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# *A critical review of methods for analyzing freshwater eutrophication*

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*Review*

# A Critical Review of Methods for Analyzing Freshwater Eutrophication

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**Abstract:** Water eutrophication is a global environmental problem that poses serious threats to aquatic ecosystems and human health. The evaluation of eutrophication provides a theoretical basis and technical guidance for the management and rehabilitation of water ecosystems. In the last four decades, dozens of evaluation methods have been applied to freshwater eutrophication, but there is a clear need to optimize and standardize the most suitable methods. We have addressed this gap by presenting a systematic review of methodologies. Due to the diversity and complexity of water bodies, no single evaluation method was identified that would adequately represent eutrophication under all scenarios. We demonstrate that lakes can best be assessed using the trophic level index (TLI) method, reservoirs and wetlands the trophic state index (TSI) and fuzzy comprehensive evaluation (FCE) method, respectively, and rivers the FCE method or back propagation (BP) neural network methods. More recently applied methodologies including spectral imaging and 3-D mapping of water quality using underwater gliders allow greater resolution and can be effective in managing waterbodies to avoid future eutrophication. The aim of this review is to guide future studies on the most appropriate methods available for assessing and reporting water eutrophication.

**Keywords:** water quality; evaluation methods; BP neural network; fuzzy comprehensive evaluation (FCE); trophic state index (TSI); trophic level index (TLI)

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## 1. Introduction

Water eutrophication has become an increasingly serious problem worldwide [1]. Water eutrophication refers to the phenomenon whereby an excess of nitrogen (N), phosphorus (P), and other inorganic nutrients enter a relatively closed and slow-flowing water body (such as lake, reservoir, river and freshwater wetland) stimulating the proliferation of algae and other plankton in the water, resulting in lower dissolved oxygen (DO), increased chlorophyll-a (Chl-a) content and the deterioration of water quality. This can result in the death of fish and other aquatic life. The decomposition of algae under anoxic conditions further releases nutrients such as N and P back into water for the next generation of algae to utilize [2] (Figure 1). Eutrophication can result in toxic cyanobacteria blooms in lakes and waterways and the proliferation of algae in coastal areas [1], manifesting in the death of native aquatic organisms, reduction in biodiversity, and impacts on human health (Figure 1).

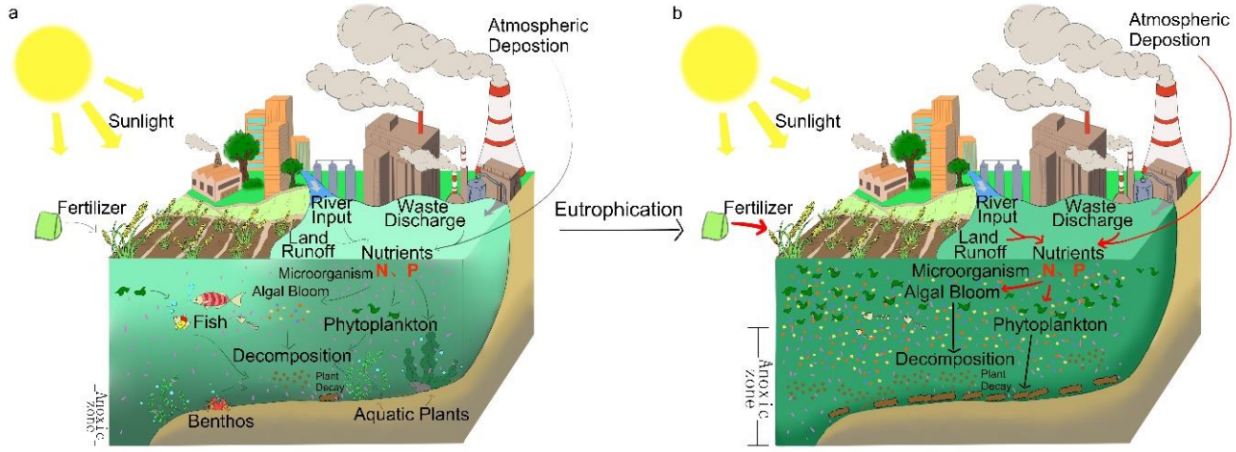


**Figure 1.** (**a**) Sources of nutrient inputs and the cycling of nutrients in the water body, (**b**) Demonstration of eutrophication and its effects in the water body.

The occurrence of eutrophication has been increasing globally since the 1960s. The number of eutrophic lakes increased from 41 to 61% between the late 1970s to the late 1990s [3,4]. In 2012, 63% of the world's inland water bodies were eutrophic with the area accounting for 31% of all water bodies [5,6]. In 2019, among the 107 lakes (reservoirs) monitored in China, 5.6% were middle-eutrophic (the trophic level index (TLI): $60 \leq \text{TLI}\ (\sum) \leq 70$) and 23.4% were light-eutrophic ($50 \leq \text{TLI}\ (\sum) \leq 60$), while 61.7% were mesotrophic and 9.3% oligotrophic [7,8]. The proportion of large lakes (lakes with an area of more than 500 square kilometers) with each trophic state (eutrophic, mesotrophic, and oligotrophic) is shown in Figure 2 and represents the number of lakes and lake surface area globally in 2018. It was shown that the southern regions of South America (Patagonia plateau) and Central Asia (Qinghai-Tibet Plateau) are primarily oligotrophic, while the large lakes in southeast and mid-northern North America (south Canada and the southeast United States), East Asia (East China), and Central Africa are eutrophic. In terms of the number of lakes, Oceania had the highest proportion of large lakes with oligotrophication (23.1%), Europe had the highest proportion of large lakes with mesotrophication (35.2%), and Africa had the highest proportion of large lakes with eutrophication (88.8%). In terms of surface area, North America has the highest proportion of oligotrophic large lakes (49.8%), Asia has the highest proportion of mesotrophic large lakes (71.2%) and Africa has the highest proportion of eutrophic large lakes [9]. The majority of eutrophic water was located in Africa, Oceania, South America, North America, Europe and Asia [9,10]. For example, Victoria Lake in Africa and Erie Lake in North America [11,12].

Different eutrophic water bodies use different methods to evaluate their state of eutrophication and their evaluation parameters are also diversified. Total nitrogen (TN) and total phosphorus (TP) content are key drivers for water eutrophication, resulting in an increased concentration of Chl-a [13,14]. Therefore, in this review, we selected the concentration of TN, TP and Chl-a as the key water quality indicators (Table 1). These values in the table are the average values of local eutrophication water indicators, measured at the time specifically mentioned in the references. Here, eutrophic water from 21 studies worldwide is described with middle-eutrophic and hyper-eutrophic ($\text{TLI}\ (\sum) \geq 70$) water bodies commonly reported [15]. Importantly, this review has also identified that there are many methods (criteria) used to evaluate the eutrophication level of water, which makes direct comparison between studies challenging [16]. In 1982, the OECD (Organization for Economic Co-operation and Development) set the criteria for trophic status of lakes and defined ultra-oligotrophic (Table 1). In Table 2, most of the methods have similar eutrophication water quality parameters, but some of the evaluation methods are unique.

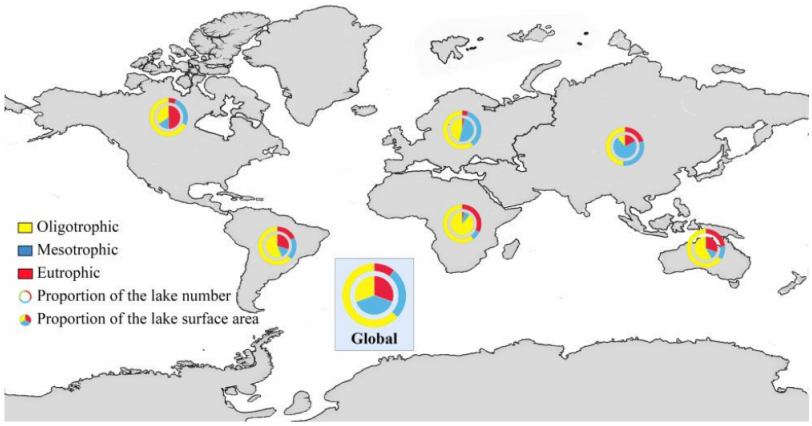


**Figure 2.** Global distribution of water eutrophication. The pie chart of the outside circle corresponds to the proportion of the number of large lakes in each eutrophication state in the continent, and the pie chart of the inside circle corresponds to the proportion of the surface area of large lakes in each eutrophication state in the continent (Africa, Asia, South America, North America, Oceania and Europe). Global data for the six continents of the world (except Antarctica) in 2018 [12].

Understanding water quality is a key step to better managing the problems associated with eutrophic water. To facilitate the further assessment of the existing eutrophic water bodies, an enhanced understanding and appropriate choice of an evaluation method for the eutrophication level is necessary [17]. For this reason, we present a comprehensive review of 13 water eutrophication evaluation methods and a comparative analysis of their applicability. The purpose is to find the most suitable method to evaluate water eutrophication, and further improve and develop the treatment of water eutrophication.

## 2. Methods

We searched the published papers as well as regional databases of water monitoring (Google Scholars, Web of Science and China National Knowledge Infrastructure). The search terms were "eutrophication evaluation", "water eutrophication", "evaluation method", with a time span of 1972–2020. In order to study the feasibility of the evaluation method, we set up two criteria: (1.) In order to ensure that data was not influenced by studies that assessed minor water bodies, we excluded datasets where waterbodies had an area < 1 $km^2$. We extracted the eutrophication status of 29 lakes, 17 reservoirs, 14 rivers and 9 wetlands, and the database covers waters ranging from shallow to deep, oligotrophic to hyper-eutrophic (Tables 1 and 2). (2.) Our dataset recorded meta-data including geographical location, area, average depth; the concentration of TN, TP, and Chl-a.

## 3. Globally Applied Methods for Determining the Eutrophication Status of Waters

Indicators for the evaluation of water eutrophication have commonly included the following: N content greater than 0.2–0.3 mg/L, P content greater than 0.01–0.02 mg/L, biochemical oxygen demand (BOD) greater than 10 mg/L, total number of bacteria in fresh water with a pH value of 7–9 of greater than $10^4$ units/mL, and Chl-a greater than 10 μg/L [18]. Currently, the evaluation of water eutrophication has evolved from the use of simple single indicators (N or P) to comprehensive indicators, such as the total nutrition status index. Here we describe a broad range of methodologies for the evaluation and quantification of eutrophication.

### *3.1. Methods Based on Mathematical Calculations*

#### 3.1.1. The Single Factor Index Evaluation (SFIE) Method

The SFIE method initially appeared in 1990 and consists of one factor that has the greatest impact on water quality [19].

The main idea is to compare the monitoring value of each water quality index with the concentration value of the target water quality index according to the standard table of water quality evaluation factors. If the ratio is greater than 1, then the water is judged to meet the standard level [20]. After comparing all of the evaluation factors, the worst water quality factor level is selected as the level for the entire water body [21]. The expression of the index, $I_i$, is shown in Equation (1) [22].

$$I_i = \frac{C_i}{C_{i0}}, \quad (1)$$

where $C_i$ is the actual measured value of the class I assessment pollutants; $C_{i0}$ is the starting pollution value or relevant standard of the class I assessment pollutants; $I_i \leq 1$ means the water is not polluted; $I_i > 1$ means the water is polluted. The calculation results can directly reflect the severity of water pollution [23,24].

The SFIE method can clearly and intuitively compare the measured value with the standard value, so as to quickly understand the water quality category. However, it is a comparison of one factor at one point in time and ignores the other water quality indicators [25].

#### 3.1.2. Formula Scoring (SCO) Method

This basic evaluation model is widely used and is based upon a scoring formula that is simple and can quickly and conveniently evaluate the level of water eutrophication. Its expression is shown in Equation (2):

$$M = \frac{1}{n} \sum_{i=1}^{n} M_i \quad (2)$$

where M is the score of lake eutrophication; $M_i$ is the index score value of item i to evaluate the pollutant; n is the number of indexes. According to the selected evaluation factors and their corresponding evaluation standards, the corresponding scores of each evaluation parameter are in the range of 0–100 (Table 2). The higher the total score, the higher the eutrophication level of lakes and reservoirs [24,26]. Shu used the Formula scoring method to evaluate eutrophication of 24 lakes in China. The results showed that there were 16 eutrophic lakes, accounting for 66.6% of the total number of the survey [27].

However, in applying the methodology, if a certain parameter score is significantly below (or above) score values of other parameters, the parameter should be deleted. This makes the method more subjective [28].

#### 3.1.3. The Algal Dominant Species Evaluation Method

Algae are an important component of the biological resources in aquatic ecosystems. As the community structure and growth of algae are directly affected by the changes in the water ecological environment, they can be used to assess water eutrophication. This method initially appeared in 1993 and is primarily used for rivers that tend to be polluted and have a population of algae [29]. The qualitative and quantitative collection of phytoplankton in water is used to determine whether the water is eutrophied [30].

The algae comprehensive index (K) further refines the algal population structure and determines the water eutrophication level, which is then expressed as:

$$K = (\textit{Cyanophyta} + \textit{Chlorococcales} + \textit{Centricae} + \textit{Euglena})/\text{species of desmidiales}, \quad (3)$$

when $k \geq 3$, it is hyper-eutrophic, when $1 \leq K < 2$, it is middle-eutrophic, when $k < 1$, it is light-eutrophic [31]. Zhou et al., evaluated the algal diversity of 4 tributaries of The Yangtze River in China, and the results showed that the nutrient levels of the 4 tributaries all belonged to the middle-eutrophic status, and the maximum algal cell density was $6.036 \times 10^6$ cells/L.

**Table 1.** Nutritional status of water eutrophication and evaluation method (criteria) in lakes, reservoirs, rivers, and freshwater wetlands.

| Evaluation Method (Criteria) | Water | Nutrient (N) (mg/L) | Nutrient (P) (mg/L) | Chl-a [9] (μg/L) | Documented Eutrophication | Reference |
|---|---|---|---|---|---|---|
| **NI** [1] | Lugano Lake, Switzerland | NA [10] | TP [4]: 0.140 | NA | Hyper-eutrophic (1960~2001) | [32] |
| | Viroi Lake, Albania | $NH_4^+$: 0.090 $NO_3^-$: 0.670 | NA | NA | Eutrophic (2013~2014) | [33] |
| | Olympic Forest Park wetland, China | TN [5]: 0.300~2.100 | TP: 0.040~0.180 | NA | Light-eutrophic (2016) | [34] |
| **TLI** [2] | City Park Lake, Louisiana, USA | TN: 0.682 | TP: 0.330 | 35.1 | Eutrophic (2000~2001) | [35] |
| | Idku Lake, Egypt | NA | $PO_4^{3-}$: 0.200~0.430 | 39.9~104.2 | Hyper-eutrophic (2016) | [36] |
| | Jinhe River, China | TN: 0.240~8.340 | TP: 0.019~0.490 | 1.6~92.7 | Eutrophic (2007~2011) Hyper-eutrophic (2012~2014) Middle-eutrophic (2015) | [37] |
| | Guanshan Wetland, China | TN: 0.520~2.200 | TP: 0.019~1.040 | 1.0~37.0 | Light-eutrophic (2014~2016) | [38] |
| **Improved TLI** | Chaohu Lake, China | TN: 1.500~2.680 | TP: 0.150~0.230 | 13.2~21.9 | Light-eutrophic (2000~2006) Middle-eutrophic (2007~2017) | [39] |
| **TSI** [3] | Erie Lake, USA | NA | TP: 0.115 | 58.0 | Blue-green algae bloom (1965~1979) Declined quality (1995~2004) | [40,41] |
| | Lyng Lake, Danish | TN: 2.400 | TP: 0.370 | 73.0 | Hyper-eutrophic (1999) | [42] |
| | Ramgarh Lake, India | NA | NA | NA | Hyper-eutrophic (2015) | [43] |
| | Bütgenbach Reservoir, Belgium | $NH_4^+$: 0~0.480 | $PO_4^{3-}$: 0~0.110 | 0~39.4 | Hyper-eutrophic (2007) | [44] |
| | Ecbatan Reservoir, Egypt | TN: 2.200 | TP: 0.075 | 5.8 | Middle-eutrophic (2018) | [45] |
| | Dawangtan Reservoir, China | $NH_4^{+-}$N: 0.180~0.710 TN: 0.820~2.760 | TP: 0.020~0.090 | NA | Middle-eutrophic (2019) | [46] |

**Table 1.** *Cont.*

| Evaluation Method (Criteria) | Water | Nutrient (N) (mg/L) | Nutrient (P) (mg/L) | Chl-a [9] (μg/L) | Documented Eutrophication | Reference |
|---|---|---|---|---|---|---|
| **TSI** | Rietvlei nature reserve wetland, South Africa | TN: 0.358~6.000 | TP: 0.081~0.371 | NA | Middle-eutrophic (2005~2006) | [47] |
| | Xuanwu Wetland, China | TN: 2.010~2.110 | TP: 0.160~0.310 | NA | Hyper-eutrophic (2011) | [48] |
| **FCE [6]** | Pamvotis Lake, Northwest Greece | $NH_4^+$: 0.250<br>$NO_3^-$: 0.560 | NA | NA | Eutrophic (2002) | [49] |
| | Honghu Lake, China | TN: 1.410 | TP: 0.065 | 2.6~3.7 | Middle-eutrophic (2005~2006) | [50] |
| | Berg River, South Africa | TN: 2.170 | TP: 0.700 | NA | Hyper-eutrophic (2007) | [51] |
| **BP neural network [7]** | Dianshan Lake, China | TN: 1.086 | TP: 0.029 | 3.0 | Light-eutrophic (2011) | [52] |
| | Gaozhou Reservoir, China | TN: 0.358 | TP: 0.046 | 1.4 | Mesotrophic (2011) | [53] |
| **OECD [8] classification** | Wastewater | $NO_3^-$: 0.352 | TP: 0.003 | 0.8 | Ultra-oligotrophic | [14] |
| | Ennerdale Water | $NO_3^-$: 0.333 | TP: 0.008 | 1.05 | Oligotrophic | [14] |
| | Buttermere | $NO_3^-$: 0.175 | TP: 0.004 | 1.43 | Oligotrophic | [14] |
| | Crummock Water | $NO_3^-$: 0.193 | TP: 0.007 | 2.075 | Oligotrophic | [14] |
| | Coniston Water | $NO_3^-$: 0.365 | TP: 0.008 | 3.585 | Oligotrophic | [14] |
| | Derwentwater | $NO_3^-$: 0.199 | TP: 0.015 | 3.275 | Mesotrophic | [14] |
| | Grasmere | $NO_3^-$: 0.253 | TP: 0.016 | 5.655 | Mesotrophic | [14] |
| | Loweswater | $NO_3^-$: 0.529 | TP: 0.013 | 7.68 | Mesotrophic | [14] |
| | Bassenthwaite Lake | $NO_3^-$: 0.384 | TP: 0.022 | 6.37 | Mesotrophic | [14] |
| | Ullswater | $NO_3^-$: 0.254 | TP: 0.012 | 5.44 | Mesotrophic | [14] |
| | Blelharn Tarn | $NO_3^-$: 0.827 | TP: 0.039 | 18.345 | Eutrophic | [14] |
| | Esthwaite Water | $NO_3^-$: 0.695 | TP: 0.031 | 22.355 | Eutrophic | [14] |

[1] NI, nemerow index; [2] TLI, trophic level index method; [3] TSI, trophic state index method; [4] TP, total phosphorus; [5] TN, total nitrogen; [6] FCE, fuzzy comprehensive evaluation method; [7] BP, back propagation; [8] OECD, Organization for Economic Co-operation and Development; [9] Chl-a, chlorophyll-a;[10] NA, not available.

#### 3.1.4. The Nemerow Index (NI)

The Nemerow water quality index first proposed in 1974 focuses on the most serious pollution factors [54]. The method can also be used to assess heavy metal pollution in water [25]. The NI method considers the average value of evaluation indexes and the impact of the most serious pollution evaluation indexes on water quality. However, the weight of pollution factors is not considered, thus the method has potential to underrepresent the current level of eutrophication. Therefore, different correction methods to correct the NI have been adopted, for example (Equation (4)):

$$PI = \sqrt{\frac{\left(\frac{C_i}{L_{i,j}}\right)_{MAX}^2 + \frac{C_i^2}{L_{i,jAug}}}{2}} \quad (4)$$

where PI is the water quality index; $C_i$ is the measured concentration of a pollutant (i is the number of water quality items), (mg/L); $L_{i,j}$ is the maximum allowable value of i water quality parameters for the purpose of j water (mg/L) (j is the purpose of the water; the purpose of water is divided into three categories: used by human in direct contact, used by human in indirect contact and not used by humans.) [54]. Alberto et al., investigated of the eutrophication of Lugano Lake using this method and showed that it was hyper-eutrophic [32].

#### 3.1.5. The Trophic Level Index (TLI) Method

TLI is widely used for eutrophication assessments of lakes, rivers and freshwater wetlands in China. It uses the chemical oxygen demand ($COD_{Mn}$), TN, TP, secchi disk (SD), and Chl-a as the evaluation indices of water eutrophication to calculate the nutritional state (Table 2). The calculation includes Equations (5)–(11):

$$\mathrm{TLI}(\sum) = \sum_{j=1}^{m} w_j \,\mathrm{TLI}(j). \quad (5)$$

Calculation formula of the TLI nutritional status evaluation index [55] is as follows:

$$\mathrm{TLI(chl)} = 10(2.5 + 1.086\ln\mathrm{chl}), \quad (6)$$

$$\mathrm{TLI(TP)} = 10(9.436 + 1.624\ln\mathrm{TP}), \quad (7)$$

$$\mathrm{TLI(TN)} = 10(5.453 + 1.694\ln\mathrm{TN}), \quad (8)$$

$$\mathrm{TLI(SD)} = 10(5.118 - 1.94\ln\mathrm{SD}), \quad (9)$$

$$\mathrm{TLI}(COD_{Mn}) = 10(0.109 + 2.661\ln COD_{Mn}) \quad (10)$$

Formula for calculating the weight of each index [30]:

$$\omega_j = \frac{r_{ij}^2}{\sum_{j=1}^{m} r_{ij}^2} \quad (11)$$

where $r_{ij}$ is the correlation of the basic parameter Chl-a and the j-th parameter; m is the number of basic parameters to be evaluated.

The evaluation criteria for the TLI method are oligotrophic, TLI ($\sum$) $\leq$ 30; mesotrophic, 30 < TLI ($\sum$) $\leq$ 60; light-eutrophic, TLI ($\sum$) $\leq$ 70; mid-eutrophic, 70 < TLI ($\sum$) $\leq$ 90; hyper-eutrophic, TLI ($\sum$) > 90 [55,56] (Table 2).

Because the eutrophication parameters of water are constantly changing, for some waterbodies that have been reevaluated across long periods of time, the correlation and weight of Chl-a and TP, TN, and SD display change over time. Therefore, the commonly used TLI index formula based on the original weight cannot accurately evaluate the nutritional status of water. To evaluate the eutrophication status of water accurately, it is necessary to improve the comprehensive nutritional status index method (an improved TLI). This is done by modifying the correlation coefficient of the TLI method equation, so it is more suitable for the current status of the water body. The improved TLI is Equation (12):

$$\mathrm{TLI}\,(\sum) = 0.6286\mathrm{TLI(Chl\text{-}a)} + 0.1093\mathrm{TLI(TP)} + 0.1936\mathrm{TLI(TN)} + 0.0685\mathrm{TLI(SD)} \quad (12)$$

#### 3.1.6. The Trophic State Index (TSI) Method: Carlson Index

In 1977, Carlson synthesized a number of eutrophication indicators, with the SD as the core, combined $COD_{Mn}$, Chl-a and TP, calculated these parameters into TSI, and successively graded the nutritional status of lakes [57,58] (Table 2). The evaluation method overcomes the limitation of single factor evaluation and is one of the main methods for assessing lake eutrophication [59]. Its expression is shown in Equations (13)–(16) [60,61].

Maryam et al. assessed Ecbatan reservoir using Carlson's index, and showed that the reservoir is middle-eutrophic [45].

$$\mathrm{TSI(SD)} = 10\left(6 - \frac{\ln \mathrm{SD}}{\ln 2}\right) \quad (13)$$

$$\mathrm{TSI(COD_{Mn})} = 10\left(6 - \frac{1.21 - 0.76 \ln}{\ln 2}\right) \quad (14)$$

$$\mathrm{TSI(Chl\text{-}a)} = 10\left(6 - \frac{2.04 - 0.68 \ln \ \mathrm{Chl\text{-}a}}{\ln 2}\right), \quad (15)$$

$$\mathrm{TSI(TP)} = 10\left(6 - \frac{\ln \frac{48}{\mathrm{TP}}}{\ln 2}\right) \quad (16)$$

The revised trophic state index ($\mathrm{TSI_M}$) based on Chl-a is a widely used assessment method for eutrophication in China that can make up for the deficiency of the TSI. It is a trophic state index based on the concentration of Chl-a, and its expression is shown in Equations (17)–(19) [62,63]:

$$\mathrm{TSI\ (Chl\text{-}a)} = 10\left(2.46 - \frac{\ln \mathrm{Chl\text{-}a}}{\ln 2.5}\right) \quad (17)$$

$$\mathrm{TSI\ (SD)} = 10\left(2.46 - \frac{3.69 - 1.53 \ln \mathrm{SD}}{\ln 2.5}\right), \quad (18)$$

$$\mathrm{TSI\ (TP)} = 10\left(2.46 - \frac{6.71 - 1.15 \ln \mathrm{TP}}{\ln 2.5}\right) \quad (19)$$

3.1.7. Stochastic Assessment Method (Empirical Frequency)

The water quality indexes including $\mathrm{COD_{Mn}}$, TN, TP, SD, and Chl-a are treated as random variables in the stochastic assessment method. It is necessary to deduce the empirical frequency of each water quality index and use the weighted average method to calculate the empirical frequency of lake eutrophication level. The following is the empirical frequency (P) calculation equation [64] (Equation (20)):

$$\mathrm{P} = \frac{\mathrm{m}}{\mathrm{n} + 1} \times 100\% \quad (20)$$

where m is the water sample number; n is the sample size; P of each random variable is calculated. According to the coefficients related to $\mathrm{COD_{Mn}}$, TN, TP, SD, and Chl-a, the weight, $\mathrm{W_i}$, of each water quality index in the eutrophication assessment is obtained. It is applicable to the weighted average equation. Thus $\mathrm{P} = \mathrm{W_i} \times \mathrm{P_i}$. Furthermore, the lake eutrophication evaluation frequency standard can be obtained (Table 2). Xie et al., used the stochastic assessment method and the fuzzy comprehensive evaluation (FCE) method to evaluate the eutrophication of 30 lakes in China. The data showed that the evaluation results of 19 lakes were completely consistent, indicating that the two methods were reliable in their evaluation of lake eutrophication [65].

### *3.2. Methods Based on Models*

3.2.1. The Fuzzy Comprehensive Evaluation (FCE) Method

The basic idea of the FCE method is to establish the index monitoring data of each factor and membership standard of each level. Then a membership degree matrix is formed. The membership degree matrix of weight-setting factors is then multiplied to obtain a dataset for the evaluation of water eutrophication [66]. The method is based on the measured values of the physical and chemical parameters of water quality [67,68] shown in Equation (21):

$$\mathrm{D_{A(u)}} = \mu_{\mathrm{A(u)}} - \mu_{\mathrm{Ac(u)}} \quad (21)$$

The following are the specific steps of this method. (1) Establish a set of water quality evaluation factors and classification sets. (2) Establish a single factor evaluation matrix. (3) Determine the weight of each factor. (4) Establish an evaluation model [62,69] (Table 2). The relationship between each index and classification is listed in Table 2. This method considers the contribution of all factors and can reduce subjectivity. This method has been shown to be more suitable for rivers and freshwater wetlands [70].

According to the mathematical fuzzy operation rules, the average weighted model is used as the fuzzy operator. In addition, the fuzzy matrices A and R (A is the weight distribution matrix, and R is the fuzzy relation matrix between the evaluation factors and their relative evaluation standards) are combined to obtain the hierarchical setting of the evaluation standard of the fuzzy subset [71]. According to the principle of its maximum membership degree, the $(B_n)$ max (B is a fuzzy subset of the standard hierarchical setting; n = 1, 2, hierarchical setting) is selected as the result of the comprehensive water quality evaluation [25]. Fang evaluated the eutrophication of the region and the whole lake based on the FCE method. The results showed that most of the region and the whole lake are mesotrophic [72].

#### 3.2.2. The Back Propagation (BP) Neural Network

The BP neural network model is a nonlinear mathematical model based on neural network methodology [30,73]. It was first proposed in 1986 [74]. It is a feedforward multilevel neural network with a transfer continuity function, and it is the most widely used neural network model [75,76]. This model uses a BP algorithm as the learning algorithm of the network and does not need to establish mathematical equations. It weights the differentiable nonlinear functions in the software MATLAB, which can be used to analyze the influencing factors of water eutrophication [20,77] (Table 2).

The BP neural network model simulates a biological neural network for processing information [31,78,79]. Its training method is the error backpropagation algorithm (the BP algorithm), which constantly modifies the network weights and thresholds to minimize the mean square error [80,81]. For detailed formulas of the BP neural network model, please refer to Shao [82].

The BP neural network is a nonlinear system that is adaptive, self-organized, self-learning, anti-interference, and fault-tolerant. It has a strong adaptability to various evaluations and is widely used [22,24]. Compared with other methods, this method eliminates the influence of setting the weight of each pollution factor and relying on an empirical equation. Cui evaluated the eutrophication degree of 24 lakes in China based on the MATLAB neural network and eutrophication evaluation criteria. The results showed that there were 2 mesotrophic lakes, 3 light-eutrophic lakes, 10 middle-eutrophic lakes and 9 hyper-eutrophic lakes [52].

#### 3.2.3. The One-Dimensional Normal Cloud Model (ONCM) Method

The ONCM method is a recently developed evaluation method [83] where the eutrophication level is divided into six grades. The evaluation factor corresponds to the nutrition level and is expressed by a comprehensive cloud (Table 2). Table 2 shows the relationship between $E_x$, $E_n$ and $H_e$, and the classification.

According to the evaluation factors and standards, three digital characteristics of the cloud model can be determined using the following equation [84] (Equations (22)–(24)):

$$E_x = \frac{(B_{min} + B_{max})}{2}, \quad (22)$$

$$E_n = \frac{(B_{max} - B_{min})}{6}, \quad (23)$$

$$H_e = k, \quad (24)$$

where $B_{min}$ and $B_{max}$ are the minimum and maximum boundaries of $V_{Qa}$ (the evaluation factor), and k is a constant.

According to the determined cloud model parameters $E_x$, $E_n$ and $H_e$, the indexes of the evaluation factors TN, TP, SD, and Chl-a, the corresponding comprehensive cloud models are generated using the positive normal cloud generator and the half cloud generator (the ascending cloud and descending cloud, respectively) [85].

#### 3.2.4. The Multidimensional Normal Cloud Model (MNCM) Method

The multidimensional normal cloud model is an extension of the one-dimensional normal cloud model and uses an improved selection of the correlation coefficient of the cloud model. It can more comprehensively reflect the water eutrophication level [86]. The degree of water eutrophication can be divided into n levels. The model is established by taking multidimensional evaluation factors as one dimension of the multidimensional cloud model. The MNCM method determines three numerical characteristics, select the appropriate evaluation factors and their evaluation criteria, and generates one-dimensional and multidimensional cloud models based on these evaluation factors [40]. Then, the established model is used to confirm the maximum degree of certainty, it can be directly judged that each evaluation factor is located in the level of water samples with different nutritional levels [87,88].

The MNCM is used to evaluate the eutrophication of 6 lakes in China. The results show the MNCM method can judge the eutrophication degree of different water bodies at the same level, which proves the feasibility and effectiveness of the method [86].

**Table 2.** Water eutrophication evaluation parameter and classification.

| Method | Parameter | | | | | | Classification | Reference |
|---|---|---|---|---|---|---|---|---|
| SCO [1] | $COD_{Mn}$ (mg/L) | TN (mg/L) | TP (mg/L) | SD (m) | Chl-a (mg/L) | Score | | [26] |
| | ≤0.15 | ≤0.020 | ≤0.001 | ≥10.0 | ≤0.0005 | ≤10 | Oligotrophic | |
| | >0.15, ≤0.3 | >0.020, ≤0.030 | >0.001, ≤0.0025 | <10.0, ≥8.0 | >0.0005, ≤0.0010 | >10, ≤20 | | |
| | >0.3, ≤0.4 | >0.030, ≤0.050 | >0.0025, ≤0.005 | <8.0, ≥5.0 | >0.0010, ≤0.0020 | >20, ≤30 | Mesotrophic | |
| | >0.4, ≤2.0 | >0.050. ≤0.300 | >0.005, ≤0.025 | <5.0, ≥1.5 | >0.0020, ≤0.0040 | >30, ≤40 | Eutrophic | |
| | >2.0, ≤4.0 | >0.050, ≤0.300 | >0.025, ≤0.050 | <1.5, ≥1.0 | >0.0040, ≤0.0100 | >40, ≤50 | Light-eutrophic | |
| | >4.0, ≤8.0 | >0.300, ≤0.800 | >0.025, ≤0.050 | <1.0, ≥0.5 | >0.0100, ≤0.0260 | >50, ≤60 | Mid-eutrophic | |
| | >8.0, ≤18.0 | >0.800, ≤2.000 | >0.050, ≤0.200 | <0.5, ≥0.4 | >0.0260, ≤0.0650 | >60, ≤70 | | |
| | >18.0, ≤25.0 | >2.000, ≤6.000 | >0.200, ≤0.600 | <0.4, ≥0.3 | >0.0650, ≤0.1600 | >70, ≤80 | Hyper-eutrophic | |
| | >25.0, ≤40.0 | >6.000, ≤9.000 | >0.600, ≤0.900 | <0.3, ≥0.2 | >0.1600, ≤0.4000 | >80, ≤90 | | |
| | >60.0 | >14.000 | >1.300 | <0.12 | >1.0000 | >90, ≤100 | | |

**Table 2.** *Cont.*

| Method | Parameter | | | | | | Classification | Reference |
|---|---|---|---|---|---|---|---|---|
| TLI (Σ) [2] | $COD_{Mn}$ (mg/L) | TN (mg/L) | TP (mg/L) | SD (m) | Chl-a (mg/L) | TLI | | [89] |
| | ≤0.15 | ≤0.02 | ≤0.001 | ≥10.0 | ≤0.0005 | | | |
| | >0.15, ≤0.40 | >0.02, ≤0.05 | >0.001, ≤0.004 | <10.0, ≥5.0 | >0.0005, ≤0.0010 | ≤30 | Oligotrophic | |
| | >0.40, ≤1.00 | >0.05, ≤0.10 | >0.004, ≤0.010 | <5.0, ≥3.0 | >0.0010, ≤0.0020 | | | |
| | >1.00, ≤2.00 | >0.10, ≤0.30 | >0.010, ≤0.030 | <3.0, ≥1.5 | >0.0020, ≤0.0040 | >30, ≤50 | Mesotrophic | |
| | >2.00, ≤4.00 | >0.30, ≤0.50 | >0.030, ≤0.050 | <1.5, ≥1.0 | >0.0040, ≤0.0100 | | | |
| | >4.00, ≤8.00 | >0.50, ≤1.00 | >0.050, ≤0.100 | <1.0, ≥0.5 | >0.0100, ≤0.0300 | >50, ≤60 | Light-eutrophic | |
| | >8.00, ≤10.00 | >1.00, ≤2.00 | >0.100, ≤0.200 | <0.5, ≥0.4 | >0.0300, ≤0.0640 | >60, ≤70 | Mid-eutrophic | |
| | >10.00, ≤25.00 | >2.00, ≤6.00 | >0.200, ≤0.600 | <0.4, ≥0.3 | >0.0640, ≤0.1600 | | | |
| | >40.00 | >9.00 | >0.900 | <0.2 | >0.4000 | >70 | Hyper-eutrophic | |
| $TSI_M$ [3] | | $TSI_M$ (TP) | | $TSI_M$ (SD) | | $TSI_M$ (Chl-a) | | [61] |
| | | ≤2.0 | | ≤4.4 | | ≤24.6 | Oligotrophic | |
| | | >2.0, ≤11.9 | | >4.4, ≤18.2 | | >24.6, ≤32.2 | Mesotrophic | |
| | | >11.9, ≤35.1 | | >18.2, ≤42.1 | | >32.2, ≤39.7 | Eutrophic | |
| | | >35.1, ≤45.2 | | >42.1, ≤50.1 | | >39.7, ≤47.6 | Light-eutrophic | |
| | | >45.2, ≤65.2 | | >50.1, ≤68.3 | | >47.6, ≤70.2 | Mid-eutrophic | |
| | | >65.2 | | >68.3 | | >70.2 | Hyper-eutrophic | |
| Empirical Frequency | $COD_{Mn}$ (mg/L) | TN (mg/L) | TP (mg/L) | SD (m) | Chl-a (mg/L) | Empirical Frequency | | [64] |
| | ≤0.3 | ≤0.030 | ≤0.0025 | ≥10.0 | ≤0.001 | ≤14.3 | Oligotrophic | |
| | >0.3, ≤0.4 | >0.030, ≤0.050 | >0.0025, ≤0.0050 | <10.0, ≥5.0 | >0.001, ≤0.002 | >0.4, ≤28.6 | Mesotrophic | |
| | >0.4, ≤2.0 | >0.050, ≤0.300 | >0.0050, ≤0.0250 | <5.0, ≥1.5 | >0.002, ≤0.004 | >0.4, ≤42.9 | Eutrophic | |
| | >2.0, ≤4.0 | >0.300, ≤0.500 | >0.0250, ≤0.0500 | <1.5, ≥1.0 | >0.004, ≤0.010 | >0.4, ≤57.1 | Light-eutrophic | |
| | >10.0, ≤25.0 | >2.000, ≤6.000 | >0.2000, ≤0.6000 | <0.4, ≥0.3 | >0.065, ≤0.160 | >71.4, ≤85.7 | Mid-eutrophic | |
| | >25.0 | >6.000 | >0.6000 | <0.3 | >0.160 | >85.7 | Hyper-eutrophic | |
| | DO (mg/L) | $BOD_5$ (mg/L) | $COD_{Mn}$ (mg/L) | $NH_3$-N(mg/L) | Cyanogen (mg/L) | As (mg/L) | Cr (mg/L) | F (mg/L) | |
| | ≥8.0 | ≤3.0 | ≤15.0 | ≤0.5 | ≤0.005 | ≤0.05 | ≤0.01 | ≤1.0 | Class I |
| | <8.0, ≥6.0 | ≤3.0 | ≤15.0 | ≤0.5 | >0.005, ≤0.050 | ≤0.05 | >0.01, ≤0.05 | ≤1.0 | Class II |
| | <6.0, ≥5.0 | >3.0, ≤4.0 | >15.0, ≤20.0 | >0.5, ≤10.0 | >0.050, ≤0.200 | >0.05, ≤0.20 | >0.01, ≤0.05 | ≤1.0 | Class IV |
| | <5.0, ≥3.0 | >4.0, ≤6.0 | >20.0, ≤30.0 | >1.0, ≤2.0 | >0.200 | >0.20 | >0.01, ≤0.05 | >1.0, ≤1.5 | Class IV |
| | <1.0 | >10.0 | >40.0 | >2.0 | >0.200 | >0.20 | >0.10 | >1.5 | Class V |

**Table 2.** *Cont.*

| Method | Parameter | | | | | Classification | Reference |
|---|---|---|---|---|---|---|---|
| | $COD_{Mn}$ (mg/L) | TN (mg/L) | TP (mg/L) | Chl-a (mg/L) | value | | |
| BP neural network | ≤0.3 | ≤0.03 | ≤0.0025 | ≤0.001 | $0 \leq y < 1$ | Oligotrophic | [75] |
| | >0.3, ≤0.4 | >0.03, ≤0.05 | >0.0030, ≤0.0050 | >0.001, ≤0.005 | $1 \leq y < 2$ | Mesotrophic | |
| | >0.4, ≤2.0 | >0.05, ≤0.30 | >0.0050, ≤0.0300 | >0.005, ≤0.025 | $2 \leq y < 3$ | Eutrophic | |
| | >2.0, ≤4.0 | >0.30, ≤0.50 | >0.0300, ≤0.0500 | >0.025, ≤0.050 | $3 \leq y < 4$ | Light-eutrophic | |
| | >4.0, ≤10.0 | >0.50, ≤2.00 | >0.0500, ≤0.2000 | >0.050, ≤0.500 | $4 \leq y < 5$ | Mid-eutrophic | |
| | >10.0 | >2.00 | >0.2000 | >0.500 | $y \geq 5$ | Hyper-eutrophic | |
| | $E_x$ [7] | | $E_n$ [8] | $H_e$ [9] | | | |
| ONCM [5] | ≥15.0 | | 5.0 | 0.01 | | C1 | |
| | <15.0, ≥7.5 | | 5.0 | 0.01 | | C2 | |
| | <7.5, ≥3.8 | | 5.0 | 0.01 | | C3 | |
| MNCM [6] | <3.8, ≥1.3 | | 5.0 | 0.01 | | C4 | |
| | <1.3, ≥0.7 | | 5.0 | 0.01 | | C5 | |
| | <0.2 | | 5.0 | 0.01 | | C6 | |

[1] SCO, formula scoring method; [2] TLI, trophic level index; [3] TSI, trophic state index; [4] FCE, fuzzy comprehensive evaluation; [5] MNCM, multidimensional normal cloud model; [6] ONCM, one-dimensional normal cloud model; [7] $E_x$, digital characteristics of the cloud model; [8] $E_n$, digital characteristics of the cloud model; [9] $H_e$, digital characteristics of the cloud model.

### *3.3. Methods Based on Spectral Imaging*

#### 3.3.1. Remote Sensing

Water quality assessment using remote sensing is based on the spectral characteristics, and statistical analyses of water quality parameters. This forms a water quality parameter inversion model. The spectral characteristics of water are mainly determined by plankton content, suspended matter content (turbidity), nutrient content (yellow matter, salinity index), other pollutants, bottom morphology (underwater topography), water depth, surface roughness and other factors. This technology has the advantages of producing a large amount of information, and it is less limited by surface conditions [90].

The spectral characteristics of water reflect the scattering and absorption of light radiation by a wide range of photochemically active substances in the water. Satellite imagery was originally obtained from Landsat Thematic mapper (TM), spot satellite images of France, and NOAA/AVHRR. Satellite remote sensing (HJ1B-CCD and GF-2 PMS2) is currently used to research inland water quality [91]. The eutrophication of Pamvotis Lake in Ioannina, Greece, was studied using the application of Chl-a detection algorithms based on Sentinel-2 satellite image data. The results showed that Pamvotis Lake is a eutrophic lake, and the highest Chl-a concentration was located in the east and south-east of the lake [92]. The Normalized Difference Vegetation Index (NDVI) derived from the Moderate-resolution Imaging Spectroradiometer (MODIS) imagery was used to investigate duckweed blooms and other floating vegetation in Lake Maracaibo, Venezuela. The data showed that there were different amounts of duckweed and floating vegetation in the lake from 2003 to 2006 [93]. The Landsat TM image data and hyperspectral remote sensing data also has been used to assess water eutrophication [94,95]. The consequences show that the calculation results of these data can accurately analyze water quality, indicating that remote sensing technologies have the potential to be applied to water quality monitoring in large-scale basins (Table 3).

**Table 3.** The remote sensing parameters and TM radiation of lake data.

| Monitoring Parameters | SS [1] (mg/L) | SD [2] (m) | DO [3] (mg/L) | $COD_{Mn}$ [4] (mg/L) | $BOD_5$ [5] (mg/L) | TN [6] (mg/L) | TP [7] (mg/L) | Reference |
|---|---|---|---|---|---|---|---|---|
| Monitoring parameters AVG [8] | 37.53 | 0.33 | 8.83 | 4.05 | 2.07 | 4.39 | 1.30 | |
| Radiation data MW [9]/($cm^2$·SR [10]) | TM1 [11] | TM2 | TM3 | TM4 | TM5 | TM6 | TM7 | [95] |
| Radiation data AVG | 0.687 | 0.554 | 0.267 | 0.033 | 0.010 | 0.086 | 0.002 | |
| Monitoring parameters | T (°C) 17.3~20.9 | pH 7.5~8.9 | TUB [12] (NTU) 18.5~110.0 | | HDO [13] (% Sat.) 18.9~207.6 | | Chl (μg/L) 4.79~219.1 | [96] |

[1] SS, suspended solids; [2] SD, secchi disk; [3] DO, dissolved oxygen; [4] $COD_{Mn}$, chemical oxygen demand; [5] BOD5, biochemical oxygen demand; [6] TN, total nitrogen; [7] TP, total phosphorus; [8] AVG, average value; [9] MW, megawatt; [10] SR, steradian; [11] TM, thematic mapper; [12] TUB, Turbidity; [13] HDO, high dissolved oxygen.

### 3.3.2. Multiple Equipment

With the progress of modern continuous monitoring technology, the analysis technology of integrated data of multiple equipment, such as the unmanned aerial vehicle (UAV) and underwater glider (UG), has emerged, which can carry out real-time, continuous and intuitive monitoring of water bodies. UAVs can carry a range of remote sensing equipment including photography, multi and hyperspectral imaging that can be used to quantify Chl-a and other water quality parameters [96]. The UG is an underwater robot and collects water quality information ($COD_{Mn}$, pH) enabling a 3-dimensional map of water quality indices to be developed [97].

## 4. Methods Best Suited to Describe the Degree of Eutrophication

Water eutrophication is a complex chemical, biological and physical process that is affected by many factors, and these indicators and standards are not universally applicable [50]. There are different evaluation methods for multiple eutrophic waters (Figure 3). We discussed and analyzed the advantages and disadvantages of these methods, and chose the methods (TLI, TSI, BP neural network or FCE and FCE) with high frequency and the most accurate results to describe the degree of waters (lakes, reservoirs, rivers and freshwater wetlands) eutrophication. It is better to choose traditional calculation formulas to evaluate eutrophication with limited funds. The higher technical methods (e.g., UAV and UG) require a certain amount of funds.

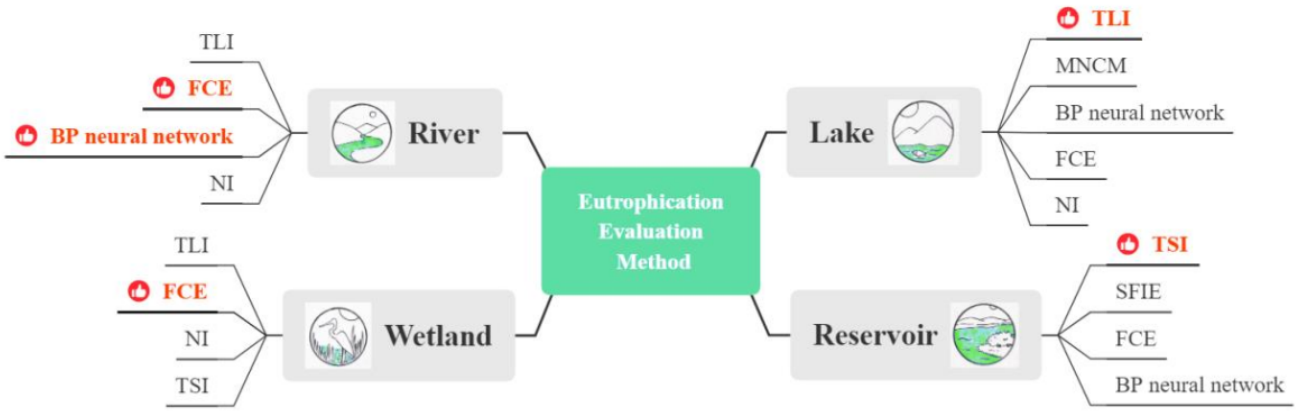


**Figure 3.** Evaluation methods applied to different waters (lakes, reservoirs, rivers and wetlands). The best methods identified in this work is written in red color.

### *4.1. The TLI Method for Lake Eutrophication*

Lakes are a large and complex system. Lakes can be divided into deep and thermally stratified lakes or shallow and non-stratified lakes. Here, we focus on the shallow and non-stratified lake systems [14]. The evaluation of lake eutrophication is based on a series of indicators related to a lake's nutritional status and interrelations of these factors (e.g., $COD_{Mn}$, TN, TP and Chl-a). Due to the complex chemical effects of various pollutants in the water, the eutrophication assessment of lake water is a difficult nonlinear prediction problem [56]. Currently, the basic methods for the evaluation of lake eutrophication include the following [98]: the TLI method, the MNCM method, the BP neural network method, the FCE method, and the NI method [72]. Among these, the selection of cloud model parameters (expected value, $E_x$; entropy, $E_n$; hyper entropy, $H_e$) used in MNCM method is inherently uncertain, indicating that the operational formula used in this method is not mature enough. Further research is needed on how to reasonably select cloud model parameters and how to combine the cloud model with other theories [99]. The BP neural network model was established by MATLAB software, and the network can be trained with enough calibration samples to avoid subjective influences. The methodology has been shown to accurately depict the level of eutrophication. However, there may be local minimum values in the BP neural network calculation, which is not good enough for the accuracy of this algorithm. Moreover, the local minimum point may appear in the squared sum function of the error, which is unfavorable to the operation of the algorithm. Therefore, the BP neural network method required further development [100]. However, the TLI method uses $COD_{Mn}$, TN, TP, SD and Chl-a as the evaluation indexes [101] to overcome the one-sidedness of a single factor evaluation of eutrophication [102]. We, therefore, suggest that the TLI is currently the most suitable method for the evaluation of lake eutrophication.

### *4.2. The TSI Method for Reservoir Eutrophication*

Reservoirs (artificial lakes) have been built for flood control, irrigation, power generation and fish farming [103]. Currently, the evaluation methods for reservoir eutrophication primarily include the TSI method [104], the SFIE method [105], the FCE method [106], and the BP neural network method. It should be noted that, when the above methods are used to evaluate and analyze the eutrophication of the reservoirs, the results are often more objective. Of all the methods, the SFIE method is most influenced by individual water quality indicators. Therefore, it lacks objectivity, and although the FCE method focuses on the subordination degree of different monitoring indexes to different water qualities, it fails to consider the inevitable randomness and other uncertainties in the evaluation process. This can lead to deviations in the evaluation results. However, the TSI method dismisses the traditional single indicator as presented by the SFIE method and integrates multiple factors, focuses on the comparison of water quality between tested water and its water function area, and effectively analyzes the fuzziness of the degree of eutrophication and water quality category [107]. Hence, it is particularly applicable for the evaluation of reservoir eutrophication [108].

### *4.3. The BP Neural Network or the FCE Method for River Eutrophication*

Evaluation of river eutrophication has used the BP neural network method, the FCE method [109], the TLI method, and the NI method [110]. Among these, the BP neural network method provides a comprehensive evaluation following calibration. The method can avoid the subjectivity of determining the evaluation index and index weight, thus better reflecting the level of water pollution [111]. The FCE method can describe water quality both qualitatively and quantitatively, and it objectively considers the contribution of various factors [37]. Nevertheless, based on the complexity of a river system, water environment and the complex water quality dataset obtained by water environmental monitoring, a variety of evaluation methods should be used to evaluate and manage water quality. Therefore, the BP neural network method and the FCE method are more suitable to evaluate river eutrophication.

### *4.4. The FCE Method for Freshwater Wetland Eutrophication*

The protection of wetland aquatic environments is particularly important. Here, we discuss the freshwater wetlands, such as the Rietvlei wetland. The eutrophication evaluation methods for freshwater wetlands primarily include the FCE method [112], the TLI method [113], the NI method, and the TSI method. The NI method has the advantages of a simple mathematical description. This easily leads to the degradation of water quality if the change level in the range is omitted [114]. The FCE method uses the degree of membership to indicate the classification range of eutrophication, which can better reflect the difference and continuity of water quality levels. This method considers the influence of a series of different indicators on water eutrophication and can determine the weight of each pollution index in the overall evaluation. In addition, it can determine the membership degree of an evaluation index, which can objectively reflect the eutrophication status of the water. Consequently, the FCE method is considered most suitable for the evaluation of eutrophication of freshwater wetlands.

## 5. Conclusions and Perspectives

Algal blooms caused by water eutrophication have become a global environmental and human health risk, and they are very frequent in many regions [104,115]. In this review, we evaluated the most common methods used to assess the levels of eutrophication in lakes, reservoirs, rivers, and freshwater wetlands. To effectively manage eutrophication, it is essential to have adequate metrics for the level and extent of contamination. The water assessment methods recommended in this review all have universal applicability with suitable accuracy. As a mature method, the TLI and TSI has been widely recognized for the evaluation of eutrophication of lakes and reservoirs. A river system is a complex water environment, and there was no consensus found for the optimal evaluation method. BP neural network methodology and the FCE method have, however, been commonly used for the evaluation of rivers. The FCE method is more appropriate to evaluate freshwater wetland eutrophication, and the analysis results have high credibility that can objectively reflect freshwater wetland eutrophication.

Introduction of new methodologies and ability to capture remote data will allow improvements in the assessment of eutrophication. In particular: (1) the integration of data from new monitoring tools such as underwater gliders and unmanned aerial vehicles, remote sensing, and meteorological and hydrological data with traditional assessments will allow the status of eutrophication to be accurately reported and will enable improved management of eutrophication. (2) The evaluation of freshwater eutrophication should pay attention to the differences in the ecological environment. For example, four kinds of water bodies (lakes, reservoirs, wetlands and rivers) correspond to different recommended evaluation methods (TLI method, TSI method, FCE method or BP neural network methods and FCE method). (3) Methodologies should consider the utilization of existing and big data sets, numerical model reanalysis, and neural networks. This mathematical approach can make up for a shortage of survey data and the limitation of evaluation methods while improving the accuracy of evaluation results.

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