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ORIGINAL PAPER

A fuzzy social vulnerability evaluation from the perception of disaster bearers against meteorological disasters

Mei Cai[1,2] · **Guo Wei**[3]

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Abstract

Because of climatic hazards and extreme weather events, meteorological disasters attract more and more attention of government, national, and international agencies. Every event tests people's ability to cope with meteorological disasters and generates the need for disaster risk research and assessments. Social vulnerability is an important measure of disaster risk assessments. Social vulnerability assessment problem can be viewed as a multi-criteria decision-making problem. In order to satisfy the perception of special disaster bearers, we need a local-context approach to construct a social vulnerability evaluation index system. The key to this approach is to identify the evaluation criteria structure by analyzing the complicated information gathering from special disaster bearers. It's natural to use fuzzy language to express disaster bearers' preferences in a complicated context. This paper attempts to describe the interrelationship between the evaluation factors with linguistic preferences since linguistic variables can better reflect the vagueness of human being. The fuzzy interpretive structural modeling (FISM) approach has been employed to develop the structural relationship between social vulnerability evaluation factors. In FISM, we apply some computational models of computing with words to quantify the fuzzy interrelationship. Finally, we give an example to show the process of our method.

Keywords Social vulnerability · Disaster bearers · Fuzzy interpretive structural modeling (FISM) · Linguistic variables

✉ Mei Cai
caimei@nuist.edu.cn

[1] Key Laboratory of Meteorological Disaster (KLME), Ministry of Education and Collaborative Innovation Center on Forecast and Evaluation of Meteorological Disasters (CIC-FEMD), Nanjing University of Information Science and Technology, Nanjing, China

[2] School of Management Science and Engineering, Nanjing University of Information Science and Technology, Nanjing 210044, China

[3] Department of Mathematics and Computer Science, University of North Carolina At Pembroke, Pembroke, NC 28372, USA

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1 Introduction

Extreme weather events often lead to meteorological disasters. Take the disaster of southern China in 2008 as an example. This disaster was caused by low temperature, frost and snow. It blocked several provinces' highway traffic. The economic loss was serious. A total of 162 people died of this disaster (National Bureau of Statistics, 2009). Meteorological disasters occur globally with increasing frequency. Extreme weather events test the ability of government, national, and international agencies to cope with meteorological disasters and generate the needs of disaster risk research and assessments. In the past decades, many innovative approaches have been applied to disaster risk research and assessments. Disaster risk research and assessments become across disciplinary domains. Traditional disaster risk assessment often only compares disasters from the aspect of the dollar value of potential losses or impacts (Zhang 2004). Those studies would like to use climatic indices such as precipitation to make simulation models of risk assessment. The main difference between previous research and the new disciplinary research is that policymakers and researchers pay more attention to understand the perception of human wellbeing to meteorological disasters. So, it is necessary to integrate social science and artificial intelligence into meteorological research.

When the government is required to make effective preparedness, response actions, and adaptation plans, it is the first step to assess social vulnerability. Although disaster bearers may experience a similar natural hazard, they have a different perception of the same natural hazard. Because of the different human perception and the different abilities to handle the hazard, the respond and result of meteorological disasters are quite different. The vulnerability of hazard bearing body is closely related to human factors. The characteristics of disaster bearers can worse some not serious natural phenomena into serious disasters (Montz and Gruntfest 2002). Therefore, the study on social vulnerability is a meaningful subject according to the differences in hazard bearing body. Introducing interdisciplinary approaches into evaluating the social vulnerability of hazard bearing body is the key to the research.

Social vulnerability research shows social vulnerability is a consequence of human behavior. It's the inability of people or society when they have to suffer multiple stressors. Researchers desire to propose new tools to understand the characteristics of social vulnerability because society is a complex item. Olga and Mary (2010) suggested that vulnerability may vary differently among neighborhoods. Morss (2010) analyzed a flooding disaster and combined physical and social indicators together into vulnerability assessments. Olga and Mary (2010) used a GIS-based methodology to access vulnerability, which integrated meteorological and social characteristics. Depietri et al. (2013) considered a range of social and ecological variables into the assessment of social vulnerability and got good result. A set of indicators which is used to measure the multi-dimensional aspects of social vulnerability was proposed by the Spanish Red Cross in 2005. Although some researchers began to realize the importance of social and behavioral aspects, we still need to characterize and quantify social vulnerability indicators from the perception of disaster bearers.

In another hand, how to use these indicators to form an evaluation system which can reflect the difference of geographic locations and local contexts is still a difficult problem. Some approaches (Bello-Orgaz et al. 2016; Chen et al. 2013) tried to integrate vulnerability indicators across disciplinary domains. Some quantification method of evaluating vulnerability indexes based on the AHP method is proposed. Generally, social vulnerability is a relative measure among regions, and the relations among these indicators are too complex to objectively assess. The regional disaster bearers must be involved in the process of establishing an evaluation system.

Above analysis tell us local-context social vulnerability is more and more important in the future because the hazard bearing body is special in a different circumstance. So, at least two aspects deserve further improvement when we assess social vulnerability. The first one is how to represent and clear the complicated relation among vulnerability indicators. The second one is how to represent ambiguous information in the process of social vulnerability assessment.

To represent the complicated relation among vulnerability indicators. We need to construct a local-context evaluation criteria system. Some useful tools were proposed to identify the evaluation criteria structure, such as Interpretive Structural Modeling (ISM) (Agarwal et al. 2007; Chidambaranathan et al. 2009). Ravi and Shankar (2005) used the ISM tool to solve the vendor selection problem considering the interaction between attributes. Govindan et al. (2012) adopted the ISM methodology to solve the third-party logistics provider selection problem.

The other key point is to make decision makers express their opinions easily. Traditionally, a decision maker needs to consider several factors when assessing social vulnerability. The numerical expression of social vulnerability measurement cannot accurately reflect the real decision environment. Some approaches using only exact numerical values cannot satisfy the needs of establishing a multiple evaluation criteria structure. Primarily based on human's fuzzy thinking, decision makers' preferences are uncertain and inaccurate. Fuzzy set theory is a nice tool to solve such problems. When we attempt to qualify human's concept or perception, the natural language may be used instead of numerical values. Maybe the perception does not need high accuracy. The linguistic variable is a good tool to approximate human activities (Herrera et al. 2009). Xu et al. (2018) applied linguistic preference relations into the decision-making process of earthquake shelter selection problem. Some models (Liu et al. 2019a, b; Xu et al. 2019) to optimize the consensus reaching process for fuzzy relations in decision-making problems were also proposed.

In this paper, we simplify social vulnerability assessment as a multi-criteria decision-making (MCDM) problem and try to analyze it deeply. Since the complexity of social vulnerability assessment, we only study the formulation of criteria structure of MCDM. We assume the criteria structure is a hierarchical structure. When the number of factors becomes large, it is difficult to manage those factors and their importance. We intend to define some ways to deal with subjective human judgments and try to transform them into some well-defined factors. We apply ISM based on linguistic variables to form the criteria structure of assessing social vulnerability process. FISM based on linguistic variables is proposed in this paper. The rest of this paper is organized as follows. In Sect. 2, we present a brief review of linguistic variables and ISM. Section 3 constructs a theoretical framework of a local-context social vulnerability evaluation against meteorological disasters. In Sect. 4, we provide a FISM based on linguistic variables. Further, the procedure and algorithm of FISM in criteria formulation stage are given. A numerical example is also shown in Sect. 4. And finally, some concluding remarks are included in Sect. 5.

2 Preliminaries

A. Representation of linguistic variables

In real world, human beings often provide their knowledge or preferences with uncertain information. Under most situations, any uncertainty can be represented as a probabilistic distribution. However, it becomes more common than before that uncertainty has a non-probabilistic nature. Linguistic variables provide tools to model and manage such uncertainty (Zadeh 1975b). Linguistic computational models are important techniques of computing with words which are first proposed by Zadeh (1996). CWW (Mendel et al. 2010; Zadeh 1996) as the methodology for reasoning, computing is very important for overcoming precise computing paradigm's limitations. CWW has been used to solve some kinds of decision problems for reducing the gap between human reasoning and computing.

Conventional systems of computation do not have the capability to deal with linguistic valuations (Mendel et al. 2010). All these researches mean that words would be converted into a mathematical representation.

The concept of linguistic variables is proposed by Zadeh (Zadeh 1975a, b, c). Representation model needs to make the translation between human beings and computers. There are two ways to bridge the gap in man–machine communication. One is to structure a map between linguistic information and fuzzy sets, which is called the extension principle. The other is to structure a map between linguistic information and the indexes of the linguistic terms which is called symbolic computational model (Herrera and Martinez 2000). Because the second one is easy to understand, the symbolic computational model has been accepted widely. We define the linguistic labels $S = \{s_0, s_1, \dots, s_g\}$ with $s_0 < s_1 < \cdots < s_g$ to represent a vague concept, as shown in Fig. 1.

In this paper, we will use linguistic information whose semantics are shown in Fig. 1 for modeling preferences evaluations. In the following analysis, we will apply symbolic computational model into our local-context evaluation criteria system.

B. Operational laws based on the symbolic computational model

The symbolic models discard fuzzy sets and membership functions, which make computations directly on the indexes or symbols of the linguistic labels. Herrera and Martinez (2000) defined linguistic 2-tuple which is a kind of symbolic representation model. Let $S = \left\{s_0, s_1, \dots, s_g\right\}$ be a linguistic term set. Linguistic variables (s_i, α) can be translated to a value $\beta \in [0, g]$. The translation and retranslation functions are as follows (Herrera and Martinez 2000):

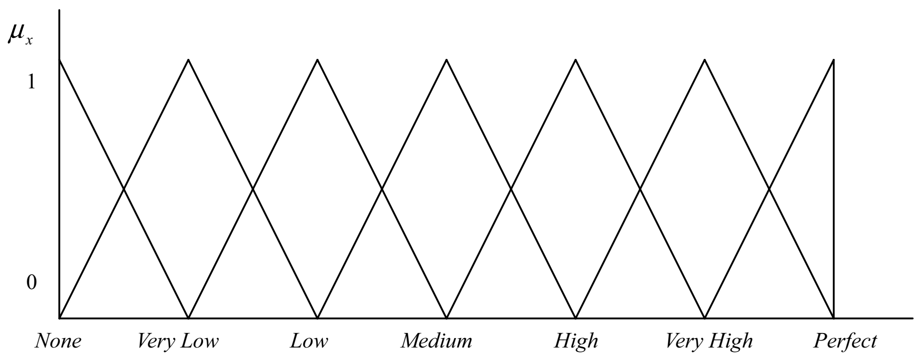

Fig. 1 A set of seven terms with their semantics

$$\Delta : [0, g] \rightarrow S \times [-0.5, 0.5),$$
$$\Delta(\beta) = (s_i, \alpha), \text{with} \begin{cases} s_i, & i = round(\beta) \\ \alpha = \beta - i \end{cases} \tag{1}$$

$$\begin{aligned} &\Delta^{-1} : S \times [-0.5, 0.5) \rightarrow [0, g] \\ &\Delta^{-1}(s_i, \alpha) = i + \alpha = \beta \end{aligned} \tag{2}$$

Because of the function (1) and (2) constructing a relationship between numerical values and 2-tuples. Based on this form, some aggregation operators are proposed.

Wang and Hao (2006) proposed the concept of proportional 2-tuple, which is represented as $(\alpha s_i, (1-\alpha)s_{i+1}) \in \overline{S}$. They also gave the functions of constructing a relationship between numerical values and proportional 2-tuples.

$$\pi(\alpha s_i, (1-\alpha)s_{i+1}) = i + (1-\alpha) \tag{3}$$

$$\pi^{-1}(x) = ((1-\beta)s_i, \beta s_{i+1}) \tag{4}$$

where $i = E(x)$, E is the integral part function, $\beta = x - i$.

In the literature, many types of characteristic values have been used to present linguistic variables. We can see these defuzzification types are also symbols of linguistic variables. Now we list some useful defuzzification forms (Wang and Hao 2006):

(1) *Expected value*

$$EV(s_i) = \frac{a+b+c}{3} \tag{5}$$

(2) *Center of gravity*

$$\mathrm{COG}(s_i) = \int_{\mathrm{R}} x\mu(x)\mathrm{d}x \Big/ \int_{\mathrm{R}} \mu(x)\mathrm{d}x \tag{6}$$

(3) *Mean of maxima.*

$$MeOM(s_i) = b \tag{7}$$

Here, we assume $\mu(x)$ is the membership function of the linguistic variable. The linguistic variable is presented as a triangular fuzzy number which is denoted as (a, b, c).

In addition to the above, Xu (2004) proposed the concept of virtual linguistic terms. (Cai et al. 2014); Dong et al. (2009) extended the 2-tuple representation models and gave another presentation form called the numerical scale (*NS*). These models have received a quite good acceptation, and some applications to decision making have been researched (Fan and Liu 2010; Gong et al. 2013; Liu et al. 2010; Martinez and Herrera 2012; Martinez et al. 2010; Porcel and Herrera-Viedma 2010; Wei 2010). The range of symbolic computational model's applications in decision making is quite wide.

C. Interpretive structural model

ISM methodology is a useful tool to cope with complicated MCDM process. Distinguishing from a mere aggregation of criteria, ISM is a system which is represented by a graph.

The various steps of an ISM are summarized from (Ansari et al. 2013) and Govindan et al. (2012):

- *Step 1* Factors are listed. We can brainstorm a list of the exhaustive and sufficient list of parameters under consideration by most influential individuals in the company. Brainstorming, experience, and knowledge are useful tools to identify factors.
- *Step 2* Contextual relationship among factors is established. Pairs of factors would be examined.
- *Step 3* A Structural Self-Interaction Matrix (SSIM) is constructed based on the result of step 2. Factors are listed with tree shape form.
- *Step 4* Reachability matrix is developed from step 3. Check the transitivity of SSIM.
- *Step 5* The reachability matrix obtained from Step 4 is partitioned into different levels.
- *Step 6* A digraph graph is obtained. Remove the transitive links which are shown in the above reachability matrix.
- *Step 7* Identify the importance of criteria, after the ISM digraph is built.

3 A theoretical framework of social vulnerability evaluation from the perception of disaster bearers

A. Introduction and motivation

Social vulnerability is a subjective concept. Margolis (1994) called the mental states and processes as representational theory of mind (RTM). To deeply understand RTM, two points need to be made. The first one concerns the properties of representations; the second one concerns the conceptual structure or relation of these properties. These semantic properties are difficult to understand. And the perception of natural hazards and disasters involves intuitive judgments, beliefs, and attitudes of people. The subjective nature of the perception of natural hazards influences people's decisions. Many factors and their mutual interactions affect the perception of natural hazards. Disaster bearers are mostly composed of non-experts. When people make choices, their behaviors are largely dependent on their perceptions. People's attitude to risk may be different. Someone may be risk-on, and others may be risk-off. Their different attitudes towards risk are also needed considering. That's the two main reasons why we evaluate social vulnerability evaluation from the perception of disaster bearers.

The different perception of disaster bearers can be reflected through evaluation indicators. Indicators used to evaluate social vulnerability varied because indicators which are good for one setting may not be appropriate in another (Rygel et al. 2006). The importance of the differences among disaster bearers is not recognized seriously. Individuals' responses to risk are subjective. That is why the same hazard can lead to a different loss in different regions. It is critical for translating an inexplicit concept into a visual and explicit evaluation framework. In this section, we exploit a practical tool that can be used for accessing social vulnerability, considering the subjectivity of disaster bearers.

B. Construction of social vulnerability evaluation index system

Social vulnerability can be measured from three perspectives (Cardona 2011; Wilhelmi and Morss 2013):

(a) *exposure* the susceptibility of human settlements and environment to be affected by a dangerous phenomenon;
(b) *sensitivity* predisposition of society and ecosystems to suffer harm resulting from human settlements. It contains environmental sensitivity and ecological frangibility.
(c) *coping capacity* People's ability to cope with disasters and save themselves. This ability is influenced by natural and social conditions.

Social vulnerability is expressed as follows:
Social vulnerability = (exposure; sensitivity; coping capacity).
Some approaches which decompose one dimension into more concrete and readily available factors from different angles and perspectives. The influence of some indicators may more important for some regions than others. So, the unified evaluation index system is not suitable for social vulnerability evaluation. Vulnerability evaluation should be tailored to local conditions, people and society.

Social vulnerability evaluation is a typical MCDM problem. Analytic hierarchy process (AHP), which makes use of hierarchical structure to handle MCDM, can be used to cope with the social vulnerability evaluation process. Identification of evaluation criteria structure is the key problem in AHP. We define the evaluation system as a tree shape with the top indicators (exposure; sensitivity; coping capacity) and the low-level specific sub-indicators of each father indicator. The combinational method of AHP and Interpretive Structural Modeling (ISM) approach is applied here to evaluate the vulnerability.

There are two steps. The first one is to select tailored sub-indictors and assign sub-indictors into several different layers. So, complicated indicators can be organized in a tree shape. The second one is to assign weights to every indicators and sub-indictors, and we can get a global evaluation value of social vulnerability through the aggregating process.

Construction of social vulnerability evaluation index system involves the following steps:

a. Identifying the disaster bearers;
b. Collecting the expression of social vulnerability according to every disaster bearer;
c. Extracting the indicators of expressions and extracting the conceptual structure or relation of these indicators;
d. Selection of unified linguistic set to express disaster bearers' preferences;
e. Identify the relationships among the selected indicators;
f. Forming a local-context criteria structure organized;
g. Using AHP method to aggregate globe evaluation of social vulnerability.

The process is shown in Fig. 2. The most difficult thing is to identify local-context criteria structure in stage e. We will discuss the problem in Sect. 4.

4 Fuzzy interpretive structural modeling in criteria formulation stage for social vulnerability evaluation

A. Local-context criteria structure

Local-context criteria structure is a criteria structure based on the perception of disaster bearers. Because indicators are mainly based on the subjective judgment from different government level (some are experts, some are not), it is difficult to determine indicators

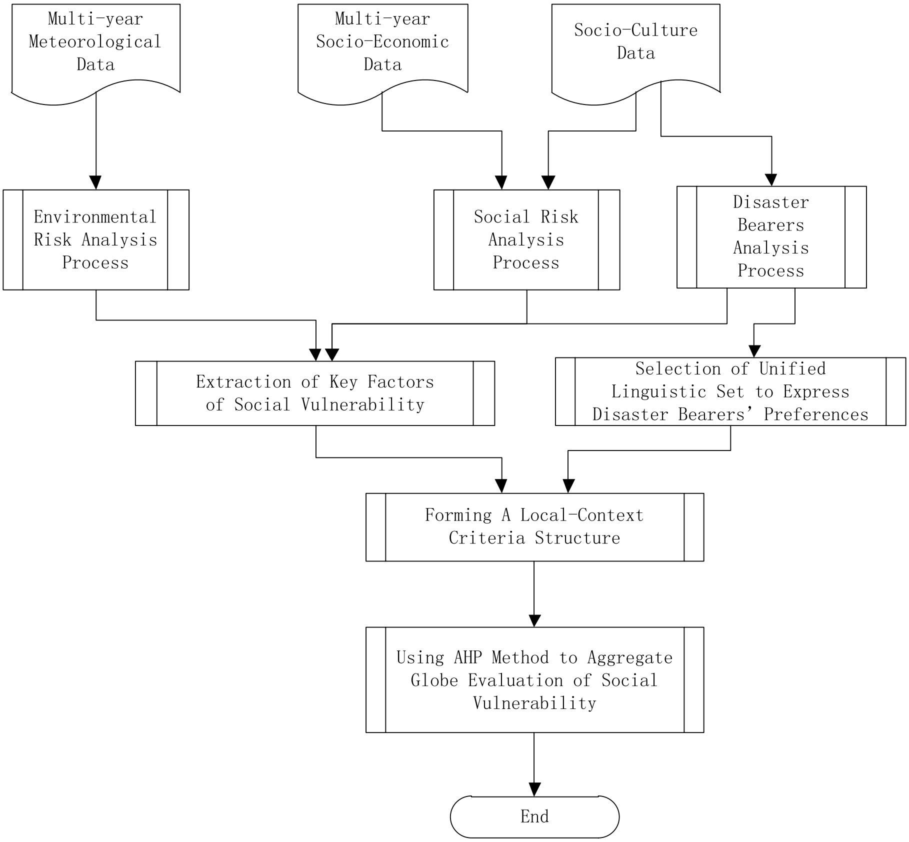

Fig. 2 Process of social vulnerability Evaluation

and the relative relations between indicators, due to the inability and uncertainty of a non-expert to express his/her preferences. So, we need a systematic way to consider what indicators should be put into the hierarchy, what the complicate relations are. We use FISM to get the criteria structure.

Firstly, use brainstorming to obtain all potential indicators. The indicators form a criterion set$C = \{c_1, c_2, \dots, c_n\}$.

Secondly, conduct a questionnaire or interview with non-experts to get the rough relation of all potential indicators. As social and behavioral information is always uncertain, non-experts cannot identify the indicators, not to mention the relationship between them. We ask questions such as "how much indicator c_i affect indicator c_j?" to non-experts. Because they are subjective questions, the linguistic variables can better reflect the vagueness of human being. We assume a set $S = \{s_0, s_1, \dots, s_g\}$ with $s_0 < s_1 < \cdots < s_g$. For example, Fig. 1 shows a set of seven terms. And non-experts can choose some terms to represent their assessments. Triangle membership function which is denoted by (a, b, c) represents a linguistic variable. For analyzing indicators, the linguistic variable $\pi_{ij} \in S$ not only represents a relationship of "leads to", but also means the degree of indicator c_i affecting indicator c_j.

Finally, we use the next subsection to cope with the information gathered in previous steps. We can construct an evaluation criteria structure for MCDM.

B. Fuzzy interpretive structural modeling

Indicators $C = \{c_1, c_2, \dots, c_n\}$ will be analyzed to obtain a hierarchical structure, which shows the interrelationship of the indicators and their levels. For the uncertain indicators as we analyze above, we apply fuzzy logic into ISM which we call FISM. The FISM can help us to obtain a local-context evaluation criteria structure. The major steps are as follows:

1. Constructing a fuzzy structural self-interaction matrix (FSSIM)

We get the FSSIM with linguistic variables. FSSIM can be described as below:

$$\begin{bmatrix} 0 & \pi_{12} & \pi_{13} & \cdots & \pi_{1n} \\ \pi_{21} & 0 & \pi_{23} & \cdots & \pi_{2n} \\ \pi_{31} & \pi_{32} & 0 & \cdots & \pi_{3n} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \pi_{n1} & \pi_{n2} & \cdots & \pi_{n(n-1)} & 0 \end{bmatrix}$$

2. Partitioning the reachability matrix

The relational indicators are converted into binary digits 0 and 1 to get reachability matrix.

Firstly, the linguistic preferences in FSSIM are transformed into 1 or 0 to get the matrix $D = [d_{ij}]_{n \times n}$, according to the following rules:

(1) If $EV(\pi_{ij}) \leq 0.5$, then d_{ij} in the matrix D becomes 0.
(2) If $EV(\pi_{ij}) > 0.5$, then d_{ij} in the matrix D becomes 1.

After constructing the relation matrix with numerical values, we check its transitivity, such as formula (8) and (9) (Huang et al. 2005):

$$M = D + I \tag{8}$$

$$M^* = M^k = M^{k+1} \tag{9}$$

where I is the unit matrix, k denotes the power, and M^* is the reachability matrix.

Then, we calculate the reachability set and the antecedent sets with Eqs. (10), (11) (Warfield 1974).

$$R(e_i) = \{e_i \,\middle|\, m_{ji}^* = 1\} \tag{10}$$

$$A(e_i) = \{e_i \,\middle|\, m_{ij}^* = 1\} \tag{11}$$

where m_{ij} denotes the value of the ith row and the jth column of matrix M^*. Then, according to Eq. (12), the levels and relationships between the elements can be determined.

$$R(e_i) \cap A(e_i) = R(e_i) \tag{12}$$

We use the graph to describe the elements relationships.

3. Identify the importance of criteria

After the FISM digraph is built, we can see the hierarchy clearly. Then we will discuss how to transform relative importance information represented by linguistic labels to numerical weights. Here, we use the symbolic computational model of linguistic labels to solve our problem.

Firstly, we mark every criterion in a hierarchical structure with relative importance information. According to the structure, we construct several subsets to retain the relation information. Subset $A_i = \{c_l, \ldots, c_p\}$ contains the indicators which have a direct relation with indicator c_i. When the criterion c_j is in A_i, π_{ij} describes the contribution of c_j doing to confirm the above level c_i.

Secondly, defuzzify linguistic labels.

Let φ be a defuzzification function of linguistic information π_{ij}. We use expected value of Eq. (5) as the defuzzification function.

$$\phi(\pi_{ij}) = EV(\pi_{ij})$$

Thirdly, get the numerical weights. We give the rule of obtaining the numerical weightings of criteria:

(1) If $\sum_{c_j \in A_i} \varphi(\pi_{ij}) = 1$, we call it linguistic fact, the weight of c_j,$w_j = \varphi(\pi_{ij})$.
(2) If $\sum_{c_j \in A_i} \varphi(\pi_{ij}) > 1$, we call it linguistic overfact, the weight of c_j, $w_j = \varphi(\pi_{ij}) / \sum_{c_j \in A_i} \varphi(\pi_{ij})$.
(3) If $\sum_{c_j \in A_i} \varphi(\pi_{ij}) < 1$, we call it linguistic underfact, the weight of c_j, $w_j = \varphi(\pi_{ij}) / \sum_{c_j \in A_i} \varphi(\pi_{ij})$.

Finally, we get a complete criteria structure. The following work is to get global social vulnerability. Since such techniques are mature, we repeat no more.

C. A numerical example

Suppose a disaster bearer cannot tell the evaluation criteria and their relationships accurately. We will use an ordered linguistic term set$S = \{s_0, s_1, \ldots, s_4\}$, which is represented in Table 1. to answer the question "how much indicator c_i affects indicator c_j with respect to our interests or preferences?" We give the selection criteria in Table 2.

SSIM based on the selection criteria in Table 2 is established according to the information collected from questionnaires of disaster bearer. Then SSIM can be described below.

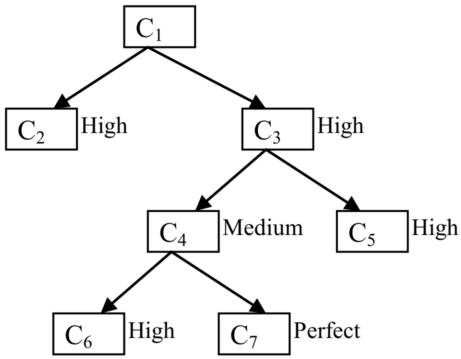

Fig. 3 Criteria structure with linguistic weights

Table 1 The ordered linguistic term set S

Label set S		
s_0	None	(0, 0, 0.25)
s_1	Low	(0, 0.25, 0.5)
s_2	Medium	(0.25, 0.5, 0.75)
s_3	High	(0.5, 0.75, 1)
s_4	Perfect	(0.75, 1, 1)

Table 2 The selection indicators and descriptions of indicators

Selection indicators	Descriptions
c_1 Resistance ability index	It shows the ability to resist meteorological disasters influences
c_2 Emergency plan index	This index is judged by experts and front-line staff
c_3 Emergency goods and materials index	It refers to the ability to deliver the right quantity disaster-relief goods and materials to the disaster bearers at the right time
c_4 Family structure index	Family structure index is about the number of a family and the structure of the family
c_5 Traffic composition index	It is used to evaluate the effect of different means of transport which can directly decide the speed of rescue
c_6 Gender, age and population growth index	It is about the percentage of female-headed household, female, elderly people
c_7 Socioeconomic status and infrastructure index	It is about the percentage of illiterate people. The situation of children aged 15 and above with high education is also shown in this index

Table 3 Interaction of all levels

e_i	$R(t_i)$ Reachability set	$A(t_i)$ Antecedent set	$R(t_i) \cap A(t_i)$ Intersection set	
1	1	1, 2, 3, 4, 5, 6, 7	1	Level 1
2	1, 2	2	2	Level 2
3	1, 3	2, 3, 4, 5, 6, 7	3	Level 2
4	1, 3, 4	4, 6, 7	4	Level 3
5	1, 3, 5	5	5	Level 3
6	1, 3, 4, 6	6	6	Level 4
7	1, 3, 4, 7	7	7	Level 4

Table 4 Defuzzification of linguistic labels

Label set S		Defuzzification
s_0	None	0.08
s_1	Low	0.25
s_2	Medium	0.5
s_3	High	0.75
s_4	Perfect	0.92

$$\begin{bmatrix} - & \text{High} & \text{High} & \text{Low} & \text{Low} & \text{None} & \text{None} \\ \text{None} & - & \text{Low} & \text{Low} & \text{None} & \text{None} & \text{Low} \\ \text{None} & \text{Low} & - & \text{Medium} & \text{High} & \text{None} & \text{None} \\ \text{None} & \text{None} & \text{Low} & - & \text{Low} & \text{High} & \text{Perfect} \\ \text{None} & \text{Low} & \text{None} & \text{Low} & - & \text{Low} & \text{None} \\ \text{Low} & \text{Low} & \text{Low} & \text{None} & \text{None} & - & \text{Low} \\ \text{Low} & \text{Low} & \text{None} & \text{Low} & \text{Low} & \text{Low} & - \end{bmatrix}$$

Matrix D is described as below

$$D = \begin{bmatrix} - & 1 & 1 & 0 & 0 & 0 & 0 \\ 0 & - & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & - & 1 & 1 & 0 & 0 \\ 0 & 0 & 0 & - & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 & - & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & - & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & - \end{bmatrix}$$

After constructing the relation matrix, we can get follows function through formula (8) and (9)

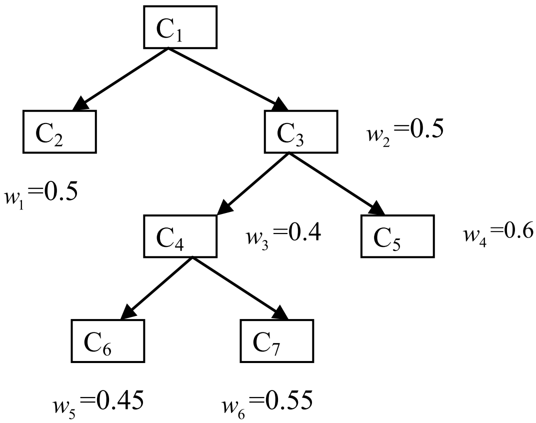

Fig. 4 Criteria structure with numerical weights

$$M^* = M^2 = M^3 = \begin{bmatrix} 1 & 1 & 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}^2 = \begin{bmatrix} 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1 & 1 & 1 & 1 \\ 0 & 0 & 0 & 1 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

The matrix is partitioned, by assessing the reachability and antecedent sets for each variable; see Table 3.

ISM digraph for the indicators selection process is as follows:

Finally, we identify the importance of criteria. Defuzzification of linguistic labels using Eq. (5) can be seen in Table 4.

We obtain the relative weightings of criteria through the rule in the above section (Fig. 3).

$$\begin{aligned} w_1 &= \frac{0.75}{0.75 + 0.75} = 0.5 = w_2 \\ w_3 &= \frac{0.5}{0.5 + 0.75} = 0.4 \\ w_4 &= \frac{0.75}{0.5 + 0.75} = 0.6 \\ w_5 &= \frac{0.75}{0.75 + 0.92} = 0.45 \\ w_6 &= \frac{0.92}{0.75 + 0.92} = 0.55 \end{aligned}$$

The final criteria structure is shown in Fig. 4.

We get a complete criteria structure in Fig. 4. The following work is to get the global value of social vulnerability. There are many sophisticated methods to solve such a problem, nothing more needs to be said on the subject.

5 Conclusion

Most techniques used in social vulnerability evaluation assume the perception of social vulnerability process is explicit, and the evaluation criteria structure is known. But in some situations, the structure is unknown and is difficult to get. We think every social vulnerability process is unique, and every process should satisfy special perception of disaster bearers. So, a local-context criteria structure is necessary. We permit non-experts using linguistic variables to express their vagueness. We deeply analyze the relationship between indicators and construct a local-context evaluation system. We can construct a configuration with weightings to represent the relationships between the criteria, especially when the relationships between the criteria are complicated, and cannot be represented by numbers. This paper proposes a method which combines the methods of the ISM and approaches of computing with words. We also use an example to show the process of our method.

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Compliance with ethical standards

Conflict of interest The authors declare no conflict of interest.

Human and animal rights This article does not contain any studies with human. Participants or animals performed by any of the authors.

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