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Research article

TOPSIS model with combination weight for demand assessment of flood emergency material supplies

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Abstract: Assessing the urgency of emergency material demand in disaster scenarios improves dispatching efficacy and enhances emergency management agencies' operational efficiency during post-disaster relief. Taking the July 20 flood in Henan, China, as a case study, this paper assesses the urgency of emergency material demand in flood disaster scenarios. The objective weights and subjective weights of the evaluation indicators are calculated using the coefficient of variation method and the order relation analysis method, respectively. Then this paper combines these calculated weights on the basis of maximizing deviation, and the technique for order preference by similarity to an ideal solution (TOPSIS) method is used to judge the demand urgency of disaster sites. Finally, a cloud model is introduced to visualize the urgency evaluation results obtained from the single weighting method and the combination weighting method by generating cloud maps. The results demonstrate that the hyper-entropy value of the cloud digital features obtained by the combination weighting is 0.0432 (the smallest among the methods), indicating the least uncertainty and a relatively small degree of dispersion. At the same time, the condensation rate of cloud droplets in the cloud map generated by the combined weighting method is higher, indicating that the combined weighting method has lower uncertainty compared with the single weighting method and is superior to the single weighting method in efficiency. Moreover, through sensitivity analysis, it is evident that when the weight of the most important evaluation indicator varies within the range of [0.1192, 0.3881], the TOPSIS method based on combined weighting demonstrates strong robustness.

Keywords: flood disaster; demand urgency; combination weighting method; single weighting method; TOPSIS; cloud model
Mathematics Subject Classification: 62P12, 62P25

1. Introduction

Against the background of global warming, extreme weather events occur frequently, and the occurrence of natural disasters and the disaster risk borne by cities also increases [1]. Flood disasters account for 40% of urban disasters, are the main source of urban disasters, and have become one of the important natural disasters affecting urban development [2].

From 2008 to 2022, China's flood disasters caused 9812 deaths and direct economic losses of 3,165.513 billion yuan. In 2019, large-scale rainfall in six southern provinces affected 5.58 million people, causing total losses of 91 deaths and 23.18 billion yuan. In 2021, a rainstorm happening in Henan province on 20 July had a profound impact, affecting a total of 14,786,000 individuals, resulting in the tragic loss of 398 lives and inflicting direct economic damages estimated at 133.7 billion yuan. Following the 2021 Henan deluge, North China experienced another historic rainfall from 28 July to 2 August 2023, triggering catastrophic flooding across Beijing–Tianjin–Hebei. Flood-induced losses significantly impede socioeconomic development, making scientifically executed post-disaster rescue operations crucial for loss reduction and emergency efficiency.

Many scholars have undertaken extensive research endeavors in the realm of flood disaster risk assessment, which has brought up a diverse array of methodological approaches. Among them, Wu et al. [3] pioneered an ontology-driven Bayesian network model, leveraging observational data to quantify complex interdependencies among flood-influencing factors, thereby offering an original example for regional risk evaluation. Building on historical disaster databases, Luu et al. [4] integrated multiple linear regression analysis with the technique for order preference by similarity to an ideal solution (TOPSIS), creating an explainable model of a comprehensive national flood risk map for Vietnam. Meanwhile, Cai et al. [5] proposed a hydrodynamic–GIS hybrid model to assess flood risks in Yifeng, Jiangxi Province, enabling precise risk mapping. In urban contexts, Chen et al. [6] employed the analytic hierarchy process (AHP) for weight determination, subsequently integrating TOPSIS to develop a comprehensive framework for assessing urban resilience in the context of rain and flood disasters. This model evaluated cities' resilience levels under such hazardous scenarios. Further innovations include those of Su et al. [7], who employed game theory-based combination weighting to harmonize subjective and objective indicator weights, coupled with GIS spatial analysis for multidimensional flood risk assessment in Wuwei, Gansu Province. Addressing emergency logistics, Zhang et al. [8] introduced an intelligent scheduling model for multi-disaster scenarios, incorporating two-dimensional Euclid distance weighting to optimize uncertain material demand and delivery timelines. Based on the empirical analysis of the heavy rain disaster in Henan Province in 2021, the phased emergency material dispatching scheme from the rescue point to the disaster point was obtained. Similarly, Wang [9] enhanced TOPSIS with gray correlation analysis, combining entropy-weighted and AHP-derived coefficients to classify the urgency of disaster sites' material needs, validated through a case study of Hubei's 2016 flood.

With the flood disaster in Henan Province in July 2021 as an example, the practicability of the established model was verified. The main contributions of this article are as follows:

(1) Previous flood risk assessment studies have overlooked the urgency of emergency material demands while relying on conventional single-weighting approaches for indicator quantification. To address these limitations, this study proposes a novel combined weighting methodology for flood risk evaluation. Unlike traditional methods, this hybrid framework strategically integrates subjective and objective weighting techniques, thereby eliminating the over-reliance on data statistics inherent in purely objective methods and reducing the arbitrariness associated with subjective weight assignments.

(2) This study evaluated the criticality of emergency material demand across diverse disaster sites in the aftermath of large-scale flooding events, examining the urgency for emergency supplies amidst the context of a flood disaster, considering that the urgency of demand allows for a more targeted rescue effort in disaster-stricken areas.

(3) Moreover, this study advances the theoretical framework of post-disaster resource management by establishing a robust foundation for optimizing emergency material allocation. The findings provide decision-makers with actionable insights to enhance distribution strategies, while offering emergency management agencies evidence-based tools to improve operational efficiency in disaster responses. These contributions hold significant implications for both scholars and practical emergency preparedness.

The general structure of the article is as follows: In Section 2, the definitions included in this study are explained. In Section 3, the research methods of various scholars in the case of flood disasters are listed. In Section 4, a fusion of subjective and objective weighting methodologies is devised, aiming to achieve a comprehensive evaluation framework. It introduces the steps of determining the weights by the coefficient of variation method, the order relation analysis method, and a combination weighting method based on maximizing deviation, and elucidated the application of the TOPSIS method for assessing demand urgency across disaster sites. Finally, the cloud model is introduced. In Section 5, an evaluation framework for the urgency of emergency material demand is formulated, and its practical applicability is validated through a case study of the flood event on 20 July in Henan Province, China. To assess the combined weighting method's efficacy, we conduct a comparative analysis by means of data visualization. In addition, sensitivity analysis is performed to verify the robustness of the TOPSIS method based on combinatorial weighting. In Section 6, the main research findings are systematically summarized, the methodological limitations are objectively analyzed, and potential improvement directions are proposed for future studies.

2. Preliminaries

This chapter introduces three definitions of triangular fuzzy numbers for further research.

Definition 2.1. [10] Let a mapping on the universe map it to the closed interval [0,1], that is

$$\mu_{\tilde{A}} : U \to [0,1],\ \mu \mapsto \mu_{\tilde{A}} \in [0,1]. \tag{2.1}$$

In this case, it is said that this mapping determines a fuzzy subset $\tilde{A}$ of U, $\mu_{\tilde{A}}$ represents the membership function of A, and $\mu_{\tilde{A}}(u)$ is called the membership degree of μ to A. Fuzzy subsets are also called fuzzy sets.

Definition 2.2. [11] If the membership function

$$\mu_M : U \to [0,1]$$

of the fuzzy number M set on the universe R can be expressed as

$$\mu_M(x)=\begin{cases}\dfrac{x}{m-l}-\dfrac{l}{m-l}, & x\in[l,m],\\ \dfrac{x}{m-u}-\dfrac{u}{m-u}, & x\in[m,u],\\ 0, & x\in(-\infty,l]\cup[u,+\infty),\end{cases} \tag{2.2}$$

the fuzzy number M is termed a triangular fuzzy number, where $l \le m \le u$. Here, l and u denote the upper and lower bounds of the triangular fuzzy number M , respectively, while m represents its median, with a membership degree of l . Hence, the triangular fuzzy number M is denoted as

$$M=(l,m,u).$$

Definition 2.3. [12] Let a triangular fuzzy number

$$M=(l,m,u)$$

have its gradient average integral $R(M)$ as follows:

$$R(M)=\frac{1}{6}(l+4m+u). \tag{2.3}$$

For the triangular fuzzy numbers

$$M_1=(l_1,m_1,u_1) \text{ and } M_2=(l_2,m_2,u_2),$$

the gradient average integrals are $R(M_1)$ and $R(M_2)$, respectively, and the comparison rules are as follows: if

$$R(M_1)<R(M_2),$$

the triangular fuzzy number M_1 is less than M_2.

3. Research on assessment methods for flood emergency material demand

With the occurrence of large-scale flood disaster events, scholars attach growing significance to the dispatch and evaluation of emergency materials in the case of flood disasters. In Table 1, an overview of the diverse investigative methodologies employed by various scholars in the context of flood disaster research is presented. According to the findings from a comprehensive literature review, most scholars use a single weighting method to assign weights to evaluation indicators when conducting comprehensive evaluations, while a few scholars use a combination weighting method. At the same time, we can also find that there are few articles considering the urgency of demand in the evaluation of scheduling emergency materials for flood disasters. There are two drawbacks in the evaluation research of other scholars. First, outcomes may overlook human-determined factors, causing biases in the actual situations. Second, the efficiency of emergency supply dispatch remains suboptimal. Given the reasons mentioned above, this study provides valuable reference implications. The advantage of this paper lies in incorporating a combined weighting approach for allocating significance to evaluation indicators, while simultaneously considering the urgency of the requirement for emergency supplies. This strategy aimed to resolve the shortcomings mentioned above, thereby enhancing the overall effectiveness of the evaluation process. In addition, to enhance the precision and credibility of the outcomes, we utilize both the coefficient of variation methodology and the order relation analysis to determine the objective and subjective weights, respectively. Furthermore, this paper employs the maximizing deviation technique to integrate these weights comprehensively. This not only avoids neglecting decision-makers' experiential knowledge, which introduces bias, but also avoids the problem that mitigates subjective weighting's arbitrariness, which distorts the evaluation outcomes [13]. Therefore, the method based on combination weighting is more scientific and reasonable for evaluating the urgency of emergency material demand under flood disasters. In future research, we aim to extend the application of this methodology to various additional fields.

In Table 1, ANP stands for analytic network process; DEM stands for digital elevation models; GIS stands for geographic information system; VIKOR stands for VlseKriterijumska Optimizacija I Kompromisno Resenje; CRITIC stands for criteria importance though intercriteria correlation.

Table 1. Research on flood assessment methods.

Author	Evaluation method	Indicator	Weighting method
Levy et al. [14]	ANP	Flood defense, shelter in place, and evacuate; shelter in place and evacuate; evacuate; flood defense; shelter in place	Single weighting
Li et al. [15]	Hesitant fuzzy VIKOR	Resistance; coping capacity; recovery; adaptive capacity	Single weighting
Nivolianitou et al. [16]	AHP	Physical features; organizational aspects; contextual features	Single weighting
Ou-Yang et al. [17]	AHP, GIS	Rainstorm intensity; flood frequency; disaster-inducing environment partition; direct economic losses; duration of suspended transportation; costs of repairing water damage to engineering projects	Single weighting
Huang et al. [18]	AHP, ArcGIS	Flood depth; duration of flooding; ground elevation; slope; population density; land utilization; hospital distance; emergency shelter distance	Single weighting
Zhang et al. [19]	AHP, ArcGIS	Flood depth; population density; GDP per area	Single weighting
Wang [9]	Entropy method, AHP, improved TOPSIS	Degree of building damage; degree of road damage; demand gap rate; proportion of affected population; affected population; proportion of elderly and children	Combination weighting
Li et al. [20]	CRITIC, gray relational analysis	Population disaster; crops are affected; houses collapsed; loss of water-conserving flood control equipment; economic losses	Single weighting
Yuan et al. [21]	AHP	Maximum submergence depth; maximum flood velocity; submerged duration; DEM; slope; population density; GDP density; land use type	Combination weighting
Zhou et al. [22]	Gray relational analysis; TOPSIS	Emergency command and rescue support requirements; post-disaster emergency rescue needs; basic living security needs; public infrastructure support requirements	Combination weighting
Song and Sun [23]	ANP	Disaster level; personnel situation in the disaster area; environmental factors affected by disasters; material demand	Single weighting

4. Discussion

Upon the establishment of the evaluation indicator system, it is crucial to determine the weight of each indicator, tailored to their appropriate significance in influencing the evaluation's outcomes, within the urgency evaluation model. The existing methods for determining indicator weights mainly include the maximizing deviation method, principal component analysis, the coefficient of variation method, the entropy weight method, etc. Divergent implementation mechanisms across methods produce varying indicator weights, introducing inherent weighting biases, which result in different final evaluation results for the same evaluation object. To reduce single-weight bias, this study implements a composite weighting approach integrating multiple determination techniques.

Subjective weighting methods depend on the decision-makers' experience and judgment, introducing inherent subjectivity and arbitrariness [24]. Meanwhile, objective weighting methods lack decision-makers' involvement and broader applicability, potentially yielding indicator weights that are misaligned with practical realities [25]. However, the combination weighting method is beneficial to match the determination of important degree and the objective information of the actual indicators, it can take into account not only the subjective judgment of expert, but also the objective change of measured indicators [26]. Therefore, this paper adopted the combination weighting method, which combines objective weights and subjective weights to carry out the combination weighting for the evaluation indicator system. Employing the coefficient of variation method for objective weights reduces human factor biases and enhances the outcome's objectivity. After determining the objective weights, experts assign the subjective weights by referring to the results of the objective weights, using the order relation analysis method, and then assign the subjective and objective weights according to the idea of maximizing deviation. Compared with single weights, combined weights can make the evaluation results more accurate. Finally, the TOPSIS method is used to calculate the relative closeness degree of the samples being evaluated, in order to assess the urgency of the demand of the disaster site. Following a disaster, the urgency of material requirements at the site dictates a proportionately higher priority level in the subsequent rescue operations; conversely, the lower the urgency level, the lower the priority level of rescue.

In this section, this paper introduces the coefficient of variation method, the order relation analysis method, and the maximizing deviation method. At the same time, the TOPSIS method and the cloud model are introduced for demand urgency assessment.

4.1. Determination of objective weights

The coefficient of variation is used to measure the degree of variation or dispersion between two or more samples [27]. Indicators with higher degrees of variation receive proportionally greater weights**.** Conversely, indicators exhibiting lesser degrees of variation should receive correspondingly diminished weights. The calculation process is as follows:

Step 1. Original data preprocessing. Let the initial decision matrix X_{mn}, m be the number of evaluation objects in the decision matrix, and let n be the number of indicators of evaluation objects. The expression of the decision matrix is as follows:

$$X_{mn} = \left(x_{ij}\right) = \begin{pmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{pmatrix}, \tag{4.1}$$

where x_{ij} represents the value of the j th evaluation indicator of the i th sample.

Due to the different units and magnitudes of each indicator, the original data of each indicator in the sample cannot be used for direct evaluation, so it is necessary to conduct nondimensional processing of the sample data. The process is as follows for the benefit indicators:

$$x_{ij}{}' = \frac{x_{ij} - \min_{i=1}^{m} x_{ij}}{\max_{i=1}^{m} x_{ij} - \min_{i=1}^{m} x_{ij}}. \tag{4.2}$$

For the cost indicators, it is

$$x_{ij}{}' = \frac{\max_{i=1}^{m} x_{ij} - x_{ij}}{\max_{i=1}^{m} x_{ij} - \min_{i=1}^{m} x_{ij}}. \tag{4.3}$$

Step 2. Calculate the mean value μ_j and standard deviation σ_j of the evaluation indicator of item j.

$$\mu_j = \frac{1}{m}\sum_{i=1}^{m} x_{ij}{}', \tag{4.4}$$

$$\sigma_j = \sqrt{\frac{\sum_{i=1}^{m}\left(x_{ij}{}' - \mu_j\right)^2}{m-1}}. \tag{4.5}$$

where $j = 1, 2, \cdots, n$.

Step 3. Calculate the coefficient of variation CV_j of the j th evaluation indicator.

$$CV_j = \frac{\sigma_j}{\mu_j}, \tag{4.6}$$

where $j = 1, 2, \cdots, n$.

Step 4. The calculation formula of indicator weight W_j is as follows:

$$W_j = \frac{CV_j}{\sum_{j=1}^{n} CV_j}. \tag{4.7}$$

4.2. Determination of subjective weights

The order relation analysis method constitutes an enhanced subjective weighting technique, building upon the fundamental principles of the analytic hierarchy process [28], which simplifies the calculation of the analytic hierarchy process, and does not need to test consistency, so it has higher operability and intuitiveness. The steps of order relation analysis to determine the weight are as follows:

Step 1. The evaluation indicators $\left(x_1, x_2, \cdots, x_n\right)$ are arranged in descending order of importance, $\left(h_1 \succ h_2 \succ \cdots \succ h_n\right)$, so as to determine the order relationship.

Step 2. Determine the importance of the adjacent indicator as follows:

$$B_p = \frac{D_{p-1}}{D_p}, \tag{4.8}$$

where $p = 2, 3, \cdots, n$, among them, the ratio of $\frac{D_{p-1}}{D_p}$, B_p is used to represent the importance value of indicator h_{p-1} and h_p, D_p represents the evaluation result of the pth expert on the indicator.

The assignment and description of B_p are shown in Table 2.

Table 2. Assignment and description.

Assignment of B_p	Assignment specification
1.0	Indicator $h_{p\text{-}1}$ is as important as indicator h_p
1.2	Indicator $h_{p\text{-}1}$ is slightly more important than indicator h_p
1.4	Indicator $h_{p\text{-}1}$ is obviously more important than indicator h_p
1.6	Indicator $h_{p\text{-}1}$ is strongly more important than indicator h_p
1.8	Indicator $h_{p\text{-}1}$ is extremely more important than indicator h_p

Step 3. Determine the weight ω_n as follows:

$$\omega_n = \left(1 + \sum_{p=2}^{n} \prod_{i=p}^{n} B_i\right)^{-1}, \tag{4.9}$$

$$\omega_{p-1} = B_p \omega_p. \tag{4.10}$$

According to Eq (4.9) the weight of the nth indicator can be determined as ω_n, where B_p represents the ratio of the importance of the $p-1$th indicator to that of the pth indicator. Calculate the weights of $1, 2, \cdots, n-1$ indicators using Eq (4.10) and represent them as ω_{p-1}.

Step 4. Determine the final weight ω_j. Assuming that the set ω_j comprises the weight ω_{p-1} of the $1, 2, \cdots, n-1$th indicator and the weight ω_n of the nth indicator, we then have:

$$\omega_j = \left(\omega_{p-1}, \omega_n\right). \tag{4.11}$$

4.3. Combination weighting method based on maximizing deviation

Drawing upon the principle of maximizing deviation, the combined weight is computed. If the difference between the indicator values is large, the impact on the evaluation result is large and the weight is large; otherwise, the weight is small [29]. The steps for combinational weighting using maximizing deviation are as follows:

Step 1. Let the combined weight vector be

$$\xi = \left(\xi_1, \xi_2, \cdots, \xi_n\right)^T,$$

where

$$\xi = \alpha\omega + \beta W, \tag{4.12}$$

α and β are linear representation coefficients of the combination weight and satisfy $\alpha \geq 0, \beta \geq 0$. The Euclidean distance, represented by the sum of squares, more accurately reflects the positional relationship and degree of change of α and β in space. The linear combination of α and β cannot effectively constrain the distribution range of variables in the geometric sense, as the sum of squares, so let

$$\alpha^2 + \beta^2 = 1.$$

Step 2. Calculate the total deviation of the evaluation object

$$\Omega = \sum_{j=1}^{n}\sum_{i=1}^{m}\sum_{k=1}^{m} \xi_j \left| x_{ij}' - x_{kj}' \right|. \tag{4.13}$$

Step 3. The optimization model is solved so that the combined weight vectors can maximize the deviation. The optimization model is as follows:

$$\begin{cases} \max \Omega = \sum_{j=1}^{n}\sum_{i=1}^{m}\sum_{k=1}^{m} \left(\alpha\omega_j + \beta W_j\right)\left| x_{ij}' - x_{kj}' \right|, \\ s.\,t.\ \alpha^2 + \beta^2 = 1, \\ \alpha \geq 0, \beta \geq 0. \end{cases} \tag{4.14}$$

Step 4. Construct a Lagrange function as follows:

$$L\left(\alpha, \beta\right) = \sum_{j=1}^{n}\sum_{i=1}^{m}\sum_{k=1}^{m} \left(\alpha\omega_j + \beta W_j\right)\left| x_{ij}' - x_{kj}' \right| + \varphi\left(\alpha^2 + \beta^2 - 1\right), \tag{4.15}$$

where φ is the Lagrange multiplier.

Step 5. Find the partial derivative of $L\left(\alpha, \beta\right)$. Then the values of α and β can be obtained by solving

$$\begin{cases} \alpha = \dfrac{\sum_{j=1}^{n}\sum_{i=1}^{m}\sum_{k=1}^{m} \omega_j \left| x_{ij}' - x_{kj}' \right|}{\sqrt{\left(\sum_{j=1}^{n}\sum_{i=1}^{m}\sum_{k=1}^{m} \omega_j \left| x_{ij}' - x_{kj}' \right|\right)^2 + \left(\sum_{j=1}^{n}\sum_{i=1}^{m}\sum_{k=1}^{m} W_j \left| x_{ij}' - x_{kj}' \right|\right)^2}}, \\ \beta = \dfrac{\sum_{j=1}^{n}\sum_{i=1}^{m}\sum_{k=1}^{m} W_j \left| x_{ij}' - x_{kj}' \right|}{\sqrt{\left(\sum_{j=1}^{n}\sum_{i=1}^{m}\sum_{k=1}^{m} \omega_j \left| x_{ij}' - x_{kj}' \right|\right)^2 + \left(\sum_{j=1}^{n}\sum_{i=1}^{m}\sum_{k=1}^{m} W_j \left| x_{ij}' - x_{kj}' \right|\right)^2}}. \end{cases} \tag{4.16}$$

Step 6. By bringing the values of α and β into Eq (4.12), the combined weight vector

$$\xi = \left(\xi_1, \xi_2, \cdots, \xi_n\right)^T$$

can be obtained.

4.4. TOPSIS method to calculate the urgency of demand

TOPSIS determines the optimal scheme by comprehensively evaluating the weighted distances from each candidate solution to the ideal solution and the negative ideal solutions, so as to ensure the comprehensive evaluation of the contribution of all attributes. The calculation steps are as follows [30]:

Step 1. The decision matrix X_{mn} needs to be normalized to avoid errors caused by the dimensions and range of fluctuation. Using global standardization, the normalized decision matrix Y_{mn} is obtained

$$Y_{mn} = \left(y_{ij}\right)_{m\times n} = \begin{pmatrix} y_{11} & \cdots & y_{1n} \\ \vdots & \ddots & \vdots \\ y_{m1} & \cdots & y_{mn} \end{pmatrix}, \tag{4.17}$$

where $y_{ij} = x_{ij}'$, $i = 1, 2, \cdots, m$, $j = 1, 2, \cdots, n$.

Step 2. The TOPSIS method is used to determine the normalized positive ideal solution

$$\overline{Y} = \left(\overline{y}_1, \overline{y}_2, \cdots, \overline{y}_n\right) \in R^n$$

and the normalized negative ideal solution

$$\underline{Y} = \left(\underline{y}_1, \underline{y}_2, \cdots, \underline{y}_n\right) \in R^n.$$

Step 3. The Euclidean distance d_i^+ between the i th evaluation object and the optimal object, and the d_i^- between the i th evaluation object and the worst object are calculated, respectively, as

$$d_i^+ = \sqrt{\sum_{j=1}^{n}\left(y_{ij} - \overline{y}_j\right)^2}, \tag{4.18}$$

$$d_i^- = \sqrt{\sum_{j=1}^{n}\left(y_{ij} - \underline{y}_j\right)^2}. \tag{4.19}$$

where $i = 1, 2, \cdots, m$.

Step 4. The relative closeness degree of the i th evaluation object is expressed as

$$C_i = \frac{d_i^-}{d_i^- + d_i^+}, \tag{4.20}$$

where $i = 1, 2, \cdots, m$, C_i is used to indicate the relative closeness between the evaluation target and the negative ideal solution. The higher the value of C_i, the more urgent the demand of the i th disaster site for emergency materials [31].

4.5. Introducing the cloud model for comparison

The cloud model represents a mathematical framework rooted in the principles of fuzziness and probability theories, formulated by Li et al [32]. It can well reflect the influence of random factors on the decision results [33]. This model facilitates the transition between qualitative and quantitative domains, effectively addressing the intricacies of ambiguity and randomness inherent in complex decision-making scenarios [34]. Currently, it has earned widespread adoption within the realm of decision-making, underscoring its utility and applicability.

In order to show the superiority of combination weighting, this paper compares the weighting results of the coefficient of variation method, the order relation analysis method, and maximizing deviation with those of the combination weighting method. The cloud map includes cloud droplets, which represent specific quantitative values and reflect a concrete realization of the qualitative concept [35]. Cloud model theory generates comparative maps for four weighting methods, with droplet condensation intensity analysis revealing their relative strengths and limitations. The basic concepts of the cloud model are as follows [36]:

U is a quantitative domain and C is a qualitative concept. There is an element x in the domain U, which is a random realization of the qualitative concept C, and the membership degree

$$\mu(x) \in [0,1]$$

of x to C is a stable random value, that is,

$$\mu : U \to [0,1], \forall x \in U, x \to \mu(x).$$

If

$$x \sim N\left(Ex, En'^2\right)$$

is satisfied, where

$$En' \sim N\left(Ex, En^2\right),$$

then the membership degree of x to C is

$$\mu(x) = e^{-\frac{(x-Ex)^2}{2(En')^2}}. \tag{4.21}$$

The digital characteristics of the cloud model are composed of the expected value Ex, entropy En, and hyper-entropy He, which are quantitative descriptions of qualitative concepts. The cloud model carries out qualitative and quantitative conversion through the cloud generator, which is divided into forward and reverse [37]. Forward cloud generators convert qualitative digital features into quantitative outputs through N cloud droplets. The inverse cloud generator functions to transform a designated quantity of sample data into numerical characteristics, thereby accomplishing a transition from quantitative analysis to qualitative insights. First, the digital characteristic parameters corresponding to the relative degree of closeness C_{ic} obtained by the four types of weighting methods are calculated, namely the expected value Ex_c, entropy En_c, and hyper-entropy He_c, where $i = 1, 2, \cdots, m$, $c = 1, 2, 3, 4$. The specific calculation process is as follows:

Step 1. Calculate the mean value

$$\bar{X}_c = \frac{1}{m}\sum_{i=1}^{m} C_{ic} . \tag{4.22}$$

Step 2. Calculate the variance

$$S_c^{\ 2} = \frac{1}{m-1}\sum_{i=1}^{m}\left(C_{ic} - \bar{X}_c\right)^2 . \tag{4.23}$$

Step 3. The digital characteristic parameters of the cloud model are

$$Ex_c = \bar{X}_c , \tag{4.24}$$

$$En_c = \sqrt{\frac{\pi}{2}} \times \frac{1}{m}\sum_{i=1}^{m}\left|C_{ic} - \bar{X}_c\right| , \tag{4.25}$$

$$He_c = \sqrt{\left|S_c^{\ 2} - En_c^{\ 2}\right|} . \tag{4.26}$$

Given the known values of the expected value, entropy, and hyper-entropy, the process of producing cloud droplets via the forward cloud generator algorithm can be outlined as follows.

(1) According to the digital characteristics $\left(Ex_c, En_c, He_c\right)$ of the cloud model, a normal random number En_c' with the expected value Ex_c and the standard deviation He_c is generated.

(2) Generate a normal random number x with the expected value Ex_c and the standard deviation $\left|En_c\right|$, where x is a cloud drop in the discourse domain space.

(3) Calculate the membership degree $\mu(x)_c$ of x as follows:

$$\mu(x)_c = e^{-\frac{\left(x - Ex_c\right)^2}{2\left(En_c'\right)^2}} . \tag{4.27}$$

(3) Repeat Steps (1)–(3) until N cloud drops are generated.

Here, $N = 3000, c = 1, 2, \cdots, 4$.

4.6. Method flow chart

The flow chart of the urgency evaluation system of demand for flood disaster emergency materials constructed in this paper is shown in Figure 1.

(1) The objective weight is determined by the coefficient of variation method.
(2) Determination of subjective weight is achieved by the order relation analysis method.
(3) The combination weight is determined by maximizing deviation.
(4) The TOPSIS method calculates the urgency of demand.
(5) We take the catastrophic flood on 20 July in Zhengzhou as an example for case analysis.
(6) We draw the cloud map of demand urgency and get the result through comparison.

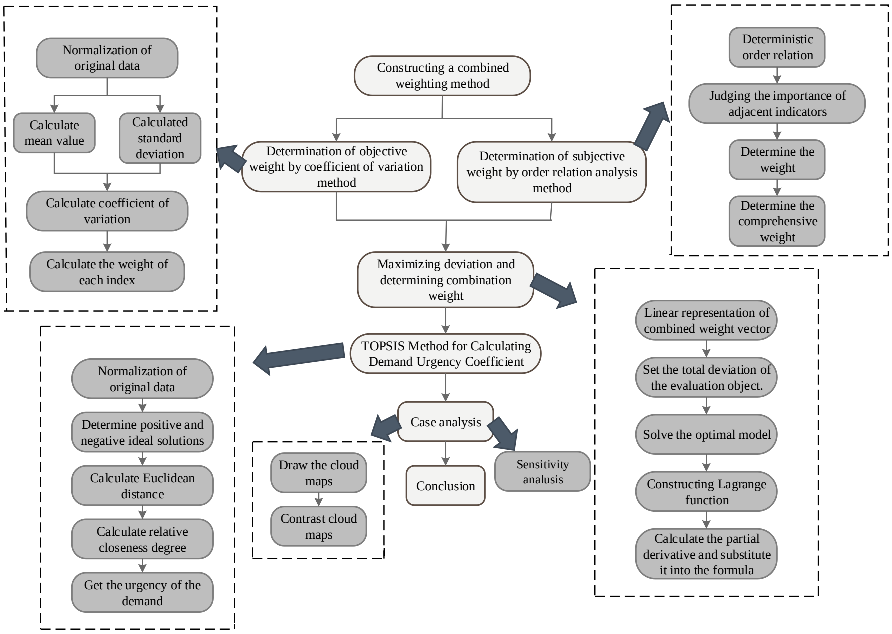

Figure 1. Flow chart of the method.

5. Case analysis

5.1. Determine the evaluation system for the urgency of demand

On the basis of the existing research, this paper comprehensively considers the characteristics of large-scale flood disasters and the specific characteristics of emergency materials' distribution, and selects three factors, namely the environment, the materials, and the population, as the secondary indicators of the evaluation system for the urgency of material demand at disaster sites [38,39]. The damaged area, daily precipitation, material demand, material shortage, population density, and the death toll are the indicators of the evaluation system for the urgency of material demand. This paper takes the 20 July flood in Zhengzhou as an example and selects seven material demand points in Zhengzhou, Gongyi, Xinzheng, Dengfeng, Xinmi, Xingyang, and Zhongmu counties. The details of the disaster locations are presented in Table 3 for comprehensive reference; the data in Table 3 are come from multiple sources including news reports, disaster investigation reports, and historical meteorological records.

Table 3. Basic disaster data of the disaster sites.

Region	Damage area (km^2)	Daily precipitation (mm)	Material demand (10,000 pieces)	Material shortage	Population density (10,000 people per km^2)	Death toll (number)
Zhengzhou	1010.3	552.5	56	Extremely serious	0.2013	75
Gongyi	1041	478.9	44	Extremely serious	0.0754	64
Xinzheng	873	196	22	Serious	0.09	2
Dengfeng	1220	192.8	26	Serious	0.0598	12
Xinmi	1001	254.9	28	Very serious	0.0808	46
Xingyang	908	432.2	52	Extremely serious	0.0804	58
Zhongmu	1416	280.3	18	Relatively serious	0.0496	0

A diagram of the framework of the evaluation system is illustrated in Figure 2. The secondary indicators include three factors: the environmental factor, which comprises the damage area and daily precipitation; the material factor, which includes material damage and material shortage; and the population factor, which consists of population density and the death toll. Further details are provided in Figure 2.

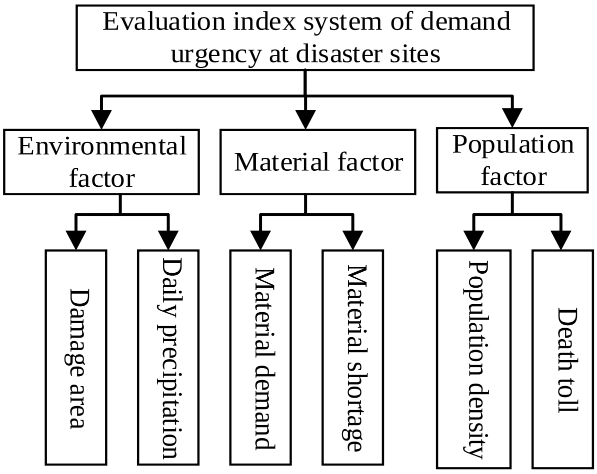

Figure 2. Urgency evaluation system of material demand at disaster sites.

5.2. Transform fuzzy indicator

The existence of seemingly inaccurate information, which is well processed by fuzzy logic, is a very common occurrence in the social sciences, and thus in decision making processes [40]. In Table 3, the degree of material shortage is a fuzzy indicator. Before calculation, it is necessary to convert the fuzzy indicator into triangular fuzzy numbers [41], as shown in Table 4.

Table 4. Transformation of fuzzy language and triangular fuzzy number.

Fuzzy language	Triangular fuzzy number
Extremely serious	(0,0,0.1)
Very serious	(0,0.1,0.3)
Relatively serious	(0.1,0.3,0.5)
Serious	(0.3,0.5,0.7)
Relatively good	(0.5,0.7,0.9)
Good	(0.7,0.9,1)
Very good	(0.9,1,1)

According to Table 4, the fuzzy indicators are converted into triangular fuzzy numbers, and the resulting triangular fuzzy decision matrix is as follows:

$$R=\begin{bmatrix} 1010.3 & 552.5 & 56 & (0,0,0.1) & 0.2013 & 75 \\ 1041 & 478.9 & 56 & (0,0,0.1) & 0.0754 & 64 \\ 875 & 196 & 22 & (0.3,0.5,0.7) & 0.09 & 2 \\ 1220 & 192.8 & 26 & (0.3,0.5,0.7) & 0.0598 & 12 \\ 1001 & 254.9 & 28 & (0,0.1,0.3) & 0.0808 & 46 \\ 908 & 432.2 & 52 & (0,0,0.1) & 0.0804 & 58 \\ 1416 & 280.3 & 18 & (0.1,0.3,0.5) & 0.0496 & 0 \end{bmatrix}.$$

Now, we normalize the matrix. Among the evaluation indexes, the material shortage is the cost indicator, and the rest are the benefit indicators. Meanwhile, the gradient average integral of triangular fuzzy numbers is calculated according to the literature [12], and the normalized matrix after conversion is as follows:

$$R'=\begin{bmatrix} 0.2529 & 1 & 1 & 1 & 1 & 1 \\ 0.3094 & 0.7954 & 1 & 1 & 0.1701 & 0.8533 \\ 0 & 0.0089 & 0.1053 & 1 & 0.2663 & 0.0267 \\ 0.639 & 0 & 0.2105 & 0 & 0.0672 & 0.16 \\ 0.2357 & 0.1726 & 0.2632 & 0.7931 & 0.2057 & 0.6133 \\ 0.0645 & 0.6656 & 0.8947 & 1 & 0.203 & 0.7733 \\ 1 & 0.2433 & 0 & 0.4138 & 0 & 0 \end{bmatrix}.$$

The objective weights of the evaluation indicators were obtained by the coefficient of variation method as follows:

$$W=(0.0503,0.1202,0.1305,0.3003,0.1569,0.2418).$$

5.3. Determine the weight of the evaluation indicators

Each evaluation indicators' objective weight was determined utilizing the coefficient of variation approach, while the subjective weight was ascertained through the implementation of the order relation analysis method. Finally, the comprehensive weight of maximizing deviation was utilized to derive the final weight. The weights obtained by each weighting method are presented in Table 5.

Table 5. Weighting obtained by each weighting method.

Weighting method	Damage area	Daily precipitation	Material demand	Material shortage	Population density	Death toll
Coefficient of variation (W_j)	0.0503	0.1202	0.1305	0.3003	0.1569	0.2418
Order relation analysis (ω_j)	0.3053	0.1908	0.1908	0.1363	0.1136	0.0631
Combination weighting (ξ_j)	0.2010	0.1465	0.1501	0.2142	0.1258	0.1623

5.4. Determine the relative degree of closeness

Applying the combined weights through TOPSIS generates the relative degrees of closeness for flood-affected regions, as detailed in Table 6.

Table 6. Relative degree of closeness of each region.

Region	Relative degree closeness C_{i1}
Zhengzhou	0.7290
Gongyi	0.6382
Xinzheng	0.0983
Dengfeng	0.2670
Xinmi	0.4261
Xingyang	0.5716
Zhongmu	0.3914

The urgency of the disaster points' demand, from high to low, are ranked as Zhengzhou>Gongyi>Xingyang>Xinmi>Zhongmu>Dengfeng>Xinzheng. That is, among the seven major disaster sites of the rainstorm on 20 July in Zhengzhou, the urgency of material demand in Zhengzhou was the highest, and that of Xinzheng County was the lowest. The reason for this result is that Zhengzhou has a relatively low terrain. When a large amount of rainwater quickly accumulates in a short time, the water accumulation in low-lying areas will be more serious and will become difficult to drain quickly. At the same time, the number of affected people in Zhengzhou is relatively large. However, Xinzheng County has a relatively high terrain, a small population density, and is located far from rivers with good drainage facilities. This could explain why it has a low material demand.

5.5. Comparison of the methods

To ascertain the validity and rationale of the combined weighting approach in evaluating the urgency of flood disaster emergency material requirements, this paper employs a solitary weighting methodology to assign weights, subsequently deriving the urgency of the demand for each affected region. These results are then juxtaposed against the outcomes yielded by the combined weighting technique for a comprehensive analysis. In this paper, three weighting methods, namely the coefficient of variation method, the order relation analysis method and maximizing deviation, are used for single weighting. As stated above, the weight of the six indicators obtained by the coefficient of variation method is W_j, and the weight of the six indicators obtained by the order relation analysis method is ω_j. Suppose that the weight of six indicators is ω_j', calculated by using the maximizing deviation method. The corresponding relative degrees of closeness $C_{i2} - C_{i4}$ are calculated by the weights obtained by the three methods. The outcomes of the computations are displayed in Table 7 for review and analysis

$$\omega' = \left(0.1304, 0.1842, 0.1928, 0.1558, 0.1632, 0.1736\right).$$

5.5.1 Line chart comparison

The relative degrees of proximity obtained by the four weighting methods in Table 7 are drawn as a line chart, and the changes in the line are observed. In Figure 3, the horizontal coordinate is the region, and the vertical coordinate is the relative degree of closeness.

Table 7. Comparison of the evaluation results.

Region	C_{i1}	C_{i2}	C_{i3}	C_{i4}
Zhengzhou	0.7290	0.8535	0.6718	0.7764
Gongyi	0.6382	0.6880	0.6004	0.6440
Xinzheng	0.0983	0.1071	0.0962	0.1118
Dengfeng	0.2670	0.1680	0.3168	0.2311
Xinmi	0.4261	0.4887	0.3541	0.3997
Xingyang	0.5716	0.6537	0.5164	0.5867
Zhongmu	0.3914	0.2826	0.4462	0.3306

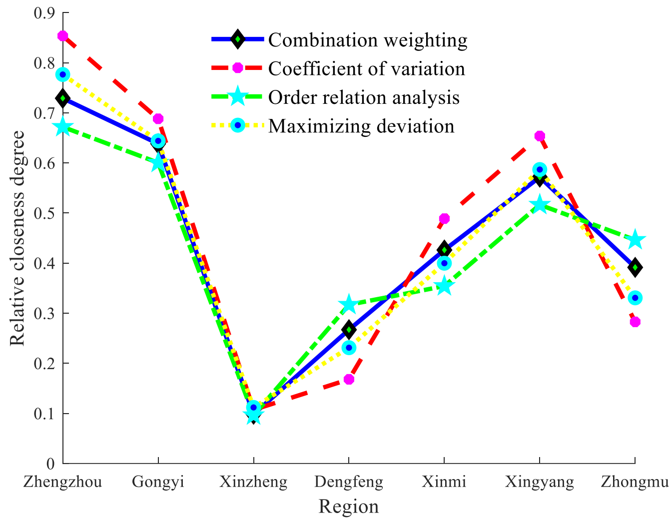

Figure 3. Method comparison chart.

In Figure 3, the trend of the line graphs obtained by the combined weighting method and the maximizing deviation method are relatively similar, while the trend of the line graphs obtained by the coefficient of variation method and the order relation analysis method are different. However, the variation trend of the four lines is roughly the same, which verifies the rationality of the method. From the perspective of the methods' characteristics, the line graph obtained by the combined weighting method is located between the objective weighting method and the subjective weighting method, representing a balance of the advantages of both sides and better performance. The combined weighting method's integrated characteristics ensure higher credibility.

5.5.2. Comparison of cloud maps

Given the relative degree of closeness C_{ic} obtained by four types of weighting methods, we calculate the corresponding clouds' digital characteristic parameters, namely, En_c and He_c, where

$$i=1,2,\cdots,m;c=1,2,\cdots,4.$$

The outcomes of the computations are displayed in Table 8 for review and analysis.

By observing the data of the cloud model's digital characteristics, it is found that the hyper-entropy obtained by the combined weighting method is 0.0432, and the result is the smallest, which means that the uncertainty of the result is the least [42]. According to the cloud model's digital characteristics obtained by calculation, we draw the cloud map of the urgency of demand obtained by the four weighting methods. The higher the degree of cloud drop condensation in the cloud model's visualization diagram, the more ideal the qualitative concept expressed; that is, the better the effect of evaluating the urgency of the demand.

Table 8. Comparison of the clouds' digital characteristics.

Weighting method	Ex_c	En_c	He_c
Combination weighting	0.4459	0.2152	0.0432
Coefficient of variation	0.4631	0.2978	0.0872
Order relation analysis	0.4288	0.1860	0.0542
Maximizing deviation	0.4401	0.2460	0.0603

Figures 4–7 are the generated cloud maps, where the horizontal coordinate represents the value of cloud drops, and the vertical coordinate represents the membership degree $\mu(x)_c$ of element x in the discourse domain U. Each point in the figure is a cloud drop generated by the forward cloud generator process.

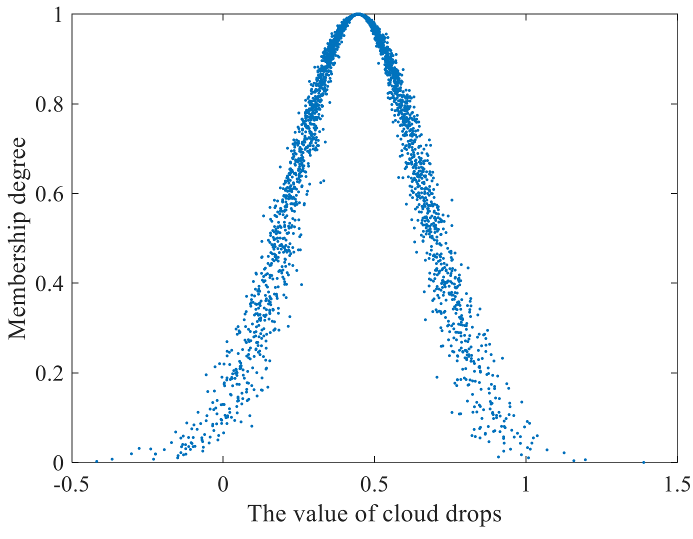

Figure 4. The cloud map obtained by C_{i1}.

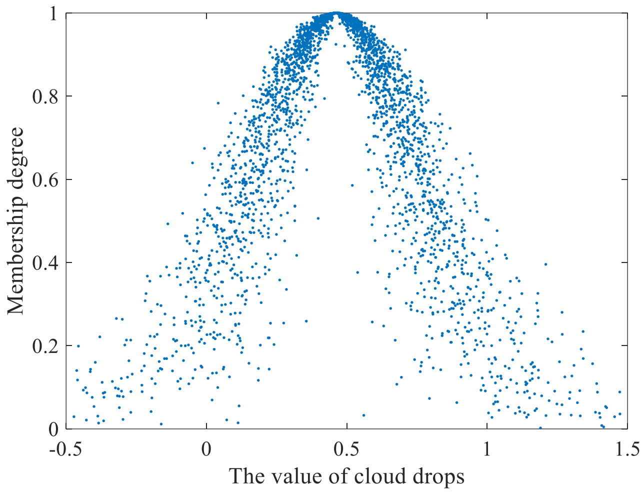

Figure 5. The cloud map obtained by C_{i2}.

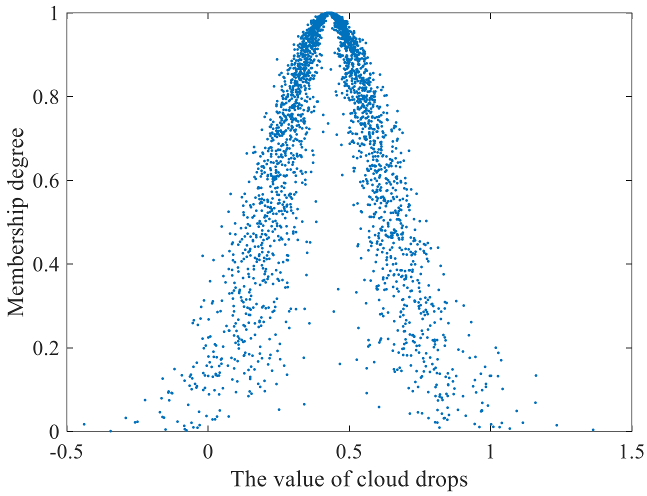

Figure 6. The cloud map obtained by C_{i3}.

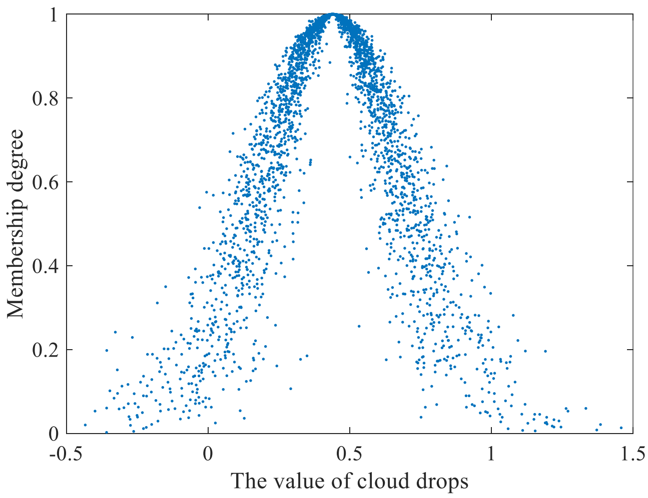

Figure 7. The cloud map obtained by C_{i4}.

Through observation, it can be seen that among the cloud maps obtained by the four types of weighting methods, the cloud map corresponding to the combined weighting method has the highest degree of cloud drop condensation and the smallest cloud thickness, indicating that the results obtained by this method are the most acceptable, and the evaluation result regarding the urgency of demand is the best. Therefore, by observing the data in Table 8 and Figures 4–7, it can be concluded that the combined weighting method can effectively evaluate the urgency of material demand at the demand points for emergency materials to maximize the distribution of materials for emergency rescue within a limited time.

5.5.3. Sensitivity analysis

To verify the reliability of the combined weighting method in evaluation, this study conducted a sensitivity analysis by increasing and decreasing the weight of the most critical indicator by 2%. After 30 experimental trials, we observed whether the ranking results of the evaluated objects changed under repeated weight adjustments.

Through expert discussions and numerical studies, the “material shortage” indicator was identified as the most critical factor, with an original weight of 0.2142 in the combined weighting system. During weight adjustments, the remaining indicators’ weights were proportionally normalized to maintain a total sum of 1. The initial ranking derived from the original combined weights was

Zhengzhou>Gongyi>Xingyang>Xinmi>Zhongmu>Dengfeng>Xinzheng;

that is,

Region 1>Region 2>Region 7>Region 6>Region 4>Region 3>Region 5.

To investigate the impact of weight variations in the material shortage indicator on the evaluation’s outcomes, we systematically adjusted its weight by increasing and decreasing it by 2%. These adjusted weights were then incorporated into the TOPSIS method for computational analysis. For each adjustment direction (increase/decrease), 30 independent computational iterations were performed to generate distinct regional ranking results. Ultimately, these ranking outcomes were visualized as radar charts (Figures 8 and 9), where S_0 denotes the result obtained from the original data, S_ε denotes the ε th experimental iteration ($\varepsilon = 1, 2, \cdots, 30$). This methodology enables a comprehensive geometric representation of the ranking’s stability across experimental configurations.

As shown in Figure 8, during the 30 incremental weight adjustment experiments for the material shortage indicator, the comprehensive evaluation rankings derived from the TOPSIS method remained stable, with the consistent order

Region 1>Region 2>Region 7>Region 6>Region 4>Region 3>Region 5.

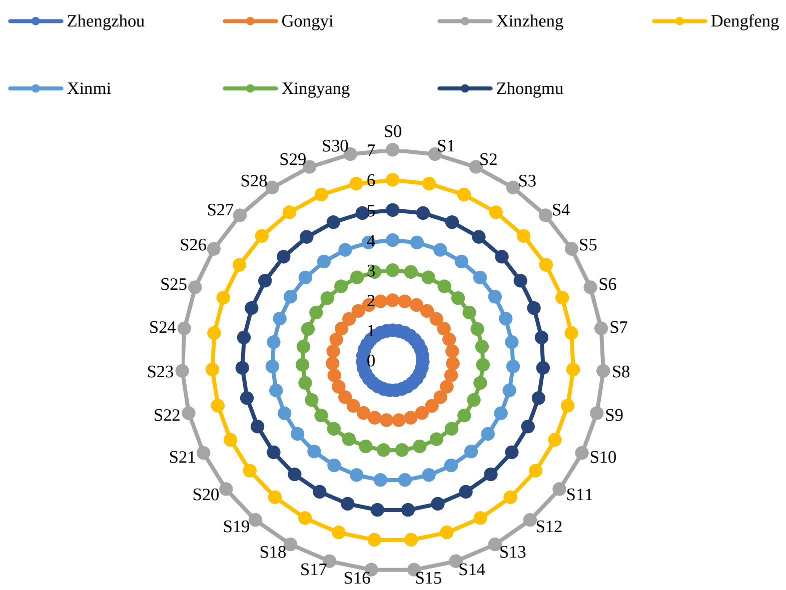

Figure 8. Incremental experimental radar chart.

Figure 9 reveals that in the 30 decremental weight adjustment experiments, a positional swap between Regions 4 and 5 occurred at the 30th iteration, while the other regions maintained their original relative rankings.

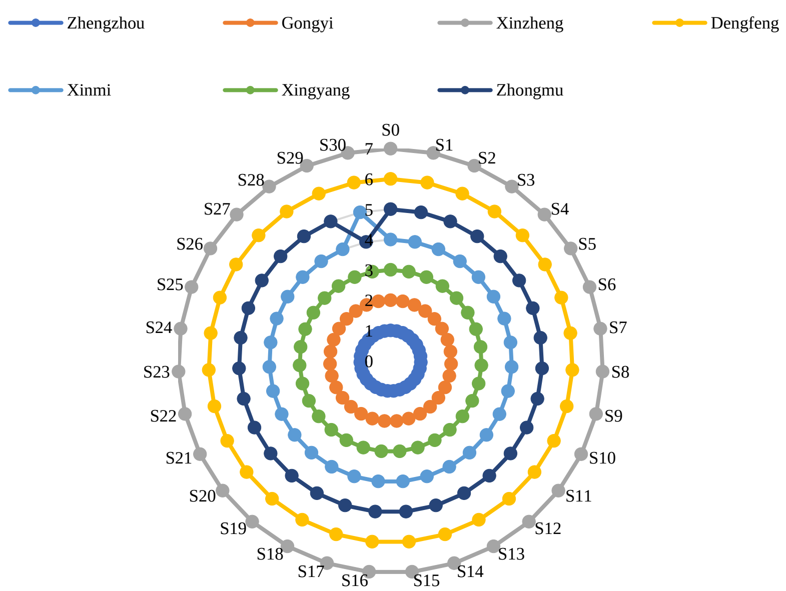

Figure 9. Diminishing experimental radar chart.

The reasons for rank reversal may be the following:

(1) Decreasing an indicator's weight diminishes its contribution to both the positive and negative ideal solutions, altering the distance relationships between the evaluated objects and these reference points.

(2) Weight reduction weakens the indicator's decision-making impact. If the indicator originally played a critical role in determining specific rankings, its diminished importance may significantly

alter the comprehensive scores, triggering positional changes.

In summary, when the weight is decreased, the ranking order of the evaluated objects remains stable throughout the first 29 experiments; when the weight is increased, the ranking order remains consistent across all 30 experiments. This demonstrates that the TOPSIS method, based on combined weighting, exhibits strong robustness when the weight value of material shortage varies within the range of [0.1192, 0.3881].

6. Conclusions

Within the realm of urban governance and emergency preparedness, the assessment of demand urgency amidst natural disasters holds significant importance. Drawing upon existing research, this paper establishes an evaluation indicator system for assessing the urgency of demand at disaster sites which refers to the criteria of environment, resources, and population demographics within the context of flood disasters. The fuzzy data were processed by triangular fuzzy numbers, and the fuzzy indicators were transformed into triangular fuzzy numbers. The objective weights were established through the coefficient of variation method, and experts referred to these results and applied the order relation analysis approach to establish the subjective weights. Finally, the TOPSIS method was used to calculate the relative degree of closeness, and the weight of each indicator was based on the comprehensive weight obtained from the principle of maximum deviation, which is helpful to evaluate the urgency of disaster sites' demand. To ascertain the accuracy of the weight assignment approach, these three single weighting methods were used to calculate the relative degree of closeness of each disaster-affected area. A line chart was drawn according to the relative closeness between the single weighting methods and the combination weighting method, and the results were compared. Subsequently, based on proximity indices, the digital attributes of the cloud model were derived. Utilizing the forward cloud generator, a cloud map was constructed, thereby visually representing the outcomes.

By observing the line chart, it can be found that the combination weighting method balances the advantages of the objective weighting method and the subjective weighting method, and the variation trend of the obtained line chart is relatively reliable. By comparing the cloud model's digital characteristics and cloud maps obtained by the combined weighting method and the single weighting method, it can be found that the hyper-entropy of the cloud model's digital characteristics obtained by the combined weighting method is the smallest, which is 0.0432, indicating that the uncertainty of the results is the least and the degree of dispersion is also relatively small. At the same time, the cloud map obtained by the combined weighting method has the highest degree of cloud drop condensation and the smallest cloud thickness, indicating that it can reflect the actual situation of emergency material demand against the background of a flood disaster more truly. In addition, in the sensitivity analysis, when the weight of the most important evaluation indicator (material shortage) remained within the critical threshold of [0.1192, 0.3881], the TOPSIS method based on combination weighting had strong robustness.

Therefore, the method of combination weighting can assess the urgency of the demand of disaster sites more accurately, providing a reference for regional flood risk assessment and disaster prevention as well. In the event of such flood disasters, emergency supplies can be distributed in a targeted manner by calculating the degree of urgency of demand to resolve the immediate needs of people in affected areas and avoid more casualties.

This paper evaluates the urgency of emergency material demand in the case of flood disasters. However, there are still many deficiencies in this study and further in-depth research is needed.

(1) In terms of the types of emergency materials, the material demand studied in this paper basically summed the amount of all materials; the difference in the demand for different types of emergency materials at the disaster site was not considered (e.g., basic living supplies, medical supplies, hygiene and cleaning materials, energy and lighting resources, among others). Future studies should prioritize detailed investigations to refine supply-demand data, employing predictive methods for estimations of specific material types.

(2) In this paper, material shortage is a fuzzy index with some subjectivity, which may lead to deviations in the results. In follow-up studies, material shortage can be replaced with more measurable indicators, or experts can be invited to evaluate and verify it to ensure the rationality and scientific nature of the indicators.

(3) This paper only evaluates the urgency of demand for emergency materials. The planning of emergency material distribution routes and more effective material distribution methods can be carried out later. For example, incorporating the urgency of demand into the emergency logistics route optimization model, while prioritizing the demand of disaster-affected areas, a target model can be constructed, and optimization algorithms can be employed to simulate and solve the model. Algorithm selection requires enhancements addressing the limitations of robustness, interpretability, and computational efficiency. The optimized model should then be compared with other models through a comparative analysis to fully demonstrate the efficiency and superiority of the selected algorithm.

Author contributions

Bingbing Xu: study conception and design, writing the first draft, comments; Wenguang Yang: study conception and design, guidance and submission, comments; Lanxiang Yi: study conception and design, data collection and analysis, commenting; Dekun Kong: study conception and design, data collection and analysis, comments; Ruitian Liu: study conception and design, data collection and analysis, comments. All authors have read and approved the final version of the manuscript for publication.

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Conflict of interest

The authors declare that no conflicts of interest are associated with this publication.

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