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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 difference. 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 different number of 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 city development and in the ecological environment maintenance (Zhang et al. 2022). With the increase of urbanization levels, urban river is highly affected by human interference (Zhang et al. 2021). Human activity will

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deteriorate the water quality of urban river. Meanwhile, the water quality of urban river in turn influences city life (Yu et al. 2021). 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 (Tang et al. 2022).

Water quality index (WQI) is an effective manner to depict the state of water quality and to estimate water quality classes (Vijay and Kamaraj 2021). Chinese Environmental Quality Standards for Surface Water listed 24 physicochemical parameters, and defined different thresholds to divide each physicochemical parameter into 6 six water quality classes (Xu 2005a). Staff can choose any number of the physicochemical parameters to assess the water quality in application, and the worst assessment of these selected physicochemical parameters is generally used to represent the water quality (Yan et al. 2005). Obviously, only using the worst assessment to represent the water quality is strict and harsh, and neglects the effect of other parameters. So, Xu (2005b) proposed a comprehensive WQI for urban river water quality assessment by using 5 physicochemical parameters listed in the Chinese Environmental Quality Standards for Surface Water. Different from using the Chinese standard, Wu et al. (2021a) built a comprehensive WQI in the range of 0 to 100 by using 15 physicochemical parameters and empirical weights. Amiri et al. (2021) designed a WQI in the range of 0 to 300 by using 16 parameters and the empirical weights. Although some studies unified the WQIs within the range of 0 to 100, these WQIs still set different thresholds to determine the water quality classes (Uddin et al. 2021).

Different thresholds, various water quality parameters and manual weights are the main factors restricting the application of these WQIs. Therefore, these WQIs only can be used to assess the water quality in a certain environment (Gupta and Gupta 2021). To overcome the defect of manual weights, some studies used the ratio of the measured value to standard value to determine the weights of different parameters (Chakravarty and Gupta 2021). Since the standard value is decided subjectively, many researches adopted the entropy weight method to assign the weights to various water quality parameters automatically (Wang et al. 2021a).

To assess the water quality easily, many researches focus on developing WQImin model which only consists of few crucial water quality parameters. In (Nong et al. 2020; Wang et al. 2021b), the crucial parameters were selected from heterogeneous water quality parameters to build WQImin by using stepwise multiple linear regression analysis. In (Kim et al. 2021), 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 (Gebler et al. 2018; Kadkhodazadeh and Farzin 2021). However, these methods will assign the negative weight or the extreme weight to the water quality parameter, which will lose the physical meaning, lead to overfitting problem and show low generalization ability.

To address the aforementioned problem, this paper proposes an enhanced beetle antennae search algorithm based comprehensive water quality index for urban river water quality assessment. The main contributions are as follows.

1. This paper developed a comprehensive WQI to assess the water quality of urban river by using entropy weight and water quality classes.

2. An objective function with minimized mutual information, maximum coefficient of variation and maximum water quality difference is developed to select the crucial water quality parameters

3. An enhanced beetle antennae search (BAS) algorithm is proposed to build the WQImin model with excellent generalization ability, by optimizing the weights of the crucial parameters under the constraints with certain physical meaning.

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 Sect. 5.

## 2 Study Area and Materials

### 2.1 Study Area

This paper focuses on the urban river water quality assessment. Xi'an (107.4~109.49°E, 33.42~34.45°N) is the largest city in northwest China and is located in the center of the Guanzhong plain to the south of the Qinling mountains, as shown in Fig. 1. 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. Annual precipitation is 522.4 mm~719.5 mm. The rainfall is the highest in July, and September is another rainy month. The total length of Xi'an moat is 14.7 km, and its storage capacity is 1.27 million $m^3$ approximately.

### 2.2 Data Source

With the rapid urbanization of Xi'an city, this development has had dramatic effects on the water environment (Yang et al. 2019). Xi'an moat experienced 3 environmental governance from 1998 to 2009, but it still exists environmental problems. As Fig. 1 shows, 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.

Water samples were collected into brown sterile glass bottles from 0.5 m below a water level and were used to physicochemical characteristics analysis. 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. The methods for sample analysis are based on the standard methods for the examination of water and wastewater (APHA (American Public Health Association) 2017). The water samples were only collected 2 times from December 2019 to April 2020 due to the impact of COVID-19. In the rest of the time, the water samples were collected every half a month. The statistical characteristics of these physicochemical parameters are summarized in Table 1.

Fig. 1 The sampling points in Xi'an moat

As Table 1 shows, the water of Xi'an moat presents alkaline and the contents of TN is high in general. NH$_3$-N, TP and Chl-a show the large standard deviation (SD) resulting from existing some extreme values.

# 3 The Proposed WQI and WQImin Model

## 3.1 Comprehensive WQI

To evaluate the water quality classes, this paper employs the thresholds of pH, DO, TN, NH3-N, TP and COD published in Chinese environmental quality standards for surface water. Meanwhile, this paper adopts the thresholds of Tur, Chl-a and SD, which are

**Table 1** Statistical characteristics

| Parameters | Min. | Max. | Mean | SD |
|---|---|---|---|---|
| pH | 4.2 | 31 | 19.86 | 7.27 |
| DO (mg/L) | 6.8 | 9.6 | 8.2 | 0.58 |
| TN (mg/L) | 4.38 | 9.6 | 8.2 | 0.58 |
| NH$_3$-N (mg/L) | 6.8 | 9.6 | 8.2 | 0.58 |
| TP (mg/L) | 4.38 | 12.91 | 8.11 | 1.51 |
| COD (mg/L) | 0.95 | 10.72 | 4.02 | 1.55 |
| Tur (NTU) | 2.39 | 15.82 | 7.30 | 2.56 |
| Chl-a (ug/L) | 10.4 | 194.28 | 51.21 | 35.96 |
| SD (m) | 0.445 | 1.623 | 0.93 | 0.20 |

defined based on the Chinese standards and listed in Kocer and Sevgili (2014); Wu et al. (2021b). Table 2 presents the classification criteria of different water quality parameters.

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 terms of the $i$th parameter, the measured value is defined as $X_i$. In the light of the classification criteria, the water quality index of the $i$th physicochemical parameter can be formulated as follows.

$$WQI_i = C_{i1} + C_{i2}$$

where $C_{i1} = \{1, 2, 3, 4, 5\}$ implies the water quality class of the $i$th parameter. In terms of the water quality class $C_{i1}$, the range of measured value is from $S_{iu-1}$ to $S_{iu}$, which can be obtained from Table 2. Therefore, $C_{i2} = (X_i-S_{iu-1})/(S_{iu}-S_{iu-1})$ indicates the location of water quality within the class $C_{i1}$ (Liu et al. 2021). 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.

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

**Table 2** The classification criteria

| Parameters | Class I | Class II | Class III | Class IV | Class V |
|---|---|---|---|---|---|
| pH | 6–8 | 8–9 or 5–6 | 9–10 or 4–5 | 10–11 or 3–4 | 11–13 or 2–3 |
| DO (mg/L) | ≥7.5 | ≥6 | ≥5 | ≥3 | ≥2 |
| TN (mg/L) | ≤0.2 | ≤0.5 | ≤1.0 | ≤1.5 | ≤2.0 |
| NH$_3$-N (mg/L) | ≤0.15 | ≤0.5 | ≤1.0 | ≤1.5 | ≤2.0 |
| TP (mg/L) | ≤0.02 | ≤0.1 | ≤0.2 | ≤0.3 | ≤0.4 |
| COD (mg/L) | <15 | ≤15 | ≤20 | ≤30 | ≤40 |
| Tur (NTU) | <10 | <20 | <30 | <60 | <100 |
| Chl-a (ug/L) | ≤1 | ≤10 | ≤15 | ≤40 | ≤50 |
| SD (m) | ≥3 | ≥2 | ≥1 | ≥0.6 | ≥0.4 |

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 $WQI_i$ and is determined by entropy weight method (Ye 2010).

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

$$E_i = -\frac{1}{\ln n} \sum_{k=1}^{n} p_{ik} \ln p_{ik}$$

where $M$ and $n$ are the number of physicochemical parameters and number of samples respectively. $E_i$ is the entropy of the $WQI_i$, and $P_{ik}$ implies the probability of the $k$th sample in $WQI_i$.

$WQI_i$ can reflect the water quality of these physicochemical 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 assess the water quality of urban river easily, this paper establishes the 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 depicted the temporal variability of the measured value $X_i$ (Jalilibal et al. 2021); $V_2 = \left| \frac{1}{4} \sum_{k=1}^{n} WQI_i - 1 \right|$ is the water quality difference, which can describe the inferior and superior water quality class of the $i$th parameters in comparison with the water quality of class IV. $V_3$ is the average mutual information between the measured value $X_i$ of $i$th parameter and other parameters, and can be formulated as follows (Gao et al. 2022).

$$V_3 = \frac{1}{M - 1} \sum_{i \neq j} \left[ \sum \sum P(X_i, X_j) \log \left( \frac{P(X_i, X_j)}{P(X_i)P(X_j)} \right) \right]$$

### 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 inspired by the foraging behavior of longhorn beetles. Different from the classic particle swarm optimization (PSO) (Liang et al. 2021) and gravitational search algorithm (GSA) (Gao et al. 2021a), BAS algorithm can converge to the global optimization solution by only using one particle, which makes BAS simple and fast as well as easy to implement (Li et al. 2020). 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 $\overrightarrow{D}$. The positions of the right antenna $x_r^t$ and left antenna $x_l^t$ can be calculated as follows

$$x_r^t = x^t + d^t\overrightarrow{D}$$
$$x_l^t = x^t - d^t\overrightarrow{D}$$

where $d^t = t/R$ is the distance between two antennas, and $R$ is a constant. 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.

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

where $\delta^t$ represents the step size of each iteration; $\eta$ is the decay rate and is set to 0.95 generally.

The random unit vector $\overrightarrow{D}$ 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 $f(x^t) < f(x_{best})$, $x^t$ is assigned to $x_{best}$. The formulation for update the position is defined as follows.

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

in which the step size $\delta^t$ is modified as follows.

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

where $\delta_0$ is the initial step size. $\delta^t$ will decrease with the epoch, and it will increase depending on probability $\eta$, 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.

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

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

## 3.4 Procedure for Water Quality Assessment

This paper proposes a novel method for urban river water quality assessment. The general procedures are summarized as follows and the flowchart is shown in Fig. 2.

Step 1. Collect the water and measure the physicochemical parameters.
Step 2. Calculate the comprehensive WQI based on the classification criteria.
Step 3. Select the crucial parameters according to coefficient of variation, water quality difference and mutual information.
Step 4. Design the constraints with certain physical meaning and optimize the weights of the WQImin model by using the enhanced BAS algorithm.
Step 5. Assess the water quality and report the results.

To report the results, all the WQImin models are estimated based on the criterion of the Pearson correlation coefficient (PCC), MSE, and mean absolute percentage error (MAPE) (Guo et al. 2021; Gao et al. 2021b). These formulas are defined as follows.
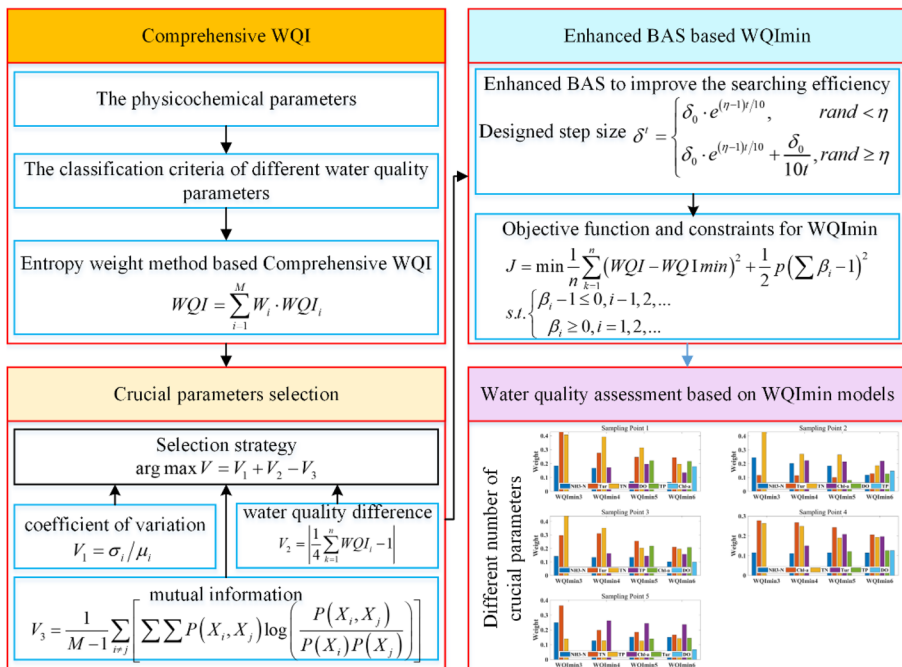


**Fig. 2** The procedure for water quality assessment

$$PCC = \frac{Cov(WQI, WQImin)}{\sqrt{var(WQI)var(WQImin)}}$$

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

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

where $n$ is the number of samples.

## 4 Results and Discussion

### 4.1 Water Quality Assessment Using Comprehensive WQI

To reveal the urban river water quality, the comprehensive WQI is applied to 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.

As Fig. 3 shows, the concentrations of TN, TP, COD and Chl-a exceed the water quality threshold of Class IV in the most cases. It is strict and inaccurate to assess the water quality as inferior Class V by only using the worst assessment of the physicochemical parameters to represent the water quality (Ban et al. 2014). Hence, this paper designs the comprehensive WQI for water quality assessment. WQI of Chl-a and WQI of DO manifest significant seasonal variation resulting from the changes of temperature and sunlight intensity
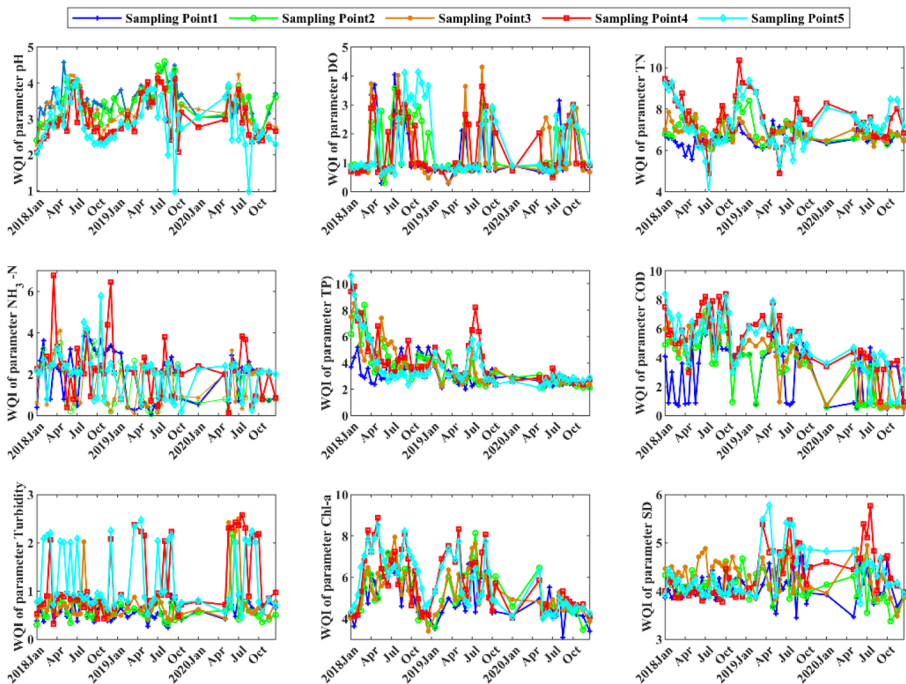


**Fig. 3** $WQI_i$ of different parameters

(Asgari et al. 2021; Bajany et al. 2021). 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.

As Fig. 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, Fig. 5 displays the comprehensive WQI of Xi'an moat. The comprehensive WQI shows significant periodic changes and seasonal difference. The water quality of Xi'an moat is getting better gradually due to the environmental governance. The average value of the comprehensive WQI is 3.54. The maximum value and the minimum value are 4.76 and 2.56 respectively. The comprehensive WQI indicates that the water quality is in the range of Class II to Class IV. 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 waste water.
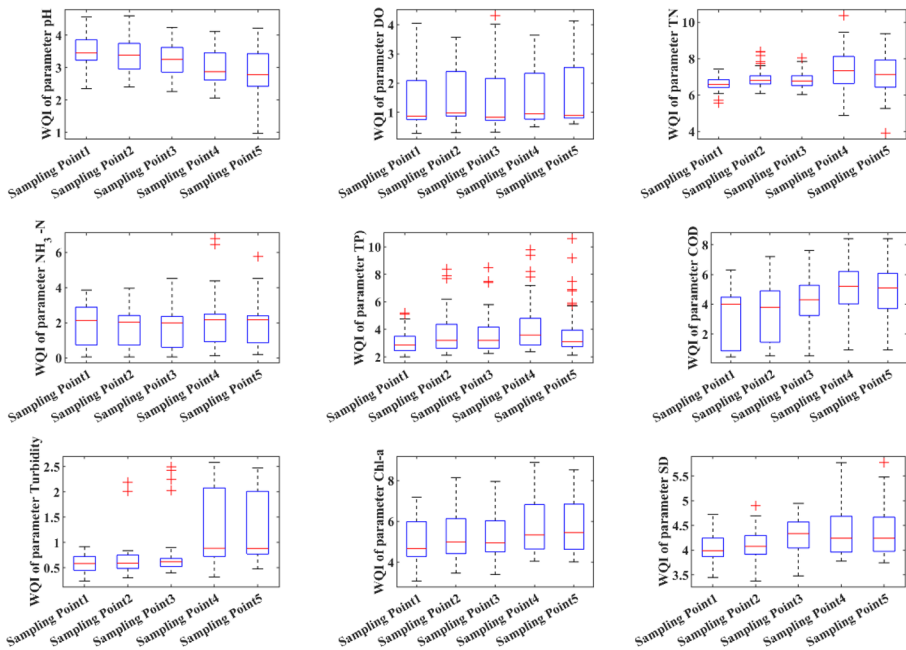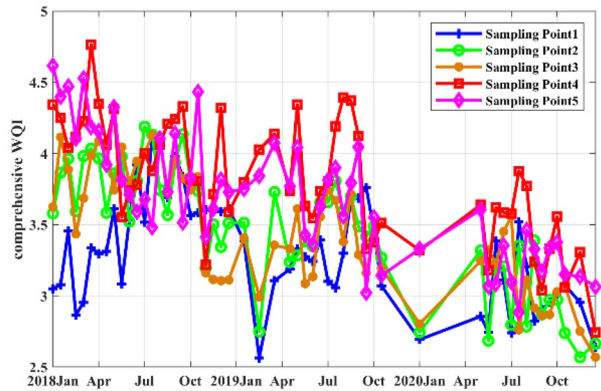


**Fig. 4** The statistical $WQI_i$

**Fig. 5** The comprehensive WQI



To further reveal the water quality, Figs. 6 and 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.

As Fig. 6 shows, the comprehensive WQI indicates that sampling point 1 possesses the best water quality. Sampling point 4 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. This phenomenon may due to the plenty of rainfall in autumn and the severe air pollution in winter and spring. Xi'an city employs coal as the major energy source for urban heating in winter and spring, which will lead to severe air pollution. Due to the less windy in winter and spring, the atmospheric deposition will pollute the urban river. Besides, 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

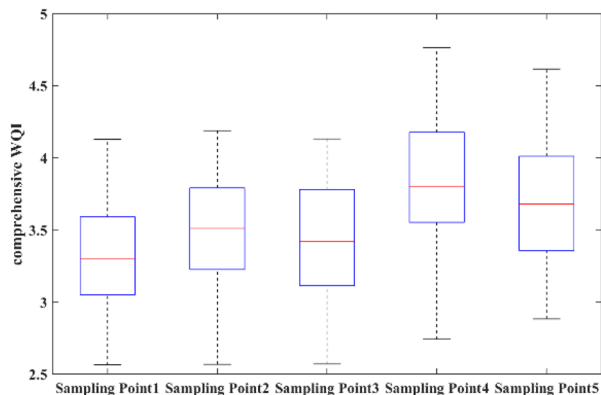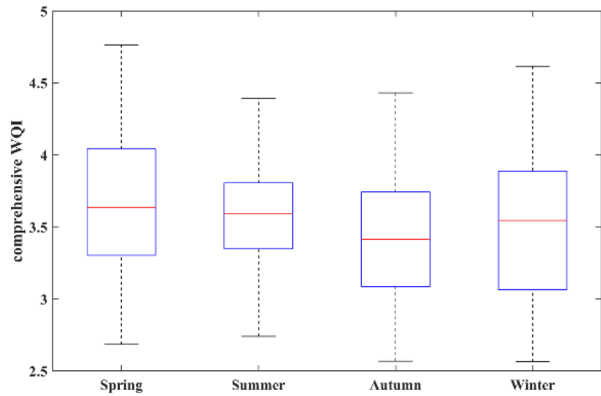**Fig. 6** The spatial distribution of the comprehensive WQI

quality parameters are figured out according to the classification criteria listed in Table 2. Then, the score $V$ of every water quality parameters is calculated according to the designed strategy. Table 3 lists the score $V$ in different sampling points.

As listed in Table 3, 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 3.

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.

As Fig. 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

**Table 3** The score $V$

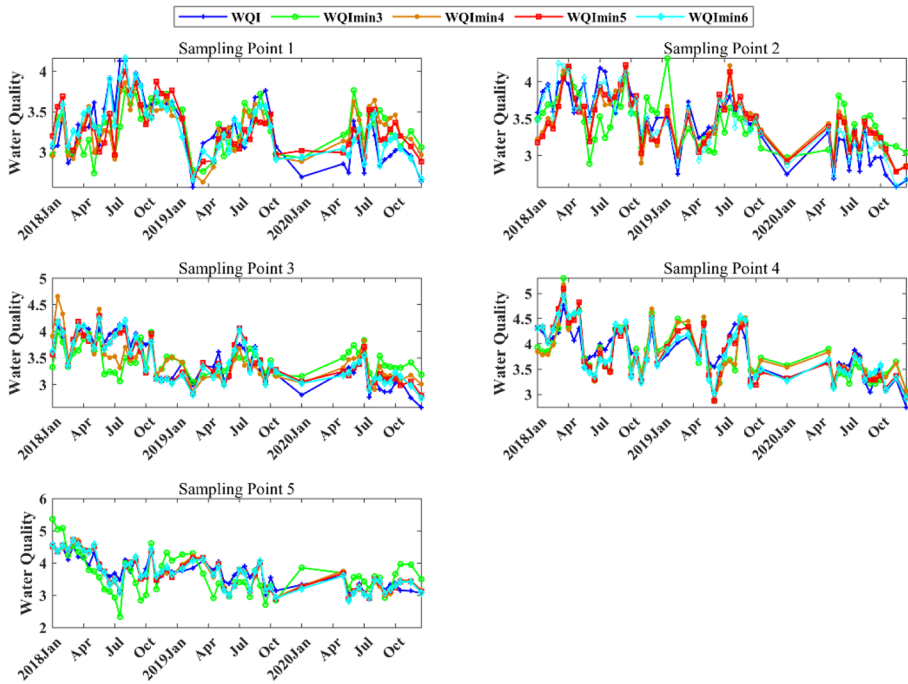|  | Score $V$ in descending order | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| sampling point 1 | $NH_3$-N | Tur | TN | DO | TP | Chl-a | COD | SD | pH | T |
| sampling point 2 | $NH_3$-N | Tur | TN | Chl-a | DO | TP | COD | pH | SD | T |
| sampling point 3 | $NH_3$-N | Tur |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

**Fig. 8** The WQImin models

assessment. In order to display the performance clearly, Table 4 lists the MSE, MAPE and the PCC between the WQImin model and the comprehensive WQI.

As Table 4 listed, the WQImin model with more crucial parameters will exhibit better performance. The PCC values between the WQImin with 6 crucial water quality

**Table 4** 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 |

**Table 5** 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 |

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 5 and Fig. 9 lists the optimized weights of these WQImin models.

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, PSO and GSA. Figure 10 shows the convergence rates of these algorithms for building WQImin models on sampling point 1.

As Fig. 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 evolved direction and the modified step size can improve the performance of BAS.

As shown in Figs. 8, 9 and 10, Tables 4 and 5, 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
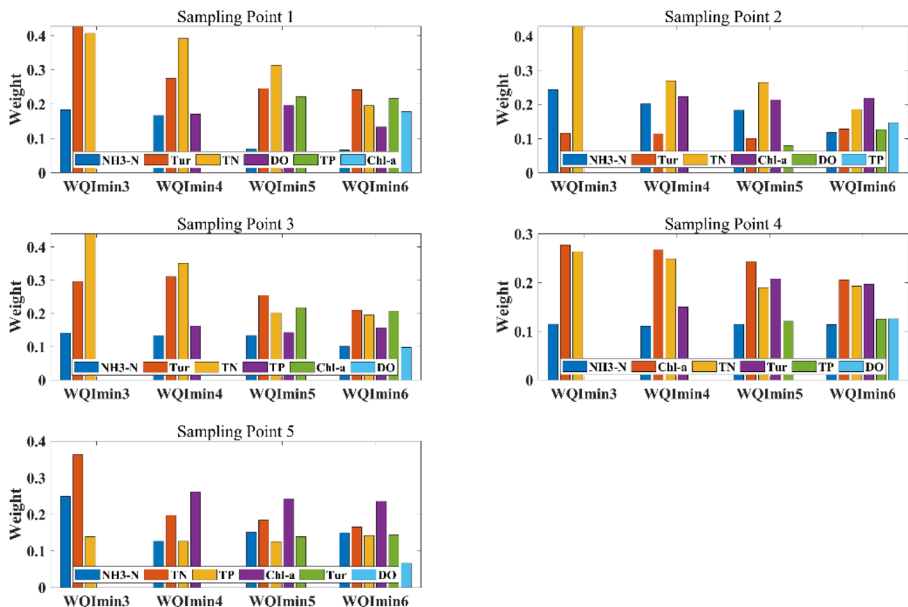


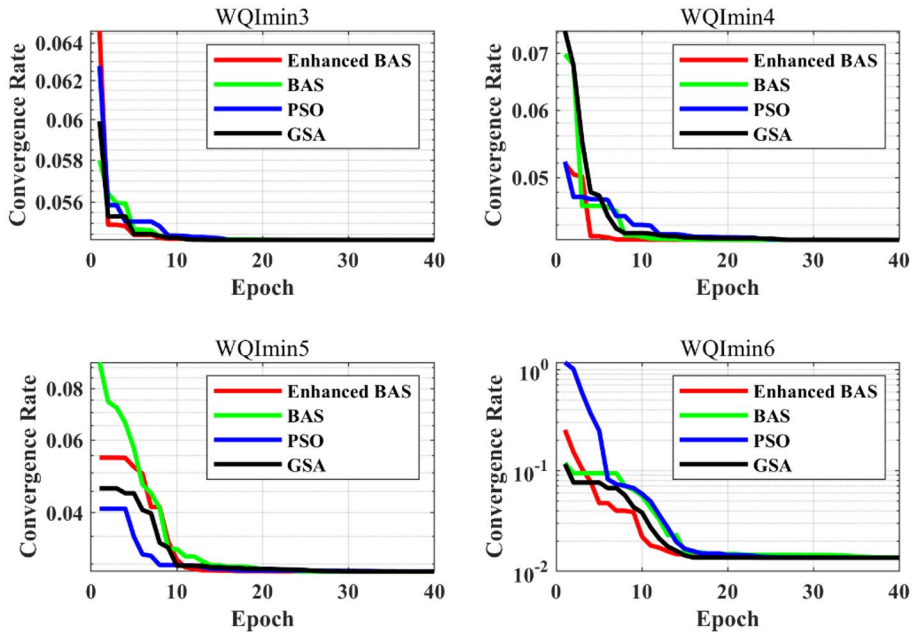**Fig. 9** The optimized weights

**Fig. 10** The convergence rates

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.

**Data Availability** Data are available on request.

## Declarations

**Ethical Responsibilities** The manuscript complies with all the ethical requirements; the paper was not summited to any journal at a time. All the sources and contributors were acknowledged properly.

**Consent to Participate** All authors are informed and consent to participate.

**Consent for Publication** All authors consent to the publication.

**Conflict of Interest/Competing Interests** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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