ORIGINAL PAPER

A fuzzy comprehensive evaluation model for flood risk based on the combination weight of game theory

Chengguang Lai · Xiaohong Chen · Xiaoyu Chen · Zhaoli Wang · Xushu Wu · Shiwei Zhao

Received: 6 September 2014/Accepted: 3 February 2015/Published online: 13 February 2015 © Springer Science+Business Media Dordrecht 2015

Abstract As a result of global warming, the occurrences of floods have increased in frequency and severity. Flooding often occurs near rivers and low-lying areas, which makes such areas higher-risk locations. Flood-risk evaluation represents an essential analytic step in preventing floods and reducing losses. However, the uncertainty and nonlinear relation between evaluation indices and risk levels are always difficult points in the evaluation process. Fuzzy comprehensive evaluation (FCE), an effective method for solving random, fuzzy and multi-index problems, has led to progress in understanding this relation. Thus, in this study, an assessment model based on FCE is adopted to evaluate flood risk in the Dongjiang River Basin. To correct the one-sidedness of the single weighting method, a combination weight integrating subjective weight and objective weight is adopted based on game theory. The evaluation results show that high-risk areas are mainly located in regions that include unfavorable terrain, developed industries and dense population. These high-risk areas appropriately coincide with the integrated risk zoning map and inundation areas of historical floods, proving that the evaluation model is feasible and rational. The results also can be used as references for the prevention and reduction of floods and other applications in the Dongjiang River Basin.

Keywords Flood risk \cdot Fuzzy comprehensive evaluation \cdot Game theory \cdot Analytic hierarchy process \cdot Entropy weight \cdot The Dongjiang River Basin

C. Lai · X. Chen

Center for Water Resources and Environment, Sun Yat-sen University, Guangzhou 510275, China

C. Lai · X. Chen

X. Chen · Z. Wang (🖾) · X. Wu · S. Zhao School of Civil and Transportation Engineering, South China University of Technology, Guangzhou 510641, China e-mail: wangzhl@scut.edu.cn

Key Laboratory of Water Cycle and Water Security in Southern China of Guangdong High Education Institute, Sun Yat-sen University, Guangzhou 510275, China

1 Introduction

Floods are considered to be the most common natural disaster, and they have caused significant economic damage and loss of life worldwide (Eric et al. 2009; Stefanidis and Stathis, 2013). Statistics show that from 1900 to 2013, flooding caused approximately 7 million deaths and losses of more than US \$600 billion worldwide (Disaster Profiles 2013). Although significant effort has been made to reduce the occurrence of such disasters, the loss of lives and properties continues to remain at high levels due to increases in flooding (Alexander 1993; Cui et al. 2002; Pall et al. 2011). Moreover, flooding events are expected to increase in frequency and intensity due to rising sea levels, and due to more frequent and extreme precipitation events (Ramin and McMichael 2009; Stijn et al. 2013). Furthermore, it has been suggested that inadequate land-use policies combined with major human activity on flood plains could increase flood damage due to higher exposure and vulnerability (Jonathan et al. 2013). In China alone, more than two-thirds of the land is classified as flood-risk areas of various types and levels, and the annual economic loss caused by flooding accounts for approximately 3.15 % of the country's total national economic output; approximately 50 % of the population and 70 % of the properties are located in flood-affected zones (Zou et al. 2013). Therefore, flooding has been and will continue to pose major challenges. Within this context, analysing the spatial distribution characteristics of flood risk and evaluating the degree of risk are of paramount importance for flood insurance, floodplain management, flood disaster evacuation, disaster warning, disaster evaluation, flood influence evaluation and the improvement of the public's awareness of flood risk (Jiang et al. 2009).

The flood-risk system theory states that flood-risk evaluation is a synthetic assessment and includes the analysis of three main factors: disaster-inducing factor, hazard-inducing environment and hazard-bearing body (Zou et al. 2013). In general, the disaster-inducing factor is a driving factor in flooding, the hazard-inducing environment provides an easy formation environment for flooding and the hazard-bearing body is affected by the flooding. The disaster-inducing factor and hazard-inducing environment are regularly regarded as 'hazards,' while the hazard-bearing body as regarded as 'vulnerability.' Since flood-risk evaluation is a synthesis involving several variables, multiplicity, complexity, uncertainty and inaccuracy inevitably exist often during the process, which is a worldwide problem of multi-principle and multi-level fuzzy synthetic evaluation (Jiang et al. 2009). Fuzzy comprehensive evaluation, a fuzzy mathematics method, is convenient for expressing and processing random, fuzzy, insufficient or inexact data and other distribution information (Ronald and Robert 1997a, b), and has been applied to risk evaluation (Feng and Luo 2009; Jin et al. 2012; Li 2013). However, the determination of a suitable weight is a significant step in these applications. Subjective weight (SW) and objective weight (OW) both have limitations. For example, SW is strongly affected by expert knowledge as well as many biases, resulting in high subjectivity (Zou et al.). OW does not consider differences among indices, and it ignores practical situations (Jin et al. 2014). Therefore, a combination weight (CW), with the advantages of both SW and OW, should be used to solve the aforementioned problems. Game theory (GT), a mathematical modeling of strategic interaction among rational and irrational agents, specializes in solving conflicts among two or more participants (Wu et al. 2014). SW and OW, analogously, can be regarded as two participants of the game, and CW is the result of the 'weight' game. However, little attention has been paid to the concept of GT for determining a comprehensive weight in flood-risk evaluation.

Therefore, the main objectives of this study are (1) to present a weighting method of GT integrating SW and OW, (2) to construct an evaluation model based on FCE and (3) to analyze flood-risk distribution in the study areas. This study has high scientific and practical merits in terms of flood-risk management, prevention and reduction of floods and other applications in the study areas.

2 Study areas and data

2.1 Study areas

The Dongjiang River, a major tributary of Pearl River Basin, China, is approximately 562 km long with a drainage area of 27,363 km², accounting for approximately 5.96 % of the Pearl River Basin (Fig. 1). The Dongjiang River Basin, an economically advanced area with dense population, is predominantly made up of six cities: Ganzhou, Heyuan, Huizhou, Dongguan, Guangzhou and Shenzhen. The river is also the major water source for these cities and for Hong Kong. In particular, it has provided approximately 80 % of Hong Kong's annual water demands in recent years (Jiang et al. 2007). Located in the subtropical climate region, the basin is subjected to both tropic cyclonic and typhoon-type rains every year, making it prone to flooding (Liu et al. 2010). For example, at the Xintian and Heyuan precipitation stations in the basin, maximum 24-h precipitation was, respectively, measured as 448 and 327.2 mm in June 1959. These rainfall events formed a super flood,



Fig. 1 Map of the Dongjiang River Basin

resulting in 78 deaths and 443 injuries. In addition, 159,000 hm² of farmland was submerged, and 11,900 water conservancy projects were destroyed. Moreover, two of the downstream cities, Guangzhou and Shenzhen, are ranked as the first and fifth highest risk for future flood losses among 136 major coastal cities (Stephane et al. 2013), respectively. In consequence, a severe challenge in flood-risk management of the Dongjiang River Basin exists due to both natural and social factors. A systematic study of flood-risk evaluation in the Dongjiang River Basin is urgently needed.

2.2 Index selection and data sources

The selection of risk index varies among study areas according to the specific characteristics of each location (Mahyat et al. 2013). One index can have a high degree of impact on flood risk in a specific area, which may not be considered in another area (Kia et al. 2012). According to the actual conditions of the disaster-inducing factor, hazard-inducing environment and hazard-bearing body, combined with an extensive literature review (Jiang et al. 2009; Zou et al. 2013; Yang et al. 2013), 10 indices (Fig. 2) were selected; they are described below.

Maximum three-day precipitation (M3DP, mm): this index represents precipitation and is calculated according to daily precipitation data at the 62 observational weather stations of the basin recorded during the 1960–2005.

Typhoon frequency (TF, number/year): as special tropical cyclones, typhoons frequently affect the basin and are accompanied by torrential rain, which aggravates the



Fig. 2 Characteristic distributions of evaluation indices. *M3DP* maximum three-day precipitation, *TF* typhoon frequency, *RD* runoff depth, *DEM* digital elevation model, *DMR* distance to the main road, *DR* distance to river, *SL* slope, *PD* population density, *GDP* gross domestic product density, *CAP* cultivated acreage proportion

degree of the disaster. According to typhoon records, the annual mean frequency is determined by counties.

Runoff depth (RD, mm): this index directly reflects the rainfall intensity and indirectly reflects situations regarding land-use type and agrotype of the underlying surface.

Digital elevation model (DEM, m): this index reflects the terrain's surface. In general, areas in low elevation are prone to flooding because rainfall easily flows from highlands to lowlands under natural conditions.

Distance to the main road (DMR, m): a road is a transportation medium for lives and property. People living in areas close to main roads can quickly escape and transport their property. Moreover, relief supplies and rescuers can be swiftly transferred to disaster areas using roads.

Distance to the river (DR, m): regions near rivers may be easily flooded because of dyke breaching or overtopping. On the contrary, regions far away from rivers are safe. The rivers are set to 0 but the value increases as the distance to rivers increased.

Slope (SL, °): this index reflects the degree of topographic change. Mountain areas generally have severe slopes that prevent the collection of water, whereas lowlands or flatlands have gentle slopes that result in a constant threat of flooding.

Population density (PD, people/km²): this index reflects the population distribution in 2005.

Gross domestic product density (GDP, 10 000 yuan/km²): this index reflects the property distribution in 2005.

Cultivated acreage proportion (CAP, %): this index reflects agricultural development in 2005. A higher proportion relates to more development of agriculture in the basin.

2.2.1 Data sources

The data sources are as follows. M3DP and RD were accessed from the Hydrology Bureau of Guangdong Province (http://www.gdsw.gov.cn/wcm/gdsw/index.html). TF was obtained from the Weather Bureau of Guangdong Province (http://www.grmc.gov.cn/). SRTM DEM with the scale of the raster 90 m \times 90 m was obtained from the United States Geological Survey (http://data.geocomm.com/dem/), and then, it was changed into DEM with the scale of the raster 100 m \times 100 m. SL and DR were extracted from DEM using geographic information system (GIS) techniques. PD and GDP were obtained from the shared site of the National Fundamental Geographic Information System (China)(http://www.ngcc.cn/). CAP and DMR were obtained from the Chinese Academy of Science (http://www.cas.cn/) and the Highway Bureau of Guangdong Province (http://www.gdhighway.gov.cn/), respectively. Using GIS techniques, the 10 indices were transformed into grid layers with the scale of the raster set to 100 m \times 100 m \times 100 m, and the basin was divided into 2,736,295 grids.

3 Methodology

3.1 Evaluation procedure

FCE divides data into several risk levels according to a predetermined grading standard, which eliminates possible fuzziness and uncertainty (Jiang et al. 2009). In addition, this method synthesizes and evaluates several individual components of a process as a whole (Lu et al. 1999). Determining a suitable weight is a critical step during the evaluation

process. To overcome the shortcomings of SW and OW, a CW based on GT is proposed in the fuzzy comprehensive evaluation model.

The evaluation process includes the following steps. First, suitable indexes are selected and are transferred to grid form so that they can be conveniently processed by the GIS technique. Each index's comprehensive weight is then calculated according to the GT concept. SW and OW are, respectively, determined by the analytic hierarchy process (AHP) and entropy weight (EW). Next, a grading standard of risk index in the study basin is constructed. Afterward, membership degree is calculated according to the membership function, and the comprehensive membership degree is computed using CW. Lastly, risk level is determined on the basis of maximum comprehensive membership degree. Five levels are used to measure the risk degree: lowest, lower, medium, higher and highest risks. The main software implemented includes Arc.GIS and Excel.

3.2 Weight definition

3.2.1 Subjective weight based on AHP

SW is generally determined by the decision maker's intentions and is strongly affected by expert knowledge as well as many biases. AHP, an efficient and flexible framework based on psychology and mathematics, is an ideal SW method. Its multi-criteria decision-making technique provides a systematic approach for assessing and integrating the effects of various factors, involving several levels of dependent or independent qualitative and quantitative information (Saaty 1990). AHP has been tested in handling regional complicated problems of various standards and indices (Stefanidis and Stathis 2013; Zou et al. 2013).

By analysing the relations among indexes, this method builds a hierarchical organization, including goal, criterion and sub-criterion levels, to objectively form a multi-level analysis model (Fig. 3). The goal level is a problem's objective, and the criterion level



Fig. 3 Hierarchical structure of the flood-risk index in Dongjiang River Basin

includes factors which have influence on the objective decision. The sub-criterion level contains indices subordinated to those belonging to the criterion level. Judgment matrices are established, and a weight vector is determined according to these matrices.

A consistency ratio (CR) must be computed [formula (1)] to check the discordances between the pairwise comparisons and the reliability of the obtained weights (Stefanidis and Stathis 2013). The value must be <0.1 to be accepted; otherwise, it is necessary to recalculate the weight.

$$CR = \frac{CI}{RI}$$
(1)

where RI is a random index representing the consistency of a randomly generated pairwise comparison matrix. Its reference standard, shown in Table 1, was computed and recommended by Saaty (1980). CI represents the consistency index computation:

$$CI = \frac{\lambda_{\max} - 1}{n - 1} \tag{2}$$

where λ_{max} represents the sum of the products between the sum of each column of the comparison matrix and the relative weights, and *n* is the size of the matrix.

3.2.2 Entropy weight

As a parameter measuring the degree of randomness or disorder, the concept of entropy originates from thermodynamics and represents heat energy that cannot be used to generate work (Li et al. 2012). Shannon first applied entropy to the information theory in 1948, which became the measurement of ordering of one system (Shannon 1948). As an OW, EW is based on the information entropy theory and reflects the useful information content offered by each index (Yan et al. 2014; Jesmin and Sharif 2014). The calculation is accomplished in the following steps:

Step 1 Construct a judgment matrix **Y** with *m* evaluation objects and *n* risk indices as

$$Y = \left(y_{ij}\right)_{m \times n} (i = 1, 2, \cdots, n; j = 1, 2, \cdots, m)$$
(3)

Step 2 Different indices have various range and dimension values; thus, they must be converted to a unified standard in the same evaluation system. Normalization is used to eliminate the effects of value range and dimension. The judgment matrix can be normalized to a standard matrix B according to formula (4). The former equation in formula (4) is suitable for a positive index such that a larger attribute value relates to higher risk. The latter is suitable for a negative index such that a larger attribute value relates to lower risk.

$$b_{ij} = \frac{x_{ij} - x_{\min}}{x_{\max} - x_{\min}} \quad \text{or} \quad b_{ij} = \frac{x_{\max} - x_{ij}}{x_{\max} - x_{\min}} \tag{4}$$

n	1	2	3	4	5	6	7	8
RI	0	0	0.58	0.9	1.12	1.24	1.32	1.41
n	9	10	11	12	13	14	15	
RI	1.46	1.49	1.52	1.54	1.56	1.58	1.59	

Table 1 Random index (RI) values computed and recommended by Saaty (1980)

where x_{ij} is the index attribute value, and x_{max} and x_{min} are the maximum and minimum among the attribute values, respectively.

Step 3 According to the information theory, calculate the index's entropy value H_i as the following formula:

$$H_i = -\frac{1}{\mathrm{Ln}m} \sum_{j=1}^m f_{ij} \mathrm{Ln} f_{ij} \tag{5}$$

where $f_{ij} = \frac{b_{ij}}{\sum_{j=1}^{m} b_{ij}}$; i = 1, 2, ..., n; j = 1, 2, ..., m; and $0 \le H_i \le 1$.

Step 4 The EW of each index can be calculated as

$$w_i = \frac{1 - H_i}{n - \sum_{i=1}^n H_i}$$
(6)

where i = 1, 2, ..., n, and meets the condition $\sum_{i=1}^{n} w_i = 1$. Formula (6) shows that a smaller entropy value relates to a larger EW, indicating that the index is important.

3.2.3 Combination weight based on game theory

As previously mentioned, SW is strongly affected by expert knowledge and many biases. OW ignores the decision maker's subjective information and practical situations. CW, integrating SW and OW through a certain algorithm, is more reasonable in the evaluation process.

GT is a study of strategic decision making. In particular, it is the study of mathematical models of conflict and cooperation between intelligent rational decision makers (Roger 1991). In GT, each participant's objective is to maximize the expected value of his own payoff, and the decision made by all participants is also rational for each individual participant. Therefore, all participants reach an independent but collective decision that maximizes all of the participants' expected utility payoffs, suggesting that the decision includes the consensus or a compromise. This factor is known as the Nash Equilibrium. Similarly, SW and OW are independent results that may conflict. As a cooperative result, CW suggests solving the conflicts by finding a compromise between them. There is no doubt that the most satisfied CW is that reaching Nash Equilibrium, according to GT. The GT calculation steps of CW with two or more participants are as follows:

Step 1 Obtain *n* weights according to *n* types of weighting methods, and then construct a basic weight vector set $W = \{w_1, w_2, \dots, w_n\}$. A possible weight set is combined by *n* vectors with the form of arbitrary linear combination as

$$W = \sum_{k=1}^{n} \alpha_k w_k^T \ (\alpha_k > 0) \tag{7}$$

where w is a possible weight vector in set W, and α_k is the weight coefficient.

Step 2 Determine the most satisfied weight vector w^* of the possible weight vector sets according to the concept of GT, suggesting that a compromise was reached among *n* weights. Such a compromise can be regarded as optimization of the weight coefficient α_k , which is a linear combination. The optimization aim is to minimize the deviation between *w* and *w_k* using the following formula:

$$\min \left\| \sum_{j=1}^{n} \alpha_j \times \boldsymbol{w}_j^T - \boldsymbol{w}_i^T \right\|_2 \quad (i = 1, 2, \cdots, n)$$
(8)

According to the differentiation property of the matrix, the condition of optimal firstorder derivative in formula (8) is as

$$\sum_{j=n}^{n} \alpha_j \times \boldsymbol{w}_i \times \boldsymbol{w}_j^T = \boldsymbol{w}_i \times \boldsymbol{w}_i^T \quad (i = 1, 2, \cdots, n)$$
(9)

The corresponding system of linear equations is

$$\begin{bmatrix} \mathbf{w}_1 \cdot \mathbf{w}_1^T & \mathbf{w}_1 \cdot \mathbf{w}_2^T & \cdots & \mathbf{w}_1 \cdot \mathbf{w}_n^T \\ \mathbf{w}_2 \cdot \mathbf{w}_1^T & \mathbf{w}_2 \cdot \mathbf{w}_2^T & \cdots & \mathbf{w}_2 \cdot \mathbf{w}_n^T \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{w}_n \cdot \mathbf{w}_1^T & \mathbf{w}_n \cdot \mathbf{w}_2^T & \cdots & \mathbf{w}_n \cdot \mathbf{w}_n^T \end{bmatrix} \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \vdots \\ \alpha_{n1} \end{bmatrix} = \begin{bmatrix} \mathbf{w}_1 \cdot \mathbf{w}_1^T \\ \mathbf{w}_2 \cdot \mathbf{w}_2^T \\ \vdots \\ \mathbf{w}_n \cdot \mathbf{w}_n^T \end{bmatrix}$$
(10)

Step 3 Calculate the weight coefficient $(\alpha_1, \alpha_2, \dots, \alpha_n)$ according to formula (10), and then normalize it with the follow formula:

$$\alpha_k^* = \alpha_k / \sum_{k=1}^n \alpha_k \tag{11}$$

Lastly, CW will be obtained as

$$\boldsymbol{w}^* = \sum_{k=1}^n \alpha_k \cdot \boldsymbol{w}_k^T \tag{12}$$

A CW based on GT integrates various weights through the processes of intercomparison and intercoordination, although they are not simple physical processes. The CW integrating SW and OW in this paper was obtained by following the above steps.

3.3 Fuzzy comprehensive evaluation

3.3.1 Grading standard

The grading standard varies among study areas according to various natural and social attributes. For example, the M3DP of the Dongjiang River Basin ranges from 130.70 to 332.75 mm because the basin is located in a humid region of South China. However, the M3DP in southwestern China is no more than 20 mm because most of the areas are in arid or semi-arid regions. The M3DP in southwestern China may be at the lowest risk level when using the grading standard of the Dongjiang River Basin, which is obviously unreasonable. Therefore, the grading standard depends on actual local conditions (Jiang et al. 2009). The specify classification method is as follow: the grading criteria of M3DP were determined according to the article of Jiang (Jiang et al. 2009). TF was exactly classified into five classes from one to five. Generally in China, the regions with an elevation of more than 500 m are called 'mountain,' the ones with an elevation of less than 200 m are called 'plain' and the one between 500 and 200 m are called 'hill.' This paper determined the critical values of DEM based on the classification of mountain, hill and plain. According to

6

500

200

40

2

1000

500

60

Table 2 Grading standard of hood-fisk indices in the Dolighang Kiver basin										
Index	Lowest risk V ₁	Lower- risk V ₂	Medium- risk V ₃	Higher- risk V ₄	Highest risk V ₅					
M3DP (mm)	130	160	190	220	250					
TF (N a^{-1})	1	2	3	4	5					
RD (mm)	800	950	1000	1100	1200					
DEM (m)	500	350	200	80	50					
DMR (m)	1000	4000	8000	10,000	20,000					
DR(m)	1000	500	200	100	50					

Grading standard of flood risk indices in the Dongijong Piver Pasin

55

25

10

5

M3DP maximum three-day precipitation, TF typhoon frequency, RD runoff depth, DEM digital elevation model, DMR distance to the main road, DR distance to the river, SL slope, PD population density. GDP gross domestic product density, CAP cultivated acreage proportion

25

100

20

10

15

200

50

20

the technical regulations of land-use currency survey in China (Agricultural Zoning Committee of China 1984), the slope is classified as: $<2^{\circ}$, 2° - 6° , 6° - 15° , 15° - 25° , $>25^{\circ}$. Based on the aforementioned classification, the critical values of SL were determined as 2°, 6° , 15° , 25° and 35° . Historical floods usually inundated the region near the rivers of the basin. Therefore, the critical values of DR were determined as 50, 100, 200, 500 and 1000 m according to the threat levels of floods. There are few valuable references of grading criteria for the index RD, DMR, PD, POP and CAP, and this paper used the method of Natural breaks (Jenks) to obtain the critical values and made some amendment. Natural breaks (Jenks) is a method that data are classified according to the inherent natural group features of the data samples. ArcMap identifies break points by picking the class breaks that best group similar values and maximize the differences between classes. The features are divided into classes whose boundaries are set where there are relatively big jumps in the data values. The critical values of the grading standard in the Dongjiang River Basin are shown in Table 2.

3.3.2 Membership function

Since indices vary in range and dimension values, a unified standard is needed in the same evaluation system, which can be solved by membership function. In addition, this function is used to change uncertainty into certainty by fuzzy sets, wherein fuzziness is quantified to obtain a fuzzy evaluation matrix (Sun et al. 2014). If there are n indexes and five risk levels, the membership degree of each level can be determined through the piecewise linear function (descending semi-trapezoid, ascending semi-trapezoid and triangle) in fuzzy mathematics, as shown in Fig. 4. u_{ij} is the membership degree of index i and level j (i = 1, 2, ..., n; j = 1, 2, ..., 5). x_i is the attribute value of index i having two membership degrees u_{i2} and u_{i3} , as shown in Fig. 4. According to the critical value of the grading standard (Table 2), the value of the fuzzy membership function of each positive index $r_{ii}(x_i)$ related to the five risk levels is calculated according to formulas (13)–(17). However, the negative index is calculated by $1 - r_{ii}(x_i)$. This step changes uncertainty to certainty

SL (°)

PD ($P \text{ km}^{-2}$)

CAP (%)

GDP (10,000 yuan km⁻²)



Fig. 4 Fuzzy membership function

and properly solves the problems of uncertainty and the nonlinear relation between the index and level.

$$r_{i1}(x_i) = \begin{cases} 1 & (x_i \le V_1) \\ \frac{V_2 - x_i}{V_2 - V_1} & (V_1 < x_i < V_2) \\ 0 & (x_i \ge V_2) \end{cases}$$
(13)

$$r_{i2}(x_i) = \begin{cases} 0 & (x_i \le V_1 \text{ or } x_i \ge V_3) \\ \frac{x_i - V_1}{V_2 - V_1} & (V_1 < x_i < V_2) \\ \frac{V_3 - x_i}{V_3 - V_2} & (V_2 < x_i < V_3) \end{cases}$$
(14)

$$r_{i3}(x_i) = \begin{cases} 0 & (x_i \le V_2 \text{ or } x_i \ge V_4) \\ \frac{x_i - V_2}{V_3 - V_2} & (V_2 < x_i < V_3) \\ \frac{V_4 - x_i}{V_4 - V_3} & (V_3 < x_i < V_4) \end{cases}$$
(15)

$$r_{i4}(x_i) = \begin{cases} 0 & (x_i \le V_3 \text{ or } x_i \ge V_5) \\ \frac{x_i - V_3}{V_4 - V_3} & (V_3 < x_i < V_4) \\ \frac{V_5 - x_i}{V_5 - V_4} & (V_4 < x_i < V_5) \end{cases}$$
(16)

$$r_{i5}(x_i) = \begin{cases} 0 & (x_i \le V_4) \\ \frac{x_i - V_4}{V_5 - V_4} & (V_4 < x_i < V_5) \\ 1 & (x_i \ge V_5) \end{cases}$$
(17)

3.3.3 Comprehensive evaluation and final risk level

An evaluation matrix \mathbf{R} shown as formula (18) is constructed according to formulas (13)–(17). The element r_{ij} in \mathbf{R} represents a raster layer of membership degree. After the determination of index weight and the evaluation matrix \mathbf{R} , the comprehensive membership degree is calculated by formula (19).

$$\boldsymbol{R} = \begin{bmatrix} r_{11} & r_{12} & \dots & r_{15} \\ r_{21} & r_{22} & \dots & r_{25} \\ \dots & \dots & \dots & \dots \\ r_{i1} & r_{i2} & \dots & r_{i5} \end{bmatrix} (i = 1, 2, \dots, n)$$
(18)

Deringer

$$\boldsymbol{B} = \boldsymbol{W} \times \boldsymbol{R} = [w_1, w_2, \dots, w_i] \times \begin{bmatrix} r_{11} & r_{12} & \dots & r_{15} \\ r_{21} & r_{22} & \dots & r_{25} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ r_{i1} & r_{i2} & \dots & r_{i5} \end{bmatrix} = [b_1, b_2, b_3, b_4, b_5] \quad (19)$$

where W is the index weight vector. b_1, b_2, b_3, b_4 , and b_5 are the comprehensive membership degrees and represent the raster layers of comprehensive membership. The final risk of FCE can be obtained according to the maximum membership degree law (Xue and Yang 2014). In this method, the maximum comprehensive membership degree is chosen as the representative value of risk level, which corresponds with the lowest, lower, medium, higher and highest risks, respectively. For example, if b_1 is the maximum, the risk will be classified as lowest; if b_5 is the maximum, the risk will be classified as highest.

4 Results and discussion

4.1 Weight analysis

SW is calculated by AHP; the hierarchical organization is constructed as shown in Fig. 3. The comprehensive risk is the goal level determined by the criterion level comprising disaster-inducing factor, hazard-inducing environment and hazard-bearing body. The subcriterion level contains the 10 risk indices subordinated to the criterion level. Ten experts were invited to participate in the judgment and then took an average of their judgment value. Four judgment matrices, one goal matrix and three criterion matrices were established with respective CRs of 0.0662, 0.0158, 0.0013 and 0.0225, all of which meet the conditions CR < 0.1. Then, an SW based on AHP was finally determined. EW was determined through the aforementioned calculation steps using the raster calculator in GIS. The CW values based on GT were finally integrated with SW and OW coefficients, $\alpha_1 = 0.7276$ and $\alpha_2 = 0.2724$. The detailed results are shown in Table 3.

In Table 3, the weight of AHP assumes M3DP, PD and RD as three of the most important indices among the 10 and DMR as the least important. However, since the intentions are generally affected by expert knowledge as well as many biases owing to various opinion, these subjective interpretations in many cases do not depend on the internal law of index data and may cause unreasonable results. The EW regards GDP as the most important index, and PD and CAP as the least important; the remaining indices have relatively average values. The EW is based on the internal law of index data and reflects the useful information of the index. However, it does not consider the differences of each index and ignores practical situations, causing dissatisfied results that are far removed from

Table 3 Index weights obtained using the three methods

M3DP	TF	RD	DEM	DMR	DR	SL	PD	GDP	CAP
0.1648	0.0723	0.1260	0.0873	0.0531	0.0873	0.0747	0.1538	0.1067	0.0740
0.1087	0.1014	0.1087	0.1078	0.1099	0.1077	0.1078	0.0621	0.1213	0.0645
0.1495	0.0802	0.1213	0.0929	0.0686	0.0929	0.0837	0.1289	0.1107	0.0714
	M3DP 0.1648 0.1087 0.1495	M3DP TF 0.1648 0.0723 0.1087 0.1014 0.1495 0.0802	M3DP TF RD 0.1648 0.0723 0.1260 0.1087 0.1014 0.1087 0.1495 0.0802 0.1213	M3DP TF RD DEM 0.1648 0.0723 0.1260 0.0873 0.1087 0.1014 0.1087 0.1078 0.1495 0.0802 0.1213 0.0929	M3DP TF RD DEM DMR 0.1648 0.0723 0.1260 0.0873 0.0531 0.1087 0.1014 0.1087 0.1078 0.1099 0.1495 0.0802 0.1213 0.0929 0.0686	M3DP TF RD DEM DMR DR 0.1648 0.0723 0.1260 0.0873 0.0531 0.0873 0.1087 0.1014 0.1087 0.1078 0.1099 0.1077 0.1495 0.0802 0.1213 0.0929 0.0686 0.0929	M3DP TF RD DEM DMR DR SL 0.1648 0.0723 0.1260 0.0873 0.0531 0.0873 0.0747 0.1087 0.1014 0.1087 0.1078 0.1099 0.1077 0.1078 0.1495 0.0802 0.1213 0.0929 0.0686 0.0929 0.0837	M3DP TF RD DEM DMR DR SL PD 0.1648 0.0723 0.1260 0.0873 0.0531 0.0873 0.0747 0.1538 0.1087 0.1014 0.1087 0.1078 0.1099 0.1077 0.1078 0.0621 0.1495 0.0802 0.1213 0.0929 0.0686 0.0929 0.0837 0.1289	M3DP TF RD DEM DMR DR SL PD GDP 0.1648 0.0723 0.1260 0.0873 0.0531 0.0873 0.0747 0.1538 0.1067 0.1087 0.1014 0.1087 0.1078 0.1099 0.1077 0.1078 0.0621 0.1213 0.1495 0.0802 0.1213 0.0929 0.0686 0.0929 0.0837 0.1289 0.1107

M3DP maximum three-day precipitation, *TF* typhoon frequency, *RD* runoff depth, *DEM* digital elevation model, *DMR* distance to the main road, *DR* distance to the river, *SL* slope, *PD* population density, *GDP* gross domestic product density, *CAP* cultivated acreage proportion, *AHP* analytic hierarchy process, *EW* entropy weight, *GT* game theory

the maker's intentions. For example, although PD should be larger in our subjective intentions because lives are regarded as the vitally important hazard-bearing body, 0.0621 appears very far from the actual conditions. Therefore, both AHP and EW have advantages as well as disadvantages. AHP can flexibly reflect the intentions of the makers but does not consider the data internal law, and EW can show the internal law and useful information but ignores practical situations. Results of Table 3 show that the CWs values are quite similar with the AHP's results. Actually, the weight coefficients reaching the Nash Equilibrium decide the proportion of SW and OW. CW makes some abnormal values more reasonable by significantly reducing AHP's M3DP and increasing the EW's PD. Therefore, a CW based on GT has advantages and overcomes the problems of one-sidedness of single weight.

4.2 Risk distribution analysis

Fifty layers of membership degree were obtained according to formulas (13)–(17) using the raster calculator in GIS, which were used to construct the evaluation matrix R. The comprehensive membership degree was calculated by multiplying the matrix R and the index weight of GT according to formula (19). According to the maximum membership degree law, the maximum risk level can be obtained using the 'highest position' function in GIS, suggesting that the final evaluation map has been derived, as shown in Fig. 5.

According to Fig. 5, the highest risk zones are mainly located in Baoan, Longgang, southern Huiyang, central Huidong and Longmen. The higher-risk zones are concentrated in Dongguan, northeastern Huiyang, northern Boluo and northern Huidong. The medium-risk zones are located mainly in Zijin, northern Huizhou and northern Dongyuan. The lower-risk zones lie mainly in Heping, Longchuan, Dingnan, Anyuan and Xunwu, and the lowest risk zones are in Xinfeng, Lianping and western Dongyuan. Essentially, the flood risk in the south basin is higher than that in the north basin, and the risk in urban areas is higher than that in rural and mountainous regions. The higher-risk and highest risk zones occupy approximately 23.02 % (Table 4).

The higher and highest risk areas generally have adverse natural conditions, such as greater precipitation, lowlands, flatlands and gentle slopes, which are conducive to quick and effective collection of rainfall, resulting in vulnerability to flooding and waterlogging. Furthermore, these zones exhibit denser population and more developed industries, leading to substantial losses in life and property. Taking Baoan as an example, this district is located in the downstream region of Pearl River Delta, one of the richest regions in China. Unfortunately, however, according to the risk distribution, an area of approximately 262 km^2 (92 %) is in the highest risk zones. This district has the greatest precipitation at more than 200 mm of M3DP and lands lower than 20 m of DEM as well as a dense population of more than 1500 people per hm² and a high GDP of more than 20 million yuan per hm². There is no doubt that this zone has by far the highest risk. On the contrary, lower-risk and lowest risk zones are far from rivers or are distributed in mountainous areas with few residents and properties. For example, Heping, a mountainous county in northern Guangdong, has approximately 2224.43 km² (97 %) in the lower-risk and lowest risk zones. Despite having high levels of precipitation, these areas have smaller PD, GDP density and CAP. Thus, their risk levels are relatively low.

Therefore, comprehensive flood risk is determined by natural conditions and social factors. Most of the high-risk zones, exhibiting a major threat to local residents, usually have adverse disaster-inducing factors and hazard-inducing environments as well as a large number of hazard-bearing bodies. Preventative actions, including engineering and non-



Fig. 5 Flood-risk assessment map of the Dongjiang River Basin

Table 4	Areas	percentages	of	various	risk	levels	in	Dongjiang	River	Basin
---------	-------	-------------	----	---------	------	--------	----	-----------	-------	-------

Risk level	The lowest risk	The lower risk	The medium risk	The higher risk	The highest risk
Areas (km ²)	6866.86	7104.21	7093.59	3369.68	2928.62
Percentage (%)	25.10	25.96	25.92	12.31	10.70

engineering measures, should be taken in these areas to prevent flooding and to reduce losses as much as possible.

4.3 Results verification

Validation is used to judge the evaluation results of flood risk using other data to validate the reliability of higher and highest risk areas. An integrated risk zoning map of flood-

waterlogging disasters, which was drawn according to the historical flood statistics of Guangdong Province, shows that the high-risk areas in Dongjiang River Basin are mainly in Longgang, Huiyang, Huidong, Boluo, Longmen and Dongguan (Atlas of Guangdong Province 2003). The higher-risk and the highest risk zones of this study can better overlap these regions. Many historical major floods occurred in the Dongjiang River Basin (Zhang 1997). For example, a flood in July 1915 submerged most areas of Boluo, Huiyang, Dongguan and Longmen, and a super flood in June 1959 submerged most areas of Huiyang, Boluo, Dongguan and Longmen, both resulting in substantial losses of lives and properties. In addition, a flood caused by typhoon rain in September 1964 inundated Baoan, Huidong and Huiyang. Obviously, Fig. 6 shows that these submerged areas are nearly identical to the higher and highest areas revealed in this study, which proves the rationality of the evaluation results. Therefore, the assessment map has great scientific and practical merits in terms of flood-risk management, prevention and reduction of floods, and other applications in the Dongjiang River Basin.



Fig. 6 Submerged areas of integrated risk zoning map and three historical floods

5 Conclusions

The main results of this study are summarized in the following points.

- 1. Flood-risk evaluation, a significant non-engineering measure of preventing floods and reducing losses, is a synthetic assessment and analysis method involving many risk indices. FCE is an effective method for solving random, fuzzy and multi-index problems in the evaluation. In this study, 10 flood-risk indices were selected to construct the index system. The application of FCE was developed to evaluate flood risk in the Dongjiang River Basin. The assessment model can better describe the complicated nonlinear relations between the evaluation index and flood-risk level. This model has a visualization effect on the GIS interface and is advantageous for comparative analysis among study areas, which is convenient for analysing the spatial pattern and inherent law of flood risk.
- 2. CW, based on a weighting method of GT that integrates SW calculated by AHP and OW calculated by entropy theory, was adopted in FCE. As a cooperative result, CW suggests solving the conflicts by finding a compromise between SW and OW. The CW based on GT can reflect the decision maker's intentions and the useful information content offered by each index, making it have both advantages of SW and OW and overcome the limitations of one-sidedness of a single weight.
- 3. The evaluation results show that the flood risk in the south basin is higher than that in the north and that the risk in urban areas is higher than that in rural and mountainous areas. Approximately 23.02 % of the basin is in high risk, which includes Baoan, Huidong, Huiyang, Longmen, Boluo, Longgang and Dongguan. Unfavorable terrain environments, developed industries and dense population are contributing factors for high flood risk. A comparison of an integrated risk zoning map and historical flood data reveals that the high-risk areas identified in this study correlate with the dangerous areas prone to submersion, proving the evaluation model and the results to be reasonable. Preventative actions of both engineering measures and non-engineering measures should concentrate on these dangerous areas.

Acknowledgments The research is financially supported by the National Natural Science Foundation of China (Grant No. 51209095, 51210013, 51479216), the National Science and Technology Support Program (Grant No. 2012BAC21B0103), the Public Welfare Project of Ministry of Water Resources (Grant No. 201201094, 201301002-02, 201301071), and the project for Creative Research from Guangdong Water Resources Department (Grant No. 2011-11). The authors greatly appreciate the reviewers and the editors for their critical comments that greatly helped in improving the quality of this paper. The authors also special thank to the Springer Correction Team for the help in improving the publication quality.

References

Agricultural Zoning Committee of China (1984) Technical regulations of land-use currency survey in China Alexander DE (1993) Natural disasters. University College London Press, London

- Cui P, Dang C, Zhuang JQ (2002) Flood disaster monitoring and evaluation in China. Environ Hazards 4:33–43
- EM-DAT. Disaster Profiles (2013) The OFDA/CRED international disaster database. Accessed 28 Dec 2013. Available at http://www.emdat.be/database
- Editorial Staff of Atlas of Guangdong Province (2003) Atlas of Guangdong Province (in Chinese). Guangdong Map Publishing House, Guangzhou

Eric G, Valerie B, Pietro B (2009) A compilation of data on European flash floods. J Hydrol 367:70–78 Feng LH, Luo GY (2009) Practical Study on the fuzzy risk of flood disasters. Acta Appl Math 106:421–432

- Jesmin FK, Sharif MB (2014) Weighted entropy for segmentation evaluation. Opt Laser Technol 57:236–242
- Jiang T, Chen YQ, Xu CY et al (2007) Comparison of hydrological impacts of climate change simulated by six hydrological models in the Dongjiang Basin, South China. J Hydrol 336:316–333
- Jiang WG, Deng L, Chen LY et al (2009) Risk assessment and validation of flood disaster based on fuzzy mathematics. Prog Nat Sci 19:1419–1425
- Jin JL, Wei YM, Zou LL et al (2012) Risk evaluation of China's natural disaster systems: an approach based on triangular fuzzy numbers and stochastic simulation. Nat Hazards 62:129–139
- Jin FF, Pei LD, Chen HY et al (2014) Interval-valued intuitionistic fuzzy continuous weighted entropy and its application to multi-criteria fuzzy group decision making. Knowl-Based Syst 59:132–141
- Jonathan DW, Jennifer LI, Suzana JC (2013) Coastal flooding by tropical cyclones and sea-level rise. Nature 504:44–52
- Kia MB, Pirasteh S, Pradhan B et al (2012) An artificial neural network model for flood simulation using GIS: Johor River Basin, Malaysia. Environ Earth Sci 67(1):251–264
- Li Q (2013) Fuzzy approach to analysis of flood risk based on variable fuzzy sets and improved information diffusion methods. Nat Hazards Earth Syst Sci 13:239–249
- Li XG, Wei X, Huang Q (2012) Comprehensive entropy weight observability–controllability risk analysis and its application to water resource decision-making. Water Res 38(4):573–579
- Liu DE, Chen CH, Lian YQ et al (2010) Impacts of climate change and human activities on surface runoff in the Dongjiang River Basin of China. Hydrol Process 24(11):1487–1495
- Lu RS, Lo SL, Hu JY (1999) Analysis of reservoir water quality using fuzzy synthetic evaluation. Stoch Environ Res Risk Assess 13:327–336
- Mahyat ST, Biswajeet P, Mustafa NJ (2013) Spatial prediction of flood susceptible areas using rule based decision tree (DT) and a novel ensemble bivariate and multivariate statistical models in GIS. J Hydrol 504:69–79
- Pall P, Aina T, Stone DA et al (2011) Anthropogenic greenhouse gas contribution to flood risk in England and Wales in autumn 2000. Nature 470:382–385
- Ramin BM, McMichael AJ (2009) Climate Change and health in Sub-Saharan Africa: a case-based perspective. EcoHealth 6(1):52–57
- Roger BM (1991) Game theory: analysis of conflict. Harvard University Press, Cambridge
- Ronald EG, Robert EY (1997a) Analysis of the error in the standard approximation used for multiplication of triangular and trapezoidal fuzzy numbers and the development of a new approximation. Fuzzy Sets Syst 91(1):1–13
- Ronald EG, Robert EY (1997b) A parametric representation of fuzzy numbers and their arithmetic operators. Fuzzy Sets Syst 91(2):185–202
- Saaty T (1980) The analytic hierarchy process. McGraw-Hill, New-York
- Saaty T (1990) How to make a decision: the analytic hierarchy process. Eur J Oper Res 48:9-26
- Shannon C (1948) A mathematical theory of communication. Bell Syst Tech J 5(1):3-53
- Stefanidis S, Stathis DR (2013) Assessment of flood hazard based on natural and anthropogenic factors using analytic hierarchy process (AHP). Nat Hazards 68:569–585
- Stephane H, Colin G, Robert JN et al (2013) Future flood losses in major coastal cities. Nat Clim Change 3(9):802–806
- Stijn T, Patrick M, Tjeerd JB et al (2013) Ecosystem-based coastal defence in the face of global change. Nature 504:79–83
- Sun ZY, Zhang JQ, Zhang Q et al (2014) Integrated risk zoning of drought and waterlogging disasters based on fuzzy comprehensive evaluation in Anhui Province, China. Nat Hazards 71:1639–1657
- Wu TY, Lee WT, Nadra G et al (2014) Incentive mechanism for P2P file sharing based on social network and game theory. J Netw Comput Appl 41:47–55
- Xue XH, Yang XG (2014) Seismic liquefaction potential assessed by fuzzy comprehensive evaluation method. Nat Hazards 71:2101–2112
- Yan JH, Feng CH, Li L (2014) Sustainability assessment of machining process based on extension theory and entropy weight approach. Int J Adv Manuf Technol 71:1419–1431
- Yang XL, Ding JH, Hou H (2013) Application of a triangular fuzzy AHP approach for flood risk evaluation and response measures analysis. Nat Hazards 68:657–674
- Zhang CZ (1997) Flood, drought and wind damage in Guangdong Province (in Chinese). Jinan University Press, Guangzhou
- Zou Q, Zhou JZ, Zhou C et al (2013) Comprehensive flood risk assessment based on set pair analysisvariable fuzzy sets model and fuzzy AHP. Stoch Environ Res Risk Assess 27:525–546