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Long-term Water Quality Variations and Chlorophyll a Simulation with an Emphasis on Different Hydrological Periods in Lake Baiyangdian, Northern China

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ABSTRACT. Eutrophication and water quality degradation comprise one of the most important environmental problems associated with protecting freshwater. Here, systematical analyses of trends, qualitative and quantitative analyses of water quality variables, and simulations of eutrophication were conducted to evaluate biochemical oxygen demand (BOD), total phosphorus (TP), total nitrogen (TN), dissolved oxygen (DO), chlorophyll a (Chl a), and Secchi disk data (SD) based on separate hydrological periods to enhance our understanding of lake ecosystem restoration. Long-term trends were identified using seasonal-trend decomposition with local error sum of squares, while non-supervised artificial neural networks were used to identify qualitative characteristics, and quantitative characteristics were measured using statistical analyses. Numerical simulation of Chl a by the hybrid evolutionary algorithm provided a theoretical solution for ecological warnings. The results were as follows: (1) declining trends in BOD, TP, TN, DO and Chl a were observed during long-term seasonal decomposition after December 2006, but SD increased after June 2003; (2) partitioned K-means maps revealed quantitative characteristics with heterogeneous changes during three hydrological periods, with BOD, TN, SD and Chl a showing the highest clustering quality; (3) BOD and DO showed clear relative hierarchies when compared with other parameters based on quantitative analysis; (4) Chl a simulation revealed heterogeneous changes in the three hydrological periods, and sensitivity analyses indicated that BOD was highly sensitive to Chl a, but TP was not. The sensitivities of other parameters changed during different hydrological periods. The methods described here can be used as preliminary management tools for degraded lakes.

Keywords: artificial neural networks, chlorophyll *a*, hybrid evolutionary algorithm, hydrological period, Lake Baiyangdian, water quality variations

1. Introduction

Eutrophication and degradation of water quality owing to external nutrient overloads have significant impacts on lake ecosystems (Boesch, 2002), and the need to reduce eutrophication and improve water quality has been widely recognized (Galloway et al., 2008). Depending on the prevailing views, shallow lakes are influenced by nutrient concentrations and hydrological variations that have been predicted by mathematical models (Scheffer, 1989) and documented by field observations (Blindow et al., 1993; Scheffer et al., 1994). Scheffer (1989) concluded that shallow lakes with high nutrient loadings could "switch" their state if they were impacted by a strong external or internal force. Such forces commonly mentioned include a dramatic change in water level (Blindow et al., 1993), a major flushing event (Gulati and Van Donk, 1989), or a dramatic reduction in vegetation (Van Donk and Gulati, 1995).

Measures to improve water quality include the restoration or expansion of aquatic plants known to be capable of removing nutrients from the surface water (Coveney et al., 2002; Meuleman et al., 2002). Reduction of nutrient concentrations in the surface water should primarily be directed toward the reduction of an inflow of excess pollutants from point and non-point sources (Köhler et al., 2005). However, reduction of excess pollutants is often only partially achieved owing to the acceptable cost limits. The degree of nutrient removal and reduction of nutrient concentrations from surface water is actually influenced by the relative lake area covered by emergent vegetation and thus by the morphometry of the lakeshore (Dobson and Frid, 1998). Accordingly, understanding the relationships between vegetation and nutrients can facilitate ecosystem restoration. Coops et al. (1996) concluded that vegetation biomass was dependent on water levels during different hydrological periods and their dynamics in freshwater systems. Bodensteiner and Gabriel (2003) found that a suitable water level was necessary for maintenance of vegetation. Water level fluctuations may be used to promote the expansion of emergent vegetation (Coops et al., 2004), which could then improve water quality. Hence, hydrological variations coupled with nutrient concentrations have great impacts on lake ecosystems.

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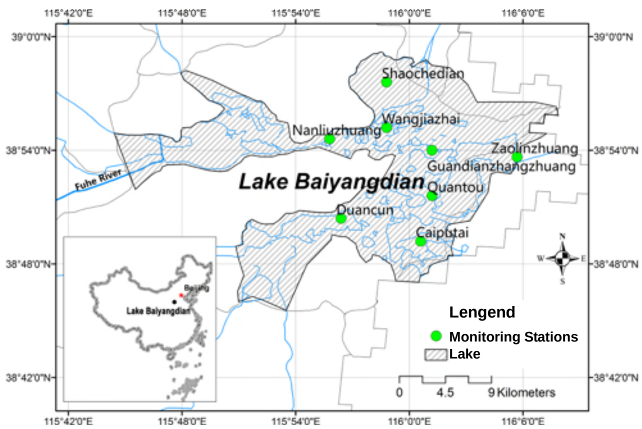

Figure 1. Locations of Lake Baiyangdian and monitoring stations.

However, the extent of combined impacts have not been distinguished or evaluated. Moreover, stresses on lake ecosystems will be exacerbated by the steadily increasing human demands for water, as well as by climate change and shifts in water availability during seasons in which irrigation and ecological demands are high (Bernhardt et al., 2005; Postel et al. 1996). This pattern and intensity of hydrological variability significantly change the biotic structure and activity, which thus influences the improvement of ecological restoration. In addition, hydrological variations in different hydrological periods also have strong effects on water quality and lake eutrophication. Moreover, aquatic vegetation coverage significantly influences the self-purification capability of the lake. As a consequence, problems associated with water quality at the basin scale cannot be resolved without a profound understanding of ecological effects during different hydrological periods. Therefore, it is important to measure variations in nutrients during different hydrological seasons.

It is well-known that nitrogen (N) and phosphorus (P) are the main nutrients in lake ecosystem because their supply rates most often control aquatic plant primary production and biomass formation (Howarth and Marino, 2006; Paerl, 2009). Physicochemical variables such as dissolved oxygen (DO), biochemical oxygen demand (BOD) and Secchi disk data (SD) have long been regarded as important indicators of pollution and measures of the health of aquatic ecosystems (Raj and Azeez, 2009). Moreover, chlorophyll a (Chl *a*) is considered a principal indicator of the trophic state of lakes (Boyer et al., 2009). Nonlinear variations of environmental variables, such as the physical and chemical properties of water quality, are affected to different degrees by pollution, which has long been problematic to ecological field data. Conventional clustering and numerical simulating methods cannot separate their effects adequately; however, new techniques with artificial neural networks (ANN) methods (i.e., self-organization map clustering, and hybrid evolutionary algorithm (HEA)) provide a potential means of separating the respective effects of such environmental variables (Chon, 2011). This represents an opportunity to examine the effects of water quality variables in different hydrological periods, much more critically than has been possible before.

In this study, systematical analyses of trends, qualitative and quantitative analyses of water quality variables and Chl a simulations were conducted with an emphasis on separate hydrological periods (high water period, mean water period and low water period) in Lake Baiyangdian to enhance our understanding of lake ecosystem restoration. Moreover, simulation of Chl a with other parameters using the HEA model was conducted to facilitate lake management. Our main objectives were to: (1) unveil long-term qualitative and quantitative characteristics of water quality variations in Lake Baiyangdian; (2) reveal the regional characteristics of Chl a during three hydrological periods; and (3) propose an effective warning method for better management of lake ecosystem restoration.

2. Materials and Methods

2.1. Study Area

Lake Baiyangdian, the largest natural freshwater body in the North China Plain, is located 130 km south of Beijing (48°43' ~ 39°02' N and 115°38' ~ 116°07' E) (Figure 1). The lake consists of 143 lake islands with 36 villages and 67 km^2 of reed marshes. The lake surface area is 366 km^2, and the total catchment is 31,200 km^2. Lake depth varies according to hydrological conditions, but is usually less than 2.0 m (Xu et al., 1998). The annual mean precipitation in the study area is 419.9 mm, and the annual mean evaporation is about 1,550 mm. Since the 1980s, Lake Baiyangdian has decreased in size and dried up frequently.

Lake Baiyangdian has long suffered from eutrophication, and much of its original area has converted to swamps. During 2000 to 2009, the water quality conditions (mean ± standard error) at the field monitoring stations were as follows: BOD, 5.27 ± 0.15 g/m^3; total phosphorus (TP), 0.22 ± 0.01 g/m^3; total nitrogen (TN), 4.14 ± 0.23 g/m^3; DO, 9.10 ± 0.13 g/m^3; Chl a, 11.88 ± 0.87 g/m^3; SD, 34.37 ± 1.36 cm. Nutrient loadings to Lake Baiyangdian are predominantly caused by non-point sources from tourism, municipal sewage and industrial wastewater from large enterprises as well as from village and township plants. The deterioration of water quality has led to a decrease in biodiversity (Zhong et al., 2008; Cui et al., 2010; Liu et al., 2006). The characteristics of the lake are summarized in Table 1.

2.2. Data Source

In this study, hydrological data and water quality data from 2000 to 2009 were obtained from Anxin Environmental Bureau. In general, water samples were collected once per month from eight sampling points by national monitoring stations around the lake from 1999 to 2009. Meanwhile, field experiments were conducted from July 2009 to October 2010 at Nanliuzhuang Station and Wangjiazhai Station. The analytic methods used were based on the Guidebook to Chemical Analysis of Inland Surface Waters edited by the Water Conservancy Ministry of China (GB3838-2002) (State Environmental Protection Administration of China, 2002). The water samples were passed th-

Table 1. Limnological Properties Reflected by the Databases of Lake Baiyangdian (2000–2009)

Classification criteria	High water period (Min/Mean/Max)	Mean water period (Min/Mean/Max)	Low water period (Min/Mean/Max)
Duration	1st July -30th September	1st October -30th November	1st December -30th June
Hydrological parameters:			
Precipitation (mm)	1.5/80.53/168.9	0/21.98/100.5	0/19.2/146.1
Evaporation (mm)	112.9/164.13/246.3	30.8/72.78/118.3	13.5/130.35/298.8
Water level (m)	5.75/6.66/7.44	5.75/6.59/7.5	5.7/6.69/7.51
Water quality parameters:			
BOD (g/m^3)	0/4.62/25.8	0/4.49/20.8	0/5.77/51.8
TP (g/m^3)	0.015/0.25/2.89	0.007/0.25/1.89	0.01/0.2/3.82
TN (g/m^3)	0/3.85/39.2	0/4.06/35.8	0/4.28/41.2
DO (g/m^3)	0.28/6.62/15.3	0.35/8.33/20	0/10.38/23.4
SD (cm)	0/31.87/250	0/41.84/200	0/33.31/240
Chl a (g/m^3)	0/16.44/188	0/14.48/173	0/9.17/254

rough a 0.45-μm filter prior to analysis. The dilution and seeding method was applied to BOD analysis, while the ammonium molybdate spectrophotometric method and gas-phase molecular absorption spectrometry were used for determination of TP and TN, respectively. The detection limits of these methods were 0.5 mg/L, 0.01 mg/L and 0.050 mg/L, respectively. An electrochemical probe method was used to measure DO. The hot ethanol extraction spectrophotometric method and Secchi disk were used to analyze Chl a and SD, respectively.

2.3. Methods

Although it is assumed that the emission rate of nutrients from point sources is stable during a certain period (e.g., one year), the contribution of these sources differs during each hydrological period. Thus, quantitative analysis of each water quality parameter was conducted using traditional statistics during each hydrological period. The methods used to analyze long-term trends, qualitative analysis of water quality variables and Chl a numerical simulation are described below.

2.3.1. Long-term Seasonal Decomposition by Seasonal-trend Decomposition Using Local Error Sum of Squares (STL) Method

To evaluate overall patterns within intra-annual variations for the time series data of water quality (2000 ~ 2009), we employed a graphically based approach, the seasonal-trend decomposition using the STL method. This method is a graphics based statistical method for time series analysis (Qian et al., 2000). STL is an iterative nonparametric procedure that uses repeated loess (local error sum of squares) fitting (Sellinger et al., 2007). Generally, a time-series of monthly monitoring data may be considered the sum of three components, a high-frequency seasonal component, a low-frequency long-term component (or trend), and a residual component (variation not explained by time), which are expressed as:

$$Y_{year,\ month} = T_{year,\ month} + S_{year,\ month} + R_{year,\ month} \qquad (1)$$

where $Y_{year,\ month}$ is the observed value for a given year and month, $T_{\mathrm{year,\ month}}$ is the trend component, $S_{year,\ month}$ is the seasonal component, and $R_{year,\ month}$ is the residual term.

The median polish process uses median values for trend and seasonal components, and the STL method uses one continuous loess line for the long-term trend component and 12 month-specific loess lines for the seasonal component. As with median polishing, fitting is conducted for each component iteratively until the resulting trend and seasonal components are no longer different from the estimates of the previous iterations. The nonparametric nature of the STL method makes it flexible for revealing nonlinear patterns in seasonal data. Because each month is a subseries in the fitted loess model, the seasonal pattern can change with time revealing changes in timing, amplitude, and variance that occur in the seasonal cycle.

As with all nonparametric regression methods, the STL method requires subjective selection of smoothing parameters. There are two smoothing parameters in the model representing the window widths of the seasonal and long-term components. We selected window widths of 21 months and 61 months for seasonal and long-term components, respectively, to visually elucidate trends. The procedure was implemented in the R program with the “state” library. For more details, please refer to the study conducted by Cleveland et al. (1990).

2.3.2. Qualitative Analysis by Non-supervised ANN

A non-supervised ANN introduced by Kohonen (1988) and Hecht-Nielsen (1989) was applied to ordinate, cluster and map data from each hydrological period (Kohonen, 1995). The principal approach is called self-organizing mapping (SOM), in which the neurons of the non-supervised ANN learn to distinguish between similar and dissimilar features of the normalized input data, which can be mapped as clustered inputs. In this context, the term non-supervised indicates that the learning algorithm is not guided by known output patterns, but instead learns the patterns from features of the inputs.

The SOM creates a low-dimensional topological map using the unit weight vector of each map as a clustering center of input vectors. The map units are usually arranged in a regular or hexagonal grid. During the unsupervised learning process, the best-matching weight vector of the input pattern and its topological neighbors on the map are updated together. Therefore, the neighboring map units have similar weight vectors. The relationships among weight vectors are well preserved on the topological map. The maintenance of similarity relationships makes the visualization of the structure of environmental data patterns more easily understandable. In addition to the clustering process, SOM also projects input data nonlinearly onto a low-dimensional map (i.e. a two-dimensional map). For any input vector, a corresponding unit on the map will be specified such that the map unit's weight vector and input vector have the closest distance. Similar inputs are projected close to each other on the map.

The training algorithm of SOM is iterative. At the beginning, the weight vectors can be initialized linearly. For input vector x, the map unit with the weight vector closest to x is considered the best-matching unit of x. The weight vector of the best-matching unit is denoted by mc. During each learning step t, the weight vectors of both the best-matching unit and its topological neighbors on the map are updated:

$$m_i(t+1) = m_i(t) + \alpha(t)\, h_{ci}(t)\, [x(t)- m_i(t))] \qquad (2)$$

where m_i is the n-dimensional model vector with each map unit i, $x(t)$ is the input vector, $h_{ci}(t)$ is the neighborhood function around the best-matching unit, and $\alpha(t)$ is the learning rate.

There are two methods in which SOM can be utilized for environmental data classification. In one method, map units are labeled according to the training patterns most frequently project onto them after the clustering process. New patterns are classified into the classes of the map unit and weight vector they are closest to. In the other method, the weight vector is clustered into different classes using the information pertaining to the map structure, e.g., the U-matrix, instead of using the labels of input patterns after the clustering process. For the latter case, prior knowledge regarding similar labels is not needed (Liu et al., 2005). In this study, the latter case was used for classification.

This study utilized the SOM method in combination with the clustering techniques described for the U-matrix method and K-means method by calculating the Euclidian distances of data features for the classification. First, the environmental data were classified into two-dimensional units through training of the SOM. Next, all environmental data patterns were divided into clusters using the clustering techniques of the U-matrix method and, subsequently, the K-means method, to visualize and better understand the features of the environmental data. The U-matrix map visualized the relative distances between neighboring data of the input data space as shades of grey. The light areas in the U-matrix visualize neighboring data with the smallest distances belonging to a region or cluster. The black colors represent the largest distances between neighboring data and denote borders between clusters. The K-means algorithm partitioned the input data space into a specified number of clusters based on the U-matrix (Lau et al., 2006; Wilson and Recknagel, 2001). The corresponding partitioned map for the three periods was defined in Table 1 and shown as Figure 4a. For more details, variants, and different methods of computing SOMs, please refer to Kaski et al. (1998).

2.3.3. Numerical Simulation by HEA

Evolutionary algorithms (EA) are adaptive methods that mimic processes of biological evolution, natural selection and genetic variation. EA search for suitable representations of a problem solution with genetic operators and the principle of "survival of the fittest". Due to their merits of self-organization, self-learning, intrinsic parallelism and generality, EA have been successfully applied to pattern recognition, economic prediction, optimum control and parallel processing (Cao et al., 2006; Bäck et al., 2002). The HEA evolves the structure of the rule set by using genetic programming, and optimizes the random parameters in the rule set by using a general genetic algorithm (GA). The HEA uses genetic programming (GP) to generate and optimize the structure of rule sets and a GA to optimize the parameters of a rule set. GP (Banzhaf, 1998) is an extension of GA in which the genetic population consists of computer programs of varying sizes and shapes. In standard GP, computer programs can be represented as parse trees, while leaf nodes represent elements from a terminal set. These symbolic programs are subsequently evaluated by "fitness cases". Fitter programs are selected for recombination to create the next generation by using genetic operators such as crossover and mutation. This step is iterated for consecutive generations until the termination criterion of the run has been satisfied. A general GA is used to optimize the random parameters in the rule set.

The HEA is able to produce formulas of rule-based equation discovery, and was introduced to forecast and explain algal population dynamics in lakes (Cao et al., 2006). Two main attributes of the HEA are use of GP, which evolves the structure of parsing trees (Banzhaf, 1998), and use of the general GA for optimization of random parameters in the rule sets (Jeong et al., 2010). The basic flowchart of the HEA is shown in Figure 2. The principal procedure of the rule set evolution is similar to the framework of replication and reproduction of genes. In the initial stage, a 200-sized population of rule sets is randomly generated and this population, P(t), is evolved under HEA sequential procedures by genetic operators such as crossover (vector and tree level) and mutation (tree level). This is one attribute of the HEA for structure optimization using those genetic operators in GP. The random parameters in each rule set of the population are then optimized by GA, which is another attribute of the HEA in the present study. Selection of the best-predicting model is based on the determination coefficients (r^2) between the observed and predicted values. The deepest rule search is set at less than 3, which means the maximum number of model parameters in a search space is 3. A 'trial and error' algorithm is used in ecological informatics to select the best model. The models showing the highest determination coefficients for both training and testing data are filtered. Among the filtered models, the model that produces the changing patterns closest to the observed Chl a is finally selected as the best-predicting model. Using the best-predicting model, several sensitivity analyses are implemented. First, we evaluate the utility condition between 'THEN' and 'ELSE' functions. This is done by varying the data of the parameters used in the 'IF' function, between mean ± standard deviation. The utility of the 'THEN' or 'ELSE' function is represented by 1 (used) and 0 (not used). Sensitivity analysis is used to estimate the output sensitivity from input variables so that it is useful to evaluate the applicability of models. The figures of sensitivity analysis are displayed in two graphs of 'THEN' and 'ELSE' parts of the model, and the data are sorted by an 'IF' condition of the model and then substituted into the sub tree sectors of the model. The range of parameter variation is determined by the mean and standard deviation.

Long-term time series data were divided into training data (January 2000 to December 2007) and validating data (January 2008 to December 2009). The experimental data were obtained from field monitoring conducted at Nanliuzhuang Station and Wangjiazhai Station from January 2010 to October 2010. The tested data were scattered without strict data intervals.

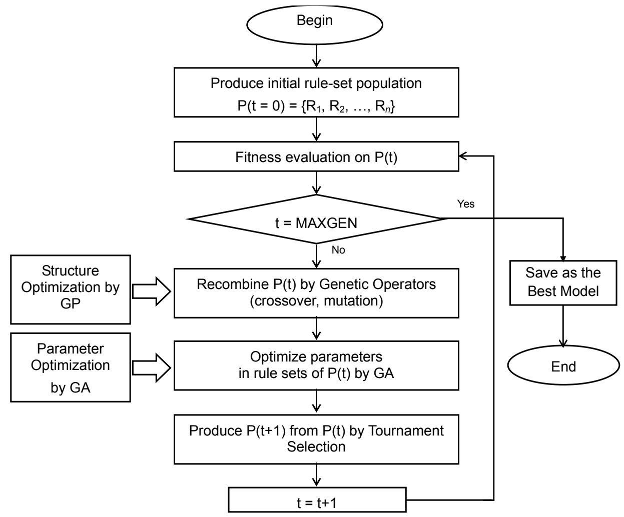

Figure 2. Flowchart depicting the HEA application process.

3. Results

3.1. Long-term Seasonal Decomposition of Water Quality

The nonparametric nature of the STL approach makes it possible to identify nonlinear trends and seasonal interactions that would be missed by traditional trend detection methods. The STL decomposes the water quality time series into three components, a smoothed long-term trend, a seasonal cycle of varying amplitude, and residuals (Figure 3). The long-term trend lines indicate an irregular decline in BOD, TP, TN, DO and Chl a after December 2006, while an increasing trend is shown in SD after June 2003 (Figure 3). Trend curves with an irregular periodicity of over 2 year oscillations were also detected. However, short-term seasonal variations in water quality were regular in seasonal cycles of varying amplitudes (Figure 3).

3.2. Qualitative Analysis of Water Quality

Figure 4 provides a qualitative display of water quality parameters. The results show that ordination and clustering by non-supervised ANN can be integrated into a powerful tool for analysis of complex ecological relationships in data. The hydrological seasonal patterns for water quality from 2000 to 2009 show a significant intuitively difference (Figure 4). BOD and TN display regular similar clusters, with the highest value being observed in low water season (Figures 4b and 4d). However, TP, DO, Chl a and SD show different hydrological seasonal patterns. The highest value of Chl a is observed in the mean water season (Figure 4g), while the highest values of TP, DO and SD are observed in the no–high water season, no–high water season and no–low water season, respectively (Figures 4c, 4e and 4f). The results reveal that Chl a is distinctive from SD, BOD, TP, TN and DO.

3.3. Quantitative Analysis of Water Quality

Figure 5 shows the annual average variations in water quality of the lake during three hydrological periods. During 10 years, changes in TP, TN, SD and Chl a in three hydrological periods showed "tightly twisted curves" (Figures 5b, 5c, 5e and 5f), while changes in BOD and DO were relatively loose (Figures 5a and 5d). The basic trend in BOD were low water season > high water season > mean water season, while that of SD was low water season > mean water season > high water season. The highest value of TN was 5.55 ± 1.17 g/m^3 in the low water period in 2004, and the highest value of TP was 0.40 ± 0.15 g/m^3 in the mean water period in 2007. Both the highest values of BOD and DO were observed in the low water period (8.35 ± 1.22 g/m^3 in 2006 and 11.45 ± 0.47 g/m^3 in 2007, respectively). The lowest values of BOD and DO were observed in the high water season (2.63 ± 0.12 g/m^3 in 2009, 5.04 ± 0.86 g/m^3 in 2005, respectively) (Figures 5b and 5d). During the three hydrological periods, the highest value of SD occurred in the mean water period in 2004 (75.63 ± 12.61 cm) and the lowest value was observed during the high water period in 2004 (5.42 ± 3.85 cm) (Figure 5e). The curves of variations in Chl a during the three hydrological periods are divided into two periods: smoothly fluctuating curves in 2000 to 2005, and greatly fluctuating periods in 2005 to 2009 (Figure 5f).

3.4. Chl *a* Simulation

Figures 6 to 8 show the best rule sets for Chl a for the three hydrological periods based on simulation by HEA. Obviously, the best sets of Chl *a* for the three hydrological periods show different rules (Figures 6a, 7a and 8a), as well as different sensitive parameters (Figures 6b, 6c, 7b, 7c, 8b and 8c).

During a high water season, the best set is:

$$Chl-a=\begin{cases}13.482/BOD \\ [(TN+BOD)-\sin(BOD)]<8.392 \\ \sin[SD\times(-1.656)]\times(-27.418)+SD+BOD \\ [(TN+BOD)-\sin(BOD)]>8.392\end{cases} \tag{3}$$

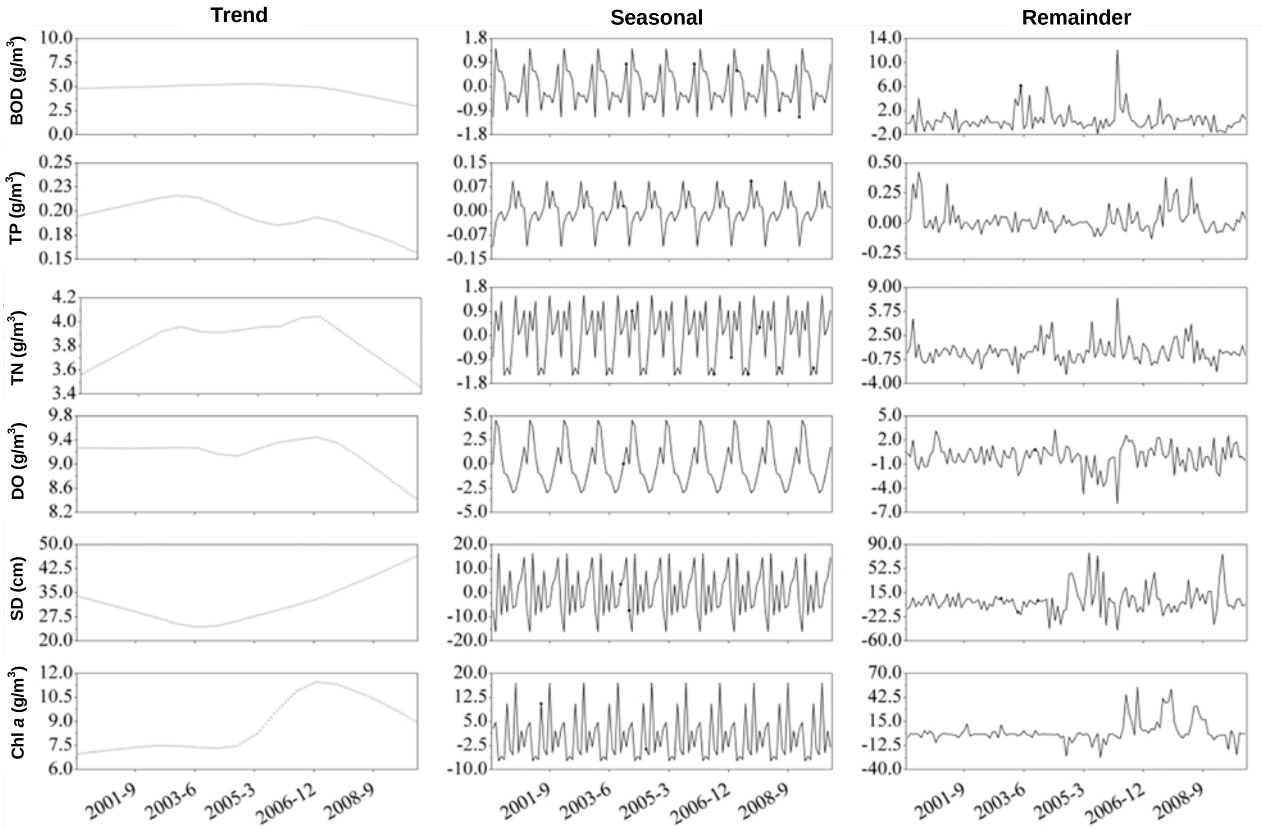

Figure 3. Results of the STL method with depictions of the long-term water quality component (the left row), seasonal component (the middle row), and residuals (the right row).

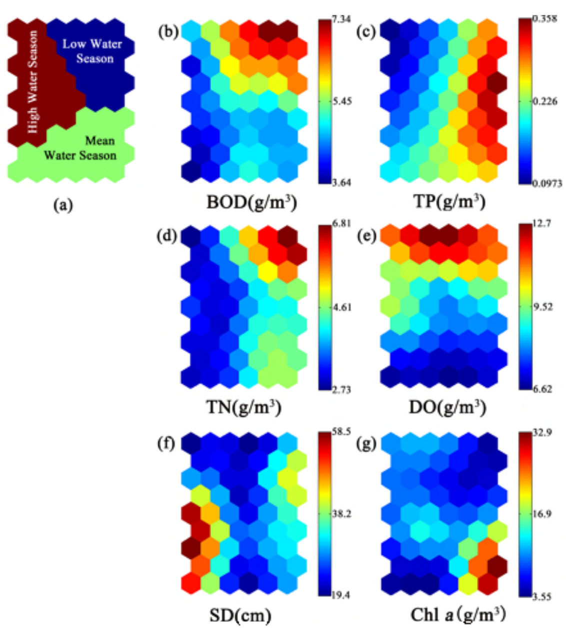

Figure 4. Ordination and clustering of hydrological period of Lake Baiyangdian by non-supervised ANN and visualized partitioned K-means map: (a) Partitioned map, (b) BOD, (c) TP, (d) TN, (e) DO, (f) SD, (g) Chl *a*.

The fitted curve shows basic consistency with the observed data, and the value of R^2 is 0.81.

Sensitivity analyses of Chl a for high water season were also plotted (Figures 6b and 6c), and the results revealed that the sensitivity of Chl a to BOD and TN is always high. When the value of [(TN + BOD) – sin(BOD)] is less than 8.392, a smaller BOD indicates a higher Chl a concentration with a linearly decreasing trend. However, when the value is larger than 8.392, the concentration of Chl a changes nonlinearly with increases of TN and BOD (Equation 3).

During a mean water season, the best set is:

$$
Chl-a=\begin{cases}\cos[(5.491-DO)+2.476]+\cos[(BOD+TN)]\\ +7.203,\\ if\ [(\mathrm{TN}>3.294)\ \&\ (\mathrm{TN}<7.816)]\ \mathrm{OR}\\ [(\mathrm{TN}>=1.574)\ \&\ (\mathrm{BOD}<7.656)]\\ \\ SD+\{[(-4.487)-\cos(TN)]/\sin[(DO/TN)]\},\\ if\ [(\mathrm{TN}<3.294)\ \mathrm{OR}\ (\mathrm{TN}>7.816)]\ \mathrm{OR}\\ [(\mathrm{TN}<1.574)\ \&\ (\mathrm{BOD}>=7.656)]\end{cases} \tag{4}
$$

The fitted curve shows normal variation with the observed data, and the value of R^2 is 0.73.

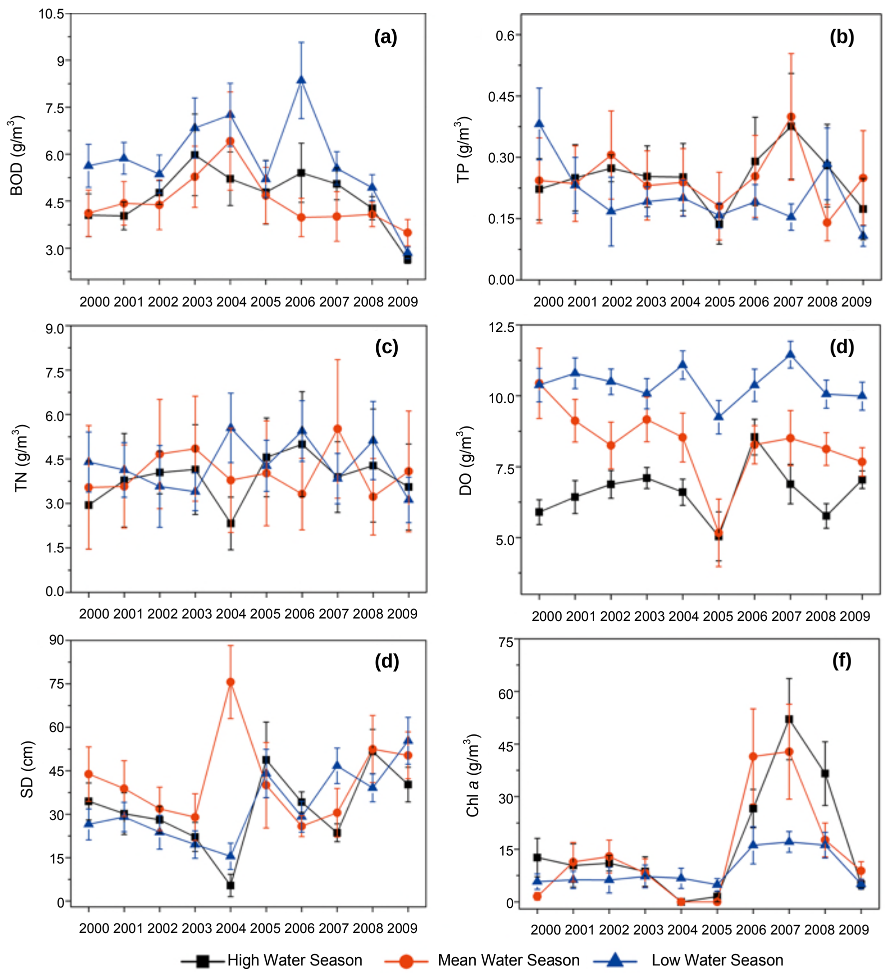

Figure 5. Annual average variations in water quality parameters in the lake during three hydrological periods (2000–2009): (a) BOD, (b) TP, (c) TN, (d) DO, (e) SD, (f) Chl *a*.

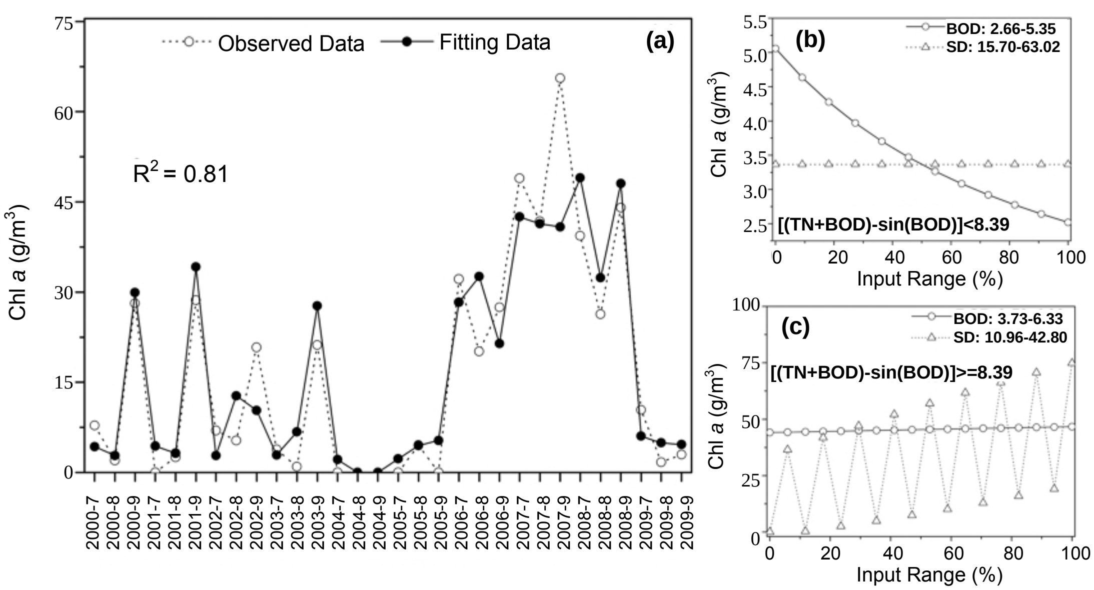

Figure 6. Results of numerical simulation and sensitivity analysis of Chl a by HEA during high water seasons: (a) for numerical simulation; (b) and (c) for sensitivity analyses.

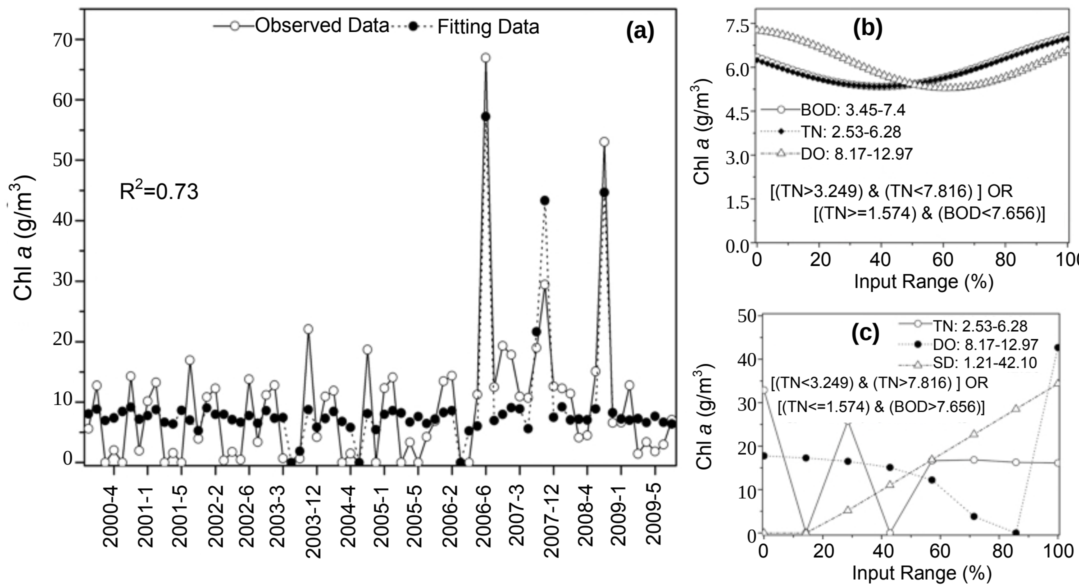

Figure 7. Results of numerical simulation and sensitivity analysis of Chl *a* by HEA during mean water seasons: (a) for numerical simulation; (b) and (c) for sensitivity analyses.

Sensitivity analyses of Chl a for the mean water season were also plotted (Figures 7b and 7c). The results showed that the sensitivity of Chl a is always high for BOD, TN, DO and SD. When the parameters satisfy the conditions in Equation 4, the sensitivity variations display differences among different conditions.

In a low water season, the best set is:

$$Chl-a=\begin{cases}14.26/\ln[|\ln(|SD|)|]\times\sin(\ln(|(SD\text{ - }22.44)|),\\ \mathit{if}\ (BOD\geq 4.906)\ OR\ \{[(BOD>4.891)\&(DO\leq 4.816)]\\ OR[(DO\leq 4.816)\ OR\ (BOD\geq 4.906)]\}\\ \\ \{BOD/\ln[|(SD/14.685)|]\}\times 9.079/\ln[|(SD/TN)|],\\ \mathit{if}\ (BOD\leq 4.906)\ OR\ \{[(BOD<4.891)\&(DO>4.816)]\\ OR[(DO>4.816)\ OR\ (BOD<4.906)]\}\end{cases} \tag{5}$$

The fitted curve shows nearly perfect variation with the observed data, and the value of R^2 is 0.94.

The sensitivity analyses of Chl a for low water season are plotted in Figures 8b and 8c. The results showed that the sensitivity of Chl a for BOD, TN and SD is always high. When TN and SD satisfy the conditions in Equation 5, a smaller value of SD can lead to a higher of concentration Chl a with a linear decrease. However, a larger concentration of TN can cause a higher concentration of Chl a with a linear increase. The variation in sensitivity BOD differs among conditions.

Based on comparison of the three hydrological periods, a larger SD owing to improved water transparency usually indicates a lower Chl a concentration. The sensitivity of Chl a to SD changes was also high for all three hydrological periods, which indicates a positive trend as high levels limit underwater light for photosynthesis. In addition, Chl a shows little sensitivity to changes in TP and DO, especially TP. Overall, the results demonstrated that ordination and clustering by non-supervised ANN and simulation by HEA can be integrated into a powerful tool for analysis of complex ecological relationships in time series data (Figures 4, 5, 6, 7 and 8). Moreover, Chl a is distinctive from BOD, TN, DO and SD, despite differences in the trophic state and morphometry of the lake.

As shown in Figure 9, less scattering and denser values around the straight line were displayed during the three hydrological periods. The Chl a simulation had a testing R^2 of 0.8608, 0.9054 and 0.9591 for the high water period, mean water period and low water period, respectively. The significant levels are all below 0.001. Therefore, the best rule sets for the respective hydrological seasons can be a potential index for early warning of ecosystem degradation, which should be integrated into lake management in future.

4. Discussion

It is clear that qualitative analysis of water quality presented by a non-supervised ANN provides a proper tool for development of cluster and visual maps, which could be a useful framework for lake research. The methods presented here will further facilitate "basic research on complex interactions (that) will lead to explanations for the variability and unpredictability that presently hamper lake management efforts…" (Carpenter, 1988). However, parameters with qualitative ordination and clustering by non-supervised ANN were only shown to be highly indicative for testing hypotheses regarding algal specific preferences for water quality and environmental conditions (Recknagel et al., 2006). Although the quantitative analysis by recurrent supervised ANN has led to certain achievements in fore-

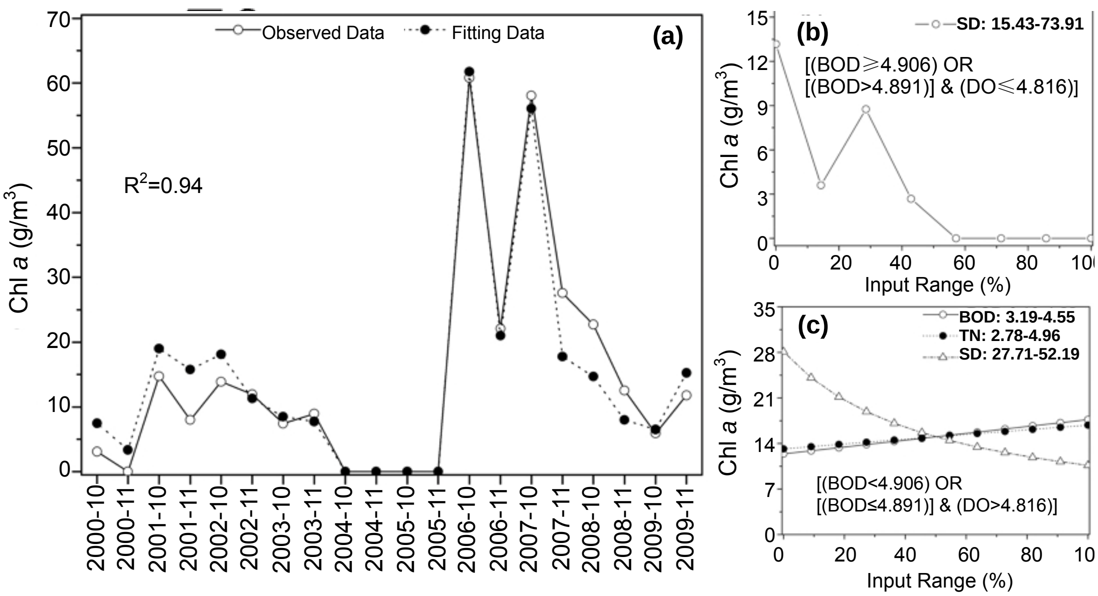

Figure 8. Results of numerical simulation and sensitivity analysis of Chl *a* by HEA in low water seasons: (a) for numerical simulation; (b) and (c) for sensitivity analyses.

casting algal blooms, it is still theoretical. Future studies should focus on practical transformation by a combination of quantitative and qualitative analyses.

The quantitative analysis of water quality with traditional statistics described the variation in time series. The three hydrological periods reflected different hydrological conditions, and demonstrated the effects on biotic processes and water quality variation. However, these water quality parameters could not contain all of the information pertaining to the freshwater ecosystem.

The HEA is still robust against multiple eco-informatics and has been developed to discover predictive rule sets in complex ecological data. The HEA has been designed to evolve the structure of rule sets by using GP and to optimize the random parameters in the rule sets by means of a GA. The HEA has been successfully applied to analysis of long-term monitoring data for shallow eutrophic lakes in Japan and Keron (Kim et al., 2000; Jeong et al., 2001; Jeong et al., 2003). Cao et al., (2006) confirmed the suitability of the HEA by comparing the model explanations and sensitivity analysis with theoretical hypotheses and experimental results in an investigation of two shallow eutrophic lakes in East Asia. Overall, the HEA provides an effective tool for exploring multiple eco-informatics.

High determination coefficients in Chl a simulation were also observed in extreme hydrological periods (high water season and low water season). It is well-known that Chl a represents the primary production of phytoplankton in lake ecosystems. The growth of phytoplankton is sensitive to water quality parameters such as TN, TP, DO, etc. (Cloern and Jassby, 2010). In extreme hydrological periods, fluctuations in water level are the most obvious features that bring a great deal of nutrients to phytoplankton growth owing to enhancement of the exchange between surface water and sediment (Xia et al., 2009; Mortazavi et al., 2012). Specifically, phytoplankton experience maturity during the high water season (July to September), and then gradually die during the low water season (October to November). Moreover, the warm temperatures during those periods can promote the diversity and appearance of phytoplankton in semiarid areas (Sellami et al., 2012). The development of cyanobacteria occurs in autumn, which results in peak values as a consequence of nutrient replenishment (Xia et al., 2004; Abrantes et al., 2006). The cyanobacteria dominance recorded in Barra Bonita Reservoir indicates that high nutrient availability is the controlling factor (Dellamano-Oliveira et al., 2008). Increases in the biomass of phytoplankton imply a close connection between Chl a and water quality parameters during high and low water season. The Chl a concentration, which represents the activities of phytoplankton in those periods, can easily be detected.

Because of a lack of high frequency time series data, the number used in the HEA model is relatively lower, which makes the simulated data easier to fit with a high determination coefficient. Maier et al. (2010) reported that inputs selected (number of inputs and input independence) can have a significant impact on performance of the ANN model. Model based approaches (i.e. HEA model) rely on the number of hidden nodes, which have the potential to mask the effect on model performance. However, the deepest rule in the HEA model is set less than 3, which indicates that the maximum model parameters is 3 for the search space. Thus, the combined effects of relatively fewer data and the deepest rule search less than 3 are likely to produce higher determination coefficients. Accordingly, it is rational to run the HEA model for the simulation.

The high accuracy determination coefficient of the Chl a simulation has been shown in many previous studies. Recknagel et al. (2006) simulated the Chl a concentrations in Lake Kasumlgaura and Lake Soyang using the EA algorithm and obtained determination coefficients of 0.97 and 0.84, respectively. The Chl a simulation using the EA algorithm in the lower Nakdong River (South Korea) showed a high accuracy with a de

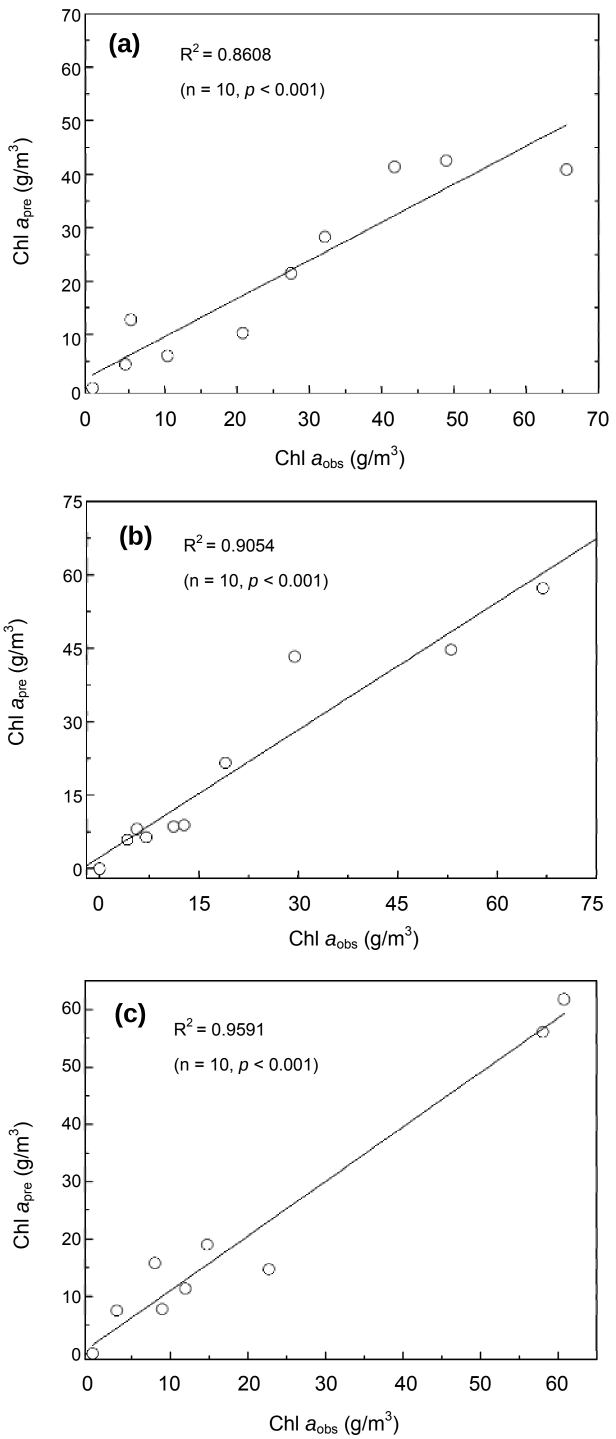

Figure 9. Scatterplots comparing observed and predicted Chl *a* concentrations using the best rule sets with experimental data for: (a) high water period; (b) mean water period; (c) low water period.

-termination coefficient of 0.83 (Kim et al., 2010).

Finally, the special regional characteristic of high frequency water recharges must be considered. In Lake Baiyangidan, water recharges have been implemented annually during the last decade, and these have usually occurred in spring and winter (mean water season) (Zhao et al., 2011). Studies indicate that algal blooms are related to hydrological conditions such as water recharges (Smayda, 2008; Cloern and Jassby, 2010; Phlips et al., 2011). Water recharges have potential effects on phytoplankton growth, and consequently on variations in Chl a. Mortazavi et al. (2012) reported that water Chl a concentrations reached peak values in Weeks Bay (Alabama, USA) during late summer and early fall, when water recharge was low (approximately low water season), and dropped to low values during mean water season. Contrary to the other two water seasons, there is a large amount of data available for the mean water season because the season covers the entire winter and spring. The large dataset can expand the search space for the best rule set in the HEA model and consequently influence the accuracy of the determination coefficient. In winter, surface water is covered with ice and the value of Chl a approaches zero, but the nutrient concentration in the water body is still active. The relationship between phytoplankton and water nutrient in this period is really weak which is the most contributions to the low accuracy for Chl a prediction due to the meaningless best rule searching in HEA model. However, the predicted accuracy can be promoted by the enhanced connections between Chl a and nutrients during spring. The range of Chl a values changes less drastically in the mean water season, with most concentrations being below 20 g/m^3. The ultimate purpose of the HEA model is to prevent algal blooms by detection of high Chl a values before blooms occur. High Chl a values were indeed detected during the mean water season (Figure 7b). For example, high Chl a concentrations were observed in June 2006 and June 2008. Thus, the determination coefficient is prone to lower accuracy in mean water season, whereas it is subject to higher accuracy during the other two hydrological seasons.

Despite differences in the trend and modeling for Chl a prediction, the results provide some potential specific strategies for lake management. Specifically, BOD should receive greater attention owing to its high sensitivity to Chl a during all three hydrological periods, as well as its unique characteristics observed on the K-means map and upon traditional statistical analysis. Furthermore, other parameters should be focused on individually based on their characteristics during different hydrological seasons. Water recharges implemented in the mean water season are rational, but the results indicate that water recharges impact Chl a concentrations during this season. In future research, a larger time series dataset should be applied to further improve the HEA model and ultimately put the result into the practice.

5. Conclusions

It is important to understand long term water quality trend variations, appropriate clusters of parameters and Chl a simulation during individual hydrological seasons to enable relevant actions to improve water quality. In this study, long term trends, qualitative and quantitative analysis of water quality variables, and Chl a simulations for Lake Baiyangdian were investigated. Based on our results, the following conclusions can be drawn:

1) In long-term seasonal decomposition, the concentrations of BOD, TP, TN, DO and Chl a showed decreasing trends after December 2006, but the SD values increased after June 2003.

2) The partitioned K-means map developed by non-supervised ANN revealed heterogeneous changes in three hydrological periods, with BOD, TN, SD and Chl a showing high clustering.

3) Quantitative variations in water quality demonstrated by traditional statistics showed a clear hierarchy of BOD and DO during the three hydrological periods, but TP, TN, SD and Chl a showed drastic fluctuation.

4) Chl a simulation by HEA also revealed heterogeneous changes during the three hydrological periods in Lake Baiyangdian. Sensitivity analyses indicated that BOD was highly sensitivity to Chl a during all three hydrological periods, while TP was insensitive. TN, SD and DO had individual effects on the concentration of Chl a under different conditions. The best rule sets in the respective hydrological periods provided potential indexes for early warnings in the degraded lake.

Systematical analyses with trend, qualitative and quantitative analysis of regional water quality variables, as well as simulations of eutrophication could enhance our understanding of lake ecosystem restoration. These analyses can be used as preliminary management tools for improvement of water quality in degraded lakes.

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