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Research Article

A Study on Evaluating Water Resources System Vulnerability by Reinforced Ordered Weighted Averaging Operator

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Evaluating the vulnerability of a water resources system is a multicriteria decision analysis (MCDA) problem including multiple indictors and different weights. In this study, a reinforced ordered weighted averaging (ROWA) operator is proposed by incorporating extended ordered weighted average operator (EOWA) and principal component analysis (PCA) to handle the MCDA problem. In ROWA, the weights of indicators are calculated based on component score coefficient and percentage of variance, which makes ROWA avoid the subjective influence of weights provided by different experts. Concretely, the applicability of ROWA is verified by assessing the vulnerability of a water resources system in Handan, China. The obtained results can not only provide the vulnerable degrees of the studied districts but also denote the trend of water resources system vulnerability in Handan from 2009 to 2018. And the indictor that most influenced the outcome is per capita GDP. Compared with EOWA referred to various indictor weights, the represented ROWA shows good objectivity. Finally, this paper also provides the vulnerability of the water resource system in 2025 based on ROWA for water management in Handan City.

1. Introduction

With the rapid development of economy, the destruction of water environment, and the continuous change of global environment, the water resources system has suffered a series of water safety problems, such as water shortage, contradiction between supply and demand, and water pollution. The problems are constantly changing the function, structure, and characteristics of the water resources system directly or indirectly, thus affecting the vulnerability of the water resources system. Therefore, it is urgent for hydrologists and disaster scholars to study the vulnerability of water resources.

Vulnerability is widely used in various fields of academic research, such as drought vulnerability [1, 2] and ecological vulnerability [3, 4]. Vulnerability is a term commonly used to describe a weakness or flaw in a system, and it is vulnerable to specific threats and harmful events [5]. Although scholars have different understanding on vulnerability, there is no uniform definition about vulnerability in the water resource system until now. Synthesizing the domestic and research results, the concept of water resources vulnerability was summarized by Zou et al. [6] as follows: the nature and state of the water resources system are affected and destroyed by the threats and damage from human activities and natural disasters, and it is difficult to restore to the original state and function after being damaged. The factors affecting the vulnerability of the water resources system contain the system itself and the stress exerted outside the system (such as climate change and human activities). The influencing factors of the water resources system itself involve its inherent structure, function, and complexity. It is generally believed that the more complex the system structure, the lower the soil and water loss rate, the stronger the groundwater regeneration capacity, the weaker the vulnerability of the system, and on the contrary, the stronger the vulnerability of the system. Considering the influencing factors mentioned above, it is necessary to apply multicriteria decision analysis (MCDA) technology to evaluate the vulnerability of the water resources system. Fortunately, the

EOWA method [7] as one effectively MCDA tool had been widely studied and applied. It considers not only the weight of the factors affecting the multicriteria decision system, but also the position of the factors in aggregation process and the weight of the experts. For example, Xiao et al. [8] discussed the problem of ordering qualitative data by using an EOWA operator and the processing of qualitative data in multi-attribute decision-making. Wei [9] put forward a group decision-making method of coal mine safety evaluation based on the EOWA operator, so as to improve the efficiency of safety management, raise the level of safety management, and reduce the cost of safety management.

The thought of EOWA is to transform fuzzy sets into specific values and multiply them by corresponding weight. And in the calculation process, order weight is considered because the important degrees of all experts are usually unequal. Due to the addition of ordered weight, the extreme value error is reduced. For example, Zarghami et al. applied the EOWA operator to group decision-making on water resources projects [10]. However, in the vulnerability assessment of the water resources system, many indicators should be considered objectively to reflect the characteristics from different aspects. However, the indicator weights of EOWA are determined artificially, which contains a large subjective arbitrariness. It is noted that the principal component analysis (PCA) can decompose the original multiple indicators into independent single indicator and carry out diversified statistics. It can not only make the independent single indicator unrelated, avoiding overlapping and cross between the indicators, but also retain the authenticity of the original indicator through dimensionality reduction thought. Thus, the multi-indicator problem can be integrated into a single-indicator form avoiding the subjective randomness of artificial decision-making by using PCA. For example, Pan and Xu [11] established a fuzzy comprehensive evaluation model based on PCA. In which, the evaluation factors were screened by PCA, and the characteristic value of the selected indicators was regarded as the weight, which reduced the influence of subjective factors and improved the accuracy of the model. Ren et al. [12] used the PCA to evaluate the integrated performance of different hydrogen energy systems and select the best scenario. Therefore, one potential methodology to handling MCDA problems and the subjectivity of weights is to incorporate the EOWA and PCA within a general framework, leading to an integrated assessment method.

Accordingly, the objective of this study is firstly to propose a reinforced ordered weighted averaging (ROWA) operator based on PCA and EOWA, to dispose the MCDA problems. The proposed operator would have the following advantages: (a) effectively reflecting the importance of different decision levels by order weight in the evaluation system, (b) avoiding overlap and cross among multiple indicators, and overcoming the subjective randomness of different weights by the cumulative contribution rate, and (c) determining the main factors affecting the evaluation system. And secondly, a case study of assessing the vulnerability of the water resources system in Handan City is offered for illustrating the applicability of the developed ROWA operator. Afterwards, the results analysis is given specifically to provide the managers with objectively evaluated solution for the vulnerability of the water resources system in the past and the future. At last, comparisons between ROWA and EOWA are conducted to further illustrate the advantages of the proposed ROWA.

2. Methodology

2.1. EOWA. For MCDM problems, two key factors (the being evaluated indicators and the weights of indicators) should be ascertained and quantified. However, the second factor is generally provided by experts and denoted in verbal terms which make the evaluation process more subjective and complex. Therefore, this study will reinforce the EOWA operator by introducing APC to improve the second factors and enhance its applicability in handling MCDM problems. Definition and concept on EOWA will be presented as follows.

Xu [7] proposed EOWA based on the ordered weighted average (OWA) operator and extended glossary of terms. The method is to transform fuzzy sets into specific values and multiply them by corresponding weight, which can be defined as follows.

Definition 1. (see [13]). $\overline{S}^n \longrightarrow \overline{S}$, if F $= F = f(s_{\alpha_1}, s_{\alpha_2}, \ldots, s_{\alpha_n}) = w_1 s_{\beta_1} \oplus w_2 s_{\beta_2} \oplus \cdots \oplus w_n s_{\beta_n} = s_{\overline{\beta}}$, where F is the total positive score of a scheme $\overline{\beta} = \sum_{i=1}^{n} w_i \beta_i$, $w = (w_1, w_2, \ldots, w_n)$ is a weighted vector associated with EOWA, $w_i \in [0,1]\,(i \in N)$, $\sum_{i=1}^{n} w_i = 1$, and input s_{β_i} is the ith largest element in a set of language data $(s_{\alpha_1}, s_{\alpha_2}, \ldots, s_{\alpha_n})$.

w_i is called ordered weight. s_{β_i} consists of two parts: indicator weight and indicator value. And indicator weights are not equal to each other in real problems [14]. Based on these, s_{β_n} of EOWA can be obtained as follows:

$$s_{\beta_n} = P_n d_n, \quad (1)$$

whereP_n is the indicator weight and d_n is the indicator value.

The advantages of EOWA are as follows: (1) it can transform fuzzy sets into specific values; (2) using ordered weights to reduce extreme value error in the calculation because the important degrees for all inputs s_{β_n} are generally unequal. All of these make the calculation results more in line with the complexity, spatial, and temporal differences and fuzziness situation.

Ordered weight w_i in the EOWA operator [7] is obtained by the minimum variable method [15, 16], and the final expression [17] is as follows:

$$w_1 = \frac{2(2n-1) - 6(n-1)(1-\theta)}{n(n+1)}, \quad (2)$$

$$w_n = \frac{6(n-1)(1-\theta) - 2(n-2)}{n(n+1)}, \quad (3)$$

$$w_i = \frac{(n-j)}{(n-1)} \times w_1 + \frac{(j-1)}{(n-1)} \times w_n, \quad \text{if } i \in \{2, \ldots, n-1\}, \quad (4)$$

where θ is an independent variable representing the optimism of the decision maker. In this study, the value of θ is 0.3 [14], representing that many criteria considered in this decision-making system are satisfied [17].

In multiobjective decision criteria, the model can be further expressed as follows [12]:

$$GS(A_j) = f(P_1 S_1(A_j), P_2 S_2(A_j), \ldots, P_n S_n(A_j)), \quad (5)$$

where $GS(A_j)$ is the comprehensive score on district j vulnerability assessment, $S_i(A_j)$ is the value of vulnerability assessment indicator i for district j, f is the ROWA operator, P_i is the weight of vulnerability assessment indicator i, and n is the number of indicators for water resources vulnerability assessment.

Moreover, when the inputs $S_i(A_j)$ have different units, it is necessary to convert them into data on interval $[0,1]$. A simple method of standardization is used [8] in this study, shown as follows:

$$S_i(A_j) = \begin{cases} \dfrac{S_i(A_j) - \min(S_i)}{\max(S_i) - \min(S_i)}, & \text{for positive inputs,} \\[2ex] \dfrac{\max(S_i) - S_i(A_j)}{\max(S_i) - \min(S_i)}, & \text{for negative inputs.} \end{cases} \quad (6)$$

Also, here the integral mean method [8] is used to assess the important degree of each district, normalized as follows:

$$CGS(A_j) = 1 - \frac{1}{n}\sum_{i=1}^{n}\left|S_i(A_j) - GS(A_j)\right|, \quad (7)$$

where $CGS(A_j)$ is the important degree of district j.

2.2. ROWA. It is noted that PCA can decompose original multiple indicators into independent single indicators and carry out diversified statistics. It can not only make the independent single indicator unrelated, avoiding overlapping and cross between the indicators, but also retain the authenticity of the original indicator through dimensionality reduction thought [18]. Therefore, the reinforced ordered weighted averaging (ROWA) operator is proposed based on EOWA and PCA in this study. ROWA would calculate the indicator weight (P_i) by component score coefficient and percentage of variance [19] based on PCA and then bring it into EOWA to calculate the vulnerability of each administrative district. Totally, the advantages of ROWA can be summarized as follows: (1) it can effectively reflect the importance of different decision levels by order weights in the evaluation system; (2) it can not only avoid overlapping and crossing of indicators but also retain the authenticity of the original indicator based on the cumulative contribution rate and thus avoid the subjective randomness; (3) it can determine the main factors affecting the evaluation system.

Specifically, the formulas for calculating the indicator weight (P_i) based on PCA are as follows:

$$P_i = \sum_{m=1}^{n}\frac{(F_{im}\times\alpha)}{\beta}, \qquad F_{im} = SCC_{im}\times\sqrt{\gamma}, \quad (8)$$

where SCC_{im} is the score coefficient of the indicator i to the component m; F_{im} is the component score of the indicator i; P_i is the weight for the vulnerability assessment indicator i; α is the contribution rate of the principal component m; β is the cumulative contribution rate of principal components; and γ is the eigenvalues of principal component m. SCC_{im}, α, β, and γ are calculated by SPSS.

And then, take P_i into formula (5) and get $CGS(A_j)$. At last, the final percentile score (F) of the vulnerability in the district j can be gained by the following formula:

$$F = CGS(A_j)\times 100. \quad (9)$$

According to calculation of EOWA and P_i, the specific solution process of ROWA can be summarized as shown in Figure 1.

Based on previous information and similar studies [20], the vulnerability of water resources systems can be classified into five classes: I, low vulnerability; II, medium vulnerability; III, medium-high vulnerability; IV, high vulnerability; and V, severe vulnerability.

2.3. Numerical Example. Here, an example is given below for clearly understanding the proposed ROWA method. Supposing that the vulnerability of the water resources system in four research areas (represented by $A1$, $A2$, $A3$, and $A4$) should be evaluated, and the related indicators are 10, whose original data are shown in Table 1.

Accordingly, the calculation step of ROWA for this problem can be summarized as follows.

Step 1. Calculate indicator weight P_i.

After calculating with PCA method, the results show that under the criterion of cumulative contribution rate ≥85%, two principal components can be obtained, and the actual cumulative contribution rate is 93.73%. And when the values of SCC_{im}, α, β, and γ are obtained, P_i can be gained based on them, shown in Table 2.

Step 2. Solve order weight w_i.

w_i is calculated according to formulas (2), (3), and (4), and the results are shown in Table 3.

Step 3. Calculate comprehensive score $CGS(A_j)$.

After P_i is calculated, raw values are transformed according to formula (6). Then, values of $GS(A_j)$ and $CGS(A_j)$ can be calculated according to formulas (5) and (7), as shown in Table 4.

Step 4. Calculate percentile score F.

F is shown in Table 4.

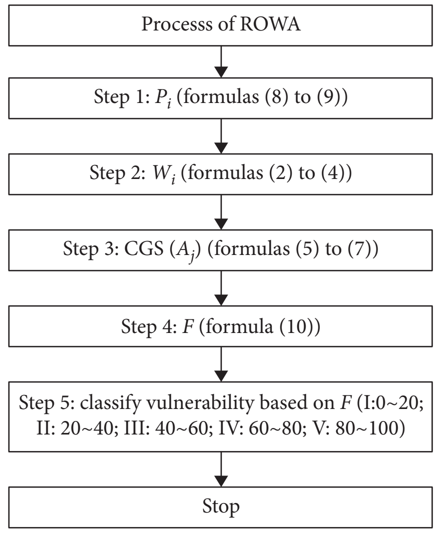

Figure 1: Process of ROWA.

Table 1: Original data.

	$C1$	$C2$	$C3$	$C4$	$C5$	$C6$	$C7$	$C8$	$C9$	$C10$
$A1$	537	6.3	1.7	0.3	6.8	15.8	1.3	0.8	4.6	130
$A2$	661	10.8	1.7	0.4	0.5	1.3	1.1	1	2.3	260
$A3$	801	2.5	1.5	0.5	88.5	36	0.8	0.9	3.2	600
$A4$	1058	5.9	1.3	0.6	39.6	26.5	0.9	1.2	2.5	580

Table 2: Weight for the vulnerability assessment indicator i.

Indicator	$C1$	$C2$	$C3$	$C4$	$C5$	$C6$	$C7$	$C8$	$C9$	$C10$
P_i	0.31	−0.02	−0.28	0.31	0.12	0.10	−0.25	0.31	−0.27	0.26

Table 3: Value of w_i.

w_1	w_2	w_3	w_4	w_5	w_6	w_7	w_8	w_9	w_{10}
0.002	0.024	0.045	0.067	0.089	0.111	0.133	0.155	0.176	0.198

Table 4: Value of $GS(A_j)$, $CGS(A_j)$, and F.

District	$GS(A_j)$	$CGS(A_j)$	F	VD
$A1$	0.07	0.60	60	IV
$A2$	0.08	0.53	53	III
$A3$	0.15	0.25	31	II
$A4$	0.14	0.31	25	II

Note. VD = vulnerable degree.

Step 5. Determine the degree of vulnerability based on score F.

Finally, according to allocation criteria, it is easy to judge the vulnerability of each region, as shown in Table 4.

It can be seen that $A1$ and $A2$ belong to high vulnerability and medium-high vulnerability, respectively, and $A3$ and $A4$ belong to medium vulnerability.

3. Case Study

3.1. The Profile of Research Area. Handan City is in the southern end of Hebei Province, southeast of North China. The geographical position is between 36°04′N~37°01′N and 113°28′E~115°28′E. Because the city of Handan is surrounded by Taihang Mountains, North China Plain, Xingtai, and Anyang tightly, it is called the southern gate of Hebei Province. Its administrative area is shown in Figure 2.

In recent years, the total amount of water resources in Handan is about $16.7 \times 10^9 \cdot m^3$, and the per capita water resources is $191 \cdot m^3$ per year, which is only 9% of the per capita level of the whole country. And by the end of 2018, the total population of Handan was 10.51×10^6 with a population density of 871 person/km^2 and the population is increasing gradually. The proportion of surface water and groundwater to total water supply is 40.5% and 59.5%,

Figure 2: Administrative region of Handan.

respectively. In the water supply, the groundwater is regarded as the main water source, resulting in long-term serious overexploitation of local groundwater and continuous decrease of groundwater level. The water resources system of Handan City is being destroyed gradually, and its vulnerability is becoming more and more obvious. Therefore, for the sustainable development of water resources, it is meaningful to make a reasonable evaluation about the vulnerability of the water resources system in Handan.

3.2. Establishment of Indicator System

3.2.1. Principles for the Establishment of an Indicator System. When constructing an assessment system of water resources vulnerability, five principles should be followed: scientific principle, operational principle, comprehensive principle, leading principle, and regional principle [21]. They play a comprehensive role in building the evaluation indicator system of water resources system vulnerability and ensure the scientificity and rationality of the evaluation indicator system.

3.2.2. Selection of Indicators and Establishment of Indicator System. Water resources system is a huge and complex system, whose vulnerability is affected by many factors. It would be best to establish an indicator system including all the factors, but this is difficult and not realistic to achieve the data of all factors. Therefore, most of the studies selected some indicators to build the evaluation indicator system based on the actual situation of the study area and data acquisition [22]. Similarly, ten indicators are selected to study the vulnerability of the water resources system in Handan City in this study. The selected indicators are as follows: annual precipitation ($10^8 \cdot m^3$) ($C1$), water conservancy regulation capacity ($10^4 \cdot m^3$) ($C2$), groundwater exploitation rate ($C3$), groundwater regeneration capacity ($C4$), annual drought index ($C5$), soil and water loss rate ($C6$), population density (person/km^2) ($C7$), per capita GDP (yuan) ($C8$), per capita water consumption (m^3) ($C9$), and water resources utilization ratio ($C10$).

3.3. Administrative Divisions and Data Notes. In this study, the research area is divided into 17 districts according to the administrative division: the three districts of the city (SS), Fengfeng Kuang Qu (FK), Wu'an County (WA), Handan County (HD), Daming County (DM), Wei County (WX), Qiuzhou County (QZ), Qiu County (QX), Jize County (JZ), Feixiang County (FX), Guangping County (GP), Cheng'an County (CA), Linzhang County (LZ), Cixian County (CX), Shexian (SX), Yongnian County (YN), and Guantao County (GT). It is noted that at the end of 2016, the city of Handan had been rezoned: Yongnian County and Feixiang County were renamed as Yongnian District and Feixiang District individually. Handan County was cancelled and divided into the city's three districts. In order to better reflect the vulnerability changes of the water resources system, the data of ten indicators in 17 districts from 2009 to 2016 and 16 districts from 2017 to 2018 are selected to analyze the successive annual trend of its vulnerability in Handan City. The related data are calculated according to Water Resources Bulletin and Statistical Yearbook of Handan City.

4. Result Analysis and Discussion

4.1. Analysis of the Water Resources System Vulnerability by ROWA. When the criterion of cumulative contribution rate is 75%, the indicator weights calculated by component score coefficient and percentage of variance were P = P = (0.079, 0.022, 0.122, 0.116, 0.051, 0.121, 0.135, 0.068, 0.125, and 0.161). And thus, the percentile score of the vulnerability of water resources systems from 2009 to 2018 can be acquired by the developed ROWA, which are shown in Figure 3. In all the studied districts, only DM appears a sustained decline from 81.50% to 60.03% during the decade and other districts show varying degrees of volatility. For example, the vulnerability of water resources systems in SS has three rising years: 2012, 2014, and 2016; in FK, there are

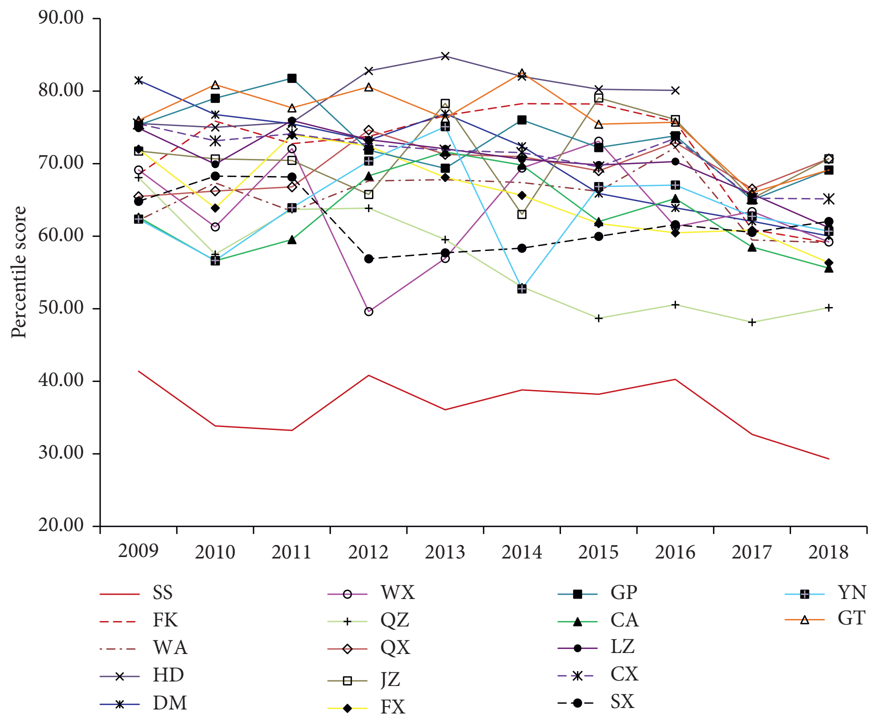

Figure 3: The percentile score of the water resources system vulnerability in Handan City.

two rising periods: from 2009 to 2010 and from 2011 to 2014; in WA, three increasing periods are from 2009 to 2012, from 2010 to 2012, and from 2015 to 2016; in HD, except for 2009, 2010, 2014, and 2016, the vulnerability of water resources systems in the other years is greater than the year before; in WX, there are also three rising periods: from 2010 to 2011, from 2012 to 2015, and from 2016 to 2017; in QZ, the two growing periods are from 2010 to 2012 and from 2015 to 2016; in QX, the three increasing periods are from 2010 to 2012, from 2015 to 2016, and from 2017 to 2018; in JZ, only the years of 2013, 2015, and 2018 are more vulnerable than the previous year; with the exception of 2011, the vulnerability has declined in all other years in FX; in GP, there are four ascending periods: from 2010 to 2011, from 2013 to 2014, from 2015 to 2016, and from 2017 to 2018; in CA, the vulnerability firstly increases from 2009 to 2013 and then decreases from 2014 to 2015, and grows again in 2016 and declines from 2017 to 2018 at last; in LZ and CX, there are the same ascending years: 2011 and 2016; in SX, three growing periods are from 2009 to 2010, from 2012 to 2016, and from 2017 to 2018; in YN, except for the years of 2010, 2014, and 2017, the vulnerability in all other years is greater than the previous year; in GT, there is an increasing trend in every two years from 2009 to 2018. In a word, although there are multiple rising periods in most districts, the percentage scores of their vulnerability decline significantly in 2018 compared to 2009 except for HD.

Correspondingly, the vulnerable degree of the studied districts in Handan City from 2009 to 2018 also can be obtained based on their percentile scores, which is denoted in Table 5. It can be known that only the average vulnerable degrees of the studied decade in SS and QZ are medium and medium-high, while other districts are high. And the percentage of districts with high vulnerability in the decade is 88.24%, 76.47%, 82.5%, 76.47%, 70.59%, 64.71%, 76.47%, 82.35%, 75%, and 56.25%, respectively. Therefore, it can be concluded that although the proportion of districts with high vulnerability was large, it is gradually decreasing.

In addition, to clearly analyze the fluctuations of vulnerability, the main factors affecting the evaluation system in every district can also be acquired by the PCA method of ROWA, shown in Table 6. In detail, the districts mainly affected by $C2$ are FK and FX; the districts of HD and CX are principally influenced by $C3$; the districts mainly affected by $C7$ are QZ and QX; the indicator of $C5$ only has a major impact on GP; the indicator of $C8$ has major implications for many districts, including WA, DM, WX, JZ, LZ, SX, and GT; and the indicator of $C10$ mainly affects SS and CA. Overall, this result would provide a good guidance for managers in water resource rehabilitation and governance.

4.2. Comparison between ROWA and EOWA. To clearly explain the impact of indicator weight on the evaluation results, the comparison of results between ROWA and EOWA is conducted. Given space constraints, this paper takes the results in 2009 and 2018 as examples, shown in Tables 7 and 8 individually. In which, symbols of EOWA-1, EOWA-2, and EOWA-3 mean the vulnerability of the water resources system in Handan City calculated by EOWA with three different indicator weights: $P1 = (0.1, 0.1, 0.1, 0.1, 0.1, 0.1, 0.1, 0.1, 0.1, 0.1)$, $P2 = (0.05, 0.05, 0.05, 0.05, 0.05, 0.05, 0.3, 0.3, 0.05, 0.05)$, and $P3 = (0.05, 0.05, 0.05, 0.05, 0.05, 0.05, 0.05, 0.05, 0.3, 0.3)$. The percentile scores of all districts by the

Table 5: Vulnerable degree of the water resources systems in Handan City from 2009 to 2018.

District	Vulnerable degree									
	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
SS	III	II	II	III	II	II	II	III	II	II
FK	IV	IV	IV	IV	IV	IV	IV	IV	IV	III
WA	IV	IV	IV	IV	IV	IV	IV	IV	III	III
HD	IV	IV	IV	IV	V	V	V	V	—	—
DM	V	IV	IV	IV	IV	IV	IV	IV	IV	IV
WX	IV	IV	IV	III	III	IV	IV	IV	IV	III
QZ	IV	III	IV	IV	III	III	III	III	III	III
QX	IV	IV	IV	IV	IV	IV	IV	IV	IV	IV
JZ	IV	IV	IV	IV	IV	IV	IV	IV	IV	IV
FX	IV	IV	IV	IV	IV	IV	IV	IV	IV	III
GP	IV	IV	V	IV	IV	IV	IV	IV	IV	IV
CA	IV	III	III	IV	IV	IV	IV	IV	III	III
LZ	IV	IV	IV	IV	IV	IV	IV	IV	IV	IV
CX	IV	IV	IV	IV	IV	IV	IV	IV	IV	IV
SX	IV	IV	IV	III	III	III	III	IV	IV	IV
YN	IV	III	IV	IV	IV	III	IV	IV	IV	IV
GT	IV	V	IV	V	IV	V	IV	IV	IV	IV

Note. VD = vulnerable degree; I = low vulnerability (0 ~ 20); II = medium vulnerability (20 ~ 40); III = medium-high vulnerability (40 ~ 60); IV = high vulnerability (60 ~ 80); V = severe vulnerability (80 ~ 100).

Table 6: The main factors affecting the evaluation system.

D	IF	D	IF	D	IF	D	IF	D	IF	D	IF
SS	C10	HD	C3	QZ	C7	FX	C2	LZ	C8	YN	C4
FK	C2	DM	C8	QX	C7	GP	C5	CX	C3	GT	C8
WA	C8	WX	C8	JZ	C8	CA	C10	SX	C8		

Note. D = district; IF = influencing factor.

Table 7: Comparison of results between ROWA and EOWA in 2009.

District	ROWA		EOWA-1		EOWA-2		EOWA-3	
	F	Rank	F	Rank	F	Rank	F	Rank
SS	41.40	1	41.58	1	40.83	1	40.55	1
WA	62.20	2	62.38	2	62.17	3	62.18	3
YN	62.36	3	62.63	3	62.15	2	61.94	2
CA	62.64	4	62.94	4	62.52	4	62.44	4
SX	64.82	5	64.97	5	64.72	5	64.79	5
QX	65.48	6	65.44	6	65.15	6	65.02	6
QZ	68.09	7	68.51	8	67.97	8	67.69	7
FK	68.52	8	68.41	7	67.89	7	68.00	8
WX	69.14	9	69.15	9	68.95	9	69.06	9
JZ	71.75	10	71.80	10	71.48	10	71.41	10
FX	72.00	11	72.29	11	71.81	11	71.74	11
LZ	74.90	12	75.02	12	74.63	12	74.75	12
GP	75.31	13	75.21	13	75.03	14	74.92	13
CX	75.50	14	75.60	15	75.29	15	75.32	15
HD	75.55	15	75.48	14	74.92	13	75.00	14
GT	75.97	16	75.94	16	75.85	16	75.76	16
DM	81.50	17	81.54	17	81.45	17	81.45	17

three EOWA methods change with the different indicator weights in both 2009 and 2018, even the orders have changed in some districts. For example, in 2009, the percentile scores of WA, YN, QZ, FK, GP, CX, and HD are (62.38, 62.17, 62.18), (62.63, 62.15, 61.94), (68.51, 67.97, 67.69), (68.41, 67.89, 68.00), (75.21, 75.03, 74.92), (75.60, 75.29, 75.32), and (75.48, 74.92, 75.00) by EOWA-1, EOWA-2, and EOWA-3, respectively, and their orders are (2, 3, 3), (3, 2, 2), (8, 8, 7), (7, 7, 8), (13, 14, 13), (15, 15, 15), and (14, 13, 14) by the three EOWA methods individually, bolded in Table 7; in 2018, the percentile scores of FK, WA, WX, JZ, and QX are (59.44, 58.58, 58.51), (59.40, 58.80, 58.66), (59.84, 58.69, 58.73),

Table 8: Comparison of results between ROWA and EOWA in 2018.

District	ROWA		EOWA-1		EOWA-2		EOWA-3	
	F	Rank	F	Rank	F	Rank	F	Rank
SS	29.31	1	30.26	1	28.37	1	28.34	1
QZ	50.15	2	50.67	2	49.60	2	49.51	2
CA	55.62	3	56.19	3	55.12	3	55.06	3
FX	56.34	4	56.83	4	55.87	4	55.78	4
FK	59.11	5	59.44	6	58.58	5	58.51	5
WA	59.12	6	59.40	5	58.80	7	58.66	6
WX	59.20	7	59.84	7	58.69	6	58.73	7
DM	60.03	8	60.53	8	59.63	8	59.60	8
YN	60.68	9	61.32	9	60.28	9	60.25	9
LZ	61.18	10	61.72	10	60.87	10	60.88	10
SX	62.03	11	62.29	11	61.93	11	61.70	11
CX	65.16	12	65.55	12	64.82	12	64.67	12
GP	69.14	13	69.39	13	68.70	13	68.70	13
GT	69.14	14	69.54	14	68.79	14	68.75	14
JZ	70.67	15	70.98	16	70.40	15	70.32	16
QX	70.69	16	70.89	15	70.42	16	70.29	15

Table 9: Vulnerability prediction of the water resources system in 2025 in Handan City.

District	F	VD	District	F	VD	District	F	VD	District	F	VD
SS	29.51	II	WX	65.44	IV	FX	63.56	IV	CX	72.87	IV
FK	72.83	IV	QZ	57.91	III	GP	76.20	IV	SX	60.92	IV
WA	67.70	IV	QX	68.00	IV	CA	64.11	IV	YN	66.92	IV
DM	75.28	IV	JZ	73.83	IV	LZ	73.69	IV	GT	78.44	IV

(70.98, 70.40, 70.32), and (70.89, 70.42, 70.29) with their orders being (6, 5, 5), (5, 7, 6), (7, 6, 7), (16. 15, 16), and (15, 16, 15) resulted from EOWA-1, EOWA-2, and EOWA-3, respectively, bolded in Table 8. By comparison, the percentile scores of WA, YN, QZ, FK, GP, CX, and HD are 62.20, 62.36, 68.09, 68.52, 75.31, 75.50, and 75.55 while their orders are 2, 3, 7, 8, 13, 14, and 15 by ROWA, respectively, in 2009; and the percentile scores of FK, WA, WX, JZ, and QX were 59.11, 59.12, 59.20, 70.67, and 70.69 with their orders being 5, 6, 7, 15, and 16 aroused from ROWA individually in 2018. It should be pointed that similar conditions have existed in other years.

In general, the results by ROWA are more effective than the ones by EOWA when the weights of indicators have changed. In practice, the weights of indicators for MCDM problems exactly change if they are determined by experts. Because the experts' numbers and/or subjectivity are constantly changing. Inversely, if the weights of indicators are calculated based on component score coefficient and percentage of variance in ROWA, the results for MCDM problems would not be affected by experts. Therefore, it can be obtained that ROWA is more objective and more fit for MCDM problems, and meanwhile provides the manager with an optimal and rational decision support system.

4.3. Vulnerability Prediction of Water Resources System. In order to provide better decision support for managers in future water resources management, the vulnerability of the water resources system in 2025 in Handan City is also assessed by the proposed ROWA based on the existing data, shown in Table 9. It can be seen that except for SS and QZ are medium vulnerability and medium-high vulnerability, respectively, all other districts have the high vulnerability with the proportion reaching 87.5%. Therefore, even by 2025, the vulnerability of the water resources system in Handan City would remain high and will require great attention.

5. Conclusions

In this study, a new ROWA method based on EOWA and PCA has been proposed for dealing with multicriteria decision-making problems. In this method, under the criterion of cumulative contribution, the percentile score can be ranked by order weight, which can effectively reduce the extreme error. In addition, the indicator weight (P_i) is calculated based on the component score coefficient and percentage of variance by PCA. Therefore, the proposed ROWA can not only avoid overlapping and crossing of indicators but also retain the authenticity of the original indicator, thus avoiding the subjective randomness. Moreover, it also can determine the main factors affecting the vulnerability, which is convenient for decision makers to make decisions.

A case of water resources system vulnerability in Handan City has been studied for demonstrating applicability of the proposed methodology. The analyses show that except for the vulnerability of the water resources system in DM has a sustained decline, other districts display varying degrees of volatility during the decade. Although the proportion of districts with high vulnerability is large, it is gradually decreasing from 2009 to 2018. And among the vulnerability assessment indicators, the one that most influenced the outcome is per capita GDP. Compared with EOWA referred to three different indicator weights, the vulnerability of the water resources system evaluated by ROWA has more rationality and objectivity. At last, the vulnerability of the water resources system in 2025 is also assessed by ROWA, which would be helpful for water management in Handan City.

Data Availability

The original data for the studied vulnerability were calculated according to Water Resources Bulletin and Statistical Yearbook of Handan City. The data can be gathered upon e-mail request to the corresponding author.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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