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Quantitative assessment of the effects of human activities on phytoplankton communities in lakes and reservoirs

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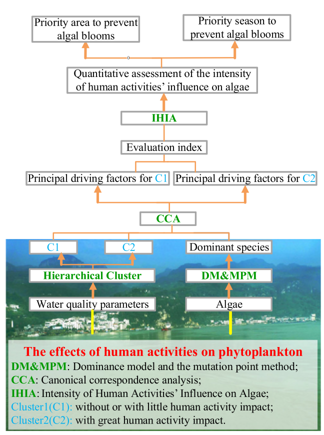
HIGHLIGHTS

- We presented a methodology for evaluation of human impact on phytoplankton.
- Quantitative assessment of human activity impact levels can be achieved.
- It can identify priority areas for the prevention and control of algal blooms.

GRAPHICAL ABSTRACT



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ABSTRACT

Global algal blooms have been severely threatening safety of drinking water and development of socio-economy. Effective prevention and accurate control of algal blooms require a quantitative assessment of the influence of human activities and identification of priority areas. However, previous studies on the quantitative assessment of the effects of human activities on algal communities are lacking, severely hindering the effective and precise control of algal blooms. This paper proposes a quantitative assessment model to evaluate the impact intensity of human activities on phytoplankton. Applications showed that the proliferation of phytoplankton were more limited by nutrients such as total phosphorus and ammonia where waters are less influenced by human activities, yet were less limited by these nutrients where there are highly intensive human activities. The density of phytoplankton in waters increased with an increase in human activity intensity, particularly in concentrated agricultural areas, which are priority areas for the prevention and control of algal blooms. The methodologies can clearly identify key areas for algal bloom prevention and control and can provide scientific evidence for water and nutrient management throughout the world, reducing the risk of algal blooms and ensuring aquatic ecosystem health and potable water safety.

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1. Introduction

Population growth and social development contribute to the increased impact of human activities on the natural environment (Halpern et al., 2008). For surface water ecosystems, as human water consumption increases daily, industrial wastewater, agricultural water withdrawal, and domestic sewage continue to flow into rivers and lakes, increasing the eutrophication of inland waters (Eom et al., 2017; Lv et al., 2014; Zhao et al., 2018a). Lakes and reservoirs are among the main carriers of surface freshwater resources. These water bodies have a slow flow rate, long water residence time, and low self-purification capacity and nutrients are more likely to accumulate to create environmental conditions favorable to algal blooms (Havens et al., 2001; Yang et al., 2012; Wang et al., 2016a).

During recent centuries, human activities have become the dominant negative factors affecting the stability of the natural environment in all spheres of the earth (Kerr, 2000; Tollefson, 2012; Yang et al., 2017). Frequent outbreaks of algal blooms have become typical events affecting the earth's atmosphere as a result of human activities (Duan et al., 2009; Isabwe et al., 2018). During recent years, algal blooms in lakes and reservoirs around the world have frequently occurred (Joehnk et al., 2008). The algal blooms are the result of large-scale reproduction of phytoplankton under suitable environmental conditions (Scholz-Starke et al., 2018), which ultimately change the dissolved oxygen (DO) conditions, eventually leading to the death of many aquatic animals and seriously damaging the health of the aquatic ecosystem (O'Boyle et al., 2016). Moreover, some phytoplankton also produce biotoxins, such as microcystin, which affect the safety of drinking water and human health (Brookes and Carey, 2011; Carmichael and Boyer, 2016; Tollefson, 2018).

The prevention and control of algal blooms is a research focus of recent years (Morse et al., 2013; Jetoo, 2018). Identification of the key driving factors for the variation of phytoplankton communities and identification of priority areas are the foundation for the prevention and control of algal blooms (Soares et al., 2009; Phlips et al., 2011; Duan et al., 2018). However, previous research determining key driving factors of the variation of phytoplankton communities is mostly focused on a single large lake and reservoir, whereas only a few comparative analyses have been conducted on multiple lakes and reservoirs (Lehman et al., 2009; Joung et al., 2011; Bucak et al., 2018). Particularly, there is a lack of studies identifying key phytoplankton driving factors and priority areas for the prevention and control of blooms in multiple lakes and reservoirs in the same region, under different gradients of human activity influence. This is unfavorable for the joint prevention and management of regional algal blooms, leading to a waste of manpower and material resources as well as a low prevention and control efficiency. The impact of human activities on phytoplankton communities has been mentioned in numerous studies (Anderson et al., 2002; Strayer and Dudgeon, 2010). However, the lack of a quantitative assessment has resulted in great uncertainty in the control of lakes and reservoirs, hindering the precise control of algal blooms. Quantitatively assessing the impact of human activities on phytoplankton communities could elucidate the extent of human activities' effects on phytoplankton communities, identify key driving factors and priority areas for prevention and control. Then, result in timely and precise measures to reduce the impact of human activities to reduce the risk of algal blooms and ensure the health of the regional aquatic ecosystem and the safety of the water supply.

Quantitative assessments of the impact of human activities on the natural environment are previously concentrated in marine ecosystems (Lorance et al., 2009; Nemati et al., 2017), wetland ecosystems (Sheng et al., 2013), river runoff (Zhang et al., 2018), and water resources assessments (Teodosiu et al., 2015). But few reports were found about the quantitative assessment of human impact on phytoplankton. In the previous quantitative assessment methods, multi-index weighted overlaying method is the most effective evaluation method (Gao and Wu, 2010; Shi et al., 2017), and it generally includes the creation of an assessment index system, weight determination, and the determination of evaluation criteria (Zhu et al., 2015). The quantitative assessment method laid scientific foundation for the wise management on the above-discussed natural environment (Korpinen et al., 2013). Lack of quantitative assessment of human impact on phytoplankton will bring great uncertainties on assessment results and therefore severely hinders the effective management on harmful alga.

The objective of this study is to develop an evaluation index of the effects of human activities on phytoplankton in combination with the selection of key driving factors in the variation of a phytoplankton community. The weight of each key driving factor was objectively determined, and the influence of human activities on phytoplankton was quantitatively evaluated, providing fundamental knowledge and a methodology for the precise control of algal blooms. Then we can identify key areas for algal bloom prevention and control, and further provide scientific evidence for accurate control of the water quality of lakes and reservoirs around the world. Our method needs little expertise so that it may be popularized for widespread use. The method and results are useful in guiding managers to implement timely and precise measures to control the impact of human activities, reduce the risk of algal blooms, and ensure aquatic ecosystem health as well as the safety of drinking water.

2. Materials and methods

2.1. Study area

The Spring City, Jinan City (36.0–37.5N, 116.2–117.7E), is bordered by Mount Tai to the south and traversed by the Yellow River; steeper topography occurs in the south than in the north (Fig. 1). Hilly areas, a piedmont clinoplain, and alluvial plains span the city from south to north. The altitude within the area ranges from −30 to 937 m above sea level, with highly contrasting relief. The semi-humid continental monsoonal climate in the city area is characterized by cold, dry winters and hot, wet summers. The average annual precipitation is 636 mm, 75% of which falls during high-flow periods. The average annual temperature is 14.3 °C. The average monthly temperature is highest during July, ranging from 26.8 to 27.4 °C, and lowest during January, ranging from 3.2 to 1.4 °C (Cui et al., 2009; Zhang et al., 2010). The city represents a typical developing city in China, with an area of 8227 km^2 and a population of 5.69 million (Zhang et al., 2007). With rapid industrial development and urbanization during recent decades, large amounts of nutrients flow into its lakes and reservoirs. Therefore, the water resources in the lakes/reservoirs are severely polluted and the risk of an algal bloom is unprecedentedly high. As a result, drinking water, and human health and well-being, are increasingly threatened (Hong et al., 2010).

2.2. Data

During the spring, summer, and autumn of 2014 and 2015, six water quality and aquatic organism samplings were conducted in 13 reservoirs and 2 lakes of Jinan City. A large number of synchronization data on water quality and aquatic organisms were obtained, which provided a rich database for the screening of dominant phytoplankton species, the identification of key driving factors, and therefore the quantitative impact assessment of human activities on phytoplankton as well as the identification of priority areas for algal bloom prevention and control.

2.2.1. Phytoplankton data

At the monitoring stations, a 1000 mL-capacity organic glass bottle was used to sample water from 0 to 2 m below the water surface. A 1.5% concentration Lugol's solution was added to the bottle as quickly as possible. In the laboratory, a 24-h sedimentation method was used

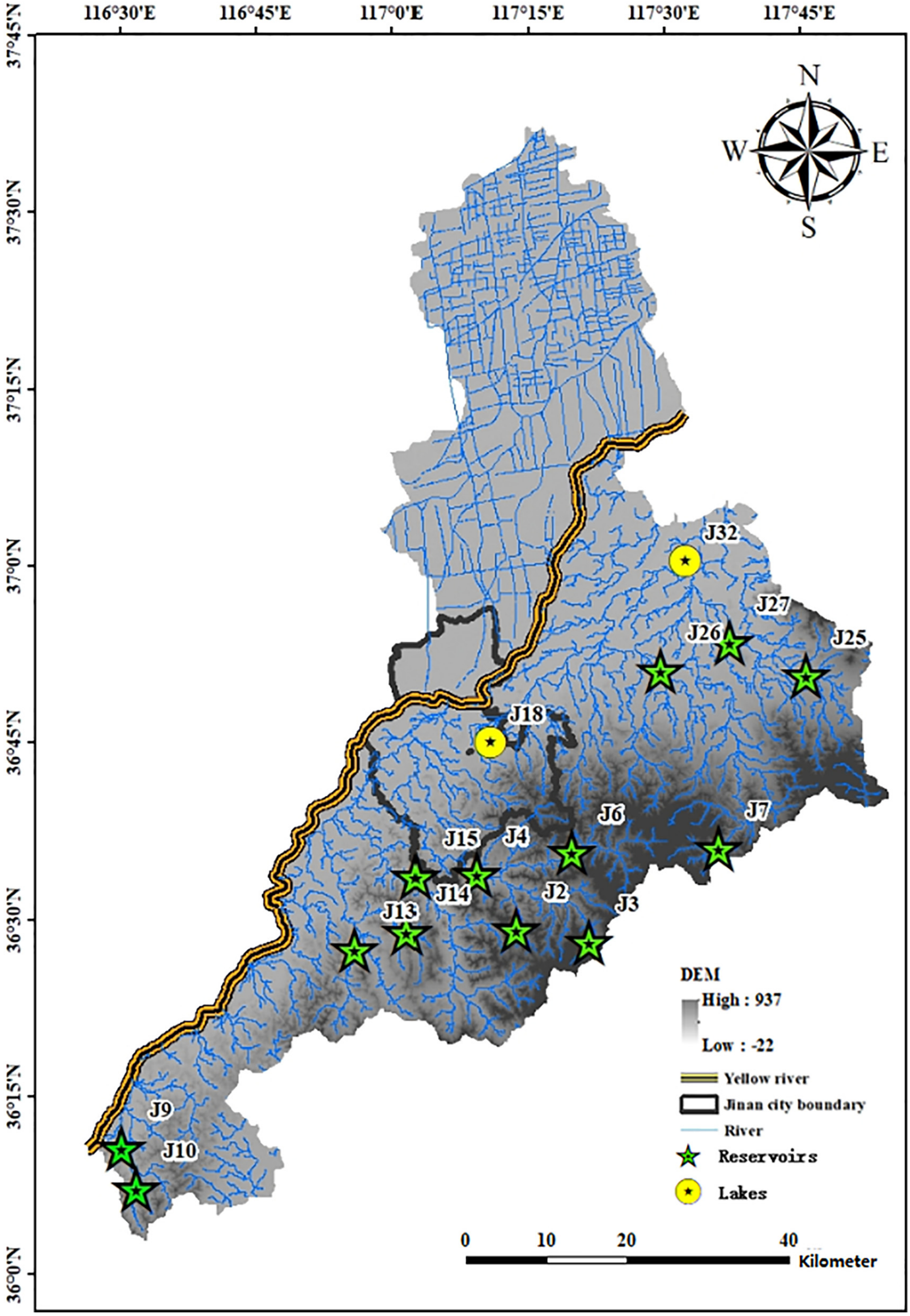

Fig. 1. Lakes/reservoirs of Jinan City and the suburban areas and locations of hydrology, water quality, and aquatic ecosystem monitoring stations.

to concentrate the phytoplankton sample to 30 mL. A 0.1-mL subsample was taken from the 30-mL concentrated sample and loaded into a 0.1-mL plankton counting chamber. Finally, the phytoplankton were counted using Utermöhl's inverted plankton microscope. Details of the techniques employed are described by Zhao et al. (2012).

2.2.2. Water quality data

During the six field investigations, 90 water samples were collected form 13 reservoirs and 2 lakes. The physical parameters listed in Table 1 were measured in situ with portable equipment and the chemical parameters in Table 2 were obtained by testing water samples collected at the monitoring stations in the laboratory within 24 h. We measured water temperature (WT), pH, and dissolved oxygen (DO) using a portable HACH PC101. An atomic absorption spectrophotometer (Thermo M6) was used for tests of zinc (Zn), cadmium (Cd), lead (Pb), copper (Cu), etc. A spectrophotometer (DR5000) was used to measure total nitrogen (TN), ammonia nitrogen (NH_3-N), hexavalent chromium, and total phosphorus (TP); an ion chromatograph (DIONEX-600) was employed to measure sulfate, fluoride, chloride, and nitrate concentrations; and an Automatic Flow Injection Analyzer (SKALAR SAN++) was used to measure cyanide, volatile phenol, and anionic detergent. Of the 27 chemicals measured, the concentrations of many of them were at or below the limits of detection for >80% of the sampling stations, and are, thus, not listed in Table 1. Details of the techniques employed are described by Zhao et al. (2015b).

2.3. Method

2.3.1. Hierarchical clustering

Cluster analysis is a statistical method for classifying samples (Murtagh and Contreras, 2017; Caesar et al., 2018). Hierarchical clustering, also known as hierarchical cluster analysis, is the most common method in cluster analysis (Pagnuco et al., 2017; Dos Santos et al., 2018). Hierarchical clustering is an exploratory factor analysis. Its purpose is to reasonably divide the samples based on certain rules, to make the distance between similar types of samples as short as possible and the distance between different types of samples as long as possible, and to find hidden data distribution and patterns from large amounts of data (Pan, 2010; Qi et al., 2017).

In this study, hierarchical clustering was performed based on the mean value of a total of six samplings of the key driving factors at each sampling station. To facilitate the calculation, data in a (n*m) matrix was pre-processed using the model $x'_{ij} = \frac{(x_{ij}-\bar{x}_j)}{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_{ij}-\bar{x}_j)}}$ $(I = 1,\dots,n;$ $j=1,\dots,m)$ with the average value $\bar{x}_j = \sum_{i=1}^{n}\frac{x_{ij}x_j}{n}$. During the establishment of a similar matrix, the widely used Euclidean distance $\left(r_{ij} = 1-\frac{\sqrt{\sum_{k=1}^{m}(x_{ik}-x_{jk})^2}}{\max\left(\sqrt{\sum_{k=1}^{m}(x_{ik}-x_{jk})^2}\right)}\right)$ was adopted (Zhao et al., 2013). The maximum Euclidean distance between clusters was calculated during hierarchical clustering using the software “SPSS Statistics 20” (Field, 2013).

Table 1
Physical and chemical environmental parameters in the Jinan City monitoring program (Zhao et al., 2015a).

Parameter	Abbreviation	Name	Unit	Range (SD)
Physical	AT	Air temperature	°C	15.0–33.1 (4.6)
	WT	Water temperature	°C	16.70–30.60 (2.85)
	Cond	Conductivity	mS/m	326–4130 (913.81)
	Trans	Transparency	cm	0–600 (111.32)
	Turb	Turbidity	degree	0.52–924 (139.53)
Chemical	Ca	Calcium	mg/l	17.63–315.83 (58.39)
	Cl	Chlorine		11.85–786.15 (176.39)
	pH	pH		7.26–8.60 (7.35)
	SO_4	Sulfate		43.47–932.22 (179.28)
	CO_3	Carbonate		0–12.50 (2.83)
	HCO_3	Bicarbonate		50.05–845.32 (132.11)
	TA	Total alkalinity		51.48–693.35 (107.60)
	TH	Total hardness		141.12–989.89 (198.71)
	DO	Dissolved oxygen		1.17–9.92 (2.41)
	TN	Total nitrogen		0.25–21.84 (4.18)
	NH_4-N	Ammonia nitrogen		0.07–9.42 (2.63)
	NO_2	Nitrite		0–1.41 (0.30)
	NO_3	Nitrate		0.05–18.85 (2.90)
	COD	Chemical oxygen demand		6.32–130.61 (20.84)
	BOD	Biochemical oxygen demand		0–35.80 (7.39)
	TP	Total phosphorus		0–3.64 (0.78)
	Fluoride	Fluoride		0.18–2.30 (0.49)

The other 10 heavy metal ions, e.g., copper, zinc and lead, were below detection and they are therefore omitted in the above table. All units of the chemical attributes are in mg/l.

Table 2
Key driving factors of phytoplankton community variation.

	Water quality: physical factors	Water quality: chemical factors
Less influenced by human activities	Water temperature(WT), Conductivity(Cond)	Total phosphorus (TP), Ammonia nitrogen (NH_4-N), Chemical oxygen demand(COD)
More influenced by human activities	Water temperature(WT), Conductivity(Cond)	Dissolved oxygen (DO), Chemical oxygen demand(COD)

2.3.2. Identifying dominant phytoplankton taxa

Abundance and biomass of biota are fundamental indices for biological monitoring. Abundance reflects the individual number of a species, while biomass reflects the size of species. Both abundance and biomass are important for the existence and health of any biotic community. In this study, they were combined to determine the dominant phytoplankton using Eq. (1) (Zhao et al., 2014) as follows:

$$I_{m,i} = \omega_1 P_{a,i} + \omega_2 P_{b,i} \tag{1}$$

where I_m is the dominance of a phytoplankton species; i is the ith phytoplankton species; $P_a$and P_b refer to, respectively, the ratios of the species' abundance and biomass to the total,$P_{a,i} = \frac{N_i}{\sum N_i}$, $P_{b.i} = \frac{B_i}{\sum B_i}$; N_i is the abundance of the i-th phytoplankton species; B_i is the biomass of the species; and ω_1 ω_2 are the weightings of abundance and biomass, respectively, $\omega_1 + \omega_2 = 1.0$. They are determined using the center of mass as shown in Eqs. (2) and (3) (Zhao et al., 2015b) as follows:

$$\begin{cases} \frac{\omega_1}{\omega_2} = \frac{a}{b} \\ \omega_1 + \omega_{2=1} \end{cases} \tag{2}$$

$$\begin{cases} a = \frac{\sum P_{a,i} N_i}{\sum N_i} \\ b = \frac{\sum P_{b,i} B_i}{\sum B_i} \end{cases} \tag{3}$$

After the dominance indices of all species were calculated, the dominant phytoplankton species of the biological community were identified by the breakpoint. The breakpoint was determined based on the curvature of the cumulative dominance Eq. (4) (Gippel and Stewardson, 1998; Zhao et al., 2015b) as follows:

$$K = \frac{\frac{d^2y}{dx^2}}{\left[1 + \left(\frac{dy}{dx}\right)^2\right]^{\frac{3}{2}}} \tag{4}$$

here κ is the curvature of the dominance curve, y is the dominance index of the phytoplankton species (I_m), and X is the order of the species (i). On the dominance curve, the curvature after a certain point is significantly smaller than the curvature before that point, which is termed the breakpoint. It is more objective to choose the dominant species in the aquatic population in this manner.

2.3.3. Canonical correspondence analysis (CCA) of key driving factors

Canonical correspondence analysis is a multivariate gradient analysis method that is designed to elucidate relationships between biological assemblages of species and environmental factors. It develops a coordinate system that is optimal for correlation analysis, and the eigenvectors define this coordinate system. Eigenvectors of environmental variables permit the identification of those variables with higher loadings and, thus have more important relationships with the biological data. CCA creates orthogonal components and a set of scores for each item. Therefore, it has been widely used to predict interactions between community structure and environmental variables (Biswas et al., 2014; Barrella et al., 2014; Godoy et al., 2002; Mansor et al., 2012; Martino and Able, 2003).

Habitat factors influencing phytoplankton communities include physical and chemical parameters. Methods using unimodal ordination with a Monte Carlo permutation test were used to select principal factors ($p < 0.05$) from the aforementioned three types of parameters that underpinned the spatial heterogeneity of the phytoplankton communities. The CCA figures were drawn using Canoco (Lepš and Šmilauer, 2003).

2.3.4. Quantitative assessment model for determining the influence of human activities on phytoplankton

At present, the quantification of the impact of human activities is mostly based on the multi-index weighted overlaying evaluation method (Gao and Wu, 2010; Shi et al., 2016). The present study combined the results of key phytoplankton driving factors to compare and analyze the differences in those factors in lakes and reservoirs subject to different human activity intensities. The water quality factors with greater differences were selected to construct an evaluation index system, and a quantitative model was developed (Eqs. (5)–(7)) to calculate the Intensity of Human Activities' Influence on Algae (IHIA), thus evaluating the effects of human activities on phytoplankton.

$$\mathrm{IHIA} = \frac{1}{n}\sum_{i=1}^{n} II_i \tag{5}$$

$$II_i = \sum_{k=1}^{L} \alpha_k IA_k \tag{6}$$

$$IA_k = \sum_{j=1}^{m} \beta_{jk} \frac{H_{ij}}{H_{sj}} \tag{7}$$

where, IHIA is the comprehensive index of the intensity of human activities on algae in a region; II_i is the impact index of the key indicators of the i-th station that is greatly affected by human activities on algae; IA_k is the effect of human activity on the k-th dominant algae; L is the total number of dominant algae; H_{ij} is the monitored value of the j-th key indicator of the i-th station; H_{sj} is the average value of multiple monitoring of the j-th indicator for the reference station (no or less human activity impact); α_k is the weight of the k-th dominant algae, which is normalized according to the dominance index (Eq. (1)) of each dominant algae; β_{jk} is the weight of the j-th indicator on the k-th dominant algae, which is obtained based on CCA analysis and the calculation of the indicator and algal data; n is the total number of monitoring stations; and m is the total number of indicators. The effects of different types of pollutants produced by human activities on algae are reflected in the impact weights.

$\beta_{jk}$was determined according to the biplot scores in the CCA sorting. If the first sorting axis can explain the relationship between the environmental variables and species, then the β_{jk} value is normalized based on the absolute values of the biplot scores in the first sorting axis of each environmental variable. If the first sorting axis cannot explain the relationship between the environmental variables and species, then the root mean square of the biplot scores in both the first and the second sorting axes were normalized to obtain the β_{jk} value.

3. Results

3.1. Spatial clustering of the sampling stations

Cluster analysis was conducted according to the water quality data obtained by sampling. To avoid dimensional influence, the data was standardized before clustering. Between-groups linkage was used as the clustering method. The clustering result is shown in Fig. 2, and the horizontal axis is the Euclidean distance.

As shown in Fig. 2, J6, J3, J4, J2, and J15 had high similarity and belonged to the same cluster; J9 and J10 had high similarity and belonged to the same cluster; J25, J26, and J27 had high similarity and belonged to the same cluster; and J18 and J32 were different than the other stations and belonged to one cluster. All stations were divided into the following five clusters with a threshold of 5.

- Cluster 1: J6, J3, J4, J2, J15, J7, J13, J14. pH and NH_4-N are at a low level, and DO is at a high level;
- Cluster 2: J9, J10. pH, DO, and NH_4-N are at a low level;
- Cluster 3: J25, J26, J27. pH and NH_4-N are at a high level, yet DO is at a low level;
- Cluster 4: J18. COD is significantly higher than all the other stations;
- Cluster 5: J32. TP is significantly higher than all the other stations.

The clustering results are shown in Fig. 3. There was a significant spatial aggregation, and stations with a close spatial distance tended to be in the same cluster. Clusters 1, 2, and 3 were all reservoirs, and clusters 4 and 5 were lakes. Cluster 1 had 8 reservoir stations, all in the southern mountainous areas at higher elevations. Besides, Cluster 2 was in the western plain area, cluster 3 was in the eastern plain area, cluster 4 was the urban lake, and cluster 5 was the agricultural area lake. The southern mountainous area where cluster 1 was located has a small population and was not affected by industry or agriculture. Therefore, the 8 reservoirs in cluster 1 represent water bodies that are less affected by human activities, and the lakes and reservoirs in the remaining clusters 2, 3, 4, and 5 are water bodies that are greatly affected by human activities.

3.2. Screening of the dominant phytoplankton

A total of 141 phytoplankton were identified, belonging to 8 phyla, 10 classes, 13 orders, 27 families, and 29 genera. The biomass and density of each phytoplankton species relative to the proportion of all species were first determined and then brought into Eqs. (2) and (3) to calculate the weights of the species density and biomass ω_1 and ω_2, respectively. Then, ω_1 and ω_2 were determined to be 0.69 and 0.31. ω_1 and ω_2 were then brought into Eq. (1) to calculate species dominance I_m, sorting the dominance from large to small and calculating the degree of accumulation to plot the dominance curve. The breakpoint was then calculated from the dominance curve (Fig. 4) as (18, 0.875), which corresponds to the species that were then selected as the dominant species in the phytoplankton population: *Phormidium tenue*, *Oscillatoria tenuis*, *Synedra ulna*, *Synedra acusvar*, *Closterium gracile*, *Microcystis aeruginosa*, *Chroococcus minutus*, *Merismopedia tenuissima*, *Raphidiopsis sinensia*, *Euglena caudata*, *Pinnularia divergentissima*, *Spirulina platensis*, *Scenedesmus quadricauda*, *Cyclotella meneghiniana*, *Cryptomons ovata*, *Cyclotella* spp., *Melosira granulata*., and *Merismopedia glauca*. These dominant species were numbered SP1 to SP18 from beginning to end.

3.3. Key driving factors of the dominant phytoplankton

According to the clustering results reported in Section 4.1, the human activity intensity in the study area can be divided into two categories (major impact and minor impact). CCA analysis was performed

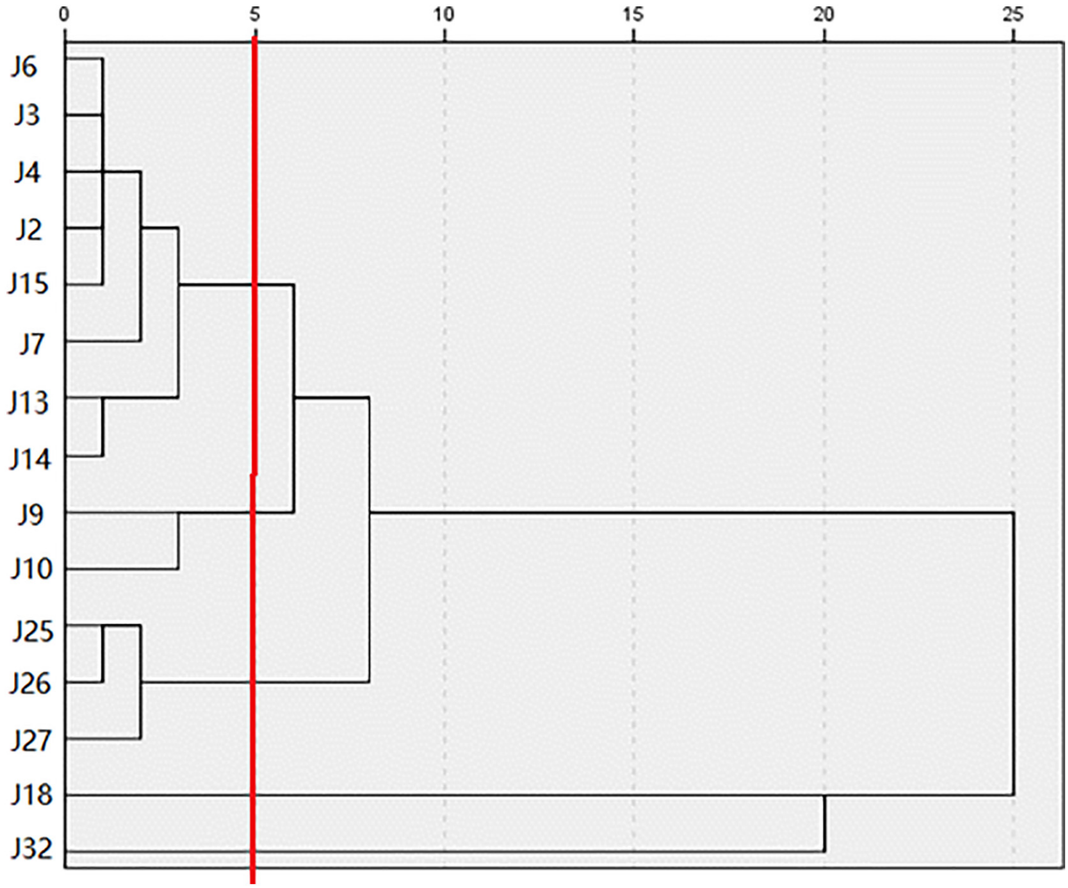

Fig. 2. Clustering results of the sampling stations (a threshold value of 5 was used for identifying the clusters).

based on the biological sampling data and water quality synchronization data from the two types of regional stations, respectively, as shown in Fig. 5. On the CCA sorting map, the line segment with arrows represents the environmental factor. The biplot scores of each environmental factor indicated the magnitude of its impact on the biocoenosis. The greater the value of the biplot scores, the greater the impact. The key driving factors of phytoplankton communities can be selected based on this principle.

It can be seen from Fig. 5 that the key water quality physical driving factors of the reservoirs less affected by human activities were water temperature and conductivity, and the key water quality chemical factors were TP, NH_4-N, and COD. The key water quality physical driving factors of lakes and reservoirs greatly affected by human activities were water temperature and conductivity, and the key water quality chemical factors were DO and COD, as shown in Table 2.

3.4. Quantitative assessment of the intensity of human activities

The differences in the driving factors between the reservoirs with minor impacts from human activities and lakes and reservoirs with major impacts from human activities were compared according to the key driving factors of phytoplankton community variation (Table 2). The water quality physical driving factors were nearly the same among the two categories. The main difference in the water quality chemical driving factors was related to TP, NH_4-N, and DO. The oxygen produced by photosynthesis of algae leads to an increase in the concentration of DO in water (Misra et al., 2011). Adequate DO can promote the decomposition of bacteria in the water, increase the nutrient utilization efficiency of algae, and lead to an increase in phytoplankton density (Misra, 2011). However, as the phytoplankton density increases, their respiratory consumption of DO also increases (Klose et al., 2012), and large-scale outbreaks of phytoplankton can isolate water-to-air contact, prevent oxygen in the air from entering the water body, and lead to a decrease in the DO content (Mhlanga et al., 2006). In general, the change in DO content in the water body is the source of phytoplankton growth (oxygen production by photosynthesis) and also a result of phytoplankton growth (oxygen consumption by respiration); thus, it is not suitable to be used as an indicator for evaluating the intensity of human activities. Therefore, TP and NH_4-N were selected as evaluation indices of human activity intensity, and Eqs. (6) and (7) were used to calculate the human activity intensity influence index (II) from each station during each sampling, as shown in Table 3. The IHIA was calculated using Eq. (5) from each station in each sampling, as shown in Table 4.

Table 3 shows that the stations with higher human activity intensities were J25, J26, J27, and J32, which were distributed in the eastern agricultural areas. These are the priority areas for future algal bloom prevention and control; thus, it is necessary to implement appropriate measures to control the impact of human activities and prevent algal blooms. To investigate the quantitative relationship between the intensity of human activity and the density of phytoplankton, a plot was generated using the mean value of the human activity intensity index at each station as the x-axis, and the total density (C) of the phytoplankton as the y-axis. The results are shown in Fig. 6. Polynomials were further used to develop the fitting equation $y = 2467x^2 - 7546.5x + 10492$, with an R^2 of 0.993. Levene's test of the equality of variances showed that the simulated C had the same distribution as that of the observed C ($F = 300.875$, $p > 0.05$), and the two data sets were considered to have homogeneity of variance. The fitting results showed that the total phytoplankton density increased with the increase in human activity intensity. The reason is that the increase in human activity intensity caused more industrial and agricultural wastewater into the lakes and

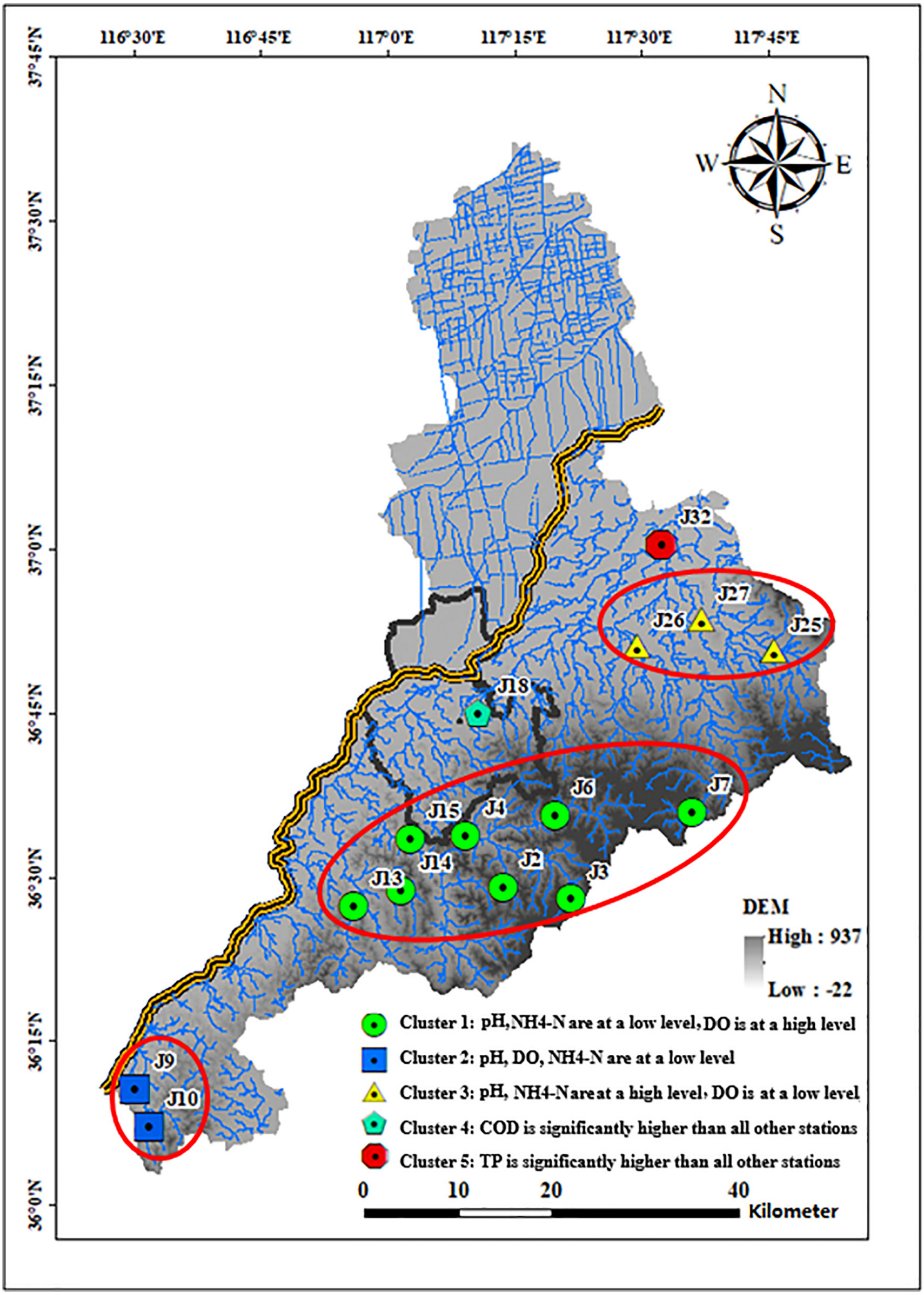

Fig. 3. Spatial distribution of the sampling station clustering results.

reservoirs. The increased concentrations of nitrogen, phosphorus and COD lead to the increment in phytoplankton density.

To investigate the effect of different seasons on the IHIA values, a histogram of IHIA from the six samplings was developed as shown in Fig. 7. It can be seen from Fig. 7 that the value of the summer IHIA was significantly higher than that of the spring and autumn. The IHIA values were not very different between the spring and autumn, and the value of the spring was slightly higher than that of the autumn.

4. Discussion

4.1. Rationality analysis of the screening results of dominant phytoplankton species

Among the 18 dominant species screened, *Phormidium tenue* had the highest dominance in the phytoplankton population at 0.26, which is representative of the phytoplankton population in the lakes and

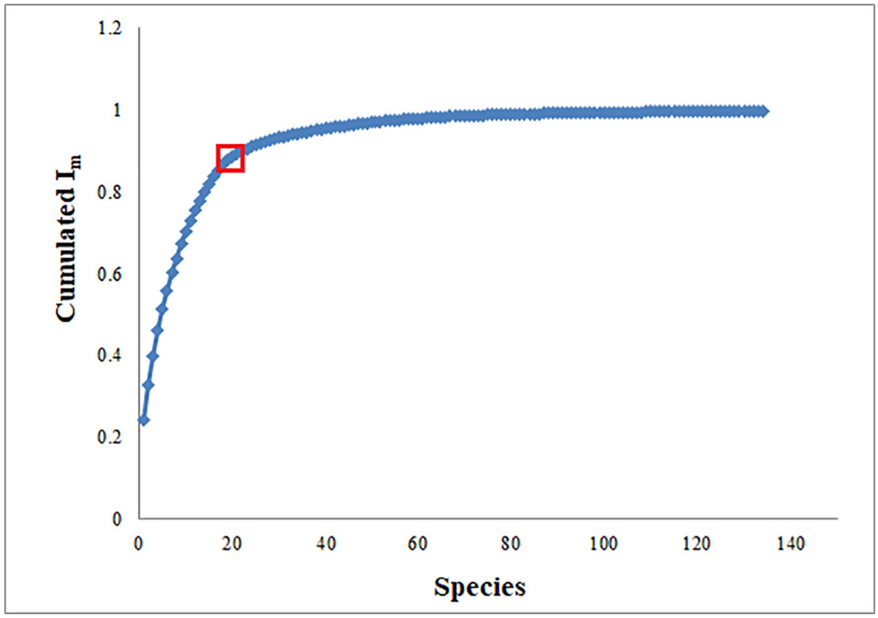

Fig. 4. Breakpoint of the dominance index for phytoplankton in the lakes and reservoirs determined using Eq. (4). (The horizontal axis represents the species in descending ordered by their dominance values (Im).)

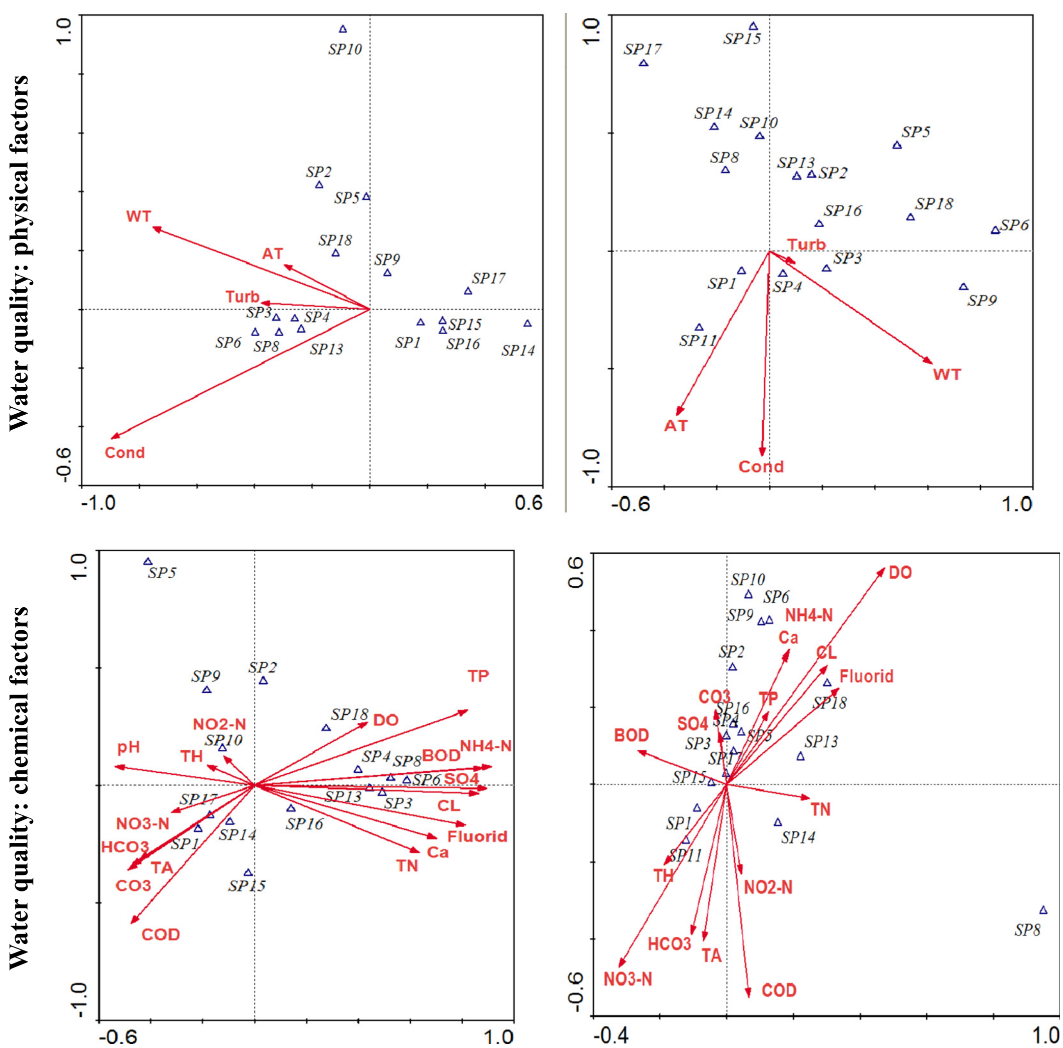

Fig. 5. Canonical correspondence analysis of biological and environmental factors of monitoring stations in reservoirs and lakes during the period 2014–2015 (the abbreviations of the parameters are listed in Table 1).

Table 3
Human activity intensity influence index (II).

		J9	J10	J18	J25	J26	J27	J32
2015	Spring	1.72	1.63	2.12	2.51	2.17	2.51	2.99
	Summer	1.9	1.81	3.02	3.94	3.68	3.45	4.15
	Autumn	1.63	1.52	1.91	2.32	2.02	2.21	2.56
2016	Spring	1.77	1.62	2.01	2.42	2.24	2.51	2.75
	Summer	1.97	1.84	2.99	3.84	3.75	3.85	4.05
	Autumn	1.33	1.48	1.87	2.31	2.04	2.15	2.28
	Average	1.72	1.65	2.32	2.89	2.65	2.78	3.13

reservoirs of Jinan City. *Phormidium tenue* has a wide niche and exists under different environmental conditions (Li et al., 2017). Nutrients such as nitrogen and phosphorus are abundant in lakes and reservoirs in densely populated areas of Jinan, but the spatial variation of COD, DO, pH is large. *Phormidium tenue* has a competitive advantage over other algae (Orlekowsky et al., 2013). They are ubiquitous and prone to outbreaks (Meng et al., 2013); *Synedra ulna* and *Synedra acusvar* are world-wide Bacillariophyta in algal blooms (Shishlyannikov et al., 2018); *Oscillatoria tenuis* and *Microcystis aeruginosa* are common bloom inducing algae and produce highly harmful algal toxins (Bouhaddada et al., 2016; Huang et al., 2008); *Merismopedia tenuissima*, *Merismopedia glauca*, and *Chroococcus minutus* are common blooming algae existing at high water temperatures and under low turbulence conditions (Drzyzga and Lipok, 2018; Marshall, 2009; Tian et al., 2014); *Raphidiopsis sinensia* (Tian et al., 2016), *Euglena caudata* (Kufner and Giani, 2017), *Spirulina platensis* (Noyma et al., 2015), *Scenedesmus quadricauda* (Zeng et al., 2015), *Cyclotella meneghiniana* and *Cyclotella* spp. (Soja-Woźniak et al., 2017) are common freshwater bloom phytoplankton. These phytoplankton have a wide range of adaptation to environmental conditions and are prone to reproductive outbreaks. They are a research focus throughout the world in regards to algal blooms (Chen et al., 2018; Duan et al., 2018; Park et al., 2017; Tian et al., 2013; Zhang et al., 2011) and are also the dominant species of the phytoplankton community in Jinan City. Using these phytoplankton as representatives, the results obtained for the relationship between the phytoplankton community and environmental factors, and the determination of the key driving factors, are more favorable to the prevention and control of algal bloom.

4.2. Comparative analysis of phytoplankton driving factors under the influence of different human activity intensities

In this study, we obtained the driving factors of reservoirs with less impact from human activities and lakes and reservoirs with greater impact from human activities. The key water quality physical factors were the same among the two categories, including water temperature and conductivity. Becker et al. (2009) also found water temperature and conductivity were the key physical driving factors of phytoplankton communities in the Faxinal Reservoir, Brazil, which is consistent with our findings. The study of Zhang et al. (2016) showed that the key physical driving factors of phytoplankton communities in Chaohu, China, were water temperature, pH, and turbidity. Turbidity was not a key driving factor in our results because the water body at the study stations had poor turbulence, the turbidity was relatively low, and the change was small (Zhao et al., 2018b). In terms of phytoplankton growth habits, their reproduction depends on an appropriate water temperature (Moller et al., 2014; Sinden and Sinang, 2016). Water temperature is the most important physical driving factor for controlling algae resuscitation, reproduction, and outbreaks (Figueredo and Giani, 2009; Hu et al., 2018).

In this study, the key water quality chemical driving factors of reservoirs with less impact from human activities were TP, NH_4-N, and COD. The main chemical driving factors obtained by Becker et al. (2009) in the Faxinal Reservoir, Brazil, were TP, nitrate nitrogen, NH_4-N, and COD. Nitrate nitrogen was not a key driving factor in our results and showed minimal temporal and spatial change in our study area (Zhao et al., 2018b). TP and NH_4-N are the main indicators of water eutrophication and are essential nutrients for algal growth and reproduction. COD is the most commonly used organic pollution indicator, and phytoplankton density is directly proportional to the COD of a water body (Yin et al., 2011). These indicators are often the key driving factors of phytoplankton in oligotrophic water bodies (Steffen et al., 2017). The key water quality chemical driving factors of lakes and reservoirs with greater impact from human activities were DO and COD. The key driving factors obtained from studies by Hou et al. (2004) at a more seriously polluted lake in Dianchi, China, and Zhu et al. (2018) at Erhai, China, were COD and DO, which is consistent with our findings. The phytoplankton density in freshwater bodies is positively correlated with DO and COD content (Han et al., 2013). An appropriate concentration of DO is necessary for algal respiration (Zhu et al., 2018). Under suitable COD conditions, DO can also promote the decomposition of microorganisms in a water body to increase the N and P content and provide essential nutrients for phytoplankton proliferation (Klose et al., 2012; Misra, 2011).

The current study compared the key water quality chemical driving factors of phytoplankton in two categories of lakes and reservoirs, and found that water bodies with less impact from human activities were limited by nutrients such as TP and NH_4-N, mainly because the nutrients in such water bodies are relatively limited, and the reproduction of phytoplankton is restricted by these nutrients (Cook and Holland, 2012; Huang et al., 2014). In water bodies with greater impact from human activities, nutrients are no longer the main limiting factor for phytoplankton reproduction because of the influx of large amounts of sewage and wastewater (Hou et al., 2004). Human activities lead to more nutrients entering the water body, and increased human activities exacerbate water eutrophication (Alimov and Golubkov, 2014; Hillbrand et al., 2014). Eutrophic water provides sufficient nutrients for phytoplankton proliferation, which in turn, leads to an increase in phytoplankton density (Li et al., 2014; Pitois et al., 2001).

4.3. Rationality analysis and countermeasures for the quantitative assessment results of human activity intensity

Spatial and temporal changes in human activities and their effects on phytoplankton in the study area were analyzed, according to the quantitative assessment results of the model. The results showed that, spatially, the stations with a higher human activity intensity influence index were distributed in the eastern agricultural area, which is the priority area for future algal bloom prevention and control. The reason is that the eastern region has flat terrain, and agriculture is highly developed in the region, which has a long farming history, leading to a large amount of fertilizers being used, resulting in major anthropogenic impact. These results are consistent with the findings of Sun et al. (2006), Giang et al. (2015), Sebastia et al. (2012). Agricultural pollution sources enter the lakes and reservoirs through the ways such as agricultural water withdrawal or rainfall, which then lead to eutrophication of the water bodies and a relatively significant impact on phytoplankton communities. To control the impact of agricultural activities on phytoplankton communities, it is necessary to essentially reduce the amount of farmland fertilization, promote reasonable irrigation, and reduce the proportion of agricultural water withdrawal into lakes and reservoirs (Tilman et al., 2001; Xie et al., 2014).

Table 4
Intensity of human activities influence on algae (IHIA).

	2015			2016		
	Spring	Summer	Autumn	Spring	Summer	Autumn
IHIA	2.24	3.14	2.02	2.19	3.18	1.92

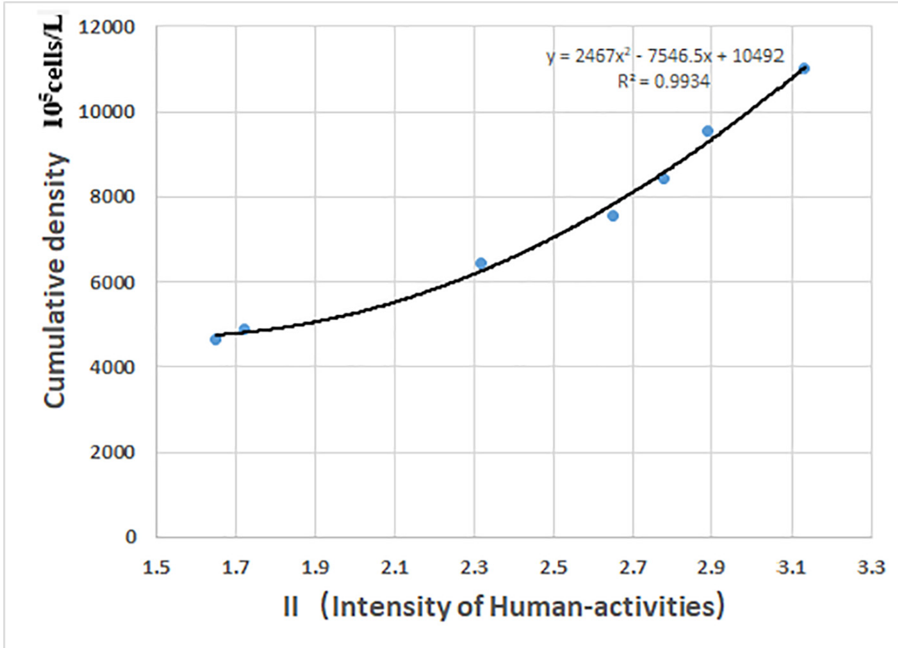

Fig. 6. Relationship between human activity intensity index and total phytoplankton density.

Temporally, the summer IHIA value in the study area was significantly higher than that of the spring and autumn. The reason is that the summer is a high-flow period in the study area, and the annual rainfall mainly occurs during the summer (Lin et al., 2014), which results in heavy loads of non-point source pollution entering into the water body (Moges et al., 2018). Thus, summer is the most serious season for non-point source pollution. A study by Lee et al. (2014) at Shihwa Lake, Korea, reported that human activities had the most impact during the rainy season, which is consistent with our conclusions. In addition, the physical conditions of summer such as a higher water temperature are more suitable for phytoplankton reproduction (Descy et al., 2016), leading to a higher risk of algal blooms. Therefore, it is necessary to reinforce the monitoring and management of water quality and phytoplankton in lakes and reservoirs during summer. On one hand, engineering measures can be implemented to reduce the non-point source pollution load entering into lakes and reservoirs (Wang et al., 2016b; Yu et al., 2011). On the other hand, different measures including reducing the water color to increase light penetration(Houser, 2006), reducing water phosphorus content to improve water clarity (Dobiesz and Lester, 2009), and introducing external cold flows into lakes and reservoirs (Lewis and Anderson, 1992) could be taken to reduce the surface water temperature (Accoroni et al., 2015; Cha et al., 2017) and regulate water pH (Liu et al., 2016; Yamamoto and Nakahara, 2005), ultimately preventing algal blooms.

5. Conclusions

Hierarchical clustering combined with geographical features was used to classify the sampling stations into two categories. A total of 18 dominant phytoplankton species were identified which are prone to mass reproduction and threaten aquatic ecosystem health. The effects of human activities on the phytoplankton community were evaluated with a newly developed quantitative assessment model which show that the variation of the phytoplankton community was mainly

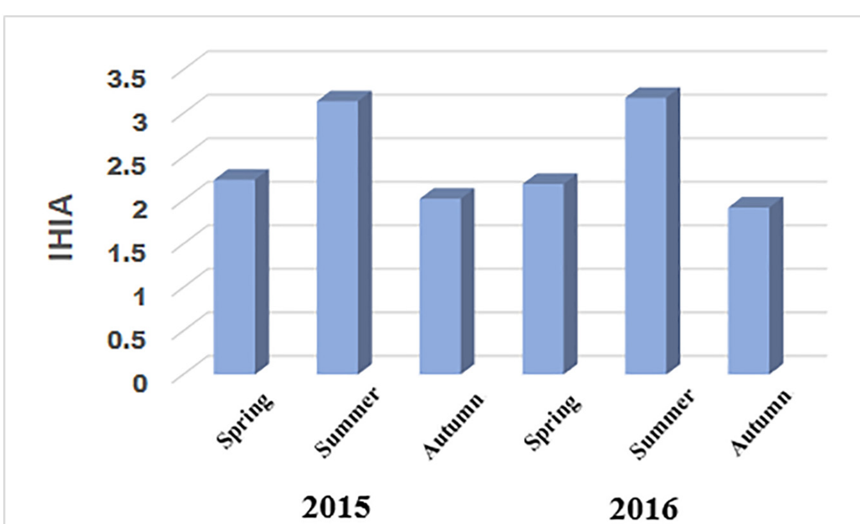

Fig. 7. IHIA values of the six samplings.

restricted by lack of nutrients in waters with less human activity impact, whereas a minor nutrient restriction occurred in waters with more human activity impact. The density of phytoplankton increased with the increase in human activity intensity because human activities increase the nutrients in water bodies, particularly in concentrated agricultural areas where rainfall causes non-point source pollution to enter the water body during the rainfall season. Therefore, the lakes and reservoirs in the agricultural area are a focus of the future and a priority area for the prevention and control of algal blooms. It is necessary to reduce the impact of human activities by controlling fertilization and agricultural water withdrawal into lakes and reservoirs. During the summer, when most of the rainfall occurs, the temperature is suitable for the reproduction of phytoplankton. It is necessary to reinforce the monitoring of water quality factors and phytoplankton, to prevent and control the outbreak of algal blooms. For water quality management, this model can identify the key driving factors based on the identification of dominant species, discover the key controlling factors for algal bloom prevention, quantitatively evaluate the impact of human activities, and further identify priority areas for algal bloom prevention and control.

The model presented in this study can be beneficially used for joint management of multiple reservoirs in the same area, and it can effectively utilize manpower and material resources to control algal blooms based on the dominant bloom-causing algal species and their key control factors in the study area. However, this study is a preliminary exploration of the quantitative assessment of regional human activities on phytoplankton community variation. Due to the relatively short data-series length and small spatial scale in the study area, there exist some unavoidable uncertainties in the results. In the future, it is necessary to lengthen the duration of the monitoring period and expand the monitoring geographic range to further improve the accuracy of the model.

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