0.4], [0.2, 0.3, 0.7, 0.8], [0.7, 0.9, 1, 1]	[0, 0, 0.1, 0.2], [0.1, 0.3, 0.7, 0.8], [0.7, 0.9, 1, 1]
4-2-7 - Efficient energy use	(0, 0, 0.1, 0.4), (0.1, 0.3, 0.6, 0.9), (0.6, 0.9, 1, 1)	[0, 0, 0.3, 0.5], [0.3, 0.5, 0.7, 0.8], [0.7, 0.9, 1, 1]	[0, 0, 0.1, 0.1], [0.1, 0.3, 0.7, 0.8], [0.7, 0.9, 1, 1]
4-2-8 - Efficient Water Use	(0, 0, 0.1, 0.4), (0.1, 0.3, 0.6, 0.9), (0.6, 0.9, 1, 1)	[0, 0, 0.3, 0.5], [0.3, 0.5, 0.7, 0.8], [0.7, 0.9, 1, 1]	[0, 0, 0.1, 0.1], [0.1, 0.3, 0.7, 0.8], [0.7, 0.9, 1, 1]
4-2-9 - Gas	(0, 0, 0.1, 0.4), (0.1, 0.3, 0.6, 0.9), (0.6, 0.9, 1, 1)	[0, 0, 0.3, 0.5], [0.3, 0.5, 0.7, 0.8], [0.7, 0.9, 1, 1]	[0, 0, 0.1, 0.1], [0.1, 0.3, 0.7, 0.8], [0.7, 0.9, 1, 1]
4-2-10 - Industrial re-supply potential	(0, 0, 0.1, 0.4), (0.1, 0.3, 0.6, 0.9), (0.6, 0.9, 1, 1)	[0, 0, 0.3, 0.5], [0.2, 0.3, 0.7, 0.8], [0.7, 0.9, 1, 1]	[0, 0, 0.1, 0.2], [0.1, 0.3, 0.7, 0.8], [0.7, 0.9, 1, 1]
4-2-11 - Waste water treatment	(0, 0, 0.1, 0.4), (0.1, 0.3, 0.6, 0.9), (0.6, 0.9, 1, 1)	[0, 0, 0.3, 0.5], [0.2, 0.3, 0.7, 0.8], [0.7, 0.9, 1, 1]	[0, 0, 0.1, 0.2], [0.1, 0.3, 0.7, 0.8], [0.7, 0.9, 1, 1]
Communication	(0, 0, 0.1, 0.4), (0.1, 0.3, 0.6, 0.9), (0.6, 0.9, 1, 1)	[0, 0, 0.3, 0.5], [0.2, 0.4, 0.7, 0.8], [0.7, 0.9, 1, 1]	[0, 0, 0.3, 0.4], [0.2, 0.4, 0.7, 0.8], [0.7, 0.9, 1, 1]
4-2-12 - Telecommunication	(0, 0, 0.1, 0.4), (0.1, 0.3, 0.6, 0.9), (0.6, 0.9, 1, 1)	[0, 0, 0.3, 0.5], [0.2, 0.4, 0.7, 0.8], [0.7, 0.9, 1, 1]	[0, 0, 0.3, 0.4], [0.2, 0.4, 0.7, 0.8], [0.7, 0.9, 1, 1]
4-2-13 - High-speed internet infrastructure	(0, 0, 0.1, 0.4), (0.1, 0.3, 0.6, 0.9), (0.6, 0.9, 1, 1)	[0, 0, 0.3, 0.5], [0.2, 0.4, 0.7, 0.8], [0.7, 0.9, 1, 1]	[0, 0, 0.3, 0.4], [0.2, 0.4, 0.7, 0.8], [0.7, 0.9, 1, 1]

Table 5
Fuzzification process.

Dimension/component/subgroups/indicators	Fuzzification		
	Initial functionality q_0 (μ_L, μ_M, μ_H)	Drop of functionality Δ_q (μ_L, μ_M, μ_H)	Repair time T_r (μ_S, μ_L, μ_{VL})
4 - *Physical infrastructure*	(0,0,0.63)	(0.92, 0.37,0)	(0,0.39,0)
4-1 - *Facilities*	(0,0.67,0.33)	(0.37,0.63,0)	(0.31,0.69,0)
Housing	(0,1,0)	(0.62,0.38,0)	(0,1,0)
Commercial Activities	(0,0.53,0.47)	(1,0,0)	(0.95,0,0)
Services	(0,0.76,0.24)	(1,0,0)	(0.23,0.77,0)
4-2 - *Lifelines*	(0,0,0.76)	(0.92, 0.37,0)	(0.9, 0.1, 0)
Healthcare	(0,0.78,0.22)	(1,0,0)	(0.72,0,0)
Evacuation	(0,0.15,0.85)	(1,0,0)	(1,0,0)
Supplies	(0.36,0.64,0)	(0,1,0)	(0,1,0)
Communication	(0,0.15,0.85)	(0.64,0.82,0)	(0.93, 0.52,0)

Table 6
Fuzzy rule table for T_r of Commercial Activities indicator.

Rule	Economic infrastructure exposure w = 0.75	Distribution commercial facilities w = 0.5	F_{out} [d]	Commercial Activities
1	S[a]	S	1	S
2	S	L[b]	1.4	S
3	S	VL[c]	1.8	L
4	L	S	1.6	L
5	L	L	2	L
6	L	VL	2.4	L
7	VL	S	2.2	L
8	VL	L	2.6	VL
9	VL	VL	3	VL

[a] Short.
[b] Long.
[c] Very Long.
[d] Granularity of the output.

the extend of overlapping of some membership functions does not affect the result of defuzzification. The method first calculates the area under the MFs and within the range of the linguistic variable, then calculates the geometric center of the area as follows:

$$CoA = \frac{\int_{x_{min}}^{x_{max}} f(x) \cdot xdx}{\int_{x_{min}}^{x\ max} f(x)dx} \tag{6}$$

where CoA is the center of area, $f(x)$ is the function that shapes the output fuzzy set after the aggregation process, x stands for the real values inside the fuzzy set support [0,1], and $x_{\min}$ and $x_{\max}$ represent the range of the linguistic variable.

Using the center of gravity method, the recovery time parameter T_R of the *Commercial Activities* indicator is defuzzified as 0.086. The defuzzification of the other indicators and components is done similarly. *Physical Infrastructure* dimension's resilience is given by inferencing the *Physical Infrastructure* functionality and recovery time parameters. The results obtained in terms of fuzzy functionalities and recovery time are listed in Table 7.

The resilience index R of the city of San Francisco is computed as $R = 0.73$. The R is a percentage that reflects the community's response to the earthquake event. That is, a higher R signifies a good response of the community. In this demonstrative example, the

Table 7
Fuzzy functionality and recovery time parameters for *Lifelines* and *Facilities* components and the *Physical Infrastructure* dimension.

Lifelines component	**Parameters**	**Results**
	q_0	0.831
	Δq	0.312
	q_1	0.518
	Tr	0.117
Facilities component	q_0	0.67
	Δq	0.328
	q_1	0.342
	Tr	0.329
Physical Infrastructure dimension	q_0	0.80
	Δq	0.31
	q_1	0.49
	Tr	0.2

obtained value of R corresponds only to the physical infrastructure dimension of the community. To establish a resilience index for a whole community, the functionality and recovery time parameters of other dimensions must be similarly evaluated and combined in the same way the available measures were aggregated.

The loss of resilience of the *Physical Infrastructure* dimension can be computed using the following equation:

$$LOR_{PhysicalInfrastructure} = 1 - R_{PhysicalInfrastructure} = 27\% \quad (7)$$

Finally, the functionality curves for the *Lifelines* and *Facilities* components and the *Physical Infrastructure dimension* are shown in Fig. 15.

From Fig. 15 it is possible to compare the functionality curves of the two components facilities and lifelines. The city of San Francisco shows more problems in facilities than lifelines. It is evident that the *LOR* of facilities is higher than lifelines. In such a case, authorities should focus more on improving facilities by prioritizing activities and choosing proper resilience measures to assure the functionality of their systems and to assign appropriate resources to get resilient communities. Results from the case scenario can be used to pursue the best strategies during the planning and management post-disaster processes as well as to manage and minimize the impacts of seismic events. The usefulness of having the final resilience metric and a graphical representation is to indicate whether the community needs to improve in terms of resilience by comparing it to a given desirable level. Using the resilience index, the user can establish immediately whether the community has a high functionality deficiency. Furthermore, by looking at the functionality curves, the user can focus on specific components and indicators that have the highest impact on resilience and determine whether the resilience deficiency is caused by a system's lack of robustness or by the restoration process.

The proposed methodology has been verified by comparing the obtained R with the result given by Ref. [22], who analyzed the same case study focusing on the estimation of the loss of resilience *LOR*. The verification phase has been conducted at each level of the framework by calibrating the shape of MFs that strongly impact results. Within the proposed approach, the shape of MFs was first estimated through the authors' opinion and it was designed to be as symmetrical as possible; then the angle points of the MFs were modified little by little to get R, and consequently *LOR*, as similar as possible to the result obtained from the benchmark system [22]. As a result of the calibration, the MFs used in the methodology are neither equivalent nor symmetrical (e.g., the width of the MF "low" may be larger than the width of the MF "high").

It should be noted that focusing on a single resilience index can result in the loss of information about indicators that have resilience deficiencies and should be improved. To manage or improve resilience, close attention should be paid to the individual indicators that influence system resilience to highlight the strengths and weaknesses. In the methodology, this is possible by exploiting the inherent hierarchical-based structure where indicators and components are combined. The application of fuzzy logic to the hierarchical framework enables changing the input values of certain indicators or components (e.g., those that show resilience deficiencies) to update the whole system and improve the resilience accordingly. In addition, the layer-based structure permits performing sensitivity and diagnostic analysis to determine the critical indicators.

5.2. *Case with partial availability of data*

The same case study has been investigated in this section, assuming partial availability of data inputs. A group of experts was asked to provide qualitative information and observations on the missing parameters within the *Physical infrastructure* dimension. The steps described in the previous section to compute the resilience index are implemented in the same manner, except for the fuzzification step. While the fuzzification process is straightforward when numerical inputs are available, qualitative information and descriptive inputs must be converted into fuzzy sets by assigning different linguistic quantifiers (i.e., states). Table 8 lists the indicators whose information is not available and the corresponding transformed values on a range [0 1], which are mainly based on expert knowledge.

Using the transformed values, it is possible to enter the corresponding membership graph and obtain the membership degrees (Fig. 14). The results obtained in terms of fuzzy functionalities and recovery time are listed in Table 9.

The resilience index R of the city of San Francisco in case of less availability of information is computed as $R = 0.53$. The loss of resilience of the Physical Infrastructure dimension can be computed using the following equation:

$$LOR_{PhysicalInfrastructure} = 1 - R_{PhysicalInfrastructure} = 47\% \quad (8)$$

Finally, the functionality curves for the *Lifelines* and *Facilities* components and for the *Physical Infrastructure* dimension are shown in Fig. 16.

The comparison between the functionality curves of the two components facilities and lifelines highlights that the *LOR* of facilities is higher than lifelines, as in the previous case. While the lifelines component performs better, showing a small drop of functionality, the facilities component has a small initial functionality (0.51) and with an additional 27% drop of functionality when the seismic event occurs. Although the obtained R is not the same as that carried out from the case with numerical data, similar results in *LOR* indicate that the proposed methodology can cope with both numerical and descriptive information. Of course, to improve the consistency of the results, more experts could be asked to provide their observations on the data input.

5.3. *Case with no available data*

In this section, the applicability of the proposed fuzzy logic-based method is demonstrated by computing the resilience of the city of San Francisco, focusing on the *Lifestyle and Community competence* dimension. It is assumed that no numerical input is available for evaluating resilience. The list of indicators and components along with observations of functionality and recovery time parameters provided by a group of experts is shown in Table 10.

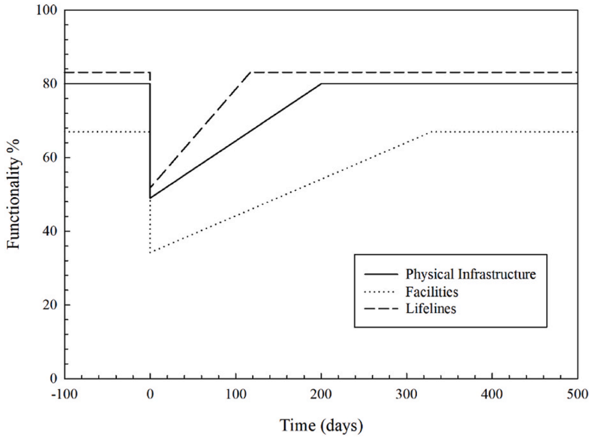

Fig. 15. Functionality curves of components *Facilities* and *Lifelines* under the dimension *Physical Infrastructure*.

Table 8
Indicators within the *Physical Infrastructure* dimension and the corresponding transformed values.

Indicators	Parameters	Field of observation	Transformed values
Sturdier housing types	q0	Medium	0.55
	Dq	Low	0.07
	Tr	Short	0.22
Economic infrastructure exposure	q0	Medium	0.6
	Dq	Medium	0.45
	Tr	Short	0.1
Community services	q0	High	0.78
	Dq	Medium	0.43
	Tr	Short	0.28
Medical care capacity	q0	Medium	0.65
	Dq	Low	0.19
	Tr	Long	0.39
Transportation	q0	High	0.88
	Dq	Low	0.15
	Tr	Long	0.55
Telecommunication	q0	Medium	0.7
	Dq	Medium	0.68
	Tr	Short	0.09

Table 9
Fuzzy functionality and recovery time parameters for *Lifelines* and *Facilities* components and the *Physical Infrastructure* dimension in case of less availability of data.

Lifelines component	**Parameters**	**Results**
	q_0	0.84
	Δq	0.503
	q_1	0.337
	Tr	0.108
Facilities component	q_0	0.51
	Δq	0.27
	q_1	0.24
	Tr	0.50
Physical Infrastructure dimension	q_0	0.81
	Δq	0.032
	q_1	0.778
	Tr	0.142

Step 1: Resilience modeling and indicators grouping.

The hierarchical framework of the analyzed dimension is depicted in Fig. 8. The indicators are clustered in 3 subgroups following the PEOPLES structure: Abilities, Neighborhood, and Security. In every subgroup, indicators and components are combined through fuzzy rules to obtain the resilience output.

Step 2: Interdependency analysis and importance factors.

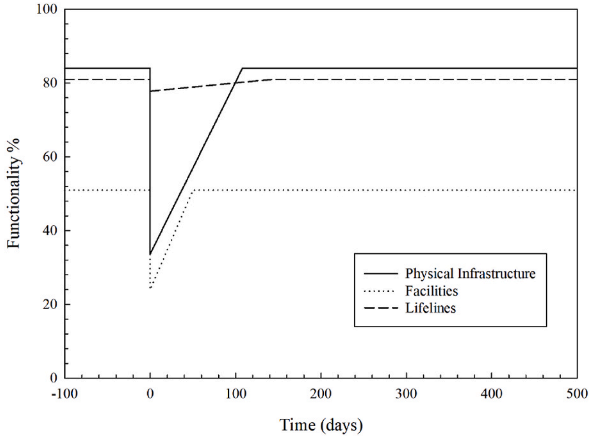

Fig. 16. Functionality curves of components *Facilities* and *Lifelines* under the dimension *Physical Infrastructure in case of less availability of data.*

Table 10
Functionality parameters of indicators within the *Lifestyle* and *Community competence* dimension.

Dimension/component/subgroups/indicators	Measure	I	Nat.	q0	Dq	Tr
5 – *Lifestyle and community competence*						
5-1 – *Collective action and decision making*						
5-1-1 – Authorities interdependency	Less than three parties are involved in the decision-making (1) otherwise (0)	2	S	Medium	Low	Short
5-2 – *Collective efficacy and empowerment*						
5-2-1 – Creative class	Percentage of workflow employed in professional occupations divided by TV	3	S	High	Medium	Very long
5-2-2 – Scientific services	Professional, scientific, and technical hours services per population divided by TV	2	S	Low	Low	Long
5-3 – *Quality of life*						
5-3-1 – Means of transport	Percentage of households with at least 1 vehicle	2	S	High	Low	Long
5-3-2 – Safety	1 crime rate	2	D	Medium	Low	Short
5-3-3 – Quality of homes	Sustainability rating systems (LEED, BREEAM) divided by maximum index number	3	S	High	High	Long
5-3-4 – Quality of neighborhood	Sustainability rating systems (LEED, BREEAM) divided by maximum index number	4	S	Low	Medium	Short

Table 11
Interdependency matrix between indicators under the *Quality of life* and *Collective actions and efficacy* components.

Indicator	Authorities Interdependency	Creative class	Scientific services	Means of transport	Safety	Quality of homes	Quality of neighborhood
Authorities Interdependency	1	0	0	0	0	0	0
Creative class	1	1	1	0	0	0	0
Scientific services	0	1	1	0	0	0	0
Means of transport	0	0	0	1	1	0	1
Safety	0	0	0	1	1	1	1
Quality of homes	0	0	0	0	0	1	1
Quality of neighborhood	0	1	0	0	0	1	1
Importance factor	2	3	2	2	3	4	4

The weighting factors of the different variables under the *Lifestyle and community competence* dimension are defined through the interdependency matrix technique. The interdependency matrix of the indicators within the Quality of life and Collective actions and efficacy components is determined in Table 11.

Weighting factors for indicators and components under the Lifestyle and Community competence dimension are carried out through Eq. (1) (see Table 12).

Step 3: Inference – Fuzzy logic.

As mentioned above, qualitative observations must be converted into fuzzy numbers on a range [0 1] to obtain the membership degrees. The indicators and the corresponding transformed values are depicted in Table 13.

Inference of indicators and components is made following the relationships between the variables provided in the hierarchical model. Finally, the *Lifestyle and Community competence*'s resilience index is given by inferencing the *Lifestyle and Community competence*

Table 12
Weighting factors of variables within the *Lifestyle and Community competence* dimension for city of San Francisco.

Component/Indicator	W
5.1 Collective action and decision making	0.5
Abilities	
5.1.1 Authorities interdependency	0.5
5.1.2 Creative class	0.75
5.1.3 Scientific services	0.5
5.2 Quality of life	1
Security	
5.1.4 Means of transport	0.5
5.1.5 Safety	0.5
Neighborhood	
5.1.6 Quality of home	0.75
5.1.7 Quality of neighborhood	1

Table 13
Indicators within the *Lifestyle* and *Community competence* dimension and the corresponding transformed values.

Authorities' interdependency	q0	Medium	0.55
	Dq	Low	0.25
	Tr	Short	0.04
Creative class	q0	High	0.75
	Dq	Medium	0.62
	Tr	Very long	0.95
Scientific services	q0	Low	0.02
	Dq	Low	0.14
	Tr	Long	0.45
Means of transport	q0	High	0.88
	Dq	Low	0.15
	Tr	Long	0.55
Safety	q0	Medium	0.47
	Dq	Low	0.023
	Tr	Short	0.11
Quality of homes	q0	High	0.95
	Dq	High	0.89
	Tr	Long	0.77
Quality of neighborhood	q0	Low	0.23
	Dq	Medium	0.5
	Tr	Short	0.14

Table 14
Fuzzy functionality and recovery time parameters for *Quality of life* and *Collective actions and efficacy* components and the Lifestyle and c*ommunity competence* dimension.

Quality of life component	**Parameters**	**Results**
	q_0	0.54
	Δq	0.51
	q_1	0.003
	Tr	0.523
Collective actions and efficacy component	q_0	0.817
	Δq	0.312
	q_1	0.505
	Tr	0.52
Lifestyle and community competence dimensiont	q_0	0.6
	Δq	0.523
	q_1	0.077
	Tr	0.54

functionality and recovery time parameters. The results obtained in terms of fuzzy functionalities and recovery time are listed in Table 14.

The resilience index R corresponding to the community's *Lifestyle and Community Competence* dimension is computed as $R = 0.45$ and the loss of resilience is estimated as 55%. Finally, the functionality curves for the components within the *Lifestyle and community competence* dimension are depicted in Fig. 17. Results show that the *Quality of life* component must be enhanced to improve the resilience index.

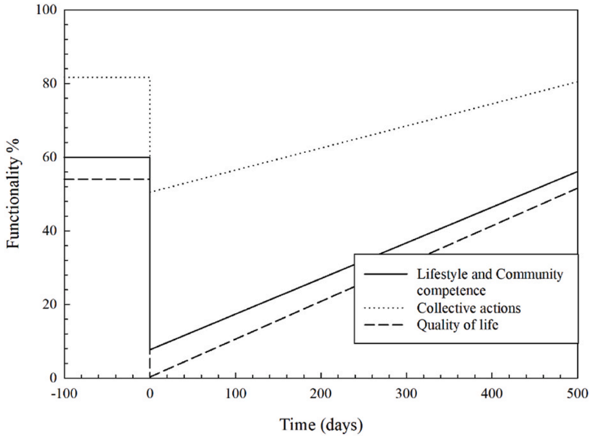

Fig. 17. Functionality curves of components within the Lifestyle and Community competence dimension.

6. Sensitivity analyses

6.1. Sensitivity analysis of fuzzy membership functions

A sensitivity study is conducted in this work to perform a series of different simulations per type of MF to reduce the subjectivity in the choice of MFs and identify the best result in terms of resilience. Such a sensitivity analysis allows understanding how the variation in the shape of the MFs affects the system's overall effectiveness. It is performed by repeating the whole fuzzy inference procedure of the *Lifestyle and Community competence* dimension while varying only the MFs (triangular, trapezoidal, and Gaussian MFs) while keeping all the other features, thus performing three different simulations. From each of the three simulations performed, information concerning the resilience output (i.e., the. resilience index) is obtained. The membership function parameters are specified in Fig. 18.

By analyzing the results, it is possible to conclude that the choice of MFs is not extremely sensitive to the final resilience output (trapezoidal 0.45, triangular 0.50, and Gaussian 0.46). Hence, it is reasonable to assume any MF.

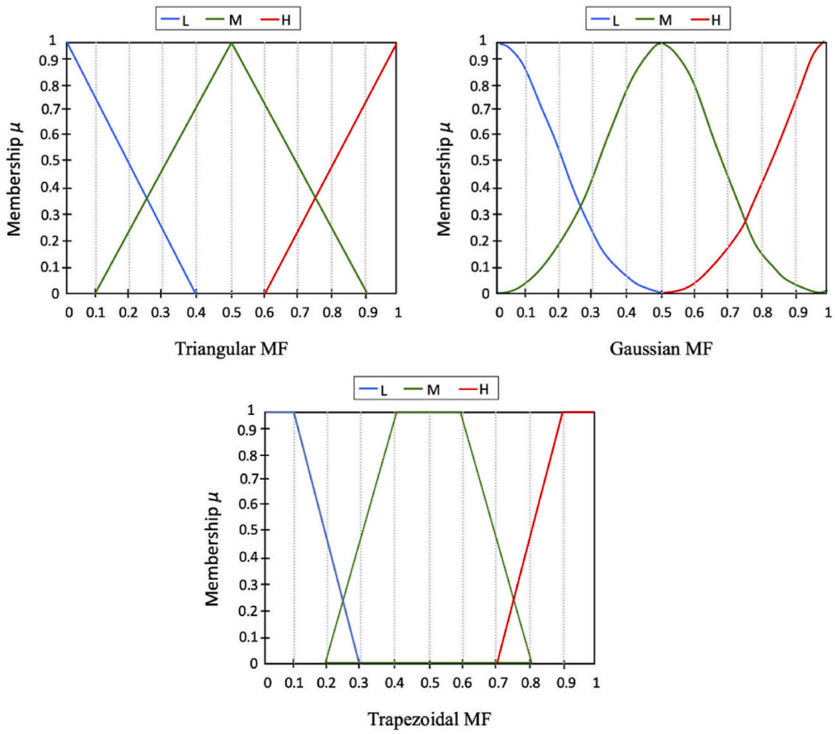

Fig. 18. Membership functions adopted in the sensitivity analysis.

Table 15
Comparison of the defuzzification methods.

	Defuzzification method	Output (Resilience)
1	COG	0.45
2	BOA	0.475
3	MOM	0.42
4	LOM	0.60
5	SOM	0.30

6.2. Sensitivity analysis of defuzzification methods

Five different defuzzification methods were employed in the analysis of *Lifestyle and Community competence* dimension to compare their applicability in terms of the output result (i.e., resilience index). These included Center of Gravity (COG), Mean of Maximum (MOM), Largest of Maximum (LOM), Smallest of Maximum (SOM), and Bisector of Area (BOA). Details of defuzzification methods can be found in Refs. [59,73]. Five simulations were performed, varying only the defuzzification method. Results are summarized in Table 15.

Based on the results, the centroid, bisector, and mean of maximum defuzzification methods generate approximately the same results of resilience index (i.e., the percentage difference between COG and BOA is 5.4%, between COG and MOM is 6.8, and finally between BOA and MOM is 12.3%); the largest of maximum method generates maximum results (i.e., 0.60), while the smallest of maximum method generates the minimal resilience value (i.e., 0.30). As pointed out by Zadeh [48], there is no general defuzzification method that can give satisfactory performance, and the choice of the best defuzzification techniques is context or problem-dependent [59]. Although the largest of maximum method is most convenient as it provides higher values of resilience, and consequently smaller values of loss of resilience, it may be not always realistic. That is, the main shortcoming of the maxima defuzzification methods is that the defuzzified value depends only on extreme values of membership and all the other values are not accounted for. Instead, using the center of gravity method, all set of membership is accounted for. Therefore, it has been preferred in this work. Details analyses of various defuzzification strategies are presented in Ref. [71].

7. Conclusion

The recent disasters worldwide have demonstrated that resilience is the solution to cope with natural and man-made threats. This paper presents a holistic framework for evaluating community resilience in response to a catastrophic event. The proposed methodology benefits from the structure of the PEOPLES framework for its implementation and deals with the complexity and vagueness that characterizes processes where human intervention is significant by implementing fuzzy logic theory.

A general indicator-based resilience model to estimate the resilience index of communities is proposed. The resilience assessment can be easily adapted to any communities of different sizes and types by changing the values of the indicators. The fuzzy logic inference method is utilized within the resilience assessment model to deal with potential uncertainties. Since indicators do not contribute equally to the resilience assessment, the contribution of every indicator towards resilience has been determined through a proposed interdependency analysis.

To illustrate the applicability of the resilience assessment model, three cases with different degrees of uncertainty are introduced. The considered hazard event is the earthquake that struck the city of San Francisco on October 17, 1989, with a magnitude of 6.0 on the Richter scale. The first case with available numerical data was used to verify the proposed methodology by comparing the model output with the result of [22], who proposed a methodology to treat the PEOPLES framework as a quantitative model by analyzing the same case study. Although Kammouh et al. [22] proposed a data-extensive methodology that requires precise input data, they succeeded in applying the methodology to the case study of San Francisco through the collection of all needed data. Therefore, their reliable results have been used for calibration and verification in this work. The fuzzy-based resilience assessment was verified by calibrating the membership functions of fuzzy sets to obtain a resilience index that approximates that of the benchmark system. Therefore, the obtained resilience index depends on the decisions made during the design of the fuzzy inference system. This is unavoidable since the main feature of fuzzy logic is to rely on expert judgment. Nevertheless, sensitivity analyses conducted on the membership functions and defuzzification methods have shown that they do not have a high impact on the final output in the proposed resilience estimation model.

Results have demonstrated that the proposed approach can cope with both numerical and descriptive inputs with different uncertainty levels; it is consistent with the existing evaluations in the literature and can be easily applied to large communities. Of course, the proposed methodology would yield less accurate results since it relies on expert judgments rather than actual data, as it is evident in the second case. This can be partially addressed by asking multiple experts. When data does not exist (which is often the case in the aftermath of a disaster), the proposed methodology should be used to plan for future events.

The results from the proposed framework are suitable for assisting decision-makers, planners, and engineers to assess and learn from the resilience of their communities against a particular event. It is worth noting that paying attention to a single resilience index alone sometimes causes system managers to lose information about the indicators that suffer from resilience deficiencies and need improvements. Therefore, paying attention to the factors influencing system resilience can bring out the strengths and weaknesses of system resilience in either the technical or organizational domain. It helps managers identify the area of the system that is more sensitive and requires more attention. Consequently, they can make a more detailed assessment and implement improvement strategies.

Future work will focus on applying the proposed approach by considering all dimensions of PEOPLES as more reliable data become available.

Credit author statement

Melissa De Iuliis: Writing – original draft, Methodology, Software, Verification. **Omar Kammouh**: Conceptualization, Supervision, Writing – review & editing. **Gian Paolo Cimellaro**: Supervision, Writing – review & editing, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

Functionality parameters of indicators within Physical Infrastructure dimension of the San Francisco city. The reported values are retrieved from [22].

Dimension/component/ subgroups/indicators	Measure	*Nat.*	q_{0u}	*TV*	q_0	q_1	Δq	T_r	*Tr Norm.*
4 - *Physical infrastructure*									
4-1 - *Facilities*									
Housing									
4-1-1 - Sturdier housing types	% Housing units not manufactured homes	D	1	1	1	0,599	0401	120	0,11
4-1-2 - Temporary housing availability	% Vacant units that are for rent	D	2,68	5	0,536	0,05	0,486	620	0,57
4-1-3 - Housing stock construction quality	100-% Housing units built prior to 1970	D	0,241	1	0,241	0145	0,096	700	0,64
Commercial Activities									
4-1-4 - Economic infrastructure exposure	% Commercial establishments outside of high hazard zones ÷ total commercial establishment	S	0,85	1	0,850	0850	0	–	
4-1-5 - Distribution commercial facilities	% Commercial infrastructure area per area ÷ TV	D	0,3	0,15	0,867	0520	0,347	160	0,15
Services									
4-1-6 - Community services	% Area of community services (recreational facilities, parks, historic sites, libraries, museums) total area ÷ TV	D	0,16	0,2	0,800	0480	0,320	430	0,39
4-1-7 - Hotels and accommodations	Number of hotels per total area ÷ TV	D	102	128	0,797	0478	0,319	130	0,12
4-1-8 - Schools	Schools' area (primary and secondary education) per population ÷ TV	D	134	140	0,957	0574	0,383	90	0,08
4-2 - *Lifelines*									
Healthcare									
4-2-1 - Mental health support	Number of beds per 100000 population ÷ TV	D	69	75	0,920	0644	0,276	35	0,03
4-2-2 - Medical care capacity	Number of available hospital beds per 100000 population ÷ TV	D	544	600	0,907	0635	0,272	35	0,03
4-2-3 - Physician access	Number of physicians per population ÷ TV	S	2,5	3	0,833	0833	0	–	–
Evacuation									
4-2-4 - Access and evacuation	Principal arterial miles per total area ÷ TV	D	172138	2E+05	0,861	0602	0,259	45	0,04
4-2-5 - Transportation	Number of rail miles per area ÷ TV	D	5412	6000	0,902	0631	0,271	72	0,07
4-2-6 - Evacuation routes	Major road agrees points per building ÷ TV	S	0,67	1	0,670	0670	0	–	–
Supplies									
4-2-7 - Efficient energy use	Ratio of Megawatt power production to demand	D	1	1	1	0,240	0760	25	0,02
4-2-8 - Efficient Water Use	Ratio of water available to water demand	D	1	1	1	0,240	0760	60	0,05
4-2-9 - Gas	Ratio of gas production to gas demand	D	0,1	1	0,100	0050	0,050	70	0,06
4-2-10 - Industrial re-supply potential	Rail miles per total area ÷ TV	D	5412	6000	0,902	0631	0,271	45	0,04
4-2-11 - Waste water treatment	Number of WWT units per population ÷ TV	D	3	4	0,750	0300	0,450	65	0,06

(*continued on next page*)

(*continued*)

Dimension/component/ subgroups/indicators	Measure	*Nat.*	q_{0u}	*TV*	q_0	q_1	Δq	T_r	*Tr Norm.*
Communication									
4-2-12 - Telecommunication	Average number of internets, television, radio, telephone, and telecommunications broadcasters per household ÷ TV	D	5	6	0,833	0500	0,333	90	0,08
4-2-13 - High-speed internet infrastructure	% Population with access to broadband internet service	D	0,9	1	0,900	0450	0,450	300	0,25

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