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USE OF ARTIFICIAL NEURAL NETWORK IN THE PREDICTION OF ALGAL BLOOMS

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Abstract—A model to quantify the interactions between abiotic factors and algal genera in Lake Kasumigaura, Japan was developed using artificial neural network technology. Results showed that the timing and magnitude of algal blooms of *Microcystis*, *Phormidium* and *Synedra* in Lake Kasumigaura could be successfully predicted. As for the newly occurring dominant *Oscillatoria*, results were not satisfactory. The evaluation of the importance of factors showed that *Microcystis*, *Phormidium, Oscillatoria* and *Synedra* were alkalophilic. The algal proliferation for *Microcystis, Oscillatoria* and *Synedra* decrease due to the increase in total nitrogen, while the growth of *Phormidium* is enhanced with more nitrogen. In addition, the algal density is affected by zooplankton grazing but with the exception of *Phormidium* due to it being poor food source. Algal responses to the orthogonal combinations of the external environmental factors, chemical oxygen demand, pH, total nitrogen and total phosphorus at three levels were modeled. Various combinations of environmental factors enhance the proliferation of some algae while other combinations inhibit bloom formation.

Key words—neural network, dominant genera, bloom, biotic response, alkalophilic

INTRODUCTION

The vast proliferation of cyanobacteria in lakes and reservoirs has become an emergent aquatic environmental issue owing to fish mortalities caused by oxygen-depletion, toxins such as microcystin and anatoxin, the occurrence of an unpalatable taste and odor, as well as the loss of recreational resources (Pinckney *et al*., 1997; Inamori *et al*., 1998; Sugiura *et al*., 1998). The development of cyanobacteria and green algae blooms are a common phenomenon in eutrophicated waters (Smith, 1990). Research on preventive technologies and monitoring methods of algal bloom have accordingly received worldwide attention.

To be able to control algal blooms, it is necessary to be able to determine the key factors governing the algal dynamics and to establish an algal response model which can effectively simulate the timing and magnitude of algal blooms. Recently, artificial neural network (ANN) technology has been applied in the prediction of algal blooms (Recknagel *et al*., 1997; Yabunaka *et al*., 1997), and the succession of several dominant cyanobacteria (Recknagel, 1997). However, the effects of different factor combinations have not been assessed in detail. Observations have shown that some selected factors in the input layer lead to "noise" affecting the output results. Therefore, an evaluation of the factors affecting the algal growth is necessary before creating an artificial neural network. Further, it is important for successful lake management to find the optimal combinations of these factors based on the availability of data and measures to regulate pollution inputs into the system.

In this study, the most commonly used computational algorithm, back-propagation, was used in ANN model to determine the nonlinear relationships between the water quality factors and the dominant algal genera. Relative importance of factors affecting algal growth was evaluated by sensitivity analysis. Finally, the optimized combinations were determined by observing the change of algal densities using the factorial orthogonal design.

STUDY SITE AND WATER QUALITY DATA

Lake Kasumigaura is the second largest lake in Japan with an area of 22,000 ha and water mean depth of 4.0 m. Mean hydrological retention time is 200 days. From 1982 to 1996, near the center of lake, the annual average water temperature and rainfall was 16.0°C and 1202 mm, respectively. Water quality data from 1982 to 1996 in Kakezaki sampling station

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used in this study were provided by the Enterprise Bureau of Ibaraki Prefecture (Annual Reports of Water Quality from 1982 to 1996).

IDENTIFICATION OF FACTORS AFFECTING THE ALGAL GROWTH

Factors affecting the growth of algae in lake ecosystems are multidimensional, including physical factors (water temperature, light radiation, and the conditioning of water environment), stimulatory or inhibitory chemicals (nutrient loading, aquatic humic substances) as well as biotic interactions (species-species competition, predation). Among these factors, temperature, light irradiance, concentration and composition of nutrients, the conditioning of water, and the rate of cell division were concluded by Bougis (1976) to be principally related to phytoplankton production. However, the latter three among the above five factors are difficult to quantify. Krientiz *et al.* (1996) concluded that uncontrolled inflow of nutrient into Northern German lakes caused major changes in the structure and the function of the planktonic primary producers. Havens (1995) assumed that two factors, water temperature (WT) and light penetration, stimulated algal growth, and lower N : P ratios to favor buoyant cyanobacteria or the dominance by large cyanobacteria. Similarly, the ratio of N : P supplies and temperature were observed to be significant environmental factors affecting the relative abundance of *M. aeruginosa* and *P. tenue* in Lake Kasumigaura (Fujimoto *et al.*, 1997). In addition, the chemical oxygen demand (COD) gradient (Seretaki, 1996) and the aquatic humic substances (AHSs) (Imai *et al.*, 1999) were also found to play an important role in the formation of the algal community. Further, pH influences the absorption rate of CO_2 during photosynthesis by phytoplankton. Typical dominant species of late summer tend to be able to utilize CO_2 at higher pH values than other species (Harris, 1986).

Additionally, the grazing effect by zooplankton (ZP) on algal blooms has been shown to be important (Bougis, 1976). Top–down consumer control, has been found to affect the community structure and biomass of algae much more than the bottom–up resource control, especially in the case of the eutrophicated lakes (McQueen *et al.*, 1986).

It can be concluded from the above studies that WT, light penetration expressed in turbidity (Turb.), dissolved oxygen (DO), COD, total nitrogen (T-N), total phosphorus (T-P), ZP as well as pH value are the determinant factors on algal proliferation.

ARTIFICIAL NEURAL NETWORK TECHNOLOGY

ANN is an appropriate technique to develop models because of its abilities to assign significance to the input parameters and map the inputs to outputs when the relationships between parameters are unknown. Especially, the backpropagation learning technique has been applied successfully in non-linear complex systems, as it can arbitrarily approximate functions by using the gradient descent algorithm or faster algorithm (Hagan *et al.*, 1996). Recently, ANN has been widely used in water resource issues (Poff *et al.*, 1996; Wen and Lee, 1998), especially in aspects of the assessment and prediction of adverse incidents. Clair and Ehrman (1998) simulated the effect of changing climate on discharge and two water quality parameters using network technology. Recknagel *et al.* (1997) used ANN to simulate and predict algal blooms in the case of four lakes with different trophic levels.

Since algae are at the bottom of the food chain in lake ecosystems, their responses can mostly be attributed to physical and chemical changes (US EPA, 1990). Accordingly, the research on models to examine interactions between environmental factors and the response of dominant algal genera has widely attracted attention.

In our study, the Neural Network Toolbox in the MATLAB (License, 160908, MathWorks, Inc., 1999) was used to create a two-layer of feedforward neural network. Input parameters were selected based on the pre-evaluation of factors and the integrity of data, and algal densities of four dominant genera, *Microcystis*, *Oscillatoria*, *Phormidium* and *Synedra* in Lake Kasumigaura were output parameters. The formulated ANN is shown in Fig. 1.

The formulated network was trained using the backpropagation algorithm. One iteration of this algorithm can be written as

$$x_{k+1} = x_k - \alpha_k g_k \quad (1)$$

where x_k is a vector of current weights and biases, g_k is the current gradient, α_k is the learning rate.

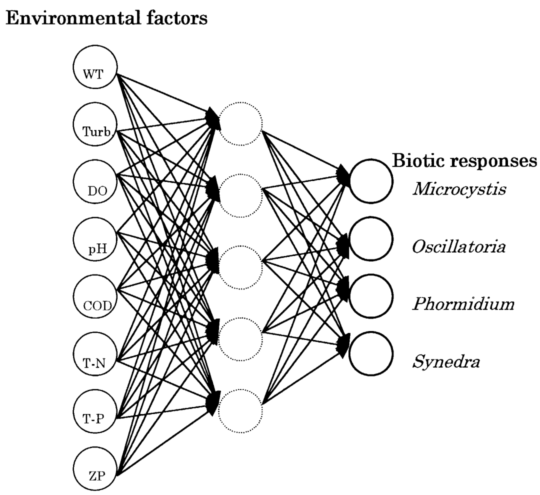

Fig. 1. An ANN model between the four dominant algae and their ambient environmental factors in Lake Kasumigaura, Japan. (◯) Input layer; (◌) Hidden layer; (◯) Output layer.

Initially, the default parameter values of the learning rate (lr = 0.1) and momentum constant (mc = 0.9), hidden neurons (40) as well as training goal (1e-2) were used. During the training the weights and biases are iteratively adjusted using the momentum method to minimize the network performance, and evaluated with the mean squared error (MSE) between the network outputs and the target outputs. If the MSE was found to be small enough and stable at the end of each learning epoch by adjusting lr, mc, epochs, the neurons and number of hidden layers, the parameter set was determined and post-process were carried out.

Data was normalized for the input layer using the method of linear insert-value, as expressed in equation (2). Due to change in algal cell density through one to four magnitudes (1–10,000), a logarithm insert-value was used to normalize the data for output layer, as shown in equation (3).

$$\bar{x} = 0.1 + 0.8\,\frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{2}$$

$$\bar{y} = 0.1 + 0.8\,\log_{\frac{y_{\max}}{y_{\min}}} \frac{y}{y_{\min}} \tag{3}$$

Here, x and y are original data of factors for the input layer and output layer respectively; $\bar{x}$ and $\bar{y}$ are their normalized data respectively; $x_{\min}$, $x_{\max}$ and $y_{\min}$, $y_{\max}$ are the minimum and maximum value for input and output layer, respectively. Moreover, if the cell density is 0 or not be tested, its corresponding normalized values are regarded to be 0.1.

The collected data set were randomly divided into two sets such as the data from April to next March for each year in 10 years in 1982, 83, 85, 86, 88, 89, 91, 92, 94, 95 made up training set and that of 5 years in 1984, 87, 90, 93, 96 constituted a test set for ANN model development. If a nonmeasured or untested factor was included in one data set, it would be cut from training or test set.

RESULTS AND DISCUSSION

Prediction of the timing and magnitude of algal blooms

MSE decreased rapidly and remained around 0. 0195 for *Microcystis*, 0.0216 for *Oscillatoria*, 0.0265 for *Phormidium* and 0.0262 for *Synedra* after 1000 epochs. The post-processed results for the four representative algae using the developed network are shown in Table 1. The trained values were significantly correlated to the measured data ($p < 0.001$) for *Microcystis, Oscillatoria*, *Phormidium* and *Synedra*, viewing from the correlation coefficient and trained data points.

Further, the trained networks were tested by comparing the simulated predictions to the measured values for the four dominant algae in the testing years. The results are shown as Fig. 2.

Table 1. Post-regressions between trained (Y) and observed (X) algal densities

Algae	Equations of best linear fit	Regression coefficients	Data points
Microcystis	$Y = 0.951X + 1600$	0.602	52
Oscillatoria	$Y = 2.800X - 624$	0.545	96
Phormidium	$Y = 1.480X + 602$	0.534	106
Synedra	$Y = 1.720X + 1460$	0.704	112

Figure 2A showed that the predictions were almost consistent with the observed values in the timing of *Microcystis*, but different in its magnitude in 1984, 1987 and 1990. Prediction of the algal bloom was two months earlier than the observations for 1993, despite an almost parallel magnitude of algal bloom. It can also be observed that *Microcystis* almost disappeared in the late 1980s, which was basically consistent with the conclusions of Takamura *et al.* (1992).

Figure 2B and C demonstrated that the *Oscillatoria* and *Phormidium* blooms were seasonally independent. In addition, it was noticed that the prediction for the *Oscillatoria* bloom was not satisfactory from Fig. 2B. We think that the fluctuation pattern of *Oscillatoria* was not significantly determined by the selected input factors, despite the sound trained results. This shows that the growth of *Oscillatoria* is likely to be limited by other unknown factors, such as habitat stability and species-species competition which will be studied in the future.

As shown in Fig. 2C and D, the fluctuation patterns of *Phormidium* and *Synedra* were comparatively well predicted. For *Phormidium,* there was a one month's shift in April for 1990, 1993 and 1996. Regarding *Synedra* blooms, the magnitudes were almost parallel, except for several deviations such as in March 1985, April 1990 and June 1993. This indicates that *Phormidium and Synedra* in Kasumigaura are sensitive to the selected input parameters.

Evaluation of importance of input factors—sensitivity analysis

To identify the sensitivity of algal density to the minor change of each input factor, and to compare the contribution of different factors to the algal proliferation, a simulation on the test set were performed further by increasing each input parameter by 10%. The calculated results showed that pH played an important role in the algal proliferation, as shown in Table 2. A 10% increase in pH value will lead to the increases of 59.1, 67.4, 100.3 and 158.9% in the densities of *Microcystis*, *Oscillatoria*, *Phormidium* and *Synedra*, respectively. Comparatively, the algal proliferation is more sensitive to the change of T-P than that of T-N, except for *Phormidium*. This is consistent with the conclusion that *Phormidium* demands more N for growth than does *Microcystis* (Fujimoto *et al.*, 1997), and also supported by

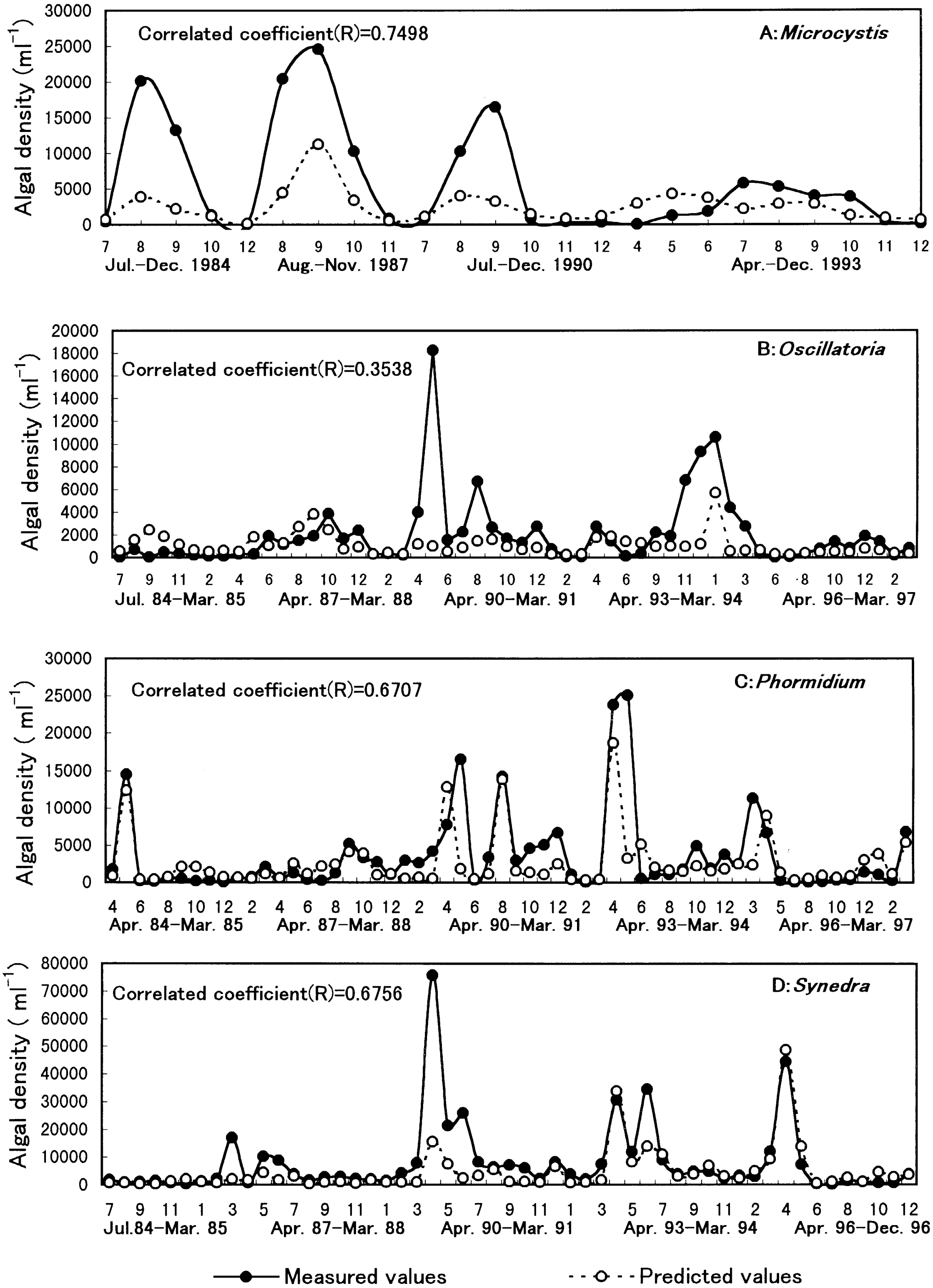

Fig. 2. Validation for four dominant algal genera in Lake Kasumigaura using the trained neural network. Time course is not continuous since some measured or untested data were included in some months.

Takamura's observations (1992) that phytoplankton proliferated from a nitrogen dependence to a phosphorous dependence in Lake Kasumigaura since late in the 1980s. Accordingly, the created ANN model can be considered to be valid.

Some new findings can be extracted from the evaluation of factor importance. For example, it was found that *Microcystis*, *Phormidium* and *Synedra* were well adapted to high temperatures, but *Oscillatoria* was less adapted to elevated temperature periods from the responses of algal densities to the change of water temperature. In addition, due to predation, the algal density will decrease with the increase of zooplankton density but with the exception of *Phormidium*. Some research found that the size fraction of algae limited the use as a food source

Table 2. Changes of four dominant algal densities with the 10% increase in each factor (mean ± standard deviation)

Input factors	*Microcystis* (%)	*Oscillatoria* (%)	*Phormidium* (%)	*Synedra* (%)
WT	4.2 ± 1.2	−5.6 ± 2.6	7.6 ± 1.4	3.1 ± 1.6
Turb.	22.1 ± 7.1	0.4 ± 0.5	22.0 ± 4.5	−0.2 ± 6.7
PH	59.1 ± 5.3	67.4 ± 4.9	100.3 ± 22.0	158.9 ± 30.7
DO	−31.0 ± 3.6	−17.4 ± 2.5	12.6 ± 1.1	21.4 ± 5.2
ZP	−13.6 ± 3.5	−23.4 ± 1.6	11.2 ± 1.3	−3.3 ± 1.2
COD	4.2 ± 3.2	16.2 ± 2.9	15.1 ± 1.9	−29.1 ± 5.1
T-N	−0.9 ± 0.4	1.2 ± 0.3	20.5 ± 3.4	−1.3 ± 0.5
T-P	9.9 ± 3.0	2.4 ± 1.1	1.7 ± 0.6	3.5 ± 1.9

Table 3. Changes of dominant algal densities with different combinations of the environmental changes at three levels using factorial orthogonal design

No.	Changes of environmental factors (%)				Biotic responses of four dominant species (%)			
	pH	COD	T-N	T-P	*Microcystis*	*Oscillatoria*	*Phormidium*	*Synedra*
1	−10	−10	−10	−10	−42.8 ± 7.0	−33.8 ± 9.4	−25.1 ± 7.1	−11.8 ± 10.3
2	−10	0	0	0	−32.4 ± 5.5	−24.1 ± 9.1	−15.8 ± 6.6	−42.5 ± 7.6
3	−10	10	10	10	6.0 ± 6.5	−22.1 ± 9.4	−6.2 ± 7.1	−40.4 ± 7.4
4	0	−10	0	10	−39.6 ± 4.7	−11.5 ± 2.0	4.3 ± 0.7	43.4 ± 14.0
5	0	0	10	−10	−7.5 ± 2.9	−32.9 ± 3.1	18.0 ± 3.4	−1.7 ± 1.7
6	0	10	−10	0	−87.9 ± 0.2	10.4 ± 1.1	3.1 ± 2.3	−16.8 ± 6.8
7	10	−10	10	0	−8.4 ± 6.9	30.1 ± 8.5	57.8 ± 6.4	133.3 ± 36.0
8	10	0	−10	10	34.3 ± 6.2	51.0 ± 7.5	38.9 ± 6.1	81.4 ± 18.5
9	10	10	0	−10	29.3 ± 9.8	63.1 ± 8.2	56.0 ± 5.3	33.6 ± 13.6

of some algae (Ferguson *et al.*, 1982). However, the particle sizes of the isolated *Phormidium* and *Oscillatoria* were well matched in Lake Kasumigaura (Sugiura *et al.*, 1998). Therefore, we assumed that *Phormidium* in the lake water was probably not edible due to its well known MIB-producer even when the temperature was below 4°C (Sugiura *et al.*, 1986). Further, it is observed that different genera have different responses to changes of DO and COD. The increase in DO concentration will stimulate the growth of *Phormidium* and *Synedra* but inhibit *Microcystis* and *Oscillatoria*, while the increase in COD concentration will stimulate the growth of *Microcystis*, *Oscillatoria* and *Phormidium* but inhibit that of *Synedra*.

Environmental control of algal bloom and optimal combination

By reducing nutrient loadings and controlling the productivity (Williamson *et al.*, 1999), human-accelerated eutrophication of lakes may be effectively restored to former conditions. Monthly averaged changes of COD, T-N, T-P and pH values, which were sensitive to anthropogenic impacts and could be prevented in practice, were empirically changed at three levels, −10, 0 and 10%. Using an orthogonal design, a Latin table of four factors at three levels ($L_9(4^3)$) was designed, and 36 simulated outputs for these new inputs were listed in Table 3.

From Table 3, all the cell density of four dominant algae would decrease by 42.8, 33.8, 25.1 and 11.8%, respectively, by lowering all four factors by 10%. In addition, the cell density of *Microcystis* would decrease by 87.9% by lowering T-N by 10%, improving COD by 10% and keeping the other two factors unchanged. The growth of *Microcystis* would be inhibited by the increment of COD under the limitation of total nitrogen. Additionally, the maximum decrease in *Oscillatoria* would reach about 33% by two approaches: (1) lowering all four factors by 10% and (2) increasing T-N by 10% and decreasing T-P by 10%, with the other factors unchanged. Regarding *Phormidium*, when the pH value decreased by 10%, algal density may be lower by 25.1, 15.8 and 6.2% for different combinations of other factors. Contrarily, an increase in pH value would induce the occurrence of *Phormidium* to some extent, which infers that pH is one of the key factors limiting the growth of *Phormidium* in Lake Kasumigaura. Interestingly, the effect on *Synedra* by decreasing pH value by 10% while the other three factors are unchanged is similar to that by decreasing pH value by 10% while improving the other three by 10%, with cell density being reduced by 42.5% and 40.4%, respectively. However, if pH and T-N were both increased by 10%, COD lowered by 10% and T-P unchanged, the cell density of *Synedra* would increase 1.3 times.

CONCLUSIONS

An ANN model to simulate the algal proliferation for the four dominant genera, *Microcystis*, *Oscillatoria*, *Phormidium* and *Synedra* was created. The factors affecting the algal growth were selected to be input parameters based on previous studies.

The proliferation of algal blooms of *Microcystis*, *Phormidium* and *Synedra* in Lake Kasumigaura was successfully predicted and validated using neural network technology. Comparatively, the prediction of *Oscillatoria* blooms, a new dominant phytoplankton since the late 1980s, was not sound except in some months. This phenomenon might be attributable to some unknown factors, such as habitat stability and the competition of other genera.

In addition, the importance of input factors was assessed by the sensitivity analysis of the constructed model. A 10% increase in pH value will lead to the increases of 59.1, 67.4, 100.3 and 158.9% in the densities of *Microcystis*, *Oscillatoria*, *Phormidium* and *Synedra*, respectively. The algal proliferation for *Microcystis*, *Oscillatoria* and *Synedra* decrease due to the increase in T-N, but *Phormidium* requires more N for growth. In addition, it was found that *Microcystis*, *Phormidium* and *Synedra* were well adapted to high temperatures, while *Oscillatoria* was less adapted to elevated temperature periods. Further the algal density will decrease by the predation of zooplankton but with the exception of *Phormidium* due to it being a poor food source.

An approach of quantifying the biotic response to combinations of different changes of the four abiotic factors (COD, pH, T-P and T-N) was developed based on the orthogonal design. The simulated outputs indicated that the dominant genera *Microcystis*, *Phormidium*, *Oscillatoria* and *Synedra* were alkalophilic. By lowering the pH value by only 10%, the growth of most of the dominated genera was markedly inhibited. In the contrary, by increasing pH values by 10% these algae were generally stimulated.

Desirable combinations of environmental factors, which would effectively inhibit algal blooms, are obtained. For example, by improving COD by 10% and lowering T-N by 10% while maintaining the other factors unchanged, the cell density of *Microcystis* would decrease by more than 80%. However, it should be noted that some combinations would stimulate the algal growth clearly.

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