



# Towards Sustainable Cities: Studying Evaluation Index of Water Environment Carrying Capacity

Jiayi Chen<sup>1</sup> · Xiaonan Tang<sup>1</sup>

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## Abstract

Water is a crucial resource for sustainable development in cities. Water carrying capacity is a vital part of the carrying capacity of various natural resources in the sustainable development of a region. Appropriately assessing water environment carrying capacity (WECC) is crucial for wise water resources management and economic and social progress advancement. This study developed a WECC evaluation index system for Suzhou, a representative city in southeastern China facing water quality challenges, with the city being an example to study the WECC in the Yangtze River Delta region. By employing principal component analysis (PCA), 20 WECC-related variables were selected from the water and environment, human society, and socio-economic system as the local WECC evaluation indicators. These indicators were weighted by PCA analysis and the entropy method, resulting in overall scores. Evaluating the data from 2001 to 2021, this study showed that the overall WECC score has increased over time. Factors such as rapid urbanization, population growth, economic and social development, and a shortage of water supply have strained the WECC in Suzhou. As an important industrial development zone in the Yangtze River Delta, the city faces significant environmental pollution and water resources problems. The results show that the primary influencing factors are total water resources, surface water resources, water consumption, urbanization rate, water consumption per 10,000 yuan of GDP, industrial value-added water consumption, and chemical oxygen demand (COD) emissions of GDP. The findings of this study help to plan the city's future development and thereby contribute to urban sustainability.

**Keywords** Water environment carrying capacity · PCA method · Entropy weighting method · Urban sustainability · Water resources

## 1 Introduction

The ecological priority evaluation of Water Environment Carrying Capacity (WECC) is a central topic in the scientific study of water resources and aquatic environments (Jia et al. 2018). Currently, economists, environmental scientists and government policymakers are

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✉ Xiaonan Tang  
Xiao.Tang@xjtlu.edu.cn

<sup>1</sup> Department of Civil Engineering, Xi'an Jiaotong-Liverpool University, Suzhou 215123, China

focusing on studying this concept. A scientific assessment can be used to quantify the level of local economic and social development that matches the water resource system (Wang et al. 2018). El-Fadel et al. (2001) first proposed the idea that global water resources were unevenly distributed, they added that strategic plans and management objectives must be devised to boost the water carrying capacity and prevent potential future water shortages. Sawunyama et al. (2006) demonstrated the importance of tiny reservoirs in water resource planning and management, they also used GIS technology to assess the carrying capacity of 12 small reservoirs in the Mzingwane sub-basin in southeast Africa. Naimi-Ait-Aoudia and Berezowska-Azzag (2014) used the idea of water footprint and the Normative Activation Model (NAM) to determine the current water carrying capacity of the Algerian region and forecast its future trends. Meanwhile, many researchers began to explore the inter-connected aspects of water resource systems rather than just studying them purposefully. The research has been gradually improved and divided into smaller modules with more precise and scientific content. Concerning water supply, demand, and sustainable development, Magri and Berezowska-Azzag (2019) investigated WECC in the Oran region using an ecosystem-based computational model. Researchers have made great achievements from the connotation to the quantitative model according to the reality of the study area (Wang et al. 2022a, b, c). However, the overall research still shows a lack of systematization and specialization, which indicates that this topic also has some shortcomings that need further investigation. The comprehensive results suggest that, currently, China's research on WECC is mostly concentrated in the northern regions where water resources are severely depleted, while neglecting the southern regions where water resources are abundant but water quality is severely lacking (Yang et al. 2015). Studying the variations in Suzhou's water supply, demand, and carrying capacity, on the one hand, can help develop scientific and practical countermeasures to improve the effective use of water resources and the smooth operation of the water environment there and, on the other hand, provide recommendations for other regions of the Yangtze River Delta or ecological economic corridors to enhance the carrying capacity of regional environmental resources.

To this end, this study investigates the urban water resource system in view of Suzhou's water quality and scarcity issues, along with a hot spot for urban water resource quantification research. The objectives include three aspects: (1) Establish an appropriate water-environmental carrying capacity index system; (2) Construct a quantitative model, and evaluate current water-environmental carrying capacity; (3) Identify the main influencing factors and then make some suggestions and measures for improving WECC. Section 2 is about the overall process of establishing the evaluation index system using the PCA method, and then assigning values to indicators, followed by Section 3, analyzing the research results and exploring methods to improve WECC. Discussions and conclusions are given in Sections 4 and 5, respectively.

## 2 Materials and Methods

### 2.1 Study Area and Data Sources

Suzhou is located in the central region of the Yangtze River Delta, China (Fig. 1). The city's total area is 8657.32 km<sup>2</sup>, of which 3609.40 km<sup>2</sup> is covered by water (42.5%) (Zhou et al. 2010). Suzhou's major urban area is low-lying, contains numerous rivers and lakes, and covers most of the surface of Taihu Lake. The three different types of



**Fig. 1** Map of Suzhou (cited from '<https://cn.bing.com/maps>')

water bodies—rivers, lakes, and mudflats—cover a combined area of 3142.9 km<sup>2</sup>, or 36.6% of the total land area (Li et al. 2021). Due to economic development, population growth and accelerated urbanization, industrial and domestic sewage discharges are increasing, and the city's water bodies are polluted to varying degrees, with a trend of declining water quality. In addition, the region has more sewage and less available water resources, which is why Suzhou has been classified by China as one of the water-stressed areas. The data obtained from the "Suzhou Water Resources Bulletin", "Suzhou Economic and Social Development Overview", "China Water Resources Bulletin", "Suzhou Statistical Yearbook", and "China Urban Statistical Yearbook" for the period 2001 to 2021. The policy documents are obtained from "Suzhou Water Affairs Bureau" (<http://water.suzhou.gov.cn/>), "Suzhou Bureau of Statistics" (<http://tjj.suzhou.gov.cn/>), "Suzhou People's Government" (<https://www.suzhou.gov.cn>), etc.

## 2.2 Research Framework

China's water resources are the main barrier to the socio-economic development of a region. Much research has been done on the WECC, but less on the Yangtze River Delta region. Therefore, a proper assessment of a region's WECC can ensure a healthy ecological environment while achieving sustainable economic and social growth. The specific evaluation framework for this study is therefore proposed in Fig. 2.

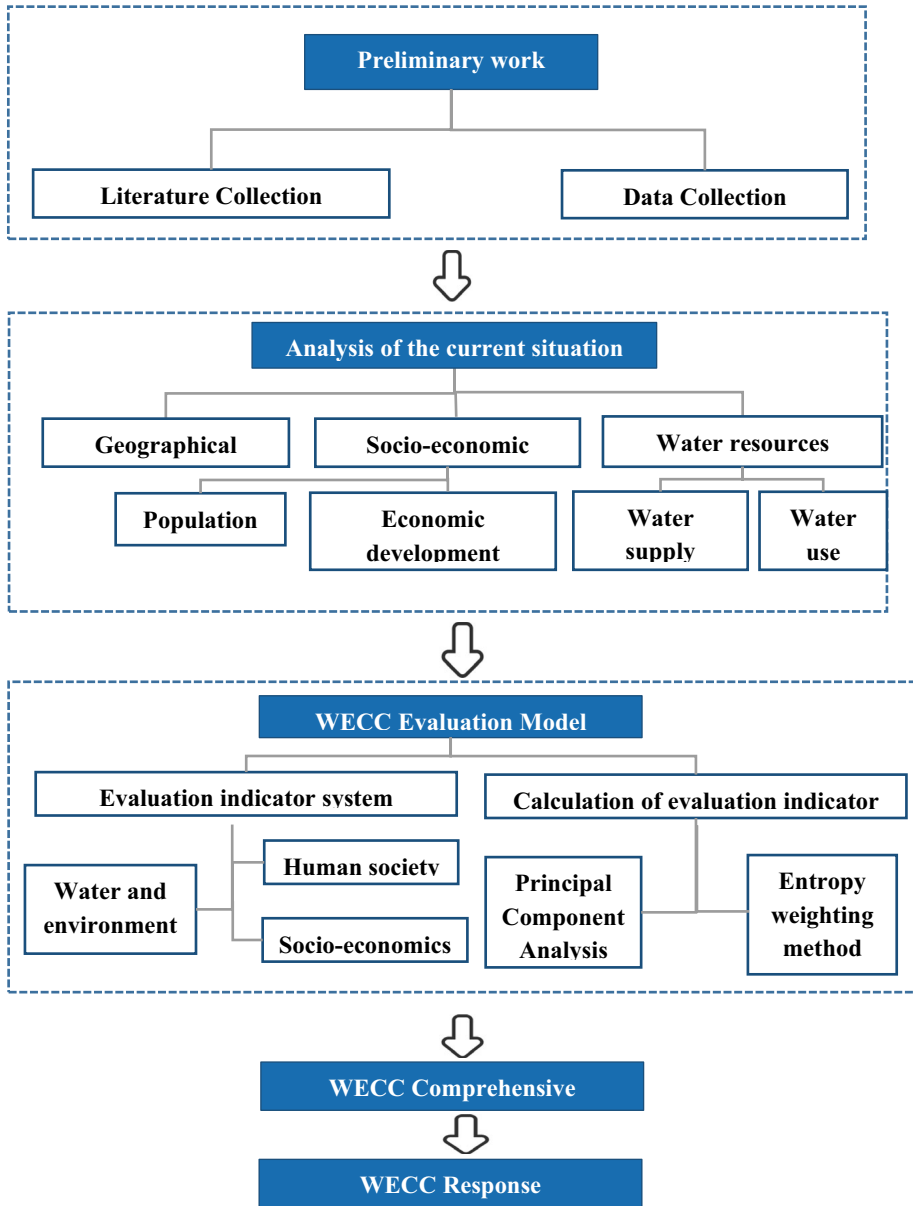


Fig. 2 Research Roadmap

## 2.3 Constructing an Evaluation Indicator System

### 2.3.1 Principles of Indicator Selection

The key to building the WECC evaluation index system is the selection of scientific and acceptable indicators; therefore, the local economic, social, and biological environment is

directly related to the water carrying capacity in the region. Based on the extensive literature review, this study considers the following principles of screening indicators. (1) Integrity principle: The evaluation index system must consider how the environment affects human society and socioeconomic systems, and how well these systems are evolving collectively (Zhang et al. 2019). (2) Regionalism principle: The indicators used for this study reflect the general characteristics and align with the actual circumstances (Chen et al. 2020). (3) Reasonableness principle: The indicators can be adapted to the current situation of water resource development and be supported in their classification (Chai and Zhou 2022). (4) Quantification principle: The selected indicators must be manageable, easy to calculate and evaluate, and have a certain degree of operability (Peng and Deng 2020). (5) Dynamism principle: The selected indicators are dynamic and can adapt to changes in water resources and the socio-economic situation (Wang et al. 2021a, b).

### 2.3.2 Process of Selecting Indicators

Based on the principle of indicator selection, this study considers relevant standards, literature and books, and selects evaluation indicators from the following three perspectives to construct an index evaluation system. (1) Water and environmental perspective: The amount of water used reflects how many water resources have been developed and used, and the level of water conservation and protection (Wang et al. 2021a, b). The rate at which water resources are used reflects the extent to which those resources are used in the region and the degree to which people are aware of the need to protect those resources. Irrigation water consumption is one of the main causes of Suzhou's high agricultural and general water demand; its effective utilization coefficient indicates the status and efficiency of water use in agriculture, and thus the carrying capacity of the environment (see Table 1). (2) Human society perspective: Indicators such as GDP per capita and domestic water consumption show the impact of human activities on water management and WECC development (Li et al. 2022). The urbanization rate indicator reflects both the demographic structure of the region and the degree of urbanization. GDP per capita most directly reflects the level of economic development. Also, the combined domestic water consumption indicator per capita is one of the indicators of regional water use and shows the harmony between population and water use. (3) Social and economic perspective: Economic development leads to changes in regional industry, population and other aspects, and also has a certain impact on the local environment. Water, as one of the basic resources, is also affected (Magri and Berezowska-Azzag 2019). The water consumption of industrial value added reflects the availability of water in regional industrial production; GDP is the simplest indicator for assessing the state of the local economy; water consumption of GDP reflects the effectiveness and financial benefits of regional water use. Moreover, chemical oxygen demand is currently the main pollutant (Song et al. 2010).

### 2.3.3 System for Evaluation Index Construction

In this study, according to the guidelines for selecting WECC indicators and the characteristics of ecological and environmental conditions, economic and social growth and water resources of Suzhou, the evaluation indicators are selected as comprehensively as possible. After the main indicators are filtered out by principal component analysis, the WECC evaluation indicator system is finally constructed. The evaluation index system is divided into two levels (from large to small): system level and indicator level (Table 1). System level

Table 1 WECC Evaluation Index System

System	Indicator Levels (I)	Indicator Level	Unit	No.
Water and environment (S1)	Precipitation	+	10 <sup>8</sup> m <sup>3</sup>	X <sub>1</sub>
	Total water resources	+	10 <sup>8</sup> m <sup>3</sup>	X <sub>2</sub>
	Surface water resources	+	10 <sup>8</sup> m <sup>3</sup>	X <sub>3</sub>
	Water consumption	-	10 <sup>8</sup> m <sup>3</sup>	X <sub>4</sub>
	Effective utilization factor of irrigation water on farmland	-	\	X <sub>5</sub>
	Water used for irrigation on farmland	-	m <sup>3</sup> /Mu	X <sub>6</sub>
	Industrial water reuse rate	+	%	X <sub>7</sub>
	Resident population	-	10,000	X <sub>8</sub>
	Population density	-	person/km <sup>2</sup>	X <sub>9</sub>
	Urbanization rate	-	%	X <sub>10</sub>
Human society (S2)	GDP per capita	+	Yuan	X <sub>11</sub>
	Per capita domestic water consumption	-	L/person.D	X <sub>12</sub>
	Combined domestic water consumption per capita	-	L/person.D	X <sub>13</sub>
	GDP	+	100 million	X <sub>14</sub>
Social economy (S3)	Agricultural water consumption	-	10 <sup>8</sup> m <sup>3</sup>	X <sub>15</sub>
	Water consumption	-	10 <sup>8</sup> m <sup>3</sup>	X <sub>16</sub>
	Water consumption per 10,000 Yuan of GDP	-	m <sup>3</sup>	X <sub>17</sub>
	Water consumption per 10,000 Yuan industrial value added	-	m <sup>3</sup>	X <sub>18</sub>
	Chemical oxygen demand emissions per 10,000 Yuan of GDP	-	kg/million	X <sub>19</sub>
	Tertiary industry to GDP ratio	+	%	X <sub>20</sub>

1 Mu = 1000/3 km<sup>2</sup>

(S): The system level refers to the multiple systems directly under the WECC. In this study, three system levels are built using the above divisions of the indicator system. Indicator level (I): The system level is specifically reflected in the indicator level. Through the above discussion on the selection of regional indicators and characteristics, 20 evaluation indicators are selected. The indicators include positive support indicators and negative pressure indicators. If the indicators are positive, the carrying capacity of the water environment can be improved; if the indicators are negative, the WECC cannot be improved.

### 2.3.4 Establishment of Core Indicators System

To reduce the dimensionality of the multidimensional variables, the data are orthogonally rotated using the maximum variance method. A few significant uncorrelated components are used to reflect the primary information of all indicators, while low correlation indicators are eliminated (Salem and Hussein 2019). Based on the index system selected above, SPSS software is used to perform PCA and Table 2 shows the rotated component matrix. The table of correlation coefficients shows that the 20 selected indicators are significantly correlated with each other and can be used for principal component analysis.

**Table 2** Rotation factor loading matrix

	Rotated component matrix <sup>a</sup>		
	Components		
	1	2	3
X <sub>11</sub>	0.970	0.202	0.024
X <sub>14</sub>	0.968	0.221	0.083
X <sub>10</sub>	0.947	0.244	-0.067
X <sub>19</sub>	-0.945	-0.272	-0.143
X <sub>7</sub>	0.927	0.316	0.130
X <sub>13</sub>	0.924	0.304	-0.021
X <sub>8</sub>	0.924	0.248	-0.169
X <sub>17</sub>	-0.902	-0.278	0.257
X <sub>9</sub>	0.896	0.239	-0.298
X <sub>5</sub>	0.891	0.335	-0.258
X <sub>15</sub>	-0.889	-0.295	0.019
X <sub>20</sub>	0.882	0.362	0.200
X <sub>12</sub>	-0.834	-0.253	0.334
X <sub>6</sub>	-0.829	-0.387	0.271
X <sub>16</sub>	-0.803	-0.327	0.335
X <sub>3</sub>	0.267	0.941	0.147
X <sub>2</sub>	0.326	0.934	0.101
X <sub>1</sub>	0.355	0.903	-0.022
X <sub>4</sub>	-0.169	-0.244	-0.931
X <sub>18</sub>	-0.576	-0.010	0.805

Extraction method: Principal component analysis

Rotation method: Kaiser normalized maximum variance method<sup>a</sup>

<sup>a</sup>The rotation has converged after five iterations

The association between each common factor and the indicator is shown by the rotational factor loading matrix: the higher the absolute value of the coefficient, the higher the correlation between the indicator and the common factor score (Yang et al. 2015; Chen et al. 2020). Generally, coefficients with absolute values above 0.5 are considered highly correlated, and indicators with low correlation are excluded. Table 2 shows that  $X_{11}$ ,  $X_{14}$ ,  $X_{10}$ ,  $X_{19}$ ,  $X_7$ ,  $X_{13}$ ,  $X_8$ ,  $X_{17}$ ,  $X_9$ ,  $X_5$ ,  $X_{15}$ ,  $X_{20}$ ,  $X_{12}$ ,  $X_6$  and  $X_{16}$  are highly correlated with the first principal component,  $X_3$ ,  $X_2$  and  $X_1$  are highly correlated with the second principal component, and  $X_4$  and  $X_{18}$  are highly correlated with the third principal component. Therefore, all selected indicators are core indicators that do not need to be eliminated, thus proving the reasonableness and scientific nature of the indicator selection process in this study (Xu et al. 2020).

## 2.4 Methods for Weighing Evaluation Indicators

### 2.4.1 Principal Component Analysis

Principal component analysis (PCA), a popular multivariate statistical analysis method that seeks to decrease many variables, can condense original variables to a small number of variables that are uncorrelated with each other and retain the majority of the original data’s information, with no or little loss to the original data, and it can also extract the appropriate number of principal components as required to effectively represent the general information of the original data (Chen et al. 2020). The variance is maximized in such a way that the first component has the greatest variance, i.e. contains the greatest amount of information of all components, and then decreases in descending order (Chen et al. 2022).

#### 1. Standardize raw data

Most indicators in the raw data have different units and large differences in magnitude. In order to eliminate this effect, Eq. (1) is used to standardize the raw data

$$X_{ij} = \frac{x_{ij} - \bar{x}_j}{S_j} \quad (i = 1, 2, 3, \dots, n; j = 1, 2, 3, \dots, p) \tag{1}$$

where  $x_{ij}$  is the initial value of the  $i^{\text{th}}$  sample’s  $j^{\text{th}}$  indicator; the  $j^{\text{th}}$  indicator’s sample mean and sample standard deviation are denoted, respectively, by the letters  $\bar{x}_j$  and  $s_j$ .

#### 2. Compute the matrix of correlation coefficients

$$R = \begin{bmatrix} r_{11} & \cdots & r_{1p} \\ \vdots & \ddots & \vdots \\ r_{p1} & \cdots & r_{pp} \end{bmatrix} \tag{2}$$

$$r_{ij} = \frac{\sum_{k=1}^n (X_{ki} - \bar{X}_i)(X_{kj} - \bar{X}_j)}{\sqrt{\sum_{k=1}^n (X_{ki} - \bar{X}_i)^2 (X_{kj} - \bar{X}_j)^2}} \tag{3}$$

where  $r_{ij}$  ( $i, j = 1, 2, 3, \dots, p$ ) is the correlation coefficient between the initial variable  $x_i$  and  $x_j$ .

#### 3. Determine the associated eigenvectors and eigenvalues for the coefficient matrix R.



- Determine the cumulative rate and primary component contributions.

Cumulative rate:

$$P_i = \frac{\lambda_i}{\sum_{k=1}^p \lambda_k} \quad (i = 1, 2, 3, \dots, p) \quad (4)$$

Primary component contributions:

$$P = \frac{\sum_{k=1}^i \lambda_k}{\sum_{k=1}^p \lambda_k} \quad (i = 1, 2, 3, \dots, p) \quad (5)$$

- Calculate principal component score coefficients

$$l_{ij} = \sqrt{\lambda_j} a_{ij} \quad (i = 1, 2, 3, \dots, p; j = 1, 2, 3, \dots, m) \quad (6)$$

$$a_{ij} = \frac{l_{ij}}{\sqrt{\lambda_j}} \quad (i = 1, 2, 3, \dots, p; j = 1, 2, 3, \dots, m) \quad (7)$$

- Calculate principal component scores

$$F_i = a_{1i}x_1^* + a_{2i}x_2^* + a_{3i}x_3^* + \dots + a_{pi}x_p^* \quad (i = 1, 2, 3, \dots, m) \quad (8)$$

$$F = \sum_{i=1}^m p_i Z_i \quad (9)$$

## 2.4.2 Entropy Method

This method reflects the amount of information contained in each indicator and determines respective weighting in a more objective way by basing weighting on the dispersion of each indicator. The entropy weighting method is based on a decision matrix composed of raw data, which can objectively reflect the information in the index data and eliminate subjective factors in assigning weights (Yang et al. 2022).

- Construct a discriminant matrix

$$X = (x_{ij})_{m \times n} \quad (i = 1, 2, 3, \dots, n; j = 1, 2, 3, \dots, m) \quad (10)$$

- Standardize data

Equation (11) is the normalized formula for positive indicators, where a greater indicator value corresponds to a higher water carrying capacity.

$$y_{ij} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)} \quad (11)$$

Equation (12) is the normalized formula for negative indicators, where a smaller indicator value corresponds to a higher water carrying capacity:

$$y_{ij} = \frac{\max(x_j) - x_{ij}}{\max(x_j) - \min(x_j)} \quad (12)$$

3. Determine the indicator's entropy value

$$p_{ij} = \frac{y_{ij}}{\sum_{i=1}^m y_{ij}} \quad (13)$$

$$e_j = -\frac{1}{\ln m} \sum_{i=1}^m (p_{ij} \times \ln p_{ij}) \quad (14)$$

where  $m$  is the number of evaluation items;  $e_j$  is the indicator's entropy value;  $y_{ij}$  is the standardized indicator value, and  $p_{ij}$  is the percentage of indicator value.

4. Determine the indicator weights

$$w_j = \frac{1 - e_j}{\sum_{j=1}^n (1 - e_j)} \quad (15)$$

where  $w_j$  is the indicator weight;  $e_j$  is the indicator's entropy value.

5. Determine the coefficients of the principal components

$$\beta_i = w_j \times \alpha \quad (\alpha = 1, 2, 3, \dots, n) \quad (16)$$

6. Determine the principal component's value

$$F_i = \beta_{1i} \times X_1 + \beta_{2i} \times X_2 + \dots + \beta_{ni} \times X_n \quad (i = 1, 2, 3, \dots, p) \quad (17)$$

where  $F_i$  is the sample's score of a principal component on the  $p^{\text{th}}$ , and  $\beta_i$  is the corresponding indicator coefficient of the principal component.

## 2.5 Analysis Process

### 2.5.1 Principal Component Analysis Process

In this study, the raw data is standardized (z-score method) using SPSS 26.0 software to obtain the new data.

#### 1. Factor analysis applicability test

The KOM and Bartlett tests are used to determine whether factor analysis is applicable. There is a correlation between the indicators. The KOM value is 0.749 in this study, which is above the 0.5 threshold. The rejection correlation coefficient is a unit array and has a significant value of 0.000 (less than 0.05), meaning that the indicators are correlated (Sun et al. 2020). The results of both tests demonstrate the factor analysis can be used to analyze these data. The interpretation of the total variance is shown in Table 3. Principal components can typically be selected when the initial eigenvalues are greater than 1 and the cumulative contribution rate is  $\geq 85\%$  (Sun et al. 2020). The first three eigenvalues are more significant than 1, and the cumulative contribution is 94.92%. This means that the three extracted principal components can reflect and explain 94.92% of

**Table 3** Total variance explained

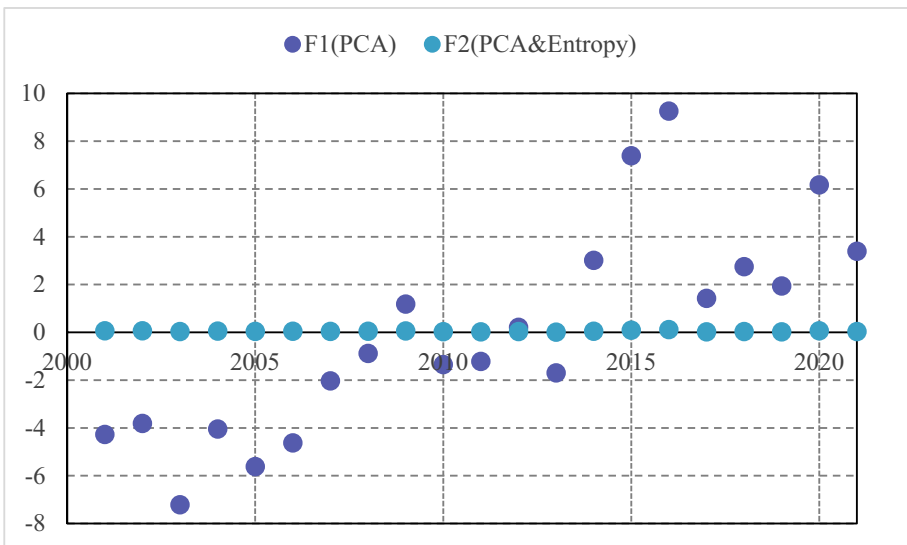
Initial Eigenvalue			
Components	Total	% of Variance	Cumulative % of Variance
PC1	15.094	75.469	75.469
PC2	2.536	12.678	88.147
PC3	1.354	6.769	94.916

the information of all indicators, thus three principal components are determined. Based on the output of the SPSS software, the three extracted principal component loads can be obtained for expressions of F1–F3.

2. **Calculate the principal component eigenvector matrix**

Eigenvectors are calculated from the principal component loading coefficients and eigenvalues. The values of each principal component for the years 2001–2021 are obtained by performing the calculation of principal components 1, 2 and 3 according to Eq. (8), and then by calculating the combined score F according to Eq. (9), the results are shown in Fig. 3. The expressions for the three principal components are

$$\begin{aligned}
 F_1 = & 0.175 X_1 + 0.168 X_2 + 0.153 X_3 \\
 & - 0.039 X_4 + 0.250 X_5 - 0.241 X_6 \\
 & + 0.247 X_7 + 0.247 X_8 + 0.243 X_9 \\
 & + 0.249 X_{10} + 0.248 X_{11} - 0.231 X_{12} \\
 & + 0.249 X_{13} + 0.248 X_{14} - 0.239 X_{15} \\
 & - 0.231 X_{16} - 0.247 X_{17} - 0.158 X_{18} \\
 & - 0.246 X_{19} + 0.239 X_{20}
 \end{aligned}$$



**Fig. 3** Total principal component scores

$$\begin{aligned}
 F_2 = & 0.303 X_1 + 0.377 X_2 + 0.409 X_3 \\
 & - 0.521 X_4 - 0.092 X_5 + 0.0672 X_6 \\
 & + 0.081 X_7 - 0.088 X_8 - 0.149 X_9 \\
 & - 0.043 X_{10} - 0.019 X_{11} + 0.154 X_{12} \\
 & + 0.005 X_{13} + 0.017 X_{14} - 0.006 X_{15} \\
 & + 0.122 X_{16} + 0.115 X_{17} + 0.445 X_{18} \\
 & - 0.068 X_{19} + 0.138 X_{20}
 \end{aligned}$$

$$\begin{aligned}
 F_3 = & 0.428 X_1 + 0.387 X_2 + 0.384 X_3 \\
 & + 0.424 X_4 + 0.061 X_5 - 0.118 X_6 \\
 & - 0.175 X_7 - 0.049 X_8 + 0.026 X_9 \\
 & - 0.114 X_{10} - 0.196 X_{11} - 0.073 X_{12} \\
 & - 0.098 X_{13} - 0.217 X_{14} + 0.094 X_{15} \\
 & - 0.126 X_{16} - 0.024 X_{17} - 0.272 X_{18} \\
 & + 0.213 X_{19} - 0.174 X_{20}
 \end{aligned}$$

## 2.5.2 PCA Combined with the Entropy Method

### 1. Calculate $e_j$ and $w_j$

The raw data for each indicator in Suzhou from 2001 to 2021 are standardized using Eqs. (11) and (12), which can be used for the following calculations. For each indicator, the weight value  $w_j$  and the entropy value  $e_j$  are obtained from Eqs. (14) and (15) respectively.

### 2. Calculate $\beta_i$

After weighting the indicators, the coefficients of each principal component are calculated by multiplying the indicator weights by the eigenvectors of the principal component correlation matrix (see Table 4).

### 3. Determine combined weight values

The values of each principal component for the years 2001–2021 are obtained by performing the calculation of principal components 1, 2 and 3 according to Eq. (17) (see Fig. 3). Note that  $F_1$  is the overall score of principal components 1, 2 and 3 calculated by the PCA method.  $F_2$  is the overall score of principal components 1, 2 and 3 calculated by the PCA combined with entropy method.

## 3 Analysis Results

### 3.1 Comprehensive System Assessment

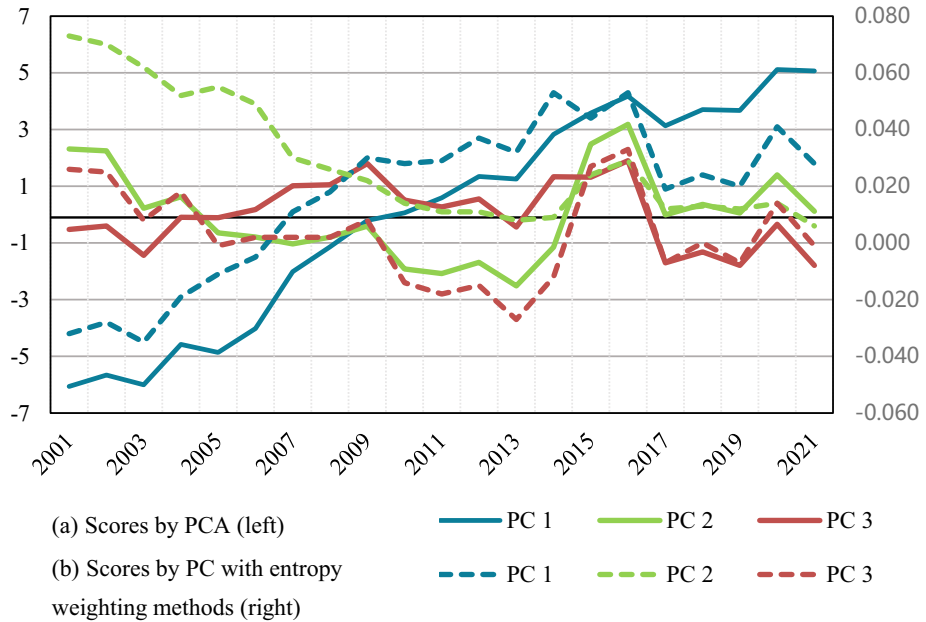
The indicators are divided into three dimensions by PCA, the year-to-year variation of the scores can be obtained by PCA combined with entropy. Figure 4 shows that the trends of each principal component are generally consistent between the two methods. The indicators with the absolute value of the principal component eigenvectors greater than 0.1 are selected and analyzed separately for each principal component, as given in Table 5.

**Table 4** Index weight system calculated by the entropy method

	$e_j$	$w_j$	PC1	PC2	PC3
$X_1$	0.918	0.064	0.011	0.019	0.027
$X_2$	0.951	0.038	0.006	0.015	0.015
$X_3$	0.955	0.035	0.005	0.014	0.013
$X_4$	0.938	0.048	-0.002	-0.025	0.020
$X_5$	0.858	0.111	0.028	-0.010	0.007
$X_6$	0.958	0.032	-0.008	0.002	-0.004
$X_7$	0.882	0.092	0.023	0.007	-0.016
$X_8$	0.957	0.034	0.008	-0.003	-0.002
$X_9$	0.944	0.043	0.011	-0.006	0.001
$X_{10}$	0.947	0.041	0.010	-0.002	-0.005
$X_{11}$	0.941	0.046	0.011	-0.001	-0.009
$X_{12}$	0.913	0.067	-0.016	0.010	-0.005
$X_{13}$	0.929	0.055	0.014	0.000	-0.005
$X_{14}$	0.918	0.064	0.016	0.001	-0.014
$X_{15}$	0.944	0.043	-0.010	0.000	0.004
$X_{16}$	0.960	0.031	-0.007	0.004	-0.004
$X_{17}$	0.974	0.020	-0.005	0.002	0.000
$X_{18}$	0.976	0.019	-0.003	0.008	-0.005
$X_{19}$	0.911	0.069	-0.017	-0.005	0.015
$X_{20}$	0.940	0.046	0.011	0.006	-0.008

### 3.2 Comparative Analysis of Principal Component

The indicators positively correlated with PC1 represent the processes of human productive life, which are part of human societies and socio-economic systems. In general, rapid urbanization and population growth have increased the demand for water resources, which is an essential pressure factor causing them to decline. The indicators negatively correlated with PC1 represent water use, consumption and wastewater discharge during economic development. With the continuous optimization of the industrial structure and the importance attached to the collection and treatment of wastewater, economic development generally is becoming less dependent on water. The economic benefits of production continue to increase, and production patterns tend towards water conservation and emissions reduction. The decline in these variables contributed to the increase in WECC, thus improving its score (Zhou 2022). As a result, the score of PC1 is negatively correlated with WECC. Among the indicators with a high correlation, the negative indicators of water consumption and COD emissions continuously decreased from 2001 to 2021, so these two negative indicators have a greater impact. The pressure on the water environment is increasing yearly due to urbanization, which also continues to increase population density. As a result, accelerating average GDP growth has led to a subsequent decline. Although the reduction in indicators such as water consumption, COD emissions, and water consumption alleviates this pressure, they still do not alleviate the pressure, and WECC continues to decline. It turns out that reducing indicators to alleviate this pressure is not sufficient to change the trend toward a lower carrying capacity. Therefore, the government needs to step up efforts in industrial restructuring, industrial wastewater treatment and reuse, sewage discharge



**Fig. 4** Principal components scores

treatment and measures to reduce water consumption, which are essential in the context of rapid economic growth and urbanization (Wang et al. 2022a, b, c).

The indicators negatively correlated with PC2 belong to the water and environment system. The analysis shows that total water resources are the most important factor affecting water and environmental systems, so problems such as deteriorating water quality and reduced self-purification capacity due to water scarcity cannot be ignored (Zhao et al. 2021). The lowest total water resources and the lowest scores for PC2 were found in 2013, while higher total water resources and the highest score were recorded in 2016. As a result, PC2 indicates a change in the number of water resources, with more water increasing the carrying capacity, so this score positively correlates with WECC, emphasising the effect of total water resources. Therefore, it is vital to improve the water reserves of cities and implement strategies such as inter-basin water transfer in space to improve WECC (Peng et al. 2021). The analysis shows a positive linear correlation: water and environmental systems are the key influencing factors on PC2. The interdependence of water and environmental systems makes the improvement dependent on both the ecological and water environments (Wu et al. 2018). On the other hand, it is also closely related to the total amount and standard of available water resources.

The effects of water use and drainage are displayed in PC3. As urbanization continues, the majority of the population is concentrated in cities, making it more challenging to achieve a spatially balanced distribution of water resources (Fang et al. 2019). Rising population concentration and continued increases in domestic water use are also putting pressure on WECC. The indicator that can alleviate this pressure is water consumption; therefore, reducing water consumption is the main direction to solve the contradictions

**Table 5** Eigenvectors of the WECC index layer in Suzhou

Evaluation Indicator Directions		+			-		
		1	2	3	1	2	3
Precipitation	X <sub>1</sub>	0.175	0.303	0.428			
Total water resources	X <sub>2</sub>	0.168	0.377	0.387			
Surface water resources	X <sub>3</sub>	0.153	0.409	0.384			
Water consumption	X <sub>4</sub>			0.424		-0.521	
Effective utilization factor of irrigation water on farmland	X <sub>5</sub>	0.250					
Water used for irrigation on farmland	X <sub>6</sub>				-0.241		-0.118
Industrial water reuse rate	X <sub>7</sub>	0.247					-0.175
Resident population	X <sub>8</sub>	0.247					
Population density	X <sub>9</sub>	0.243				-0.149	
Urbanization rate	X <sub>10</sub>	0.249					-0.114
GDP per capita	X <sub>11</sub>	0.248					-0.196
Per capita domestic water consumption	X <sub>12</sub>		0.154		-0.231		
Combined domestic water consumption per capita	X <sub>13</sub>						
GDP	X <sub>14</sub>	0.248					-0.217
Agricultural water consumption	X <sub>15</sub>				-0.239		
Water consumption	X <sub>16</sub>		0.122		-0.231		-0.126
Water consumption per 10,000 Yuan of GDP	X <sub>17</sub>		0.115		-0.247		
Water consumption of per 10,000 Yuan industrial value added	X <sub>18</sub>		0.445		-0.158		-0.272
Chemical oxygen demand emissions per 10,000 Yuan of GDP	X <sub>19</sub>			0.213	-0.246		
Tertiary industry to GDP ratio	X <sub>20</sub>	0.239	0.138				-0.174

in Suzhou's drainage (Lu et al. 2017). As the eigenvalues of PC3 are small, the amount of information expressed is small and the WECC analysis is not performed.

According to the analysis of principal components 1 and 2, they reflect the support of water and environmental systems for human production and life. PC1 represents the extent of human life and production, while PC2 represents the functional attributes. PC1 puts increasing pressure on the water environment, reducing the potential for future use as it supports urbanization and economic development. Development is essentially a pressure, but this pressure is not static and can be adjusted through economic and technical means.

### 3.3 Comparative Analysis of Indicator Layers

The amount of information that each indicator can represent in different dimensions is represented by its vector of principal component eigenvalues according to the basic principles of PCA (Table 6). In the leading indicators, water consumption is negative for PC2, where water consumption means a reduction in water resources, which puts pressure on water and environmental systems. While principal components 1 and 3 are positive, water saving is the most effective way to improve WECC. In principal components 1 and 3, water use per million yuan of industrial value added is negative, while in PC2, it is positive (Ding et al.

2015). Therefore, reducing the water consumption of industrial added value is crucial to reducing emissions and saving energy in economic development. Due to the realities of local water scarcity, this requires a reduction of water demand during industrial development and higher requirements for recycling industrial wastewater. It also necessitates the development of ideas for industrial development models that focus on low water consumption and low pollution (Wang et al. 2022a, b, c). Through the above analysis, the indicators show different practical meanings from different perspectives, depending on the actual situation and specific problems.

### 3.4 WECC Influencing Factors Explored

At the system level, water and environmental systems are the most important influencing variables on WECC. With water use moving towards strict restriction, the amount of available water resources, which serves as the ontology in carrying capacity studies, is the primary influencing element for water and ecological systems. The stressors that put pressure on the WECC are human social and socio-economic systems. At the indicator level, the PCA analysis reveals that the main factors influencing PC1 are the GDP water use and COD emissions; the most significant factors affecting PC2 is the total water resources. The primary factors influencing PC3 are factors related to water use, for example, water consumption of industrial value added. While the entropy weighting method uses weights of each indicator to determine the main factors. By comparing the two methods, the main factors are basically the same. The primary reason impacting the WECC is the burden of human production and life, which is inevitably aggravated by activities such as water consumption, and wastewater discharge. While the entropy technique is more scientific, PCA provides only three viewpoints for studying WECC and exploring the primary influencing factors as a whole.

### 3.5 Recommendations for Improving WECC

**Water and Environmental Perspectives** The ecosystem decline will directly impact the amount of water resources that can be developed locally and will also limit the social and economic growth of the study area. The aquatic ecology of Suzhou needs to be better protected and managed in order to effectively improve it and promote healthy social and economic development. At present, despite the increasing attention paid to the ecological environment by the Suzhou government, it is still unsatisfactory in some places, and more measures are needed to improve water pollution prevention and control. To solve the issue of water ecology, the government can first prioritise ecological construction and then strictly regulate sewage discharge to limit its damage. In addition, it is strictly forbidden to set up polluting enterprises near lakes and wetlands, etc., to prevent lake and river pollution

**Table 6** Meaning of each principal component

Component	Relevance	Representative
PC1	-	human socio-economic development
PC2	+	water and environmental dimension
PC3	+	water and environmental



at the source. Better control and maintenance of important rivers and lakes can bring the aquatic environment to a higher standard.

**Human Society Perspective** The city's rapid population growth directly affects domestic water use in Suzhou, but residents of some areas lack awareness of water conservation. Even if natural population growth is slowing down, increasing population density requires a greater public awareness of water conservation. As a result, Suzhou government and businesses should step up efforts to educate the public about water conservation and encourage people to adopt more efficient water-use practices. The government can also strengthen public awareness of water conservation by appropriately adjusting the tariff from a price perspective to establish rules for the efficient management and distribution of water resources. Meanwhile, the rate of urbanization can be increased to promote the growth of urban agglomerations from quantity to quality. Water use has increased with the development of public infrastructure, but rainwater recycling systems and water conservation measures can be improved to increase the effectiveness of resource use (Li et al. 2022).

**Socio-Economic Perspective** Modify Suzhou's industrial structure and layout to create an industrial structure model that is compatible with the city's development and sustainable water resources. The current industrial structure of Suzhou is rationally planned according to the ability of the city's water ecosystem to safely absorb pollution, which reduces the enormous pressure on the urban water environment from industrial wastewater discharges (Zhang et al. 2019). Suzhou has a strong economic and technological advantage to allocate more resources to cleaner production in industry and agriculture. Cleaner production can reduce water consumption and pollutant production, enhance water recycling, improve reuse rates and address the health of water bodies (Li et al. 2022). In addition to continuing to strengthen the policy and legal framework for managing water resources, the Suzhou government also needs to control industrial water use, promote the generation of new water-saving technologies, achieve integrated water use, and ensure effective implementation of water management measures. In addition, monitoring of wastewater pollution sources needs to be strengthened to ensure that industrial organizations comply with consistent discharge requirements and that online continuous monitoring systems are in place for key enterprises.

## 4 Discussions

The WECC has drawn great attention to water resources management in recent years. Due to the complexity, many questions are undefined as to what constitutes a water-carrying capacity measurement system. This study examines the WECC of Suzhou and provides scientific explanations through a series of indicators and a comprehensive evaluation, countermeasures and opinions. There are certain shortcomings in the research due to the vast number of factors involved in WECC, various uncertainties, limitations of the theoretical approach, and completeness of the underlying data (Song and Pang 2021). (1) The evaluation of WECC is a complex system. Although the review of the index system in this study is both common in the literature, it only evaluates the WECC as a whole. It does not assess or analyze the different administrative regions of Suzhou, which could be investigated in the future. (2) Accurate information on the development of the index system in this study is difficult to find, and the selection of indicators is limited. Examples include

the rate of centralized wastewater treatment, the rate of water resource development, and the amount of wastewater discharged from industrial output. Future research may consider more and representative indicators. (3) Only the WECC of Suzhou City between 2001 and 2021 is evaluated in this study. The prediction and early warning are also significant future research fields. Since rainfall and runoff vary in time and space in some areas, with seasonal variations prominent, WECC varies greatly within years, a comprehensive evaluation in terms of flood, wet and dry periods is also an important research direction in this field.

## 5 Conclusion

This study examines the weaknesses of the recent WECC study based on the literature review. The city of Suzhou is selected as the study subject to evaluate the regional carrying capacity. The WECC evaluation index system of Suzhou is built from three perspectives: water and environment, human society, social economy, depending on the planned social development and the situation of local water in the research region. PCA is used to evaluate the WECC and the indicators are weighted using PCA and the entropy method. Suzhou's WECC from 2001 to 2021 is then assessed from two perspectives: principal component comparative analysis and indicator layer comparative analysis, and the evaluation results are thoroughly analyzed, which lays the foundation for studying the potential for sustainable development of the research site and optimal water configuration in the future. The main results are:

1. Based on the literature review of various research methods on this topic, considering Suzhou's development status and the development and utilization of water resources, PCA method is used for the analysis and evaluation. Twenty evaluation indicators are thereby selected to construct a scientific indicator evaluation system from the water and environment system, human social system, and socio-economic system.
2. The PCA approach and the entropy method are used to produce weights, allowing for a logical and scientific evaluation of the WECC by combining subjective and objective evaluation techniques. The trend of each principal component score calculated by the two methods is consistent, with only small fluctuations in magnitude.
3. Based on the PCA, the three principal components are the economic, social, and human social systems, the water and environmental system, and the effects of water usage and drainage on the water environment. The primary variables affecting social and economic systems are the number of COD emissions and the water consumption of GDP. Total water resources is the main determining factor for water and environmental systems.
4. The entropy weighting technique is more rigorous for investigating the key determinants of WECC. Precipitation, water use, total water resources, COD emissions of GDP, surface water resources, effective utilization coefficient of irrigation water, and the agricultural water use are primary variables affecting WECC.
5. From the perspective of the environment and water, human society, and socio-economics, suggestions are put forward to improve WECC.

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**Data Availability** The data will be available from the corresponding author upon reasonable request.

## Declarations

**Competing Interest** The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

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