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A novel index for assessing the water quality of urban landscape lakes based on water transparency

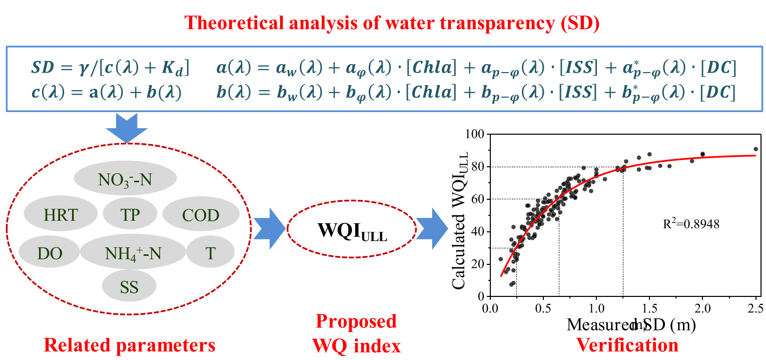
Nini Chang [a,b,c,d,e], Li Luo [a,b,c,d,e], Xiaochang C. Wang [a,b,c,d,e,*], Jia Song [a,b,c,d,e], Jiaxing Han [f], Dong Ao [g]

[a] *International Science and Technology Cooperation Center for Urban Alternative Water Resources Development, Xi'an 710055, China*
[b] *Key Laboratory of Northwest Water Resource, Environment and Ecology, MOE, Xi'an 710055, China*
[c] *Shaanxi Engineering Technology Research Center for Wastewater Treatment and Reuse, Xi'an 710055, China*
[d] *Shaanxi Key Laboratory of Environmental Engineering, Xi'an 710055, China*
[e] *School of Environmental and Municipal Engineering, Xi'an University of Architecture and Technology, Xi'an 710055, China*
[f] *Xianyang Academy of Planning and Design, Xianyang 712000, China*
[g] *School of Environmental and Chemical Engineering, Xi'an Polytechnic University, Xi'an 710048, China*

HIGHLIGHTS

- Landscape water quality closely related to water transparency (SD).
- 8 parameters were identified according to theoretical SD relation.
- A water quality index for urban landscape lake (WQI_{ULL}) was worked out.
- WQI_{ULL} value much depends on replenishing water source and amount.
- Calculated WQI_{ULL} correlates well with measured SD for 166 urban lakes in China.

GRAPHICAL ABSTRACT



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ABSTRACT

Assessment of the aesthetic and recreational value of urban landscape lakes (ULLs) is often required but there has not been a water quality index specifically applicable for such a purpose. Under a consideration that water transparency in terms of Secchi Depth (SD), to a large extent, determines the landscape effect, a study was conducted to identify the major parameters that strongly influence SD and to develop a novel water quality index. By theoretical analyses, it was found that SD is mainly influenced by the contents of chlorophyll *a*, inorganic suspended solids and organic detritus in water, which collectively relate to eight independent water quality, hydraulic, and environmental parameters, including SS, DO, COD, NH_4^+-N, NO_3^--N, TP, HRT, and water temperature T. A composite index was then proposed in the form of $WQI_{ULL} = \prod_{i=1}^{n} q_i^{w_i}$ $(n = 8)$. Using the data of field survey of 166 ULLs in China, the cumulative probability distribution curve of each sub-index q_i was characterized. Sensitive analysis was conducted for the determination of the sub-index weight (w_i) for each q_i under the consideration of two typical scenarios of ULL replenishment by stream water (traditional source) and reclaimed water (alternative source) regarding the variation of parameter on SD. With all w_i $(i = 1$ to $8)$ thus determined, WQI_{ULL} was calculated for each of the ULLs surveyed. All the calculated values of WQI_{ULL} showed a good correlative relationship with the SD values practically measured ($R^2 = 0.8948$), indicating that the novel water quality index developed could effectively indicate the satisfactory degree of the lake water quality in terms of water landscape. Further by

* Corresponding author at: Xi'An University of Architecture and Technology, No. 13, Yanta Road, Xi'an, China.
E-mail address: xcwang@xauat.edu.cn (X.C. Wang).

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comparing the dimensionless WQI_{ULL} (ranging between 0 and 100) with the practically acceptable SD based on experiences in China, the method for classification of ULLs by WQI_{ULL} calculation was formulated.
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1. Introduction

Urban landscape lakes (ULLs) are popular worldwide due to their aesthetic and recreational values. They are very often man-made ecosystems resulted from the excavation activities or the enlargement of smaller water bodies in urban areas. Moreover, ULLs are very different from other lakes: they are small in surface area, shallow in depth, and highly artificial yet more people come into contact with them than rural and natural lakes (Birch and McCaskie, 1999). Having good water quality is essential for ULLs, as the requirements and preferences of the public. However, quantify the state of ULL water quality is a challenge due to the large choice of possible water quality parameters used to describe it. Moreover, insufficient funding, particularly in developing countries, is one of the most common constraints towards long-term monitoring all water quality parameters as it is laborious and expensive. Therefore, how to evaluate the water quality status of ULLs simply and effectively becomes an issue drawing wide attention.

Traditional water quality assessments are based on the comparison of the water quality parameters of the lakes to existing water environment standards and/or criteria for various water bodies. The simplest index widely used in China is the single factor index. Nonetheless, such assessment may not provide an accurate estimate of the water quality of ULLs (Chang et al., 2019). Thus, a number of water quality parameters need to be systematically evaluated to obtain a rational depiction of the water quality status. A water quality index (WQI) combines the measures of several water quality parameters to produce a single dimensionless number, and has been widely used in the past as one of the most effective approaches to communicate information on water quality to the public and policy makers (Sutadian et al., 2016; Tripathi and Singal, 2019). Most WQIs have been used for general assessment of water quality (Sutadian et al., 2018; Tian et al., 2019), whereas some WQIs have targeted specific uses, such as the suitability assessment of the drinking water supply (Dippong et al., 2019; Mukate et al., 2019) as well as irrigation (Misaghi et al., 2017) and recreational uses (Azevedo Lopes et al., 2016). WQIs usually consider general water parameters, such as dissolved oxygen, pH, temperature, turbidity, and nutrients, among others. However, no single WQI has been globally accepted. Regarding the applicability of such WQIs to ULLs, these indices had been developed based on the information on other specific regions and areas and without considering the specific characteristics of ULLs.

ULLs as water-front enjoyment areas can provide primary contact recreational activities including swimming, and wading where the human body may come in direct contact with raw water, and second contact recreation activities including fishing, boating, and wandering where contact with the water is minimal (Smith et al., 2015). It is well known that, perception of water landscape can significantly influence the aesthetic and recreational value of these ULLs (Smith and Davies-Colley, 1992). The perception of water landscape depends on visual factors such as the physical appearance of the ULL including water transparency, water color, and turbidity (Liu et al., 2013). The water transparency is commonly estimated based on Secchi depth (SD), which is closely related to water landscapes, as the publics often respond to SD when deciding whether a water body is suitable for recreation (Lee and Lee, 2015; Smith et al., 2015). The relationship between public assessment of water quality and SD was positive and strong, with SD having predictive power of 74.2% (Lee, 2016). Hence, SD as an indicator of landscape effect is easily understood, and many non-scientists believe that a high SD is indicative of high water quality. For the limnologist, the SD is related to trophic states (Brezonik et al., 2019). Therefore, SD is required to bridge ULL water quality communication gaps between scientists and the public.

As most ULLs have small direct catchment, water replenishment is essential to maintain ecological water level and promote the renewal of water body. However, with the growing imbalance between urban water supply and demand, the traditional available sources of stream water and groundwater for the supplementation of ULLs have gradually declined. In such cases, development of alternative sources are becoming increasingly important, such as by reclaimed water use or implementing rainwater harvesting and supply systems (Ao et al., 2018). The reclaimed water from wastewater treatment plants (WWTPs) has been widely applied in ULL water replenishment due to its stability and controllability. Nevertheless, the distinct qualities of reclaimed water and stream water contribute to different effects on the water quality of ULLs replenished with these two types of water sources. To the best of our knowledge, no WQI in the literature has been constructed taking into account water transparency and replenishment water sources of the ULLs.

In this context, we propose a new water quality index for ULLs (WQI_{ULL}) considering the linkage between water transparency and other water quality parameters for assessing water quality for the purpose of water-front enjoyment. Based on the theoretical calculation of the SD, we propose a core set of parameters for use in the WQI_{ULL}. The sub-index values are obtained from quality curves depended on cumulative probability distributions. The subsequent determination of weights take into account the replenishment water sources of ULLs using sensitivity analysis, by exploring the importance of selected parameters to the water transparency. Finally, the relationship between the calculated WQI_{ULL} values using field survey data of 166 ULLs and the measured SD values is explored, in order to verify the applicability of the relatively simple index of WQI_{ULL}.

2. Material and methods

2.1. Data source

A field survey was conducted in summer 2016 for 166 ULLs covering a large area (22.55°N ~ 45.79°N, 98.28°E ~ 126.66°E) in China (Fig. 1). These monitored ULLs were selected based on their wide geographical range and morphological characteristics, diverse replenishment water sources, and prevailing water quality conditions. The surface area (A) of these ULLs ranges from 0.2 to 764 ha, and three classes were defined: small ($A \leq 5$ ha), medium ($5 \text{ ha} < A \leq 35$ ha), and large lakes ($A > 35$ ha), accounting for 24.7%, 48.2%, and 27.1%, respectively. The average water depth ranges from 0.5 to 12 m. The majority (>90%) are shallow lakes with an average depth of <5 m. These ULLs are regularly replenished by either traditional water resources (groundwater or stream water) (61.4%) or alternative water resources (reclaimed water or rainwater) (38.6%). The data on the operation and management of the ULLs, including replenishment water source, frequency, and amount, were provided by local authorities and/or managerial offices.

In the field survey, on-site sampling and water quality analysis were conducted regarding water temperature (T), dissolved oxygen (DO), suspended solids (SS), chemical oxygen demand (COD_{Mn}), ammonia (NH_4^+-N), nitrate (NO_3^--N), and total phosphorous (TP) using portable meters (for T, DO, and SS) and by Pack Test (for COD_{Mn}, NH_4^+-N, NO_3^--N, and TP using Kyoritsu Chemical-Check Lab. Corp., Japan). For each ULL, samples were collected in three consecutive days at 4 or 5 locations almost evenly covering the lake surface, and from a depth 0.5 ± 0.2 m

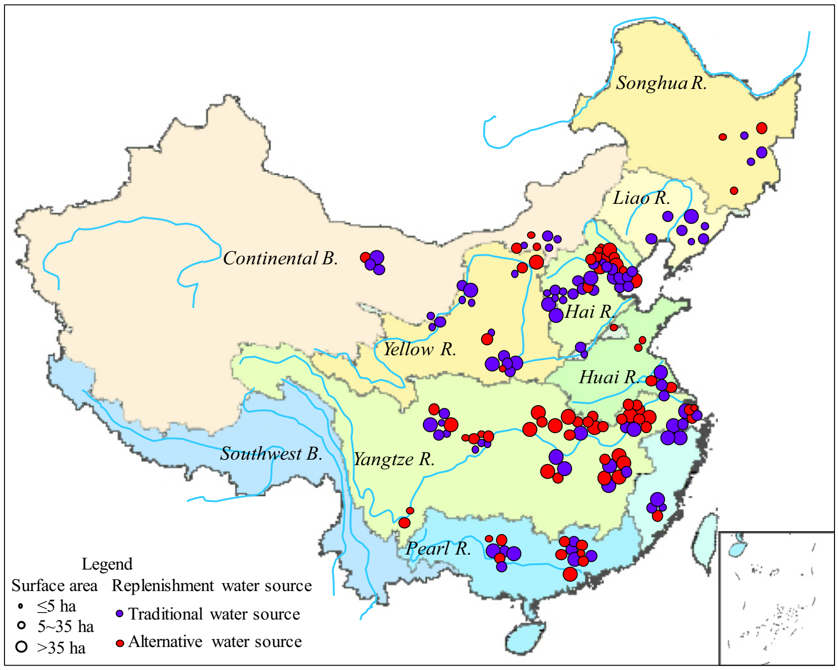

Fig. 1. Locations of 166 urban landscape lakes in China.

depending on site condition. The average hydraulic retention time (HRT) for each ULL was also evaluated according to its replenishing condition.

2.2. Methodological framework

The WQI_{ULL} was developed following a four-step framework (Tripathi and Singal, 2019) including the selection of parameters, obtaining sub-index values, establishing weights, and aggregation of sub-indices (Fig. 2).

Since the WQI_{ULL} created in the present study was adapted to ULLs, the parameters were designed to reflect the characteristics of ULLs. The water transparency in terms of SD, closely related to water landscape, acted as the basis for the development of WQI_{ULL}. By analyzing the related processes of the SD theory, appropriate and representative parameters of landscape water quality were selected. After the parameter selection, normalization was performed for the sub-index values, and the sub-index functions were created by the cumulative probability distribution curves of the selected parameters based on the field survey data from 166 widely distributed ULLs. Subsequently, weights were assigned to the selected parameters according to their relative importance and their influence on the final index. Taking into account the advantages, such as easy to perform and straightforward to interpret,

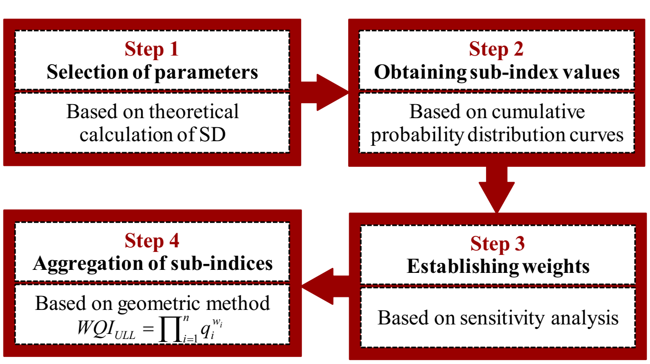

Fig. 2. Methodological framework for WQI_{ULL} development.

along with its successful application (Wan et al., 2012), the sensitivity analysis is found to be more appropriate for identifying the parameter weights in this study. The calculation of the SD was used to explore the sensitivity of each parameter to SD, and then the weights were obtained on the basis of the sensitivity coefficient of each parameter. Finally, an aggregation of the sub-indices was performed to obtain the final index value of WQI_{ULL}. Numerous aggregation methods are available in this step, such as the arithmetic, geometric, and harmonic square mean and the minimum operator (Sutadian et al., 2016). In this study, the weighted geometric mean was used to produce the final index due to its simplicity and extensive use. The final index is calculated using the following equation:

$$WQI_{ULL} = \prod_{i=1}^{n} {q_i}^{w_i} \tag{1}$$

where WQI_{ULL} is the water quality index for the ULLs; the index ranges from 0, representing the worst quality, to 100, representing the best quality; q_i is the i-th sub-index ranging from 0 to 100; n is number of parameters; w_i is the weight for the i-th parameter, ranging from 0 (least effect) to 1 (highest effect) and with $\sum_1^n w_i = 1$.

2.3. Parameter selection

Parameter selection is based on a consideration that water transparency in terms of Secchi Depth (SD) much reflects the aesthetic and recreational value of landscape water. In principle SD is an apparent optical property (AOP) which depends on the geometry of the ambient light field (Effler et al., 2017). AOP is influenced by the light attenuation processes of scattering and absorption governed by the inherent optical properties (Preisendorfer, 1986) which are determined by the composition and concentrations of several optically active constituents (West et al., 2016). According to Tyler (1968) and Preisendorfer (1986), SD can be theoretically calculated as:

$$\mathrm{SD} = \gamma/[\mathrm{c}(\lambda) + \mathrm{K}_d] \tag{2}$$

$$\mathrm{c}(\lambda) = \mathrm{a}(\lambda) + \mathrm{b}(\lambda) \tag{3}$$

where, SD is the water transparency (m); γ is the function of the contrast threshold of the human eye; λ is the wavelength (nm); $c(\lambda)$ and K_d are the depth-averaged beam and downwelling irradiance attenuation coefficients, respectively (m^{-1}); $a(\lambda)$ and $b(\lambda)$ are the total absorption and scattering coefficients of the water body, respectively (m^{-1}).

The optically active constituents that affect SD mainly include inorganic suspended particles and organic particulates such as phytoplankton and organic detritus (Håkanson and Boulion, 2003; Liu et al., 2013; Tilzer, 1988). In the authors' previous study (Ao et al., 2018), the following equations were proposed for showing the relationships between the light absorption/scattering coefficients and these optically active constituents.

$$a(\lambda) = a_w(\lambda) + a_\varphi(\lambda)\cdot[Chla] + a_{p-\varphi}(\lambda)\cdot[ISS] + a^*_{p-\varphi}(\lambda)\cdot[DC] \quad (4)$$

$$b(\lambda) = b_w(\lambda) + b_\varphi(\lambda)\cdot[Chla] + b_{p-\varphi}(\lambda)\cdot[ISS] + b^*_{p-\varphi}(\lambda)\cdot[DC] \quad (5)$$

where $a_w(\lambda)$ and $b_w(\lambda)$ are the absorption and scattering of pure water (m^{-1}), $a_\varphi(\lambda)$ and $b_\varphi(\lambda)$ are the chlorophyll-specific absorption and scattering coefficients (m^2/mg Chl*a*), $a_{p\text{-}\varphi}(\lambda)$ and $b_{p\text{-}\varphi}(\lambda)$ are the absorption and scattering coefficients of inorganic suspended solids (m^2/g ISS); $a_{p\text{-}\varphi}^*(\lambda)$ and $b_{p\text{-}\varphi}^*(\lambda)$ are the absorption and scattering coefficients of detritus carbon (m^2/g DC), respectively; [Chl*a*], [ISS], and [DC] represent phytoplankton biomass, inorganic suspended solids, and organic detritus, respectively, which measured as the concentrations of Chl*a* (μg/L), ISS (mg/L), and DC (mg/L), respectively.

Based on the relationship of SD with the substances existing in water as shown by Eq. (2) to Eq. (5), the parameters are to be selected from those closely related to the occurrence of Chl*a*, ISS, and DC in water.

2.4. Parameter normalization

Normalization of the parameters is necessary before calculating the WQI_{ULL} because the parameters are measured in different units. Threshold method was used to the normalization as follows:

$$X_i = \frac{x_i}{x_{i0}} \quad (6)$$

where X_i is the normalized value of the *i*-th parameter; x_i is the measured value of the *i*-th parameter; x_{i0} is the desired limit of the *i*-th parameter.

2.5. Sensitivity analysis

To obtain the weights for each parameter, one-at-a-time (OAT) sensitivity analysis was performed based on the theoretical calculation of the SD. As replenishment water sources have varied performances at different nutrition levels with varying effects on the SD, OAT sensitivity analysis was carried out considering different types of replenishment water sources. The ULLs were regularly replenished by stream water and groundwater as traditional sources; and rainwater (associated with rainwater harvesting, storage and supply facilities) and reclaimed water (from wastewater treatment systems) as alternative sources. Stream water was widely used traditional source, whereas reclaimed water was popularized alternative source. To this end, the sensitivity analysis considered under two scenarios (scenario 1 refers to the replenishment water sourcing from stream water, and scenario 2 refers to the replenishment water sourcing from reclaimed water) for exploring the potential influences of the parameters on the SD output. The parameter sensitivity is evaluated by sequentially perturbing one parameter at a time while the other parameters remain at the predefined base value (McKenzie et al., 2019). This process was performed using the MIKE software by embedding Eqs. (2)–(5) in the ECO Lab model (DHI, 2013). The sensitivity coefficient is defined as follows:

$$\beta_i = |\lambda_y/\lambda_x| = \left|\frac{\Delta y_i/y_0}{\Delta x_i/x_0}\right| \quad (7)$$

where, β_i is the sensitivity coefficient of the *i*-th parameter; λ_y is the variation rate of the SD affected by the *i*-th parameter; λ_x is the variation rate of the *i*-th parameter; Δy_i is the variation amplitude of the SD; Δx_i is the variation amplitude of the *i*-th parameter; y_0 is the baseline of the SD; x_0 is the baseline of the *i*-th parameter.

The weight w_i of the *i*-th parameter, which was a number between 0 and 1, was calculated using Eq. (8) based on the sensitivity coefficient:

$$w_i = \beta_i / \sum_{i=1}^{n} \beta_i \quad (8)$$

where w_i is the weight coefficient of the *i*-th parameter; β_i is the sensitivity coefficient of the *i*-th parameter; n is the number of selected parameters.

2.6. Data analysis

The data analysis was performed using the IBM SPSS Statistics 22.0 software (SPSS). The Shapiro-Wilk test was used as a normality test of the water quality data after $\log_{10}$-transformation. Subsequently, the cumulative probability distributions and fitted distributions were obtained based on the ranking of the transformed data, as listed in a frequency table. Pearson's correlations were used to identify the correlations between the two distribution curves. The relationship between the calculated WQI_{ULL} and measured SD based on the field data of 166 ULLs was determined to ensure the applicability of the results and the ability to drawn inferences from the index. Regression analysis was used to assess the relationship. The coefficient of determination (R^2) was calculated and served as a measure of accuracy and comparison of the indices (Tomas et al., 2017). The correlations were considered statistically significant at the 95% level ($p < 0.05$).

3. Results and discussion

3.1. Selected parameters

The occurrence of Chl*a*, ISS, and DC in water is closely related to a series of biological and hydraulic processes as shown in Fig. 3.

The generation of Chl*a* is through a photosynthetic process resulting in phytoplankton growth. This process mainly depends on sunlight radiation and consumption of nutrients, namely nitrogen and phosphorus. The nitrogen utilizable for phytoplankton growth can be in the form of ammonia or nitrate (Brezonik and Arnold, 2011). As a bioprocess, dissolved oxygen (DO) is also a determinative factor. Therefore, it can usually be supposed that under normal conditions NH_4^+-N, NO_3^--N, and TP (majorly in the form of PO_4^{3-}) are the main water quality parameters related to Chl*a*.

Regarding ISS, its main source is the suspended solids (SS) flowing into the water, and certain solid particles swept from the bottom sediments due to hydraulic disturbance (Madsen et al., 2001). Except for extreme conditions such as strong wind and heavy storm, the hydraulic retention time (HRT) can be taken as a parameter to characterize the hydraulic condition of a waterbody.

As for DC, its generation also relates to a complicated biological process involving the interaction between phytoplankton and zooplankton in water (Larson et al., 2007; Peng, 2010) and also the hydraulic disturbance that results in certain DC suspension from the bottom layer. As any increase of DC may ultimately result in an increase of organic concentration in terms of COD or BOD, under ordinary conditions it is reasonable to use COD or BOD as an alternative of DC for this study. For

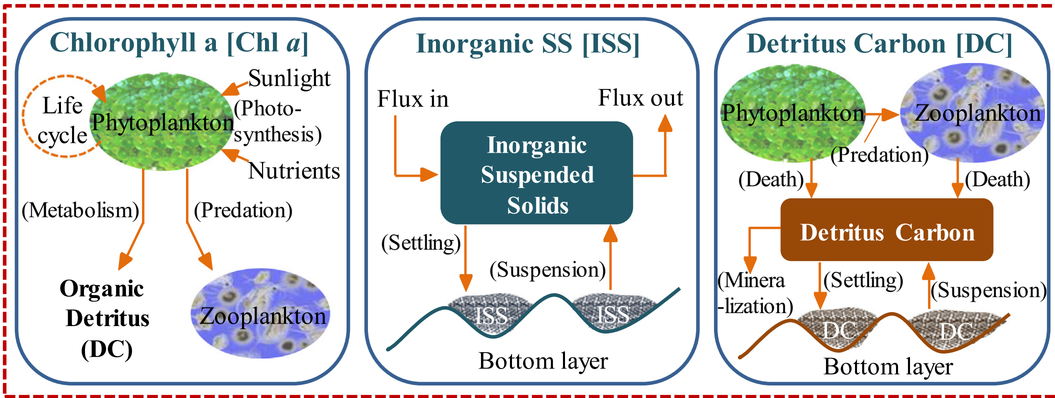

Fig. 3. Related biological and hydraulic processes to water transparency.

all the processes discussed above, water temperature (T) is an important factor to consider.

Based on the discussions above, it can be considered that the water transparency SD, although measurable by optical observation, is in fact a function of a number of independent variables such as NH_4^+-N, NO_3^--N, TP, DO, SS, COD, HRT, and T. Any variation in these parameters may bring about a change in SD because of the possibly varied concentrations of organic and inorganic particles, in terms of Chl*a*, ISS, and DC, which absorb and/or scatter light.

3.2. Corresponding sub-indices

Prior to the computation of the sub-indices, normalization of the parameters was performed using Eq. (6). The desired limit for each of the selected parameters was defined basically following the Chinese Surface Water Quality Standard (GB3838-2002). For those not specified in the standard, relevant literatures were referred (Table 1).

Then sub-index functions were created to determine the quality of the selected parameters (q_i) based on the cumulative distribution functions. The data of field survey of 166 ULLs were used for characterizing the cumulative distributions, as shown in Fig. 4; the *x*-axis represents the normalized expected range of the determined values (X_i) in the ULLs, and the *y*-axis represents the probability of the corresponding X_i; the range is from 0 to 1. The Shapiro-Wilk test showed that X_i had a lognormal distribution ($p > 0.05$). The probability density function of X_i is expressed in Eq. (9).

$$f(X_i) = \frac{1}{\sigma_i X_i \sqrt{2\pi}} \exp\left[-\frac{(\ln X_i - \mu_i)}{2\sigma_i^2}\right] \ (X_i > 0) \tag{9}$$

The cumulative distribution function is obtained using an integral transformation, as defined in Eq. (10).

$$F(X_i) = \varphi\left(\frac{\ln X_i - \mu_i}{\sigma_i}\right) = \int_0^{X_i} \frac{1}{\sigma_i X_i \sqrt{2\pi}} exp\left[-\frac{(\ln X_i - \mu_i)^2}{2\sigma_i^2}\right] dX_i \tag{10}$$

Table 1
Descriptive statistics of desired limits.

Parameter	SS (mg/L)	DO (mg/L)	COD_{Mn}[1] (mg/L)	NH_4^+-N (mg/L)	NO_3^--N (mg/L)	TP (mg/L)	HRT (d)	T (°C)
Desired limit	1[a]	DO_s[b]	2[c]	0.15[c]	0.15[c]	0.01[c]	3[d]	12[e]

[1] COD_{Mn} replaced COD because its availability from data source.
[a] Value from Abdul azis et al. (2018).
[b] DO_s is the saturation value of dissolved oxygen.
[c] Values from Grade I in Chinese Surface Water Quality Standard (GB3838-2002).
[d] Value from Qin et al. (2013).
[e] Value from Štambuk-Giljanović (1999).

where, $f(X_i)$ is the probability density function of X_i; $F(X_i)$ is the cumulative probability of X_i, in the range of 0–1; X_i is the normalized value of the *i*-th parameter; μ_i is the sample mean of the *i*-th parameter; σ_i is the sample standard deviation of the *i*-th parameter; μ_i and σ_i corresponding to the parameters, as displayed in Fig. 4.

Eq. (10) is used to obtain the q_i values of each parameter. For DO and T, the q_i had an inflection point. The DO_s for DO was considered as the q_i value of 100, i.e., the inflection point was $X_{DO} = 1$. If $X_{DO} < 1$, the value of q_{DO} increased with an increase in the DO value, whereas, if $X_{DO} > 1$, the value of q_{DO} decreased with an increase in the DO value. Therefore, Eq. (11) was used to generate the sub-index of DO. For T, the inflection point was 12 °C according to the rating curves of T from the Scottish Development Department and the Institute of Public Health Split (Štambuk-Giljanović, 1999). For $T \leq 12$ °C, $q_T = 100$, and for $T > 12$ °C, the value of q_T decreased with an increase in the T value. Consequently, the sub-index of T was computed using Eq. (12). Except for DO and T, the other six parameters had decreasing levels of water quality with an increase in the parameter values. Therefore, their sub-indices were computed using Eq. (13).

$$q_{DO} = \begin{cases} 100 \times 2[1 - F(X_{DO})], X_{DO} > 1 \\ 100 \times [2F(X_{DO})], X_{DO} \leq 1 \end{cases} \tag{11}$$

$$q_T = \begin{cases} 100, & T \leq 12 \text{ °C} \\ 100 \times [1 - F(X_T)], & T > 12 \text{ °C} \end{cases} \tag{12}$$

$$q_i = 100 \times [1 - F(X_i)] \tag{13}$$

where q_i is the *i*-th sub-index value, X_i is the normalized value of the *i*-th parameter, and $F(X_i)$ is the probability of X_i.

3.3. Determination of weights by sensitivity analysis

The base values of the eight parameters corresponding to the two scenarios are presented in Table 2. We performed 64 total simulations for the OAT sensitivity testing on each scenario: simulations were performed at eight evenly spaced values (base value ±10%, 20%, 30%, and 40%) for each of the eight parameters tested. The sensitivity coefficients were determined using Eq. (7).

Fig. 5 presents the sensitivity coefficients of the eight parameters for the two water replenishment scenarios. In scenario 1, the SS is the most important influencing factor for determining the SD output. The sensitivity coefficients of SS ranged from 0.148 to 0.236, with an average value of 0.184. The reason for the highest sensitivity of SS was attributed to SS is a key determinant of water transparency in ULLs where their aesthetic appeal may depend in part on transparency of the water

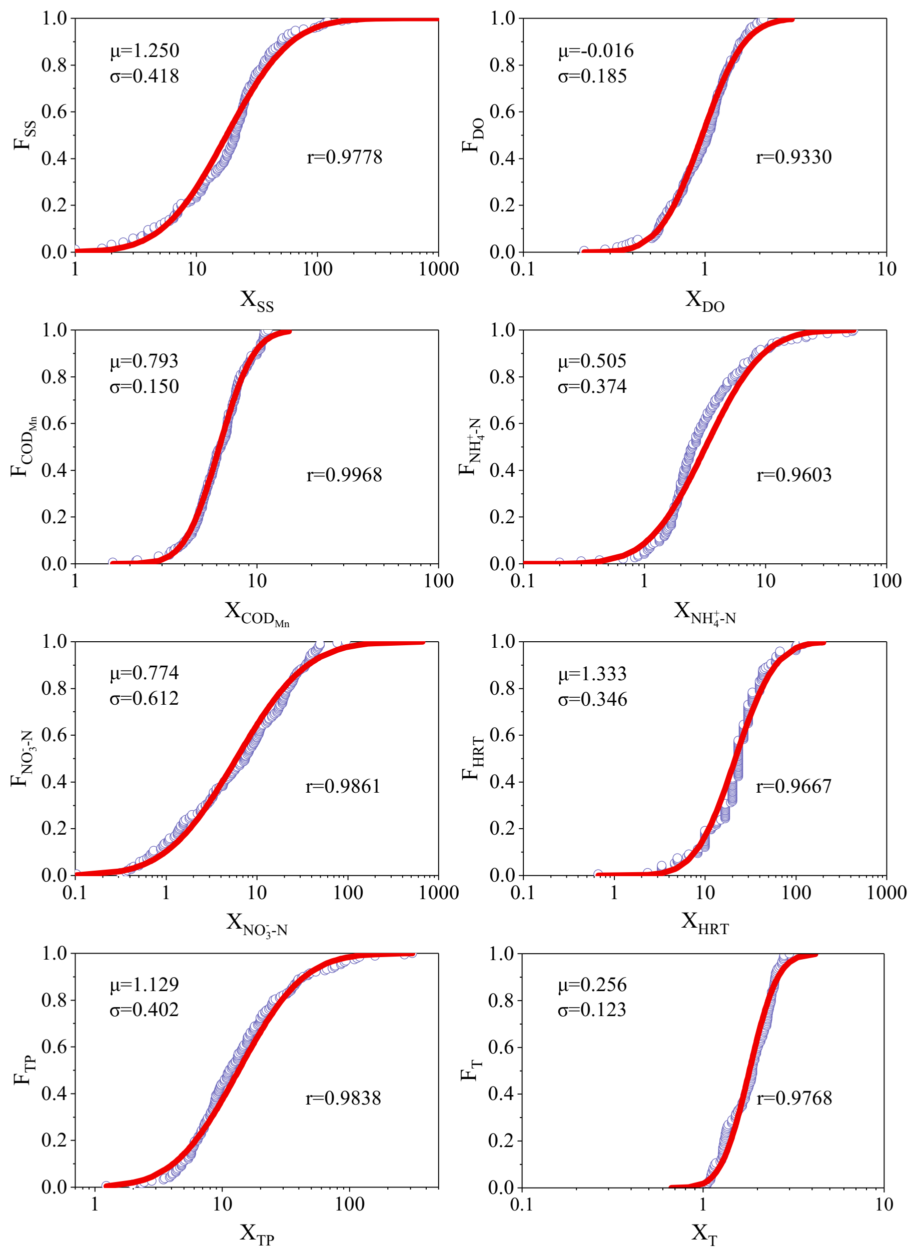

Fig. 4. Probability distribution curves for SS, DO, COD_{Mn}, NH_4^+-N, NO_3^--N, TP, HRT, and T.

(Brezonik et al., 2019). TP had the second-highest sensitivity coefficient with a range of 0.071–0.162 and an average of 0.108. This result supports earlier studies that phosphorous (instead of nitrogen) is the primary limiting factor of algae growth (Qin et al., 2013). Algae growth as a result of eutrophication is the primary determinant of SD. HRT had the third-highest sensitivity coefficient, with a range of 0.084–0.134 and an average value of 0.102. The sensitivity coefficients of NH_4^+-N and NO_3^--N were not significantly different and had similar average values (NH_4^+-N: 0.087 and NO_3^--N: 0.088). COD_{Mn} had sensitivity coefficients in the range of 0.047–0.113, with an average value of 0.074. The sensitivities of T (0.015–0.067) and DO (0.010–0.043) were relatively low. The SS, TP, and HRT were considerably more important than the other parameters in scenario 1.

Table 2
Scenarios for sensitivity analysis.

Parameter	SS (mg/L)	DO (mg/L)	COD_{Mn} (mg/L)	NH_4^+-N (mg/L)	NO_3^--N (mg/L)	TP (mg/L)	HRT (d)	T (°C)
Scenario 1	20[a]	3[b]	10[b]	1.5[b]	1.5[b]	0.1[b]	30[c]	12[d]
Scenario 2	10[e]	1.5[e]	10[b]	5[e]	10[e]	0.5[e]	15[f]	12[d]

[a] Value from Abdul azis et al. (2018).
[b] Values from Chinese surface water quality standard (GB3838-2002, Grade IV).
[c] Value from 25th percentile of the population distribution of traditional water source replenished ULLs.
[d] Value from Štambuk-Giljanović (1999).
[e] Values from wastewater reuse regulation (GB/T18921-2002).
[f] Value from 25th percentile of the population distribution of alternative water source replenished ULLs.

Fig. 5 shows different results for the sensitivity coefficients of the eight parameters in scenario 2. The first- and second-highest coefficients were observed for HRT (0.181) and COD_{Mn} (0.150), followed by T (0.080) and SS (0.070). NH_4^+-N, NO_3^--N, and TP had lower sensitivity coefficients and similar average values (NH_4^+-N: 0.060, NO_3^--N: 0.056, and TP: 0.061), whereas DO (0.041) had the lowest sensitivity coefficient. In this scenario, the highest sensitivity coefficient of HRT was attributed to the high contents of nitrogen (NH_4^+-N = 5 mg/L, NO_3^--N = 10 mg/L) and phosphorus (TP = 0.5 mg/L) in the replenishment

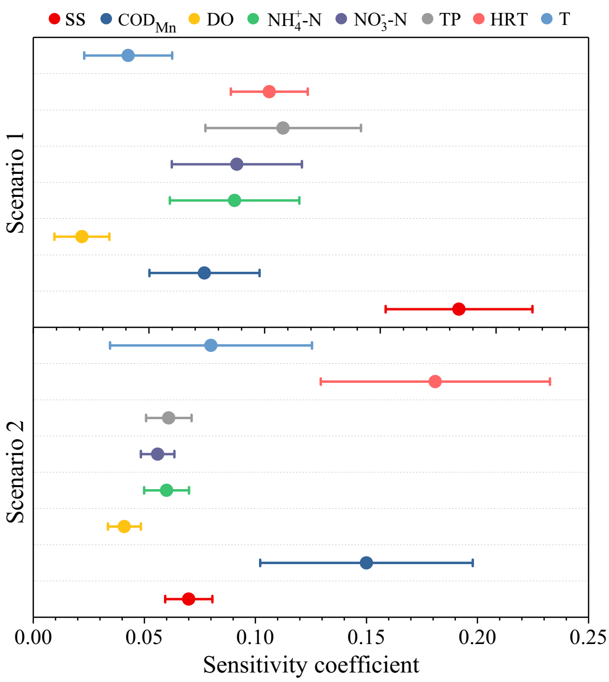

Fig. 5. Sensitivity coefficients of eight parameters for two scenarios (scenario 1 refers to replenishment water sourcing from stream water (traditional source), and scenario 2 refers to replenishment water sourcing from reclaimed water (alternative source)).

water of reclaimed water from WWTPs, which pose a high risk of algal blooms. The fact that nutrient concentrations have generally increased is, in itself, insufficient for the promotion of algal blooms. It is a change in nutrient concentrations that is leading to the supply of the right nutrients at the right time that helps to create conditions conducive to specific algal blooms (Glibert, 2020). Especially, the hydraulic retention zone is important for algal blooms whenever favorable conditions occur, which are known to influence SD. This result is consistent with the previous study of water exchange effect on eutrophication in landscape water body supplemented by reclaimed water, indicating phytoplankton production in water bodies is significantly affected by HRT (Qin et al., 2013). Moreover, the metabolism of algae may have led to changes in COD_{Mn}; significant algal mortality may have led to an increase in COD_{Mn}. Thus, the sensitivity analysis result of scenario 2 indicated that HRT and COD_{Mn} were the two most important parameters.

By comparison, the T exhibited higher sensitivity in scenario 2 than in scenario 1. T is a critical parameter as it governs the kinds and types of aquatic life, regulates the maximum DO of the water, and affects physical, chemical and biological processes in water bodies (Sutadian et al., 2018). Warmer temperature condition is thought to favor many algal blooms species, especially at a high nutrient level, which was the reason for the significant influence of the T in scenario 2 (Paerl and Scott, 2010). Similar to scenario 1, the parameter with the least sensitivity coefficient to SD was DO in scenario 2. DO is well recognized as primary indicator of lake water quality since oxygen is essential to all forms of aquatic life. Nevertheless, there was no significant relationship between SD and DO based on the theoretical calculation of SD, so as to the the least sensitivity coefficient of DO. This was also corroborated by the vast majority of ULLs presents high DO (almost always close to the saturation) and does not show much variations.

Fig. 6 presents the weights of the eight parameters for the two scenarios using Eq. (8). The ranking of the weights was as follows for scenario 1: SS (0.261) > TP (0.153) > HRT (0.145) > NO_3^--N (0.125) > NH_4^+-N (0.123) > COD_{Mn} (0.105) > T (0.058) > DO (0.030); for scenario 2: HRT (0.259) > COD_{Mn} (0.215) > T (0.114) > SS (0.100) > TP (0.087) > NH_4^+-N (0.086) > NO_3^--N (0.080) > DO (0.059). The maximum weight occurred for SS (0.261) in scenario 1 and for HRT (0.259) in scenario 2, and the minimum weights occurred for DO (scenario 1: 0.030, scenario 2: 0.059). This result was in agreement with the findings of the sensitivity analysis, which showed that SS and HRT were the most important influencing factors on the water quality for scenario 1 and scenario 2, respectively. The highest weight for SS in scenario 1 indicated that the control of the concentration of SS of the replenishment water source should be the top priority for water quality managers. Phosphorus was also the target pollutant to be controlled in landscape water management. The highest weight for HRT in scenario 2 showed that increasing the water exchange in the ULLs replenished with alternative water sources should be the top priority for water quality managers. In addition, the COD_{Mn} was also an important pollutant should be controlled in landscape water management.

3.4. Relationship between the calculated WQI_{ULL} and measured SD

The WQI_{ULL} developed in the present study considered eight parameters to characterize the water quality of ULLs: SS, DO, COD, NH_4^+-N, NO_3^--N, TP, HRT, and T. In order to evaluate the applicability of the WQI_{ULL}, the relationship between the calculated WQI_{ULL} and the measured SD of 166 ULLs was used to assess the fitting degree. As shown in Fig. 7, a close relationship between the WQI_{ULL} and the SD is clear. The WQI_{ULL} value for the 166 ULLs ranges from 9.39 to 90.80, with an average value of 55.32, and the corresponding SD values were 0.20 m, 2.50 m, and 0.65 m, respectively. The regression analysis of the relationship between the WQI_{ULL} and SD provide a coefficient of determination of $R^2 = 0.8948$ ($p < 0.05$), indicating a significant positive correlation. The high correlation supports the use of the WQI_{ULL} as a valuable tool to evaluate water landscape. Regarding ULLs with different replenishment sources, there are some differences since the source water quality influenced the parameter values and then the calculated WQI_{ULL}.

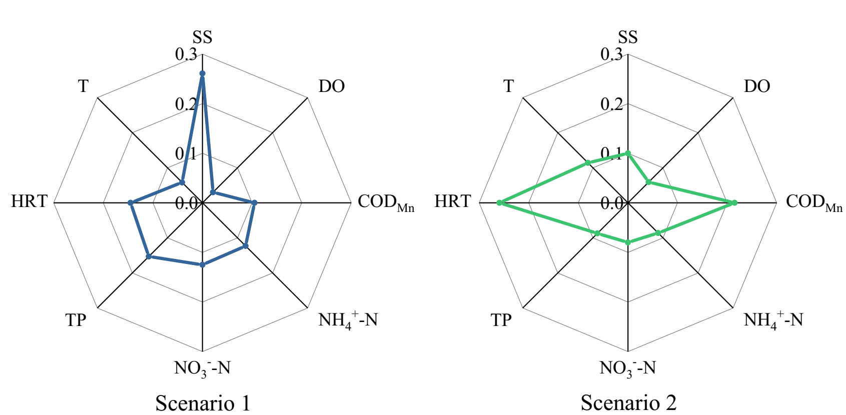

Fig. 6. Weighting coefficients of eight parameters for two scenarios.

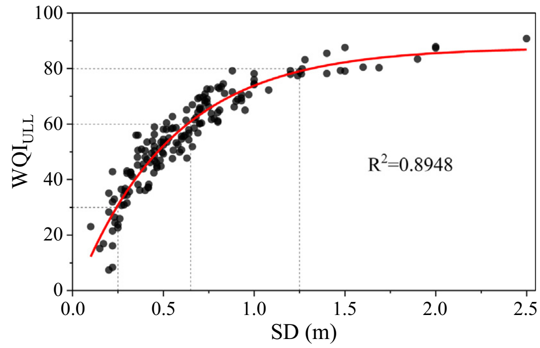

Fig. 7. Relationship between the calculated WQI_{ULL} and measured SD.

In order to ensure that landscape water quality classification is understandable, adoption of a representative indicator of satisfactory degree was necessary. Because the closely correlation between SD and public satisfactory degree (Chang et al., 2019; Lee and Lee, 2015), SD was used to classify the landscape water quality. With respect to the satisfactory degree of recreation or aesthetic appeal, water with an SD higher than 1.25 m was regarded as excellent, associated with the highest satisfaction level; 0.65 m < SD < 1.25 m was regarded as good; 0.25 m < SD < 0.65 m was regarded as acceptable; SD < 0.25 m was regarded as poor, associated with the lowest satisfaction level (Lee and Lee, 2015). These four intervals were then used to classify the data of the proposed WQI_{ULL} into four categories. According to the relationship between the calculated WQI_{ULL} and measured SD, the four categories are $WQI_{ULL} \geq 80$, excellent; 60–80, good; 30–60, acceptable; and $WQI_{ULL} < 30$ (Table 3).

It can be concluded that the developed WQI_{ULL} for ULLs provides an effective tool for communicating quality data to the public and policy makers. This index can also be used to express the general state of water quality spatially and temporally. It is also able to compare water quality of ULLs with different replenishment water sources in a simple and understandable manner, without undertaking highly technical assessment of water quality data.

4. Conclusions

The novel landscape water quality index of WQI_{ULL} has been developed in this study under the consideration that water transparency in terms of SD to a determinative degree governs the water landscape effect. Theoretical analysis has indicated that the three kinds of suspended matters in water, namely Chl*a* as a result of eutrophication, ISS due to inflow and/or hydraulic scour of sediments, and DC from exogenous and/or endogenous sources. By further analyzing the related processes, eight parameters have been identified to influence SD and therefore the landscape water quality. For the development of the WQI_{ULL} with the eight parameters as sub-indices, data of field survey of 166 ULLs have been used for characterizing the cumulative probability distribution curve of each sub-index and sensitive analysis to obtain the sub-index weight. The method of landscape water quality evaluation and classification eventually formulated in this study has shown the applicability of the relatively simple index of $WQI_{ULL} = \prod_{i=1}^{n} q_i^{w_i}$ in practical cases, as have been seen from the good correlative relationship between the calculated WQI_{ULL} and the measured SD. It is also noticeable that SD, although measurable by optical observation, is not a simple water quality factor but a function of the eight parameters identified in this study. Therefore, the novel index developed can also provide a tool to predict the variation of the landscape effect due to changes in normal quality parameters.

Table 3
Classifications proposed for the developed WQI_{ULL}.

WQI_{ULL} value	SD (m)	Classification
80–100	>1.25	Excellent
60–80	0.65–1.25	Good
30–60	0.25–0.65	Acceptable
0–30	<0.25	Poor

CRediT authorship contribution statement

Nini Chang: Conceptualization, Methodology, Software, Investigation, Writing - original draft. **Li Luo:** Formal analysis, Supervision, Writing - review & editing. **Xiaochang C. Wang:** Funding acquisition, Resources, Writing - review & editing. **Jia Song:** Data curation, Writing - review & editing. **Jiaxing Han:** Resources, Software, Supervision. **Dong Ao:** Software, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

Abdul azis, P., Mancera-Pineda, J.E., Gavio, B., 2018. Rapid assessment of coastal water quality for recreational purposes: methodological proposal. Ocean & Coastal Management 151, 118–126.
Ao, D., Luo, L., Dzakpasu, M., Chen, R., Xue, T., Wang, X.C., 2018. Replenishment of landscape water with reclaimed water: optimization of supply scheme using transparency as an indicator. Ecol. Indic. 88, 503–511.
Azevedo Lopes, F.W., Davies-Colley, R.J., Von Sperling, E., Magalhaes .Jr., A.P., 2016. A water quality index for recreation in Brazilian freshwaters. Journal of Water & Health 14, 243–254.
Birch, S., McCaskie, J., 1999. Shallow urban lakes: a challenge for lake management. Hydrobiologia 395, 365–377.
Brezonik, P.L., Arnold, W.A., 2011. Water Chemistry: An Introduction to the Chemistry of Natural and Engineered Aquatic Systems. Oxford University Press.
Brezonik, P.L., Bouchard Jr., R.W., Finlay, J.C., Griffin, C.G., Olmanson, L.G., Anderson, J.P., Arnold, W.A., Hozalski, R., 2019. Color, chlorophyll a, and suspended solids effects on Secchi depth in lakes: implications for trophic state assessment. Ecol. Appl. 29, e01871.
Chang, N., Zhang, Q., Wang, Q., Luo, L., Wang, X.C., Xiong, J., Han, J., 2019. Current status and characteristics of urban landscape lakes in China. Sci. Total Environ. 135669.
Danish Hydraulic Institute (DHI), 2013. MIKE 3 Flow Model FM: Eutrophication Model 2 Eco Lab Template – Scientific Description. DHI-Water. Environment and Health, Hørsholm, Denmark.
Dippong, T., Mihali, C., Hoaghia, M.A., Cical, E., Cosma, A., 2019. Chemical modeling of groundwater quality in the aquifer of Seini town - Somes Plain, Northwestern Romania. Ecotoxicology and Environmental Saf ety 168, 88–101.
Effler, S.W., Strait, C., O'Donnell, D.M., Effler, A.J.P., Peng, F., Prestigiacomo, A.R., O'Donnell, S.M., Perkins, M., Chapra, S.C., 2017. A mechanistic model for Secchi disk depth, driven by light scattering constituents. Water Air Soil Pollut. 228, 153.
Glibert, P.M., 2020. Harmful algae at the complex nexus of eutrophication and climate change. Harmful Algae 91.
Håkanson, L., Boulion, V.V., 2003. A model to predict how individual factors influence Secchi depth variations among and within lakes. Int. Rev. Hydrobiol. 88, 212–232.
Larson, G.L., Hoffman, R.L., Hargreaves, B.R., Collier, R.W., 2007. Predicting Secchi disk depth from average beam attenuation in a deep, ultra-clear lake. Hydrobiologia 574, 141–148.
Lee, L.H., 2016. The relationship between visual satisfaction and water clarity and quality Management in Tourism Fishing Ports. Journal of Water Resource and Protection 8, 787–796.
Lee, L.H., Lee, Y.D., 2015. The impact of water quality on the visual and olfactory satisfaction of tourists. Ocean & Coastal Management 105, 92–99.
Liu, J., Sun, D., Zhang, Y., Li, Y., 2013. Pre-classification improves relationships between water clarity, light attenuation, and suspended particulates in turbid inland waters. Hydrobiologia 711, 71–86.
Madsen, J.D., Chambers, P.A., James, W.F., Koch, E.W., Westlake, D.F., 2001. The interaction between water movement, sediment dynamics and submersed macrophytes. Hydrobiologia 444, 71–84.

McKenzie, P.F., Duveneck, M.J., Morreale, L.L., Thompson, J.R., 2019. Local and global parameter sensitivity within an ecophysiologically based forest landscape model. Environ. Model Softw. 117, 1–13.
Misaghi, F., Delgosha, F., Razzaghmanesh, M., Myers, B., 2017. Introducing a water quality index for assessing water for irrigation purposes: a case study of the Ghezel Ozan River. Sci. Total Environ. 589, 107–116.
Mukate, S., Wagh, V., Panaskar, D., Jacobs, J.A., Sawant, A., 2019. Development of new integrated water quality index (IWQI) model to evaluate the drinking suitability of water. Ecol. Indic. 101, 348–354.
Paerl, H.W., Scott, J.T., 2010. Throwing fuel on the fire: synergistic effects of excessive nitrogen inputs and global waeming on harmful algal blooms. Environmental Science & Technology 44, 7756–7758.
Peng, D., 2010. Water Pollution Control Engineering. Metallurgical Industry Press.
Preisendorfer, R.W., 1986. Secchi disk science: visual optics of natural waters. Limnol. Oceanogr. 31, 909–926.
Qin, H.P., Khu, S.T., Li, C., 2013. Water exchange effect on eutrophication in landscape water body supplemented by treated wastewater. Urban Water J. 11, 108–115.
Smith, D.G., Davies-Colley, R.J., 1992. Perception of water clarity and colour in terms of suitability for recreational use. J. Environ. Manag. 36, 225–235.
Smith, A.J., Duffy, B.T., Novak, M.A., 2015. Observer rating of recreational use in wadeable streams of New York State, USA: implications for nutrient criteria development. Water Res. 69, 195–209.
Štambuk-Giljanović, N., 1999. Water quality evaluation by index in Dalmatia. Water Res. 33, 3423–3440.
Sutadian, A.D., Muttil, N., Yilmaz, A.G., Perera, B.J., 2016. Development of river water quality indices-a review. Environmental Monitoring & Assessment 188, 58.
Sutadian, A.D., Muttil, N., Yilmaz, A.G., Perera, B.J.C., 2018. Development of a water quality index for rivers in West Java Province, Indonesia. Ecol. Indic. 85, 966–982.
Tian, Y., Jiang, Y., Liu, Q., Dong, M., Xu, D., Liu, Y., Xu, X., 2019. Using a water quality index to assess the water quality of the upper and middle streams of the Luanhe River, northern China. Sci. Total Environ. 667, 142–151.
Tilzer, M.M., 1988. Secchi disk — chlorophyll relationships in a lake with highly variable phytoplankton biomass. Hydrobiologia 162, 163–171.
Tomas, D., Čurlin, M., Marić, A.S., 2017. Assessing the surface water status in Pannonian ecoregion by the water quality index model. Ecol. Indic. 79, 182–190.
Tripathi, M., Singal, S.K., 2019. Use of Principal Component Analysis for parameter selection for development of a novel Water Quality Index: A case study of river Ganga India. Ecol. Indic. 96, 430–436.
Tyler, J.E., 1968. The secchi disc. Limnol. Oceanogr. 13, 1–6.
Wan, L., Liu, J., Zhao, Z., Dong, Y., Cheng, Z., 2012. Layered sensitivity analysis and weight determination of rock slope stability impacting factors. Water Resources and Hydropower Engineering 43, 59–62.
West, A.O., Nolan, J.M., Scott, J.T., 2016. Optical water quality and human perceptions of rivers an ethnohydrology study. Ecosystem Health and Sustainability 2, 167–180.