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Article

Impact Assessment of Climate Change on Algal Blooms by a Parametric Modeling Study in Han River

XIA Rui[1], CHEN Zhi[2]* and ZHOU Yun[1]

1 Chinese Research Academy of Environmental Sciences (CRAES), Beijing 100012, China;
2 Department of Building, Civil & Environmental Engineering, Concordia University, 1455 de Maisonneuve Blvd., West Montréal, Québec, Canada

Abstract: The potential impact of climate change on water eutrophication and ecosystems is of great international and domestic concern. This study aims to analyze the impact of climate change on algal bloom problems in large river systems by utilizing a parametric river eutrophication model that is established using indicators of climate change, hydrological regimes, water quality and nutrient loads. Specifically, the developed parametric modeling method is based on statistical and simulation methods including: Multiple Linear Regressions (MLR), Multiple Non-linear Regressions (MNR), Artificial Neural Network (ANN) based on Back-propagation (BP) algorithms, as well as an integrated river eutrophication model. The developed model was applied to Han River, which is one of the major sources of fresh water in Wuhan City, China. The impacts of climate change and human activities on the occurrence mechanisms of algal blooms in the Han River were identified by scenarios analysis. The individual assessment result indicates that the waste nutrient P load has the most significant impact (14.82%), followed by the flow rate (5.56%) and then by temperature (3.7%). For the integrated climate change assessment, it has been found that there is a significant impact (20.37%) when waste load increases and flow rate decreases at the same time. This is followed by increase of both waste load and temperature (15.82%). If temperature increases but flow rate decreases, the impact is predicted to be 11.11%. The final results point to human activities as a significant influence on water quality and the Han River ecosystem, temperature is also one of the main factors which directly contribute to algal blooms in Han River. The results in present study are expected to give theoretical supports for further relevant research on water eutrophication.

Key words: climate change impact; eutrophication; algal blooms; parametric models; Han River; China

1 Introduction

Algal blooms are generally defined as eutrophication of water bodies due to a rapid increase in the population of algae. Algal blooms can have a broad range of negative impacts on humans, animals, and aquatic ecosystems (Backer 2002; Elena *et al*. 2001). Currently, the dominant academic view seems to be that the main cause of water pollution and eutrophication is the large input of phosphorus (P) and nitrogen (N) that enters the aquatic ecosystem due to human influence (Diersing 2009; Sharpley and Sheffield 2001). We found that water eutrophication and the resulting algal blooms are primarily caused by the introduction of excess nutrients into a water system, especially phosphorus (Gamini 1997). Generally, algal blooms are common in motionless water such as a lake, fishpond or reservoir. However, this phenomenon has occurred three times between 1992 and 2000 in the Han River in Wuhan City. Though algal bloom is most commonly found in motionless water, it should be noted that Han River is the largest tributary of the Yangtze River in China. Recently, there was report that algal blooms also occurred in 2002, 2008 and 2009 (Zhang *et al*. 2006). It is very unusual for algal blooms to occur in large and free-flowing water bodies. Some studies have shown that the reason for water eutrophication is the nutrient import through human activities and the internal relationships between hydrological conditions and temperatures (Xie *et al*. 2004). Zhang *et al*. (2006) pointed out that the high fluctuation of algae concentrations in the river is primarily caused by excessive nutrients, particularly phosphorus, which can

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* **Corresponding author:** CHEN Zhi. Email: zhichen@alcor.concordia.ca.

also be potentially impacted by sunlight and hydrological conditions. Xia *et al*. (2010) emphasized that the nutrient load, water temperature and hydrology regimes are the three main reasons for Han River water eutrophication. The previous research has indicated that water quality can be directly affected through several climate-related factors in both the short and long term. Climate changes may also impact water quality even if the external nutrient loads caused by human activity are firstly considered (Middelkoop *et al*. 2001). In China, however, it is very hard to effectively control the nutrient import or water pollution caused by human activities in a short time. This makes it difficult to understand the impact mechanisms of climate change on river water quality and ecosystems. One of the key challenges of water resource management is to assess the impact of climate change on water resources and the feasible adaptations. Following this, the adverse effects of water resource issues on economic and social developments could be reduced.

Besides climate change impacts on water availability and hydrological risks, the consequences on water quality, eutrophication and the aquatic ecosystem are just beginning to be studied (Delpla *et al*. 2009; Xia *et al*. 2010). Scientific works on this important issue are still very limited, and the focus of past works has been on water quantity impacts rather than on changes in water quality. The impact of climate change on water quality through changing water regimes and temperature is still unclear and there is a lack of study differentiating between the impacts of climate change and human activities, especially for large river systems in China. Moreover, the existing and currently planned water resource programming in China does not adequately address the potential impact of climate change on water quality and water resources. One of major challenges is the lack of available and workable screening tools with which to assess such impact and then, the adaptation of water management to reduce the potential impacts of climate changes (Xia *et al*. 2010). Additionally, accurately assessing the risks and liabilities of algal blooms due to water pollution requires information support from environmental policy makers. In order to make the information more useful for the prevention, detection and remediation of algal-bloom, it is necessary to predict the potential impact of climate-change caused by human activities. The Han River basin (HRB) is a representative case where water quality and the aquatic ecosystem are significantly impacted by human activities and climate change.

Therefore, the objectives of this study are: (i) to develop river eutrophication modeling by utilizing parametric models, including Multiple Linear Regressions (MLR), Multiple Non-linear Regressions (MNR), Back-propagation Artificial Neural Network (ANN) and an integrated river eutrophication model; (ii) to analyze and compare the system modelling results based on model calibration and validation (the most suitable model will be selected and applied for single-factor and integrated climate change assessment); and (iii) to differentiate and quantify the contributions of climate change, hydrological regimes and nutrient import to the algal bloom in Han River. Finally, the impact causes of climate change on water quality and ecosystem will be discussed.

2 Study area and research methods

2.1 Study area

The Han River (Fig. 1) is the largest tributary of the Yangtze River, which originates from Ningqiang County in Shaanxi Province and covers approximately 151 000 km^2 with 1577 km length (Li *et al*. 2008). It is the most important water resource for industrial production and for people living in the Shaanxi and Hubei provinces. The Han River goes through 14 cities, and receives about 700 million tons of industrial and municipal wastewater per year, of which, 123 million tons is potable water before finally reaching Wuhan Yangtze River (Zhang *et al*. 2006). The Han River's water quality was considered to be consistently good in the 1970s and 1980s. However, with recent population increases and economic growth, the development of water resources and hydropower resources on the Han River has been intensified by dam building. Consequently, the flow regime of the Han River has been altered to some extent (Lu *et al*. 2009). Since the beginning of the 1990s, regional development of industry and agriculture has seen a steady increase in industrial wastewater, agricultural fertilizers and domestic water emissions into the river. This has meant that water pollution has become a very serious issue in some parts of the Han River. In particular, the section of the river downstream of Wuhan has seen high algal cell density concentrations (Xie *et al*. 2004). The Wuhan section of the Han River was selected for this case study since it is the source of central route of the South-North Water Transfer Project (Zhu *et al*. 2008), and its water pollution and eutrophication problems are serious. The Wuhan section of the Han River has the characteristics of a river bend. The

Fig. 1 Location of Han River in China (Lu *et al*. 2009).

Fig. 2 Sampling locations in Han River.

width is 400 m in the high-water period, and it becomes around 100 m in the drought period. The rapid urbanization and economic development in Wuhan made for the swift deterioration of Han River water quality during the 1990s.

In this study, there were two sampling sites (Fig. 2) and the distance between (A) and (B) was approximately 7750 m. The two sections are located at the downstream of the Han River. As the sample site is very close to the inlet of Yangtze River, the water quality may be considered a direct reflection of the water quality of Wuhan City and the Yangtze River.

2.2 Data screening

Algal blooms in the Han River usually occur in the springtime (from end of January to the beginning of March), and only last 7 to 15 days then disappear very quickly. Throughout most of the year, the average algal cells remain at a very low level except when algal bloom occurs. In order to find the relationship between the algal cell numbers and climate changes, only the dates in the period of algal blooms will be taken (6–7 sampling dates per year). Thus, a total of 54 groups of sampling are selected in the downstream of the Han River in the Wuhan section from 1992 to 2000. The major peaks in algal cell numbers of the year can be presented during the algal blooms. Therefore, it could be easy to find the difference of monitoring data in the algal bloom years and non-algal bloom years. The monitoring parameters include total phosphorus (TP), temperature (T), flow rate (Q), and total algal cells. All sampling data were applied to the parametric models which are analyzed using SPSS (version 13.0).

2.3 Framework and methods

In order to qualify the comprehensive contributions to the river water quality and ecosystems, a multi-level climate change assessment approach (Fig. 3) is developed to apply to this environmental issue based on following steps: (i) establishing a system modeling structure of river eutrophication based on multiple inputs and a single output. Several inputs are possible in this system including nutrient load, temperature, and hydrological regime. The single output is the total algal cell concentration which will be used to indicate the level of algal blooms. (ii) Developing a parametric river eutrophication model that refers to modeling systems which include: Multiple Linear Regressions (MLR), Multiple Non-linear Regressions (MNLR), Artificial Neural Network (ANN) based on Back-propagation (BP) algorithms, as well as an integrated river eutrophication model. All of the above models will be calibrated and validated based on the monitoring data and the model with the best simulation result will be taken for individual and integrated assessment under different scenarios. (iii) Quantifying and differentiating the contributions of climate variations, nutrient load variation as well as hydrological regime variation to assess their impacts on river eutrophication by applying single-factor and integrated climate change assessment. And (iv) discussing the principles of adaptation strategies on how to address the impact of climate change on water resources and what feasible adaptations should be applied to prevent adverse effects due to economic and social developments.

2.3.1 Regression models

In order to model the relationships between dependent variable and independent variables, a multiple linear regressions model is applied to examine the impacts of climate change on algal blooms in the Han River in China based on following equation.

$$Y_i=b_0+b_1X_{1i}+b_2X_{2i}+\ldots+b_kX_{ki}+u_i \qquad \text{for } i=1, 2, ..., n \qquad (1)$$

where the dependent variable (Y) is the total algal cells (10^4 L^{-1}) which indicates the severity of the water algal blooms. Lu *et al*. (2000) proposed that the level of algal cell concentration in the Han River should not exceed 500 $\times$ 10^4 cells L^{-1}. X_n is the input independent variables (e.g. flow rate, temperature, nutrient loads and etc.). In this study, the algal cell concentration can be used to indicate the occurrence of an algal bloom.

However, a very stark multiple linear regression model

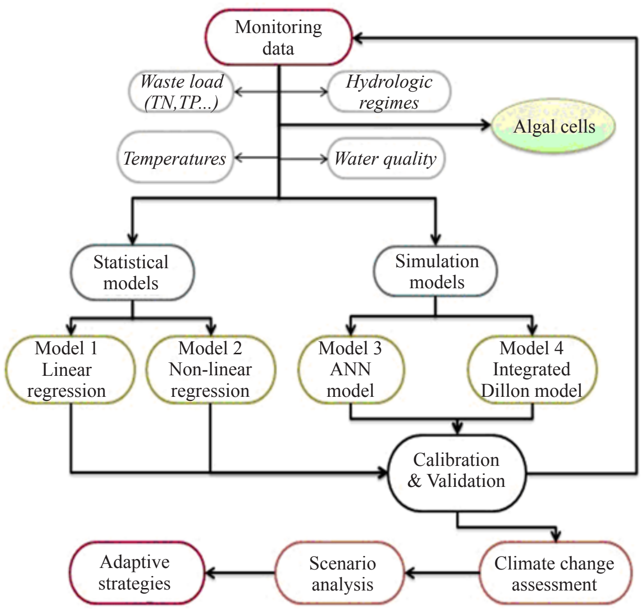

Fig. 3 Multi-level climate change assessment approach.

is not normally seen in the practice, so sometimes we need a system tool to simulate the nonlinear problems. The nonlinear regression can estimate such kind of models with arbitrary relationships between independent and dependent variables. There are some nonlinear regressions issues that can be moved to a linear domain by a suitable transformation of the model formulation. If there is more than one X variable, we have a general form of multiple nonlinear equations (ignoring the error) with several inputs (for example, there are three input variables X_1- temperature, X_2 -flow rate, and X_3 -nutrient load). We use a logarithm for both sides,

$$Y_1=\beta_0 X_1^{\beta 1} X_2^{\beta 2} X^{\beta 3} \tag{2}$$

It becomes:

$$\ln(Y) = \ln(\beta_0 X_1^{\beta 1} X_2^{\beta 2} X_3^{\beta 3}) \tag{3}$$

and,

$$\ln(Y) = \ln(\beta_0) + \beta_1 \ln(X_1) + \beta_2 \ln(X_2) + \beta_3 \ln(X_3) \tag{4}$$

where y=ln$Y$, a=lnβ_0 , x_1=lnX_1, x_2 =lnX_2, x_3= lnX_3, etc.

The equation can be finally transformed to a linear equation.

$$y=a+\beta_1 x_1+\beta_2 x_2+\beta_3 x_3+\ldots+\beta_n x_n \tag{5}$$

When the prediction of y has been calculated, we need to convert it to Y. This is done by raising e to the y power, because Y=exp(y). The exp function in Excel can be used to solve this problem. Thus, we can use the multiple linear regressions method to deal with the non-linear regression issues and in order to determine the coefficients of the regression equation.

2.3.2 Back-propagation neural network

In this study, a typical 3-4-1 Back-propagation (BP) neural network (Fig. 4) which consists of one single hidden layer is also performed in order to verify the result of regression models (Rumelhart *et al*. 1986).

If there are P^{th} training samples (I_p, T_p, p=1,2,...P), $I_p \in R^{N_1}$ is the input of the P^{th} sample, and $T_p \in R^{N_3}$ is the expected output of the P^{th} sample. Thus the error function can be defined as:

$$E=\sum_{p=1}^{P} E_p=\frac{1}{2} \sum_{p=1}^{P} \sum_{k=1}^{N_3}\left(T_{pk}-O_{pk}^{o}\right)^2 \tag{6}$$

When the network structure is confirmed,the error function E also called energy function which is consists of weights (W_{ji}^F and W_{kj}^S) and threshold values (θ_j^H and θ_k^0) as its major variables. If we expect to minimize the error function, it becomes an unconstrained nonlinear optimization problem after combining all the equations above. Thus, we can have the iterative formula for weights and threshold values by using steepest descent method (Thiang *et al*. 2009; Xie *et al*. 2004), that is:

$$\Delta W_{xy}(n+1)=\eta \sum_{p} \delta_{px} O_{py}+\alpha \Delta W_{xy}(n) \tag{7}$$

$$\Delta \theta_x(n+1)=-\eta \sum_{p} \delta_{px}+\alpha \Delta \theta_x(n) \tag{8}$$

where η is the learning rate and α is the momentum factor.

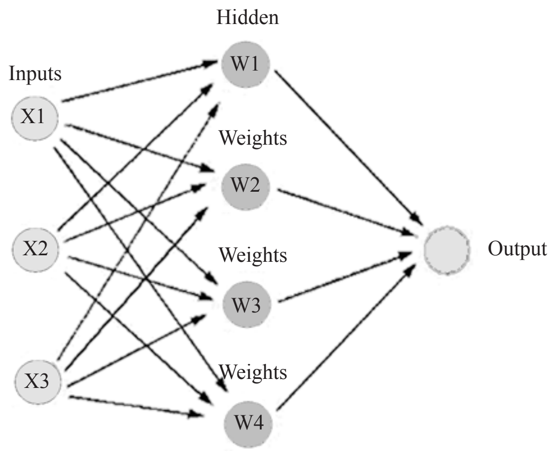

Fig. 4 Three layers back propagation neural network.

(Note: X_n is the input variables, W_n is the connecting weights between in & out put layers)

$W_{xy}(n)$ indicates the n^{th} iterative value of weights between nodes x and y of any two neighboring layers in the feed-forward network and can be expressed as W_{ji}^F or W_{kj}^S. Similarly, $\theta_x(n)$ represents the n^{th} iterative value of a certain node x in the hidden layer or outputs layer, and it can be expressed as $\theta_j^H(n)$ or $\theta_k^0(n)$.

2.3.3 Integrated river eutrophication model

The models proposed above are based on a large amount of data and parameters. Often, there is a lack of explanation or ambiguity about what has been learned. In order to assign physical meaning inside of this system and further address and solidify what is already known, the mechanisms of variables etc., a semi-physical river eutrophication model which combines empirical model and regression model is developed in this study.

Dillon and Rigler (1974) recognized there was good correlation between the phosphorus retention coefficient R and sedimentation rate coefficient Kp (Vollenweider and Dillon 1974; Dillon and Rigler 1974).The equation can be written as (Vollenweider and Dillon 1974; Vollenweider 1975):

$$P=\frac{L(1-R)}{Hq} \tag{9}$$

where L is the phosphorus load (mg m^{-2} y^{-1}), R is the retention coefficient of total phosphorus, q is the hydraulic eroding coefficient, H is the average water depth (m) and P is the average phosphorus concentration (mg L^{-1})

The Dillon model is an empirical water eutrophication model involving hydrological and water quality parameters, but it does not include any meteorological parameter such as temperatures. Therefore, in order to find its relationship to climate change impact on the basis of the mechanism model, a new integrated river eutrophication model which combines Dillon's model and multiple non-linear regressions approach is established:

$$Y_{algal} = a[\frac{L(1-R)}{Hq}]^{\beta 1} T^{\beta 2} \tag{10}$$

This integrated river eutrophication model clearly identifies the relationship between algal cells and hydrologic regime which include water depth (H), hydraulic eroding coefficient (q), waste nutrient load (L), and also temperatures (T). Thus, the result could be considered a good explanation and validation for statistical models.

3 Case study and results

3.1 Modelling results

In order to verify the forecasting ability of the MLR model, the sampling data (P,T,Q) from 1992 to 2000 was divided into two parts for model calibration and verification (Fig. 5). The data from 1992 to 1997 was used for model calibration. A new regression equation is established based on the data of the first six years. Thus, the sampling data from 1998 to 2000 was imported into the equation in order to calculate the average algal cell concentration thus establishing the credibility of the model by demonstrating its ability to replicate actual traffic patterns. In the end, the result was compared to the monitoring data so as to indicate the forecasting ability of the model.

The calibrated linear equation is obtained:

$$Y_a=608.73X_p+20.25X_T-0.365X_F \tag{11}$$

Fig.5 show the calibration and validation results of MLR, wherein calibration value (adjusted R^2) is 0.6735, a value within an acceptable range. The validation value (adjusted R^2) is 0.705 indicating that the predicted algal cells are significantly close to the monitoring data from 1998 and 2000.

The sampling data from 1992 to 1997 is used for modeling calibration and establishing a new linear regression equation. Then, sampling data from 1998 to 2000 will be imported into the equation in order to calculate the average algal cell concentration. The results are then compared with the monitoring data in order to evaluate the forecasting ability of the model (Fig. 6). The calibrated non-linear equation is:

$$Y_a = 776.39 \times \frac{X_p^{0.706} \times X_T^{1.501}}{X_F^{0.827}} \tag{12}$$

Fig.6 show the results of molding calibration with a high adjusted R^2 value of 0.887 and a validation adjusted R^2 (0.9644) which clearly indicate that the predicted value of algal cells is closely matched to the real data from 1998 to 2000.

In order to make a comprehensive comparison with the previous regressions analysis, a simple 3 layer feed-forward Back Propagation (BP) network with only one intermediate hidden layer is applied to the Han River. The model is based on FORTRAN, in which there are 36 groups of monitoring data for calibrations and 18 groups for validations. After 2000 iterations, the increasing factor, attenuation factor, limiting factor and learning factor are set as 1.1, 0.9, 0.005, and 0.13, respectively. The threshold value of output layer is computed as 0.242 and the sum square errors between the expected output and the calculated output of this BP model is 2.97%, a value within acceptable range. Some connecting weights are shown in Table 1.

The same calibration and verification methods used for the multiple linear and nonlinear regression models will

Table 1 Connecting weights of hidden layers between input & output layers.

Input layers	W1	W2	W3	W4
1	3.73621	0.07690	–0.32005	–2.35745
2	–1.631611	–3.419686	0.258331	1.312475
3	–8.917010	1.186531	7.511460	1.603760
Output layer	10.127720	–3.636879	–3.134717	1.658183
Thresholds	2.438784	0.613407	–0.792894	–0.697273

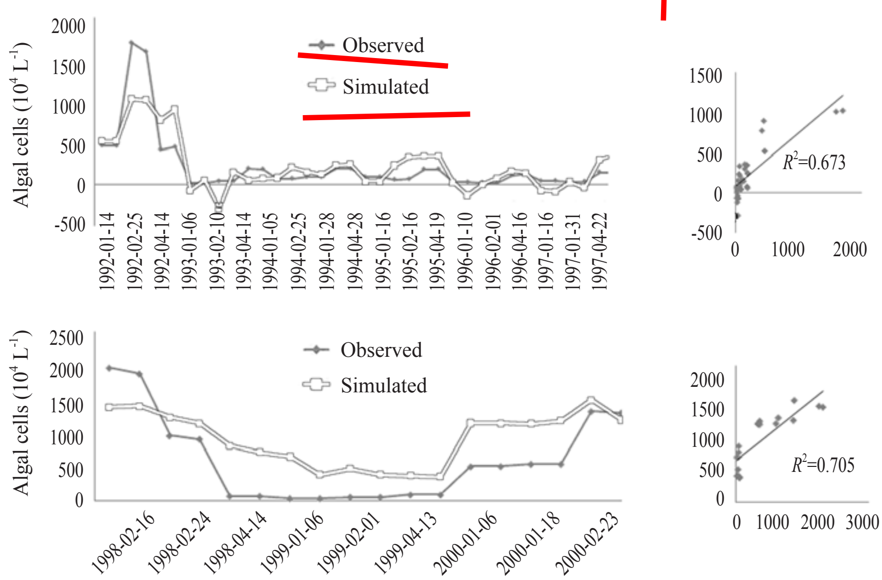

Fig. 5 MLR calibration and validation from 1992 to 2000.

(Note: negative simulation results corresponds to zero)

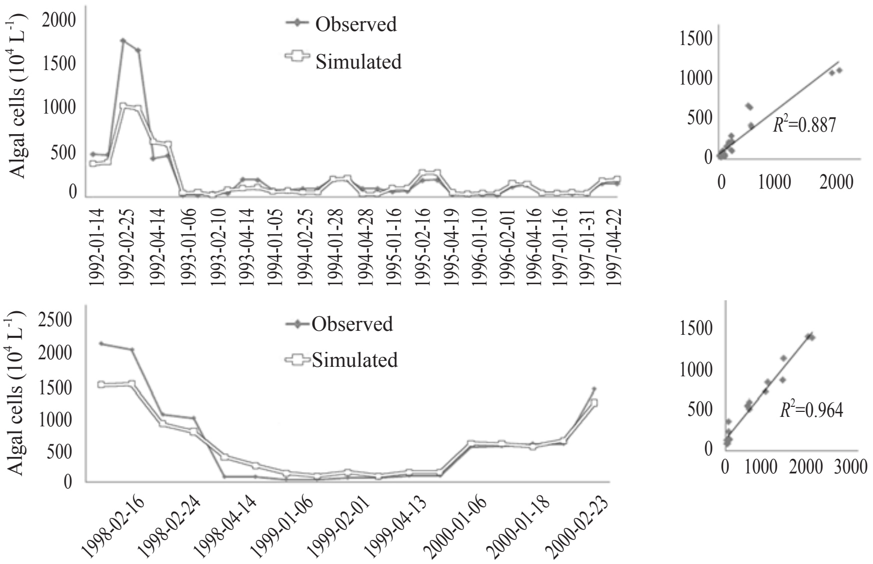

Fig. 6 MNR calibration and validation from 1992 to 2000.

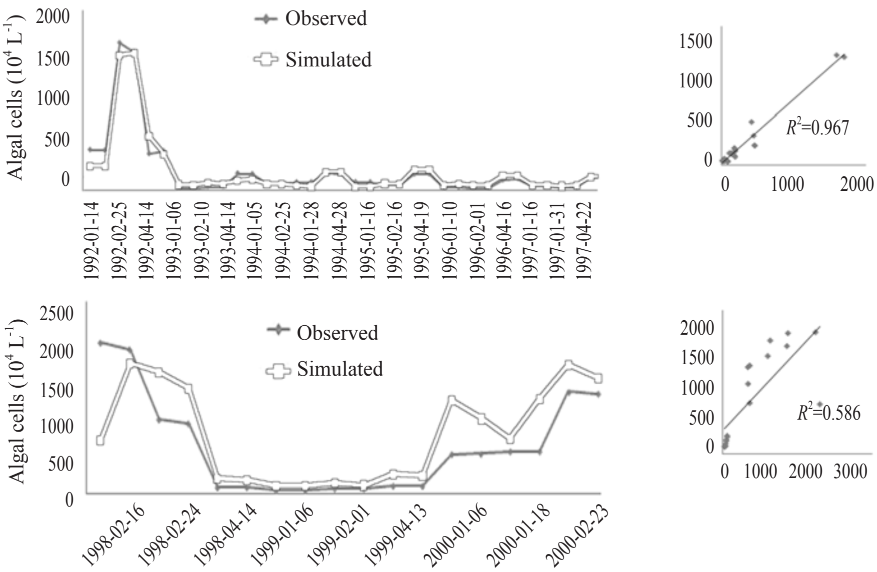

Fig. 7 ANN model calibration and validation from 1992 to 2000.

also be applied to the ANN model in order to verify the forecasting ability of this mechanism model (Fig. 7). A new linear regression equation is established based on the first six years from 1992 to 1997.

Fig. 7 indicates that the ANN has an excellent calibration efficiency (R^2=0.967) indicating the modeling outputs are very close to the observations. The adjusted R^2 for validiation 0.586 indicates that the forcasting ability of ANN model for the period is lower for validiation than for calibration. Therefore, a very common statistical phenomenon known as "over-fit" has occurred. Overfitting occurs when ANN decribes random error or noise instead of the underlying relationship. It will generally have poor predictive performance as it can exaggerate minor fluctuations in the data.

The same calibration and verification procedures in earlier sections will also be applied to the integrated Dillon model in order to verify the forecasting ability of the mechanism model (Fig. 8). A linear regression equation is established based on the sampling data in the first six years. Then, sampling data from 1998 to 2000 will be imported to the equation to calculate Y. The following is the comparison of forecasted values with the monitoring data to indicate the forecasting ability. The result indicates that the R^2 value for the integrated Dillon model is 0.702 and adjusted R^2 is 0.684 showing good fit of the model. After taking exp(0.583) = 1.791, the nonlinear regression equation is:

$$Y^{'} = 1.791[\frac{L(1-R)}{HQ}]^{0.368} T^{2.037} \tag{13}$$

Fig. 8 show the result of molding calibration. The R^2 value is 0.646 which is within an acceptable range. The validation adjusted R^2 is 0.647 which clearly indicates the predicted value of algal cells is also well matched to the real data, accurately forecasting the algal bloom from 1998 to 2000.

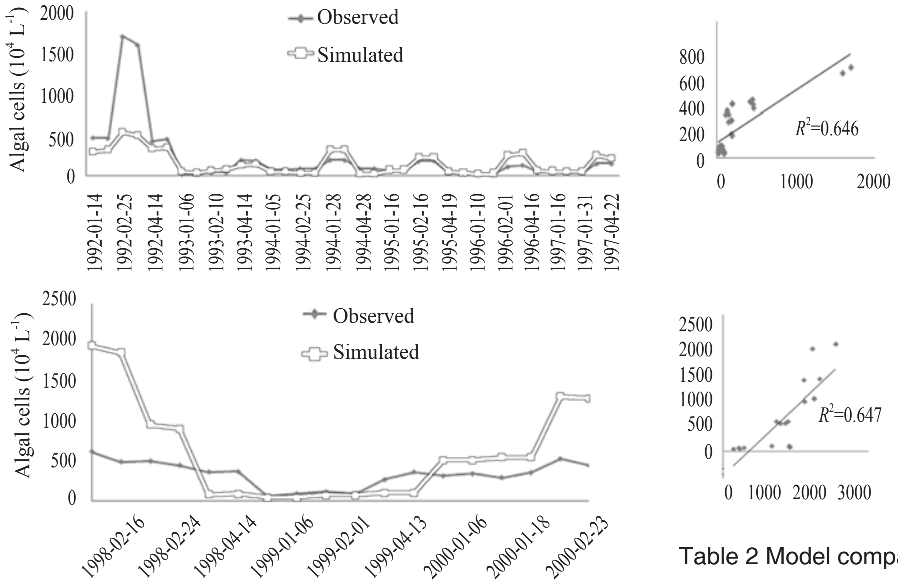

Fig. 8 Calibration and validation of Dillon model from 1992 to 2000.

3.2 Comparison of model results

The comparison results of the four models are shown in Table 2. As Table 2 shows, appropriate fit measures (adjusted R^2) results of calibration and validation for MLR are 0.643 and 0.705, respectively. This result is decent for a statistical model. However, the MLR method can often display optimal results only when the relationships between the independent variables and the dependent variable are almost linear. The results are not reliable when making predictions since most real-world environmental issues are nonlinear. The MNR model showed highest validation value (adjusted R^2 0.964) and a good calibration value (adjusted R^2 0.887) which proves that the MNR model can be used to fit non-linear relationships and is appropriate for most real case studies. The ANN model had the highest adjusted R^2 value for calibration (0.97) which proves this simulation model is useful in automatically resolving non-linear complex relationships and difficult multi-dimensional problems. However, the issue of over-fitting also occurred in this case, thus the forecasting result is variable when compared to good calibration ability. This is reflected in the low adjusted R^2 value for validation (0.59) which is the worst in all of the models. Moreover, the ANN cannot reveal the contributions from input indicators to output, so it will not be used for forecasting at this time. The adjusted R^2 for the Integrated Dillon model is less than 0.65 which is a disappointing result from a semi-physical model. The major reason for the low performance of this model is that the conditions of input parameters are too restrictive therefore, the simulating efficiency is found to be less than in statistical models.

The entire contribution analysis was not only performed using statistical system models, but was also verified by an integrated river eutrophication model. It can provide part of basic conceptual mechanisms for researchers, although the simulating ability is unsatisfactory. This kind of model has too many constraints related to required parameters, so the final result would not be satisfactory if initial data error is large. The statistical models have fewer or no constraints for inputs and outputs, so calibration and validation results are often better. Once validated by a physical or semi-physical model, it is also possible to glean reasonable results. Based on the final result of the assessment by linear method, we find only approximate results since the method assumes linear relationships and output results often show negative values. This is not reasonable in real-world cases because real time series data is mostly nonlinear due to the complicated nature of ecological systems. The nonlinear regressions model usually gives a better simulation result compared to the linear model since it is more reasonable in practice and the result can avoid negative values. On other hand, the ANN model is a powerful tool that is able to solve difficult pattern-processing problems involving non-linearity and multiple dimensions. Further, it is usually successful in molding calibration. However, the ANN model lacks accuracy for data forecasting due to its tendency to over-fit. In conclusion, (i) the MLR model is simple when used in application but is inappropriately used to model non-linear relationships; (ii) the MNR model can be moved to a linear domain by a suitable transformation of the model formulation and often has good modeling result; (iii) the ANN model is a powerful tool usually used to model complex nonlinear problems, it displays a very good calibration result but has a tendency towards overfitting. Thus, the ANN model should be used with caution when developing predictive models; and (iv) the Integrated Dillon

Table 2 Model comparison results.

Models	Multiple linear regressions	Multiple non-linear regressions	Artificial neural network	Dillon model
Calibration (Adjust R^2)	0.643	0.887	0.967	0.646
Validation (Adjust R^2)	0.705	0.964	0.586	0.647

model is a semi-physical river eutrophication model. It can provide some physical meaning inside of the system already known, but the simulating efficiency can be less than statistical models due to the restrictive conditions of input parameters. Such a model requires more physical parameters related to water environments. Therefore, after modeling comparison and analysis, the nonlinear regression model is selected for our climate change impact assessment in order to forecast the future occurrence of algal blooms more accurately.

4 Climate change assessment on river algal blooms

4.1 Single-factor climate change impact assessment

Since the nonlinear regression model was considered the best model for both calibration and forecasting ability, the model was used for climate change assessment under scenario analysis. According to the IPCC reports (IPCC 1996, 2000, 2001 and 2007), there will be a serious impact of climate change to the environment if temperature increases by 2 ℃ in the future. In the case study of the Han River, 2 ℃ was 15% of the average temperature (13.4 ℃). In order to quantify the contributions of all the parameters in a same baseline, we assume a worst case scenario: the waste load will continuously increase by 15% and flow regime will decrease by 15%. Therefore, some assumptions for impact assessment of climate change under single factors are made as follows: (i) assuming the temperature increased 2℃ from 1992 to 2000, and input waste load P and flow rate are fixed; (ii) assuming the input waste load P increases by 1 unit (mg m^{-2} y^{-1}) and the rest of the variables stay at the same values from 1992 to 2000; and (iii) assuming the flow rate is decreased by 100 m^3 s^{-1} from 1992 to 2000, and temperature and waste load are unchanged.

In this study, the probability of algal bloom occurrences in the Han River can be determined based on the following equation:

$$P = \frac{m_A}{m_T} \times 100\% \tag{14}$$

where p is the probability of algal bloom occurrence; m_A is the algal bloom months; m_T is the total months in 10 years. Since only 3 months have been selected for each year, which are January to March, the total months m_T in this case is 27 month. For example, there were 6 months in which algal blooms occurred during the selected 27 months between 1992 and 2000 at the original level of each parameter in the Han River. Thus, the probability of algal bloom occurrences is calculated to 22.2%. Then, the single-factor climate change assessment can be applied by adjusting any single factor. These results are shown in Fig. 9.

The single-factor assessment results indicate that when the temperature increases by 2 ℃, the rest of the parameters remain at the same value, so there were significant changes on algal bloom occurrence (from 22.22% to 25.93%). The report indicated that during an algal bloom that occurred in Jan 2000 (and some algal blooms which occurred in 1992 and 2000), the average algal cell count was close to the threshold. However, the count exceeded the warning line after the temperature rose. Peak values also showed moderate increases in 1992 and 1998. Compared with the observed data,the occurrence probability of algal bloom increased by 3.7% when temperatures increased.

When input waste load (P) increases by 1 unit (mg m^{-2} y^{-1}) and the rest of the variables stay at the same values, there is an increased probability of algal bloom occurrence from 22.22% to 37.04%. For example, the algal cell concentrations in April 1995, April 1998 and Jan 2000 reach the warning line. It should also be noted that the peak value also highly increased in 1992 and 1998.

When flow rate decreased by 100 m^3 s^{-1}, there was a small change in algal bloom occurrence probability, which increased from 22.22% to 27.77%. It should be noted that the algal blooms occur in 1992, 1998 and Jan 2000 according to our model. Also, there is a potential risk of algal bloom in January 1992 with a value very close to the threshold. After increasing Q, the probability of algal bloom increases by 5.56%.

4.2 Integrated climate change impact assessment

In practice, the impact of climate change, hydrological regime change and human activities usually occur at the

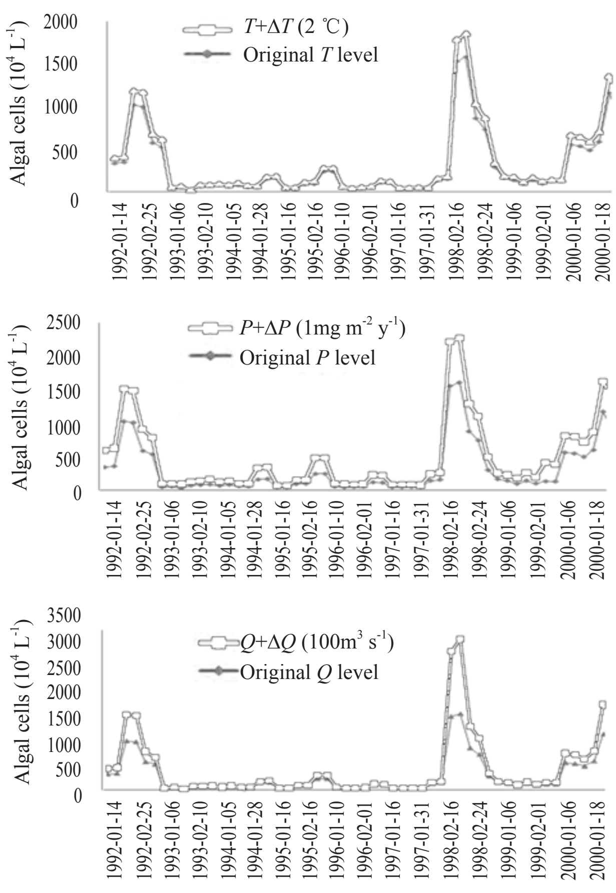

Fig. 9 Single-factor climate change assessment results.

same time. In order to see the comprehensive results of their influences on algal cell concentrations, two of the indicators will be changed at same time with the remaining one indicator fixed. Just as in single factor assessment, several assumptions are made for the integrated climate change impact assessment in the worst conditions: (i) assuming temperatures increase by 2 ℃ but flow rate decreases by 100 $m^3\ s^{-1}$ from 1992 to 2000 and the input waste load P is fixed; (ii) assuming the temperature increases by 2 ℃ and the input waste load P increases by 1 unit (mg $m^{-2}\ y^{-1}$) from 1992 to 2000 while the flow rate is fixed; (iii) assuming the flow rate and the waste load P both change while the temperature stays at the same level; and (iv) assuming all of the variables change from 1992 to 2000, the results are shown in Fig. 10.

These results indicate that if temperature (T) and the flow rate (Q) both change but the (P) load is fixed, there is a change of algal bloom occurrence probability from 22.22% to 33.33%. It is predicted that algal blooms will occur in 1992, 1998 and 2000 and there is a potential risk in April 1995 and April 1998.

When temperature and water waste load both change and flow rate stays the same, there is a large change in algal bloom occurrence probability, from 22.22% to 40.74% as predicted by our model. The algal blooms were predicted to occur in 1992, 1995, 1998 and 2000. Potential risk is predicted in April 1995, April 1994 and April 1998.

When flow rate and the waste load (P) both change while the temperature (T) stays at the same level, there is a significant increase of algal bloom occurrence probability by 20.37% (from 22.22% to 42.59%) as calculated by our model. The model predicted an algal bloom occurrence in 1992, 1994, 1995, 1998 and 2000.

In the worst conditions, if all the indicators Q, P and T are simultaneously changing, there is an increase of algal bloom occurrence probability by 29.63% (from 22.22% to 51.85%), as predicted by our model. The algal blooms are predicted to occur in 1992, 1994, 1995, 1998, 1999 and 2000. There is also a potential risk in April 1997 and February 1999. Comprehensive results are summarized in Table 3.

Table 3 Comprehensive results of scenario analysis.

Indicators (%)	ΔT	ΔQ	ΔP	ΔT +ΔQ	ΔP +ΔT	ΔP +ΔQ	ΔP+ΔQ +ΔT
Probabilities	25.93	27.77	37.04	33.33	40.74	42.59	51.85
Contributions	3.7	5.56	14.82	11.11	15.82	20.37	29.63

The individual and integrated climate change impact assessment and the interactions and contributions of human activities, hydrological regimes and temperature to river algal blooms are determined. For the individual climate change assessment: the waste nutrient P load has the most significant impact (14.82%), followed by the flow rate (5.56%) and then by temperature (3.7%). For the integrated climate change assessment, it has been found that there is a significant impact (20.37%) when waste load increases and flow rate decreases at the same time. This is followed by increase of both waste load and temperature (15.82%). If temperature increases but flow rate decreases, the impact is predicted to be 11.11%.

5 Discussion

It is well proven that the human activity, which in this case is represented by the waste nutrient loads, can play an important role on the growth and reproduction of algae. The impact factor for waste nutrient inputs into the system is 14.82% which is even higher than the sum of temperature and flow rate (11.11%). Also when the waste load is included in the integrated assessment, the impact of temperature (3.7%) is increased to 15.82%, and the impact of flow rate (5.56%) is increased to 20.37%. Moreover,

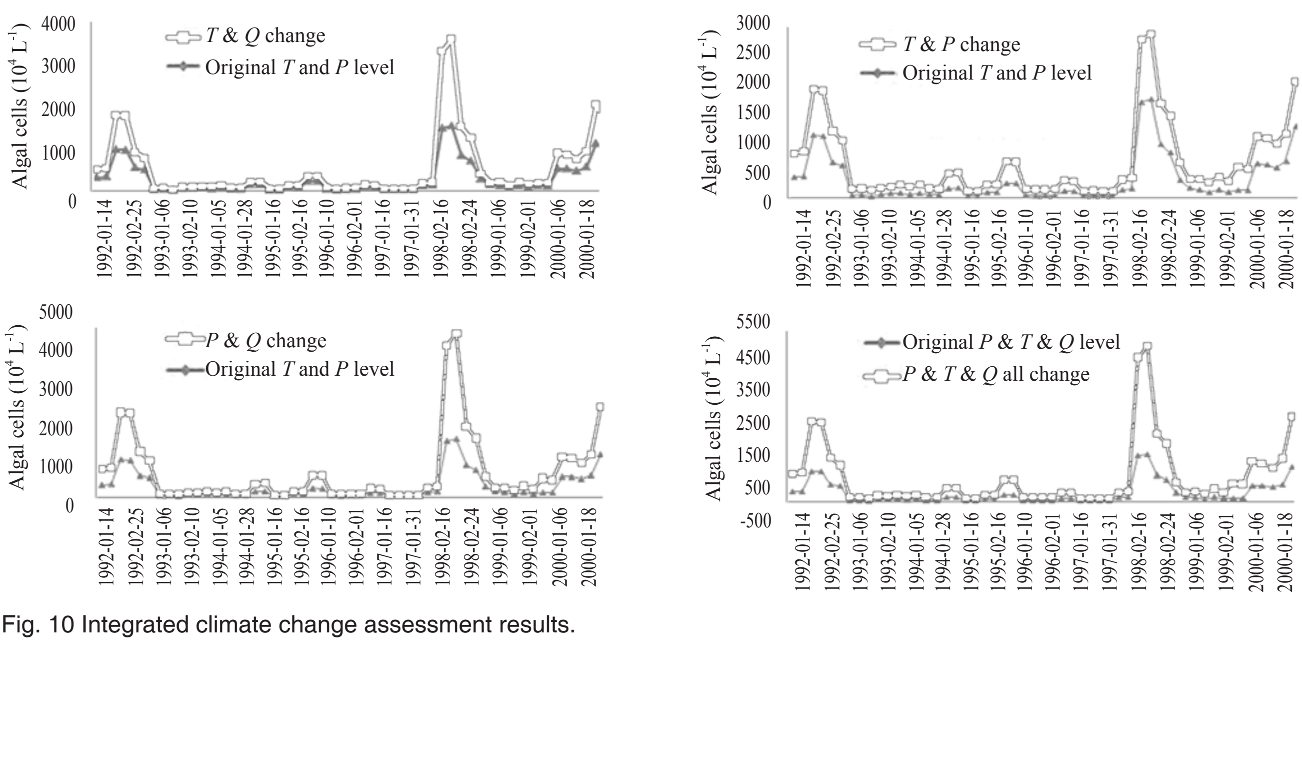

Fig. 10 Integrated climate change assessment results.

when both temperature and flow rate increase, the increased input waste load will increase the risk from 11.11% to 29.63%. Thus, there is no doubt that the control of waste load is the key issue in minimizing the probability of algal bloom occurrence. The primary source of phosphorus is industrial wastewater. In particular, where the Han River flows past a nitrogen fertilizer plant, an excessive amount of phosphate is discharged into the river. Also, a large number of domestic water emissions reach the river. Relevant implications should be assessed and adaptations should be conducted.

The hydrologic regime is the second most important impact factor (5.56%) in algal bloom formation, according to our model. The study result shows the flow rate is negatively correlated to the total algal cell concentration, especially when the input waste load and the flow rate change at same time. In this case, the probability of algal bloom occurrence will be significantly increased (20.37%). Moreover, with decreased flow rate and an increase in temperature, the impact is increased from 3.7% to 11.11% and the impact of waste load is increased from 14.82% to 20.37%. Finally, if the input waste load and the temperature both change, the decreasing of flow rate will increase the algal bloom risk from 15.8% to 29.63%. The monitoring data clearly shows that when the algal blooms occurred in 1992, 1998 and 2000, the water level and the flow rate were low resulting in a localized, semi-stagnant environment. The water flow dilution effect was greatly reduced resulting in stagnation in the fixed total amount of nutrient load, causing an increase in the concentration of nutrients which in turn led to algal bloom conditions. In addition, the accumulation of phosphorus in the river sediment (caused by settling to the bottom and the formation of a river silt layer) provides sufficient phosphorus to accelerate algal bloom formation.

It is clearly shown that the impact of temperature (3.7%) contributes to and is sufficient to increase the likelihood of algal blooms. When the temperature increases, the impact of flow rate on algal bloom formation (5.56%) increases to 11.11%, and the impact of waste load (14.82%) also increases to 15.82%. Furthermore, when the flow rate and waste load both change and the temperature increases, the impact factor will increase from 20.37% to 29.63%. Fig. 11 indicates that temperature plays a key role in river eutrophication according to this model, especially when

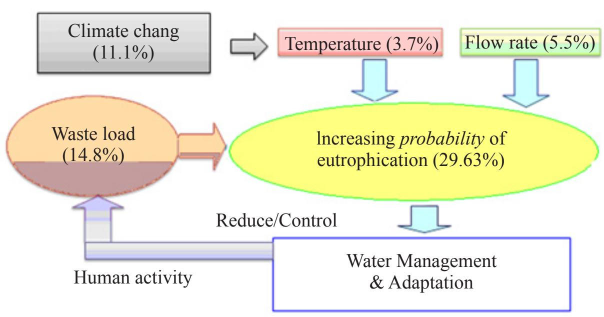

Fig. 11 Contribution of indicators.

the input load and the flow rate are both within a danger threshold. Compared with the historical data, the result of this study has confirmed that temperature has significant impact on the growth of algae. From the collected data, we find that water temperature in 1992 has increased significantly compared to 1991 and the highest temperatures in 1998 and 2000 reached 32 ℃. These values are among the highest recorded in history for the Han River. Therefore, it is easy to see that increased temperatures can lead to an increased risk of algal bloom occurrence.

For the further studies, some other useful indicators regarding to the climate change and hydrological regime could be involved, such as: precipitation, water level and etc., long term continuous monitoring in different regions is suggested to support basic data in order to give a more comprehensive analysis of climate change impact. Moreover, the major conceptual limitation of all regression techniques is to ascertain relationships, but can never be sure about an underlying causal mechanism. It should be used with caution when developing predictive models because the prime disadvantage of ANN is that they are tend towards overfitting. This phenomenon can lead an investigator to misinterpret an ANN's good performance on a training/calibration data set. The river eutrophication model that developed in this study can solve the above problems since it can provide some physical meaning inside of the system already known, but due to the conditions of input parameters being too restrictive, the simulating efficiency can be less than statistical models. A comprehensive fuzzy risk assessment could be established in the future based on combination of statistical models and simulation models in order to avoid the these limitations.

6 Conclusion

In the present study, a set of parametric river eutrophication models are developed for assessing the contributions of climate change and human activity impacts to the water quality of the Han River. The single-factor and integrated climate change assessment approaches are conducted to quantify and differentiate the impacts of climate change and human actives to the river algal blooms. Assessment results indicated that human activity plays an important role in the algae growth and reproduction. Thus, waste import control is the key factor in reducing the occurrence probability of algal bloom. The hydrologic regime is the second most important impact factor in algal bloom. The flow rate is negatively correlated to the total algal cell concentration. The impact of temperature on algal bloom was low, whereas it significantly impacted on algal bloom when input load and flow rate were both within the danger threshold. For further study, it is suggested that a combination of statistical models and simulation models is employed in order to establish a comprehensive fuzzy risk assessment. This should be done by taking an interval value of different modeling results. As well, long term water quality monitoring in different regions is still required in order to give a more comprehensive analysis of climate change impact on algal bloom. This assessment approach can be also applied to other environmental issues, such as climate change related ground-water contamination, air pollution, solid waste management, etc.

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气候变化对汉江水华影响评价的参数模型分析方法及其应用研究

夏 瑞[1]，陈 志[2]，周 云[1]

1 中国环境科学研究院，北京 100012；

2 康考迪亚大学 工程与计算机学院，加拿大魁北克蒙特利尔1455 de Maisonneuve Blvd.

摘　要：气候变化对河流和湖泊水环境的影响是当前国际国内关注的热点问题和学科前沿问题之一。但是由于其复杂性和不确定性，目前对该问题的科学研究和成果仍然十分有限。本文针对水质污染中的富营养化问题，以中国南水北调中线工程调水区的汉江流域为例，开发和应用了多元线性回归、多元非线性回归、人工神经网络及河流富营养化模型等多种评价方法，建立了与气象要素、水文要素、营养盐负荷相联系的多输入单输出富营养化系统参数模型，深入分析了在人类活动和经济发展所产生的影响以外，气候变化在此基础上对水体富营养化的增益作用。最后本文通过单因子和多因子分析法，甄别出不同情景下各要素对汉江水华的影响。通过计算得出，当其中某一项要素变化而其他两项不变时，其导致河流富营养化的贡献度依次为：污染负荷（14.82%）、水文要素（5.56%）、气象要素（3.7%）；当污染负荷和水文要素同时变化时对水华的贡献度最大（20.37%），其次是当污染负荷和气象要素同时变化其贡献度为（15.82%），最后为水文要素和气象要素同时变化时的贡献度为（11.11%）。研究结果表明，对于中国这样的发展中国家来说，当控源和治污不能在短时间内达到良好的效果的时候，气候因素会增加水污染的风险性。即使水体内部污染源稳定，气候变化依然会通过改变水温和水文情势进而影响水体富营养化程度。最后本文通过多种方法比较，根据预测和评估得出的结果制定相应的防治对策，从而对今后的相关研究可起澄清概念和指明方向的作用。

关键词：气候变化影响；富营养化；水华；参数模型；汉江；中国