Analyzing the algal bloom risk and its relationship with environmental variables in urban landscape water

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Abstract: Longjing Lake is an urban landscape lake located in the Chongqing Expo Garden, Chongqing City, China. In order to assess the lake condition for eutrophication, the water quality and phytoplankton community in Longjing Lake was investigated monthly in 2016. A total of 53 genera of phytoplankton belonging to eight phyla were identified. The dominant organisms included Pseudanabaena, Ankistrodesmus and Cryptomonas, with Pseudanabaena being the most dominant, (dominance value = 0.7163). One-way ANOVA showed significantly larger Pseudanabaena abundance but lower biotic indices (Shannon-Wiener index (H), richness index (Dm), evenness index (J) and Simpson diversity index (D)) in June through September compared to other months (p < 0.05). A stepwise discriminant function analysis was employed to develop predictive model for assessing the level of algal bloom risk. The input variables for the model included water temperature (T), chemical oxygen demand (COD) and dissolved oxygen (DO). By measuring the values of T, DO, and COD concentrations, thus, lake managers could understand the temporal variation in phytoplankton biomass, and analyze the risk of algal bloom. Since the model developed in this study use only three easy-to-measure variables, its application can help in rapid assessment of algal bloom risk.

1. Introduction

China is presently experiencing rapid urbanization to satisfy the economic growth of the country. With this urban expansion, there have been significant land use changes, from ecological land to impervious surfaces, and a rapid increase in the amount of untreated effluent [1]. Therefore, numerous previously pristine lakes are surrounded by construction with excessive human induced nutrient inputs (mainly nitrogen and phosphorus), such as Lake Chaohu, Taihu and Dianchi [2]. One critical problem faced by urban lakes is the cultural eutrophication which leads to excessive phytoplankton growth, and sometimes further deteriorates into algal blooms (e.g. cyanobacteria blooms). Such blooms can harm aquatic communities, limit recreational and economic functions of lakes, and even threaten human health. Thus, controlling eutrophication and mitigating algal blooms are important and essential issues for urban lake management.

Numerous physic-chemical variables have been linked to the dominance of cyanobacteria and the development of blooms in freshwater systems. Generally, phosphorus and nitrogen were the principal drivers that determine the variation in production and biomass of cyanobacteria [3,4]. As growth limiting nutrients, total phosphorus (TP), total nitrogen (TN), the TN / TP ratio have been frequently
applied to predict the occurrence of cyanobacteria blooms [5,6,7]. Temperature and light intensity were the other two primary factors favoring cyanobacteria dominance [8-11]. In numerous lakes, surface water temperature and euphotic depth have been taken into account when developing predictive models [12,13]. Except for the above variables, moreover, other environmental parameters including chemical oxygen demand (COD) [14], pH [15], transparency [16], turbidity [17], alkalinity and water color [18] are also related to the cyanobacteria biomass and dominance. Thus, it is complex and challenging to model cyanobacteria dominance and the occurrence of bloom.

It should be noted that cyanobacteria were a large and morphologically diverse group [19]. The habitats and ecological requirements for different cyanobacteria species were diverse and depended on the genera and even on the strain [20]. Thus, solely modelling the total cyanobacteria abundance or Chlorophyll-a levels can be misleading for guiding lake management [6,21,22]. Hudnell (2008) indicated that the best way to identify the reason for cyanobacterial blooms was analyzing the relationship between the dominant species of Cyanophyta and the principle factors [23]. As such, developing a capacity to predict the abundance of the dominant species and to assess in which conditions they will arise is very critical for bloom management.

Chongqing, which is one of the four direct-controlled municipalities of China, has been experiencing rapid urbanization since the late 2000’s. Due to urban expansion and the massive real estate development, large amount of small pristine lakes were surrounded by dense residential communities, becoming the precious and important places for citizens to enjoy recreation and the serenity of nature. In China, although many researchers have tried to model and predict the occurrence of cyanobacteria blooms [21,24,25], few studies have been conducted in small urban landscape lakes. In this study, therefore, we selected an urban landscape lake in Chongqing city, and continuously measured the water quality and phytoplankton communities for a year. Our primary goal was to determine the factors that were closely related to cyanobacteria dominance, and develop a capacity to predict the risk of bloom occurrence.

2. Materials and methods

2.1. Study sites

Longjing Lake is an urban landscape lake located in Chongqing Expo Garden with tourist and recreational activities year round (Figure 1). It covers an area of 530,000 m² with an average depth of 10 m and a maximum depth of 30 m. The total volume of water is approximately 663 million m³, which is supplied by precipitation and input from an upstream river. The annual average temperature is 18.2 °C, with the mean maximum of 29 °C recorded in July and mean minimum of 7 °C recorded in January. The main pollutants result from tourist activities, waterbird guano and domestic sewage produced by restaurants in the Expo Garden.
2.2. Field sampling and laboratory work
Six sampling sites were selected according to the Standard Methods for Observation and Analysis in Lake Eutrophication [26] (Figure 1). Water samples were collected from the surface water once a month from January to December in 2016. Physicochemical parameters including water temperature (T), pH, dissolved oxygen (DO), oxidation reduction potential (ORP) and electrical conductivity (EC) were measured in situ using a Hach multi-meter (HQ40D, Hach Company, USA). Transparency was obtained using a 20 cm Secchi disk with a diameter. Water samples for total phosphorus (TP), soluble reactive phosphorus (SRP), total nitrogen (TN), ammonium nitrogen (NH$_4^+$-N), nitrite (NO$_2^-$), nitrate (NO$_3^-$), suspended solids (SS), chemical oxygen demand (COD), fecal coliform (FC) and Chlorophyll-a (Chl a) were collected and stored for laboratory analyses following standard methods. In the laboratory, all these variables were measured according to the Chinese government standard methods for the analysis of water and wastewater (2002).

Phytoplankton samples were collected simultaneously with water samples and kept in 1 L bottles and preserved with 30 mL Lugol’s iodine solution. The samples were then concentrated to 50 mL after sedimentation for 48 h, and a subsample of 0.1 mL was enumerated in a hemacytometer (0.0025 m$^2$ area, 0.1 mm depth) using a binocular microscope at an eyepiece magnification of 10× and an objective magnification of 40×. The numbers of cells of different phytoplankton species were determined in 100 random fields. The identification and classification of phytoplankton species were carried out based on Freshwater Algae in China and Atlas of Common Freshwater Algae in China [27,28].

2.3. Biological metrics
The characteristics of phytoplankton communities were described using Margalef (1967) richness index (Dm), Pielou (1966) evenness index (J), Shannon-Wiener index (H) and Simpson diversity index (D) [29,30]. These phytoplankton metrics are commonly applied for water quality assessments, and significant changes in these values indicate environmental disturbances and associated degradation of the environment [15,31].

2.4. Statistical analysis
To identify the dominant species, the dominance values of each phytoplankton species was calculated...
using the formula proposed by Jiang et al. [32], as shown in Eq. (1):

\[ Y = \frac{n_i}{N} \times f_i \]  

(1)

Where \( Y \) is the dominance value, \( n_i \) is the number of individual cells of a given species \( (i) \) within a given area during the monitoring period, \( N \) is the total number of individuals of all species during the monitoring period, \( f_i \) is the frequency of species \( i \), which is calculated by the ratio of the number of samples with species \( i \) to the total number of samples monitoring period. The species with a dominance value larger than 0.02 was considered to be the dominant species during the monitoring period [32].

A stepwise discriminant function analysis was employed to develop the predictive model. Firstly, samples from different sites were categorised in relation to their existing Chlorophyll-a. Each data point of Chlorophyll-a was assigned a categorical code viz., equal or above 60 mg/L = 1 (high risk blooms) and below 60 mg/L = 2 (relatively low risk blooms) [33]. Thus, the data points in June - September with Chlorophyll-a above 60 mg/L were categorized as group 1 and data points in other months with Chlorophyll-a below 60 mg/L were categorized as group 2. Then, stepwise discriminant function analysis was employed to explore the key environmental factors associated with the difference between groups 1 and 2. A data set containing response variables is separated into a number of predefined groups using a composite variable called a discriminant function (DF) [34,35]. The DF is a linear combination of explanatory variables and can be expressed as:

\[ DF = a + b_1 x_1 + b_2 x_2 + b_3 x_3 + \ldots + b_n x_n \]  

(2)

where \( a \) is the constant, \( b_i \) is the discriminant coefficient assigned to a given selected variable, \( x_i \) is the score of the explanatory variable, and \( n \) is the number of the explanatory variable.

Since the accuracy and usefulness of discriminant analysis greatly depends on the normality of the data set, all the explanatory variables, except pH, were transformed to \( \log_{10} (x + 1) \) before analysis. During stepwise discriminant function analysis, the inclusion and exclusion of variables were determined by an F-threshold criterion (minimum partial F to enter was 3.84, maximum partial F to remove was 2.71) in the SPSS statistical package [35]. One-way analysis of variance (ANOVA) was used to test the significant difference in Shannon-Wiener index (H), Margalef richness index (Dm), Pielou evenness index (J), Simpson diversity index (D) and cell densities of the dominant species between group 1 and 2. SPSS 20.0 was applied to perform ANOVA and stepwise discriminant function analysis.

3. Results
The results of this study were presented and discussed from three aspects: the assessment of water quality and trophic state in Longjing Lake, the temporal variation in phytoplankton community, and the exploration of physio-chemical variables linked to risk of bloom occurrence.

3.1. Characteristics of environmental factors
The mean values for physiochemical variables for each sampling month are summarized in Table 1. No water quality variables exceeded the grade IV water quality standard guideline except TN in February and BOD in June.

| Parameter | Units | Jan       | Feb       | Mar       | Apr       | May       | Jun       | Jul       |
|-----------|-------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|
| T         | °C    | 11.6±0.42 | 10.47±0.56| 14.27±0.19| 21.28±0.57| 25.13±1.21| 27.22±1.11| 32.38±0.84|
| SD        | m     | 1.53±0.15 | 1.71±0.11 | 0.92±0.15 | 0.73±0.13 | 0.73±0.04 | 0.69±0.07 | 0.53±0.03 |
| pH(field) | pH    | 7.93±0.09 | 7.94±0.13 | 8.54±0.16 | 9.02±0.13 | 9.24±0.16 | 8.93±0.09 | 9.29±0.07 |
| DO        | mg/L  | 6.3±0.65  | 8.95±0.47 | 11.9±0.84 | 13.11±1.03| 17.27±0.98| 11.64±1.12| 12.16±0.63|
| EC        | uS/cm | 491.17±3.76| 502.33±4.2| 474.67±4.62| 393.7±1.11| 377.7±0.7 | 434.8±1.98| 350.83±13.5|
| ORP       | mV    | 142.1±2.2 | 153.8±19.1| 92.87±25.76| 145.7±47.95| 101.1±53.4| 78.5±33.6 | 49.6±24.66|
| COD       | mg/L  | 3.5±0.82  | 5.2±0.73  | 6.4±0.41  | 5.4±0.82  | 5.0±0.66  | 9.96±0.74 | 9.3±1.97  |
| BOD       | mg/L  | 2.11±1.94 | 2.6±1.87  | 5.46±1.79 | 4.44±0.93 | 2.22±0.9  | 8.7±1.12  | 4.7±0.31  |
Table 1. Statistical descriptives for environmental variables measured in group 1 (June – September) and group 2 (other months).

| Parameter | Units | Group 1 | Group 2 | p     |
|-----------|-------|---------|---------|-------|
| T         | °C    | 28.10±2.82 | 17.16±5.02 | 0.000 |
| SD        | mg/L | 0.60±0.15  | 1.31±0.55  | 0.000 |
| pH (field)| pH   | 9.07±0.30  | 8.35±0.52  | 0.000 |
| DO        | mg/L | 11.11±1.53 | 9.17±4.46  | 0.007 |
| EC        | uS/cm| 390.1±47.1 | 445.9±45.4 | 0.000 |
| ORP       | mV   | 71.4±40.8  | 119.9±48.5 | 0.000 |
| COD       | mg/L | 8.34±1.79  | 5.16±1.86  | 0.000 |
| BOD       | mg/L | 5.13±2.51  | 4.70±5.90  | 0.000 |
| NH₄-N     | mg/L | 0.23±0.056 | 0.27±0.114 | 0.295 |
| TP        | mg/L | 0.06±0.022 | 0.099±0.056 | 0.031 |
| STP       | mg/L | 0.023±0.023 | 0.048±0.033 | 0.003 |
| SRP       | mg/L | 0.008±0.007 | 0.036±0.034 | 0.001 |
| TN        | mg/L | 1.16±0.178 | 1.30±0.496 | 0.608 |
| STN       | mg/L | 0.42±0.104 | 0.80±0.338 | 0.000 |
| SS        | mg/L | 24.86±30.22 | 8.04±3.92  | 0.000 |

One-way ANOVA showed that environmental variables, except NH4+-N and TN, were significantly different (p < 0.05) between group 1 (June – September) and 2 (the other months) (Table 2). T, DO, pH, COD, BOD, STN and SS increased significantly (p < 0.05) in group 1 (June – September), while SD, EC, ORP, SRP, STP, TP and fecal coliform deceased significantly (p < 0.01) in these months.

Table 2. Statistical descriptives for environmental variables measured in group 1 (June -September) and group 2 (other months).

| Parameter | Units | Group 1 | Group 2 | p     |
|-----------|-------|---------|---------|-------|
| T         | °C    | 28.10±2.82 | 17.16±5.02 | 0.000 |
| SD        | mg/L | 0.60±0.15  | 1.31±0.55  | 0.000 |
| pH (field)| pH   | 9.07±0.30  | 8.35±0.52  | 0.000 |
| DO        | mg/L | 11.11±1.53 | 9.17±4.46  | 0.007 |
| EC        | uS/cm| 390.1±47.1 | 445.9±45.4 | 0.000 |
| ORP       | mV   | 71.4±40.8  | 119.9±48.5 | 0.000 |
| COD       | mg/L | 8.34±1.79  | 5.16±1.86  | 0.000 |
| BOD       | mg/L | 5.13±2.51  | 4.70±5.90  | 0.000 |
| NH₄-N     | mg/L | 0.23±0.056 | 0.27±0.114 | 0.295 |
| TP        | mg/L | 0.06±0.022 | 0.099±0.056 | 0.031 |
| STP       | mg/L | 0.023±0.023 | 0.048±0.033 | 0.003 |
| SRP       | mg/L | 0.008±0.007 | 0.036±0.034 | 0.001 |
| TN        | mg/L | 1.16±0.178 | 1.30±0.496 | 0.608 |
| STN       | mg/L | 0.42±0.104 | 0.80±0.338 | 0.000 |
| SS        | mg/L | 24.86±30.22 | 8.04±3.92  | 0.000 |
3.2. Characteristics of phytoplankton community

A total of 53 genera of phytoplankton belonging to eight phyla were identified in Longjing Lake during the sampling period. Among these genera, eight species, including *Pseudanabaena Chiorella, Scenedesmus, Ankistrodesmus, Cyclotella, Synedra, Cryptomonas, Trachelomonas*, had an occurrence frequency of 100% during the sampling year. Moreover, *Pseudanabaena, Ankistrodesmus* and *Cryptomonas* were considered to be the dominant species with dominance values $Y$ of 0.7163, 0.09189 and 0.0776, respectively (Table 3). It should be noted that *Pseudanabaena* was the most dominant, with a dominance value far greater than those of *Ankistrodesmus* and *Cryptomonas*. The cell densities of *Pseudanabaena* and *Ankistrodesmus* in group 1 (June – September) were significantly larger ($p < 0.001$) than those in group 2 (the other months). However, there is no significant difference between group 1 and group 2 for the cell densities of *Cryptomonas*.

Table 3. The dominance values of three dominant species and their cell density in group 1 (June – September) and group 2 (other months).

| Specific name | Occurrence frequency | Relative proportion | Dominance value | Number of individuals per liter in group 1 | Number of individuals per liter in group 2 | $p$ |
|---------------|---------------------|---------------------|-----------------|-------------------------------------------|--------------------------------------------|-----|
| *Cyanophyta*  |                     |                     |                 |                                           |                                            |     |
| *Pseudanabaena* | 1                   | 0.7163              | 0.7163          | 1.33×10⁸±1.205×10⁸                           | 9.189×10⁶±1.331×10⁷                      | 0.000 |
| *Chlorophyta* |                     |                     |                 |                                           |                                            |     |
| *Ankistrodesmus* | 0.9722              | 0.0945              | 0.09189         | 1.716×10⁷±1.05×10⁷                           | 2.108×10⁶±2.399×10⁶                      | 0.000 |
| *Cryptophyta* |                     |                     |                 |                                           |                                            |     |
| *Cryptomonas*  | 0.9583              | 0.081               | 0.0776          | 3.31×10⁶±3.396×10⁶                           | 6.916×10⁵±1.12×10⁶                      | 0.129|

The temporal variations of phytoplankton indices (Shannon-Wiener index (H), Margalef richness index (Dm), Pielou evenness index (J) and Simpson diversity index (D)) are shown in figure 2 (a – d, respectively). After an initial decreasing trend from January to August, all four indices showed an increasing trend from August to December. Figure 2e and f present the concentrations of chlorophyll a (Chla) and algal cell densities in different months. It was interesting that the trends of Chla concentration and algal cell density were exactly opposite to the trends of the four biotic indices, all of which were lowest in June – August. Figure 2g shows the relative abundance of different algae groups. In June - September, Cyanophyta exhibited a relative richness greater than 50%. Further, the relative richness of *Pseudanabaena*, which was far greater than *Ankistrodesmus* and *Cryptomonas*, was also greater than 50% in June - September (Figure 2h).

One-way ANOVA indicated that the values of Shannon-Wiener index (H), Margalef richness index (Dm), Pielou evenness index (J) and Simpson diversity index (D) in group 1 (June – September) were significantly lower ($p < 0.001$) than those of group 2 (the other months) (Table 4). In contrast, the Chla concentrations, algae cell densities, and richness of Cyanophyta and *Pseudanabaena* in group 1 was significantly larger ($p < 0.05$) than group 2 (Table 4).

Table 4. Statistical descriptives of the biotic indices (H, Dm, J, D), Chla concentration, algae cell density, relative abundance of Cyanophyta and *Pseudanabaena* in group 1 (June - September) and group 2 (other months).

| Specific name               | Group 1          | Group 2          | $p$  |
|-----------------------------|------------------|------------------|------|
| Shannon-Wiener index (H)    | 0.84±0.46        | 2.0±0.4          | 0.000|
| Margalef richness index (Dm)| 1.91±0.49        | 3.11±0.67        | 0.000|
| Pielou evenness index (J)   | 0.3±0.14         | 0.69±0.14        | 0.000|
| Simpson diversity index (D) | 0.37±0.19        | 0.73±0.12        | 0.000|
| Chla (ug/L)                 | 124.1±141.3      | 30.3±23.2        | 0.000|
| Cell density ($\times10^6$) | 159.1±133.4      | 26.1±26.6        | 0.017|
| Relative abundance of Cyanophyta | 0.779±0.15    | 0.264±0.171      | 0.000|
Table 5 shows the spatial characteristics of the phytoplankton community structure and biomass. The results of one-way ANOVA suggested that there were no significant difference of phytoplankton indices (Shannon-Wiener index (H), Margalef richness index (Dm), Pielou evenness index (J) and Simpson diversity index (D)) between each sampling site ($p > 0.05$). Besides, the abundance of phytoplankton community and *Pseudanabaena* had no significantly spatial differences as well (Table 5).

### Table 5. Statistical descriptives of the biotic indices (H, Dm, J, D), Chla concentration, algae cell density, relative abundance of *Pseudanabaena* in each sampling site in Longjing Lake.

|                      | S1       | S2       | S3       | S4       | S5       | S6       |
|----------------------|----------|----------|----------|----------|----------|----------|
| Relative abundance of *Pseudanabaena* | 0.77 ±0.15 | 0.23±0.186 | 0.01      |
| Shannon-Wiener index (H) | 1.64±0.71  | 1.61±0.72 | 1.58±0.70 | 1.51±0.70 | 1.66±0.70 | 1.66±0.77 |
| Margalef richness index (Dm) | 2.78±0.81  | 2.65±0.95 | 2.68±0.87 | 2.44±0.61 | 2.79±0.79 | 2.94±1.02 |
| Pielou evenness index (J)  | 0.57±0.24  | 0.57±0.24 | 0.56±0.24 | 0.55±0.24 | 0.57±0.24 | 0.56±0.25 |
| Simpson diversity index (D) | 0.59±0.22  | 0.65±0.24 | 0.64±0.23 | 0.62±0.25 | 0.59±0.22 | 0.58±0.25 |
| Chla (ug/L)             | 83.5±96.1  | 87.6±75.1 | 79.9±75.3 | 99.8±90.1 | 86.1±77.8 | 102.8±120 |
| Cell density (×10⁶)     | 62.3±90    | 78.2±104  | 79.4±105  | 72.0±92   | 67.7±114  | 67.2±101  |
| Relative abundance of *Pseudanabaena* | 0.43±0.3   | 0.42±0.3  | 0.39±0.3  | 0.38±0.3  | 0.39±0.3  | 0.39±0.4  |

#### 3.3. Key factors affecting phytoplankton community

Discriminant function analysis selected three environmental variables of temperature (T), dissolved oxygen (DO) and chemical oxygen demand (COD) for the discrimination between samples in group 1 (June – September) and 2 (the other months) (Table 6). The standardized discriminant coefficients of T, DO and COD were 0.837, 0.795 and 1.004, respectively. Therefore, the discriminant function (DF) can be expressed as followed:

$$\text{DF} = 0.837 \text{T} + 0.795 \text{DO} + 1.004 \text{COD} \quad (3)$$

The Wilk’s lambda was 0.234 ($p = 0.000$), which indicated that the discriminant function was highly significant. The function at group centroid is the group means of explanatory variables. In this study, the centroid functions of group 1 and 2 were 2.386 and -1.325, respectively (Table 6). Thus, cases with DF values close to 2.386 were classified into group 1 and those near -1.325 were in group 2. In this study, 98.2% of original groupings were correctly classified (Table 6).

### Table 6. Statistical results of discriminant analysis.

| Wilks’λ  | Standardized canonical discriminant function coefficients | Functions at group centroids | Correctly classified |
|----------|----------------------------------------------------------|-----------------------------|---------------------|
| DF = 0.234 ($p = 0.000$) | T = 0.837 | DO = 0.795 | COD = 1.004 | Group 1 | Group 2 | 98.2% |
|          | 2.386 | -1.325 |             |          |          |      |
|          | 0.837 | 0.795 | 1.004       | 98.2%    |         |      |
Figure 2. Temporal variations of the characteristics of phytoplankton community in Longjing Lake. (a) Shannon-Wiener index (H); (b) Margalef richness index (Dm); (c) Pielou evenness index (J); (d) Simpson diversity index (D); (e) Chlorophyll a concentration; (f) Algae cell density (mean values); (g) Relative abundance of different phyla (mean values); (h) Relative abundance of dominant species (mean values).

4. Discussion
In Longjing Lake, the water quality variables, and structure and biomass of phytoplankton community in June – September were significantly different with in the other months. *Pseudanabaena* was the dominant species of Cyanophyta, with the highest relative abundance in June – September. Using the discriminant analysis, water temperature, chemical oxygen demand and dissolved oxygen were identified to indict the temporal variation of *Pseudanabaena* abundance.

In this study, most of these variables did not exceed these guidelines throughout the year, which indicates that the water quality in Longjing Lake was safe for use as landscape water. However, the concentration of Chl a in Longjing Lake was greater than 20 µg/L throughout February – October (Figure 2e), which indicated the eutrophic state for lakes [36,37]. Furthermore, the mean Chl a concentration in June – September was even greater than 100 µg/L, and significantly higher than in the other months. This result indicated the extreme hypereutrophic status in June – September serious threatened the lake health as landscape water [36]. Meanwhile, the concentration of nutrient factors
(TP, STP, SRP and STN) in June–September, was significantly lower than that in the other months (Table 2). Generally, phytoplankton requires multiple nutrients for growth, especially nitrogen and phosphorus. Thus, the depletion of nutrients during this highly eutrophied period (June–September) could be attributed to the strong uptake by bloom levels of phytoplankton biomass [38]. Besides, due to photosynthesis activities from increased phytoplankton populations, the enhanced carbon dioxide consumption and oxygen release in the surface water resulted in significantly higher DO and pH in June–September than in the other months [39]. The significantly increased COD in June–September could be related to the degradation of phytoplankton [40]. Yin et al. suggested that extracellular release of COD from phytoplankton was an important COD source [40]. The storm runoff in summer might contribute to the increased COD as well. Fecal coliform in Longjing Lake was mainly from domestic sewage within the garden, waterbird guano and rainfall runoff. The significantly lower fecal coliform in June–September can be attributed to the higher temperature [41], solar radiation [42] and reduced tourism activities during those months.

Although three genera of phytoplankton (Pseudanabaena, Ankistrodesmus and Cryptomonas) were considered to be dominant in Longjing Lake, Pseudanabaena had a dominance value far greater than the other two (Table 3). In particular, the relative richness of Pseudanabaena in summer (June–September) was greater than 0.5, significantly larger than other seasons (Table 4). Due to the abnormal proliferation of Pseudanabaena, moreover, the growth of other species was inhibited with the biotic indices (Shannon-Wiener index (H), Margalef richness index (Dm), Pielou evenness index (J) and Simpson diversity index (D)) in summer significantly lower than in other months (Figure 2). Pseudanabaena is a filamentous, non-heterocystous planktonic cyanobacterium containing parietal thylakoids and polar gas vesicles [43]. For decades, Pseudanabaena species have been frequently reported as cyanobacteria bloom components [44]. Compared to other phytoplankton, Pseudanabaena possessed three particular traits favoring its superior competition in summer. First, Pseudanabaena had the capacity of regulating the ratio of the accessory phytosynthetic pigments phycocyanin and phycocetrhyhin, which helped them to adapt the prevailing light spectrum [45]. Chomerat et al. showed that the high irradiance in summer promoted the dominance of Pseudanabaena[46]. Second, the gliding motility of Pseudanabaena, allowed them mitigate in stratified lakes between well-lit surface waters and nutrient rich bottom waters [47,48]. Thus, Pseudanabaena could better exploit stratified conditions in summer. Third, the filamentous morphology of Pseudanabaena, which may clog filtering appendages, makes them the low preference foods for zooplankton grazers [48]. All the above advantages enhanced the dominance of Pseudanabaena in summer, and suppressed the development of their competitors. Thus, Pseudanabaena, which had an occurrence frequency of 100% during the sampling year (Table 3), posed the highest risk of forming summer blooms in Longjing Lake.

Initially, samples were divided into two groups due to the significant difference on the abundance of dominant species (Pseudanabaena). After calculation and statistical analysis, however, the abundance and structure of whole phytoplankton communities were significantly different between groups. Comparing to those in group 2 (the other months), the phytoplankton communities in group 1 (June–September) showed significantly higher Chla concentration and cell density, but lower evenness and diversity (Table 4). According to Merel et al., cyanobacteria bloom is the phenomenon accompanied by a significant production of biomass and a diminution of phytoplankton diversity [9]. In Longjing Lake, thus, samples in groups 1 (June–September) and 2 (the other months) could be considered to indicate high and low risk of cyanobacteria bloom, respectively.

Three explanatory variables, including T, DO and COD, were identified as predictors for the risk of cyanobacteria (Pseudanabaena) bloom occurrence in Longjing Lake.

Water temperature is one of the most important factors influencing phytoplankton community structure and abundance. Generally, the growth and replication rates of phytoplankton would increase with the rising water temperature until it passed the optimal temperature range for growth. Compared to other phytoplankton species, however, Cyanobacteria species have relatively higher optimal temperature ranges (often above 25°C), and generally grow better at higher temperatures [39,48].
Beaulieu et al. indicated that water temperature has a direct effect on cyanobacteria biomass and dominance [12]. Moreover, due to the increase in water temperature strengthening the vertical stratification of lakes, many buoyant cyanobacteria could better exploit these stratified conditions than those non-buoyant phytoplankton species [8]. In this study, we observed significantly greater cyanobacteria (mainly *Pseudanabaena*) biomass and relative abundance in summer (June – September) than in other months (Table 4). This result was consistent with other studies in which water temperature had a strong positive effect on the probability of cyanobacteria bloom outbreak [11,49]. Due to the closely relationship, water temperature has been determined as one of the significant predictors of cyanobacteria bloom in numerous models [10,12,21].

COD was the amount of oxygen required to oxidize dissolved and particulate matters. In aquatic ecosystems, besides the terrestrial inputs atmospheric deposition, the release of dissolved organic matter from phytoplankton and lysed cells could be the most important sources of COD [40]. In numerous studies, moreover, the high levels of anomalous COD were measured during phytoplankton bloom [31,40,50]. In Longjing Lake, while the *Pseudanabaena* abundance reached highest level in summer (June – September), the concentration of COD increased to maximum values (Figure 2 and Table 2). Studies in many other urban lakes of China indicated that COD was positively correlated with *Pseudanabaena* abundance [14,51]. Therefore, the COD concentration could be used to evaluate *Pseudanabaena* abundance pattern and bloom risk in Longjing Lake.

The DO concentration is an important indicator of the aquatic ecosystem health. In freshwater system, the factors related to DO include water depth, temperature, air pressure, photosynthesis, degradation of organic matter and respiration of living species [35,52]. Generally, temperature and dissolved oxygen exhibit inverse relationship since warmer water become saturated more easily with oxygen. In the present study, however, the DO indicated a positive discriminatory ability similar to water temperature. Moreover, the DO levels in summer (June – September) were significantly higher than in other months (Table 2), which contradicted the conventional DO – temperature relationship. We suggested this could be attributed to high oxygen production from the increased algal abundance. Although the importance of measuring oxygen to understand the behaviour of algal biomass has been highlighted by previous researchers, further studies were required to identify the reasons for the positive relationship of DO in the equation. Thus, 24 hour measures of dissolved oxygen were recommended to reveal the relationship between DO and algal abundance.

By constructing discriminant functions (DFs), discriminant analysis has been commonly applied to formulate prediction models in a wide variety of fields [35]. After model development, the model validation is necessary to assess the predictive accuracy. In this study, the application of discriminant analysis generated a discriminant function (DF) that indicates T, COD and DO were associated with the changes in the phytoplankton community. Prior to using the discriminant function (DF) to predict *Pseudanabaena* dominance and abundance, however, model validation should be performed using the data set of other years. Thus, further study was recommended to validate the accuracy of the discriminant function (DF).

5. Conclusion
In most time of the year (February – October), the Longjing Lake was in eutrophic state. *Pseudanabaena* was the most strongly dominant species with high risk of developing into bloom in summer (June – September). Moreover, the growth of *Pseudanabaena* had significantly negative effect on the biodiversity of phytoplankton community. By using discriminant analysis, T, COD and DO were identified to be associated with the variations in *Pseudanabaena* dominance and abundance. The elevation in water temperature favored the *Pseudanabaena* dominance and abundance, while the increase in *Pseudanabaena* abundance resulted in high COD and DO. By measuring the values of T, DO, and COD concentrations, therefore, lake managers could understand the behavior of *Pseudanabaena* biomass, and analyze the risk of *Pseudanabaena* bloom.
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