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Biogeographic distribution patterns of algal community in different urban lakes in China: Insights into the dynamics and co-existence

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ABSTRACT

Urban lake ecosystems are significant for social development, but currently we know little about the geographical distribution of algal community in urban lakes at a large-scale. In this study, we investigated the algal community structure in different areas of urban lakes in China and evaluated the influence of water quality parameters and geographical location on the algal community. The results showed that obvious differences in water quality and algal communities were observed among urban lakes in different geographical areas. Chlorophyta was the dominant phylum, followed by cyanobacteria in all areas. The network analysis indicated that algal community composition in urban lakes of the western and southern area showed more variations than the eastern and northern areas, respectively. Redundancy analysis and structural equation model revealed that nutrients and pH were dominant environmental factors that affected the algal community, and they showed higher influence than that of iron, manganese and COD_{Mn} concentration. Importantly, algal community and density exhibited longitude and latitude relationship. In general, these results provided an ecological insight into large-scale geographical distributions of algal community in urban lakes, thereby having potential applications for management of the lakes.

Introduction

Urban lakes play an irreplaceable role in urban environment and providing public with physical and mental enjoyment (Matus-Hernández et al., 2019). Besides, the urban lakes not only maintain the balance of surface and ground water, but also are important for maintenance the urban ecosystem (Henny and Meutia, 2014). There are a number of distinguishing characteristics by shallow depth, slow flow rate and small surface area of the urban lakes (Chen et al., 2013). In addition, urban lakes are remarkably different from natural lakes and more urban populations are in contact with them (Birch and McCaskie, 1999). In recent decades, lake ecosystems in China have undergone significant changes due to human and natu-

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ral activities (Yang et al., 2020). Urban lake eutrophication has become an important and serious environmental problem in China (Jin et al., 2005). Algal blooms caused by eutrophication have seriously affected the aquatic ecosystem, human health and economic development (Zhu et al., 2010). Thus, knowledge of algal diversity and biogeographic distribution pattern in urban lakes are important, that can provide insights into restoration of lake ecosystem functions.

Research on large-scale biogeographic distribution pattern of microbial communities, is crucial for the characterization of microbial diversity. Previous biogeographical studies have largely focused on rivers (Shi et al., 2020), wheat fields (Sun et al., 2020) and wastewater treatment plants (Zhang et al., 2019) as study sites for determining microbial diversity and variations in the communities. More recently, there has been an increasing need for finding out further information on the lake ecosystems in biogeography – an approach which studies the structure of microbial community in an even better fashion (Liu et al., 2018). Many evidences suggest that microbial biogeography research of urban lakes is critical for revealing the process of microbial community succession. For example, Bai et al. (2020) used high-throughput sequencing to explore bacterioplankton communities from 25 lakes in the middle and lower reaches of Yangtze River and showed that the distribution of bacterial taxa was limited by geographical distance. Moreover, Chen et al. (2020) demonstrated that algal communities in urban lakes among the sixteen provinces of China had a correlation with geographical locations. Studies on the biogeography of algal community can enhance our knowledge on the composition of algal community across lake ecosystems in China and worldwide. However, currently we know little about whether the algal community shows a geographic variation, and how the geographical location drives the composition of algal community.

In recent years, correlation-based network analysis tool has been widely applied to explore the interactions of microbial community (Cao et al., 2018). Previous studies on microbial community structure in oceans, rivers and lakes have used network analysis to explore the driving factors that shape the community structure (Eiler et al., 2012). For the application of ecological network analysis, Escalas et al. (2019) constructed co-occurrence networks to study the driving factors of phytoplankton community dominance in urban fringe and its ecological consequences. Apart from analyzing the dominant phytoplankton community, the analysis was also used to predict algal blooms control based on the ecological network (Mao et al., 2018). In previous studies, network analysis was applied to find the response of microbial communities to geographic pattern and environmental factors (Ma et al., 2016). Moreover, only few studies focused on algal community structure in urban lakes in China with large-scale geographical distribution pattern, despite an earlier study has shown that the structure of algal community is correlated with geographical position and environmental factors to a great extent (Chen et al., 2020). Therefore, ecological network analysis is meaningful for the studying the algal community structure of urban lakes at a large-scale geographical pattern. In addition, this study presents structural equation modeling (SEM) which is used for exploring algal community structure in urban lakes. SEM is a multivariate statistical tool that reveals a network of relationships between direct and indirect variables (Arhonditsis et al., 2006). Given the importance and complexity of microbial community, SEM has become a powerful tool to study these variables (Russo et al., 2019). In earlier studies, SEM has been used to reveal interplay of environmental and biological factors to bacterial communities (Yu et al., 2015), and to explore the environmental factors that contributed to the effect of phytoplankton communities in lakes and rivers in China (Rao et al., 2018).

Due to the distinctly different geographical location and natural conditions in the east, west, south and north of China, and the cultural and economic characteristics, the distribution of microbial communities in different regions in China is distinct. It has been shown widely that the microbial distribution is closely related to their respective natural environments (Shi et al., 2020; Sun et al., 2020; Zhang et al., 2019). For instance, Zhang et al. (2018) investigated the composition of bacterial and fungal community of urban lakes in Xi'an, China and emphasized the significant differences of water bacterial communities in different urban lakes. Despite the more knowledge on the algal diversity in lakes, it is of great significance to study the algal community structure of urban lakes with large-scale geographical distribution pattern as compared to studying in a single region.

To this end, the objectives in this study were to: (1) investigate the water quality and algal community in 16 urban lakes from different regions in China, (2) assess the distribution and co-existence patterns of algal community structure, and (3) explore the relationships between the water quality parameters, geographical locations and algal community by bioinformatics analyses. With this work, we aimed to provide useful insights into the distribution of algal community and restoration and management of urban lake ecosystems in China and worldwide.

1. Materials and methods

1.1. Study area and sample collection

In the present study, sixteen study sites located in the east (Jinan, Shanghai, Hangzhou and Hefei), west (Lanzhou, Xi'an, Chengdu and Shizuishan), south (Kunming, Guangzhou, Changsha and Bijie) and the north (Siping, Ordos, Taiyuan and Beijing) of China were selected (**Appendix A Fig. S1**). Detailed information of these urban lakes, including longitude, latitude, temperature, population, built years and areas of lake are provided in **Appendix A Table S1**. The water samples from the urban lakes were collected in October 2019. In each sampling site, the surface water samples (0.5-1.0 m) were gathered in triplicate using sterile polypropylene containers (Zhang et al., 2018). All the samples were placed in a cooler and transferred to the laboratory at the Institute of Environmental Microbial Technology, Xi'an University of Architecture and Technology (IEMT-XAUAT) (Chen et al., 2020). Each sample was divided into two subsamples: one subsample was used for physicochemical analyses while the other subsample was preserved in Lugol's solution for algal identification (Wang et al., 2020).

1.2. *Water quality analysis*

The physico-chemical properties of the sample were determined using the following methods. The pH was measured using a pH meter (Hach, USA) in the field (Chen et al., 2020). Total nitrogen (TN), total phosphorus (TP), nitrite nitrogen (NO_2^--N), nitrate nitrogen (NO_3^--N), and ammonium nitrogen (NH_4^+-N), were measured by following the standard methods (Yan et al., 2020). Iron (Fe) and manganese (Mn) concentrations were measured using flame atomic absorption spectrometry (FAAS, AA 6800, Shimadzu, Japan) (Yan et al., 2020). Permanganate index (COD_{Mn}) was measured using spectrophotometer with the DR6000 (Hach, Loveland, CO, USA) (Zhang et al., 2018).

1.3. *Identification and counting of algae*

The algal identification and enumeration were done in triplicate with samples collected from each urban lake using a Nikon microscope (50i, Nikon, Japan) (Yan et al., 2020). For each sample, the volume of water sample was adjusted to 500 mL and added 1% acidic Lugol's solution before settling for 48 hr. Then the algal cells gathered on the 0.45 μm polycarbonate membrane were concentrated to 10 mL. The concentrated sample with 0.1 mL was counted by a counting chamber under 400 $\times$ microscope magnifications and the cells were recorded as $\times 10^4$ cells per liter. Individual algal cells were enumerated and identified from 20 to 30 ocular fields, and for the samples with low abundance, more field were counted (Lee et al., 2015).

1.4. *Statistical analysis*

One-way ANOVA was used to analyze the correlations among urban lakes, the water quality parameters, algal cell concentration and sampling locations with the Tukey HSD post-hoc test (P-value < 0.05) (using SPSS 25.0, IBM, Armonk, NY, USA). The algal community at the phylum level under the effect of geographic pattern was analyzed using Circos software (version 0.69, http://circos.ca/) (Balcom et al., 2016). Furthermore, a heat map profile was established by using R software (version 3.2.3), revealing the relationships between algal community at the genus level and their spatial distributions. The interrelation between physico-chemical properties and algal community among different areas were revealed by the redundancy analysis (RDA) by using CANOCO software (version 4.5, Wageningen, The Netherlands). The Spearman correlation values were used to construct the network. Only significant ($P < 0.05$) and robust ($|r| > 0.6$) associations were used to create network (Qu et al., 2019). Structural equation modeling (SEM) was applied to evaluate the relative influence of water quality parameters and geographical location of algal community. SEM analysis was conducted by using R Software (version 3.6.2, R core team, Vienna, Austria) and utilized partial least squares path modelling (PLS-PM) (Isabwe et al., 2018).

2. Results and discussion

2.1. *Water quality characteristics*

The temperature measured at each sampling site and other representative information are given in **Appendix A Table S1.** The average temperature recorded (2019.10) for sixteen cities was 15.6°C and the value ranged from 8.5 to 25.5°C. The lowest temperature was recorded in Guangzhou, while the highest temperature was recorded in Siping. The temperature showed an upward trend from north to south, and there was an obvious variation between the locations in east and west. Latitude, the area of land and sea and terrain were responsible for temperature of different regions, thus those factors indirectly affecting the environment of urban lakes. The mean values of nine water quality parameters (pH, TN, NO_3^--N, NO_2^--N, NH_4^+-N, TP, COD_{Mn}, Fe and Mn) determined in the water and the consequence of one-way ANOVA test for sixteen urban lakes (DML, SL, WL, JY, QJC, YH, XH, SX, HD, DCL, MX, BY, NH, YZ, BH, YKZ) are presented in **Table 1**. The statistical differences were diverse between the geographical location of different urban lakes and water quality parameters except for Mn concentration. The maximum pH (8.66 ± 0.42) was observed in SX lake, and the minimum pH (7.71 ± 0.01) values were noted in NH lake ($F = 27.427$, $P < 0.001$). In case of nutrient, the concentrations of TN, NO_3^--N, NO_2^--N and TP significantly varied with locations. The highest concentrations of TN, NO_3^--N, NO_2^--N and TP were occurred in BY lake, with mean values of 15.84 ± 2.19, 9.08 ± 0.44, 2.56 ± 0.12 and 0.56 ± 0.07 mg/L ($F = 71.428$, $P < 0.001$; $F = 865.138$, $P < 0.001$; $F = 547.328$, $P < 0.001$; $F = 40.438$, $P < 0.001$), which were significantly higher than those in other locations. However, the NH_4^+-N concentrations varied from 0.03 ± 0.01 mg/L in WL lake to 0.55 ± 0.10 mg/L in MX lake ($F = 15.579$, $P < 0.001$). The COD_{Mn} measured during the research period showed significant differences ($F = 54.026$, $P < 0.001$). The COD_{Mn} of water in XH lake reached up to 31.58 ± 4.35 mg/L and as low as 0.78 ± 0.02 mg/L in DML lake, which attributed to the geographic difference. With respect to Fe and Mn concentrations, our measurements showed that the Fe concentration ranged from 0.00 ± 0.00 to 0.28 ± 0.15 mg/L and showed significant differences ($F = 5.325$, $P < 0.001$), whereas the value of Mn concentration was in the opposite trend ($P > 0.05$). The results indicated the existence of interrelations between the geographical location and water quality parameters. A previous study (Nõges, 2009) revealed that the concentration of nitrogen and phosphorus was lower in lakes at high latitudes and elevations. Similarly, Liu et al. (2010) investigated eutrophication parameters from 103 lakes across China and demonstrated that water quality parameters were influenced by geographical location. In the current study, the differences in the trophic levels of different urban lakes indicated that spatial variations in geographical locations can reflect the differences in the nutrient levels of the lakes

Table 1 also shows that the mean values of water quality parameters and the consequence of one-way ANOVA test in east, west, south and north of China. The water quality of urban lakes in these regions showed statistical differences. The pH values were ranged from 7.59 in the east to 8.25 in the west ($F = 6.364$, $P < 0.001$). The present work in agreement with the study by Wu et al. (2017), in which the pH of the Shahu Lake was in the average of 8.65, revealing alkaline nature of the water quality in the semiarid loess area of northwest China. The highest concentrations of TN, NO_2^--N, NH_4^+-N and TP were found in urban lakes located in the south, with an average of 6.28 mg/L ($P < 0.01$), 0.66 mg/L ($P < 0.05$), 0.39 mg/L ($P < 0.05$)

Table. 1 – Water quality parameters of urban lakes in different areas (2019.10), China

Urban Lakes	**pH**	**TN (mg/L)**	**NO_3^--N (mg/L)**	**NO_2^--N (mg/L)**	**NH_4^+-N (mg/L)**	**TP (mg/L)**	**COD_{Mn} (mg/L)**	**Fe (mg/L)**	**Mn (mg/L)**
Daming Lake (DML)	7.79 ± 0.02ef	10.96±0.20b	6.79±0.03b	0.03±0.00bc	0.27±0.01cdef	0.06±0.00def	0.78±0.02e	0.00±0.00b	0.00±0.00a
Swan Lake (SL)	8.40±0.04abc	0.53±0.14d	0.27±0.10c	0.05±0.03bc	0.11±0.06efg	0.02±0.01f	2.25±0.28de	0.05±0.00b	0.00±.0.00a
West Lake (WL)	7.00±0.04h	0.62±0.14d	0.38±0.02c	0.00±0.00c	0.03±0.01g	0.16±0.05cd	1.80±0.1de	0.03±0.03b	0.00±0.00a
JingYue (JY)	7.18±0.06h	1.41±0.14d	0.41±0.12c	0.08±0.01bc	0.32±0.09cde	0.20±0.01bc	3.56±0.36cde	0.02±0.01b	0.00±0.00a
QuJiangChi (QJC)	8.26±0.11abcd	1.31±0.28d	0.30±0.07c	0.01±0.00bc	0.07±0.02fg	0.04±0.01ef	3.30±0.30cde	0.01±0.00b	0.00±0.00a
YiHai (YH)	7.85±0.02def	1.38±0.06d	0.29±0.09c	0.00±0.00c	0.14±0.01defg	0.03±0.01f	5.48±0.23cde	0.02±0.01b	0.01±0.00a
XingHai (XH)	8.21±0.20abcde	1.68±0.13d	0.25±0.03c	0.00±0.00c	0.37±0.01abc	0.13±0.00cdef	31.58±4.35a	0.02±0.00b	0.00±000a
ShengXian (SX)	8.66±0.42a	0.58±0.13d	0.29±0.03c	0.03±0.02bc	0.15±0.02defg	0.02±0.01f	0.59±0.10e	0.04±0.00b	0.00±000a
HuaDu (HD)	7.78±0.07ef	1.04±0.39d	0.22±0.16c	0.06±0.05bc	0.08±0.06fg	0.08±0.05def	7.88±1.28bc	0.02±0.01b	0.01±0.00a
Dianchi Lake (DCL)	7.99±0.01cdef	6.52±1.71c	0.23±0.03c	0.00±0.00c	0.40±0.05abc	0.30±0.05b	6.28±0.99bcd	0.28±0.15a	0.01±0.00a
MeiXi (MX)	8.34±0.02abc	1.72±0.50d	0.16±0.00c	0.00±0.00c	0.55±0.10a	0.16±0.01cd	5.04±1.05cde	0.01±0.01b	0.01±0.01a
BiYang (BY)	8.19±0.01bcde	15.84±2.19a	9.08±0.44a	2.56±0.12a	0.54±0.01ab	0.56±0.07a	10.84±2.61b	0.02±0.01b	0.01±0.00a
NanHu (NH)	7.71±0.01g	1.87±0.16d	0.49±0.08c	0.10±0.08bc	0.34±0.13bcd	0.06±0.01def	3.80±0.13cde	0.04±0.01b	0.04±0.05a
YingZe (YZ)	8.21±0.02abcde	1.08±0.12d	0.15±0.05c	0.08±0.01bc	0.32±0.04cde	0.16±0.01cd	2.92±0.37cde	0.04±0.02b	0.01±0.00a
BeiHu (BH)	8.12±0.02cdef	1.32±0.15d	0.52±0.01c	0.15±0.00b	0.23±0.02cdefg	0.12±0.01cdef	3.92±0.62cde	0.03±0.02b	0.01±0.00a
YiKeZhao (YKZ)	8.60±0.05ab	1.18±0.30d	0.27±0.04c	0.08±0.00bc	0.31±0.07cde	0.14±0.01cde	6.64±1.14bcd	0.01±0.01b	0.01±0.00a
ANOVA	***	***	***	***	***	***	***	***	NS
East	7.59±0.55b	3.38±4.39ab	1.94±2.80a	0.04±0.03ab	0.18±0.12b	0.11±0.07b	2.10±1.00b	0.03±0.02a	0.00±0.00a
West	8.25±0.29a	1.24±0.40b	0.28±0.02a	0.01±0.01b	0.18±0.11b	0.06±0.04b	10.24±12.44a	0.02±0.01a	0.00±0.00a
South	8.08±0.21a	6.28±5.91a	2.42±3.84a	0.66±1.10a	0.39±0.19a	0.28±0.18a	7.51±2.17ab	0.08±0.11a	0.01±0.00a
North	8.16±0.32a	1.36±0.31b	0.36±0.15a	0.10±0.03ab	0.30±0.04ab	0.12±0.04b	4.32±1.39ab	0.03±0.01a	0.01±0.02a
ANOVA	***	**	NS	*	*	***	*	NS	NS

Values showed as means and standard deviations (n = 3). Different lowercase letter represents statistical significance. *$P < 0.05$, **$P < 0.01$, and ***$P < 0.001$ represent statistical significance using One-way ANOVA followed by a post hoc Tukey's honestly significant difference (HSD) test. NS means no significance.

and 0.28 mg/L ($P < 0.001$), in which the NO_2^--N concentration was 66 times higher than that of western area. However, there was no significant correlation between NO_3^--N concentration and geographical distribution was observed in this study ($P > 0.05$). Besides, COD_{Mn} concentration of urban lakes varied from 2.10 to 10.24 mg/L ($F = 3.29$, $P < 0.05$), with the highest and lowest in the west and east, respectively. Fe concentration of urban lakes ranged from 0.02 to 0.08 mg/L, and a poor correlation between different areas were observed ($P > 0.05$). Similar pattern was observed for Mn concentration as well. In the present study, compared with the northwest region, the urban lakes in the southeast region have the worst water quality and this may be related to the economic development in the region and the population density, as well as variation in the climate. The urban lakes are exposed to more intensive anthropogenic impacts with developed economy and dense population, which consequently led to the deterioration of the water quality. For instance, Zhou et al. (2017) emphasized on how Chinese economic development had a pernicious impact on the water quality. Another study by Yuan et al. (2019) showed that highly urbanized areas with high population density negatively impact the surface water quality. With rapid economic development and dense urban population in the southeast coastal areas of China, the urban lake ecosystem is greatly affected by human activities. Xu et al. (2020a) focused on the effects of climate change and human activities on TN and TP in Lake Taihu. In semi-humid and semi-arid regions in northwestern of China, the highest NH_4^+-N and TP were found in the lakes which distinguishes them from the reservoirs. In general, the reservoirs are less affected by human activities than urban lakes (Lu et al., 2018).

2.2. *Ecological dynamics of algae in urban lakes*

The algal cell concentration in different urban lakes are shown in **Fig. 1a**, which indicate that differentiation in algal cell concentration in urban lakes is obvious. Among all lakes, the highest richness was observed in YKZ lake and the lowest value was found in WL lake, and these differences were statistically significant ($F = 100.522$, $P < 0.001$). Moreover, the algal cell concentration observed in YKZ lake was much higher than in other lakes. Consequently, based on the distribution pattern of algae biomass, the nutritional status of different urban lakes can be determined. For example, Touzet (2011) identified the trophic state of western and northwestern Irish lakes based on the geographical pattern of phytoplankton biomass. Algal blooms are a good indicator of lake eutrophication and urban lakes with scarce water circulation contribute to the nutrient enrichment (Pineda-Mendoza et al., 2020). A previous study found that eutrophication brought about algal blooms and influenced the whole ecological function of urban lakes (Morris et al., 2006). In general, algal blooms in lakes are universal phenomena which can be correlated with the environmental parameters that vary on spatial scales. In earlier research, the cell density of different algae and their responses to the water quality parameters in an urban river showed that the major influencing factors for algal cell density were water temperature, dissolved oxygen (OD) and pH (Yang et al., 2019). With the development of urban industry and agriculture, a large amount of nitrogen and phosphorus was found to be discharged into lakes (Paerl et al., 2015). In the present study, the high value of nutrient concentration found in the BY lake indicated that nitrogen was one of the key factors bloom formation in the eutrophic lakes. Additionally, the increase of algal biomass with increasing temperature and light intensity has been widely observed in the study of algal cultures (Singh and Singh, 2015). Therefore, the variation in the light intensity and temperature could be described as crucial factors influencing the algal biomass in different urban lakes.

The analysis also revealed a clear regional difference among algal cell concentration of urban lakes (**Fig. 1b**). The algal cell concentration in different areas ranged from high to low in north, west, south, and east in turn ($F = 8.211$, $P < 0.001$). In this work, YKZ lake located in north had highest algal density, where as other northern urban lakes had relatively low algal cell concentrations. The average relative density of the algae observed in the west was similar to south and the whole of east had low values. Previous work has shown that a clear regional gradient in east, west, south and north of Finland in the phytoplankton biomass (Arvola et al., 2011). In central China, Liang et al. (2020) selected 38 lakes in Wuhan city to study the impacts of urban development on lake ecosystems taking diatom communities as main parameters and the results showed that the diatom communities showed significant variation on the urban to rural gradient. As urban lakes have more contact with people. The effects of rural-urban differences on lake algal biomass can be considered in future study.

2.3. *Composition and abundance of algal community*

In the present study, the identified algae taxa from 16 urban lakes were ascribed to 6 phyla – Cyanophyta (Cyanobacteria), Bacillariophyta, Dinophyta, Euglenophyta, Chlorophyta, and Chrysophyta (**Fig. 2**). Cyanobacteria is now considered as prokaryote and belongs to the domain 'Bacteria' however, in this study we considered cyanobacteria as part of the algal community. It is noteworthy to mention that Chlorophyta was the most common phylum, accounting for 57.19% of the total algal community. A similar observation was made by Zhou et al. (2019) and they indicated that members of Chlorophyta (51.79%) were dominant in Moon lake, and this observation is consistent with our present study. Moreover, a previous research reported that members of Bacillariophyta (diatoms) were dominant in 16 urban lakes (Chen et al., 2020). In our study, YKZ lake had the highest proportion of Chlorophyta with 94.00%, followed by SX (92.07%), QJC (88.96%), and HD (84.52%). Cyanophyta (now known as Cyanobacteria) accounted for 32.12% of the total algal population across all urban lakes and they were found to be abundant in DCL lake (86.17%), followed by YZ (79.10%), BH (65.15%), and YH (57.27%). Also, Bacillariophyta accounted for 9.79% (58.04% in SL, 33.30% in WL, 31.82% in DML and 28.00% in JY). Surprisingly, 0.86% proportion of the algal community was belonged to Euglenophyta. And the least percentage observed were Dinophyta and Chrysophyta in YZ and QJC lake, respectively (**Fig. 2a**). These results indicated that the composition of algal community in 16 urban lakes was different. Environmental conditions may affect the composition of algal community. It has been demonstrated that environmental factors may exhibit more differences when habitat are different, but may show less dif-

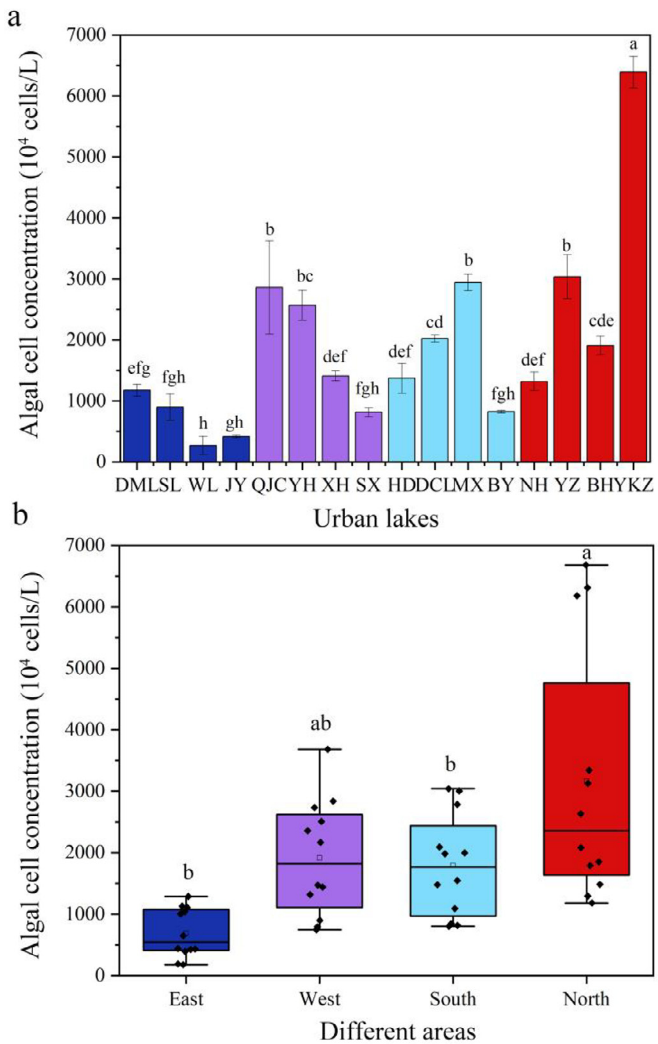

Fig. 1 – (a) Algal cell concentration of different urban lakes. lowercase letters represent significant differences at the 0.05 level. The error bar is the standard deviation (n = 3). (b) Algal cell concentration of urban lakes in different areas. The boxplot consists of five numerical points: minimum, lower quartile, median, upper quartile, and maximum, in descending order. The solid black rhombuses represent the actual data point. The hollow black rhombuses represent the mean of the data points.

ferences under same regions. (Chen et al., 2020). We also found that Cyanophyta but not Chlorophyta was dominant in some urban lakes, which may be attributed to the geographical environment with the sampled lakes.

Total phytoplankton taxa derived from different geographical regions of China (accounting for 41.87% in the north, 25.31% in the west, 23.69% in the south, and 9.13% in the east). The dominant phylum observed across four regions was Chlorophyta. Specifically, Chlorophyta accounted for 64.51% in the west, and 61.06% in the north, 48.49% in the east, 45.89% in the south (Fig. 2b). A similar observation was made in a study in Finland in which, a clear regional difference in the phytoplankton community was observed (Arvola et al., 2011). In river ecosystems, Yang et al. (2019) revealed that the algal community of the urban river in northern China was mainly comprised of Cyanophyta, followed by Chlorophyta, and Bacillariophyta. However, Heino et al. (2010) found that diatoms in stream are not extensively distributed at large geographical areas. Thus, understanding the variation in algal community structure also necessitates recognizing the differences of their distribution in lakes and rivers. A lot of reports have suggested that the co-existence of bacteria of that affect phytoplankton community (Mayali and Azam, 2004). The complexity of the symbiotic mechanism between algae and bacteria in different urban lakes is also a factor that contributes to the regional differences in the distribution of algal communities.

The algal community at the genus level was further explored by creating a systematic heat map with 55 algal genera, as shown in **Appendix A Fig. S2**. In general, the heat map profile indicated that algal communities in urban lakes of different regions were distinct. For instance, *Synedra* sp. was the dominant genus in SL lake of the east areas (49.60%). In other urban lakes in the east areas, *Chlorella* sp. were the dominant genus in DML (33.10%), WL (31.55%), and JY (56.80%).

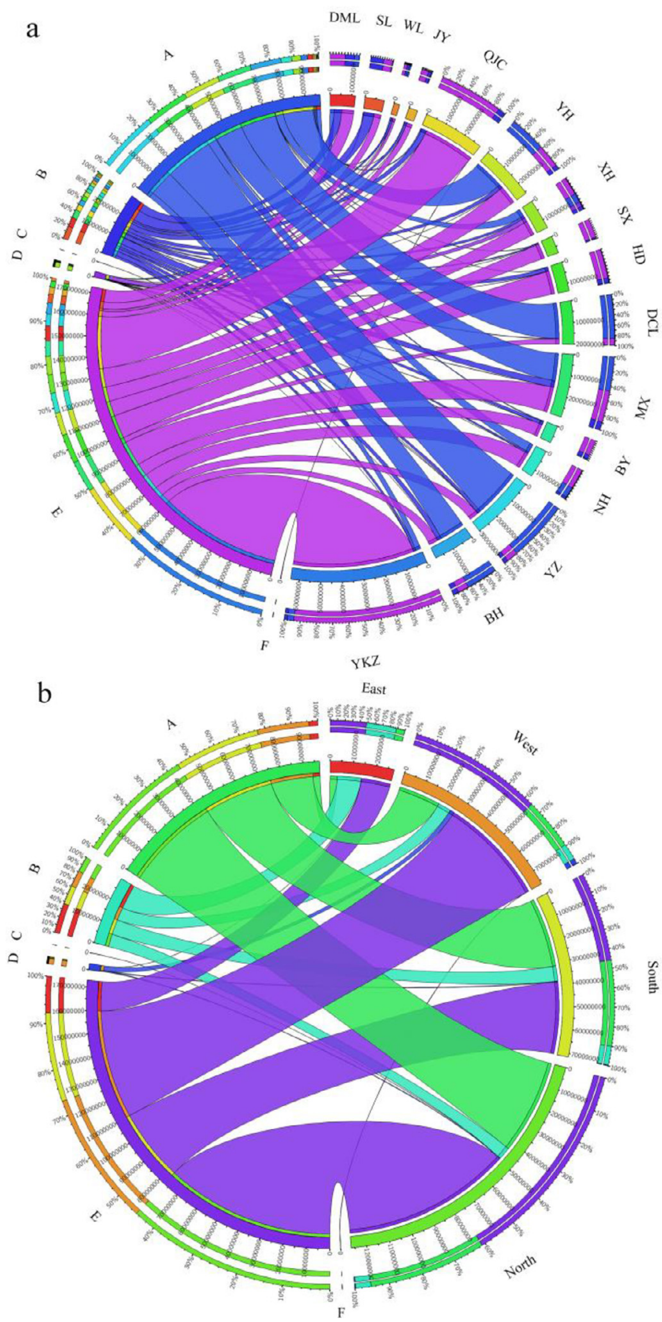

Fig. 2 – Circos representation of algal communities at phylum level of urban lakes in October, 2019. (a) algal communities at phylum level of urban lakes. (b) algal communities at phylum level of urban lakes in different areas. The bands of different colors and areas represent algal communities of urban lakes from different phyla levels. (A) Cyanophyta, (B) Bacillariophyta, (C) Dinophyta, (D) Euglenophyta, (E) Chlorophyta, (F) Chrysophyta. The data were visualized via Circos software (http://circos.ca/).

The whole western urban lakes were dominated by *Chlorella* sp. Notably, high level of *Chlorella* sp. was observed in SX lake (91.18%). In the south areas, the dominant genera in urban lakes like HD, DCL, MX and BY were *Staurastrum* sp. (32.25%), *Microcystis* sp. (85.42%), *Pseudanabaena* sp. (35.57%) and *Chlorella* sp. (74.05%), respectively. In north areas, *Rhabdogloea* sp. was the dominant genus in YZ (46.77%) and BH (32.10%) lakes. In NH and YKZ lakes, *Chlorella* sp. was the commonly observed algal genus with abundance rate of 42.97% and 80.88%, respectively. In a previous study, Lv et al. (2011) investigated the phytoplankton composition in 15 urban lakes in Wuhan city and showed that the dominant algae were *Microcystis aeruginosa* and *Euglena caudate* in summer and *Cryptomonas ovata* and *Cyclotella* in winter. The results obtained from the current study indicated that *Chlorella* sp. was dominant in autumn. In addition, Stomp et al. (2011) examined

Table. 2 – Five networks properties of algal community at genus level

Parameters	East	West	South	North	Whole
Average degree	5.371	12	10.14	7.429	4.254
Avg. weighted degree	4.44	13.816	10.247	6.112	3.054
Network diameter	8	4	4	4	7
Graph density	0.158	0.293	0.241	0.218	0.069
Modularity	0.459	0.377	0.394	0.436	0.613
Connected components	1	2	1	1	1
Avg. clustering coefficient	0.493	0.697	0.591	0.565	0.393
Avg. path length	2.958	1.884	2.085	2.168	3.607
Nodes	35	42	43	35	63
Edges	94	252	218	130	134

the phytoplankton communities in freshwater collected from lakes and reservoirs dispersed across the United States and demonstrated that phytoplankton distribution could be subject to geographic variation. Our results showed that structural patterns of algal communities were related to geographical regions. Geographical variation in algal community is not be determined by a single factor, but by multiple environmental variables.

2.4. *Ecological network analysis*

Network analysis has become an increasingly important tool to explore the cooccurrence patterns of microbial communities in the study of ecosystem (Zhao et al., 2016). The co-occurrence networks have also been applied to bacterial community in different geographical distributions (Zhang et al., 2019). In our study, network analysis was used at genus level to assess the underlying interactions among algal communities in different areas (**Fig. 3**) and the properties of networks are shown in **Table 2**. The network consists of nodes and edges and the nodes represent algal genera, whereas edges represent positive correlations and negative correlations between species. There are modules generated and the potential co-occurrence of algal genera is expressed by the same color module. Our results suggest that algae in urban lakes from the western and southern regions have stronger relationships compared to the eastern and northern regions. This phenomenon is also supported by the spatial patterns of network that cause the degree values to be higher in the western and southern regions while network modularity values tend to be lower in these regions. The observed numbers of nodes and edges from the western and eastern networks are less than southern and northern. Network density is the lowest in the network of west while the east, south and north networks exhibit higher and more similar density. Two indexes reflecting the connection of the algal species, average clustering coefficient and average path length, are inversely proportional in networks. The significant difference of networks analysis indicated that the correlation between t phytoplankton communities varies with the geographical regions ($P < 0.05$). The variations of algal organisms across different regions, which could result from the response to environmental drivers or from the interactions between organisms (Escalas et al., 2019).

It has been demonstrated that different environmental conditions would affect the interactions among algal communities. While species of similar ecological niches may exhibit competition (negative correlations) under the scarcity of environmental resources, mutualism (positive associations) may reflect from the resource-rich conditions (Cao et al., 2018). Given that algal interactions may contribute to lake functions more than biodiversity, this geographic shift in algal community provides new insight into studying microbial biogeographic pattern and impacts on lake-associated function. The combination of geographical distribution and network analysis of microbial community revealed that each region has unique ecological characteristics (Eiler et al., 2012).

To explore the relationships between environmental factors ang algal communities, environmental factors were added to network (**Appendix A Fig. S3**). Focusing on a set of modules in our network, which was represented by the largest module (Module 1), we found more interactions of algal species. The largest node (algal cell density) had the strongest relationships with algal community among the environmental variables. This comment is consistent with Liu et al. (2019), cyanobacterial biomass in reservoirs was most closely related to eukaryotic plankton. Besides that, NO_2^--N, NH_4^+-N are also key environment variables which cannot be ignored in this network. The results indicated that the environmental factors of different geographical locations were strongly associated with the algal community composition ($P < 0.05$). The distribution pattern of algal community attribute to a variety of factors such as climate and rainfall event. The climate in southern China is relatively humid and rainy, while the climate in northern China is relatively dry with less rainfall, which also contributes to the difference in the algal community. Many previously studies indicated that a higher temperature was one of the main reasons for the occurrence of algal bloom and the impact of rainfall is closely related to algal community. As an example, Shaw et al. (2001) suggested that the changes in rainfall may significantly promote the growth of cyanobacteria. In some reports, sediments were found to show most prevalent impacts on the algal community and lake ecosystem functioning. Izagirre et al. (2009) clearly indicated that sediments led to show changes in algal community structure and diatoms increased with high silt.

2.5. *Influence of environmental variables and geographical pattern on algal community structure*

The RDA showed that environmental variables and geographical pattern potentially influenced the algal community in urban lakes (**Fig. 4**). Algal community-environment correlations for RDA1 and RDA2 explained 42.0% and 23.2% respectively, which indicated that there was a poor correlation between environmental factors and algal community distribution. Algal communities in YKZ, MX, YZ, QJC, YH, DCL, DML and BY lake (positive values of the RDA Y-axis) were relatively different from BH, XH, NH, HD, SL, SX, JY, and WL lake communities (negative values of the RDA Y-axis). One possible interpretation is that regional differences in algal community composition reflect the biogeography of algal community. The Monte Carlo permutation tests showed that algal cell concentration, TN, and NO_3^--N were the primary factors influenc-

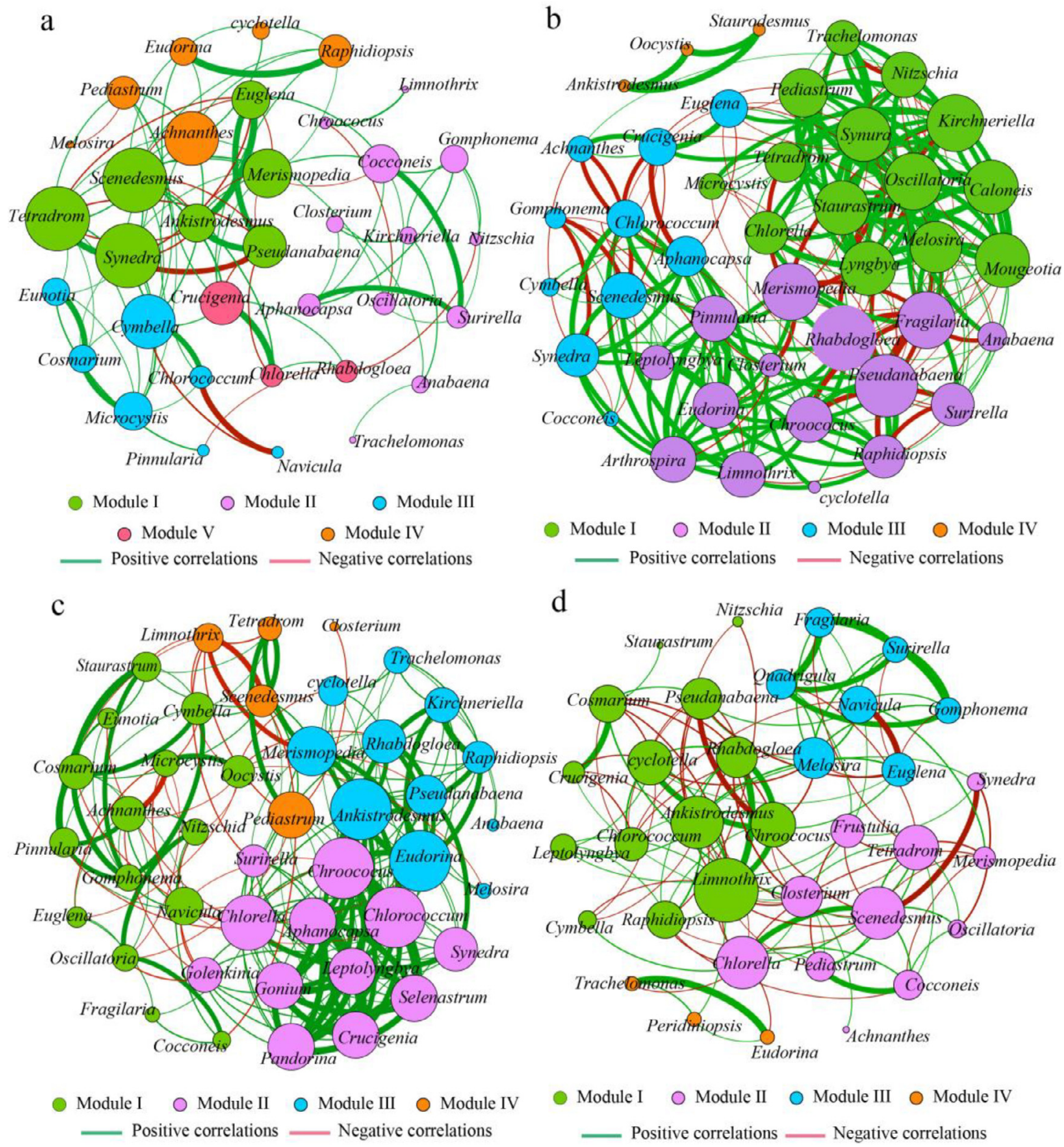

Fig. 3 – Network of co-existence algal community at the genus level based on Spearman's correlation significant analysis (*P* < 0.05). The (a), (b), (c) and (d) represents East, West, South and North sampling sites, respectively. The nodes were colored according to modularity class. The size of each node represents value of betweenness centrality.

ing the algal community. Algal cell concentration had a significant influence on the algal communities in MX, YZ, QJC and YH lakes (Fig. 4). Algal cell density, an important environmental factor, can significantly affect the phytoplankton community in lakes (Xu et al., 2017). Nitrogen and phosphorus concentrations have become crucial factors for predominant algal species in lakes with stagnant water. It is suggested that phytoplankton community structure was primarily affected by nutrients (Zhu et al., 2010). In this respect, Arvola et al. (2011) revealed that nutrients were the main drivers for phytoplankton growth despite geographical location. pH is also a significant factor that shapes the structure of the algal community. In an earlier study, Ren et al. (2015) found that pH was the pivotal factor which impacted the bacterioplankton community assembly in natural freshwater lakes. Similar assembly of phytoplankton had a connection with pH change, which confirmed that pH was an influential variable of community composition for freshwater phytoplankton community of northwestern Mexico (Matus-Hernández et al., 2019).

Van der Gucht et al. (2007) stated that the microbial community can exhibit prominent biogeographic pattern across different spatial scales. A distinct feature of our study is that urban lakes were selected in different geographical regions. Geographical location is a special environmental variable considered in current study and a study of this type is necessary. Xu et al. (2020b) evaluated the contribution of geographical pattern to microbial eukaryotic community in the Zhe-Min Coastal Current. In the present study, we have developed SEM to assess the linkages between algal community and en-

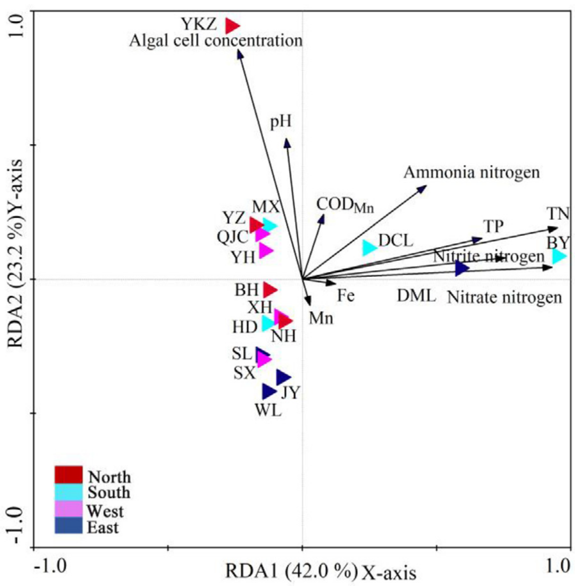

Fig. 4 – Redundancy analysis (RDA) of algal communities of urban lakes in different geographical patterns. Different color right-triangle represent four regions of sampling points. For algal community, RDA1 explained 42.0%, and RDA2 explained 23.2% of the total variance. The main factors of the water quality parameters are represented by arrows (TN: total nitrogen; TP: total phosphorus).

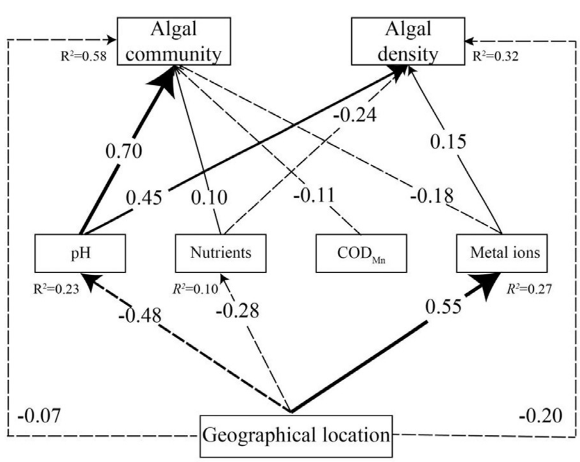

Fig. 5 – The path of partial least squares path model (PLS-PM) showing effects of geographical location (longitude and latitude) and water quality parameters on algal communities of urban lakes in different areas. Solid and dashed black lines represent positive and negative effects, respectively. The thicker line indicated that the higher absolute value of the coefficient are received by PLS-PM. The goodness-of-fit index was 0.397 for this path.

vironment variables, including geographical distribution pattern (Fig. 5). The model revealed a good fit to the original data. Additionally, geographical location variables had positive direct effect on metal irons and negative influences on pH and nutrients. Although geographical location strongly influences the metal ions, the later exhibited little positive and negative influence on the algal community and density, respectively. More importantly, pH was a significant factor that affected on the algal community and density under the impact of geographical location. Compared with the algal community, the geographical location had a stronger response to algal density. Thus, further notarizing the geographical location made a contribution to differential algal communities in different regions. This relationship between the algal community structure and the geographical location of urban lakes was further found to be associated. Our findings suggested that composition of algal community was driven by a combination of geographical location (latitude and longitude) and environmental factors in urban ecosystems at a large scale. The results further agreed with Romina Schiaffino et al. (2011), who demonstrated that bacterioplankton community composition was influenced by geographical location and environmental factors. In their review on bacterioplankton biogeography, they reported that latitude had a remarkable impact on total bacterioplankton abundance. Interestingly, in the current study, geographical location of urban lakes was represented by latitude and longitude. A previous study has indicated that there was a strong correlation between geographic distance and benthic algal community structures (Yang et al., 2018). However, latitude was seemed more conducive than geographical distance in explaining the biogeographic pattern of algal community (Sales et al., 2012). Overall, based on the analysis of algal community in urban lakes of different areas, that environmental variations and geographical pattern were found to synergistically influence the algal community.

3. Conclusions

This study suggests that algal community structure was affected by both geographical pattern and multiple environmental factors. At a large regional scale, the algal community showed biogeographical pattern in the studied Chinese urban lakes - the composition of algal community in urban lakes in east, west, south, and north China were different. A total of 6 phyla and 55 genera were identified from urban lakes in different areas among which, the phylum Chlorophyta was the most dominant, followed by Cyanophyta (Cyanobacteria). The co-occurrence network analysis revealed that the interaction of geographical pattern and algal organism resulted in the unique algal community structure of different urban lakes. The analysis of the relative contribution of environmental variables and geographical location revealed that the geographical location and environmental variables synergistically influenced the algal community structure. This study highlights the importance of considering geographical distribution pattern in algal community studies in urban lakes as such study provide valuable information for the management of eutrophic urban lakes.

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Appendix A. Supplementary data

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jes.2020.07.024.

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