

# MODIS observations of cyanobacterial risks in a eutrophic lake: Implications for long-term safety evaluation in drinking-water source

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MODIS observations of cyanobacterial risks in a eutrophic lake: Implications for longterm safety evaluation in drinking-water source

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1	MODIS observations of cyanobacterial risks in a eutrophic lake:
2	implications for long-term safety evaluation in drinking-water
3	source
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#### 17 Abstract:

18 The occurrence and related risks from cyanobacterial blooms have increased world-wide 19 over the past 40 years. Information on the abundance and distribution of cyanobacteria is fundamental to support risk assessment and management activities. In the present study, an 20 21 approach based on Empirical Orthogonal Function (EOF) analysis was used to estimate the concentrations of chlorophyll a (Chla) and the cyanobacterial biomarker pigment 22 phycocyanin (PC) using data from the MODerate resolution Imaging Spectroradiometer 23 (MODIS) in Lake Chaohu (China's fifth largest freshwater lake). The approach was 24 25 developed and tested using fourteen years (2000-2014) of MODIS images, which showed significant spatial and temporal variability of the PC:Chla ratio, an indicator of 26 cyanobacterial dominance. The results had unbiased RMS uncertainties of <60% for Chla 27 28 ranging between 10 and 300 µg/L, and unbiased RMS uncertainties of <65% for PC between 10 and 500 µg/L. Further analysis showed the importance of nutrient and climate conditions 29 for this dominance. Low TN:TP ratios (<29:1) and elevated temperatures were found to 30 31 influence the seasonal shift of phytoplankton community. The resultant MODIS Chla and PC products were then used for cyanobacterial risk mapping with a decision tree classification 32 33 model. The resulting Water Quality Decision Matrix (WODM) was designed to assist authorities in the identification of possible intake areas, as well as specific months when 34 35 higher frequency monitoring and more intense water treatment would be required if the location of the present intake area remained the same. Remote sensing cyanobacterial risk 36 37 mapping provides a new tool for reservoir and lake management programs.

38 Keywords: Remote sensing; PC; Algal bloom; Lake Chaohu; Cyanobacterial dominance

# 39 I. Introduction

40	Freshwater is one of the planet's most valuable resources and an essential life-sustaining
41	element and necessary for the survival of nearly all ecosystems. However, insufficient
42	availability and ongoing degradation of this resource is threatening 1.1 billion people around
43	the globe (UN 2006). One growing threat is the increasing frequency of cyanobacterial
44	blooms in freshwater lakes and reservoirs (Chorus and Bartram 1999, Paerl et al. 2011), 87%
45	of the surface freshwater suitable for drinking (Schneider 1996). Cyanobacteria can produce
46	a variety of toxins with negative effects on human health and aquatic life (WHO 2011). The
47	threat posed by cyanobacterial blooms has increased over the past 40 years (Chorus and
48	Bartram 1999, Duan et al. 2009, O'Neil et al. 2012).

49

50 With increased population pressure and depleted groundwater reserves, surface water both from rivers and lakes/reservoirs is becoming more used as a raw water source (Falconer and 51 Humpage 2005). The monitoring of water bodies and freshwater supply systems for 52 53 cyanobacteria and cyanotoxins is not yet common practice in most countries in the world, as 54 sampling and analysis are time-consuming and labor intensive (Chorus and Bartram 1999, Hunter et al. 2010). There is a clear need for timely detection and quantification of 55 cyanobacterial blooms to control public health risks due to compromised drinking-water 56 57 sources.

58

59 Remote estimation of the concentrations of phytoplankton pigments provides helpful

60	information to assess the risk of cyanobacterial blooms. The estimation of Chlorophyll a
61	(Chla) has been used to provide basic information on plankton biomass and its distribution
62	has been used for decades (Morel and Prieur 1977), but cannot be used to specifically
63	determine the abundance of cyanobacteria when other phytoplankton groups co-occur (Duan
64	et al. 2012a, Hunter et al. 2009). The estimation of phycocyanin (PC) is a good indicator of
65	cyanobacteria biomass, but is often more challenging in optically complex waters (Bresciani
66	et al. 2014, Qi et al. 2014b, Simis et al. 2005). The relative contribution of cyanobacteria to
67	total phytoplankton biomass, the ratio of the PC to Chla concentrations (PC:Chla), can be
68	used to indicate cyanobacterial dominance (Duan et al. 2012a, Shi et al. 2015a, Simis et al.
69	2007). Specifically, remotely sensed Chla and PC:Chla products are used in risk assessment
70	models based upon the World Health Organization guidance levels for recreational
71	waterbodies (Hunter et al. 2009, Shi et al. 2015a). This suggests that remote sensing might
72	be able to make a significant contribution to cyanobacterial hazard identification and risk
73	assessment.

74

There are a number of sensors designed for ocean color remote sensing. MODIS Terra/Aqua systems provide a very useful instrument for regular monitoring and long term studies (2000-) of lake and reservoir conditions (<u>Olmanson et al. 2011</u>, <u>Wang et al. 2012</u>), with algorithms ranging from simple empirical regressions to semi-analytical inversions which have successfully been used to estimate Chla concentrations (<u>Kerfoot et al. 2008</u>, <u>Moses et</u> <u>al. 2009</u>, <u>Wang et al. 2011</u>). However, unlike global ocean products, there are no standard Chla products in coastal and inland waters, where optically active constituents vary

82	independently (IOCCG 2000). Importantly, MODIS Terra/Aqua bands from 412 to 869 nm
83	are often saturated in coastal and inland waters due to elevated atmospheric and water
84	turbidity, as these systems were mainly designed for ocean use with a highly sensitivity and
85	narrow dynamic range (Hu et al. 2012). For inland waterbodies, novel Chla retrieval
86	approaches must be developed using non-saturating bands present in the land and
87	atmosphere based sensors (Qi et al. 2014a). In addition, MODIS does not has a 620 nm band,
88	making it difficult to build direct PC algorithms based on radiative transfer (Kutser et al.
89	2006, Tao et al. 2017). In recent years, artificial intelligence approaches, neural network
90	models, support vector machine (SVM) algorithms and Empirical Orthogonal Functions
91	(EOF), have been used to estimate of pigment concentration (Bonansea et al. 2015, Craig et
92	al. 2012, Schiller and Doerffer 2005, Sun et al. 2009). These models are focused on reducing
93	the dimensionality of remotely sensed data and bringing out features that would not
94	normally be evident. They do not directly address the bio-optical properties of the specific
95	phytoplankton pigment, but rather empirically address changes that are due to the variability
96	of the bio-optical properties within a set of multiple images.

97

98 Lake Chaohu supports an important commercial fishing industry as well as tourism and 99 recreation activities (Xu et al. 2005). The western section of Lake Chaohu was, until 2007, 100 the major potable water source for Hefei City (the capital city of Anhui province, China). 101 The eastern lake is still the main drinking-water source for Chaohu City. Due to the 102 increasing occurrence of cyanobacterial blooms in the eastern lake, authorities are looking 103 for new approaches to manage water supplies to this city with nearly 1 million people

104	(Zhang et al. 2015). The objectives of this study were: 1) to develop and evaluate
105	MODIS-based algorithms to estimate Chla and PC using EOF approaches, and explore
106	potential benefits of EOF analytics under thick aerosol; 2) to derive a satellite series
107	spatial-temporal distributions of Chla, PC and PC:Chla in 2000-2014 and explore their
108	influencing factors; 3) to assess the potential health risk of cyanobacterial blooms in current
109	drinking-water sources and recommend the possible future sites for drinking-water source.
110	While there are a number of studies using MODIS to quantify cyanobacteria, cyanobacteria
111	blooms, and cyanobacteria bloom phenology (Becker et al. 2009, Kutser et al. 2006, Wynne
112	et al. 2013); this is the first study to focus on cyanobacterial dominance and their driving
113	forces over such an extensive dataset.

# 114 II. Materials and Methods

# 115 **2.1 Study area**

116	Lake Chaohu (117.24° –117.90° E, 31.40° –31.72° N) is the fifth-largest freshwater lake of
117	China, with an average water depth of 2.5 m and a surface water area of 770 $\text{km}^2$ . Its
118	residence time is about 150 days in the rainy season and 210 days in the dry season (Tu et al.
119	1990). Nine rivers contribute 90% of the total water inflow to the lake (Yang et al. 2013),
120	while the Yuxi River outflows from eastern lake area to the Yangtze River (Fig. 1). Before
121	the 1960s, Lake Chaohu was well-known for its scenic beauty and for the importance of its
122	fisheries and lake-related economic activities (Xu 1997). However, the lake has suffered
123	from eutrophication and frequent cyanobacterial blooms in recent decades (Kong et al. 2013,
124	Zhang et al. 2015), due to local rapid population growth and economic development.
125	Nutrient-rich inflows to the west lake from the Nanfei River, Shiwuli River and Pai River
126	which discharge about 10 million tons per year of untreated domestic and industrial
127	wastewater from Hefei City (capital of Anhui Province) (Xu et al. 2005) This has led to an
128	elevated eutrophication of the western lake, where the mean concentrations of TP and TN
129	were significantly higher than these in the eastern lake (Yang et al. 2013). As a result of
130	increasing eutrophication and the reoccurrence of cyanobacterial blooms, the water supply to
131	Hefei City was changed to Dongpu Reservoir from western Lake Chaohu in 2007 (Zhang et
132	al. 2015). Note that the west, central, and east lake segments are hereinafter termed WL, CL,
133	and EL, respectively.

# 134 **2.2 Data**

#### 135 **2.2.1 Field data**

136	Water samples and optical data were collected at 15 sampling stations during seven field
137	investigations between May 2013 and April 2015 in Lake Chaohu (Fig.1 and Table 1), with
138	a total of 259 sampling points collected. Water samples were collected at the surface (~30
139	cm water depth) with a standard 2-liter polyethylene water-fetching instrument. The samples
140	were stored in cold dark condition before filtering in laboratory conditions.
141	
142	PC was measured using a spectrofluorophotometer (Shimadzu RF-5301, 620-nm excitation
143	and 647-nm emission) and a reference standard from Sigma Company (Duan et al. 2012b,
144	Qi et al. 2014b). Chla was measured spectrophotometrically using NASA recommended and
145	community-accepted protocols (Mueller et al. 2003). Suspended particulate matter (SPM)
146	concentrations were measured gravimetrically on pre-combusted and pre-weighed 47 mm
147	GF/F after drying overnight at 105°C overnight (Cao et al. 2017, Duan et al. 2012b).

# 148 2.2.2 MODIS Data

149 Cloud free data granules covering the study region between February 2000 and December 150 2014 were obtained from the U.S. NASA Goddard Space Flight Center (GSFC) (Table S1). 151 Level-0 data were processed using SeaDAS version 7.2 to generate calibrated at-sensor 152 radiance. An initial attempt to use SeaDAS to generate above-water remote-sensing 153 reflectance ( $R_{rs}$ ) (Wang and Shi 2007) was unsuccessful due to elevated aerosol

concentrations and sun glint, even after adjusting the processing options (e.g., the default 154 155 limit of aerosol optical thickness at 869 nm was increased from 0.3 to 0.5, and the default 156 cloud albedo was raised from 2.7% to 4.0%, etc.) (Duan et al. 2014, Feng et al. 2012). The  $R_{\rm rc}$  was derived after correction for Rayleigh scattering and gaseous absorption effects (Hu et 157 al. 2004). As the ocean bands were frequently saturated over Lake Chaohu due to the turbid 158 atmospheric and lake conditions; they were not employed in this study. The 250m MODIS 159 bands at 645 nm and 859 nm and the 500 m bands at 469 nm, 555 nm, 1240 nm, 1640nm 160 and 2130 nm cover a higher dynamic range than the ocean bands and, therefore, rarely 161 162 saturate in turbid waters (Hu et al. 2012). As the 1240 nm, 1640 nm and 2130 nm bands often contain substantial noise due to detector artifacts (Wang and Shi 2007), only four 163 bands at 469, 555, 645, and 859 nm were employed in this study. 164

# 165 **2.3 MODIS Chla and PC products**

According to past and present field measurements, Lake Chaohu has three general optical conditions: "clean" water, a highly turbid state dominated by elevated concentrations of suspended matter, and a cyanobacteria-bloom-dominated (<u>Tao et al. 2017</u>). Of the three conditions, water with high-suspended matter had a higher  $R_{rc}$  compared to clear water areas, but this difference was much smaller than that between these water conditions and bloom-dominated waters. Bloom-dominated reflectance in the near-infrared band (859 nm) showed a high differentiation.

173

174 Following earlier studies in waters with high concentrations of suspended matter, we used

FAI=0.02 as the threshold for the pixels of pure cyanobacterial bloom (Hu et al. 2010). 175 176 However, three situations arise which reduce the effectiveness of FAI class separation: 177 water-land boundary effects, bands with striping noise, and small-scale cyanobacterial blooms. To reduce the misidentification of non-bloom conditions for bloom conditions near 178 179 land boundaries, all images were visually inspected; the distribution of the number of pixels in each scene that were affected by a water-land boundary effect was determined. The bloom 180 and non-bloom images were classified using the standard far outlier threshold (the average 181 value plus two standard deviations: 285 pixels or 17.80 km<sup>2</sup>); among the 1806 scenes of 182 183 MODIS images, 1156 scenes with non-bloom (class I) conditions, and 650 scenes with 184 bloom conditions (class II).

185

186 The general approach followed multi-step process (Fig. 2), which began with the Raleigh correction of MODIS L0 data to determine reflectance R<sub>rc</sub>. The floating algae index (FAI) 187 was applied to each scene and the distribution of pixels with FAI>0.02 was derived. Using a 188 189 standard far outlier threshold (average value plus two standard deviations), an area threshold (285 pixels or 17.80 km<sup>2</sup>) was used to differentiate the non-bloom images (class I) and 190 bloom (class II) images. If the area of cyanobacterial bloom was smaller than 17.80 km<sup>2</sup>, it 191 was considered a non-bloom image and Model I was employed. If the bloom area was larger 192 193 than this threshold, it was considered to be a bloom image, and Model II was employed. The input parameters of the Model I and Model 2 were determined by regression of EOF 194 195 decomposition values with in situ measured Chla and PC concentrations, respectively.

196

EOF is used to reduce multi-band reflectance data to uncorrelated and independent variables 197 198 (i.e., EOF modes) which are then applied to retrieve water quality parameters (Barnes et al. 199 2014, Craig et al. 2012, Qi et al. 2014a). The development of the EOF algorithms followed three steps: (1) The first step was to normalize the R<sub>rc</sub> spectra to derive the NR<sub>rc</sub> data, and 200 perform an EOF analysis (eg. using the princomp function in MATLAB<sup>TM</sup>) on NR<sub>rc</sub>. The 201 output of the EOF decomposition includes the score vector of each EOF mode; each score 202 vector is a linear composition of the four original bands. The output also includes the load 203 value of each band, namely, the coefficients for the linear combination from the original 204 205 bands to the score vector of each mode; and the variance contributions that describe the degree of the original band variance explained by each EOF mode. (2) The second step was 206 to use a training set of in-situ samples to implement a linear regression analysis with the 207 208 score values of EOF modes. The relationship between EOF modes and changes in the concentrations of phytoplankton pigment (Chla or PC) (e.g. using the regress function in 209 MATLAB<sup>TM</sup>) followed: 210

211 
$$\beta_0 + \beta_1 T_1 + \beta_2 T_2 + \beta_3 T_3 + \beta_4 T_4 = \text{pigment concentration}$$
(1)

where  $T_1$ ,  $T_2$ ,  $T_3$ , and  $T_4$  were the score values of the four modes and ( $\beta_{0-4}$ ) were the regression coefficients. (3) The final step was to apply the EOF based Chla or PC algorithms to the MODIS image datasets. More detail are well described in Tao et al. (2017).

# 215 **2.5 Cyanobacterial risk mapping**

216 A decision tree classification model (Fig. S1) based on Chla and PC:Chla was developed to

217	assess cyanobacterial risk (Hunter et al. 2009). This approach was inspired by the WHO
218	guidance levels, which uses the concentration of cyanobacterial cells (or an equivalent
219	concentration of Chla) to estimate the level of risk (WHO 2011). However, the WHO
220	guidance levels do not differentiate the actual biomass of cyanobacteria from that of the total
221	phytoplankton biomass (Tyler et al. 2009). To indicate the relative contribution of
222	cyanobacteria to total biomass, several previous studies used a proxy indicator (Duan et al.
223	2012b, Shi et al. 2015a, Simis et al. 2007), expressed as the ratio of the PC concentration to
224	the Chla concentration. We used this ratio, PC:Chla, to indicate waters with a cyanobacterial
225	dominance .

## 226 **2.6 Accuracy assessment**

The algorithm performance was assessed using four indices, namely the relative root mean
square error, unbiased RMSE (URMSE) in relative percentage (100%), mean normalized
bias (MNB), and normalized root mean square error (NRMS), defined as:

230 
$$\operatorname{RMSE}_{\mathrm{rel}} = 100 \sqrt{\frac{1}{n} \sum_{i=1}^{n} (\varepsilon_i)^2}$$
(2)

231 
$$\text{URMSE}(\%) = \sqrt{\frac{1}{n} \sum_{i=1}^{n} \left(\frac{y_i - x_i}{0.5(y_i + x_i)}\right)^2} \times 100\% \tag{3}$$

(4)

(5)

232 
$$MNB = 100mean(\varepsilon_i)$$

NRMS = 
$$100$$
stdev $(\varepsilon_i)$ 

where  $\varepsilon_i$  represents the relative difference between algorithm-retrieved and measurement concentrations for the *i*<sup>th</sup> measurement; *y* is the algorithm result and *x* is the measurement, and *n* the sample size. URMSE was used to avoid deviations that cause skewed error distributions. MNB is a measure of the systematic errors, NRMS is a measure of random errors.

# 239 **III. Results**

### 240 **3.1 Algorithm development and validation**

- 241 Large spatial and temporal variabilities in Chla and PC were observed during the 7 cruises
- 242 (Table 1). Chla ranged from 6.85 to 1229.83 μg/L, PC ranged from 8.88 to 4807.72 μg/L,
- and PC:Chla varied between 0.09 and 50.39. Spatially, Chla and PC were much higher in
- 244 WL than those in CL and EL. Temporally, the average Chla and PC were highest in summer
- 245 (from May to September) while bloom initiation occurred in early spring (April).

246

The Chla algorithm was developed using 87 data pairs from MODIS and in situ data (half the data set) (Fig. 3a). There was a statistically significant correlation between the EOF-modeled Chla and measured Chla, with a coefficient of determination ( $R^2$ ) of 0.64 and RMSE<sub>rel</sub>=70.12%. The data were scattered around the 1:1 line, and the Chla algorithm overestimates Chla with MNB=19.17% and NRMS=67.45%. The PC algorithm showed similar performance with  $R^2$ =0.60, and lower uncertainties in all statistical measures (RMSE<sub>rel</sub>=38.33%, MNB=26.98%, NRMS=73.50%) (Fig. 3c).

254

The performance of the Chla and PC algorithms was assessed using the remaining 93 datasets, and the results showed significant correlations between modelled and *in situ* concentrations. For Chla,  $R^2=0.40$ , RMSE<sub>rel</sub>=58.38%, MNB=18.68%, and NRMS=62.74% (Fig. 3b); while for PC,  $R^2=0.40$ , RMSE<sub>rel</sub>=57.96%, MNB=38.11%, and NRMS=69.92% (Fig. 3d). The performance of the algorithm was acceptable considering that four land bands

and a partial atmospheric correction were used. Importantly, the error bars of Chla and PC also showed reasonable results (Figs. 3e and 3f). Additionally, the retrieved PC patterns from MODIS are spatially consistent in two conditions (Bloom and Non-bloom) with MERIS PCI products (<u>Tao et al. 2017</u>), which have provided reliable PC estimations in other inland water bodies (Qi et al. 2014b).

# 265 **3.2 Long-term trend and variability**

The EOF-based algorithms were used to derive a long-term Chla and PC values from available MODIS data, and these values were integrated with annual and monthly means.

# 268 **3.2.1 Chla**

The seasonal mean EOF-derived satellite Chla showed significant spatial and temporal 269 variability (Fig. S2). In general, Chla was highest in the western lake (WL) compared to the 270 central and eastern lake areas (CL and EL). The WL is highly eutrophic due to the high 271 272 degree of urban wastewater brought to the lake through the Nanfei, Shiwuli and Pai rivers (Fig. 1), which discharge millions of tons per year of wastewater from Hefei City. CL 273 274 showed the lower Chla as it receives the much clearer waters from the Hangbu, Baishishan 275 and Zhao rivers, which account for nearly half of the total freshwater input into the whole 276 lake. The annual mean Chla of WL was consistently higher than that of CL and EL, and ranged from 21.16 µgL<sup>-1</sup> in 2004 to 75.65 µgL<sup>-1</sup> in 2012, with a long-term mean of 277  $36.97\pm16.19 \ \mu g L^{-1}$  for the 15-year period (Fig. 4a). For EL, Chla ranged from 19.49  $\mu g L^{-1}$  in 278 2001 to 44.18  $\mu$ gL<sup>-1</sup> in 2012 (mean = 31.01±8.42  $\mu$ gL<sup>-1</sup>). Chla in CL was the lowest, ranging 279

280	between 16.34 $\mu$ gL <sup>-1</sup> in 2005 and 39.63 $\mu$ gL <sup>-1</sup> in 2010 (mean = 27.19 $\pm$ 7.42 $\mu$ gL <sup>-1</sup> ). Of the
281	three lake segments, WL showed the highest inter-annual variability, with a 15-year standard
282	deviation (SD) of 16.19 $\mu$ gL <sup>-1</sup> , and followed by EL (8.42 $\mu$ gL <sup>-1</sup> ) and CL (7.42 $\mu$ gL <sup>-1</sup> ). All
283	three lake segments exhibited similar temporal patterns with increasing Chla trend, and Chla
284	in each segment between 2000 and 2006 was significantly lower than between 2007 and
285	2014. Chla showed a noticeable decrease in 2014 in EL. In general, years with large positive
286	anomalies included 2007 and 2014, while years with large negative anomalies included 2000
287	and 2006.

288

Seasonal dynamics showed multiple Chla maxima in September (CL and EL) and October (WL) and annual minimum in April in the entire lake (Figs. S3 and 5a). All three lake segments in February showed a second Chla peak due to high amount of Bacillariophytes present in early spring (no similar PC peak) (Deng et al. 2007). WL showed the highest Chla through the seasonal cycle (21.96-63.63  $\mu$ gL<sup>-1</sup>), followed by EL (19.26-54.95  $\mu$ gL<sup>-1</sup>) and CL (17.31-51.87  $\mu$ gL<sup>-1</sup>).

#### 295 **3.2.2 PC**

296 Compared with Chla, estimated PC showed more significant spatial variability (Figs. S4 and 297 S5). Annual mean PC was consistently high in WL with peaks in 2000, 2001 and 2009, and 298 relatively low in CL and EL throughout the study period (2000-2014) (Fig. 4b). High PC 299 values further extended to the CL and EL in 2011. The long-term mean in WL was 300  $62.02\pm19.94 \ \mu gL^{-1}$ , while long-term means were  $17.01\pm6.10 \ \mu gL^{-1}$  and  $19.36\pm4.85 \ \mu gL^{-1}$  in 301 CL and EL, respectively.

302

303	Seasonal distributions showed higher PC observed in summer and autumn (June-October)
304	(Figs. 5b. and S4). Mean PC reached annual maxima in August (EL) or September (WL and
305	CL). Similar to the annual mean statistics, WL showed the highest mean PC through the
306	seasonal cycle (66.27 $\pm$ 52.46 $\mu$ gL <sup>-1</sup> ); in contrast to CL (18.16 $\pm$ 8.81 $\mu$ gL <sup>-1</sup> ) and EL
307	$(21.68\pm10.80 \ \mu g L^{-1})$ . For all three lake segments, seasonal variability overwhelmed
308	inter-annual variability.

309 3.2.3 PC:Chla

PC:Chla distributions, derived from Chla and PC products mentioned above showed large 310 spatial and temporal variability (Figs. 6 and 7). From 2000-2014, PC:Chla showed a general 311 decreasing trend in WL with significant inter-annual variability (Fig. 4c). In WL, PC:Chla 312 ranged from 0.67 in 2010 to 2.58 in 2001, with an average value of 1.72±0.56. Annual mean 313 PC:Chla in CL and EL were lower, with long-term means of 0.62±0.24 and 0.64±0.21, 314 respectively. Similar the Chla and PC patterns, monthly PC:Chla also showed significant 315 seasonality, but with highest PC:Chla in the late spring and summer (April-August) (Figs. 5c 316 and 7). This seasonal variation confirmed previous field surveys on the dominance of green 317 algae and diatom in the spring, and a shift to cyanobacteria in summer contributing 70%-90% 318 319 to the total phytoplankton biomass (Deng et al. 2007, Li et al. 2015).

# 320 IV. Discussion

## 321 **4.1 Algorithm performance**

There are several studies for estimating pigments such as Chla and PC. For Chla, the ratio of 322 323 near-infrared (around 700-710nm) to red (around 665-685nm) reflectance, to highlight the 324 differences between the absorption maximum and minimum of pigment and water, has been successfully applied to a wide range of turbid water bodies (Dekker 1993, Mittenzwey et al. 325 326 1992). This method depends on empirical linear regression to predict Chla of lakes water. Using similar bands ratio but based on radiative transfer modelling (Gordon et al. 1975), 327 Gons developed a semi-analytical algorithm for Chla retrieval (Gons 1999). Furthermore, a 328 three-band model was also developed to estimate Chla concentration (Dall'Olmo et al. 2003), 329 330 and the two band ratio model was regarded as a special case of the three-band model 331 (Gitelson et al. 2008). Similar to Chla, PC can be detected based on the absorption feature around 620 nm (Bryant 1994), and current algorithms are based on the quantification of the 332 333 reflectance trough at this region in remotely sensed data (Ruiz-Verdu et al. 2008, Simis et al. 2007). However, these algorithms developed in inland waters are designed using field 334 measured remote sensing reflectance  $(R_{rs})$ , and depend strongly on the absolute accuracy of 335 satellite-based  $R_{rs}$  (Duan et al. 2012a, Le et al. 2013). In fact, accurate cyanobacterial 336 pigments retrievals, especially for PC, from satellite measurements in inland waters have 337 been notoriously difficult to develop due to the complex and highly variable nature of these 338 339 waters.

340

18

MODIS was designed for oceanic waters and easily saturated over turbid waters. Even 341 342 without saturation, the requirements of the atmospheric correction on aerosol optical 343 thickness (<0.3 at 859 nm) make valid MODIS  $R_{rs}$  retrievals extremely sparse in those waters (Qi et al. 2014a). This would produce the limited number of MODIS bands, together 344 345 with the large uncertainties in the full atmospheric correction over turbid waters. Given the difficulties in atmospheric corrections and the nature of the optical variability in Lake 346 Chaohu, the EOF approach provided reasonable results to derive long-term cyanobacteria 347 distribution information. This is especially true when considering the Chla and PC patters 348 349 are reasonable (Figs. S2-S5) and low sensitivity to high SPM concentrations contained and atmospheric aerosols perturbations (Fig. S6). The three RGB images in three subsequent 350 days on 5 and 7 January 2007 were generated from data collected under different conditions 351 352 (Figs. S6a- S6c). Figs. S6a- S6b showed an example where significant turbidity changes occurred in most of the lake waters in two subsequent days on 6 and 7 January 2007, yet 353 their corresponding PC (Figs. S6d- S6e) and Chla images (Fig. S6) showed tolerance to such 354 355 significant turbidity changes, as revealed by the very similar PC and Chla distribution patterns for pixels both impacted and not impacted by the turbid changes. Fig. S6c shows 356 another example where the PC and Chla EOF algorithms are both insensitive to 357 perturbations due to thick aerosols. Despite the whole lake experience significant aerosols, 358 yet the PC (Fig. S6f) and Chla (Fig. S6i) values under this condition were similar to those 359 derived under non-thick aerosols from another two days (Figs. S6d- S6e, S6g- S6h). This 360 361 might be due to the spectral normalization which partially remove the sediments and aerosol effects while retaining most the spectral information; of the four spectral bands, three visible 362

363	bands contain information from cyanobacterial pigments. This has also been confirmed in
364	Lake Taihu and Tampa bay (Le et al. 2013, Qi et al. 2014a).

365

It is important note that the use of EOF and single-lake training provides a solution for one lake, and possibly nearby lakes. The solution is not likely to transfer to other locations well, and the two algorithms may not be able to move directly to other lakes. Given that the lake is of high importance for drinking water supply, and given that the method used to 'train' the model is transferable with the requirement for additional field work, the approach will nevertheless be of interest to water management authorities elsewhere.

# **4.2 Cyanobacterial dominance and its driving factors**

Cyanobacterial dominance in anthropogenically impacted eutrophic lakes is an increasing problem that impacts ecosystem integrity and human and animal health (<u>Downing et al.</u> <u>2001</u>). Understanding the cause of cyanobacterial dominance has been a focal point of classical and contemporary limnological research (<u>Havens et al. 2003</u>). The established long-term Chla, PC concentrations and their ratio (Figs. 8a-8c) provide an opportunity to further evaluate the driving forces that control cyanobacterial biomass and potential relation with physical variability in temperature and nutrients.

380

381 Since the earliest studies of phytoplankton ecology, nutrients have been invoked as one of 382 the variables controlling phytoplankton community structure and a predictor of the 383 dominance of cyanobacteria. However, the annual mean Chla and PC in the three lake

384	segments do not demonstrate significant positive correlations with annual mean TN and TP
385	(Fig. 4). In fact, TN and TP showed a general decreasing trend throughout the 15 years (Figs.
386	8d-8e); in contrast, Chla and PC increased, in particular in the years after 2009. The 15-year
387	time-series between Chla and PC and nutrients did not show significant correlations (Fig. 8).
388	Generally, nutrient enrichment is a prerequisite to cyanobacterial dominance and bloom
389	formation, and numerous bioassay experiments have demonstrated that phosphorus and at
390	times nitrogen can act as the limiting resource (Droop 1974, Tilman et al. 1982, Xu et al.
391	2010). This is also confirmed by that the high Chla and PC patterns primarily occupied in
392	WL and tended to decrease from the western to the eastern region in Lake Chaohu (Figs. 5
393	and 6), consistent with the distribution of nutrients determined from field samples (Figs.
394	8d-8f). However, the role of nutrient concentrations in controlling cyanobacteria dynamics
395	might be limited due to elevated concentrations and low inter-annual variation, and they are
396	likely in excess of algal growth demand. Note that the annual minimum nutrient
397	concentrations (TN: 1.50 mg/L in 2007; TP: 0.10 mg/L in 2010) during 2000-2014 in Lake
398	Chaohu exceeded cyanobacteria growth requirements (TN: 1.26 mg/L, TP: 0.082 mg/L)
399	recommended to maintain bloom-free conditions in Lake Taihu (Xu et al. 2014), which is at
400	a similar latitude and is dominated by Microcystis blooms. This explains why cyanobacterial
401	blooms can still thrive for much of the year in Lake Chaohu, despite the efforts being
402	undertaken to control nutrient loading.

403

404 Compared with TN or TP, the TN:TP ratio has been shown to impact the phytoplankton 405 species composition, where low N:P favours the production of cyanobacterial blooms (Liu et

406	al. 2011, Tilman et al. 1982). When nutrients are not limiting, the molar elemental ratio
407	(Redfield ratio) N:P in most phytoplankton is 16:1 (Redfield 1934). A TN:TP ratio of 29:1
408	differentiates between lakes with cyanobacterial dominance (TN:TP<29:1 by mass) and
409	lakes without such dominance (TN:TP>29:1) in temperate lakes (Smith 1983). Subsequent
410	multi-lake surveys and controlled experiments have generally supported this hypothesis
411	(Havens et al. 2003). TN:TP rarely went above 29:1 in CL (4 months) and EL (6 months) in
412	168 months between 2001 and 2014; while this threshold was surpassed in 18 months of 84
413	months between 2008 and 2014. The nutrient data in WL was only collected during
414	2008-2014. Using this threshold, all PC:Chla data in WL during 2008-2014 were
415	reorganized and separated into two categories. In months with TN:TP larger than 29:1, the
416	corresponding average PC:Chla was 0.64; while months below 29:1, averaged 1.91 PC:Chla
417	(Figs. 8c and 8f). Note that the annual relative cyanobacteria to total phytoplankton biomass
418	(PC:Chla) (Figs. 4c and 6) in three lake segments especially WL showed a slight decreasing
419	trend in recent years, compared with an increasing TN:TP value (Fig. 4d); and they
420	displayed a significant negative correlation in the entire lake ( $r = -0.39$ , $p < 0.5$ ). The
421	mechanism proposed to link cyanobacterial dominance to a low TN:TP ratio is that all
422	species of cyanobacteria are better able to compete for nitrogen than other phytoplankton
423	when N is scarce. Therefore, when excessive P loading creates a surplus supply of
424	phosphorus, N becomes relatively scarce and cyanobacteria are predicted to become
425	dominant ( <u>Smith 1983</u> ).

426

427 Seasonal succession in the phytoplankton assemblages has been observed in many eutrophic

428	lakes, and temperature has been associated as an important factor responsible for the
429	seasonal shift of phytoplankton community (Elliott et al. 2006). Field surveys showed that
430	there was nearly 200 phytoplankton species mainly including Chlorophytes (101 species),
431	Cyanophytes (46 species) and Bacillariophytes (28 species) in Lake Chaohu (Deng et al.
432	2007), and the dominated group shifted from green algae and diatoms in the spring to
433	cyanobacteria in the summer and autumn (Deng et al. 2007, Li et al. 2015). This is
434	consistent with our monthly Chla, PC and PC:Chla values (Figs. 5a-5c and 7). Chla reached
435	its first peak in February (Fig.5a) due to quick increasing of diatom (Bacillariophytes),
436	which was a superior competitor at temperatures below 15 °C (Tilman et al. 1986). PC and
437	PC:Chla showed their first peaks during summer between June and September with
438	increasing temperature (Figs. 5b and 5c). It has been reported that diatoms dominated under
439	conditions of low water temperature in Lake Chaohu (Deng et al. 2007). However,
440	cyanobacteria generally grow better at higher temperatures than other phytoplankton species
441	such as diatoms and green algae, and this gives cyanobacteria a competitive advantage at
442	elevated temperatures (Elliott et al. 2006, Joehnk et al. 2008, Paerl and Huisman 2008). Fig.
443	9 shows that the monthly mean temperatures were well correlated with PC ( $r = 0.71$ , Fig.
444	9b), but low with Chla or PC:Chla ( $r < 0.22$ , Figs. 9a and 9c). This is because cyanobacteria
445	contribute a large proportion, 90% or more of the total phytoplankton biomass, at higher
446	temperatures, in particular in the summer (Li et al. 2015). Additionally, there are two
447	cyanobacteria taxa in Lake Chaohu, Anabaena dominance in spring was overcome by
448	increasing Microcystis dominance in summer (Yu et al. 2014, Zhang et al. 2016). This will
449	also result in increasing PC concentrations with increasing temperature, and large seasonal

450 variations of Chla and PC:Chla.

451

452	Factors causing the dominance of a phytoplankton group are often difficult to reveal because
453	several interacting factors including hydrodynamic effects are usually involved which are
454	not necessarily the same in different environments (Dokulil and Teubner 2000). Nutrients
455	and temperature are generally regarded as the most important factors affecting
456	phytoplankton community succession, but their relative importance depends on the lake and
457	its location, changes in (wind-driven) turbulence, light availability, and nutrient balance. It
458	has been reported that many diatoms are superior phosphorus competitors and inferior
459	competitors for light and nitrogen at temperatures below 15 °C, whereas many cyanophytes
460	species are superior nitrogen and inferior phosphorous competitors, showing their
461	competitive potential at temperatures above 20 °C (Deng et al. 2007, Tilman et al. 1986).
462	However, when nutrient concentrations are higher than cyanobacteria growth requirement,
463	warm water would increase activity rates of cyanobacteria and enhance the probability of
464	cyanobacterial dominance (Duan et al. 2009, Liu et al. 2011, Wagner and Adrian 2009). A
465	recent study of cyanobacterial dominance based on 1000 US lakes demonstrates that the
466	relative importance of these two factors was dependent on lake trophic state: Nutrients play
467	a larger role in oligotrophic lakes, while temperature is more important in mesotrophic lakes;
468	Only eutrophic and hyper-eutrophic lakes exhibit a significant interaction between nutrients
469	and temperature (Rigosi et al. 2014). In Lake Chaohu, nutrient concentrations are so high
470	that cyanobacteria growth is mainly controlled by temperature and light availability. The
471	incidence of cyanobacteria blooms will certainly increase under future climate warming, if

472 there is no significant nutrient reduction.

#### 473 **4.3 Implication for safety evaluation in drinking-water source**

Harmful cyanobacterial blooms pose a threat to freshwater ecosystems used for 474 drinking-water supply due to the production of cyanotoxins such as microcystins (MCs), 475 which act as a protein phosphatase inhibitors and tumour promoters, causing acute and 476 chronic poisoning in humans and animals, particularly liver injury (Falconer et al. 1983, 477 Paerl and Huisman 2009). MCs are produced by several cyanobacterial genera including 478 479 Microcystis and Anabaena (Chorus and Bartram 1999), the dominant species in Lake 480 Chaohu (Yu et al. 2014, Zhang et al. 2016). As a water shortage city, Chaohu City with nearly 1 million people has only one drinking-water source in the EL section of Lake 481 Chaohu (Fig.1). In fact, Hefei City used to rely on the WL section as its principal 482 483 drinking-water source until it was forced to find an alternative source due to heavy cyanobacterial blooms around 2007. 484

485

Previous efforts have shown the effectiveness of using a decision tree for cyanobacterial risk monitoring and assessment (<u>Carvalho et al. 2011</u>, <u>Hunter et al. 2009</u>, <u>Shi et al. 2015a</u>, <u>Tyler</u> <u>et al. 2009</u>). Using the present EOF based approach on data from Lake Chaohu during 2000-2014, spatial and inter-annual variations of cyanobacterial risk indicated a high heterogeneity (Figs. 10 and 11). Most of the lake remains at low and no risk, only the WL occasionally displayed a medium risk in the years 2004-2009 and 2011-2014. No high risk years were observed. As expected, the WL showed the highest occurrence of low and

493	medium risk rank in the entire lake. The EL was dominated by low and no risk while the
494	conditions of the CL were usually no risk. The years 2000, 2001, 2003, 2005, 2009 and 2011
495	showed the largest areas of low risk. Seasonal distribution confirmed an increased risk
496	during the months with the highest temperature (July-September), and a reduced risk in the
497	winter. It's also worthy noticing that the largest spatial variability was revealed in September,
498	while WL with medium risk rank and CL and EL were both with no risk. This may be the
499	result the prevailing southeast wind in this period that increased the transport of surface
500	algae to the west. In such conditions, re-accessing the WL for domestic water supply to
501	Hefei City remains problematic.
502	
503	To meet the current drinking-water requirement for Chaohu City, the distribution of past risk
504	conditions around the source was used to create a distributed water quality decision matrix
505	(WQDM, Table 2). Using annual monthly mean Chla and PC in 5 km buffer zones around
506	the drinking-water source in EL derived from MODIS (2000-2014), WQDM was derived
507	first using the threshold Chla and PC:Chla values obtained from the decision tree (Fig. S1).
508	Then these values were derived from satellite data products and a WQDM was generated
509	using these values. Results indicated that there were generally low risks, and occasionally
510	medium risks, while none risk occurred between January and March during winter. This
511	present a significant problem for the drinking water supply to Chaohu City with potential
512	increases in human health related risks.

513

514 One possible way to remediate the problem would be to move the drinking-water source to

515	another site in Lake Chaohu. By considering the WQDM, based on areas with the highest
516	frequency of no risk, it's possible to identify the most appropriate water intake areas of the
517	lake, considering the past 14 years of data (Figs.12a-12d). Several areas in the CL were good
518	candidates, with 60% or more frequency with no risk (Fig.12a); however, with a 30%
519	frequency of low risk (Fig.12b). The closest of these areas was almost 30 km from Chaohu
520	city. There was no location with 100% frequency no risk (Fig.12d).

521

Another option would be supplement water treatment during the periods of the year that are 522 most prone to increased risk in the area of the domestic water intake in the EL. Focused 523 water treatment in this period to remove MCs would reduce risk for the population of 524 Chaohu city while not incurring the costs of year round treatment. In general, there were low 525 and occasionally medium risks in the 5 km buffer zones around the present day 526 drinking-water source area, with no risk conditions never occurring only between January 527 and March (Table 2). As low risk means the surface water contained  $5 \sim 25 \ \mu g L^{-1} PC$  and 528 10-50  $\mu$ gL<sup>-1</sup> Chla (Fig. S1), this translated to an equivalent to 0.80~3.98  $\mu$ gL<sup>-1</sup> MCs (Shi et al. 529 <u>2015b</u>). This is higher than the threshold  $(1 \ \mu g L^{-1})$  suggested by WHO for drinking water 530 531 (Otten et al. 2012).

532

The combination of identifiable thresholds that lead to increased risk of compromised water supplies and regular monitoring using remote sensing provides a new tool for the management of lakes used for domestic water supplies. It is also worth mentioning that present satellite constellations would allow for relatively rapid detection of changes in lake

537	state, allowing for early warning and mitigation of the drinking water quality during intake.
538	By building spatially explicit historical datasets, it possible to estimate the relative risk of
539	positioning (or repositioning) water intakes. When cost or infrastructure limitations prohibit
540	the access to low risk lake areas, temporally focused actions to improve treatment (or
541	increased monitoring) with respect to local conditions can be made. The ultimate solution
542	will be to reduce nutrient loads of surface waters, but complex in-lake processes and nutrient
543	storage do not allow for simple linear solutions.

# 544 V. Conclusions

545 In this study, we used an EOF approach to estimate the concentrations of Chla and PC from MODIS in Lake Chaohu. Based on 1806 MODIS images acquired from 2000 to 2014, we 546 found that PC:Chla ratio has a great potential to detect the cyanobacterial dominance, and 547 the nutrient and climate conditions favor this dominance. Additionally, long-term 548 cyanobacterial risk in Lake Chaohu was assessed with a Water Quality Decision Matrix 549 based on MODIS Chla and PC products. The results provide new insights that could assist 550 authorities in the identification of possible intake areas, as well as specific months when 551 higher frequency monitoring and more intense water treatment would be required using the 552 553 present intake area in Lake Chaohu. This study demonstrates that remotely sensed cyanobacterial risk mapping provides a new tool for management programs for this and 554 similar lakes and reservoirs. 555

556

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Date	Ν	Chla (	μg/L)	PC(µį	g/L)	SPM(	mg/L)	PC:Chla			
		Mean	Range	Mean	Range	Mean	Range	Mean	Range		
201305	56	56         42.50±55.58         8.19-257.65		130.79 <u>+</u> 190.87	12.48-909.92	38.21±17.27 10.00-92.86		4.62 <u>+</u> 7.48	0.55-50.39		
201306	31	165.80 <u>±</u> 304.65	15.16-1229.83	513.56 <u>+</u> 1603.55	30.74-4807.72	79.06±63.24	27.00-324.00 2.46±0.7		1.45-4.36		
201307	45	54.62 <u>+</u> 56.64	12.75-260.80	111.94 <u>+</u> 196.12	9.85-776.55	111.29 <u>+</u> 55.11	38.00-244.00	1.76±1.15	0.22-5.25		
201309	25	160.83 <u>+</u> 251.75	20.11-1131.96	254.98 <u>+</u> 552.82	12.48-2682.32	50.12 <u>+</u> 26.33	20.00-138.00	1.17 <u>±</u> 0.56	0.46-2.66		
201409	33	44.57 <u>+</u> 28.43	16.63-157.87	72.47 <u>±</u> 111.36	6.57-558.76	67.27 <u>±</u> 20.22	19.00-112.00	1.35 <u>+</u> 0.99	0.13-3.54		
201501	30	54.36 <u>+</u> 36.89	17.86-138.55	42.50 <u>+</u> 55.97	9.85-321.27	31.80 <u>+</u> 10.05	12.00-65.00	1.10 <u>±</u> 0.98	0.09-4.11		
201504	39	16.25 <u>+</u> 13.44	6.85-85.87	22.46±20.99	8.88-113.33	61.16 <u>±</u> 25.00	26.00-133.00	1.98 <u>+</u> 1.38	0.53-7.39		

Tabel 1. Water quality properties collected in Lake Chaohu. Chla: chlorophyll-a; PC: Cyanobacteria phycocyanin pigments; SPM: suspended particulate

matter.

Table 2. Cyanobacterial risk levels in 5 km buffer zones around the drinking-water source in Lake Chaohu established from MODIS observations during 2000-2014 and a decision tree (Fig. S1). Note that blue means no risk, green means low risk, yellow means medium risk, and white means insufficient MODIS data available.

Year Month	00	01	02	03	04	05	06	07	08	09	10	11	12	13	14
Jan.	\														
Feb.															
Mar.										\					
Apr.															
May															
Jun.															
Jul															
Aug.	\														
Sep.															
Oct.															
Nov.															
Dec.															

Fig.1 Location and distribution map of Lake Chaohu, China. Note that the red circle located near Chaohu City is 5 km surrounding zones around drinking-water source.

Fig.2 The processing procedure of MODIS Chla and PC products

Fig.3 Algorithm training and validations: (a) Chla training; (b) Chla validation; (c) PC training; (d) PC validation; (e) Chla error bar; (f) PC error bar.

Fig.4 Annual mean of (a) Chla, (b) PC and (c) PC:Chla ratio derived from MODIS for the three lake areas; (d) Annual mean of TN, TP and TN:TP for whole lake.

Fig.5 Monthly mean of (a) Chla, (b) PC and (c) PC:Chla ratio derived from MODIS for the three lake areas; (d) Monthly mean of TN, TP and TN:TP for whole lake.

Fig.6 Annual mean PC:Chla distributions derived from MODIS (2000-2014) in Lake Chaohu. Note that there are distinct boundary effects due to aerosol thicknesses (Tao et al., 2017), and long-term time-series data would contain some errors near the lake coast.

Fig.7 Monthly mean PC:Chla distributions derived from MODIS (2000-2014) in Lake Chaohu. Similar to annual mean PC:Chla product, there are distinct boundary effects due to aerosol thicknesses especially in summer seasons (Tao et al., 2017), and long-term time-series data would contain some errors near the lake coast.

Fig.8 Time-series of satellite-derived phytoplankton pigments (a-c) and in situ measured nutrients (d-f) from the three lake segments. The long-time series nutrients data are provided by local Chaohu Management Bureau. Note that the blue dash line show the data with TN:TP larger than 29:1.

Fig.9 Relationship between (a) Chla, (b) PC and (c) PC:Chla and monthly mean temperature in entire lake.

Fig.10 Annual mean risk rank distributions derived from MODIS (2000-2014) in Lake Chaohu.

Fig.11 Monthly mean risk rank distributions derived from MODIS (2000-2014) in Lake Chaohu.

Fig.12 The frequency (a-c) and mean (d) of risk rank distributions derived from MODIS (2000-2014) in Lake Chaohu: (a) No (b) Low (c) Medium (d) Mean. Note that there is no high risk rank in Lake Chaohu.





**Risk Rank** 





![](_page_51_Figure_1.jpeg)

![](_page_52_Figure_1.jpeg)

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![](_page_59_Figure_1.jpeg)

![](_page_60_Figure_1.jpeg)

MODIS algorithms are developed to estimate chlorophyll a (Chla) and phycocyanin (PC) concentrations.

Long-term Chla, PC and PC:Chla maps are derived from 2000-2014 MODIS data in a eutrophic lake.

Low TN:TP and elevated temperatures influence the seasonal shift of phytoplankton community.

Cyanobacterial risk mapping provides a tool for safety evaluation in drinking-water source.