A PARAMETRIC MODELING STUDY OF THE CLIMATE CHANGE IMPACT ON RIVER EUTROPHICATION AND WATER QUALITY

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ABSTRACT

A Parametric Modeling Study of the Climate Change Impact on River Eutrophication and Water Quality

Xia Rui

The potential impact of climate change on river eutrophication and ecosystems are emerging problems that are of great concern to international and domestic societies. Scientific research and developing methods to address these problems are challenging. 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 involving indicators of climate changes, 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 modeling method has been applied to the Wuhan section of Han River, which is one of major freshwater sources in China. The predicted probability of algal bloom occurrence for the next 40 years by the method is used to identify the impacts of climate change and human activities on the formation mechanisms of river

algal blooms under three scenarios. The principles of possible adaptation options are discussed in this thesis.

The modeling results indicate the temperature is one of the direct factors contributing to river eutrophication and the change of river water quality. It has also been recognized that the climate change, which can alter water temperature and hydrological regimes, in conjunction with human activities can significantly influence water quality and the river ecosystem. The present study is expected to give theoretical supports and directions for further relevant research.

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LIST OF SYMBOLS

A	Area of the surface water (m^2)
DO	Dissolved Oxygen (mg/L)
COD	Chemical Oxygen Demand (mg/L)
TKN	Kjeldahl Nitrogen (mg/L)
f(x)	Sigmoidal functions
L	Length of river (km)
N/P	Nitrogenratio
NH_3	Ammonia (mg/L)
NO_3	Nitrate (mg/L)
H	Average water depth
b	Regression coefficient
Y	Model outputs
r	Pearson correlation coefficient
t	Time (s)
T	Surface water temperatures (℃)
ρ	Correlation coefficient
V	Volume of river (L^3)
TP	Total phosphorus (m/L^3)
TN	Total nitrogen (m/L^3)

R^2	Coefficient of determination
$\overline{R}$	Adjusted coefficient of determination
q	River flow rate (m^3/s)
Q	Annual volume of water discharged (L^3/t)
K_p	Net sedimentary loss coefficient (T^{-1})
L_p	Phosphorus loading in unit area ($mg/m^2 \cdot yr$)
R_p	Retention coefficient of total phosphorus
q	Hydraulic eroding coefficient
VIF	Variance inflation factor
W_n	Connecting weights in the nth layer
W_I	Inflow discharges (m^3/s)
W_{out}	Outflow discharges (m^3/s)
W_{ji}^F W_{kj}^S	Connecting weights
u	Error
θ_j^H θ_k^O	Threshold values in the BP network
X	Continuous variable
η	learning rate
α	Momentum factor
$\theta_x(n)$	nth iterative value of a certain node x in outputs layer
ΔT	Variation of temperatures (℃)
ΔP	Variation of Phosphorus loads ($mg/m^2 \cdot yr$)
ΔQ	Variation of flow rate (m^3/s)

LIST OF ABBREVIATIONS

ABs	Algal Blooms
ANN	Artificial Neural Network
AAAS	American Association for the Advancement of Science
BP	Back-Propagation
CCA	Climate Change Assessment
CSIRO	Commonwealth Scientific and Industrial Research Organization
EEA	European Environment Agency
EPA	Environment Protection Authority
HRB	Han River Basin
IPCC	Intergovernmental Panel on Climate Change
MLR	Multiple Linear Regression
MNR	Multiple Non-linear Regression
SST	Total Sum of Squares
SSR	Regression Sum of Squares
SSE	Error Sum of Squares
WQA	Water Quality Assessment

CHAPTER 1 INTRODUCTION

1.1 Overview

The impact of climate change on water quality is of great concern to scientists and governments worldwide. With the economic growth and industrial development, 'greenhouse gases', especially CO_2, are emitted continuously to the atmosphere leading to global climate change (Rundgren *et al.*, 2005; Lenihan *et al.*, 2008). Global climate change is likely to have significant effects on the hydrological cycle (IPCC, 1996). The hydrological cycle may become intensified, with more evaporation and more precipitation, but the extra precipitation is likely to be distributed unequally around the globe. Some parts of the world may see significant reductions in precipitation, or major alterations in the timing of wet and dry seasons (Arnell, 1999). Climate change can have far reaching consequences for water resources (Arnell, 2003), water quality (Hejzlar *et al.*, 2003; Webb *et al.*, 2003) and the overall water ecosystem (Beaugrand and Reid, 2003; EA, 2005; Hiscock *et al.*, 2004; Moss *et al.*, 2003; Sommer *et al.*, 2004; Wilby *et al.*, 2006). A strong climate and water-quality relationship was found between air and water temperatures and nutrient concentrations. The level of effective precipitation also appeared to exert a significant influence on water quality which is, in contrast with the influence of air temperature, less direct (Tibby and Tiller, 2007). Changes in water quality during storms, snowmelt, and periods of elevated air temperature or drought may exceed the thresholds of ecosystem tolerance, and thus lead to aquatic ecosystem degradation. Continued climate induced stress would increase the frequency with which ecosystem thresholds are exceeded and thus lead to chronic water quality changes (Murdoch *et al.*, 2000; Xia *et al*, 2010).

The figure 1.1 indicates the interactions among climate change impacts on water cycles, water environments and ecosystems (Xia *et al.,* 2010). It indicates that climate change impacts are shown in following major aspects: (1) climate changes will lead to variation of precipitations causing the change of hydrological regimes, and then impact the water quality; (2) climate changes will also lead to variation of temperatures causing degradation of water quality index coefficients and self purification capacity, and thus lead to the concentration of water quality changes; (3) climate changes will lead to extreme hydrological events and some unexpected water pollution may occur; (4) climate changes will lead to temperature increases, thus changing the algal growth rate which would cause the eutrophication problems.

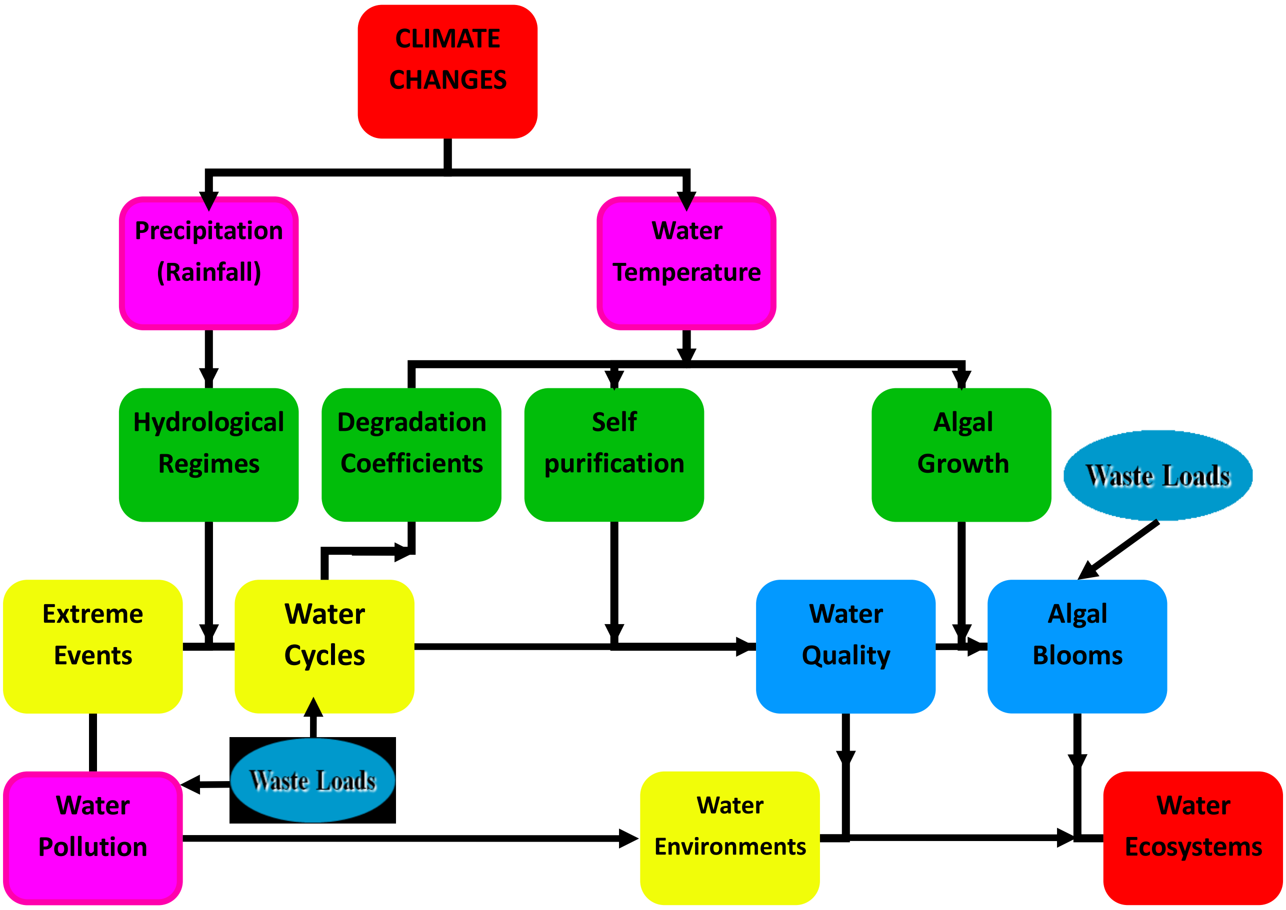


Fig. 1.1 Interactions of "Climate Change - Water Cycle - Water Environment - Ecosystem" (Xia *et al.,* 2010)

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). The existing and currently planned water projects as well as water resource programming in China do not account for the potential impact of climate change. One of major challenges is the lack of available and workable screening tools to assess such impact and thus adapt water management to include the potential impacts of climate change (Xia *et al.,* 2010). Fortunately, climate change is increasingly recognized as an important regulatory factor, capable of influencing water quality and the structural properties of aquatic ecosystems (Law *et al.*, 2009). However, the impact mechanisms of climate change on water quality and ecosystem are still not fully understood.

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 (Elena *et al*., 2001; Klein et.al., 2002). According to the European Environment Agency, “the main source of nitrogen pollutants is run-off from agricultural land, whereas most phosphorus pollution comes from households and industry, including phosphorus-based detergents.”(Klein *et al.,* 2002). Phosphorous is the primary agent in freshwater eutrophication, because many algae obtain N from the atmosphere so P is often the limiting nutrient (Sharpley and Sheffield, 2001). Thus, there has been a tendency that water eutrophication that leads to algal blooms is primarily caused by excess nutrients, particularly phosphorus (Gamini, 1997). However, an unhealthy water cycle and water temperature changes could also impact the internal loading of nutrients. For example, the sediments in the bottom of lake or river can act as either sinks or sources for water-borne phosphorus. Sediments can increase water eutrophication risks due to variation of water temperature and water cycles even when external P sources are regulated (see Fig. 1.1) (Murdoch *et al.*, 2000; Whitehead *et al.*, 2009). Thus climate changes may also possibly impact water quality even if the external nutrient loads caused by human activity are taken into control. The Han River Basin (HRB) is a representative case that water quality and the aquatic ecosystem are significantly impacted by both human activities and climate change.

Generally, Algal Blooms (ABs) are common in motionless water such as a lake, fishpond or reservoir. However, algal blooms have occurred three times between 1992 and 2000 in the Wuhan section of Han River which is the largest tributary of the Yangtze River in China. In recent times there also have been three reported algal blooms in years: 2002, 2008 and 2009 (Zhang, 2006). It is very unusual for algal blooms to occur in this kind of large and free-flowing water body. Some studies have shown that the cause of this eutrophication is the nutrient load due to human activities but also partially due to internal relationships between hydrological conditions and temperatures (Xie *et al.,* 2004). Xia *et al.,* (2010) also emphasized that the nutrient load, water temperature and hydrology regimes are the three main reasons that caused the Han river eutrophication. Zhang (2006) also pointed out the high variation of algae concentrations in the river is primarily caused by excessive nutrients, particularly phosphorus and sometimes nitrogen (Gamini,1997) though this can also be potentially impacted by sunlight and hydrological conditions. Therefore, the input nutrient load and climate change are the two key factors impacting on water eutrophication (Oberholster, 2009). However, China is known as a developing country with a large land area and population, and sometimes it is very hard to effectively control the nutrient load input or water pollution caused by human activities in a short time. This in turn makes it difficult to understand the impact mechanisms of climate change on the river water quality and the river ecosystem. One of the key challenges of water resource management is to assess the impact of climate change on the water resource and the feasible adaptations to reduce adverse effects of economic and social developments.

1.2 Research Objectives

Accurately assessing the risks and liabilities related to the increased threat of algal blooms in rivers due to water pollution will be the key to provide the necessary information and support to policy makers. In order to make this information more useful for the prevention, detection and remediation of algal-bloom problems, it is necessary to predict the potential impact of climate-change caused by human activities such as pollution. Therefore, an integrated assessment of climate change impacts on river eutrophication and the aquatic ecosystem will be developed and performed as the following steps:

1) to establish a system modeling structure to the Han River algal blooms where the water eutrophication problem is terrible as a case study based on multiple inputs and a single output. Multiple inputs include: (a) nutrient loads, (b) temperatures, (c) hydrological regimes, and (d) water quality. The output is the total algal cells concentration which will indicate the severity of algal blooms. Corresponding data screening and preparation will be performed based on the historical pollution events and correlation analysis.

2) to develop a parametric river eutrophication modeling systems which will include: (a) Multiple Linear Regressions (MLR), (b) Multiple Non-linear Regressions (MNR), (c) Artificial Neural Network (ANN) based on Back-propagation (BP) algorithms, as well as (d) an ecological (Dillon) model. All of the above models will be calibrated and validated using the monitoring data.

3) to quantify the contributions of impact of climate change and human activities on algal bloom problems in the large river systems based on the single-factor and integrated assessment under different scenarios.

4) to make predictions in probability of algal bloom occurrence for the next 40 years based on the proposed modeling methods under three emissions scenarios.

5) to discuss the principles of possible adaptation options for how to solve the impact of climate change on water resources and what feasible actions should be taken to keep economic and social developments from causing adverse effects.

1.3 Organization of the Thesis

This thesis is organized in the following seven chapters:

The foreword has summarized the background and significance of the selected topic, as well as the objectives of this study;

Chapter 2 reviews the traditional and most recent literature on climate change impacts on water quality. It then identifies some research gaps among published results and proposes what needs to be recognized in practice along with a detailed literature review of the previous research and models related to this topic.

Chapter 3 introduces theoretical background and methodologies of parametric models, as well as a an empirical model related to water eutrophication.

Chapter 4 provides detailed applications of all models described in Chapter 3 on real river algal blooms case studies. System model results will be analyzed and compared based on model calibration and validation.

Chapter 5 demonstrates an single-factor and integrated climate change impact assessment based on the best available simulation results. In this section, not only the contribution of indicators will be computed but also the probability of algal bloom occurrence in the next 40 years will be forecasted, based on three emissions scenarios.

Chapter 6 presents a discussion of overall result analysis; the contents and principles of adaptation options and adaptability construction will be made.

Chapter 7 concludes with a brief summary, a list of contributions and future research recommendations.

CHAPTER 2 LITERATURE REVIEW

2.1 Perspective of Climate Change Impacts on Water Quality and Ecosystem

The impacts of climate change on hydrology have been studied extensively (Pfister *et al*., 2004; Middelkoop *et al*., 2001; Xia and Zhang, 2005; Xia and Zhang, 2008; Xia *et al*, 2010). However, the focus of past studies has been on water quantity impacts (e.g., flooding and droughts) rather than on changes in water quality (Drago *et al.*, 2005). Recently, the potential impacts of climate change on surface water quality and ecosystem have been increasingly acknowledged (Murdoch *et al.*, 2000, Whitehead *et al.*, 2009). The IPCC Fourth Assessment Report (Kundzewicz *et al.*, 2007) began to consider the impacts of climate change on water quality although not in great detail. The EU Euro-limpacs Project, a multi-partner, 20-million Euro research project, is investigating the impact of climate change on water quality and river, lake and wetland ecosystems across Europe (Battarbee *et al.*, 2008). Also in China, one project funded by the Ministry of Water Resources is to analyze the impacts of climate change on Chinese water resources, including its impacts on water quality and water ecosystems. Results of previous studies have indicated that water quality can be directly affected through several climate-related mechanisms in both the short and long term (Tu, 2009; Park *et al.*, 2009). These include the impacts of air temperature increase, as well as changes in hydrological factors amongst others

(Murdoch *et al.*, 2000). The most immediate impact of climate change is expected to be in river and lake water temperatures which is influenced by air temperature (Hammond and Pryce, 2007). Hence, air temperature is the key variable affecting water temperature in most biological systems, and also strongly influencing water chemistry, biochemical reactions and growth and death of biota (Blenckner *et al.*, 2007; Malmaeusa *et al.*, 2006). Tibby and Tiller (2007) analyzed over 15 years of water quality monitoring data from three lakes in western Victoria, Australia, and found that there are strong relationships between climate change and water quality in these lakes of varied size and salinity (Xia *et al*, 2010).

Extreme events (e.g., floods and droughts), the frequency of which is predicted to increase, also modify water quality through direct impacts of dilution or concentration of dissolved substances. More intense rainfall and flooding could result in increased loads of suspended solids (Lane *et al.*, 2007) and contaminant fluxes (Longfield and Macklin, 1999) associated with soil erosion and fine sediment transport from the land (Leemans and Kleidon, 2002). Lower minimum flows imply smaller volume for dilution and higher nutrient concentrations. Reduced dilution will increase organic pollutant concentrations, with increased biological oxygen demand (BOD), and hence lower dissolved oxygen (DO) concentrations in rivers (Prathumratana *et al.*, 2008; Van and Zwolsman, 2008). Drought–rewetting cycles may impact water quality as it enhances decomposition and flushing of organic matter into streams (Evans *et al.*, 2005). The impacts of climate change on water quality and the aquatic ecosystem are getting more attention. However, there are still some problems that need to be improved in the future. There are a lack of studies differentiating the impacts of climate change and human activities. The impacts of climate change on water quality and the aquatic ecosystem through changing water regimes are still unclear, and most adaptations proposed before are idealistic or impracticable (Xia *et al.*, 2010).

Some recent studies (Xia and Zhang, 2008) have shown that human activities' impact on water quality in China are very significant, largely due to population stress and economic development. Expansions in areas such as in urban and agricultural development, river development (i.e., water project construction), water use, and in particular overexploitation of ground water resources have caused an increase of human impact on water quality. The scarcity of water resources is aggravated by unequal spatial and temporal distribution due to huge population and booming economy. Recently, the deterioration of water quality and ecosystem health in rivers has become increasingly prominent. Changes in land use alter biological, physical and chemical processes in watersheds and thus significantly affect the quality of adjacent surface waters. In addition, sewage linked to human activities can directly destroy water quality and ecosystem health. Besides sewage, climate change can both mitigate and exacerbate the degradation of water quality. Moreover, when point source pollution is reduced in China, climate change is expected to result in increasing impacts in the future (Xia *et al.,* 2010)

2.2 A Summary of River Algal Blooms

Algal blooms are generally defined as eutrophication of water bodies due to a rapid increase or accumulation in the number of algae cells or phytoplankton in freshwater as well as marine environments (Yabunaka *et al.,* 1997; Zheng *et al.,* 2006). Algal blooms are often green, but they can also be other colors depending on the species of algae such as blue, yellow-brown or red and are most common in spring or early summer. According to the research from Environment Agency (EA), most of the algal blooms in water bodies are often *diatom algae*, blue algae (Cyanobacteria), green algae and etc.. This phenomenon is the result of an excess of nutrients, particularly phosphorus. Excess carbon and nitrogen have also been suspected as cause (Diersing, 2009). Algal blooms not only occur in freshwater but also in marine environments. Algal blooms may also include toxic events which are called Harmful Algal Bloom (HABs), such as “Red tide” which is often used to describe HABs in marine coastal areas. Those species are “a small subset of algal species that negatively impact humans or the environment” (Diersing, 2009). In some cases algal blooms are natural phenomena. However, in many parts of the world algal blooms are increasing due to human activities, and this can have a negative impact on wildlife as well as human health (Zheng *et al.,* 2006)

Freshwater algal blooms can also have a broad range of negative impacts on humans, animals, and aquatic ecosystems. The risks are as follows (Donnelly, 1997):

1. Decaying algae depletes oxygen from the water, leading to low or no oxygen conditions where fish and other animals may be unable to survive.
2. Some algae that contribute to blooms also produce toxins that threaten the safety of drinking water sources and can harm both humans and animals by contaminating the food chain.
3. Algal blooms will also cause deterioration of water quality through the build-up of high biomass. They may degrade the aesthetic value of water bodies through floating algal masses and by generating an unpleasant odor.

Although the threshold level of algal bloom is different depending the water body in question and environmental conditions, the threshold of an algal bloom was generally defined when concentration of chlorophyll in the water exceeds 30μg/L or when the number of algal cells exceeds 5 million per liter (Lu *et al.,* 2000). Increasingly, algal blooms are a public health concern and an ecological problem in wetlands, waterways and oceans (World Bank, 2001). Biomass accumulation is an important process before the appearance of algal blooms, so the change of algal growth rate is of great significance for the early warning of algal blooms (Gamini, 1997; Lu *et al*, 2000).

As economic developments and human activities increase, there have been some studies indicating that river eutrophication and algal blooms have become a serious environmental problem. For instance, Australia experienced the largest recorded toxic river algal bloom in history in November of 1991. In 1992 the first river algal bloom was formed in the Han River of China which is the largest tributary of the Yangtze River (Xie, 2003). The Department of Environmental Quality (DEQ) stated that in August 2007, an algal bloom occurred in the Potomac River off the coast of Colonial Beach in USA, and turned the water a reddish-brown color (Dunn, 2007). In 2009, a blue-green algal bloom occurred that extended some 1,000 km along the Murray River on the border of New South Wales and Victoria downstream from Hume Dam over a two month period. Recently, The Environment Protection Authority (EPA) has investigated several reports of a red substance forming slicks in the Derwent estuary in England. Despite the above events of river algal bloom occurring in different countries and environmental conditions, they all have similar circumstances of climate change and run-off of nutrients. For example, most of the above algal blooms occurred at a time of low river flow (around 200's ml/day) along with hot or still conditions. Therefore, the global climate change is likely to have significant effects on the hydrological cycle (IPCC, 1996), which is linked to potential river eutrophication problems.

2.3 Previous Modeling Studies to Assess Climate Change Impact on Water Quality

2.3.1 Statistical Models

Multiple regressions analysis is a statistical method, the purpose of which is to learn more about the relationship between several independent or predictor variables and a dependent or criterion variable. The general computational problem that needs to be solved in multiple regression analysis is to fit a straight line to a number of points. Over the past decades, the multiple regressions analysis as a "black-box" typed model has been widely used for analyzing and forecasting environmental problems in the social and natural sciences. It is a very useful and conventional statistical method which can be used to infer causal relationships between the independent and dependent variables in a proper mathematical expression. There have been a lot of water environmental cases studies applied for multiple regressions approaches. For instance, Biggs (2000) applied multiple regression model combining dissolved nutrient data for predicting the effects on algal biomass of streams and river eutrophication. He suggested that managing nutrient supply could not only reduce the magnitude of maximum biomass, but also reduce the frequency and duration of benthic algal proliferations in streams. Chesoh *et al*. (2007) applied regression model to predict the chlorophyll-A concentration as an index of potential occurrence eutrophication in Songkhla Lake in Thailand. A predictive statistical model has been developed for estimating when water quality conditions are conducive to high Chlorophyll-a levels, and the model provided a practical lake water management tool for eutrophication surveillance. Climate-change mediated eutrophication does not only apply to lakes and rivers. They emphasized that global warming will exacerbate water eutrophication. Most previous studies address these environmental problems by using multiple linear regressions or non-linear regressions approach. It is not common to see these two models combined together to analyze the problems of river water quality. Moreover, the regression results from most of the above studies were not compared with another well-known simulation model which is the Artificial Neural Network (ANN) model.

2.3.2 Simulation Models

An Artificial Neural Network (ANN) is a powerful tool can be used to simulate any complex functions and nonlinear problems. A neural network usually consists of an interconnected group of artificial neurons, and it processes information using a connectionist approach to computation. ANNs are versatile tools to extract information out of complex data, and which have been implemented in diverse aspects such as in ecological modeling (Park *et al*, 2003; Lek and Gugan, 1999, 2000), predicting population and community development (Tan and Smeins, 1996; Recknagel *et al.,* 1997; Chon *et al.,* 2000), or patterning complex relationships (Lek *et al.,* 1996; Tuma *et al.,* 1996). Most of these studies used one of two ANNs: a self-organizing map (SOM) (Kohonen, 1982) for clustering input vectors, and a backpropagation algorithm (BP) (Rumelhart *et al.,* 1986) for predicting biotic attributes with biotic and/or abiotic variables. The most well-known supervised ANN model solved this problem, which is the “back-propagation network (BPN)" developed by Rumelhart *et al.* (1974), Hinton and Williams (1986). The solution is that the errors for the units of the hidden layer are determined by back-propagating the errors of the units of the output layer. It is a multilayer feed-forward network based on the error back-propagation training algorithm. This method used a steepest descent back-propagation training algorithm, and the error of the output signal of a neuron is used to adjust its weights such that the error decreases and the error in hidden layers is estimated proportional to the weighted sum of the (estimated) errors in the layer above. However, there have not been many studies applying BP network on river eutrophication problems, The potential impacts of climate change included changes in snowfall, snowmelt, rainfall amount and intensities. The ANN was capable of identifying complex nonlinear relationships between input and output data sets without prior knowledge of internal structure of a system. However, most authors proposed the use of regression analysis or ANN as simulation models to deal with environmental cases, but the proposed approach wasn't explained by any conceptual and mechanism model. This meant that the final results are without any knowledge of its internal workings. In contrast, a statistical model such as multiple linear and nonlinear regression may be employed to approximate a nonlinear system (Chen *et al*., 1990; Leontaritis and Billings, 1985). But physical significance or structural information of the system will be lost if such black-box models are attempted (Gawthrop *et al*., 1993; Gray *et al*., 1998; Tan *et al.,* 2002). Therefore, an integrated assessment model combined with a half physical representation can verify those black box models.

2.3.3 Water Eutrophication Models

Compared to the above statistical model, a empirical model or sometimes called "semi-physical" typed model usually provides a physical representation, but some of the physics is approximated (Tan *et al.*, 2002). This model is usually a combination of stochastic and deterministic models (Jacobsen *et al.,* 1996). For application in water environments there have been many water eutrophication models. Vollenweider (1969) first published a nutrient loading model which describes the relationships between mean water depth and various measures of water quality in the last century, and Dillon (1974) simplified this theoretical formula based on finding correlations between the phosphorus retention coefficient R and sedimentation rate coefficient Kp. Thus those are typical water eutrophication models which are commonly recognized as empirical models or white box model (also called glass box or clear box) systems, where all necessary information is available (Aris, 1978). This kind of empirical model contains parameters of water quality and hydrological regimes, but could not indicate any climatic parameters such as temperature and precipitation. There has been some pervious research that tried to include such factors. For instance, Straten and Keesman (1991) successfully developed stochastic first-order error propagation based on the extended Kalman filter (EKF), and robust Monte Carlo set-membership procedure (MCSM) which are applied to water quality assessment**,** generating a projective forecast of the algal dynamics in a lake in response to management actions that force the system into a different mode of behavior. They emphasized that the grey-box models have larger predictive capabilities than black-box models. Sjoberg

(1999) proposed a grey box stepwise algorithm to identify a nonlinear model of a rotational system, and the initialization algorithm of the study improves the changes avoiding similar kinds of problems with local minima for nonlinear black box and grey box models. Madsen *et al.* (2001) proposed a grey box model which was set up to describe concentrations of total nitrogen and inorganic nitrogen. Taking denitrification into account allows descriptions of generalized approximations for the dynamic physical and biological system and quantification of the uncertainty of the results. Carstensen *et al.* (2006) established a nonlinear time series grey box model based on knowledge of the waste water treatment processes. Tan and Li (2007) developed an evolutionary simulation model identification methodology that makes the best use of *a-prior* knowledge on a clear-box model with a global structural representation of the physical system under study, whilst incorporating accurate black-box models for immeasurable and local nonlinearities of a practical system.

Most of above researches were only focused on solving the eutrophication problems in lakes, reservoirs and other fields, and there have not been many specific case studies describing climate change impact on the algal bloom of the river or other large bodies of water. Moreover, climate change impact on the river water environment is a very complex system, which contains human activity (e.g. waste load), hydrological conditions (e.g. water flow rate, water level), temperatures and etc. So far, many of the relevant studies have separately analyzed the effect of human activities and global warming from this complex water environment system, but there is a lack of comprehensive research to formulize the interaction between human activity and climate change on the river algal bloom. Therefore, an integrated climate change assessment approach based on the combination of statistical and simulation models will be proposed in the following sections.

2.4 Summary

This Chapter reviews the most recent literature on climate change impact on water quality. Typical modeling approaches and techniques used for the analysis of climate change impacts on the water quality are addressed, emphasizing the statistical and simulation modeling system which includes multiple linear regressions, nonlinear regression approaches, ANN and a water eutrophication models.

The literature review indicated that there is a need for more studies:

1. The previous research has indicated that water quality can be directly affected through several climate-related mechanisms on both short and long term. However, 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 are still unclear, and there are a lack of studies on climate change impact on water quality, especially for large river systems in China.

2. The impacts of climate change on water quality are getting more attention in recent years, but there have not been many systematical assessments refer to the interactions between human activities, temperature, water quality and hydrological regimes. There are also a lack of studies differentiating between the impacts of climate change and human activities. Quantifying contributions from human activities and climate change on river water quality has not been identified so far.

3. Most of previous studies related to climate change are more focused on solving eutrophication problems in lake systems such as fishponds, small lakes and reservoirs. There have not been many specific case studies describing climate change impact on water quality in the large river systems.

4. The statistical models such as regressions and ANNs are powerful for simulating and forecasting environmental problems. However, there is lack of a comprehensive modeling which addresses the application of climate change impact assessment on river water quality. Furthermore, most of the statistical models just imports the collection data to calculate the outputs without providing some necessary physical meaning, and lack sufficient support from concept or mechanism models.

Therefore, in this study, it is possible to extend previous studies in the following areas:

1. This study can not only point out the direct impact of climate change on water quality in both short and long term, but can also quantify the contributions associated with climate change and human activities, as well as different hydrological regimes.

2. An parametric river eutrophication system model can be developed based on application of both statistical and simulation data models. All modeling results will be compared for their advantages and limitations for water environmental assessments. The final assessment result can be applied to a real case study to address climate change impact on river water quality and eutrophication problems.

3. The comprehensive modeling result not only indicates the relationships between multiple inputs to outputs, but also can provide some necessary physical conceptions to explain the mechanisms of climate change impacts on water environments.

4. The emission scenarios analysis will be applied based on the overall results, which can be used to predict the future occurrence of probabilities in the next 50 years, thus corresponding implications to climate changes can be made as well.

CHAPTER 3 METHODOLOGIES

3.1 Multiple-linear Regressions Model

A multiple linear regressions (MLRs) method is a multivariate statistical technique used to model the linear correlations between a single dependent variable Y and two or more independent variables (x1, x2, …. , X*n)* (Sykes, 1999). In multiple linear regressions, there are i^{th} explanatory variables (observations), and the linear relationship between the dependent variable and the explanatory variables is represented by the following equation 3.1 :

$$Y_i = b_0 + b_1X_{1i} + b_2X_{2i} + \dots + b_kX_{ki} + u_i \quad \text{for } i = 1, 2, ..., n \qquad (3.1)$$

where b_0 is the constant term and X_1 to X_2 are the coefficients relating the i^{th} explanatory variables to the variables of interest. Note that in this equation, the regression coefficients (or coefficients *b*) represent the independent contributions of each independent variable to the prediction of the dependent variable (Sykes, 1999).

The equation can be expressed in a form of linear matrix:

$$\rightarrow \quad \begin{bmatrix} y_1 \\ y_2 \\ \dots \\ y_n \end{bmatrix} = \begin{bmatrix} b_0 \\ b_2 \\ \dots \\ b_k \end{bmatrix} \times \begin{bmatrix} 1 & x_{11} & x_{21} & x_{k1} \\ 1 & x_{12} & x_{22} & x_{k2} \\ \dots & \dots & \dots & \dots \\ 1 & x_{1n} & x_{2n} & x_{kn} \end{bmatrix} + \begin{bmatrix} u_1 \\ u_2 \\ \dots \\ u_n \end{bmatrix} \qquad (3.2)$$

The multiple regression models in matrix notation then can be expressed as:

$$\rightarrow \qquad Y = Xb + u \qquad (3.3)$$

where b is a column vector of 1 (for the intercept) + k unknown regression coefficients. Recall that the goal of multiple regressions is to minimize the sum of the squared residuals. Regression coefficients that satisfy this criterion are found by solving the set of normal equations

$$X'Xb = X'Y \qquad (3.4)$$

When the X variables are linearly independent (i.e., they are nonredundant, yielding an X'X matrix which is of full rank), there is a unique solution to the normal equations. Premultiplying both sides of the matrix formula for the normal equations by the inverse of X'X gives

$$(X'X)^{-1}X'Xb = (X'X)^{-1}X'Y \qquad (3.6)$$

or

$$b = (X'X)^{-1}X'Y \qquad (3.7)$$

The last result in the equation 3.7 is very satisfying in view of its simplicity and its generality.

3.1.1 Data Screening for Regression

(i) Linearity Analysis

An important step before applying the multiple regressions approach is to assume that there is a linear relationship between dependent variable and the explanatory variables. Scatter plots should be checked as an exploratory step in regression to identify possible departures from linearity. Scatter plots are two dimensional graphs. It involves two variables, which are explanatory variable or Independent variable and response variable or Dependent variable.

(ii) Correlation analysis

Pearson (1908) developed a correlation method can also measure the correlation of linear dependence between two variables. Suppose we have two variables *X* and *Y*, with means $\overline{X}$ and $\overline{Y}$, respectively, and standard deviations S_X and S_Y, respectively. The correlation can be computed as:

$$r = \frac{\sum_{i=1}^{n}(X_i - \overline{X})(Yi - \overline{Y})}{(n-1)S_X S_Y} \tag{3.8}$$

Thus, the result between -1 and +1 can measure the degree of correlation between two variables, a positive value implies a positive association and a negative value implies a negative or inverse association (Mike, 2008; Paul, 2008). Usually, we can determine the strength of correlation by range as: (a) very strong correlations between 0.8 ~ 1.0; (b) Strong correlations between 0.6 ~ 0.8; (c) moderate correlations between 0.4 ~ 0.6; (d) weak correlations between 0.2 ~ 0.4 and (e) moderate correlations between 0.4 ~ 0.6.

The purpose of the scatter plot and Pearson correlation is to determine if any relationship between the variables is possible. The scatter plotting is usually performed even before data analysis is considered or before testing the regression fitting model. If relationships are nonlinear, there are two recourses (Mark, 2008): (1) transform the data to make the relationships linear, or (2) use an non-linear statistical model. In this study, the correlation coefficients larger than 0.4 (moderate correlations) will be taken as sampling data.

3.1.2 Goodness of Fit

Once the regression model has been established, the goodness of fit of statistical model describes how well it fits a set of the observation data. Measures of goodness of fit typically summarize the discrepancy between the observed values and the values expected under the model in question. Some useful indicators such as residual variance and coefficient of determination (R^2) can be used to estimate the modeling efficiency.

(i) Residual Variance

The goal of linear regression is to adjust the values of slope and intercept to find the line that best predicts Y from X (Sykes, 1999). More precisely, it is to minimize the sum of the squares of the vertical distances of the points from the line.

Several regression statistics are computed as functions of the sums-of-squares terms:

$$\text{SST} = \sum_{i=1}^{n}(y_i - \bar{y})^2 \quad \text{sum of squares, total;}$$

$$\text{SSR} = \sum_{i=1}^{n}(\hat{y}_i - \bar{y})^2 \quad \text{sum of squares, regression;}$$

$$\text{SSE} = \sum_{i=1}^{n}(y_i - \hat{y})^2 \quad \text{sum of squares, error.} \qquad (3.10)$$

The regression equation is estimated such that the total sum-of-squares can be partitioned into components due to regression and residuals (Markus, 2009):

$$\text{SST} = \text{SSR} + \text{SSE} \qquad (3.11)$$

(ii) Coefficient of determination (R^2)

Coefficient of determination, R^2 (Sykes, 1999; Ethington, 2005), is an indicator of how well the model fits the data, for example: an R^2 close to 1.0 indicates that we have accounted for almost all of the variability with the variables specified in the model. The calculation of R^2 is 1 minus the ratio of residual variability. When the variability of the residual values around the regression line relative to the overall variability is small, the predictions from the regression equation are good. The explanatory power of the regression is computed from the sums-of-squares terms as following equation:

$$R^2 = \frac{SSR}{SST} = 1 - \frac{SSE}{SST} \qquad (3.12)$$

However, the value of R^2 is related to the size of sample "n", and R^2 also increases with increasing sample size. Thus the adjusted R^2 is one of the several statistics that attempt to compensate for this artificial increase in accuracy (Markus, 2009). the adjusted R^2 given by:

$$\overline{R} = 1 - (1 - R^2)\frac{n-1}{n-k-1} \tag{3.13}$$

,where n is the observation value and k is the explanatory variables

3.1.3 Significance of Regression Test

(i) Test on the whole regression model (F –test)

This test checks the significance of the whole regression model and it can be also used to simultaneously check the significance of a number of regression coefficients. The F statistic is the regression mean square (MSR) divided by the residual mean square (MSE). If the significance value of the F statistic is small (i.e., smaller than 0.05), then the independent variables can explain the variation in the dependent variable. If the significance value of F is larger than say 0.05, then the independent variables do not explain the variation in the dependent variable, and the null hypothesis that all the population values for the regression coefficients are 0 is accepted. In other words, an F-test with a significance level less than 0.05 indicates that at least one of the variables in the model helps to explain the dependent variable (Sykes, 1999).

For example: $$F_0 = \frac{MS_R}{MS_E} \tag{3.14}$$

If the null hypothesis H_0 is the true then the statistic F_0 follows the F distribution with k degrees of freedom in the numerator and n-(k+1) degrees freedom in the denominator. The null hypothesis H_0 is rejected if the calculated statistic F_0 is such that :

$$F_0 > f_{a,k,n-(k+1)} \tag{3.15}$$

(ii) Test on Individual Regression Coefficients (t-test)

The t test is used to check the significance of individual regression coefficients in the multiple linear regressions model. Adding a significant variable to a regression model makes the model more effective, while adding an unimportant variable may make the model worse. The hypothesis statements to test the significance of a particular regression coefficient β_j are:

$$H_0: \beta_j = 0$$

$$H_0: \beta_j \neq 0$$

The test statistic for this test is based on the t distribution (Mark, 2008):

$$T_0 = \frac{\beta_j}{se(\beta_j)} \tag{3.16}$$

This test can measure the contribution of a variable while the remaining variables are included in the model.

3.2 Multiple Non-linear Regressions Model

In practice, a very stark multiple linear regression model is not normally seen, so sometimes we need a system tool to simulate the nonlinear problems. The nonlinear regression approach is a method of finding a nonlinear model of the relationship between the dependent variable and a set of independent variables. Nonlinear regression can estimate models with arbitrary relationships between independent and dependent variables. In order to fit this, the linear least squares can be adapted to create new nonlinear variables from data. If new variable properly is constructed, the curved function of original variables can be expressed as a linear function of those new variables, and this transformation is often called linearization (Baker, 2006). There are some nonlinear regressions problem that can be moved to a linear domain by a suitable transformation of the model formulation. For example, consider a non-linear equation which is commonly used such as the constant elasticity model, application includes supply, demand, cost, and production functions. The constant elasticity equation (Baker, 2006):

$$Y = \mathrm{A}X^{\beta}u \tag{3.17}$$

where X is some continuous variable that's always bigger than 0; A is constant determines the scale; β is the elasticity of Y with respect to X; u is the error has a mean of 1 and is always bigger than 0.

Consider the nonlinear equation which will be always complex to calculate for multiple x variables. If we take the logarithm of both sides of that equation, we will get $\ln(Y) = \ln(A) + b \ln(X) + \ln(u)$. For this equation, if create the variable $\ln(Y)$ and also a variable for the base-e logarithm of X, written as $\ln(X)$, we can use the regular least squares method to fit the curve $Y = AX^b$ to sampling data (Baker, 2006).

When applying this approach to a environmental problem, 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, X_2, and X_3). We take a logarithm for both sides,

$$Y_1=\beta_0 X_1^{\beta 1} X_2^{\beta 2} X^{\beta 3} \quad (3.18)$$

It becomes:

$$\ln(Y) = \ln (\beta_0 X_1^{\beta 1} X_2^{\beta 2} X_3^{\beta 3}) \quad (3.19)$$

and,

$$\ln(Y) = \ln(\beta_0) + \beta_1 \ln(X_1) + \beta_2 \ln(X_2) + \beta_3 \ln(X_3) \quad (3.20)$$

where $y = \ln Y$, $a = \ln\beta_0$, $x_1 = \ln X_1$, $x_2 = \ln X_2$, $x_3 = \ln X_3$, etc.

The equation can be finally transformed to a linear equation

$$y = a + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \ldots + \beta_n x_n \quad (3.21)$$

As with the growth-decay model, 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 deal with this problem. Thus, we can use multiple linear regressions method to deal with the non-linear regression problem and in order to determine the coefficients of regression equation.

3. 3 Artificial Neural Network Model

This study focuses the most well-known supervised ANN model, which is “Back-Propagation (BP) network" (Rumelhart, Hinton, and Williams 1986*)*, and it is a multilayer feed-forward network based on the error back-propagation training algorithm. This algorithm uses steepest descent back-propagation training algorithm. The error of the output is used to adjust its weights such that the error decreases, and the error in hidden layers is estimated proportional to the weighted sum of the errors in the layer above.

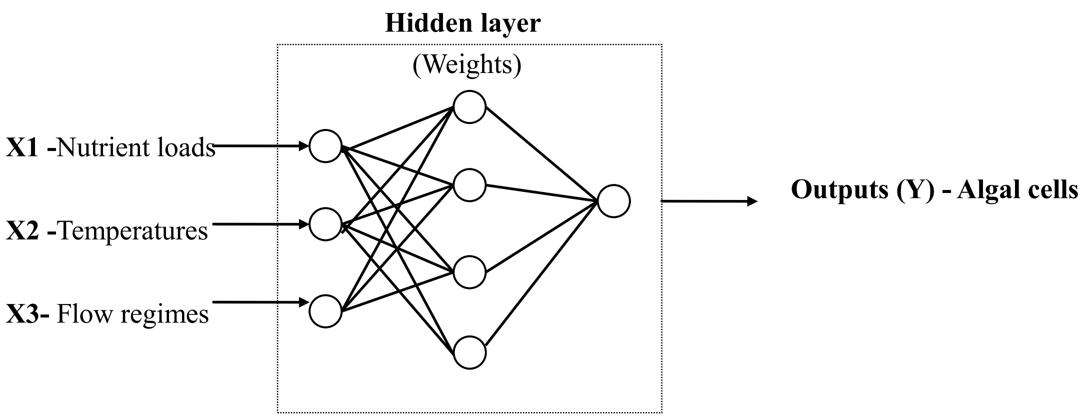


Fig. 3.1 Three layers back propagation neural network

A typical BP neural network (Fig. 3.1) consists of at least three layers of units: an input layer, at least one intermediate hidden layer, and an output layer. In puts are independent variables (e.g. Nutrients, Temperature and etc.), output is dependent variable (e.g. algal cells). When a BP network is cycled, an input pattern is propagated forward to the output units through the intervening input-to-hidden and hidden-to-output weights (Kohonen, 1997; Khalil, 2006). This algorithm is based on the error correction learning rule. The errors propagate backwards from the output nodes to the inner nodes. Back-propagation calculates the gradient of the error of the network regarding the network's modifiable weights (Paul, 1994). The basic principles of the back propagation algorithm are: (1) the error of the output signal of a neuron is used to adjust its weights such that the error decreases, and (2) the error in hidden layers is estimated proportional to the weighted sum of the (estimated) errors in the layer above.

The typical calculation producers of BP network are as follows (Thiang, 2010; Xie *et al.,* 2004): Assuming the neuron nodes for the input layer, hidden layer and outputs layer are N_1, N_2 and N_3, respectively, the transfer functions of neurons of input layer and hidden layer are the Sigmoidal functions:

$$f(x) = \frac{1}{1+e^{-x}} \tag{3.38}$$

If there are P^{th} training samples $(I_p, T_p, p = 1,2,\cdots,P)$, $I_p \in R^{N_1}$ is the input of the P^{th} sample, and $T_p \in R^{N_3}$ is the expected outputs of the P^{th} sample. Then, the process of the input signal which is forward propagated from the input layer to the output layer can be expressed in the following equations:

$$net_i^I = I_{pi} \tag{3.39}$$

$$O_{pi}^I = net_i^I = I_{pi} \tag{3.40}$$

$$net_j^H = \sum_{i=1}^{N_1} W_{ji}^F O_{pi}^I - \theta_j^H \tag{3.41}$$

$$O_{pj}^H = f(net_j^H) \tag{3.42}$$

$$net_k^O = \sum_{j=1}^{N_2} W_{kj}^S O_{pj}^H - \theta_k^O \tag{3.43}$$

$$O_{pk}^O = f(net_k^O) \tag{3.44}$$

where i =1, 2, …, N_1; j =1, 2, …, N_2; k =1,2, …, N_2. Also, net_i^I , net_j^H , and net_k^O represent the net inputs of a certain node "i" of the input layer, "j" of the hidden layer and "k" of the output layer, respectively. W_{ji}^F and W_{kj}^S represent the weights of node "j" of the hidden layer to "i" of the input layer and node "k" of the output layer to the "j" of the hidden layer . θ_j^H and θ_k^O are the threshold value of node "j" of the hidden layer and "k" of the output layer, respectively. O_{pi}^I, O_{pj}^H, O_{pk}^O indicate the outputs of a certain node "i" of the input layer, "j" in the hidden layer and "k" of the output layer , respectively, when the P^{th} sample is imported in the feed forward network.

Obviously, after importing the input vector I_p, the input vector O_{pk}^O （$k = 1,2,\cdots,N_3$）is probably different from the expect output T_{pk}（$k = 1,2,\cdots,N_3$）, because the variation of weights and threshold values (W_{ji}^F , W_{kj}^S , θ_j^H ,θ_k^O). Thus the error function can be defined as:

$$E = \sum_{p=1}^{P} E_p = \frac{1}{2}\sum_{p=1}^{P}\sum_{k=1}^{N_3}(T_{pk} - O_{pk}^O)^2 \tag{3.45}$$

When the network structure is confirmed，the error function E also called energy function which is consisted weights (W_{ji}^{F} and W_{kj}^{S}) and threshold values (θ_{j}^{H} and θ_{k}^{O}) with 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, that is:

$$\Delta W_{xy}(n+1) = \eta \sum_{p} \delta_{px} O_{py} + \alpha \Delta W_{xy}(n) \tag{3.46}$$

$$\Delta \theta_{x}(n+1) = -\eta \sum_{p} \delta_{px} + \alpha \Delta \theta_{x}(n) \tag{3.47}$$

$$\Delta W_{xy}(n+1) = W_{xy}(n+1) - W_{xy}(n) \tag{3.48}$$

$$\Delta \theta_{xy}(n+1) = \theta_{xy}(n+1) - \theta_{xy}(n) \tag{3.49}$$

where η is the learning rate and α is the momentum factor. $W_{xy}(n)$ indicates the n^{th} iterative value of weights between nodes x and y of any two neighboring layers in the feed-forward network, and it can be expressed as $W_{ji}^{F}(n)$ or $W_{kj}^{S}(n)$. 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 $\theta_{k}^{O}(n)$. For node x in the output layer:

$$\delta_{px} = (T_{px} - O_{px}^{O}) O_{px}^{O} (1 - O_{px}^{O}) \tag{3.50}$$

For node x in the hidden layer,

$$\delta_{px} = O_{px}^{H} (1 - O_{px}^{H}) \sum_{x'} \delta_{px'} W_{x'x} \tag{3.51}$$

In the above equation 3.51, node x' is in the higher layer of node x, and it explains the processing of error back-propagation.

3.4 An Integrated River Eutrophication Model

It is known that the input nutrient load is the main cause of water eutrophication, and the some river that occurred algal blooms almost has the same hydrological conditions (i.e., low flow rate and low water level) as the lakes. Thus, the Wuhan cross-section of Han River could be consider as a large lake system. In order to establish a primary hydrological mechanism model to analyze the impacts of hydrologic conditions (water flow rate, water level) and input P load on the river eutrophication system, the Vollenweider model which is the most common model used for lake eutrophication problem can be applied for this river case study.

Vollenweider (1969) first published a nutrient loading model which describes the relationships between the mean water depth and various measures of water quality. Numerous researchers have modified the basic model or developed new models in order to derive nutrient loading rate criteria for water quality management purposes.

Vollenweider (1975, 1976) and Dillon (1975) discovered that a lake's response to the P loading also relates to the water residence time and hydraulic loading rate. Then, Vollenweider (1976) describes the statistical relationship of areal annual phosphorus loading to a lake normalized by mean depth and hydraulic residence time to predict lake phosphorus concentration.

Vollenweider (1969) described the mass balance of phosphorus in a lake as:

$$V \frac{dP}{dt} = Q_1 P_1 - QP - K_p VP \tag{3.21}$$

where V is lake volume [L^3]; P is lake phosphorus concentration [M/L^3]; t is time [T]; Q is annual volume of water discharged [L^3/t]; K_p is net sedimentary loss coefficient [T-1].

However, the most difficult problem with this model is the determination of the sedimentation rate coefficient. All other parameters could be determined directly. Dillon (1974) recognized there was good correlation between the phosphorus retention coefficient R and sedimentation rate coefficient Kp, which can be determined directly as: (Vollenweider and Dillon, 1974; Dillon and Rigler, 1974a)

$$R = 1 - \frac{\Sigma Q_{out} P_{out}}{\Sigma Q_I P_I} = 1 - \frac{W_{out}}{W_I} \tag{3.22}$$

where P_I is the input phosphorus concentration and W_I is the inflow discharge; P_{out} is the output phosphorus concentration and W_{out} is the outflows discharge. The equation can be written as (Vollenweider and Dillon, 1974):

$$P = \frac{L(1-R)}{Hq} \tag{3.23}$$

where L is loading of total phosphorus; R is retention coefficient of total phosphorus; q = hydraulic eroding coefficient ; H = average water depth; P = average phosphorus concentration.

Compared to the statistical model, although the peculiarities of what is going on inside the system are not entirely known, a certain model based on both insight into the system and experimental data is constructed. This model does, however, still have a number of unknown free parameters which can be estimated using system identification (Nielsen, 2000). One example is the Monod saturation model for microbial growth (Wimpenny, 1997). The model contains a simple hyperbolic relationship between substrate concentration and growth rate, but this can be justified by molecules binding to a substrate without going into detail of the types of molecules or types of binding. This kind of modeling is also known as semi-physical modeling (Forssell, 2001).

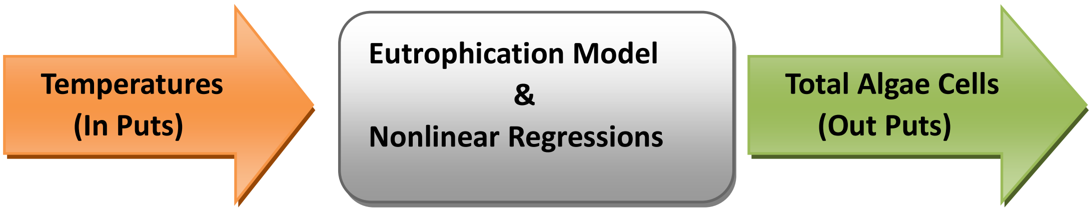


Fig. 3.2 Integrated river eutrophication model

The Vollenweider or Dillon model in this study is an empirical model of water eutrophication with hydrological and water quality parameters, and 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 (Fig. 3.2) which combines Dillon model and multiple non-linear regressions approach is established using following steps:

First, general non-linear regression equation is:

$$Y = \alpha\, X_1^{\beta 1}\, X_2^{\beta 2}\, X_3^{2} \ldots X_n^{\beta n} \tag{3.24}$$

Appling the indicators of phosphorus and temperatures into the nonlinear regression equation, we have:

$$Y_{\text{algae}} = \alpha\, P^{\beta 1}\, T^{\beta 2}$$

Substituting Dillon (1974) equation, that is:

$$P = \frac{L(1-R)}{Hq} \tag{3.25}$$

we have an integrated river eutrophication model:

$$Y_{\text{algal}} = \alpha \left[\frac{L(1-R)}{Hq}\right]^{\beta 1} T^{\beta 2} \tag{3.26}$$

Finally, an integrated river eutrophication model which combines multiple nonlinear regressions and Dillon method has been established, and it clearly identifies relationship between algal cells to hydrologic regime which are water depth (*H*), flow rate (*Q*), and waste nutrient load (*L*), also temperatures (*T*). Thus, the result could be considered a good explanation and validation to those statistical models.

3.5 Scenarios Analysis for Climate Change Impact Assessment

Once the results of the regression models are established, finding how to analyze the climate change and human-mediated impact on algal blooms is a key step.

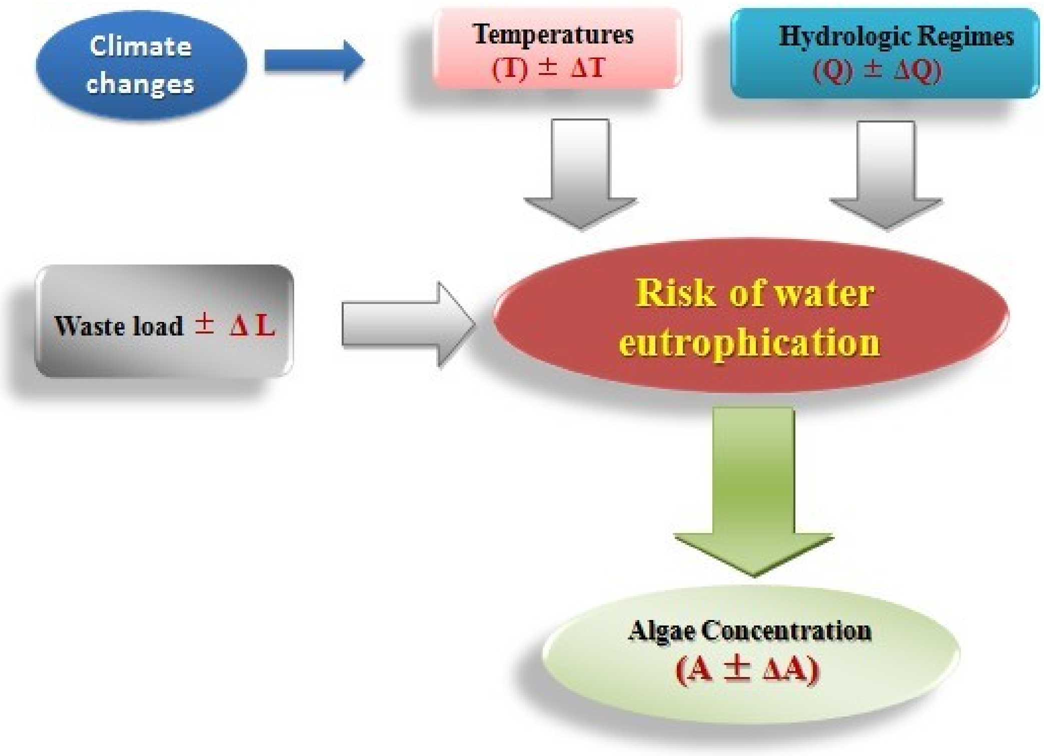


Fig. 3.3 Scenario analysis of climate change impact assessment

The above figure (Fig. 3.3) shows the relationship between algal blooms and climate change, hydrological regime and human influences. In order to systematically analyze the impact of each indicator of the algal bloom, we need to determine the Δ L, ΔT and ΔQ to the output ΔA. Then the scenario analysis under different conditions can be applied to this model. It can then be divided into two stages which are the single-factor assessment and the integrated assessment.

3.5.1 Single Factor Assessment

Single-factor assessment is where only one variable is changed while another two variables are fixed. Outputs are then analyzed so that the impact of that variable can be determined. For the Han River case study, there are several assumptions based on monitoring data and guidelines which are made during 1992 to 2000. Based on the yearly average of temperature (13.12°C) during 1992 to 2000, it is assumed that the temperature will increase by 2°C due to the global warming effect, which means the temperature will increase 15% regarding to yearly average value. In order to assess human activities and hydrological regimes, the based on this assumptions for the Han River case study, it was assumed that the flow rate will be decreased 15% which is approximated to 100 m^3/s based on the yearly average flow rate due to evaporation increase, and input nutrient load will increase 15% which is approximately 1 $mg/m^2.yr$ at same time because of economic and industrial development during 1992 to 2000. In the worth condition, the climate change assessment will be applied on this case study as following steps:

a) Assume the temperature (T) increases ΔT which is 2ºC during the years 1992 to 2000, and the value of phosphorus load (P) and flow rate (Q) are fixed, then the impact of temperature on algal cells can be determined. The impact of flow rate and phosphorus load on algal cells can be also identified by fixing any other two indicators.

b) Assume the flow rate (*Q*) decreases. ΔQ which is -100 m^3/s during the years 1992 to 2000, and the value of *T* (temperature) and L_p are fixed. Then, the impact of flow regime on algal cells can be determined;

c) Assume L_p increases ΔL in 1 mg/ m^2.yr during the years 1992 to 2000, and the value of *T* (temperature) and *Q* (flow rate) are fixed, then the impact of input nutrient loads on algal cells can be determined. Thus, this result will indicate the impact any single factor has on the river algal bloom. The same method can be applied on multiple nonlinear regression approach, ANN and Dillon models.

3.5.2 Integrated Assessment

In the most of situations multiple indicators will impact simultaneously, thus the integrated climate change assessment will be applied to the river eutrophication system. Similar to the individual analysis, integrated analysis changes two variables and another one is fixed. The analysis of the variation of the outputs can allow the impact of the variables to be determined. For example:

a) Assume the temperature (*T*) and L_p phosphorus load both increase ΔT and ΔL which are 2ºC and 1 mg/ m^2 yr during the years 1992 to 2000 respectively. The value of *Q* is fixed, then the impact of temperature and P load on algal cells ΔA_1 can be determined.

b) Assume T and Q are both changing. ΔT and ΔQ are 2ºC and -100m^3/s during the year of 1992 to 2000, respectively. The value of L_p is fixed, then the impact of temperature and flow regime on algal cells ΔA_2 can be determined;

c) Assume the L_p and Q are both variable. ΔL and ΔQ are 1 mg/ m^2.yr and -100m^3/s during the years 1992 to 2000, respectively. If the value of T is fixed, then the impact of flow rate and P load on algal cells ΔA_3 can be determined.

If all indicators are changing at same time, the variation of total algal cells ΔA_4 can be finally defined. Therefore, the value of ΔA_1, ΔA_2, ΔA_3, ΔA_4 can be compared to qualify the comprehensive contributions of indicators.

3.6 Summary

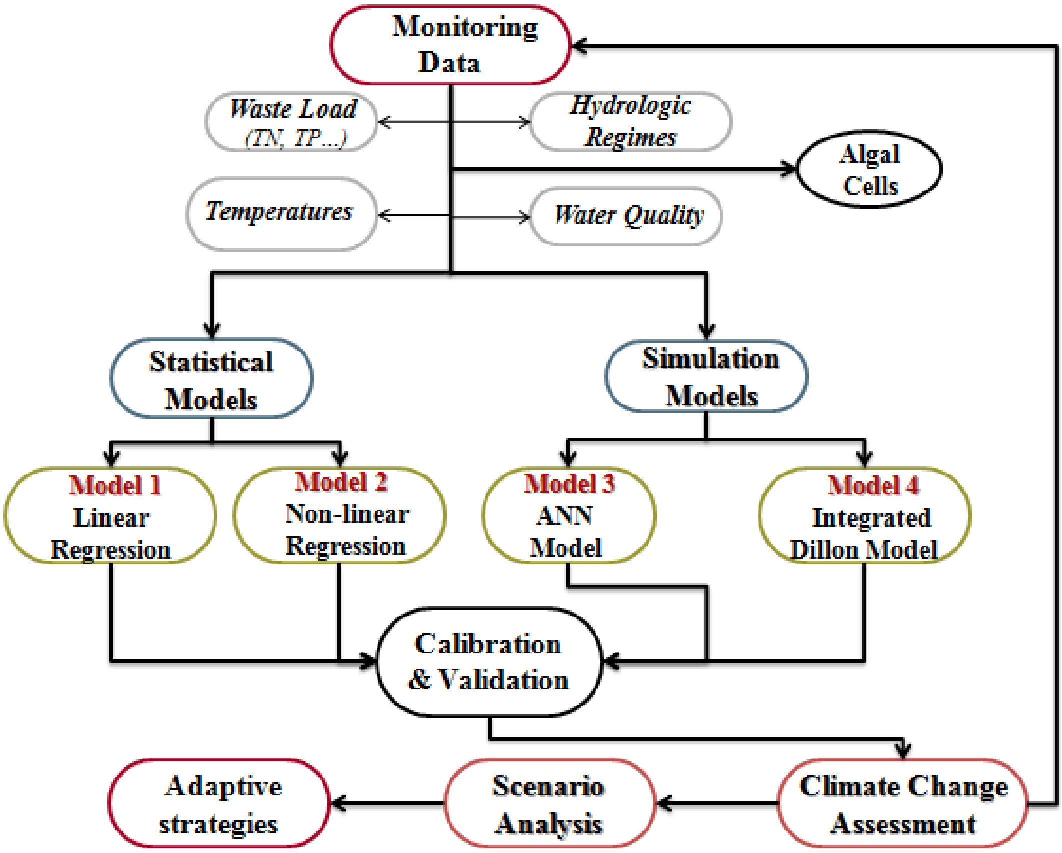


Fig. 3.4 Flow chart of multi-level climate change impact assessment

As indicated in Fig. 3.4 (above), this chapter presents a development of multi-level climate change impact assessment model. In order to qualify the comprehensive contributions to the river water quality and ecosystems, a multi-level climate change assessment approach is developed to apply to this environmental problem based on following steps: (1) Establish a system modeling structure of a river eutrophication based on multiple inputs and a single output. Several inputs are possible in this system including: (a) nutrient load, (b) temperature, (c) hydrological regime, and (d) water quality. The single output is the total algal cell concentration which will be used to indicate the level of algal blooms. Corresponding data screening and preparation will be performed based on the historical pollution events and correlation analysis. (2) Develop a parametric river eutrophication model that refers to modeling systems which include: (a) Multiple Linear Regressions (MLR), (b) Multiple Non-linear Regressions (MNLR), (c) Artificial Neural Network (ANN) based on Back-propagation (BP) algorithms, as well as (d) an integrated river eutrophication model. All of the above models will be calibrated and validated based on the monitoring data, the model with the best simulation result will be taken for individual and integrated assessment under different scenarios. (3) Quantifying the contributions of nutrient load indicators to river eutrophication. This method involves fixing the variables of hydrological regime and climate and then computing the output of algal cell concentration by changing the concentration of nutrient loads (e.g. TP, TN). (4) Quantifying the contributions of hydrological regime (e.g. water flow) to river eutrophication. This method fixes the variables of nutrient load and climate and then computes the output of algal cell concentration by changing the hydrological regime. (5) Quantifying the contributions of climate variation (e.g. temperature) to river eutrophication. This method involves fixing the variables of nutrient load and hydrological regime then computing the output of algal cell concentration by changing the climate (temperatures). (6) Quantifying the contributions of climate variations, nutrient load variation as well as hydrological regime variation together to comprehensively assess their impacts on river eutrophication. (7) Forecast the probabilities of algal bloom occurrence in the Han river for next 50 years based on three emissions scenarios. (8) Discuss the principles of adaptation strategies on how to solve the impact of climate change on water resources and what feasible adaptations should be taken to prevent adverse effects due to economic and social developments. In the following sections, this multi-level system approach will be applied to a real representative case study of the Han River in China in order to assess the impact of climate change and human activities on river water quality.

CHAPTER 4 A RESEARCH ON ALGAL BLOOMS OF THE HAN RIVER

4.1 Study Area

The Han River (see Fig. 4.1) is the largest tributary of the Yangtze River. It originates from Ningqiang County of Shaanxi province, and covers approximately 151 000 km^2 with a total length of 1577 km (Yang *et al.,* 1997; Shen and Liu, 1998). It is the most important water resource for industrial production and for people living in the Shan Xi 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, 2006). The Han River is one of major freshwater sources in China, and it plays a critical role in promoting the socioeconomic development of the Han River Basin (HRB). The rapid processes of urbanization and economic development brought about a swift deterioration of river water quality during the 1990s. The environmental capacity of the river is expected to decrease further and the water quality problem in the basin will become more prominent over time (Zhu *et al*., 2008).

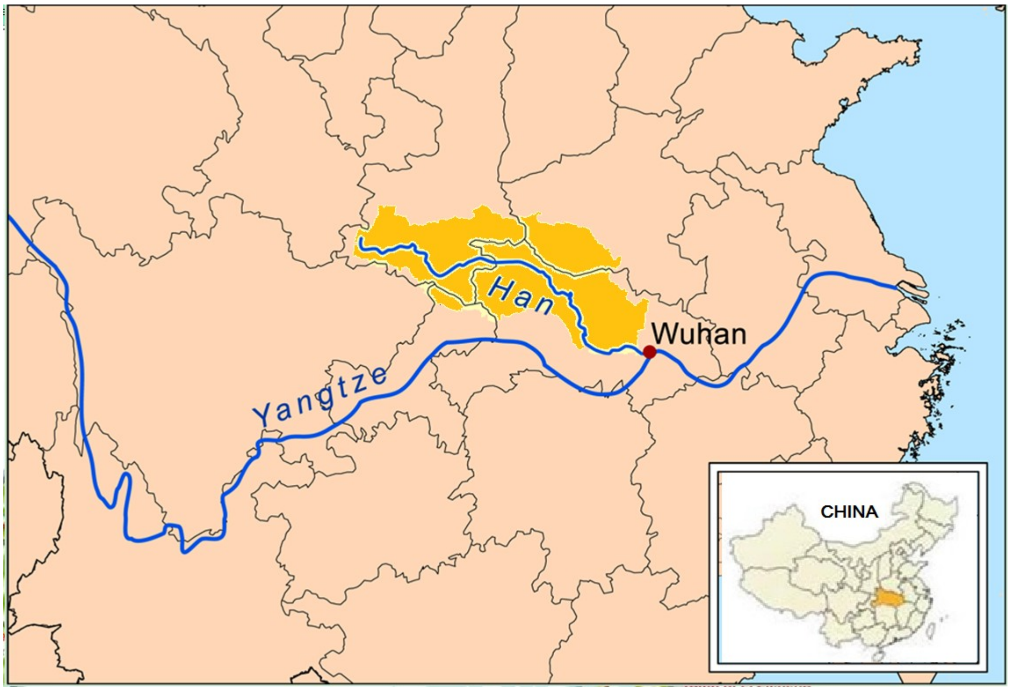


Fig. 4.1 Location of Han River in China (Lu *et al.*, 2009)

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). Another important potential risk that could impact Han River water quality is the South-to-North water transfer project (see Fig. 4.2)

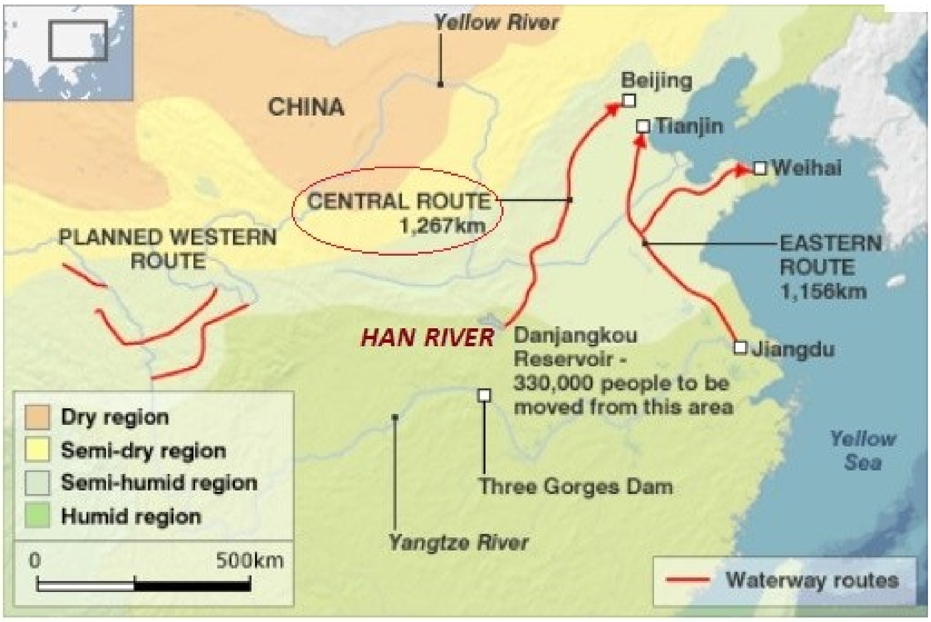


Fig. 4.2 China's South-to-North Water Diversion Project (Xie *et al.,* 2004)

The South–North Water Transfer Project is a multi-decade infrastructure project of the People's Republic of China to better utilize available water resources. This is to be achieved through the South-North Water Diversion Project (SNWD). Whilst the main thrust is to divert water from the Yangtze River to the Yellow sea and the Hai River, other spin-off plans are also loosely included. In China, Southern water is plentiful, northern water scarce, the Chinese Water Works Department conducted several studies on the project. After decades of study, the South-North Water Transfer Project settled on three different proposals for routes, and the Han River plays a critical role in the central route of SNWD project. Thus northern regions receiving water originating from the Han river would be severely impacted negatively if the source of the transfer water is seriously polluted.

Table 4.1 Status comparison of three algae bloom in Han River (Xie *et al.,* 2004)

	First algal bloom	Second algal bloom	Third algal bloom
Time (y.m.d)	1992.Jan.14.～Feb.25	1998.Feb.16～Mar	2000.Jan.6～Mar
Algae cells (10^4/L)	1670	1900	1300

The total density of algal cells has significantly increased in the Wuhan section of the Han River between 1992 and 2000 (Table 4.1) with algal blooms usually occurring at the end of winter and the beginning of spring. The most common algal species in algal blooms was found to be brown diatoms, followed by the green algae (Xie, 2004). It is more common for algal blooms in rivers to be made up of predominantly green algae. The unusual yellowish brown blooms on the Han river (Fig. 4.3) are caused by the high proportion of brown diatom algae, which also emit a characteristic foul smell..

Fig. 4.3 Han River algal blooms (Xie *et al.*, 2004)

The algal cell concentration (total numbers per liter) can indicate the intensity of an algal bloom. Lu *et al*. (2000) proposed that the level of algal cell concentration in the Han River should not exceed 500 x 10^4 cells/L. The Wuhan section of the Han River was selected for this case study since it is important to the South-North Water Transfer Project, and its water pollution and eutrophication problems are serious. The Wuhan section of the Han River has the characteristics of a river bend. The width is 400 meters in the high-water period, and it becomes around 100 meters in the drought period. Geographical coordinates of the Wuhan section of Han River are: East Longitude 113°56′21″ to 114°16′48″; northern latitude 30°40′11″ to 30°34′2″. The average yearly temperature is 16.3℃. January is the coldest month with average monthly temperature of 3.0℃, while the warmest month is July (28.8℃). Minimum to maximum temperature can be from -18.1℃ to 41.3℃. The annual precipitation and evaporation are 1204.5mm and 1449.5mm, respectively. The recent rapid onset of urbanization and economic development brought a swift deterioration of river water quality during the 1990s. The environmental capacity of the river is expected to decrease further and the water quality problem in the basin will be more prominent as time goes on (Zhu *et al.,* 2008).

4.2 Data Preparation

There were two sampling sites between the (A) and the (B) sections in a distance of approximately 7750m (Fig. 4.4). These two sections were selected because they are located downstream of the Han River section where the algal bloom problem has been most serious in recent years. As it is also very close to the mouth of Yangtze River, the water quality in these sections will directly impact on the Wuhan city and the Yangtze River.

Fig. 4.4 Sampling locations

The monitoring indicators for this case study include: total nitrogen (*TN*), total phosphorus (*TP*), Dissolved Oxygen (*DO*), Chemical Oxygen Demand (*COD*), NH_3, NO_3, Kjeldahl Nitrogen (*TKN*), N/P ratio, temperature (*T*), flow rate (*Q*), water depth (*H*) and total algal cells. The total P and N concentrations are converted to yearly average nutrient loads using following equation:

$$Nutrient.Load(mg/m^2.yr) = \frac{Tp(mg/L) \times Q(m^3/yr) \times 1000(L/m^3)}{A(m^2)} \tag{4.1}$$

Once the input nutrient loads are determined, the other input variables can be indirectly imported to the regression models. Sampling data were analyzed using Excel 2007 and SPSS (version 13.0). We have 11 input variables (i.e. P load, N load, *Q*, *h*, *T*, NH_3, NO_3,COD, DO, TKN and N/P ratio). First, using SPSS Pearson correlations method, the correlation values between *Y* (algae cell concentration) and other variables were obtained (Table 4.4). Comparing the input data (i.e. input P and N load, *Q*, h, etc.) to output data (i.e. algae cell concentration), we can find some useful relations as following table:

Table 4.2 Correlations of all indicators for climate changes impact assessment

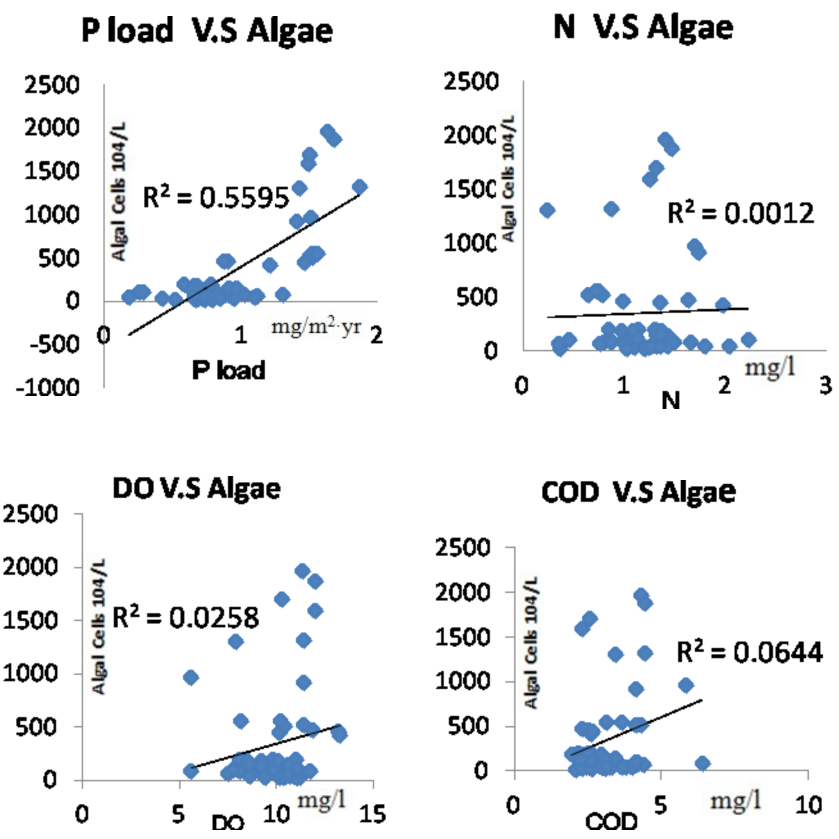
Correlations

		ALGAE	N	P	DO	COD	NH3	NO3	TNK	NPratio	t	q	h
ALGAE	Pearson Correlation												
	Sig. (2-tailed)												
	N												
N	Pearson Correlation	.034											
	Sig. (2-tailed)	.806											
	N	54											
P	Pearson Correlation	.748**	.016										
	Sig. (2-tailed)	.000	.910										
	N	54	54										
DO	Pearson Correlation	.161	.117	.088									
	Sig. (2-tailed)	.246	.398	.526									
	N	54	54	54									
COD	Pearson Correlation	.254	.104	.397**	-.330*								
	Sig. (2-tailed)	.064	.454	.003	.015								
	N	54	54	54	54								
NH3	Pearson Correlation	.136	.404**	.151	-.085	.627**							
	Sig. (2-tailed)	.326	.002	.274	.542	.000							
	N	54	54	54	54	54							
NO3	Pearson Correlation	-.141	.363**	-.157	-.109	.034	.152						
	Sig. (2-tailed)	.310	.007	.257	.434	.809	.273						
	N	54	54	54	54	54	54						
TNK	Pearson Correlation	.291*	.242	.112	.216	-.174	-.089	-.032					
	Sig. (2-tailed)	.033	.078	.420	.117	.209	.522	.816					
	N	54	54	54	54	54	54	54					
NPratio	Pearson Correlation	.017	.167	-.158	.050	-.230	-.118	.036	.301*				
	Sig. (2-tailed)	.904	.228	.253	.717	.095	.397	.799	.027				
	N	54	54	54	54	54	54	54	54				
t	Pearson Correlation	.648**	.165	.523**	-.039	.354**	.203	-.178	.287*	-.306*			
	Sig. (2-tailed)	.000	.233	.000	.778	.009	.141	.199	.036	.024			
	N	54	54	54	54	54	54	54	54	54			
q	Pearson Correlation	-.684**	.114	-.508**	-.219	-.128	-.152	.437**	-.211	.039	-.561**		
	Sig. (2-tailed)	.000	.413	.000	.112	.358	.272	.001	.126	.777	.000		
	N	54	54	54	54	54	54	54	54	54	54		
h	Pearson Correlation	-.345*	-.101	-.297*	-.361**	.168	.105	.329*	-.634**	-.290*	-.389**	.503**	
	Sig. (2-tailed)	.011	.469	.029	.007	.225	.448	.015	.000	.034	.004	.000	
	N	54	54	54	54	54	54	54	54	54	54	54	

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

The above table 4.2 clearly indicates that algal cell density only has a strong positive correlation with the input P load (0.748) and water temperature (0.648), and it also has a negative correlation with the water flow rate (-0.684). However, there is at most a weak correlation between algal concentrations and the rest of the variables. Thus those variables should be removed from our regression equation in order to have a more accurate result. Thus, the Pearson correlations coefficient is shown as a direct relation of the independent variable to each of the dependent variables and the result can be also verified on a scatter plot (Fig. 4.5) for linear correlation analysis. The R^2 of the linear equation is only showing good correlation in P-load, *T* and *Q* except the water flow rate which is a little lower, but still in an acceptable range.



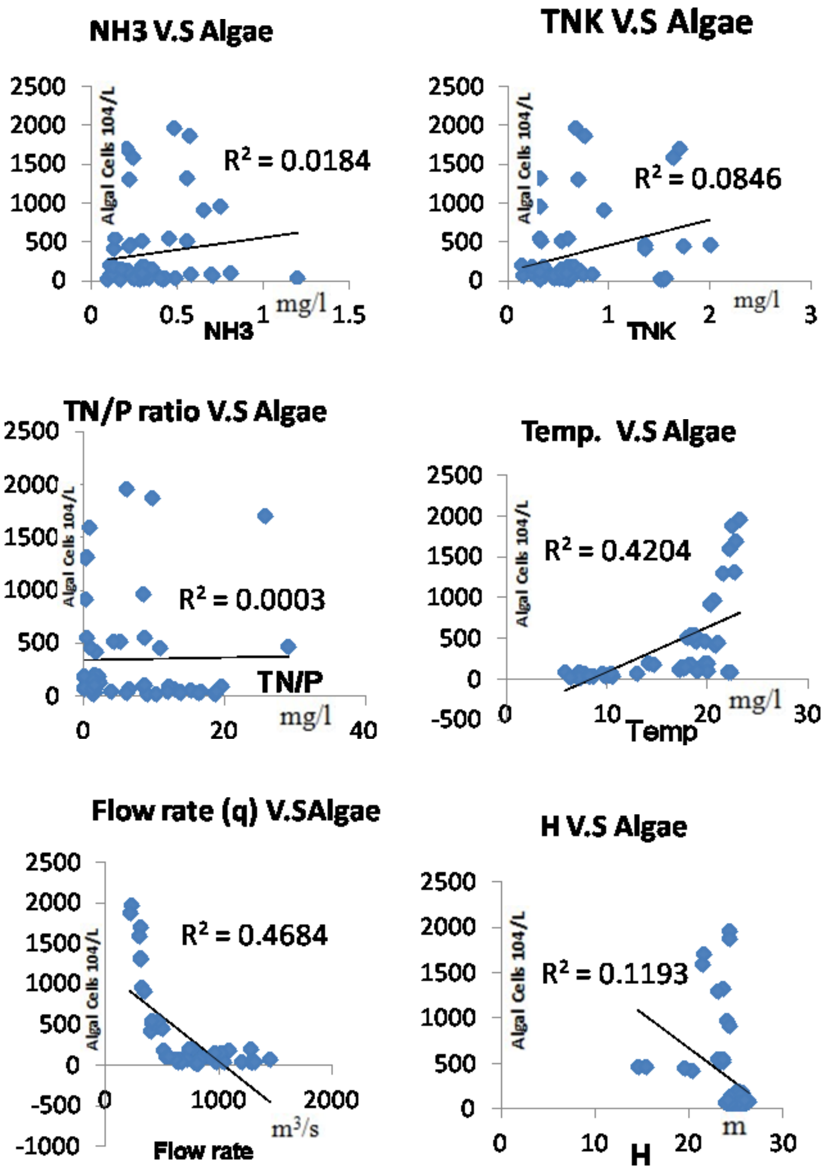


Fig. 4.5 Scatter plot diagrams for all input variables

In the Han River case study, the Pearson correlation method and the scatter diagram analyses can be applied to remove the insignificant variables. If the Pearson correlation coefficient is less than 0.5 and there also wasn't any correlation on the scatter diagram, the variables will be removed from the analysis. Moreover, since the algal bloom in the Wuhan section of Han River is mainly composed of diatoms, Qu *et al.* (2000) conducted an experiment to study the influence of N and P on population constituent of planktonic diatoms in water. The experimental result shows the concentrations of P tend to affect the population constituent of diatoms more significantly. Therefore, the water level, TN, N/P ratio, DO, COD and TKN will not be entered into the linear regression equations. Thus, as shown in Fig. 4.6, the algal concentration is calculated as the output of y1, the load (P) as input x_1, the flow rate (Q) as input $x2$ and water temperature (T) as input $x3$, the final ternary regression equation can be estimated in the following equation:

$$Y_{Algae} = \beta_0 + \beta_1 X_p + \beta_2 X_Q + \beta_3 X_T \quad (4.2)$$

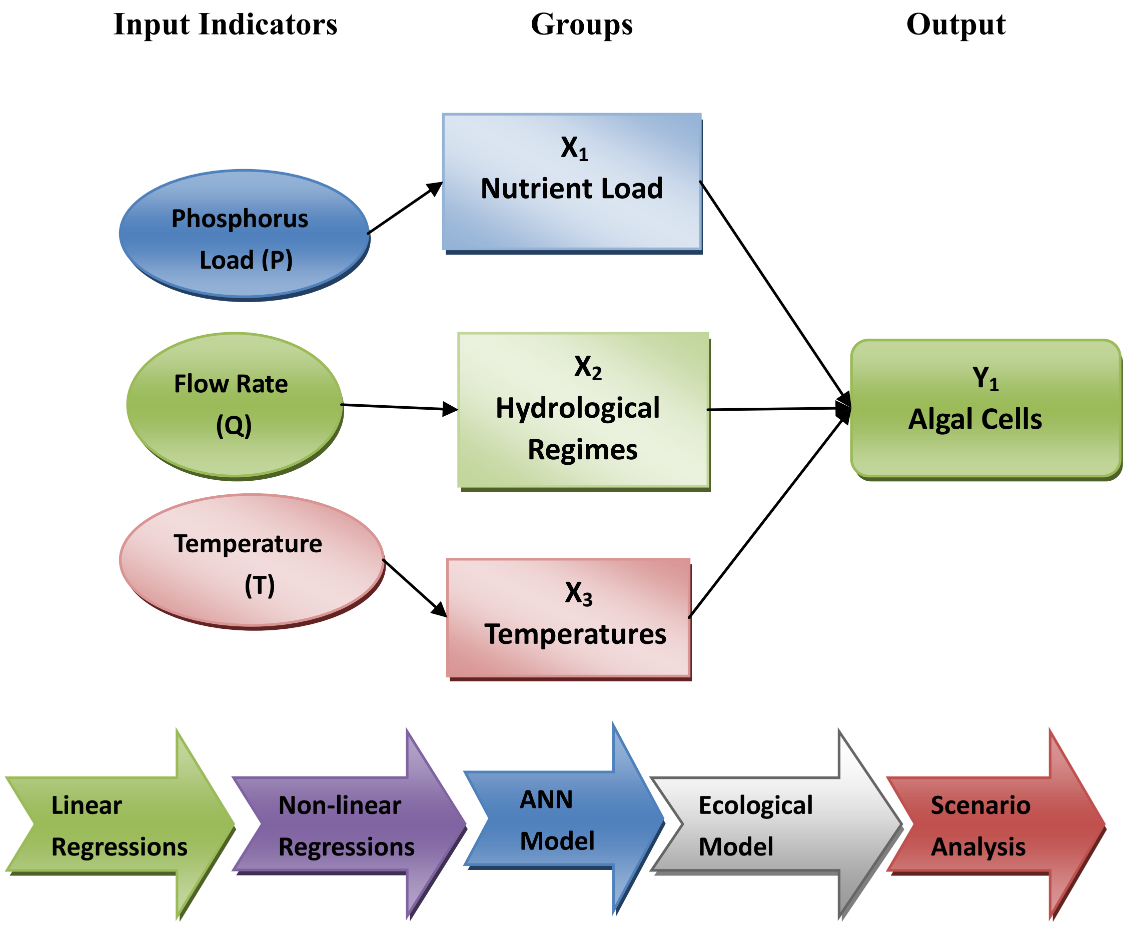


Fig. 4.6 Multi-level climate change impact assessment

4.3 Model Results

4.3.1 MLR Model Results With Calibration and Validation

The final input and outputs has been determined using the method described above to prepare the results. Some important results are as follows:

Table 4.3 MLR descriptive statistics

Variables	Mean	Std. Deviation	Samples (N)
Algae (10^4cells/L)	349.1926	509.45877	54
P-Loads (mg/m^2.yr)	.9587	.39872	54
Temperature.(°C)	14.6130	6.01291	54
Flow rate (m^3/s)	724.6030	311.41340	54

Above table 4.3 shows the mean values, standard deviations and number of samples (N) for each indicator.

Table 4.4 MLR model summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
MLR	.846(a)	.715	.698	280.07318	.715	41.789	3	50	.000

a Predictors: (Constant), q, P-Load, t

b Dependent Variable: Algae

The R^2 values indicate the model shows a good result. The coefficient of determination R^2 is 0.715, and the adjusted R^2 is 0.698.

Table 4.5 MLR coefficients

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	-118.924	226.619		-.525	.602		
	Load.P	598.134	118.814	.468	5.034	.000	.659	1.516
	Temperature.t	18.889	8.202	.223	2.303	.025	.608	1.643
	Flowrate.Q	-.526	.157	-.322	-3.359	.002	.622	1.608

a. Dependent Variable: Algae

Finally, the unstandardized coefficients have been determined. The significance value of the F statistic is small (less than 0.5) meaning the independent variables can explain the variation in the dependent variable, but the Sig.t value of constant term is 0.602 (greater than 0.5 for this linear regression). This means the constant term is not significant to impact the output. Hence it can be removed in the final equation. Also we have noticed that the collinearity statistics are both in an acceptable range (small than10) indicating there is no significant multicollinearity. Therefore, we have the final linear regression equation:

$$Y_{Con.}(10^4/L) = 598.13X_P(mg/m^2.yr) + 19.89X_T(°C) - 0.526X_F(m^3/s) \tag{4.3}$$

The above linear regression indicated the contributions of each independent variable (*X*) to the dependent variable (*Y*). For example, if temperature and flow rate are fixed, when input nutrient load is increases by 1 unit, the algal cells will also increase 598.13 (10^4/L). Same result can be applied to the temperature (19.89) and flow rate (-0.526).

Then, importing all of the observation data to the linear equation, the forecasting result of total algal concentrations with the observed values in the Wuhan section of Han River from 1992 to 2000 is shown in the following figures.

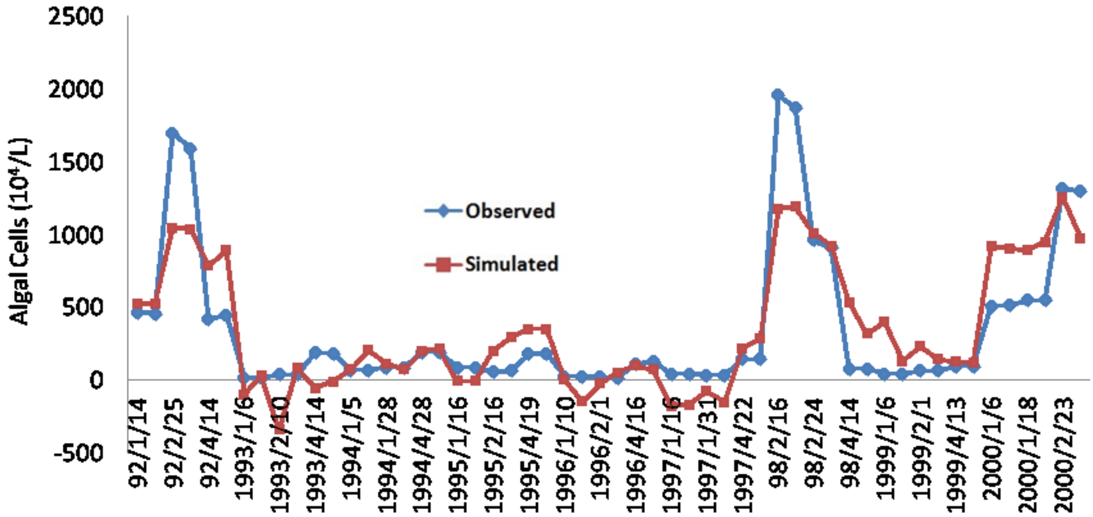


Fig. 4.7 Multiple linear regressions modeling result

*(*note: negative simulation results corresponds to zero)*

The above figure indicates the observed values and the simulated values of algal concentration are well matched (adjusted R^2= 0.698). From previous research the threshold for algal bloom in the Han River should not exceed 500 × 10^4/L of total algal cell numbers (Lu, 2000). By drawing a warning line on the graph, it is clearly shown that the algal blooms occurred in years 1992, 1998 and 2000. These algal blooms were very accurately forecasted by matching to the monitoring data. We have also noticed that some forecasting values returned negative, and this error can be ignored since it did not happen in the year of an algal bloom.

In order to verify the forecasting ability of this multiple linear regression model, the data from the years 1992 to 2000 will be divided into two parts for model calibration and verification. The first part which is from year 1992 to 1997 will be used for model calibration. A new regression equation is established based on the data of the first six years. Then, sampling data from year 1998 to 2000 will be imported to the equation to calculate the average algal cell concentration to establish the credibility of the model by demonstrating its ability to replicate actual traffic patterns. At the end, this result can be compared to the monitoring data to indicate the forecasting ability.

Table 4.6 MLR model summary (calibration) result

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
MLR	.821(a)	.674	.643	223.64090	.674	22.005	3	32	.000

a Predictors: (Constant), Flowrate.Q, Load.P, Temperature.t

b Dependent Variable: Algae

Table 4.7 MLR coefficients (calibration)

Coefficients^a

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	-245.307	251.659		-.975	.337		
	Load.P	608.734	153.844	.450	3.957	.000	.790	1.266
	Temperature.t	20.252	7.880	.316	2.570	.015	.675	1.482
	Flowrate.Q	-.365	.169	-.266	-2.154	.039	.667	1.499

a. Dependent Variable: Algae

From the table above the adjusted R^2 is 0.643 and the model is well established. The constant should also be removed because sig. t (=0.337) is greater than >0.05. Thus, the calibrated molding equation is:

$$Y_{Con.}(10^4/L) = 608.73X_P(mg/m^2.yr) + 20.25X_T(℃) - 0.365\mathrm{X}_{\mathrm{F}}(m^3/s)$$

(4.4)

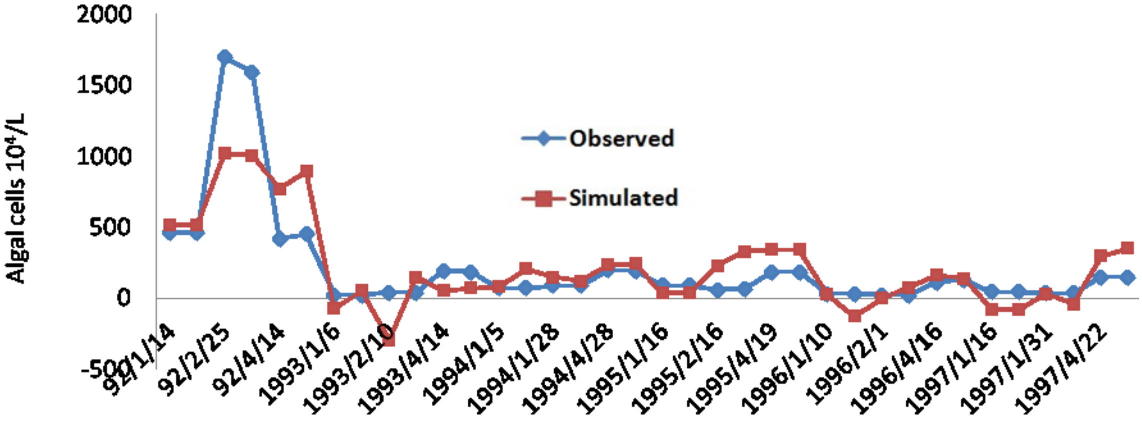


Fig. 4.8 MLR calibration from year 1992 to 1997

*(*note: negative simulation results corresponds to zero)*

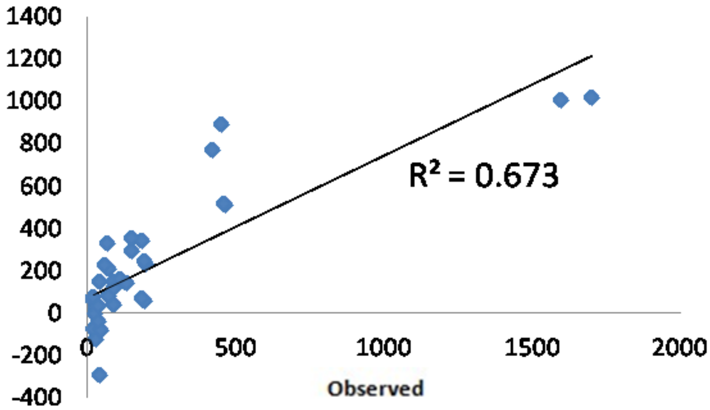


Fig. 4.9 Goodness of fit for MLR calibration

The above figures are the results of molding calibration. R^2 value is 0.6735 which is in a acceptable range. Then sampling data from year 1998 to 2000 will be imported to this calibrated equation to calculate the algal cells (*Y*).

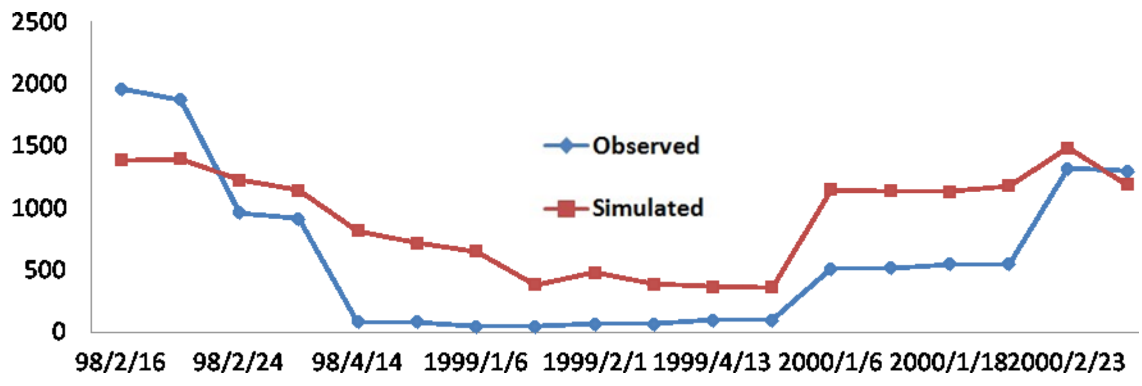


Fig. 4.10 MLR validation from year 1998 to 2000

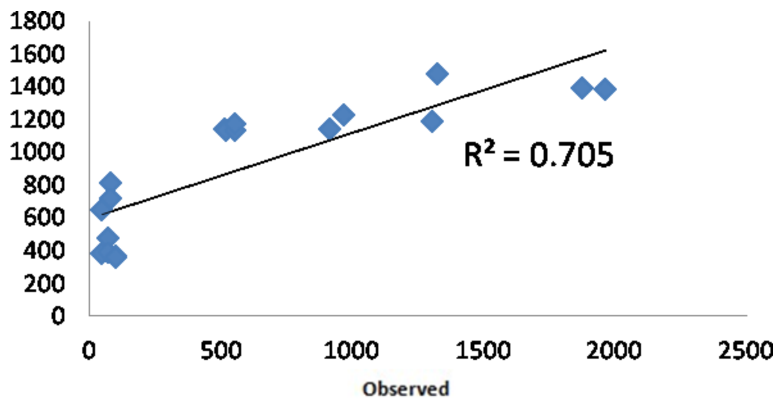


Fig. 4.11 Goodness of fit for MLR validation

This result with a high R^2 (= 0.7057) clearly indicates that the predicted value of algal cells is closely matched to the real data, accurately forecasting the algal bloom from the years 1998 and 2000.

4.3.2 MNR Model Result with Calibration and Validation

This gave a similar result to the multiple linear regressions method. The multiple non-linear regressions equation can be converted to the linear regression equation to analyze the impact of climate change. The following is the result of the SPSS test for the final model in which a very good coefficient of determination has been obtained.

Table 4.8 Model summary (MNR)

	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
MNR	.924(a)	.853	.844	.51763	.853	96.619	3	50	.000

a Predictors: (Constant), Flowrate.Q, Load.P, Temperature.t

b Dependent Variable: Algae

The R^2 value is 0.853, the adjusted R^2 is 0.844 and the Sig.F is 0.000 (<0.05).

Table 4.9 MNR coefficients

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	8.967	1.614		5.555	.000		
	Load.P	.749	.172	.271	4.345	.000	.758	1.320
	Temperature.t	1.281	.192	.454	6.673	.000	.634	1.577
	Flowrate.Q	-1.109	.201	-.401	-5.516	.000	.556	1.797

a. Dependent Variable: Algae

In the nonlinear regressions model, the constant and the coefficients both passed the t verification, and they can be applied for the following linear equation:

$$Y` = 8.967 + 0.749 X_1' + 1.281 X_2' - 1.109 X_3' \quad (4.5)$$

If, $Y' = \ln Y_{algae}$, $\beta'_0 = \ln\beta_0$, $X_1' = \ln X_{P\text{-}load}$, $X_2' = \ln X_{flow\ rate}$, $X_3' = \ln X_{temp}$

Equation 4.5 can be rewritten as：

$$Y_{algae} = \mathrm{Exp}\,(8.967)\,(X_{p\text{-}load}{}^{0.749} X_{temp}{}^{1.281} X_{flow}{}^{-1.109}) \qquad (4.6)$$

Finally, the non-linear equation will be:

$$Y_{algal} = 7843.54\ X_{p\text{-}load}{}^{0.749} X_{Temp.}{}^{1.281} X_{flowrate}{}^{-1.109} \qquad (4.7)$$

The final nonlinear regression equation is:

$$Y_{Con.}(10^4 / L) = 7843.54 \times \frac{X_P(mg / m^2.yr)^{0.749} \times X_T(°C)^{1.281}}{X_F(m^3 / s)^{1.109}} \qquad (4.8)$$

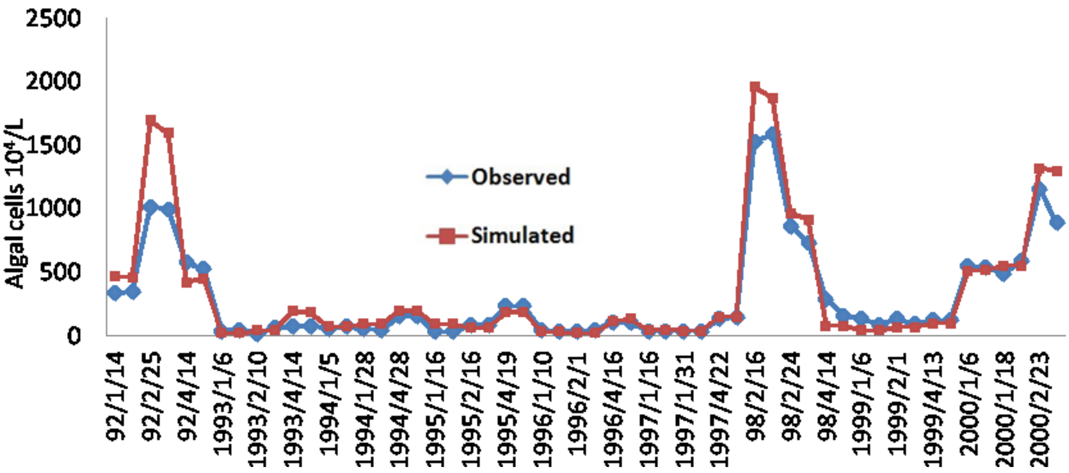


Fig. 4.12 Multiple nonlinear regressions modeling result

The final multiple non-linear regression equation is established and the degree of fit is better than the linear regression model with an R^2 value of 0.844. Some negative forecasting values shown in the result of the multiple linear regression model have disappeared. By drawing a warning line on the graph, it can be clearly seen that the algal blooms that occurred in year 92, 98 and 2000 have been very accurately forecasted.

The same calibration and verification method for the multiple linear regression models will also be applied to the nonlinear model in order to verify the forecasting ability of the model. The data from 1992 to 1997 will be used for modeling calibration and establishing a new linear regression equation. Then, sampling data from 1998 to 2000 will be imported to the equation to calculate the average algal cell concentration. Then the results are compared with the monitoring data to evaluate the forecasting ability of the model.

Table 4.10 MNR model summary (calibration)

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
MNR	.910(a)	.829	.812	.49120	.829	51.534	3	32	.000

a Predictors: (Constant), Flowrate.Q, Load.P, Temperature.t

b Dependent Variable: Algae

As shown in the above figures, the model shows a very good result with a high R^2 (= 0.829) and adjusted R^2 (= 0.812).

Table 4.11 MNR coefficients (calibration)

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	6.655	2.087		3.188	.003		
	Load.P	.706	.240	.234	2.938	.006	.847	1.180
	Temperature.t	1.501	.209	.622	7.169	.000	.711	1.406
	Flowrate.Q	-.827	.271	-.277	-3.053	.005	.650	1.540

a. Dependent Variable: Algae

Finally, the unstandardized coefficients have been determined:

$$Y_{Con.}(10^4/L) = 776.39 \times \frac{X_P(mg/m^2.yr)^{0.706} \times X_T(°C)^{1.501}}{X_F(m^3/s)^{0.827}}$$

(4.8)

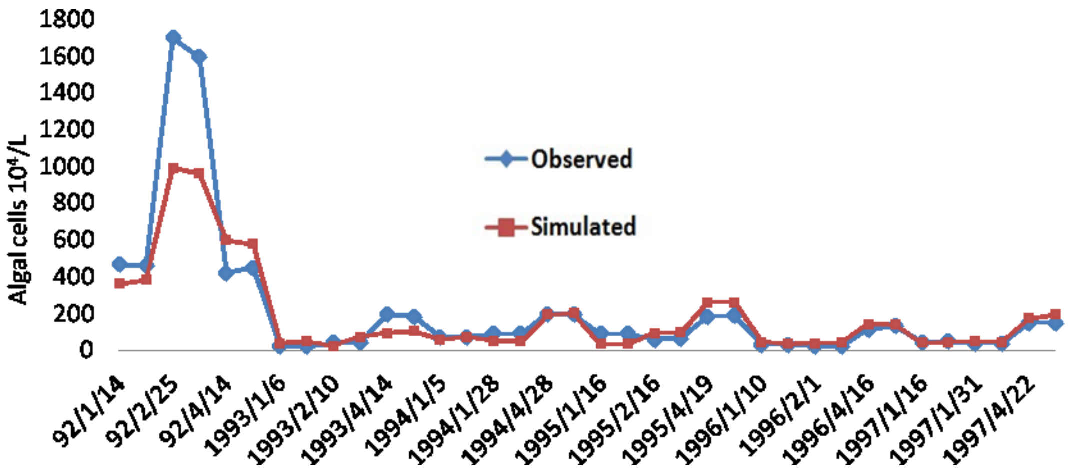


Fig. 4.13 MNR calibration from year 1992 to 1997

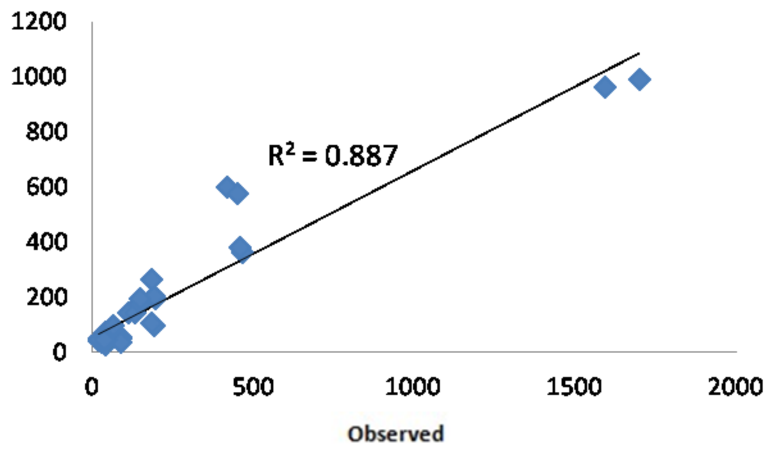


Fig. 4.14 Goodness of fit for MNR calibration

The above figures show the results of molding calibration with high R^2 value of 0.887. Then the sampling data from 1998 to 2000 will be imported to the calibrated equation to calculate the final output *Y*.

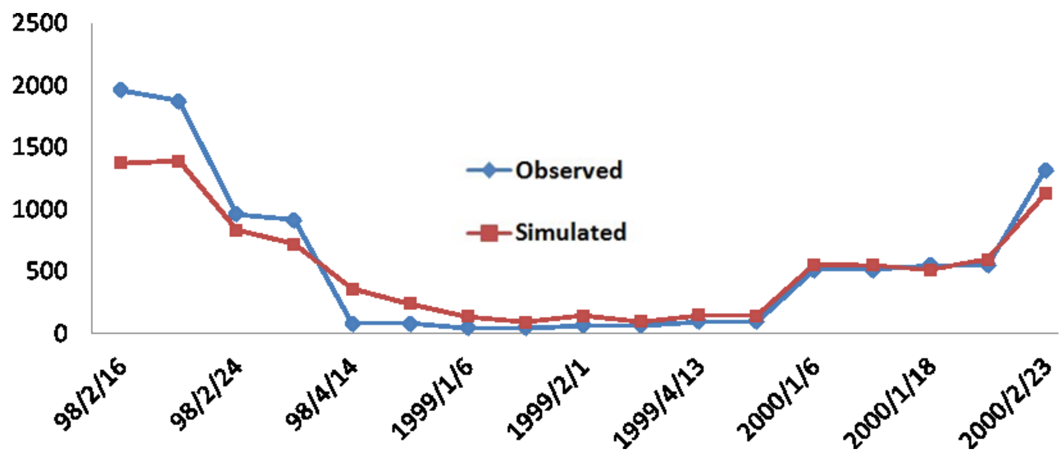


Fig. 4.15 MNR validation from year 1998 to 2000

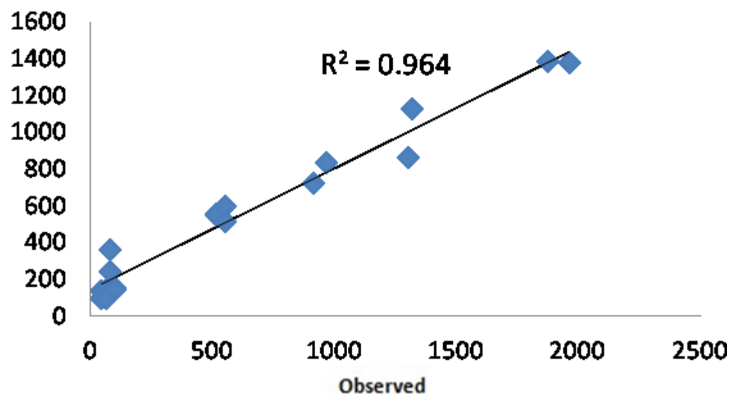


Fig. 4.16 Goodness of fit for MNR validation

The result (R^2 = 0.9644) clearly indicates that the predicted value of algal cells is closely matched to the real data from 1998 and 2000.

4.3.3 ANN Model Result with Calibration and Validation

In order to have a comprehensive comparison analysis result with the previous regressions approaches, a typical 3 layer feed-forward BP network with only one intermediate hidden layer is applied to the Han River case study, and the input and output indicators are same as the regression model. The model is based on ANN FORTRAN programming which developed by Xie (1997), and some modeling parameters are shown in the following tables:

Table 4.12 Results of parameters setting for the BP networks

Neuron nodes in input layer	Neuron nodes in hidden layer	Neuron nodes in output layer
3	4	1
Total group of samples	Number of groups for calibrations	Number of samples for validations
54	36	18
Increasing factor	Attenuation factor	Limiting factor
1.1	0.9	0.005
Learning factor	Error sum squares	Iterations
1.296871E-01	2.974093E-02	2000

Table 4.13 Connecting weights of hidden layers between in & out put layers

Input layers	*W1*	*W2*	*W3*	*W4*
1	3.73621	.07690	-.32005	-2.35745
2	-1.631611	-3.419686	.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	.613407	-.792894	-.697273

After 2000 iterations, the threshold value of output layer is computed as 0.241597, the error sum squares between the expected output and the calculated output of this BP model is 2.97% which is in an acceptable range.

The same calibration and verification methods used for the multiple linear and nonlinear regression models will be also applied to the ANN model in order to verify the forecasting ability of this mechanism model. A new linear regression equation is established based on the first six years which is from year of 1992 to 1997.

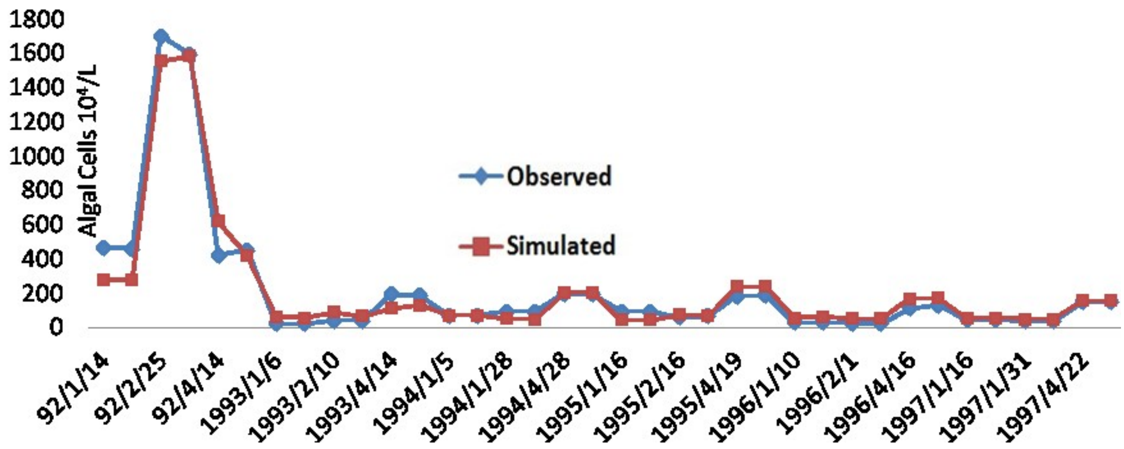


Fig 4.17 ANN calibration from 1992- 1997

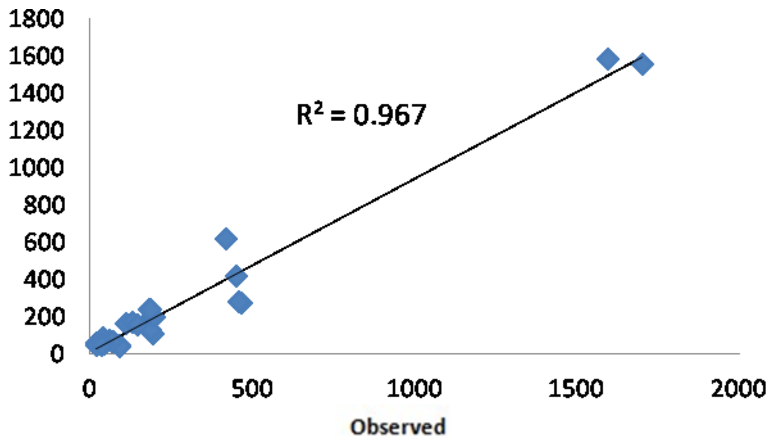


Fig. 4.18 Goodness of fit for ANN calibration

The above figure indicates the ANN has an excellent calibration efficiency with R^2 of 0.967 indicating the modeling outputs is very closely matched to the observations. Then, sampling data from 1998 to 2000 will be imported to this equation to calculate the average algal cell concentration.

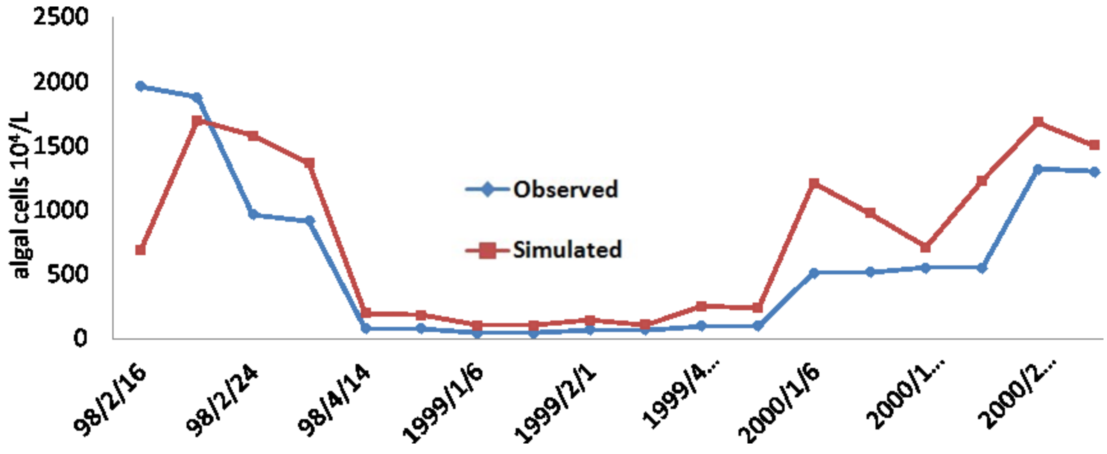


Fig. 4.19 ANN model validation from 1998 to 2000

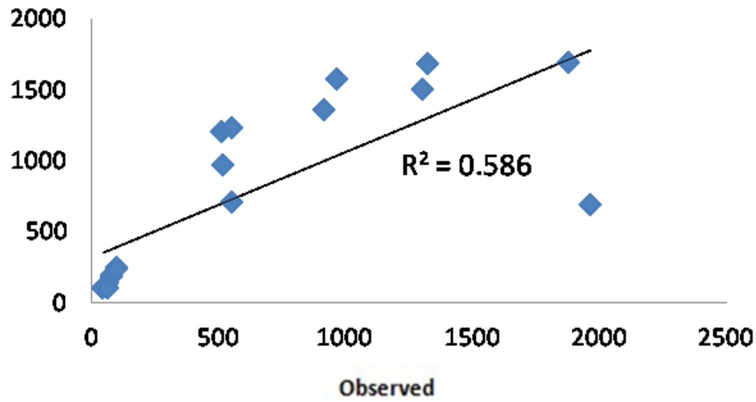


Fig. 4.20 Goodnees of fit for ANN validation

The R^2 (Fig. 4.20) is 0.586 indicating that the forcasting ability of ANN model for the period is much less good than its calibration. Here, a very common statistics phenomenon known as "over-fit" has occurred. Overfitting occurs when ANN fits random error or noise instead of the underlying relationship, and it will generally have poor predictive performance as it can exaggerate minor fluctuations in the data.

4.3.4 Integrated Dillon Model Result with Calibration and Verification

The average P concentration is calculated using following Dillon equation:

$$R = 1 - \frac{\Sigma Q_{out} P_{out}}{\Sigma Q_I P_I} = 1 - \frac{W_{out}}{W_I} \tag{4.9}$$

$$P = \frac{L(1-R)}{HQ} \tag{4.10}$$

Then, the general form of non-linear climate eutrophication model is established as:

$$\mathrm{Y}_{\mathrm{algal}} = \alpha [\frac{L(1-R)}{HQ}]^{\beta 1} T^{\beta 2} \tag{4.11}$$

Similar to the nonlinear regression model, it is converted to the multiple linear regression equation and the coefficients are calculated.

Table 4.14 Dillon model summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
Dillon	.850(a)	.722	.711	.70459	.722	66.214	2	51	.000

a Predictors: (Constant), temperature, TP

As shown in the above table, the model also shows a good result. The R^2 is 0.722 and the adjusted R^2 is 0.711.

Table 4.15 Dillon model coefficients

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	1.925	.849		2.266	.028		
	TP	.946	.227	.314	4.167	.000	.960	1.041
	temperature	2.056	.212	.730	9.684	.000	.960	1.041

a. Dependent Variable: ALGAE

Finally, the unstandardized coefficients have been determined, after taking exp 1.925, we have 6.852 for the constant. A new nonlinear regression equation is established:

$$Y' = 6.852[\frac{L(1-R)}{HQ}]^{0.946} T^{2.056} \tag{4.12}$$

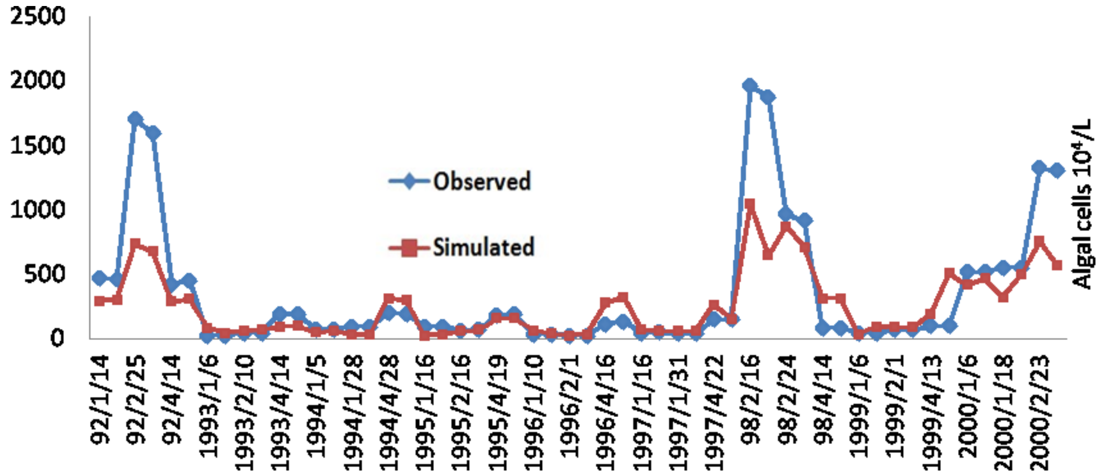


Fig. 4.21 Integrated Dillon modeling result

The integrated Dillon model is established, and this equation can not only indicate the relationship between total algal cells and temperature levels, but also can show the correlation between hydrological regimes and waste load. For example it is negatively correlated with water level (*H*), water flow rate (*Q*), and positively correlated to waste load (*L*). This integrated model can provide more information than statistical models and the degree of fit is better than the linear regression model with an R^2 value of 0.711. The model very accurately forecasted algal blooms that occurred in the years 1992, 1998 and 2000.

The same calibration and verification procedures in earlier sections will be also applied to the integrated Dillon model in order to verify the forecasting ability of the mechanism model. 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.

Table 4. 16 Dillon model Summary (calibration)

					Change Statistics				
	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
Dillon	.838(a)	.702	.684	.63784	.702	38.833	2	33	.000

a Predictors: (Constant), T, P

Table 4.17 Dillon model coefficients (calibration)

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	.583	.939		.621	.539		
	P	.368	.332	.106	1.110	.275	.983	1.017
	T	2.037	.231	.845	8.813	.000	.983	1.017

a. Dependent Variable: Algae

The result indicats 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:

$$Y' = 1.791\left[\frac{L(1-R)}{HQ}\right]^{0.368} T^{2.037} \tag{4.13}$$

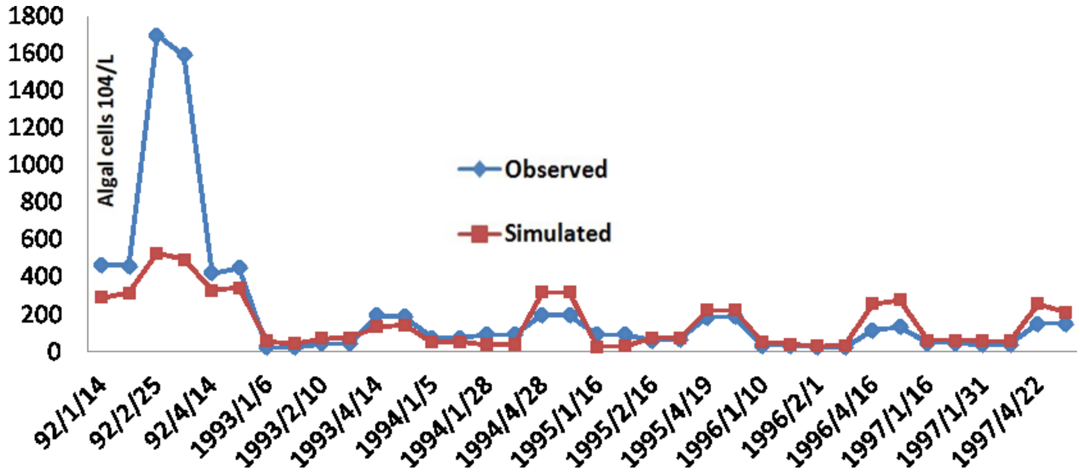


Fig. 4.22 Intergrated Dillon model calibration from year 1992 to 1997

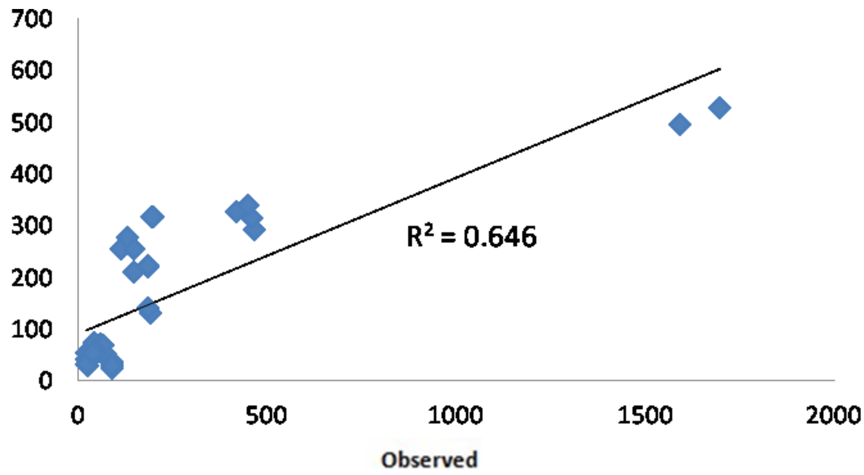


Fig. 4.23 Integrated Dillon model calibration

The above figures show the result of molding calibration. The R^2 value is 0.646 which is in an acceptable range. Then sampling data from 1998 to 2000 will be imported to this calibration equation to calculate the final output Y.

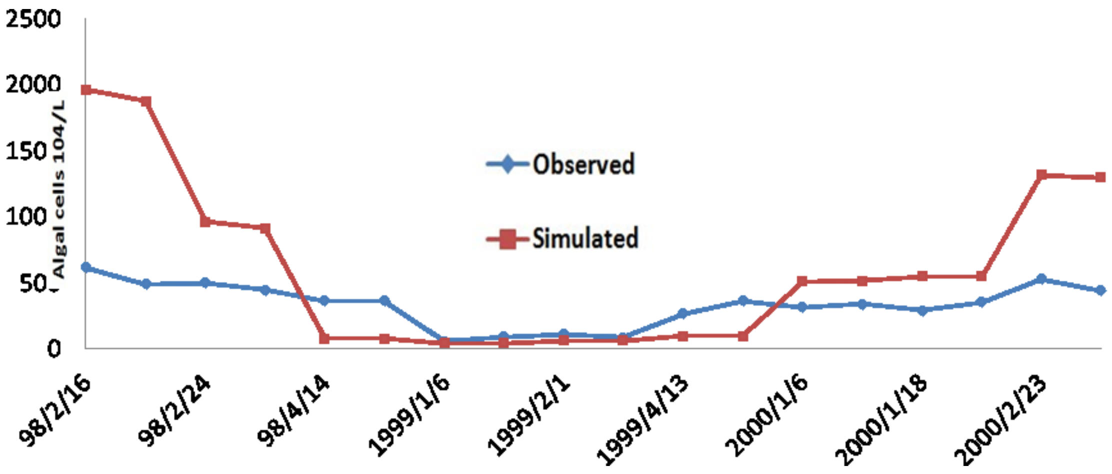


Fig. 4.24 Validation of Dillon model from year 1998 to 2000

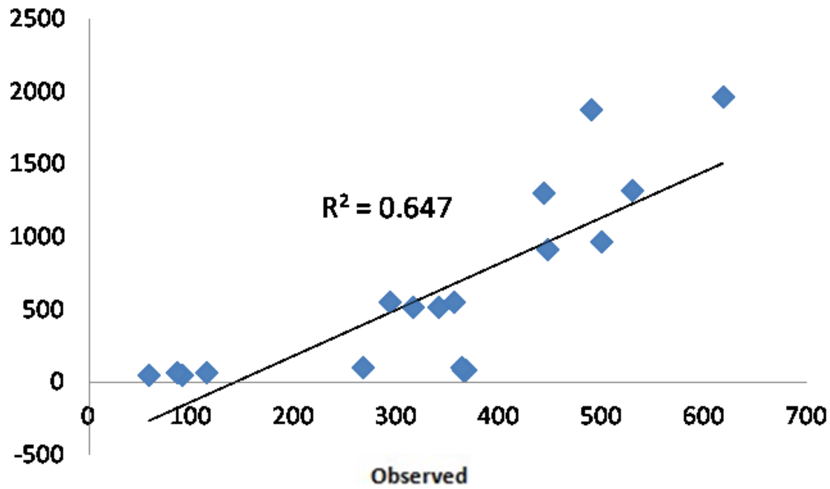


Fig. 4.25 Validation of Dillon model

The R^2 value is 0. 647, and it clearly indicates the predicted value of algal cells is also well matched to the real data, accurately forecasting the algal blooms from 1998 and 2000.

4.4 Model Results Comparison Discussions

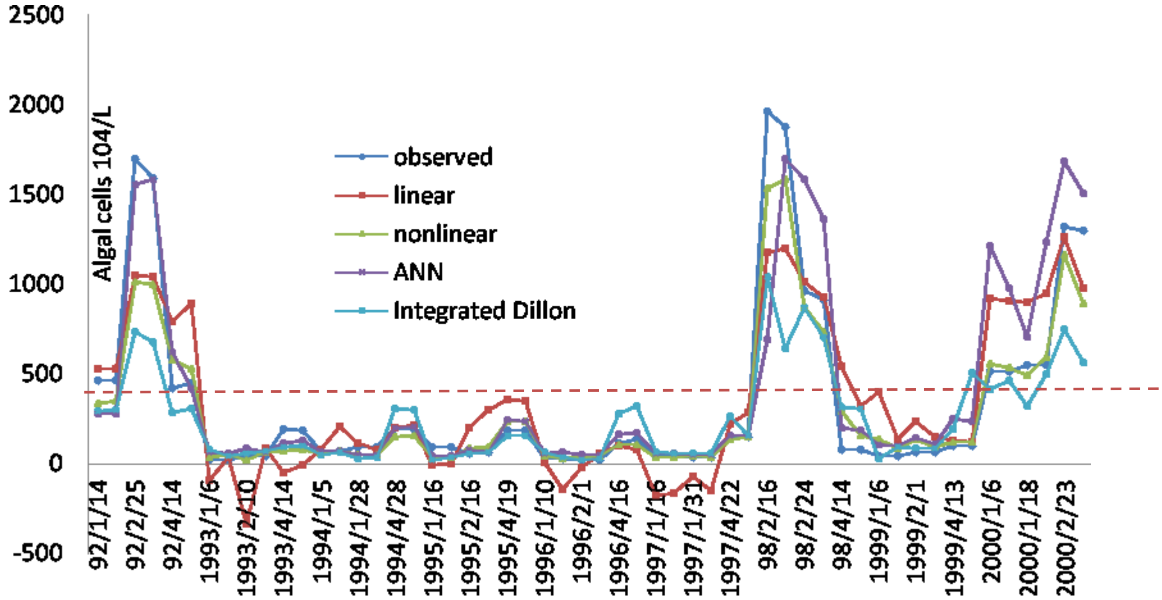


Fig. 4.26 Model result comparisons

*(*note: negative simulation results corresponds to zero)*

Table 4.18 Model comparison results

Models \ Fitting	Linear regressions	Non-linear regressions	ANN	Dillon Model
Calibration R^2	0.643	0.887	0.967	0.646
Validation R^2	0.705	0.964	0.586	0.647

By comparing the simulation results of the four models, as shown in Fig. 4.26 and Table 4.18 above, the calibration and validation R^2 results for MLR is 0.643 and 0.705, respectively, which is a good result for a statistical model. However, the MLR method can often shows optimal results only when relationships between the independent variables and the dependent variable are almost linear. The modeling result is not reliable for making prediction because it is rare to see a stark linear relationships in real environmental problems. The MNR model has the highest R^2 value (0.964) for validation and a good calibration R^2 (0.887) which is the best overall result, and this proves that the MNR model can be used to model non-linear relationships and is appropriate for most real case studies. The ANN model had the highest R^2 value for calibration (0.97) which proves this simulation model is powerful to automatically resolve non-linear complex relationships and difficult multiple dimensions problems. However, the over-fitting problem also occurred in this case, thus the forecasting result is variable when compared to good calibration ability. This is reflected in the low R^2 value for validation (0.59) which is the worst in all the models. Moreover, the ANN can not reveal the contributions from input indicators to output, so it will not be used for forecasting at this time. The R^2 for Integrated Dillon model is less than 0.65 which is a so good result for a semi-physical model. The major reason for the low performance is the conditions of input parameters based on the empirical model being too restrictive, so the simulating efficiency can be less than those statistical models. Thus, the nonlinear regression model (eq. 4.8) which has the best result both on calibration and validation will be selected for the climate change impact assessment in order to forecast the future occurrence of algal blooms more accurately.

4.5 Summary

In this study, four system modeling approaches including Multiple linear regressions model, Multiple non-linear regressions model, ANN and intregrated Dillon model are combined together and applied on a river eutriphication case study in China. All modeling results are calibrated and validated based on dividing of the monitoring data from 1992 to 2000. A comparsion of all the models shows: the linear regressions approach is the most simple to use; the non-linear regressions approach has the best performance on result simulating; the ANN model has a good value of modeling calibration but lacks validation accuracy due to over-fitting; and the intergrated Dillon model provides some part of the physical meaning of mechanisms but the simulating result is not so good because of the potential errors from too many parameters and constraints. Therefore, the river eutriohication model is developed based on statistical methods and simulation method. The model with best simulation result is the mutiple non-linear model, and this will be applied to the climate change impact assessment under different scenarios analysis.

CHAPTER 5 CLIMATE CHANGE IMPACT ASSESSMENT

5.1 Single-factor Climate Change Impact Assessment

Since the nonlinear regression model has been considered the best model for both calibration and validation ability, this model will be used for climate change assessment under scenario analysis. The probability of algal bloom occurrence is based on following equation:

$$p = \frac{m_a}{N_t} \times 100\% \tag{5.1}$$

where m_a is the occurrence of algal blooms, and N_t is total number of outcomes

Assuming the temperature increased 2 degree Celsius from 1992 to 2000 due to globe warming, and input waste load P and flow rate are fixed, the following diagram was obtained:

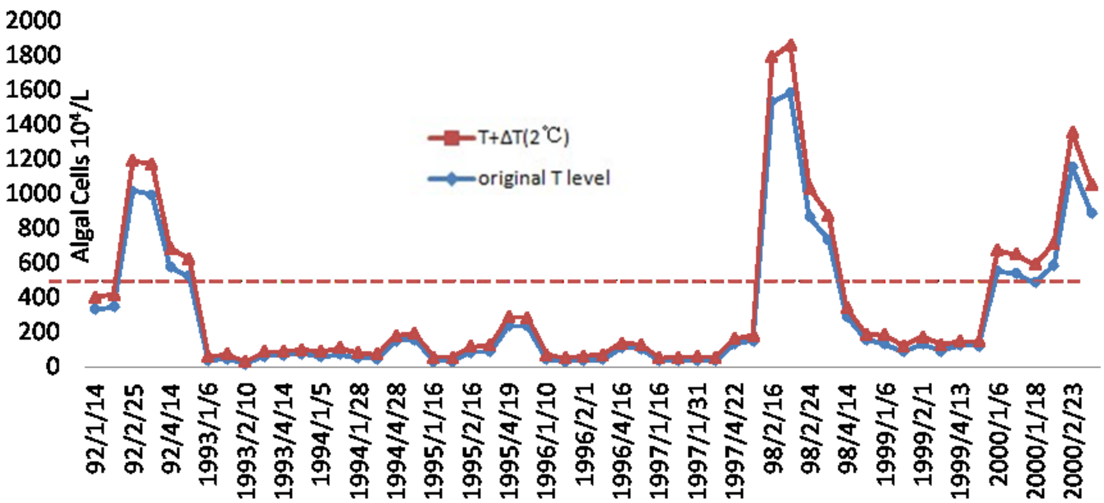


Fig. 5.1 Assessments result for an increase of 2 °C in temperature

Table 5.1 Algal bloom occurrence if temperature increases by 2 °C

Date (month)	Observations *	Temperature + 2 °C #
1992.1	0	0
1992.2	1	1
1992.4	1	1
1993.1	0	0
1993.2	0	0
1993.4	0	0
1994.1	0	0
1994.2	0	0
1994.4	0	0
1995.1	0	0
1995.2	0	0
1995.4	0	0
1996.1	0	0
1996.2	0	0
1996.4	0	0
1997.1	0	0
1997.2	0	0
1997.4	0	0
1998.2	1	1
1998.2	1	1
1998.4	0	0
1999.1	0	0
1999.2	0	0
1999.4	0	0
2000.1	1	1
2000.1	**0**	**1**
2000.2	1	1
SUM (times)	6	7
Probability	**22.22%**	**25.93%**

**1 means algal blooms occurred and 0 mean not*
 # is the assessment result if observed temperature increases by 2℃

The above Fig. 5.1 and Table 5.1 indicate that if the temperature increases by 2℃ and the rest of indicators remain at the same value, there are insignificant changes of algal bloom occurrence according to our model (from 22.22% to 25.93%). It shows that an algal bloom will occur in Jan 2000, and for some algal blooms such as April 92 and Jan 2000, the average algal cell count will reach the threshold. However, it exceeds the warning line after the temperature rise and the peak value also shows moderate increases in 1992 and 1998. Compared with the observed data the probability of algal bloom occurrence increases by 3.7% after increasing temperatures.

Assuming the waste load also increases by 1 unit (mg/m^2.yr) from year 1992 to 2000, and temperature and flow rate are fixed, we have the following:

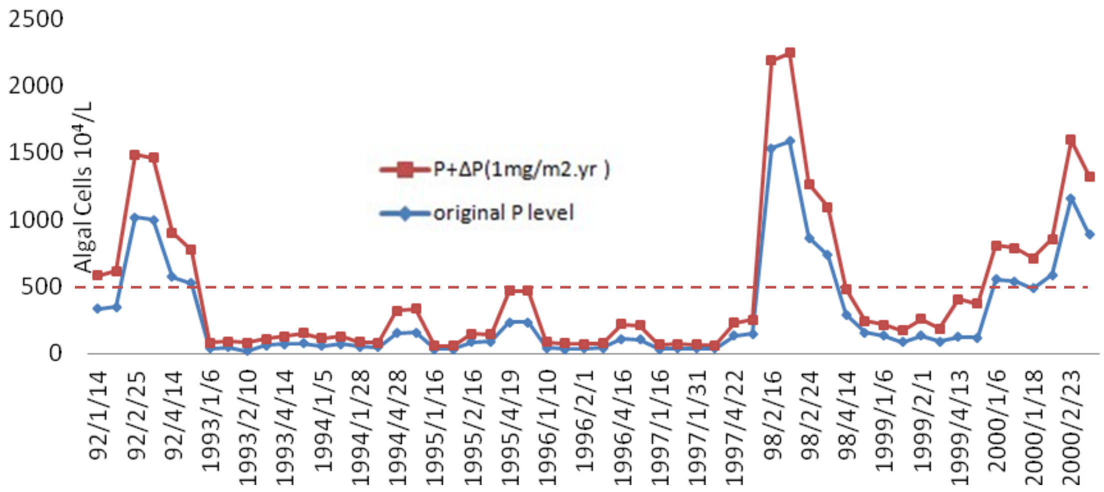


Fig. 5.2 Assessments result for an increase of 1mg/m2.yr in P-loads

Table 5.2 Assessment result if P-load increases by 1 unit

Date (month)	Observation *	P_{loads} + 1 (mg/m^2.yr) #
1992.1	**0**	**1**
1992.2	1	1
1992.4	1	1
1993.1	0	0
1993.2	0	0
1993.4	0	0
1994.1	0	0
1994.2	0	0
1994.4	0	0
1995.1	0	0
1995.2	0	0
1995.4	**0**	**1**
1996.1	0	0
1996.2	0	0
1996.4	0	0
1997.1	0	0
1997.2	0	0
1997.4	0	0
1998.2	1	1
1998.2	1	1
1998.4	**0**	**1**
1999.1	0	0
1999.2	0	0
1999.4	0	0
2000.1	1	1
2000.1	**0**	**1**
2000.2	1	1
SUM (times)	6	10
Probability	**22.22%**	**37.04%**

**1 means algal blooms occurred and 0 mean not*

 # is the assessment result if observed P-load increases by 1 unit

The above figure and table indicate that if the input waste load P increases by 1 unit (mg/m^2.yr) and the rest of the variables stay at the same values, and 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 is been also noticed that the peak value is also highly increased in 1992 and 1998.

If input P load increases by 1 unit, the algal blooms will, according to our model, occur in year 1995 as well as 1992, 1998 and 2000. There is also a potential risk of algal bloom in April 1994 and April 1999. The peak value was found moderately increased particularly in 1992 and 1998. Compared with the monitoring data, the occurrence probability in these 9 years after increasing the waste load is 44.4% which is an increase of 10%.

Assuming the flow rate is decreased by 100 m^3/s from year 1992 to 2000, and temperature and waste load are unchanged, we have the following diagram:

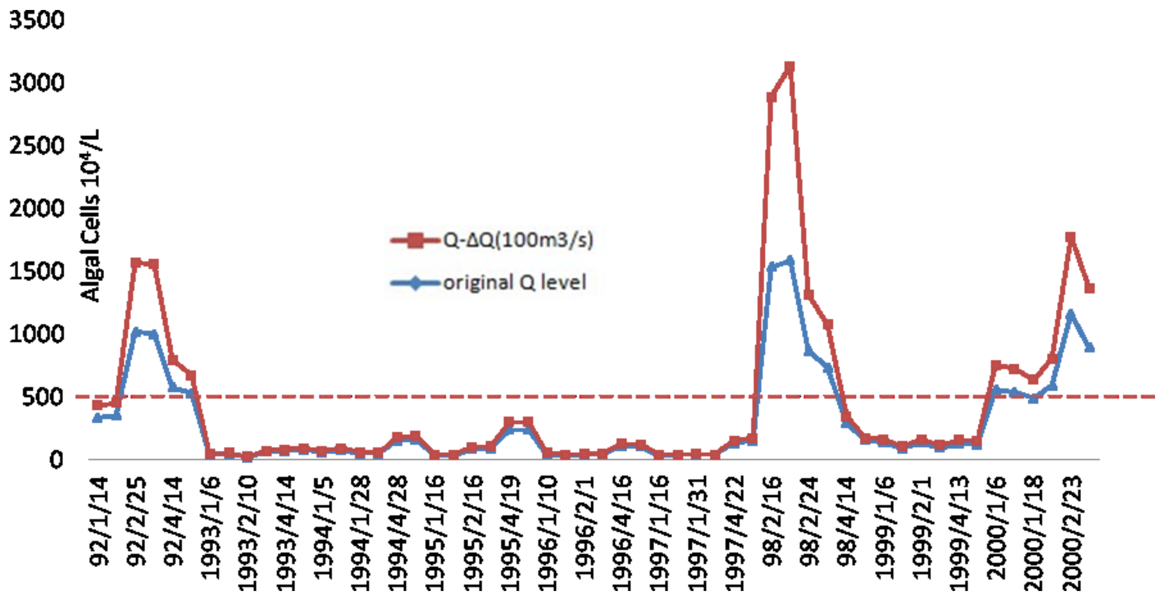


Fig. 5.3 Assessment result for an decreases of 100 m3/s in flow rate

Table 5.3 Assessment result if flow rate decreases by 100 m^3/s

Date (Month)	Observations *	Q - 100 (m^3/s) #
1992.1	**0**	**0.5**
1992.2	1	1
1992.4	1	1
1993.1	0	0
1993.2	0	0
1993.4	0	0
1994.1	0	0
1994.2	0	0
1994.4	0	0
1995.1	0	0
1995.2	0	0
1995.4	0	0
1996.1	0	0
1996.2	0	0
1996.4	0	0
1997.1	0	0
1997.2	0	0
1997.4	0	0
1998.2	1	1
1998.2	1	1
1998.4	0	0
1999.1	0	0
1999.2	0	0
1999.4	0	0
2000.1	1	1
2000.1	**0**	**1**
2000.2	1	1
SUM (times)	6	7.5
Probability	**22.22%**	**27.77%**

**1 means algal blooms occurred and 0 mean not and 0.5 mean there is a potential risk*
 # is the assessment result if observed flow rate decreases by 100 m^3/s

The result is similar to the result of temperature change. With the flow rate decreased by 100 m^3/s, there was a small change in algal bloom occurrence probability, which increases 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%.

5.2 Integrated Climate Change Impact Assessment

In practice, the impact of climate change, hydrological regime change and human activities usually occur at the 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. First, assuming temperatures increase by 2°C but flow rate decreases by 100 m^3/s from 1992 to 2000 and the input waste load P is fixed, the following diagram will be obtained:

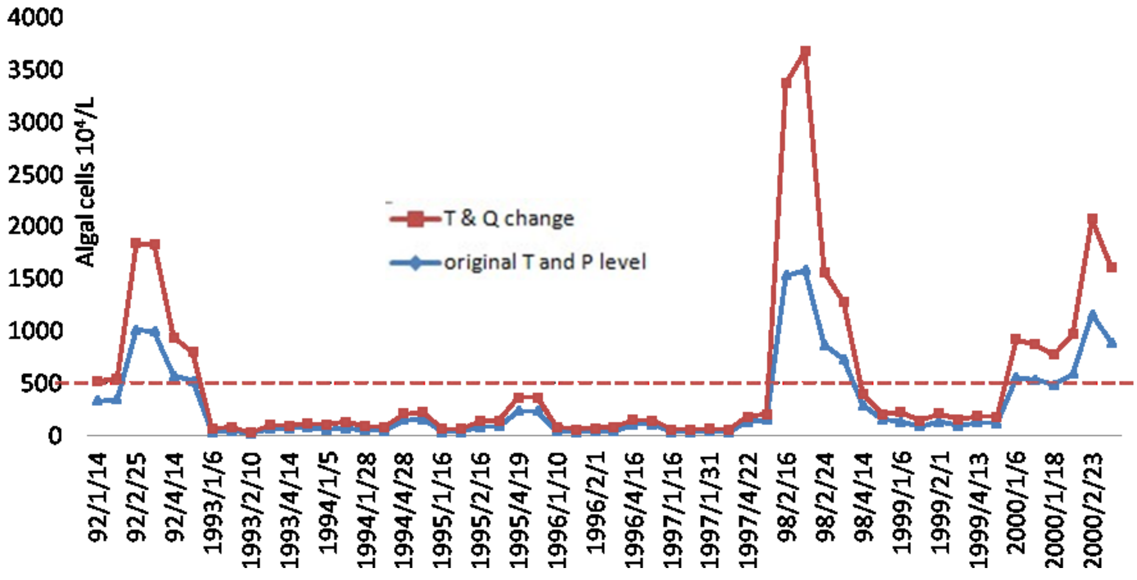


Fig. 5.4 Assessment result if T & Q both changes

Table 5.4 Assessment result if *T* and *Q* both changes

Date (month)	Observation *	T & Q both changes #
1992.1	**0**	**1**
1992.2	1	1
1992.4	1	1
1993.1	0	0
1993.2	0	0
1993.4	0	0
1994.1	0	0
1994.2	0	0
1994.4	0	0
1995.1	0	0
1995.2	0	0
1995.4	**0**	**0.5**
1996.1	0	0
1996.2	0	0
1996.4	0	0
1997.1	0	0
1997.2	0	0
1997.4	0	0
1998.2	1	1
1998.2	1	1
1998.4	**0**	**0.5**
1999.1	0	0
1999.2	0	0
1999.4	0	0
2000.1	1	1
2000.1	**0**	**1**
2000.2	1	1
SUM (times)	6	9
Probability	**22.22%**	**33.33%**

**1 means algal blooms occurred and 0 mean not and 0.5 mean there is a potential risk*
 # is the assessment result if observed flow rate decreases by 100 m^3/s

These results indicate that if temperature and the flow rate 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.

Assuming the temperature increases by 2°C and the input waste load P increases by 1 unit (mg/m^2.yr) at the same time (1992 to 2000) while the flow rate is fixed, then the following diagram is obtained:

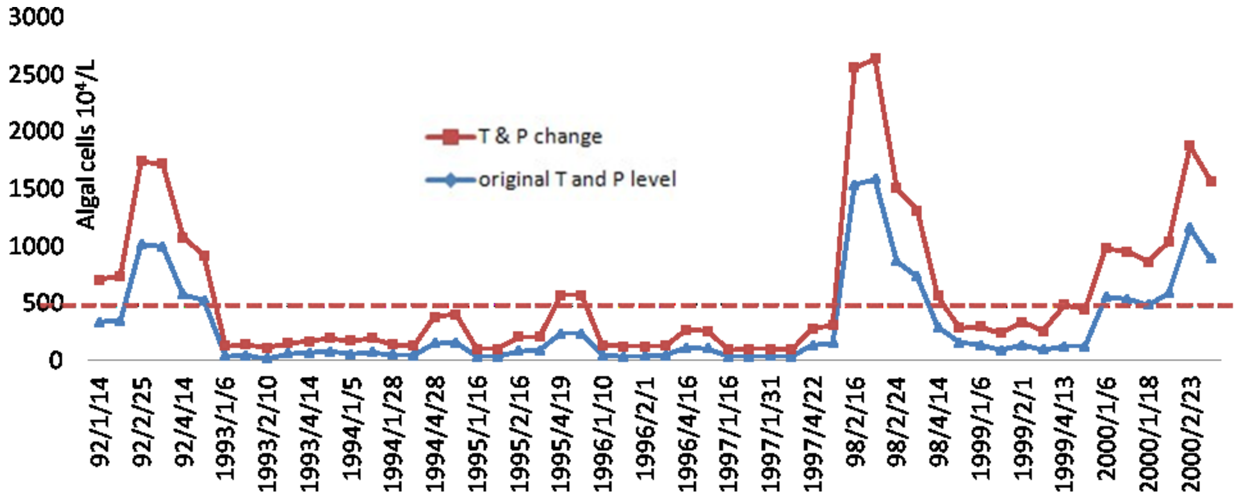


Fig. 5.5 Assessment result if P-load and *T* both changes

Table 5.5 Assessment result if Temperature and P-load both changes

Date (month)	Observation *	T & P both changes #
1992.1	**0**	**1**
1992.2	1	1
1992.4	1	1
1993.1	0	0
1993.2	0	0
1993.4	0	0
1994.1	0	0
1994.2	**0**	**0.5**
1994.4	0	0
1995.1	0	0
1995.2	0	0
1995.4	0	1
1996.1	0	0
1996.2	0	0
1996.4	0	0
1997.1	0	0
1997.2	0	0
1997.4	0	0
1998.2	1	1
1998.2	1	1
1998.4	**0**	**1**
1999.1	0	0
1999.2	0	0
1999.4	**0**	**0.5**
2000.1	1	1
2000.1	**0**	**1**
2000.2	1	1
SUM (times)	6	11
Probability	**22.22%**	**40.74%**

**1 means algal blooms occurred and 0 mean not and 0.5 mean there is a potential risk*
 # is the assessment result if temperature and P-load both changes

These results indicate that if temperature and the water waste load P both change and flow rate stays the same, and 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, and there is potential risk in

April 1995, April 1994 and April 1998.

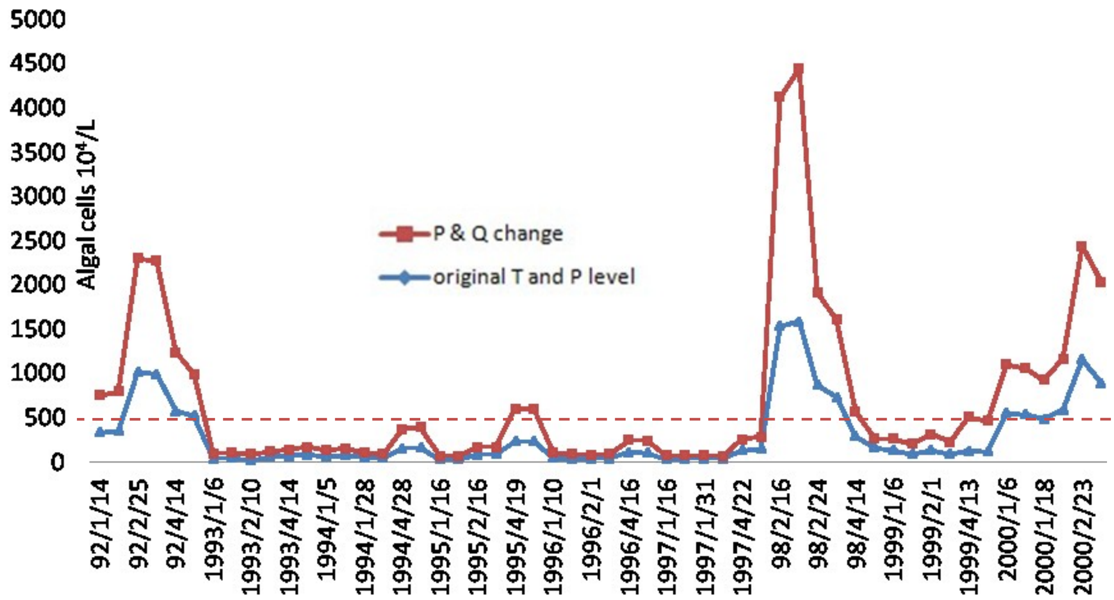


Fig. 5.6 Assessment result if Q & P-load both changes

Table 5.6 Assessment results if *T* and *Q* both changes

Date (month)	Observation *	Q & P both changes #
1992.1	**0**	**1**
1992.2	1	1
1992.4	1	1
1993.1	0	0
1993.2	0	0
1993.4	0	0
1994.1	0	0
1994.2	0	0
1994.4	0	0
1995.1	0	0
1995.2	0	0
1995.4	**0**	**1**
1996.1	0	0
1996.2	0	0
1996.4	0	0
1997.1	0	0
1997.2	0	0
1997.4	0	0
1998.2	1	1
1998.2	1	1
1998.4	**0**	**1**
1999.1	0	0
1999.2	0	0
1999.4	**0**	**1**
2000.1	1	1
2000.1	**0**	**1**
2000.2	1	1
SUM (times)	**6**	**11.5**
RISK (Probability)	**22.22%**	**42.59%**

**1 means algal blooms occurred and 0 mean not and 0.5 mean there is a potential risk*
 # is the assessment result if temperature and flow rate both changes

These results indicate that if the flow rate and the waste load P both change while the temperature stays at the same level, and 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 will occur in 1992, 1994, 1995, 1998 and 2000.

Finally, assuming the all of the variables change from 1992 to 2000, the variation of algal cell concentrations are shown on the following graphs:

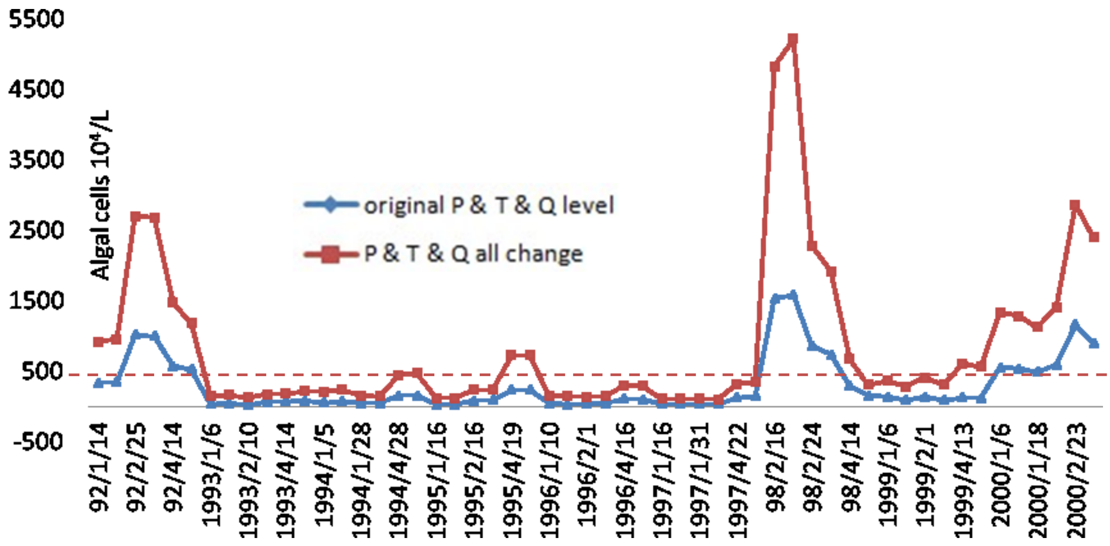


Fig. 5.7 Integrated assessment results if *P*, *Q* and *T* both changes

Table 5.7 Integrated assessment result if T, P-load and Q both changes

Date (month)	Observation	Q & P changes
1992.1	**0**	**1**
1992.2	1	1
1992.4	1	1
1993.1	0	0
1993.2	0	0
1993.4	0	0
1994.1	**0**	**1**
1994.2	0	1
1994.4	0	0
1995.1	0	0
1995.2	0	0
1995.4	**0**	**1**
1996.1	0	0
1996.2	0	0
1996.4	0	0
1997.1	0	0
1997.2	0	0
1997.4	**0**	**0.5**
1998.2	1	1
1998.2	1	1
1998.4	**0**	**1**
1999.1	0	0
1999.2	**0**	**0.5**
1999.4	**0**	**1**
2000.1	1	1
2000.1	**0**	**1**
2000.2	1	1
SUM (times)	6	14
Probability	**22.22%**	**51.85%**

**1 means algal blooms occurred and 0 mean not and 0.5 mean there is a potential risk*
 # is the integrated assessment result if temperature, P-load and flow rate both changes

The integrated result shows that if all the indicators 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, and there is a potential risk in April 1997 and February 1999. The final results are summarized in the following Table 5.8:

Table 5.8 Comprehensive result of scenario analysis

Indicator (%)	ΔT	ΔQ	ΔP	ΔT +ΔQ	ΔP +ΔT	ΔP + ΔQ	ΔP+ΔQ +Δ T
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

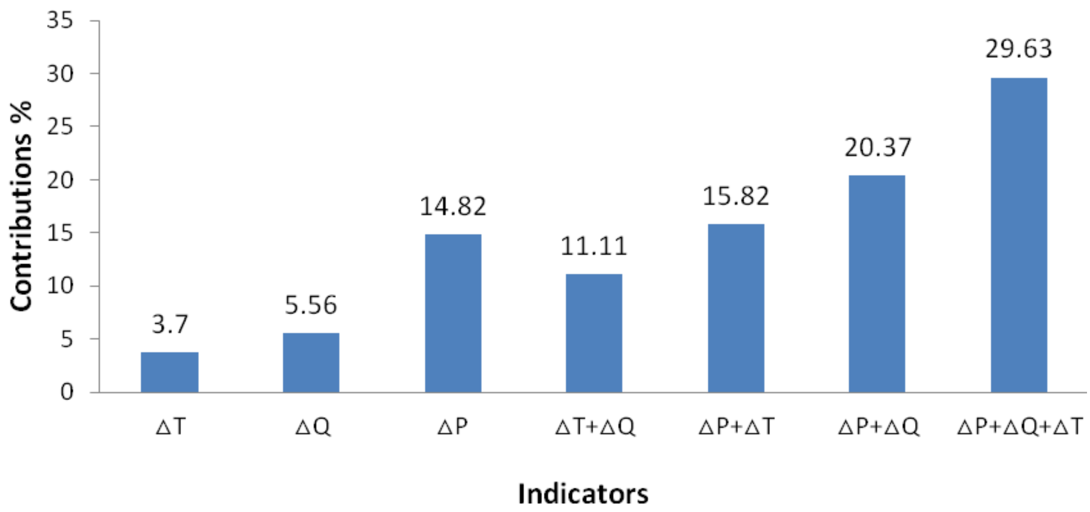


Fig. 5.8 Integrated climate change impact assessment result

The above Table 5.8 and Fig. 5.8 show the impact of each indicator on the probability of algal bloom occurrence. For the individual impact change assessment, the indicator with the greatest impact is the input P load variation. This is followed by the flow rate Q (5.56%) and the temperature T (3.7%). For the integrated climate change impact assessment, the greatest impact condition is when the input waste load P and the water flow rate and the temperature all change at the same time (29.63%).

With fixed temperature and changed input P load and flow rate, the probability of algal bloom is increased by 20.37%. If the flow rate Q is fixed and the input P load and the temperature are changed, the probability of algal bloom increases by 15.82%. If the input P load is fixed, and only the flow rate and the temperature are changed, the probability of algal bloom will increase by 11.11%.

5.3 Climate Change Impact Scenarios Analysis

In order to predict the future occurrence of algal blooms in the Han River, a model to simulate the impact of climate change on algal bloom is used. The Intergovernmental Panel on Climate change (IPCC, 2000) has analyzed the difference between observations and simulations based on a great amount of historical climate change data. Then, the data was used to simulate future climate change. In order to assess future climate change, the Special Report on Emissions Scenarios (SRES) was prepared by the Intergovernmental Panel on Climate Change (IPCC) in 2000. This report was based on data developed by the Earth Institute at Columbia University. The emissions scenarios described in the report have been used to make projections of possible future climate. The SRES scenarios were used in the IPCC Third Assessment Report (TAR), published in 2001, and in the IPCC Fourth Assessment Report (AR4) (IPCC, 2000; IPCC, 2007). The SRES scenarios had been used in the earlier IPCC Second Assessment Report of 1995. When they were developed, the range of global emissions projected across all forty of the SERS scenarios covered the 5th to 95th percentile range of the emission scenarios literature (IPCC, 2000). The SERS are often related to a lot of regulatory factors (e.g. growth of population, economic development, technological progress, environmental conditions, globalization, etc.). There should be different emission scenarios corresponding to the different status of social economy development in the future (IPCC, 2007), and the CSIRO modeling groups in Australia developed a model for simulating the future temperature and precipitation outcomes based on the three emission scenarios, A1B, A2 and B1, which is similar to the current situation in China. The predicted future climate data are provided by the CSIRO modeling groups, the Program for Climate Model Diagnosis and Inter-comparison (PCMDI) and the World Climate Research Programmers (WCRP's).

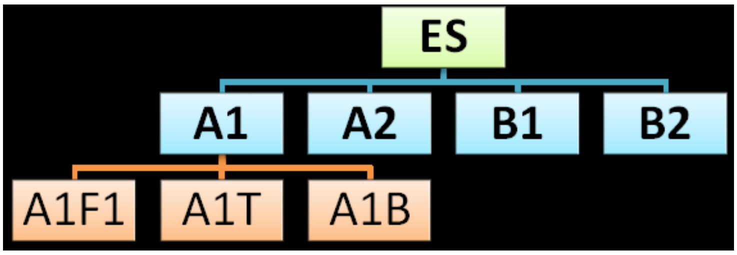


Fig. 5.9 Schematic illustration of the emission scenario groups

As shown in the above figure 5.9 (IPCC, 2000), the scenario families contain individual scenarios with common themes. The six families of scenarios discussed in the IPCC's Third Assessment Report (TAR) and Fourth Assessment Report (AR4) are A1FI, A1B, A1T, A2, B1 and B2. Scenario descriptions are based on those in AR4, which are identical to those in TAR (IPCC, 2007). Each storyline assumes a distinctly different direction for future developments, such that the four storylines differ in increasingly irreversible ways. Some key future characteristics such as demographic change, economic development and technological change will be covered (IPCC, 2000). In this study, three scenarios, A1, A2 and B1, are selected based on suitability to the study area, and the description of characteristics are shown as follows (IPCC, 2000; 2004;2007):

a. A1 emission scenario

The A1 scenarios are of a more integrated world. The A1 family of scenarios is characterized by:

- Rapid economic growth.
- A global population that reaches 9 billion in 2050 and then gradually declines.
- The quick spread of new and efficient technologies.
- A convergent world - income and way of life converge between regions. Extensive social and cultural interactions worldwide.

There are subsets of the A1 family based on their technological emphasis:

A1FI - An emphasis on fossil-fuels (Fossil Intensive).

A1B - A balanced emphasis on all energy sources.

A1T - Emphasis on non-fossil energy sources.

b. A2 emission scenario

The A2 scenarios are of a more divided world. The A2 family of scenarios is characterized by:

- A world of independently operating, self-reliant nations.
- Continuously increasing population.
- Regionally oriented economic development.
- Slower and more fragmented technological changes and improvements to per capita income.

c. B1 emission scenario

The B1 scenarios are of a world more integrated, and more ecologically friendly. The B1 scenarios are characterized by:

- Rapid economic growth as in A1, but with rapid changes towards a service and information economy.
- Population rising to 9 billion in 2050 and then declining as in A1.
- Reductions in material intensity and the introduction of clean and resource efficient technologies.
- An emphasis on global solutions to economic, social and environmental stability.

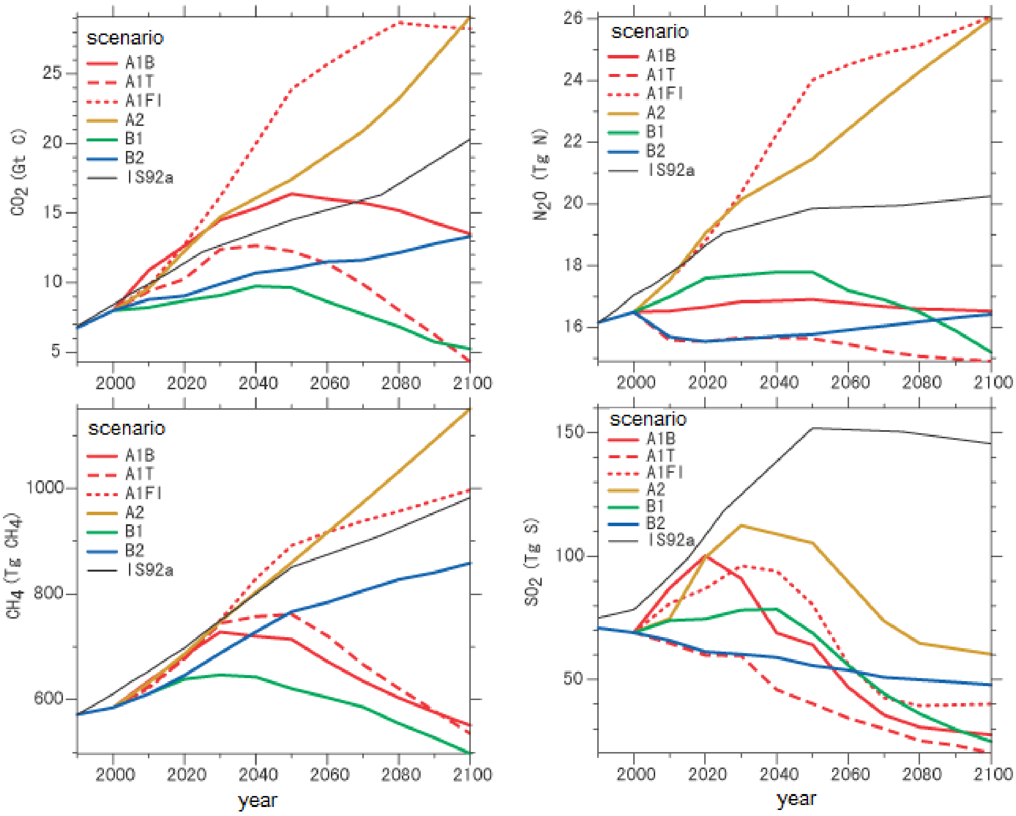


Fig. 5.10 CO_2, CH_4, N_2O and SO_2 emissions scenarios (IPCC, 2000)

In this study, the probability of algal bloom occurrences in the Han River can be determined based on the above emission scenarios:

$$p = \frac{m_A}{m_T} \times 100\% \tag{5.1}$$

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 10 years will be 30.

Since the algal blooms have occurred in 1992, 1998 and 2000, the emissions scenarios analysis will be applied to the following 10 years to see if the algal bloom occurrence is matched.

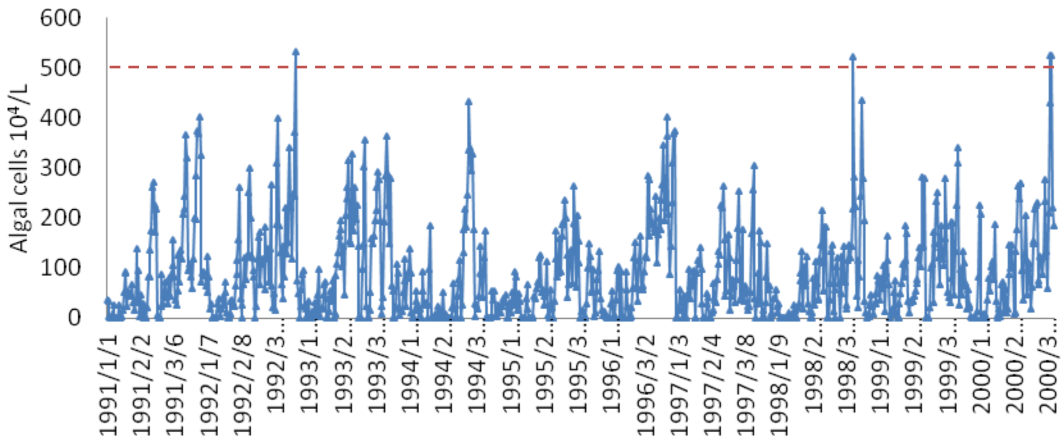


Fig. 5.11 Base year from year 1991 to 2000

The predict result in above figure shows that algal blooms occurred in 1992, 1998 and 2000 showing that the scenario is capable of forecasting river algal blooms. During the years of 1991-2000 in the Wuhan section of the Han River, the average precipitation in February was 1087.3mm and the average temperature was 16.15°C. The probability of algal bloom occurrence in these 10 years is 12.9%.

In the following sections, monthly surface water temperature and hydrological flow rate of the years 1991~2000 are compared with the 2000s (2001~2010), 2010s (2011~2020), 2020s (2021~2130) and 2030s (2031~2140) to assess the probability of algal bloom occurrence applying the emissions scenarios when the input nutrient load and the flow regimes are fixed. Analyzed results are shown in the following Table 5.9:

Table.5.9 Emissions scenarios analysis for the Han River Basin

<table>
<tr><th colspan="2" rowspan="2">Indicators</th><th colspan="2">precipitation（mm/year）</th><th colspan="2">Temperature（°C）</th><th colspan="2">Time & probability of occurrence</th></tr>
<tr><th>Average</th><th>Variation</th><th>Average</th><th>Variation</th><th>Year</th><th>Probability</th></tr>
<tr><td colspan="2">observation</td><td>1087.3</td><td rowspan="2">1.36%</td><td>16.15</td><td rowspan="2">3.80%</td><td>1992, 1998,2000</td><td>19.35%</td></tr>
<tr><td colspan="2">Baseline</td><td>1102.07</td><td>16.77</td><td>1992,1998, 2000</td><td>12.90%</td></tr>
<tr><td></td><td>2010s (Observation)</td><td>-</td><td>-</td><td>-</td><td>-</td><td>2002, 2008 2009</td><td>-</td></tr>
<tr><td rowspan="5">A1B</td><td>2010s</td><td>1129.84</td><td>2.52%</td><td>16.88</td><td>0.66%</td><td>2002, 2007,2009</td><td>12.90%</td></tr>
<tr><td>2020s</td><td>1360.99</td><td>20.50%</td><td>16.97</td><td>0.53%</td><td>2011, 2020</td><td>6.45%</td></tr>
<tr><td>2030s</td><td>1240.26</td><td>-8.87%</td><td>17.19</td><td>1.29%</td><td>2029, 2030</td><td>9.68%</td></tr>
<tr><td>2040s</td><td>1245.7</td><td>0.44%</td><td>17.94</td><td>4.36%</td><td>2,034,203,820,392,040</td><td>29.03%</td></tr>
<tr><td>SUM</td><td></td><td>14.55%</td><td></td><td>6.85%</td><td></td><td>58.06%</td></tr>
<tr><td rowspan="5">A2</td><td>2010s</td><td>1025.64</td><td>-7.45%</td><td>16.86</td><td>0.54%</td><td>2009</td><td>3.22%</td></tr>
<tr><td>2020s</td><td>1210.7</td><td>18.04%</td><td>17.27</td><td>2.43%</td><td>2012, 2019</td><td>9.68%</td></tr>
<tr><td>2030s</td><td>1269.56</td><td>4.86%</td><td>17.26</td><td>-0.06%</td><td>2023,2026, 2027</td><td>16.13%</td></tr>
<tr><td>2040s</td><td>1038.7</td><td>-18.17%</td><td>17.82</td><td>3.24%</td><td>2031, 2033, 2040</td><td>22.58%</td></tr>
<tr><td>SUM</td><td></td><td>-2.73%</td><td></td><td>6.15%</td><td></td><td>48.39%</td></tr>
<tr><td rowspan="5">B1</td><td>2010s</td><td>1131.82</td><td>2.62%</td><td>17.4</td><td>3.76%</td><td>2002, 2009</td><td>6.45%</td></tr>
<tr><td>2020s</td><td>1231.79</td><td>8.83%</td><td>17.3</td><td>-0.57%</td><td>2013, 2015</td><td>9.68%</td></tr>
<tr><td>2030s</td><td>1385.03</td><td>12.44%</td><td>16.96</td><td>-1.97%</td><td>2026</td><td>3.23%</td></tr>
<tr><td>2040s</td><td>1414.43</td><td>2.12%</td><td>17.34</td><td>2.24%</td><td>2039</td><td>3.37%</td></tr>
<tr><td>SUM</td><td></td><td>26.02%</td><td></td><td>3.46%</td><td></td><td>22.59%</td></tr>
</table>

5.3.1 A1B Scenarios Result

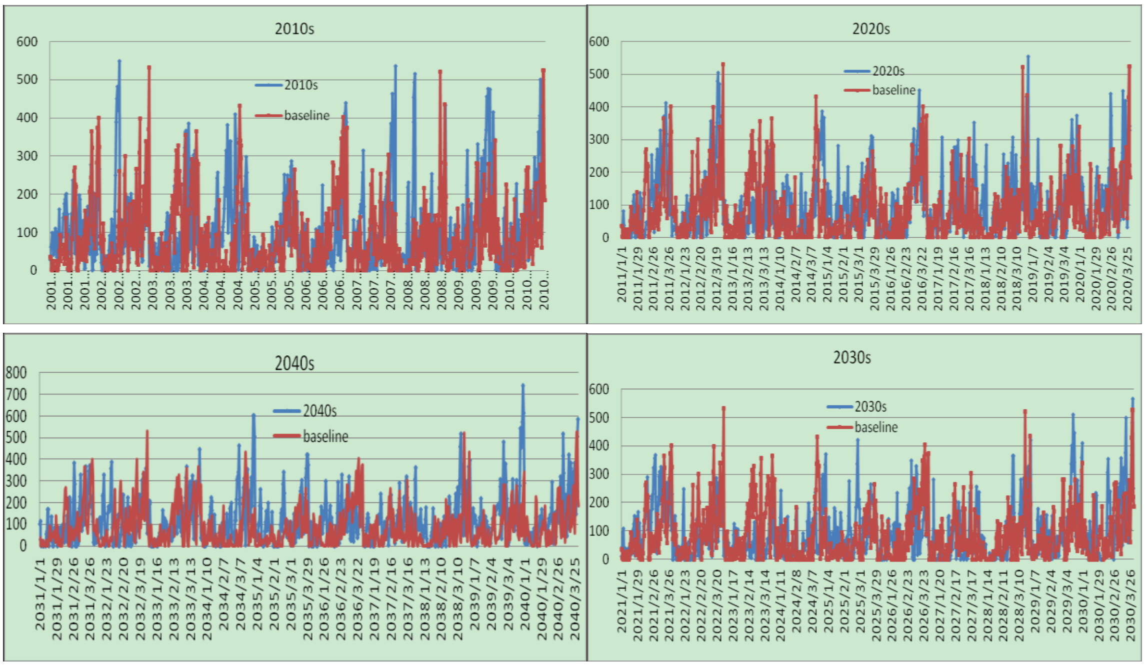


Fig. 5.12 A1B emission scenario result from year 2000 to 2040

(*unit for the X-axis is month, for Y-axis is the total algal cells concentration 10^4/L)

During the 2010s, the average precipitation is predicted to be 1129.84 mm and the average temperature is predicted to be 16.88°C. Compared with the base year, the precipitation and the temperature are increased by 2.52% and 0.63%, respectively. The river algal blooms occurred in 4 months for three years (2002, 2007 and 2009). Thus the probability of algal bloom occurrence from 2001 to 2010 is 12.9%, as predicted by the model. This result is well matched with the real historical algal bloom years that are 2002, 2008 and 2009.

During the 2020s, the average precipitation is predicted to be 1360.99 mm and average temperature is 16.77°C. Compared with the base year, this is an increase of precipitation of 23.5 % and a decrease of temperature of 0.05%. The river algal blooms occur in 2 months of the year of 2012 and 2019 according to the model. Under this model, the probability of algal bloom occurrence from 2011 to 2020 is 6.45%.

During the 2030s, average precipitation is predicted to be 1240.26 mm and the average temperature is predicted to be 17.19°C. Compared with the base year, precipitation is increased by a predicted 12.154% and the temperature is increased by 2.47%. River algal blooms are predicted to occur in 3 months in 2029 and 2030. Thus the probability of algal bloom occurrence from 2021 to 2030 is predicted to be 9.68%.

During the 2040s, the average precipitation is predicted to be 1245.7 mm and the average temperature is predicted to be 17.94°C. Compared with the base year, the precipitation and the temperature increases are predicted to be 13.17% and 6.95%, respectively. River algal blooms are predicted to occur in 9 months in 2034, 2038, 2039 and 2040. Thus the probability of algal bloom occurrence from 2021 to 2030 is predicted to be 29.03%.

5.3.2 A2 Scenarios Result

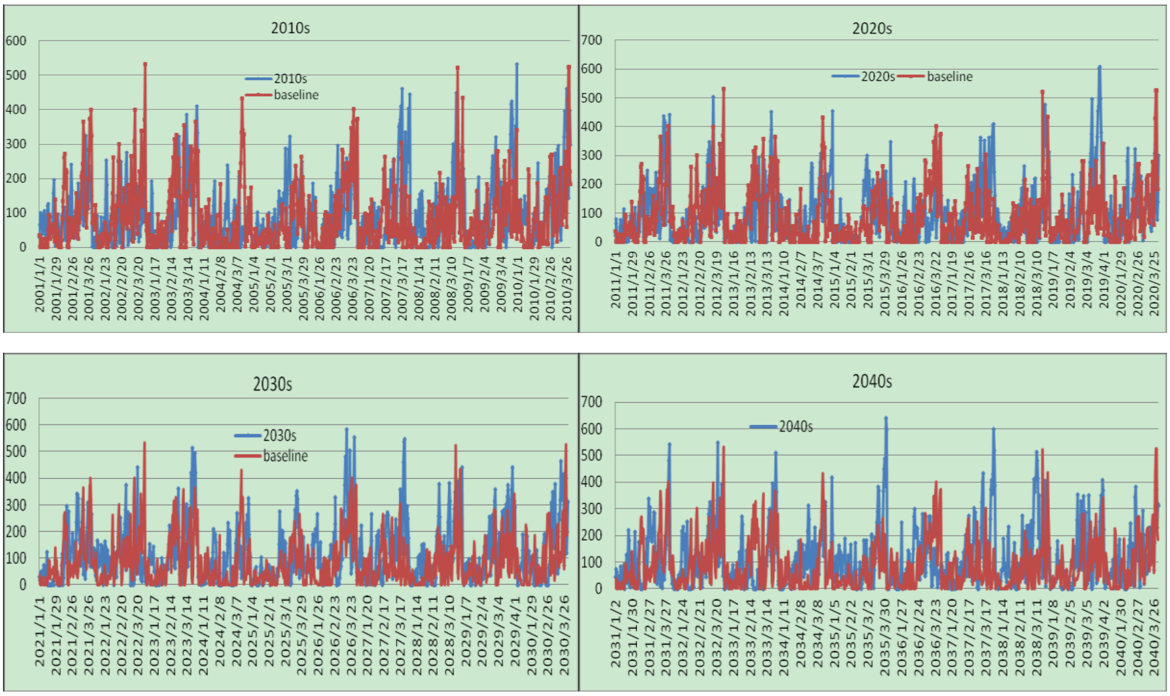


Fig. 5.13 A2 emission scenario result from year 2000 to 2040

(*unit for the X-axis is month, for Y-axis is the total algal cells concentration 10^4/L)

During the 2010s, the average precipitation is predicted to be 1025.64 mm and the average temperature is predicted to be 16.86°C. Compared to the base year, precipitation decreases 6.93% and temperature increases 0.5% in the model. River algal blooms only occurred in 1 month in 2009. Thus the probability of algal bloom occurrence from 2001 to 2010 is 3.22%. In this scenario, only the algal bloom year of 2009 matches the monitoring data.

During the 2020s, the average precipitation is predicted to be 1210.7 mm and the average temperature is predicted to be 17.27°C. Compared to the base year, precipitation is predicted to increase 9.86 % and temperature by 2.95%. River algal blooms are predicted to occur in 3 months in the year of 2012 and 2019, respectively. Thus the probability of algal bloom occurrence from 2021 to 2030 is 9.68%.

During the 2030s, the average precipitation is predicted to be 1269.56 mm and the average temperature is predicted to be 17.26°C. Compared to the base year, precipitation increases 15.2% and temperature increases 2.9% according to the model. River algal blooms occurred in 5 months in 2023, 2026 and 2027. Thus the probability of algal bloom occurrence from 2021 to 2030 is 16.13% in this model.

During the 2040s, the average precipitation is predicted to be 1038.7 mm and the average temperature is predicted to be 17.82°C. Compared to the base year, precipitation decreases 5.17% and temperature increases 6.2%, according to the model. River algal blooms are predicted to occur in 5 months 2031, 2032, 2032, 2033, 2035 and 2037. Thus the probability of algal bloom occurrence from 2031 to 2040 is predicted to be 22.58%.

5.3.3 B1 Scenarios Result

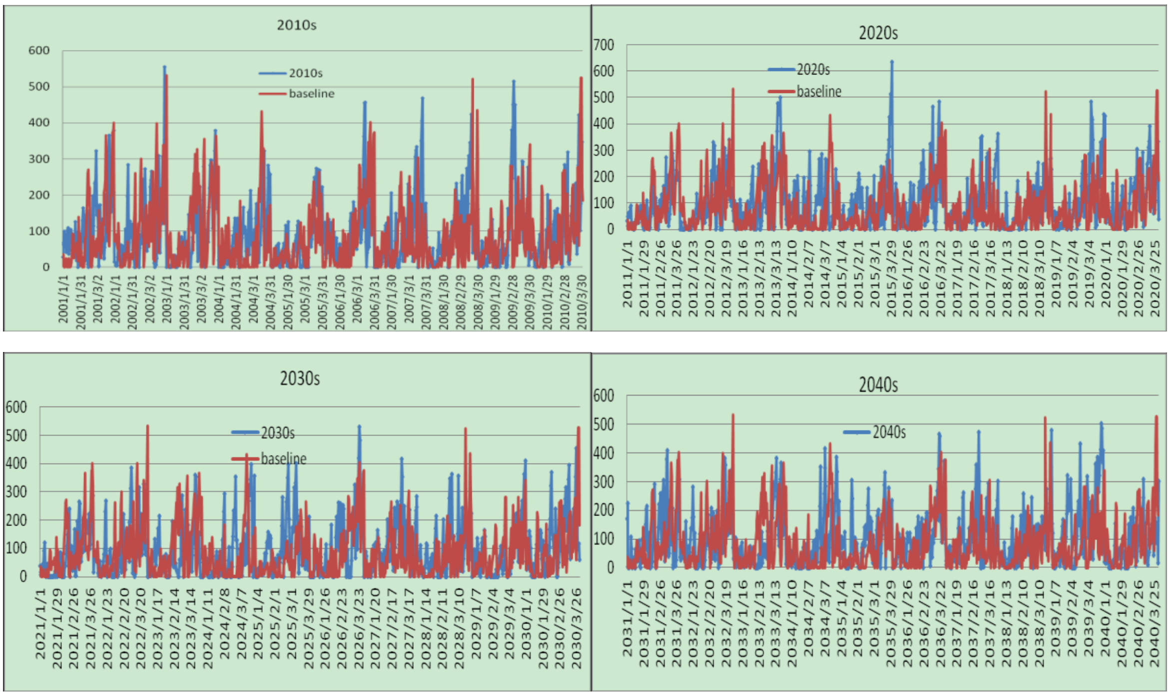


Fig. 5.14 B1 emission scenario result from year 2000 to 2040

(*unit for the X-axis is month, for Y-axis is the total algal cells concentration 10^4/L)

During the 2010s, the average precipitation is predicted to be 1131.82 mm and average temperature is predicted to be 17.4°C. Compared to the base year, precipitation increases 2.7% and temperature increases 3.73% according to the model. River algal blooms occurred in 2 months in 2002 and 2009 according to the model. Thus, in this system, the probability of algal bloom occurrence from 2001 to 2010 is 6.45%. In this result, the algal bloom years of 2002 and 2009 matches the real monitoring data.

During the 2020s, the average precipitation is predicted to be 1231.79 mm and average temperature is predicted to be 17.3°C. Compared to the base year the model predicts that precipitation increases 11.7 % and temperature increases 3.16%. River algal blooms occurred in 3 months in 2013 and 2015 according to the model. Thus the probability of algal bloom occurrence from 2021 to 2030 is 9.68% in this system.

During the 2030s the model predicts the average precipitation to be 1385.03 mm and the average temperature to be 16.96°C. Compared to the base year, precipitation increases by 25.67% and temperature increases by 1.14%, according to the model. River algal blooms only occurred in 1 month in 2026 according to the model. Thus, in this system the probability of algal bloom occurrence from 2021 to 2030 is 3.23%.

During the 2040s, the average precipitation is predicted to be 1414.43 mm and the average temperature is predicted to be 17.34°C. Compared to the base year, precipitation increases by 28.34% and temperature increases by 3.78%, according to the model. River algal blooms are only predicted to occur in 1 month in the year of 2039. Thus the probability of algal bloom occurrence from 2031 to 2040 is predicted to be 3.23%.

5.4 Summary

In this study, an integrated climate change assessment is performed under three emission scenarios. Table 5.9 in the previous section summarizes climate change and probability of algal bloom occurrence in the 40 years from 2001 to 2040 for the Han River. The results indicated that:

1. The algal bloom occurrence probability under A1 scenario is 58.06% from 2001 to 2040, which is the highest among all three different scenarios. According to the characteristic of A1B model, the economy grows rapidly and the global population reaches 9 billion in 2050, and they would contribute to the climate change impact. The average temperature and precipitation will be increased by 6.85% and 14.55%, respectively, which are the highest variation in those three scenarios during the 40 years. Therefore, the algal bloom risk is high in this integrated and well-developed word.

2. The result of A2 scenario has the second highest risk of algal bloom which is 48.39%. The temperature is increased by 6.15% and the precipitation is decreased by 2.73% during these 40 years. Since fertility patterns across regions converge very slowly, this results in continuously increasing global population. The economic development is regionally oriented primarily and the per capita economic growth and technological change are more fragmented and slower than in other storylines. Thus the areas with faster economic development would have more contributions to climate change than those more slowly developing regions under this scenario.

3. The B1 scenario corresponds to a convergent world with the same global

population that peaks in midcentury and declines thereafter, as in the A1 storyline. This scenario predicts rapid changes in economic structures toward a service and information economy, with reductions in material intensity, and the introduction of clean and resource-efficient technologies. The emphasis is on global solutions to economic, social and environmental sustainability including improved equity, but without additional climate initiatives. Precipitation and temperature are increased by 26.02% and 3.46%, respectively, during 40 years which is the slowest of three scenarios

4. These assessment results are useful for clarifying potential climate change and human activity effects on when the river system is eutrophied in the future, as well as providing support for related water pollution management and remediation decisions.

CHAPTER 6 DISCUSSION

In the present research, the mechanisms and contributions of the main factors causing algal bloom in Han River have been studied, and an integrated climate change assessment has been performed based on monitoring data, collected information and investigation work. Contributions of key factors for the Han River's algal bloom were analyzed by using a statistical model and simulation model of eutrophication. The results showed that nutrient loads along the lower section of the Han River is the predominant factor. Additionally, hydrological regime and temperature are also important factors affecting algal bloom. The Han River is characterized by slow water flow when its water level gets lower than the Yangtze River due to low precipitation and high temperatures. When the two factors happen simultaneously with higher temperatures in spring, algae grow quickly. The result of this case study indicates that the nutrient load, hydrological regime and temperature are key factors influencing water quality and the river ecosystem. Climate change is expected to affect water quality through influencing hydrological regimes. As a result, these changes lead to alteration of river water quality. Therefore, it is necessary and urgent to have a clear understanding of their contributions in response to climate change in scientific methods.

6.1 Model Analysis

A parametric river eutrophication model that is based on statistical and simulation methods is developed and applied to the Han River algal blooms case study. The final results show the multiple nonlinear regressions approach has the best calibration (0.828) and predictive ability (0.964), followed by the ANN (BP) network (calibration 0.967 and predictive ability 0.586). It is, then, followed by multiple linear regressions model (calibration 0.673 and predictive ability 0.705). The ecological model has the lowest calibration (0.646) and forecasting ability (0.647). All of the proposed models are able to predict to some extent the climate change impacts on river eutrophication assessment. The coefficients of each parameter clearly indicate a correlation between the dependent variables (X_n) and the independent variable (Y). For instance, it has been confirmed that river algal blooms are negativity correlated to hydrological regimes and positively correlated to temperature and the input nutrient waste load.

This contribution analysis was not only performed using statistical system models, but also is verified by an integrated river eutrophication model. It can provide a part of basic conceptual mechanisms for researchers, although the simulating ability is quite unsatisfactory. This kind of model has too many constraints related to required parameters, so the final result would not be satisfactory if the 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 the they are validated by a physical or semi-physical model, it can provide reasonable results as well. Based on the final assessment result, the linear method usually only presents approximate results since it assumes the relationship for everything is linear and output results often show negative values. This is not reasonable in real-world cases because real time series data are 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 and it is usually good on molding calibration. However, sometimes it lacks accuracy for data forecasting due to its tendency to over-fit. In conclusion, the advantages and limitations of proposed models can be summarized as follows:

a. Multiple linear regressions model

Advantages are:

- simple to use in application
- often shows good results when relationships between the independent variables and the dependent variable are almost linear.
- moderate calibration ($R^2 = 0.64$) and validation ($R^2 = 0.7$) results.

Limitations are:

- needs data screening, the input parameters must be linearly correlated to outputs.
- often inappropriately used to model non-linear relationships, thus it is limited when making predictions in real case studies.
- a lack of explanation about what has been learned can be a problem.

b. Multiple Non-linear regressions model

Advantages are:

- can be used to model non-linear relationships and is appropriate for most real case studies.
- can be moved to a linear domain by a suitable transformation of the model formulation.
- very good modeling result of calibration (0.89) and validation (0.97).

Limitations are:

- calculation process is much more complicated than the MLR, but some nonlinear equations (e.g. power functions) can be transformed to a linear formulation.
- The major conceptual limitation of all regression techniques is that you can only ascertain relationships, but can never be sure about an underlying causal mechanism.

c. Artificial Neural Networks

Advantages are:

- able to automatically resolve non-linear complex relationships between variables without the need for prior assumptions about the nature of those relationships.
- able to solve difficult pattern-processing problems involving non-linearity and multiple dimensions.
- can be implemented in any application and allow fast processing of large amounts of information.
- often good in model calibration (0.97) and has the abilities of promotion and generalization.

Limitations:

- It should be used with caution when developing predictive models because the prime disadvantage of ANN is that they are tend towards overfitting, also known as overtraining. This phenomenon can lead an investigator to misinterpret an ANN's good performance on a training/calibration data set.
- It cannot indicate the exact contributions of each input indicator to the output, thus it is inconvenient for applying a single factor impact assessment;

d. Integrated river eutrophication model

Advantages:

- It is a semi-physical model that combines a empirical model and a statistical model, thus it can provide some physical meaning inside of the system already known. Results can explain the mechanisms of variables.

Limitations:

- Due to the conditions of input parameters being too restrictive, the simulating efficiency can be less than statistical models.
- model requires more physical parameters related to water environments

6.2 Discussion of Climate Change Impacts on River Algal Blooms

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. It 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%. Therefore, the interactions and contributions of each variable input to algal bloom can be summarized as follows:

a. It is well proven that the human activity, which in this case is represented by the waste load, 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%. If both temperature and flow rate are increased, 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 to minimize 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 to the river. Moreover, a large number of domestic water emissions reach the river. Relevant implications should be assessed and adaptations should be conducted.

b. The hydrologic regime is the second most important impact factor in algal bloom formation, according to our model. The study result shows the flow rate is negatively correlated the total algal cell concentration, especially when the input waste load and the flow rate change at same time, 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 settlement to the bottom and the formation of a river silt layer) which provides sufficient phosphorus to accelerate algal bloom formation.

c. It is clearly shown that the impact of temperature (3.7%) does exist 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%. This indicates that temperature plays a key role in river eutrophication according to this model, especially when 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 diatoms. From the collected data, the water temperature in 1992 has increased significantly compared to 1991, and the highest temperature in 1998 and 2000 reached 32°C, which is almost 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.

6.3 Implications for Water Quality and Ecosystem Management

Even though climate change could significantly alter water eutrophication and ecosystem, it is predicted under our model that human activities contribute much more than climate change to algal blooms in the Han river. This implies that adaptive management can minimize some climate-change impacts on not only water quality but also the aquatic ecosystems. Because many of impacts of climate changes are not predictable, in order to deal with the climate changes that are taking place now and to prepare for those that are likely to happen in the future, more flexible institutional arrangements are needed in order to adapt the changing conditions, a necessary tool is the water quality and ecosystem management plan. This should take into account all significant pressures and impact of human activities on the aquatic environment. Specific and practical management options should be chosen for different regions.

In order to avoid adverse impacts of climate change on water quality and aquatic ecosystems, certainly the most important and well-known method to protect aquatic ecosystems is reducing contaminant levels. Therefore, it is vital that both point and nonpoint pollution sources should be strongly restricted. The adaptation options should also improve the ability to moderate, cope with and take advantage of the consequences of climate change. Moreover, because of uncertainty over future climate variability, management responses should have built-in flexibility to ensure that current coping strategies are consistent with future climate change. Adaptability of this nature requires environmental change monitoring and modeling, and the strengthening of basic research and practice. Management innovation is also necessary for better adaptability. In addition, relevant education and training can raise awareness and encourage more people to pay attention to this issue.

CHAPTER 7 CONCLUSION

In the present study, a set of parametric river eutrophication models have been developed for assessing the contributions of climate change and human activity impacts on river water quality. An integrated climate change assessment was applied to a real river eutrophication case study of the Wuhan section of Han River in China. This study has provided much data and information, including an overview of international research on this issue and some of my personal opinions related to climate change on water quality. A system modeling structure of river eutrophication based on multiple inputs and an output was established, in which variables include nutrient load, temperature, hydrological regimes, water quality, and total algal cell concentration. The statistical and simulation models were conducted based on system approaches of (a) Multiple Linear Regressions, (b) Multiple Non-linear Regressions, (c) Artificial Neural Network based on Back-propagation algorithms, as well as (d) the integrated river eutrophication (Dillon) model. All above models are calibrated and validated based on the monitoring data, the multiple non-linear regressions model is taken for individual and integrated climate change assessment under different scenarios since it has the best simulation result. The contributions of nutrient loads, temperature and hydrological regimes to the algal blooms are quantified by adjusting any of the variables. The final climate change assessment result indicates that the input waste load has the greatest impact (14.82%) on river algal blooms, which means that human activity plays an important role on the growth and reproduction of algae, and control of the waste load is the key issue to minimize the probability of occurrence of algal bloom. The hydrologic regime is the second important impact factor (5.56%). The study result shows the flow rate is negatively correlated to the total algal cell concentration. The impact of temperature (3.37%) was low, but can have a high impact when input load and flow rate are both in a danger threshold. Finally, the probabilities of algal bloom occurrence in the Han River for next 40 years was forecasted based on three emissions scenarios.

Based on the climate change assessment result, it is proven that water quality and eutrophication can be impacted significantly by climate change. However, scientific works on this important issue are very limited. More and deeper scientific research should be conducted in the near future. Based on the Han River case study in China, it is concluded that the degradation of river water quality and eutrophication is mainly influenced by human activities, and can be exacerbated by climate change. Climate change can affect water quality through not only working on water temperature but also altering hydrological regimes. Finally, specific and practical adaptation options and positive ways to enhance adaptability should be proposed to decision-makers.

7.1 Contributions of the Research

The research contributions of this present thesis are summarized as follows:

1) As we know, the effects of climate change on river water quality is a valuable topic but also very complex and full of challenges. So far most current research tends to be more focused on climate change impact on water quantity (e.g., flooding and droughts) rather than on changes in water quality. Relevant scientific research and practices are important for effective responses and management of water environments. In this study, an assessment framework related to climate change and human activities has been developed through examining appropriate statistical and simulation modeling methods to comprehensively quantify their contributions to river water eutrophication.

2) This study presents the application of statistical and simulation models, which include Multiple Linear Regressions, Multiple Non-linear Regressions, Artificial Neural Networks and an ecological model, in order to quantify the contributions of climate change and human activities impacts to river water quality based on a case study of algal blooms in a large river system in China. The new ecological model can be considered as a semi-physical empirical model and was considered useful for providing some necessary meaning of mechanisms compared to other

statistical models. Previously, this water eutrophication model has been only applied to water eutrophication studies in lakes and has never been used for rivers. Here, we see its possible applications in climate change impact on large river systems.

3) The comprehensive modeling results indicate the overall relationships of climate change impact on water quality, but also individually evaluate the impact of human activities and variation of hydrological regimes on river algal blooms, based on an integrated climate change assessment.

4) A single-factor assessment and an integrated climate change assessment has been conducted based on the modeling results. It can quantify the contributions of temperatures, hydrological regimes and human activities to river water quality based on the information of monitoring data in past, but is also able to forecast the probabilities of algal blooms occurrence in the Han river for next 40 years based on three emissions scenarios. This can provide useful and reasonable information about water environmental management for decision-makers in the future.

5). This study discussed the principles of adaptation strategies on how to solve the impact of climate change on water resources and what feasible adaptations should be taken to keep economic and social developments from causing adverse effects. The present study is expected to give theoretical support and directions for further relevant research, and this assessment approach can also be applied in other environmental problems, such as the climate change related water contamination, air pollution, solid waste management, etc.

7.2 Future Studies

This section highlights the scope of future work which may be conducted on the basis of the work presented here.

1. Although this study analyzed water quality and climate data of 9 years from 1992 to 2000, only information in the spring time (January to March of each year) is available due to the nature of the algal bloom phenomenon. For further studies, long term continuous monitoring in different regions is still required to support basic data in order to give a more comprehensive analysis of climate change impact.

2. More efforts should be taken to separate the impacts of climate change from human activities based on more long-term monitoring data, although it is complicated. Meanwhile, to get a better understanding of the issue, it is suggested to obtain more information about the alteration mechanisms of hydrological regimes by climate change.

3. The over-fitting phenomenon that has occurred in the ANN application in this study is problematic. In order to avoid this pitfall, validation of the ANN model with a data set not used during training is essential. Techniques such as early stopping, cross-validation and bootstrapping can be used to in future studies to minimize the modeling errors.

4. A new integrated river eutrophication model was developed in this study, but the prediction ability is not satisfactory compared with the statistical model. Future studies should be applied in this direction to improve this empirical equation to yield better results.

5. Only one statistical model, which is the multiple nonlinear regressions approach, has been used for forecasting the future climate change impact on the river water quality in 40 years. It is also suggested for the decision maker to combine the statistical model and simulation models to establish a comprehensive fuzzy risk assessment by taking a interval value of two models.

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