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Flood disaster evaluation based on adaptive fuzzy clustering iterative model and hybrid differential evolution algorithm

Zou Qiang, Liao Li and Qin Hui

ABSTRACT

In order to reasonably and rapidly evaluate flood disaster, based on a fuzzy clustering iterative model (FCI) and differential evolution algorithm (DE), an adaptive fuzzy clustering iterative model using a hybrid differential evolution algorithm (AFCI-HDE) is proposed, which has three advantages: firstly, the decision-maker's subjective preference was considered to flexibly modify the objective function; secondly, HDE was introduced to optimize the index weight vector of AFCI; thirdly, the validity of its clustering effect was more credible than that of FCI. Finally, the case study revealed that AFCI-HDE is feasible and effective by comparing the optimal fitness and clustering validity values with other approaches, which could reflect various decision-maker's preferences by simple adaptive adjustments and rapidly obtain reasonable evaluation results, thus providing a new effective approach in flood risk management.

Key words | adaptive adjustment, clustering validity, decision-maker's preference, FCI, flood disaster evaluation, HDE

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INTRODUCTION

Flooding is one of the worst natural disasters worldwide, which causes huge death, serious economic losses and social influence (He *et al.* 2017). With increasing attention to the significance of public safety, it is becoming essential to develop a reliable flood disaster evaluation model, which is the fundamental work for flood risk management and could provide a scientific basis for early warning plans before floods, disaster transformation during floods and disaster relief formulations after floods (Zou *et al.* 2012).

Nowadays, many mathematical approaches have been presented to enhance the research of flood disaster evaluation, such as support vector machines (Huang *et al.* 2010) and exponential models (Wang *et al.* 2017). But there exists an unavoidable fact that there is no popular yet applicable standard. The conventional way to establish the standard is either subjective or indistinguishable, and the drawbacks of the theoretical basis and feasible procedure limit popularization (He *et al.* 2017). Therefore, it is always a hot and interesting issue to determine grades without a standard. Fortunately, a fuzzy clustering iterative model (FCI) is just presented by Chen (1998) to identify and diagnose samples by analyzing the inherent characteristics without an evaluation standard. Considering the computational process of FCI is complicated and time-consuming, and cannot even implement global optimization with some initial conditions, intelligent optimization techniques have been respectively employed (Liao *et al.* 2014; Najafzadeh & Zahiri 2015; Zahiri & Najafzadeh 2018). Specifically, improvements of FCI have been paid more attention at present, such as FCI using a chaotic differential evolution algorithm (FCI-CDE) (He *et al.* 2011),

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FCI using an adaptive differential evolution algorithm (FCI-ADE) (Liao *et al.* 2014), FCI considering the decision-maker's preference (FCI-DP) (He *et al.* 2016), and FCI using a particle swarm optimization algorithm considering the decision-maker's preference (FCI-PSODP) (He *et al.* 2017).

In fact, it is not only necessary to consider the spatial and temporal distribution characteristics of the evaluation indices, but it is also more important to effectively consider the preference (He *et al.* 2016). FCI neglected subjective awareness and personal preference in the evaluation process, because if we implement the fuzzy clustering iteration calculation just by the objective statistical data without subjective preference constraints, the index weight vector obtained is just the weighting result in mathematical meaning, which may be contrary to the actual situation and social principle and make the evaluation results unreasonable. Therefore, FCI-DP (He *et al.* 2016) was proposed to reflect the importance of the evaluation index by the decision-maker's preference, but it was found that the iterative calculation process of FCI-DP is more complex when it just appointed an index as the most important index. If there is more information on the decision-maker's preference, the more the complexity will increase. In a more pessimistic scenario, it is even impossible to handle complicated preferences by FCI-DP. FCI-PSODP was proposed to solve the above bottleneck by coding the decision-maker's preference in PSO for optimization (He *et al.* 2017), but this leads in conclusion to the questions, does this treatment affect the performance of algorithm? If the preference is more complex, how can it be effectively described? Therefore, we should pay attention to the complexity of preference and the computational process.

Consequently, an adaptive fuzzy clustering iterative model (AFCI) was proposed to handle various preferences, with the idea that we adopt adaptive adjustments to construct the corresponding objective functions. And in order to obtain better results, a hybrid differential evolution algorithm (HDE) based on DE and a vertical crossover operator (Meng *et al.* 2014) was presented for global optimization of AFCI, with the idea that it can make use of information on different dimensions of all particles, and proved to successfully improve the convergence performance of the algorithm (Patwal & Narang 2018). Therefore, the combination of AFCI and HDE was proposed to form AFCI-HDE for flood disaster evaluation. The main contributions of this article are provided as follows:

(1) Various decision-maker's preferences can be flexibly considered by AFCI.
(2) HDE is introduced to optimize the global search of AFCI.
(3) Simulation and analysis results of flood disaster evaluation are carried out to demonstrate the reasonableness and effectiveness of AFCI-HDE.

Finally, the remainder of this paper is organized as follows. FCI is firstly introduced, and then AFCI is presented in the next section. DE is introduced and then HDE is carried out in detail in the section 'Hybrid differential evolution algorithm'. The section 'Flood disaster evaluation using AFCI-HDE' displays the procedure of the proposed methodology, i.e. flood disaster evaluation using AFCI-HDE. And a case study in Xinjiang autonomous region of China is analyzed in the section 'Case study'. Finally, conclusions are provided in the section 'Conclusions'.

ADAPTIVE FUZZY CLUSTERING ITERATION MODEL (AFCI)

Overview of FCI

The procedure of FCI is expressed as follows (He *et al.* 2011).

Assume there are n samples to form the set X:

$$X = \{x_1, x_2, \ldots, x_n\} \tag{1}$$

Assume any sample x_i has m indices, and the actual values of sample x_i are denoted as:

$$x_i = (x_{i1}, x_{i2}, \ldots, x_{im}) \tag{2}$$

Hence, the sample set is described as a $n \times m$ matrix $\mathbf{X}$:

$$\mathbf{X} = (x_{ij})_{n\times m} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2m} \\ \cdots & \cdots & \cdots & \cdots \\ x_{n1} & x_{n2} & \cdots & x_{nm} \end{bmatrix}, \quad i = 1, 2, \ldots, n; j = 1, 2, \ldots, m \tag{3}$$

where x_{ij} is the eigenvalue of index j for sample x_i, and n, m are the total number of assessment samples and assessment indices, respectively. In order to deal with values in different orders of magnitude, $\mathbf{X}$ is normalized as:

$$r_{ij} = (x_{\max}(j) - x_{ij})/(x_{\max}(j) - x_{\min}(j)) \tag{4}$$

where r_{ij} is the normalized eigenvalue of x_{ij}, obviously $0 \le r_{ij} \le 1$; and $x_{\max}(j)$, $x_{\min}(j)$ denote the maximum, minimum eigenvalue of index j, respectively. Hence, the normalized matrix $\mathbf{R}$ is calculated as:

$$\mathbf{R} = (r_{ij})_{n\times m} = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{n1} \\ r_{21} & r_{22} & \cdots & r_{n2} \\ \cdots & \cdots & \cdots & \cdots \\ r_{n1} & r_{n2} & \cdots & r_{nm} \end{bmatrix} \tag{5}$$

Assume the m indices of n samples are clustered with c classes, and the fuzzy clustering matrix is defined as:

$$\mathbf{U} = (u_{hi})_{c\times n} = \begin{bmatrix} u_{11} & u_{12} & \cdots & u_{1n} \\ u_{21} & u_{22} & \cdots & u_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ u_{c1} & u_{c2} & \cdots & u_{cn} \end{bmatrix}, \quad \sum_{h=1}^{c} u_{hi} = 1; 0 \le u_{hi} \le 1 \tag{6}$$

where u_{hi} denotes the relative membership degree of sample i belonging to class h. Then the fuzzy class center matrix is obtained as:

$$\mathbf{S} = (s_{jh})_{m\times c} = \begin{bmatrix} s_{11} & s_{12} & \cdots & s_{1c} \\ s_{21} & s_{22} & \cdots & s_{2c} \\ \cdots & \cdots & \cdots & \cdots \\ s_{m1} & s_{m2} & \cdots & s_{mc} \end{bmatrix}, 0 \le s_{jh} \le 1 \tag{7}$$

where s_{jh} is the eigenvalue of index j of class h standard. For depicting different indices' effects, we induct weights into the cluster. The index weight vector is defined as:

$$\boldsymbol{\omega} = (\omega_1, \omega_2, \cdots, \omega_m), \sum_{j=1}^{m} \omega_j = 1 \tag{8}$$

Here, a weighted general Euclidean distance $D(\mathbf{r}_i - \mathbf{s}_h)$ is used to represent the difference between sample i denoted as $\mathbf{r}_i$ and class h denoted as $\mathbf{s}_h$:

$$D(\mathbf{r}_i - \mathbf{s}_h) = u_{hi} \cdot \|\omega_j \cdot (\mathbf{r}_i - \mathbf{s}_h)\| = u_{hi} \cdot \left[\sum_{j=1}^{m} [\omega_j \cdot (r_{ij} - s_{jh})]^2\right]^{\frac{1}{2}} \tag{9}$$

In order to obtain $\mathbf{U}$ and $\mathbf{S}$, the objective function is established to minimize the general Euclidean weighted distance (GEWD) from the minimum class 1 to the maximum class c as:

$$\min\{F(\boldsymbol{\omega}, \mathbf{U}, \mathbf{S}) = \sum_{i=1}^{n}\sum_{h=1}^{c}[u_{hi}\|\omega_j(r_{ij} - s_{jh})\|]^2\} \ s.t. \quad \sum_{j=1}^{m}\omega_j = 1; 0 \le \omega_j \le 1 \tag{10}$$

Based on the Lagrange function approach, the index weight $\boldsymbol{\omega} = (\omega_1, \omega_2, \cdots, \omega_m)$, fuzzy clustering matrix $\mathbf{U} = (u_{hi})_{c\times n}$ and the fuzzy class center matrix $\mathbf{S} = (s_{jh})_{m\times c}$ are calculated as follows (He *et al.* 2017):

$$\omega_j = \left[\sum_{j=1}^{m} \frac{\sum_{i=1}^{n}\sum_{h=1}^{c} u_{hi}^2[(r_{ij} - s_{jh})]^2}{\sum_{i=1}^{n}\sum_{h=1}^{c} u_{hi}^2[(r_{ij} - s_{jh})]^2}\right]^{-1} \tag{11}$$

$$u_{hi} = \left[\sum_{k=1}^{c} \frac{\sum_{j=1}^{m}[\omega_j(r_{ij} - s_{jh})]^2}{\sum_{j=1}^{m}[\omega_j(r_{ij} - s_{jk})]^2}\right]^{-1} \tag{12}$$

$$s_{jh} = \sum_{i=1}^{n} u_{hi}^2\omega_j^2 r_{ij} \Big/ \sum_{i=1}^{n} u_{hi}^2\omega_j^2 \tag{13}$$

Finally, the optimal $\boldsymbol{\omega}$, $\mathbf{U}$ and $\mathbf{S}$ can be obtained through fuzzy clustering iterative solution via Equations (11)–(13).

Adaptive fuzzy clustering iteration model

FCI reaches $\boldsymbol{\omega}$ via Equations (11)–(13), but this may lead into local convergence and cannot implement global optimization with some initial conditions, so intelligent optimization techniques are usually combined with FCI (He *et al.* 2011; Liao *et al.* 2014). In other words, when dealing with FCI, the vital task is to build a reasonable objective function and then find a convenient optimization algorithm.

For Equation (10), a penalty function method is generally adopted to transform the optimization problem with index weight constraints into the unconstrained optimization problem (He *et al.* 2011). Therefore, if there is no decision-maker's preference, the transformed objective function is shown as:

$$\min f = F(\boldsymbol{\omega}, \mathbf{U}, \mathbf{S}) + F(\boldsymbol{\omega}) = \min \sum_{i=1}^{n}\sum_{h=1}^{c}\left[u_{hi}\|\omega_j(r_{ij}-s_{jh})\|\right]^2 + M\left(\sum_{j=1}^{m}\omega_j - 1\right)^2 \quad (14)$$

where M is the penalty factor with a very large positive number. When the decision-maker's preference is considered or changed, $F(\boldsymbol{\omega})$ in Equation (14) needs to be accordingly adjusted.

For instance, suppose that the decision-maker considers the first index is the most important of all indices, then $F(\boldsymbol{\omega})$ needs to be adaptively modified as:

$$F_2(\boldsymbol{\omega}) = M\left(\sum_{j=1}^{m}\omega_j - 1\right)^2 + M_2 \cdot \min\left(\omega_1 - \max_{2\le j\le m}\omega_j, 0\right)^2 \quad (15)$$

Then the new objective function of AFCI is replaced based on Equation (14) and shown as:

$$\min f_2 = F(\boldsymbol{\omega}, \mathbf{U}, \mathbf{S}) + F_2(\boldsymbol{\omega}) \quad (16)$$

When the decision-maker decides that the first index is the most important and the second index is the second most important, $F(\boldsymbol{\omega})$ needs to be adaptively modified as:

$$F_3(\boldsymbol{\omega}) = M(\sum_{j=1}^{m}\omega_j - 1)^2 + M_3 \cdot \min(\omega_1 - \max_{2\le j\le m}\omega_j, 0)^2 + M_4 \cdot \min(\omega_2 - \max_{3\le j\le m}\omega_j, 0)^2 \quad (17)$$

Then the new objective function of AFCI is shown as:

$$\min f_3 = F(\boldsymbol{\omega}, \mathbf{U}, \mathbf{S}) + F_3(\boldsymbol{\omega}) \quad (18)$$

When the decision-maker determines that the first index is the most important and the second index is the second most important, and the first index is slightly more important than the second index, $F(\boldsymbol{\omega})$needs to be adaptively modified as:

$$F_4(\boldsymbol{\omega}) = M\left(\sum_{j=1}^{m}\omega_j - 1\right)^2 + M_5 \cdot \min(\omega_1 - \max_{2\le j\le m}\omega_j, 0)^2 + M_6 \cdot \min(\omega_2 - \max_{3\le j\le m}\omega_j, 0)^2 + M_7 \cdot \max(\omega_1 - \omega_2 - \varepsilon, 0)^2 \quad (19)$$

Then the new objective function of AFCI is shown as:

$$\min f_4 = F(\boldsymbol{\omega}, \mathbf{U}, \mathbf{S}) + F_4(\boldsymbol{\omega}) \quad (20)$$

In Equations (15)–(20), M_2, M_3, M_4, M_5, M_6, and M_7 are penalty factors with very large positive numbers; ε is a threshold parameter to control the indices' importance, i.e. $0 < \omega_1 - \omega_2 < \varepsilon$, and its value is assigned by the decision-maker.

Various complex preferences can be digitized and targeted by corresponding adaptive adjustments, and then a global search for the objective function as in Equations (16), (18) and (20) is carried out by HDE. In the next section, HDE is introduced in detail.

HYBRID DIFFERENTIAL EVOLUTION ALGORITHM

Overview of DE

DE is a simple and powerful population-based optimization proposed by Storn & Price (1997), which has three classic evolutionary operators, i.e. mutation, crossover and selection. Suppose there are NP D-dimensional real-valued parameter vectors named as $\mathbf{X}_i^G = (x_{i,1}^G, x_{i,2}^G, \ldots, x_{i,D}^G)$ in the population, where G denotes the generation and i is the index of the parameter vector, $i = 1, 2, \ldots, NP$, $j = 1, 2, \ldots, D$. The strategy of DE is described as follows (Xie *et al.* 2017).

Mutation

Two distinct individuals $\mathbf{X}_{r2}^G$, $\mathbf{X}_{r3}^G$ are randomly selected, and $\mathbf{X}_{r1}^G$ is randomly selected in the current population, and the mutation operator is described as:

$$\mathbf{V}_i^G = \mathbf{X}_{r1}^G + F \cdot (\mathbf{X}_{r2}^G - \mathbf{X}_{r3}^G),\ r_1 \neq r_2 \neq r_3 \quad (21)$$

where $\mathbf{V}_i^G$ is the mutant vector; r_1, r_2 and r_3 denote three different integers randomly in the range of [1,NP]; and the mutation parameter F is adopted to control the amplification, which is set to be 0.5.

Crossover

This is implemented to generate the trail vector $\mathbf{U}_i^G = (u_{i,1}^G, u_{i,2}^G, \ldots, u_{i,D}^G)$ from the target vector $\mathbf{X}_i^G$ and its corresponding mutant vector $\mathbf{V}_i^G$ as follows:

$$u_{i,j}^G = \begin{cases} v_{i,j}^G & \text{if } Rand(j) \le CR \text{ or } j = Rnb(i) \\ x_{i,j}^G & \text{if } Rand(j) > CR \text{ and } j \ne Rnb(i) \end{cases} \tag{22}$$

where $Rand(j)$ is the jth evaluation of a random number generator in the range [0,1]; $Rnb(i)$ is a randomly chosen index within the range of [1,D], and the crossover parameter CR is adopted to control the discrete recombination, which is set to be 0.4.

Selection

This is implemented to choose better individuals for the next generation between $\mathbf{X}_i^G$ and $\mathbf{U}_i^G$:

$$\mathbf{X}_i^{G+1} = \begin{cases} \mathbf{U}_i^G & \text{if } f(\mathbf{U}_i^G) \text{ better than } f(\mathbf{X}_i^G) \\ \mathbf{X}_i^G & \text{else} \end{cases} \tag{23}$$

where $f(\mathbf{X}_i^G)$ is the fitness value of $\mathbf{X}_i^G$, and the better vector is selected from the two vectors by the smaller value.

Hybrid differential evolution algorithm

The operators of DE are performed among particles, and the main reason for most intelligent algorithms converging to the local optimal is that a few dimensions of the population are possibly stagnant (Meng *et al.* 2014). Hence, a vertical crossover is implemented by exchanging the useful information between different dimensions of the same individual, so as to make it possible for the stagnant dimensions to escape from the local minima. Therefore, the vertical crossover is added for DE to improve its global search ability.

Suppose the $d1$-th and $d2$-th dimensions of the individual $\mathbf{X}_i^G$ are selected to carry out the vertical crossover operation, its offspring $\mathbf{Y}_i^G = (y_{i,1}^G, y_{i,2}^G, \ldots, y_{i,D}^G)$ is reproduced by Equation (24):

$$y_{i,d1}^G = p \cdot x_{i,d1}^G + (1-p) \cdot x_{i,d2}^G, \quad d1, d2 \in N(1, D) \tag{24}$$

where p is a uniform random value in the range [0,1]. Then the selection operator is also adopted to update $\mathbf{X}_i^G$:

$$\mathbf{X}_i^{G+1} = \begin{cases} \mathbf{Y}_i^G & \text{if } f(\mathbf{Y}_i^G) \text{ better than } f(\mathbf{X}_i^G) \\ \mathbf{X}_i^G & \text{else} \end{cases} \tag{25}$$

FLOOD DISASTER EVALUATION USING AFCI-HDE

Search-variable representation of HDE

Since HDE is a real-parameter optimization algorithm, the index weight vector is selected to be the optimization variable. And the purpose of HDE is to solve the minimum optimal solution of AFCI by continuous optimization until the termination condition is satisfied.

Fitness calculation of AFCI

When $\boldsymbol{\omega} = (\omega_1, \omega_2, \cdots, \omega_m)$ is encoded as an individual of HDE, the fuzzy clustering iterative solution is implemented to calculate $\mathbf{U} = (u_{hi})_{c \times n}$ and $\mathbf{S} = (s_{jh})_{m \times c}$, and finally the objective function fitness according to the individual is calculated. The detailed steps of the fuzzy clustering iterative solution are illustrated in He *et al.* (2017). Hence, the objective value of AFCI is then calculated as the fitness for the individual of HDE.

The procedure of flood disaster evaluation using AFCI-HDE

With the detailed introduction of AFCI and HDE, as well as the search-variable representation and objective function fitness calculation in the preceding two sections, flood disaster evaluation using AFCI-HDE is described as follows.

Step 1 The target objective function is established according to the decision-maker's preference by AFCI, as in Equations (16), (18) and (20) or other function forms.

Step 2 HDE is employed to globally search for the index weight vector.

Step 3 The optimal $\boldsymbol{\omega}$ is exported by AFCI-HDE, and then optimal **S** and **U** are reached.

Step 4 Flood disaster grade for the sample x_i is obtained by Equations (26) and (27) as follows:

(1) Rank feature value equation (RFV)

$$_1H_i = \sum_{h=1}^{c} u_{hi} \cdot h \tag{26}$$

(2) Confidence criterion equation (CC)

$$_2H_i = \min\{k: \sum_{h=1}^{k} u_{hi} \ge \lambda\} \ (1 \le k \le c) \tag{27}$$

where λ is the confidence degree and set to be 0.6.

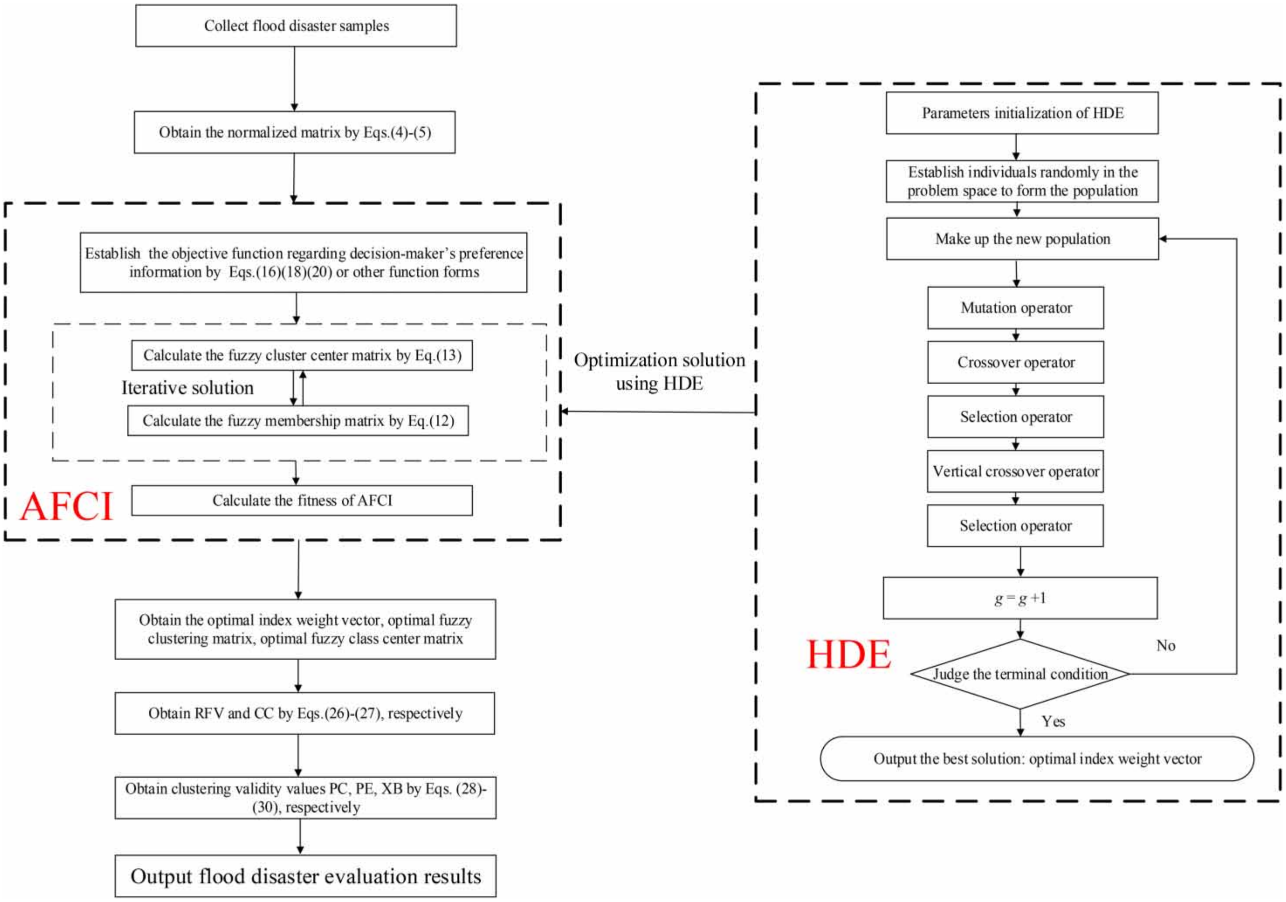

Figure 1 | Flowchart of flood disaster evaluation using AFCI-HDE.

With the above steps, we obtain the evaluation results for all the samples. The flowchart is described in Figure 1.

Finally, in order to verify the effectiveness of the proposed methodology, three well-known clustering validity functions are adopted to analyze and compare the clustering effect (Liao et al. 2013):

$$PC = \frac{1}{n} \cdot \sum_{i=1}^{n} \sum_{h=1}^{c} u_{hi}^2 \tag{28}$$

$$PE = -\frac{1}{n} \cdot \sum_{i=1}^{n} \sum_{h=1}^{c} u_{hi} \cdot \log_2 u_{hi} \tag{29}$$

$$XB = \frac{\sum_{i=1}^{n} \sum_{h=1}^{c} u_{hi}^2 \cdot \|\mathbf{r}_i - \mathbf{s}_h\|^2}{n \cdot \min_{h,k=1,2,\ldots,c;h\neq k} \|\mathbf{s}_h - \mathbf{s}_k\|^2} \tag{30}$$

where PC and PE are respectively the partition coefficient and partition entropy to reflect the closeness of data points belonging to the cluster centers, $PC \in [1/c, 1]$, $PE \in [0, \log_2 c]$; and XB is utilized to measure the distance between data points. A bigger PC indicates a better clustering effect, while a smaller PE and XB indicates a better clustering effect, and vice versa.

CASE STUDY

Flood disaster samples

Throughout the relevant research, the affected population, direct economic losses, destroyed buildings and affected areas were generally selected. Their weights are denoted as ω_1, ω_2, ω_3 and ω_4, respectively. In order to fully explain the rationality and advantages of AFCI-HDE, flood disaster samples from Xinjiang autonomous region of China were selected (He *et al.* 2017), shown in Table 1.

According to the Law of the People's Republic of China on emergency response, flood disasters are divided into four levels, such as general disaster, large disasters, major disasters, and catastrophic disasters, noted as I, II, III, IV, respectively.

Consideration of decision-maker's preference

Considering the people-oriented principle and living in harmony, the affected population is selected as one of the main preferences. Moreover, the direct economic loss is selected as another preference since the Chinese government has made economic development a prominent objective in recent years. Overall, five kinds of preference schemes are assigned as follows.

Preference 0: execute the proposed methodology without a decision-maker's preference.

Preference 1: the weight of affected population is the highest, i.e. $\omega_1 > \max(\omega_2, \omega_3, \omega_4)$.

Preference 2: the weight of direct economic loss is the highest, i.e. $\omega_2 > \max(\omega_1, \omega_3, \omega_4)$.

Preference 3: the weight of affected population is the highest, and the weight of direct economic loss is the second highest, i.e. $\omega_1 > \omega_2 > \max(\omega_3, \omega_4)$.

Preference 4: the weight of affected population and direct economic loss are close but tilt towards affected population to a certain extent, and they are both more important than other indices, i.e. $(\omega_1 > \approx \omega_2 > \max(\omega_3, \omega_4)) \cap (0 < \omega_1 - \omega_2 < \varepsilon)$. Here different ε are employed according to the decision-maker's preferences.

When using AFCI-HDE for the five preferences, we can conveniently establish the corresponding target objective functions by AFCI, the objective function for Preference 0 is Equation (14), and the objective function for Preference 1, Preference 2, Preference 3, and Preference 4 can be expressed based on Equations (16), (18) and (20).

Parameter setting

The parameters of AFCI-HDE are set as follows: in AFCI, the number of assessment samples, indices and clustering are respectively ten, four and four, and the various penalty factors are all 10^8 to satisfy all the constraints; in HDE, the population size is 40, and the number of maximum iteration is 200.

Evaluation results

The assessment results are compared with FCI (Chen 1998), FCI-CDE (He *et al.* 2011), FCI-PSO (He *et al.* 2017), FCI-PSODP (He *et al.* 2017) and the adaptive fuzzy clustering iterative model using simple DE (AFCI-DE) in Tables 2, 3, and 4. In particular, FCI-PSODP and AFCI-HDE would degenerate into FCI if there were no preference.

Table 1 | Flood disaster samples of Xinjiang

Samples	Areas	Affected population (10^4)	Direct economic loss (10^7RMB)	Destroyed buildings	Area affected by flood disasters (10^4 m^2)
1	Urumqi	6	3.48	20.69	0.1543
2	Tacheng	5.97	1.608	6.235	1.374
3	Bortala	4.35	0.177	2.843	0.2601
4	Changji	9.4	7.91	54.5	2.352
5	Tuipan	2.96	4.946	58.728	1.6673
6	Hami	2.62	1.826	5.105	0.5458
7	Bayingolin	4.54	7.88	21.713	1.0792
8	Kizilsu	5.6	0.395	1.556	0.341
9	Kashgar	20	4.43	1.89	0.214
10	Bingtuan	24.727	6.327	13.592	4.6026

Table 2 | Evaluation results with Preference 0

Preferences	Methods	Optimal index weight vector ω_1	ω_2	ω_3	ω_4	Optimal fitness	Clustering validity values PC	PE	XB
Preference 0	FCI	0.2500	0.3747	0.1640	0.2114	0.1329	0.7598	0.7154	0.0060
	FCI-CDE	0.0139	0.0244	0.8759	0.0858	0.0148	0.9282	0.2133	0.0057
	FCI-PSO	0.1091	0.0760	0.6682	0.1469	0.4251	0.8771	0.3694	0.0097
	AFCI-HDE	0.0035	0.0125	0.8142	0.1698	**0.0077**	**0.9485**	**0.1860**	**0.0019**

Table 3 | Comparisons with different preferences

Preferences	Methods	Optimal index weight vector ω_1	ω_2	ω_3	ω_4	Optimal fitness	Clustering validity values PC	PE	XB
Preference 1	FCI-PSODP	0.7924	0.0485	0.0516	0.1075	0.0241	0.7904	0.5777	0.0145
	AFCI-HDE	0.5038	0.0209	0.0401	0.4353	**0.0206**	**0.7935**	**0.5555**	**0.0036**
Preference 2	FCI-PSODP	0.0685	0.7301	0.0965	0.1049	0.0309	0.8289	0.4982	0.0493
	AFCI-HDE	0.0634	0.8264	0.0574	0.0528	**0.0293**	**0.8406**	**0.4910**	**0.0035**
Preference 3	FCI-PSODP	0.8747	0.0726	0.0126	0.0401	0.0200	0.8707	0.3695	0.0033
	AFCI-DE	0.8681	0.0592	0.0322	0.0405	0.0191	0.8743	0.3592	0.0031
	AFCI-HDE	0.8670	0.0587	0.0239	0.0504	**0.0188**	**0.8746**	**0.3577**	**0.0031**

Results with Preference 0

From Table 2, for Preference 0, the optimal fitness of FCI is 0.1329, which is more than for FCI-CDE and AFCI-HDE, indicating it is necessary to apply algorithms for FCI. Moreover, if the preference is not considered, the weights for destroyed buildings by FCI-CDE, FCI-PSO and AFCI-HDE are all above 0.66, which is relatively larger than the sum of the other three indices, is inconsistent with the national policy of people-oriented and scientific development, and fails to reflect the high concern of relevant departments for people in disaster areas. Therefore, it is necessary to consider the decision-maker's preferences for flood disaster evaluation.

Results with Preference 1–Preference 3

As a result, Preference 1–Preference 3 have respectively attracted attention according to the people-oriented principle and rapid economic development, and they are analyzed using FCI-PSODP and AFCI-HDE, shown in Table 3. By comparing the optimal fitness and three validity values, the clustering effect of AFCI-HDE is better than FCI and FCI-DE, indicating that it is necessary to employ HDE for a global search of FCI. Moreover, HDE has a strong optimization ability, and has no need to join the decision-maker's preference with operators as FCI-PSODP, so as to avoid the drawback that the optimization ability would become worse or even fall into a local optimum as additional treatments are added to the PSO. Therefore, AFCI-HDE is demonstrated to be convenient and reasonable.

Table 4 displays the results by FCI-PSODP and AFCI-HDE with Preference 3. It is concluded the two methods have identical results, i.e. samples 10, 9 and 4 are catastrophic disaster, major disaster, and large disaster, respectively; the rest of the samples belong to general disaster. However, from Table 5 we can conclude AFCI-HDE has better clustering than FCI-PSODP for all the preferences. But the index weight vector with Preference 3 indicates that the weight for affected population is far larger than for direct economic losses. Since rapid development of the economy is also playing an increasing role in social life, a balance between affected population and direct economic losses is attracting great attention.

Table 4 | Evaluation results by FCI-PSODP and AFCI-HDE with Preference 3

Samples	FCI-PSODP								AFCI-HDE							
	Fuzzy membership matrix				RFV	CC	CEV	Level	Fuzzy membership matrix				RFV	CC	CEV	Level
1	0.809	0.176	0.010	0.005	1.211	1.0	0.721	I	0.808	0.177	0.010	0.005	1.213	1.0	0.711	I
2	0.823	0.162	0.010	0.005	1.197	1.0	0.732	I	0.818	0.167	0.010	0.005	1.202	1.0	0.720	I
3	0.980	0.017	0.002	0.001	1.024	1.0	0.858	I	0.984	0.013	0.001	0.001	1.019	1.0	0.854	I
4	0.004	0.995	0.001	0.000	1.998	2.0	0.075	II	0.004	0.995	0.001	0.000	1.998	2.0	0.062	II
5	0.923	0.064	0.008	0.005	1.096	1.0	0.812	I	0.920	0.066	0.009	0.005	1.099	1.0	0.802	I
6	0.910	0.073	0.011	0.007	1.114	1.0	0.802	I	0.910	0.073	0.011	0.007	1.114	1.0	0.794	I
7	0.929	0.062	0.005	0.003	1.083	1.0	0.818	I	0.952	0.042	0.004	0.002	1.056	1.0	0.828	I
8	0.895	0.094	0.007	0.004	1.120	1.0	0.790	I	0.896	0.093	0.007	0.004	1.118	1.0	0.783	I
9	0.000	0.000	1.000	0.000	3.000	3.0	0.013	III	0.000	0.000	1.000	0.000	3.000	3.0	0.024	III
10	0.000	0.000	0.000	1.000	4.000	4.0	0.040	IV	0.000	0.000	0.000	1.000	4.000	4.0	0.050	IV

Results with Preference 4

Under certain conditions, but a little different from Preference 3, we can quickly establish Preference 4 with different ε, and achieve results using AFCI-HDE, shown in Tables 5 and 6.

It can be concluded for Preference 4 from Table 5 that samples 10 and 9 are respectively catastrophic disaster and major disaster, which is similar to the results with Preference 3; samples 4, 5 and 7 are large disaster, while samples 5 and 7 are large disaster with Preference 3. The reason for this difference is that the direct economic losses of sample 5 and sample 7 are 4.946×10^7 RMB and 7.88×10^7 RMB, respectively, which rank at fourth and second place among the samples. In particular, if sample 7 is only treated as a general disaster, the affected people in disaster areas have lack of care, which is not conducive to economic and social recovery. Under the premise of the people-oriented principle and scientific economic development, we suggest decision-makers adopt Preference 4 in practical work for flood disaster prevention and reduction.

Furthermore, in order to verify the effectiveness of the modification work, we also present the comparisons of AFCI-DE and AFCI-HDE in Table 6. We can conclude that DE and HDE have identical evaluation results for minimizing AFCI, but the precision and effectiveness of HDE performs better than DE according to the clustering validity values.

CONCLUSIONS

Flood disaster evaluation is a complex problem with multi-variable coupling factors. FCI can identify different categories by mining the samples, but cannot reflect humanization and scientification. Therefore, it is important to consider the decision-maker's preference.

However, the calculation process of FCI considering the decision-maker's preference is complex, and cannot effectively handle complex preferences. Therefore, AFCI was first proposed to adjust the target function adaptively, so as to digitally describe the decision-maker's preference. Moreover, HDE was introduced to implement the global search of AFCI. Finally, the case study was researched

Table 5 | Evaluation results by AFCI-HDE with Preference 4

	Preference 4 ($\varepsilon = 0.05$)					Preference 4 ($\varepsilon = 0.1$)					Preference 4 ($\varepsilon = 0.2$)				
Samples	Fuzzy membership matrix				Level	Fuzzy membership matrix				Level	Fuzzy membership matrix				Level
1	0.607	0.193	0.160	0.039	I	0.636	0.218	0.099	0.048	I	0.690	0.207	0.077	0.026	I
2	0.884	0.048	0.050	0.018	I	0.976	0.011	0.009	0.004	I	0.899	0.058	0.030	0.013	I
3	0.936	0.024	0.030	0.010	I	0.941	0.025	0.022	0.012	I	0.943	0.029	0.020	0.008	I
4	0.051	0.809	0.073	0.067	II	0.044	0.840	0.067	0.050	II	0.076	0.780	0.084	0.059	II
5	0.166	0.693	0.090	0.051	II	0.270	0.592	0.086	0.052	II	0.241	0.670	0.058	0.032	II
6	0.951	0.022	0.020	0.007	I	0.944	0.030	0.017	0.009	I	0.938	0.039	0.016	0.007	I
7	0.060	0.843	0.065	0.033	II	0.022	0.946	0.019	0.013	II	0.041	0.921	0.024	0.013	II
8	0.948	0.018	0.025	0.008	I	0.951	0.020	0.019	0.010	I	0.952	0.024	0.018	0.007	I
9	0.002	0.001	0.996	0.001	III	0.000	0.000	0.997	0.002	III	0.000	0.000	0.999	0.000	III
10	0.000	0.000	0.000	1.000	IV	0.000	0.000	0.000	0.999	IV	0.000	0.000	0.000	1.000	IV

Table 6 | Comparisons of AFCI-DE and AFCI-HDE with Preference 4

		Optimal index weight vector					Clustering validity values		
Preferences	Methods	ω_1	ω_2	ω_3	ω_4	Optimal fitness	*PC*	*PE*	*XB*
Preference 4 ($\varepsilon = 0.05$)	AFCI-DE	0.3263	0.3083	0.1518	0.2137	0.0299	0.7180	0.8110	0.0124
	AFCI-HDE	0.3009	0.3002	0.1307	0.2682	**0.0287**	**0.7799**	**0.6599**	**0.0047**
Preference 4 ($\varepsilon = 0.1$)	AFCI-DE	0.4357	0.3694	0.1401	0.0548	0.0291	0.7792	0.6727	0.0123
	AFCI-HDE	0.4617	0.3947	0.0803	0.0633	**0.0288**	**0.8133**	**0.5603**	**0.0059**
Preference 4 ($\varepsilon = 0.2$)	AFCI-DE	0.3530	0.2855	0.0881	0.2734	0.0289	0.7923	0.6220	0.0044
	AFCI-HDE	0.4044	0.2797	0.0637	0.2522	**0.0272**	**0.8001**	**0.5942**	**0.0043**

with various decision-maker's preferences using AFCI-HDE. For all the preferences, AFCI-HDE could quickly establish the objective function with corresponding adaptive adjustment and rapidly achieve a more effective clustering effect than FCI, FCI-PSODP, and AFCI-DE. And the evaluation results demonstrated that the proposed methodology is simple, convenient and reasonable, which have important reference value and application prospects for flood disaster evaluation. Moreover, with the aggregation of population and the rapid growth of the economy, we suggest that the decision-maker would choose Preference 4 in practical work, so as to ensure safety of people's lives and property.

Of course, the preference is fuzzy and dynamic in a practical environment, and to put forward a more accurate and comprehensive way to describe the decision-maker's preference and even decision-makers' preferences and then carry out the assessment results with the proposed methodology is our further work.

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