An Enhanced Beetle Antennae Search Algorithm Based Comprehensive Water Quality Index for Urban River Water Quality Assessment

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An enhanced beetle antennae search algorithm based comprehensive water quality index for urban river water quality assessment

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Abstract: Urban river not only has the important function in urban hydrological environment, but also is an area for entertainment. Water quality assessment is the core technique in water resource management. As the typical urban river, water samples were collected at 5 sampling points in Xi'an moat from January 2018 to December 2020, and 10 physicochemical parameters were analyzed. In this paper, a comprehensive water quality index (WQI) is designed based on the criterion of water quality classes and entropy weight method firstly. Secondly, the crucial water quality parameters is determined by using mutual information, coefficient of variation and the water quality classes. Finally, an enhanced beetle antennae search algorithm is proposed to optimize the weight values of the crucial parameters in the range 0 to 1, which represent the ratio of the crucial parameter in the minimum WQI (WQImin) model. The WQImin models with the various crucial water quality parameters are implemented for water quality assessment. The effectiveness and superiority of the proposed enhanced beetle antennae search algorithm are validated in comparison with other evolutionary algorithms. The results show that the proposed WQImin model can assess the water quality accurately.

Keywords: water quality index, mutual information, coefficient of variation, beetle antennae search algorithm.

1. Introduction

Urban river plays a crucial role in urban development and in the ecological environment maintenance [1]. With the increase of urbanization levels, urban river is highly affected by human interference [2]. Human activity will deteriorate the water quality of urban river. Meanwhile, the water quality of urban river in turn influences city life [3]. As a large developing country, Chinese cities have a salient contradiction between water quality conservation and urban development, especially in the northwest cities with the limited water resources. To realize sustainable and coordinated development of water resources, it is urgent to carry out scientific and comprehensive water quality assessment, and provide insights for subsequent pollution control [4].

Water quality index (WQI) is an effective manner to depict the state of water quality and to estimate classes of water quality [5]. Chinese government published a standard, namely Environmental Quality Standards for Surface Water (GB 3838-2002), to divide the water quality into six classes according to the defined thresholds of the physicochemical parameters [6]. On the basis of the published standard, the WQI is determined by the worst water quality parameter [7]. According to Chinese published standard, Xu [8] proposed a comprehensive WQI for urban river water quality assessment by using 5 physicochemical parameters. Different from using Chinese standard, a comprehensive WQI in the range of 0 to 100 was built by using 15 physicochemical parameters and empirical weights [9]. Another WQI in the range of 0

to 300 was designed by using 16 parameters and the empirical weights [10]. However, these WQIs only can be used to assess the water quality in a certain environment [11]. Obviously, different scales, various water quality parameters and manual weights are the main factors restricting the application of these WQIs.

Although some studies designed the WQIs within the range of 0 to 100, these WQIs set different thresholds to determine the water quality classes [12]. To overcome the defect of manual weights, the entropy weight method is adopted to assign the weights to various water quality parameters automatically [13]. However, the entropy weight method neglects the importance of the overproof parameters and may allocate approximate weights to different parameters. So, the ratio of the measured value to standard value of different water quality parameters is defined as the weights to model the WQI [14]. To use WQI easily, many researches focus on developing WQImin model which only consists of few crucial water quality parameters. In [15, 16], the crucial parameters were selected from heterogeneous water quality parameters to build WQImin by using stepwise multiple linear regression analysis. In [17], artificial neural network was applied to construct the WQI for water quality assessment. The results show that stepwise multiple linear regression analysis and artificial neural network can build an accurate WQI by using few water quality parameters [18, 19]. However, these methods will assign the negative weight or the extreme weight to the water quality parameter, which will loss the physical meaning of WQImin.

To address the aforementioned problem, this paper designs a criterion to decide the water quality classes for various parameters. Then, the comprehensive WQI is

developed by using entropy weight and water quality classes. The physicochemical parameters with minimized mutual information, maximum coefficient of variation and maximum water quality difference are selected as the crucial water quality parameters. Finally, an enhanced beetle antennae search (BAS) algorithm is proposed to optimize weights of the crucial parameters under the designed constraint, on the basis of which to build the WQImin model for water quality assessment.

The rests of this paper are organized as follows. Section 2 introduces the study area and the data source. Section 3 details the proposed methodology for building WQI and WQImin. Section 4 presents experimental results and discussion. The conclusion is summarized in Section 5.

2. Study area and materials

2.1 Study area

This paper focuses on the urban river water quality assessment. As the largest city in northwest China, Xi'an (107.4–109.49°E, 33.42–34.45°N) is located in the center of the Guanzhong plain to the south of the Qinling mountains. Xi'an moat is a typical urban river which not only has the function of interception, storage, drainage functions, but also is a place for people's living. The weather is temperate semi humid continental monsoon climate. It is hot and rainy in summer, while cold and dry in winter. The total length of Xi'an moat is 14.7km, and its storage capacity is 127m^3 approximately.

2.2 Data source

With the rapid urbanization of Xi'an city, this development has had dramatic effects on the water environment [20]. Xi'an moat experienced 3 environmental

governance from 1998 to 2009, but it still exists environmental problems. As shown in Figure 1, two water supply sources for Xi'an moat are near to sampling point 1 (from Dayu reservoir) and sampling point 4 (from reclaimed waterworks) respectively. The river flows from sampling point 1 through sampling point 2, sampling point 3, and sampling point 4 to sampling point 5.

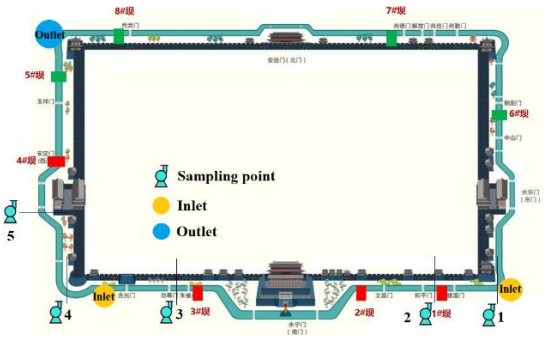

Fig.1. The sampling points in Xi’an moat

Water samples were collected into brown sterile glass bottles from 0.5 meter below a water level and analyzed the physicochemical characteristics. The methods for sample analysis are based on the standard methods for the examination of water and wastewater [21]. This paper collects 10 physicochemical parameters, which are temperature (T), pH, dissolved oxygen (DO), total nitrogen (TN), ammonia nitrogen (NH_3-N), total phosphorus (TP), chemical oxygen demand (COD), Turbidity (Tur), Chlorophyll-a (Chl-a) and Secchi Disk depth (SD) respectively, at 5 sampling points from January 2018 to December 2020. All these parameters were measured once every half a month and is shown in Figure 2.

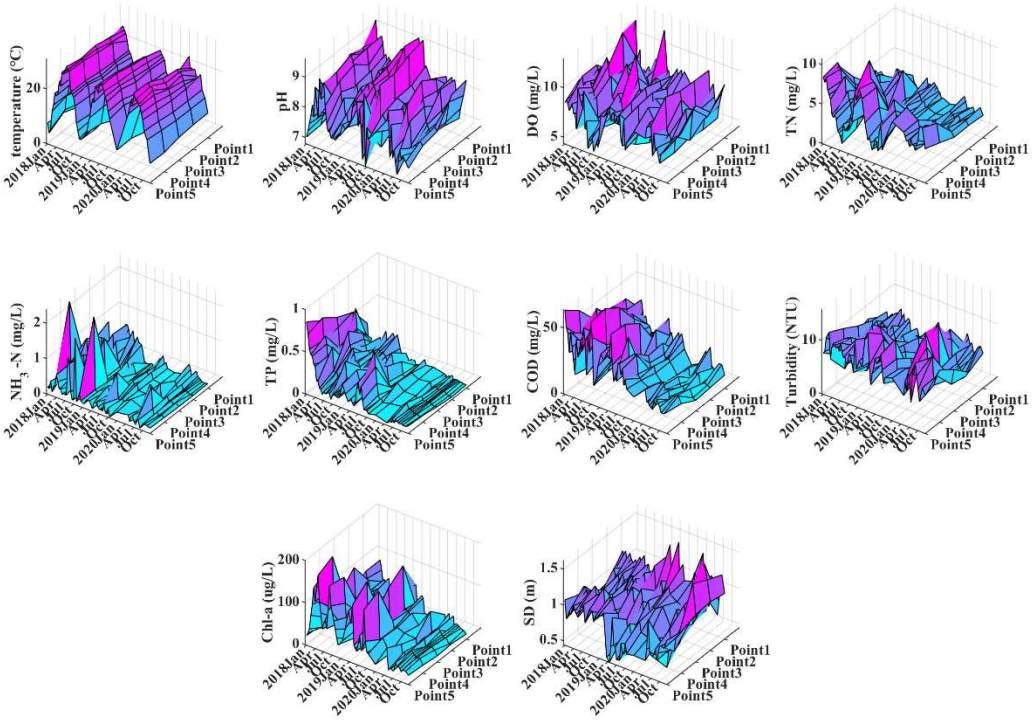

Fig.2. The collected physicochemical parameters

The water samples were only collected 2 times from December 2019 to April 2020 due to the impact of COVID-19. As Figure 2 shows, the Xi'an moat belongs to alkaline water. Chl-a and DO manifest significant seasonal characteristics due to the temperature and sunlight intensity. NH_3-N and COD exist some extreme values may resulting from the inflows of waste water and human activities. TP and TN are the major parameters of the water quality deterioration.

3. The proposed WQI and WQImin model

3.1 Comprehensive WQI

To evaluate the water quality classes, this paper adopts Chinese environmental quality standards for surface water and the water quality standards published in [22, 23]. Table 1 presents the classification criteria of different water quality parameters.

Table 1. The classification criteria

	ClassI	ClassII	ClassIII	ClassIV	ClassV
pH	7-8	8-9	9-10	10-11	<11-13
DO	≥7.5	≥6	≥5	≥3	≥2
TN	≤0.2	≤0.5	≤1.0	≤1.5	≤2.0
NH_3-N	≤0.15	≤0.5	≤1.0	≤1.5	≤2.0
TP	≤0.02	≤0.1	≤0.2	≤0.3	≤0.4
COD	<15	≤15	≤20	≤30	≤40
Tur	<10	<20	<30	<60	<100
Chl-a	≤1	≤10	≤15	≤40	≤50
SD	≥3	≥2	≥1	≥0.6	≥0.4

In this paper, the water quality parameter T is set to class IV, which satisfies the requirement of the common process water and the human body non-direct contact entertainment water. In the light of the classification criteria, the water quality index of the *i*th physicochemical parameter can be formulated as follows.

$$WQI_i = X_{i1}.X_{i2}$$

where X_{i1} refers to the water quality class of *i*th parameter; X_{i2} implies the location of water quality within the class X_{i1} [24]. If the classification of water quality is inferior to Class V, WQI_i can be defined as follows under the condition that threshold is monotonic increasing.

$$WQI_i = 6 + \frac{X_i - S_{i5}}{S_{i5}}$$

Otherwise,

$$WQI_i = 6 + \frac{S_{i5} - X_i}{S_{i5}}$$

where S_{i5} refers to the threshold of Class V. Obviously, WQI_i can describe the hazard degree of the overproof parameter. Then, the proposed comprehensive WQI is designed as follows.

$$WQI = \sum_{i=1}^{M} W_i \cdot WQI_i$$

where W_i is the weight for these parameters and is determined by entropy weight method [25].

$$W_i = \frac{1 - E_i}{M - \sum_{i=1}^{M} E_i}$$

$$E_i = -\frac{1}{\ln n} \sum_{j=1}^{n} p_{ij} \ln p_{ij}$$

where M and n are the number of physicochemical parameters and number of samples respectively. In terms of the collected jth sample of the physicochemical parameter Z_i, P_{ij} implies the probability of jth sample in the parameter Z_i.

The WQI_i can reflect the importance of different water quality parameters, and the entropy weights express the information quantity of these parameters. Under such a scenario, the comprehensive WQI can reveal the water quality reasonably.

3.2 Crucial parameters selection strategy

To easily assess the water quality of urban river, this paper establishes a WQImin model by using the crucial water quality parameters. The crucial water quality parameters should have the following characteristics. Firstly, the crucial parameters should possess visible fluctuation, which can express the temporal variability. Secondly, the physicochemical parameter with inferior water quality class or superior water quality class should be selected as the crucial parameters. Thirdly, the selected crucial parameters should have minimum information redundancy. Therefore, this paper designs a score V for crucial parameter selection and can be formulated as follows.

$$\arg\max V = V_1 + V_2 - V_3$$

where $V_1 = \frac{\sigma_i}{\mu_i}$ is the coefficient of variation of the *i*th parameter; $V_2 = |WQI_i/4-1|$ can express the importance of the *i*th parameters in comparison with the water quality of class IV. V_3 is the average mutual information between the *i*th parameter and other parameters, and can be calculated as follows.

$$V_3 = \frac{1}{M-1}\sum_{i\neq k}\left[\sum\sum P(Z_i,Z_k)\log\left(\frac{P(Z_i,Z_k)}{P(Z_i)P(Z_k)}\right)\right]$$

3.3 Enhanced BAS based WQImin

After crucial parameter selection, an enhanced BAS is proposed to optimize the weight for building the WQImin model. BAS is a global optimization method, which is simple and fast as well as easy to implement [26]. BAS is inspired by the behavior of longhorn beetles, more precisely by the process of detecting and searching. The basic BAS defines the position of the beetle as a vector x^t at the epoch *t*. The searching behavior of beetle can be depicted as a random unit vector $\vec{D}$. The positions of the right antenna x_r^t and left antenna x_l^t can be calculated as follows

$$\begin{aligned} x_r^t &= x^t + d^t\vec{D} \\ x_l^t &= x^t - d^t\vec{D} \end{aligned}$$

where $d^t = t/R$ is the distance between two antennas, and *R* is a constant [27]. Then, x_r^t and x_l^t are fed into the fitness function *f(x)* to figure out the next position according to the following formulas.

$$\begin{aligned} x^{t+1} &= x^t - \delta^t \cdot \vec{D} \cdot sign\left[f\left(x_r^t\right) - f\left(x_l^t\right)\right] \\ \delta^t &= \delta^{t-1} \cdot \eta \end{aligned}$$

where δ^t represents the step size of each iteration; η is the decay rate and is set to 0.95 generally.

The random unit vector $\vec{D}$ enables BAS to possess the global optimization performance, but it affects the searching efficiency as well. Therefore, this paper proposed an enhanced BAS to improve the searching efficiency. A variable x_{best} representing the position with the best fitness is added to the enhanced BAS, which can help BAS achieve a better direction and improve the convergence rate. If $f\left(x^t\right) < f\left(x_{best}\right)$, x^t is assigned to x_{best}. The formulation for update the position is defined as follows.

$$x^{t+1} = x^t - \delta^t \cdot \left[\vec{D} \cdot sign\left(f\left(x_r^t\right) - f\left(x_l^t\right)\right) - \frac{\left(x_{best} - x_t\right)}{\left\| x_{best} - x_t \right\|} \right]$$

in which the step size δ^t is modified as follows.

$$\delta^t = \begin{cases} \delta_0 \cdot e^{(\eta-1)t/10}, & rand < \eta \\ \delta_0 \cdot e^{(\eta-1)t/10} + \dfrac{\delta_0}{10t}, & rand \geq \eta \end{cases}$$

where δ_0 is the initial step size. δ^t will decrease with the epoch, and it will increase depending on probability η, contributing to jump out of local optimal position.

To obtain a reliable WQImin model, the proposed enhanced BAS is applied to figure out the weight. The objective function and constraints are defined as follows.

$$J = \min \frac{1}{n} \sum_{j=1}^{n} \left(WQI(j) - WQImin(j) \right)^2 + \frac{1}{2} p \left(\sum c_i - i \right)^2$$
$$s.t. \begin{cases} c_i - 1 \leq 0, i - 1, 2, ... \\ c_i \leq 0, i = 1, 2, ... \end{cases}$$

where $\frac{1}{n} \sum_{j=1}^{n} \left(WQI(j) - WQImin(j) \right)^2$ is the mean square error (MSE) [28]. c_i is the weight for the *i*th crucial parameter, and $WQImin(j) = \sum_i c_i \cdot WQI_i(j)$. $\frac{1}{2}\left(\sum c_i - 1\right)^2$ denotes the constraint of the weights, and p is the penalty factor. The constraint term implies that $c_i \in [0,1]$.

4. Results and discussion

4.1 Water quality assessment using comprehensive WQI

To reveal the urban river water quality, the comprehensive WQI is built using the physicochemical parameters from Xi'an moat. The water quality index of parameter temperature (T) is set to 4 in this paper. Figure 3 shows the WQI_i of different water quality parameters.

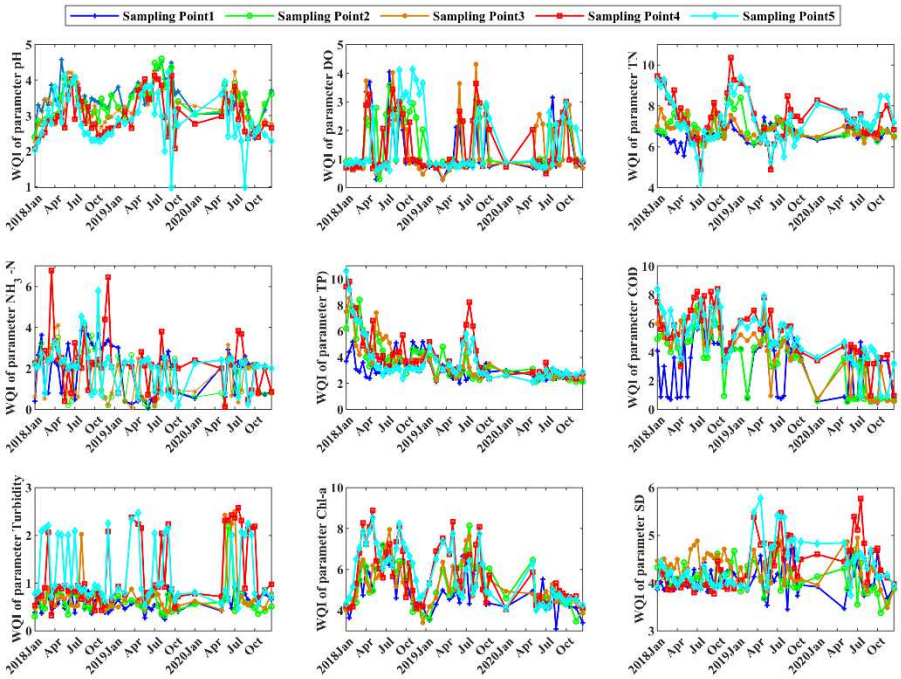

Fig.3. WQI_i of different parameters

As Figure 3 shows, the concentrations of TN, TP, COD and Chl-a exceed the standard value in the most cases. Hence, the water quality will be regarded as inferior ClassV depending on Cannikin's Law, which is strict and harsh [29]. WQI of Chl-a and WQI of DO manifest significant seasonal variation resulting from the changes of temperature and sunlight intensity [30, 31]. Meanwhile, the WQI of pH and the WQI of turbidity reflect the excellent water quality. Figure 4 is the statistical WQI_i of these parameters.

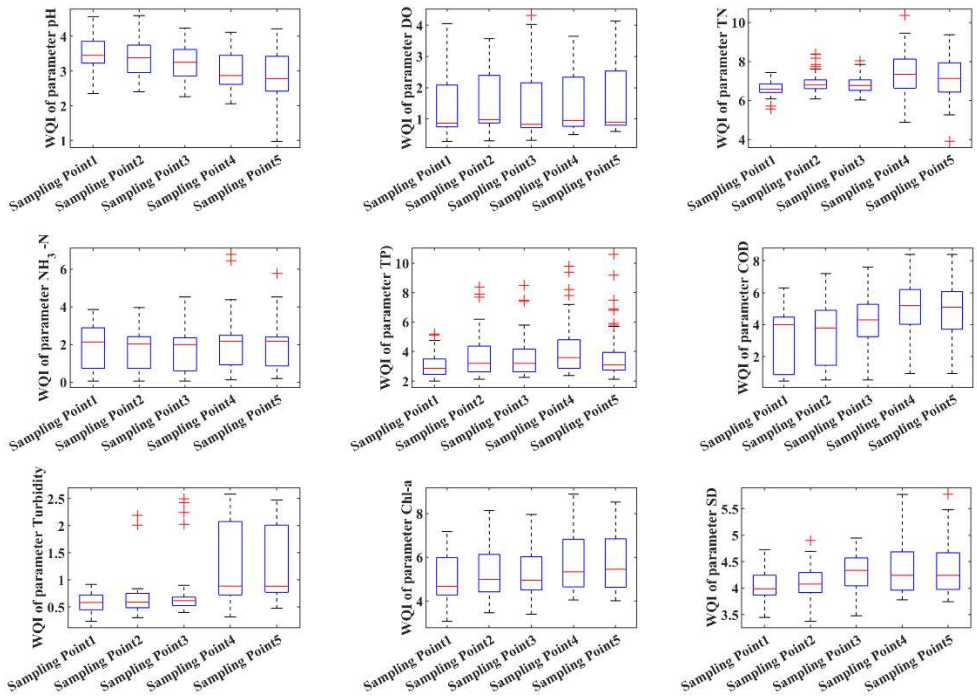

Fig.4. The statistical WQI_i

As Figure 4 shows, the WQI of parameter pH ranges from 0.97 to 4.60. The WQI of parameter DO ranges from 0.28 to 4.31. The WQI of parameter TN ranges from 3.9 to 10.36. The WQI of parameter NH_3-N ranges from 0.07 to 6.78. The WQI of parameter TP ranges from 2 to 10.6. The WQI of parameter COD ranges from 0.47 to 8.40. The WQI of parameter Turbidity ranges from 0.24 to 2.58. The WQI of parameter Chl-a ranges from 3.08 to 8.89. The WQI of parameter SD ranges from 3.38 to 5.78. WQI of NH_3-N and WQI of TP exist many extreme values may due to human interference. In terms of TN, TP, Turbidity, Chl-a and SD, the WQI values before and after sampling point 4 show significant difference resulting from the inflow of reclaimed water. All the WQI_i manifest significant changing tendency resulting from the flow direction and the input water quality of Xi'an moat.

To assess the water quality from a system perspective, Figure 5 shows the comprehensive WQI of Xi'an moat. The comprehensive WQI indicates that the water

quality is in the range of Class Ⅱ to ClassⅣ.The average value of the comprehensive WQI is 3.54. The maximum value and the minimum value are 4.76 and 2.56 respectively. Hence, this urban river water quality is suitable for the requirement of the common process water and the human body non-direct contact entertainment water. The comprehensive WQI indicates that water in sampling point 1 has the best quality, resulting from the inflow of reservoir water. The comprehensive WQI of sampling point 4 exhibits worst water quality resulting from the winding watercourse and the inflow of waster water.

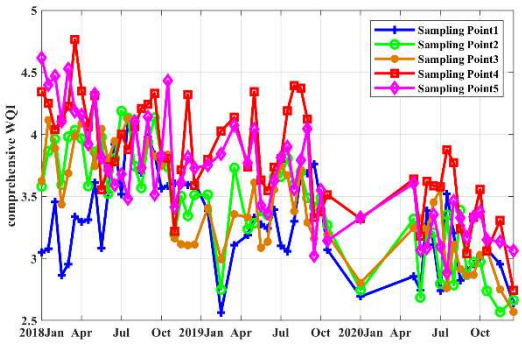

Fig.5. The comprehensive WQI

To further reveal the water quality, Figure 6 and Figure 7 present the spatial distribution and the temporal variation of the comprehensive WQI respectively. In terms of Xi'an city, spring consists of March, Aril and May, summer implies the periods of June to August, autumn means the periods of September to November, and winter refers to December, January and February.

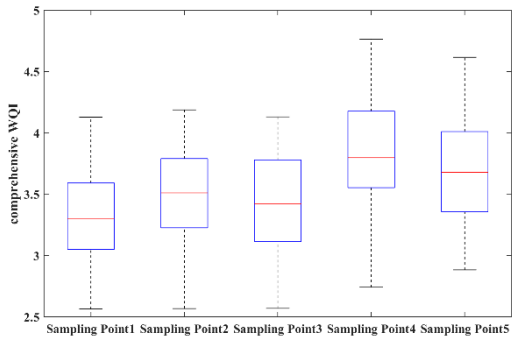

Fig.6. The spatial distribution of the comprehensive WQI

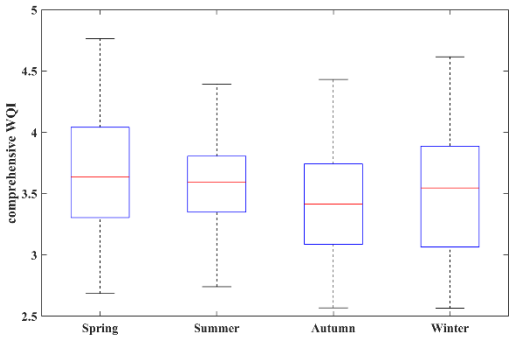

Fig.7. The temporal variation of the comprehensive WQI

As Figure 6 shows, the comprehensive WQI indicates that sampling point 1 possesses the best water quality. Sampling point 5 shows the worst water quality, resulting from the inflow of reclaimed water and the geometry of the watercourse. Figure 7 demonstrates that Xi'an moat performs the best quality in autumn, and performs inferior quality in spring. The phenomenon may due to the plenty of rainfall in autumn and the severe air pollution in winter and spring. Meanwhile, lots of pollutions will flow into Xi'an moat due to the most rainfall in summer and the frequent human activities.

4.2 Crucial parameters in Xi'an moat

In this paper, the crucial water quality parameters in different sampling points are selected independently. In terms of the sampling points, the average classes of different

water quality parameters are figured out according to the classification criteria listed in Table 1. Then, the score *V* of every water quality parameters is calculated according to the designed strategy. Table 2 lists the score *V* in different sampling points.

Table 2. The score *V*

	Score *V* in descending order									
sampling point 1	NH_3-N	Tur	TN	DO	TP	Chl-a	COD	SD	pH	T
sampling point 2	NH_3-N	Tur	TN	Chl-a	DO	TP	COD	pH	SD	T
sampling point 3	NH_3-N	Tur	TN	TP	Chl-a	DO	SD	COD	pH	T
sampling point 4	NH_3-N	Chl-a	TN	Tur	TP	DO	COD	pH	SD	T
sampling point 5	NH_3-N	TN	TP	Chl-a	Tur	DO	COD	pH	SD	T

As listed in Table 2, the physicochemical parameters NH_3-N, Tur, TN, Chl-a, TP and DO are the six crucial parameters, whichever the sampling point is monitored. NH_3-N plays the most important role in explaining WQI, followed by turbidity, TN and so on.

4.3 The performance of the enhanced BAS based WQImin

In this paper, the proposed enhanced BAS method is employed to optimize the weights of the crucial water quality parameters. To validate the effectiveness and superiority of the proposed method, the WQImin with different number of the crucial water quality parameters are established according to the order of the water quality parameters listed in Table 2. All the WQImin models are estimated based on the criterion of the Pearson correlation coefficient (PCC) [32], MSE, and mean absolute percentage error (MAPE) [33]. These formulas are defined as follows.

$$PCC = \frac{Cov\left(WQImin(j), WQI(j)\right)}{\sqrt{\mathrm{var}\left(WQImin(j)\right)\mathrm{var}\left(WQI(j)\right)}}$$

$$MSE = \frac{1}{n}\sum_{j=1}^{n}\left(WQImin(j) - WQI(j)\right)^2$$

$$MAPE = \frac{1}{n}\sum_{j=1}^{n}\left|\frac{WQImin(j) - WQI(j)}{WQI(j)}\right|^2 \times 100\%$$

where j refers to the sequence number and n is the number of samples.

Figure 8 displays the WQImin models with different number of the crucial water quality parameters at 5 sampling points. The WQImin3, WQImin4, WQImin5, WQImin6 refer to the WQImin with the first 3 parameters, first 4 parameters, the first 5 parameters and the first 6 parameters, respectively.

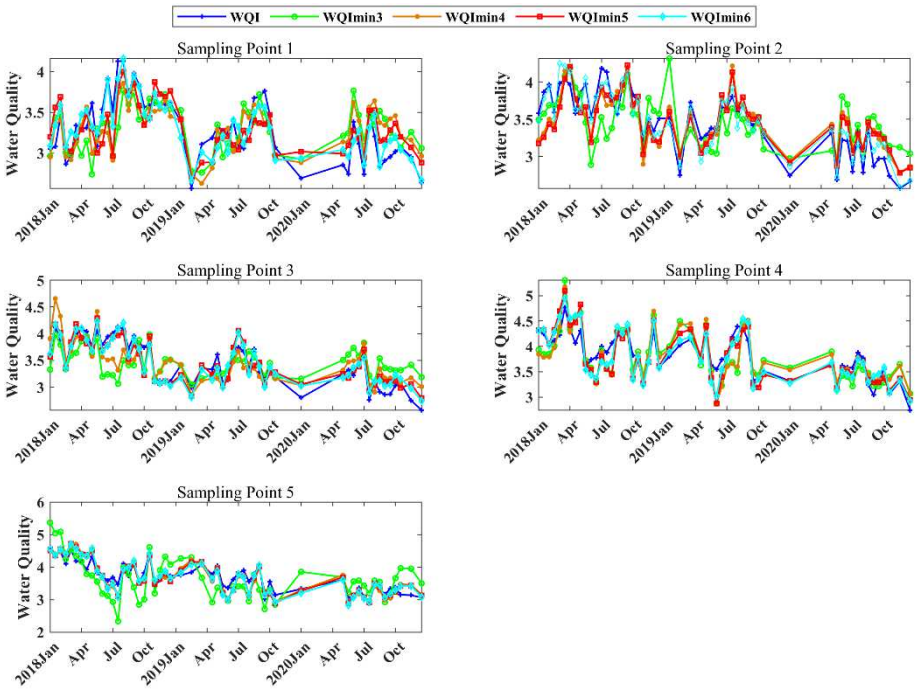

Fig.8. The WQImin models

As Figure 8 shows, all the WQImin models can reflect the changing tendency of water quality, whichever the sampling point is selected. The WQImin model with 3 crucial water quality parameters can not express the water quality accurately in some cases. The assessment of WQImin model with 6 crucial water quality parameters is

similar to that of the comprehensive WQI. The results confirm that WQImin6 model is an excellent and convenient manner with great generalization capability for urban river water quality assessment. In order to display the performance clearly, Table 3 lists the MSE, MAE and the Pearson correlation coefficient between the WQImin model and the comprehensive WQI.

Table 3. The performance of the WQImin models

		WQImin3	WQImin4	WQImin5	WQImin6
Sampling Point 1	MSE	0.1085	0.0845	0.0576	0.0273
	MAPE	0.0812	0.0723	0.0620	0.0431
	PCC	0.5180	0.6374	0.7657	0.9069
Sampling Point 2	MSE	0.1242	0.0591	0.0556	0.0187
	MAPE	0.0848	0.0595	0.0580	0.0328
	PCC	0.5869	0.8188	0.8306	0.9466
Sampling Point 3	MSE	0.1341	0.0838	0.0303	0.0219
	MAPE	0.0845	0.0674	0.0427	0.0359
	PCC	0.4826	0.7323	0.9081	0.9343
Sampling Point 4	MSE	0.0995	0.0926	0.0565	0.0450
	MAPE	0.0706	0.0655	0.0466	0.0421
	PCC	0.7700	0.7729	0.888	0.9074
Sampling Point 5	MSE	0.2305	0.0457	0.0417	0.0390
	MAPE	0.1181	0.0492	0.0455	0.0442
	PCC	0.6339	0.9083	0.9181	0.9274

As Table 3 listed, the WQImin model with more crucial parameters will exhibit better performance. The Pearson correlation coefficient values between the WQImin with 6 crucial water quality parameters and the comprehensive WQI are all beyond 0.9, which illustrates effectiveness and superiority of the WQImin model. Besides the WQImin6 model, WQImin5 and WQImin4 can assess the water quality effectively as well. Meanwhile, the weights of WQImin model are optimized in a reasonable range due to the defined objective function and constraints. Table 4 and Figure 9 lists the optimized weights of these WQImin models.

Table 4. The optimized weights

Weights	WQImin3	WQImin4	WQImin5	WQImin6
Sampling Point 1	0.1839: 0.4268: 0.4067	0.1673: 0.2752: 0.3916: 0.1704	0.0701: 0.2458: 0.3137: 0.1955: 0.2213	0.0662: 0.2419: 0.1955: 0.1339: 0.2164: 0.1785
Sampling Point 2	0.2436: 0.1155: 0.4286	0.2017: 0.1140: 0.2691: 0.2227	0.1834: 0.1002: 0.2639: 0.2134: 0.0796	0.1173: 0.1275: 0.1855: 0.2181: 0.1260: 0.1465
Sampling Point 3	0.1418: 0.2960: 0.4394	0.1338: 0.3105: 0.3509: 0.1627	0.1342: 0.2548: 0.2024: 0.1426: 0.2176	0.1008: 0.2092: 0.1956: 0.1571: 0.2068: 0.0985
Sampling Point 4	0.1151: 0.2774: 0.2633	0.1107: 0.2671: 0.2488: 0.1498	0.1145: 0.2422: 0.1894: 0.2077: 0.1205	0.1139: 0.2053: 0.1925: 0.1964: 0.1248: 0.1256
Sampling Point 5	0.2489: 0.3628: 0.1391	0.1264: 0.1976: 0.1262: 0.2617	0.1514: 0.1843: 0.1251: 0.2427: 0.1391	0.1499: 0.1655: 0.142: 0.2361: 0.1437: 0.0665

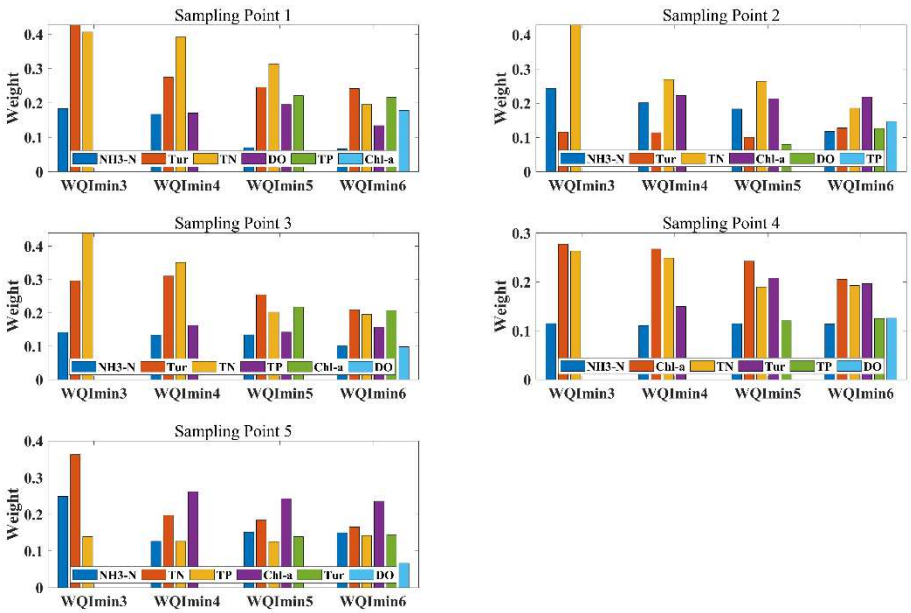

Fig.9. The optimized weights

Obviously, the weights of these WQImin models are all below to 1, and the sum of the weights is approximately equal to 1. Under such a scenario, the weight represents the ratio of different parameters in the WQImin model and the ratio of different parameters for water quality assessment. In view of the above results, it can be known that the proposed enhanced BAS based WQImin model is an effective manner with certain physical meaning for water quality assessment.

To validate the performance, the proposed enhanced BAS is compared with standard BAS, particle swarm optimization (PSO) [34] and gravitational search algorithm (GSA) [35]. Figure 10 shows the convergence rates of these algorithms for building WQImin models on sampling point 1.

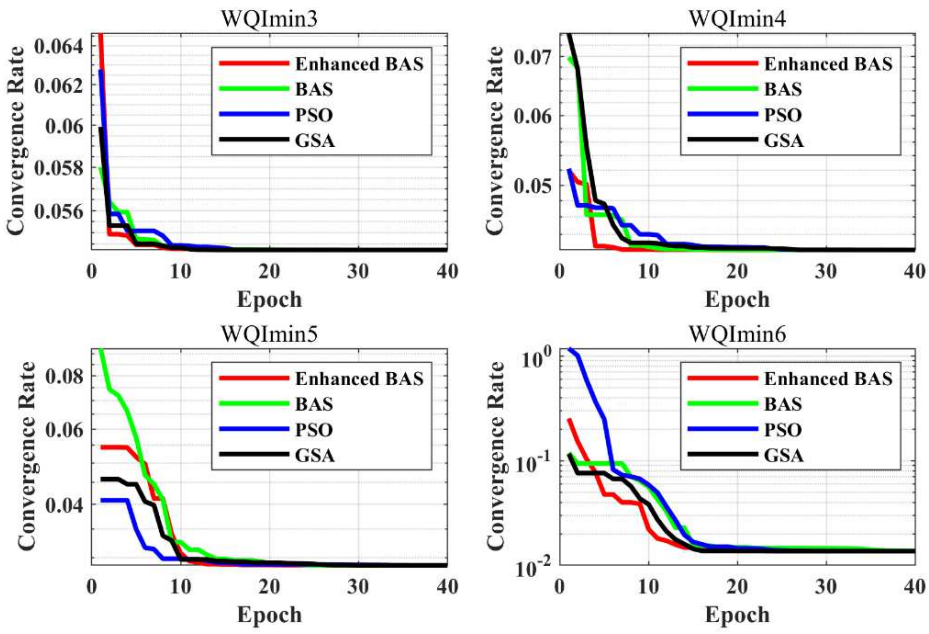

Fig.10. The convergence rates

As Figure 10 shows, all these 4 algorithms can achieve the optimal results in the end. However, the convergence rates manifest significant difference. In terms of WQImin3 and WQImin5, the convergence rates of the proposed enhanced BAS are slightly faster as compared with other algorithms. From the convergence rates of WQImin4 and WQImin6, it can be known that the proposed enhanced BAS can use less iteration than other algorithms to figure out the optimal results. The proposed enhanced BAS has a remarkable promotion in comparison with the standard BAS algorithm, since the extra direction and the modified step size can improve the performance of BAS.

As shown in Figure 8, Figure 9, Figure 10, Table 3 and Table 4, the proposed enhanced BAS can optimize the weights of WQImin models with a fast convergence rate. The values of the optimized weights range from 0 to 1, expressing the ratio of each crucial water quality parameters in the WQImin models. All the results demonstrate that the proposed enhanced BAS based WQImin model is an effective, accurate and convenient approach for urban river water quality assessment.

5. Conclusion

This paper focuses on the water quality assessment of urban river. The water samples collected from Xi'an moat and 10 water quality parameters were measured. On the basis of Chinese published standard, the classification criteria are designed to determine the water quality classes of different water quality parameters. The developed comprehensive WQI can assess the water quality from system point of view, resulting from the combination of the water quality classes and entropy weights. The proposed selection strategy can obtain the crucial water quality parameters automatically. The selection illustrates that NH_3-N, Tur, TN, Chl-a, TP and DO are the crucial parameters of Xi' an moat, and most important parameter is NH_3-N. The enhanced BAS is proposed to optimize the weights of the crucial parameters within 0 to 1, which can reveal the ratio of the crucial parameters in the WQImin model. As compared with standard BAS, POS and GSA, the convergence rates confirm the excellent performance of the proposed enhanced BAS. The WQImin model with few crucial parameters is a simple and convenient manner for urban river water quality assessment. The WQImin model with 6 crucial parameters is a precise and superior approach for urban river water

quality assessment. All the results demonstrate the enhanced BAS based WQImin model can assess the urban river water quality effectively.

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