Article:

Jiang, L, Li, Y, Zhao, X et al. (6 more authors) (2018) Parameter uncertainty and sensitivity analysis of water quality model in Lake Taihu, China. Ecological Modelling, 375. pp. 1-12. ISSN 0304-3800

https://doi.org/10.1016/j.ecolmodel.2018.02.014

Parameter Uncertainty and Sensitivity Analysis of Water Quality Model in Lake Taihu, China

Long Jiang[1,2], Yiping Li[1,2,*], Xu Zhao[1,2], Martin R. Tillotson[3], Wencai Wang[2], Shuangshuang Zhang[4], Linda Sarpong[2], Qhtan Asmaa[2], Baozhu Pan[5]

[1] Key Laboratory of Integrated Regulation and Resource Development on Shallow Lakes, Ministry of Education, Hohai University, Nanjing, 210098, China

[2] College of Environment, Hohai University, Nanjing, 210098, China

[3] School of Civil Engineering, University of Leeds, Leeds LS2 9JT, United Kingdom

[4] College of Environmental Science and Engineering, Suzhou University of Science and Technology, Suzhou, 215011, China

[5] State Key Laboratory Base of Eco-hydraulic Engineering in Arid Area, Xi'an University of Technology, Xi'an, 710048, China

*Corresponding author at: College of Environment, Hohai University, Nanjing, 210098, China

E-mail addresses: liyiping@hhu.edu.cn (Yiping Li)

Abstract: Lake Taihu was chosen as a case for parameter uncertainty and sensitivity analysis of water quality simulation in large shallow lakes. Forty parameters in Environmental Fluid Dynamic Code model (EFDC) were filtered and analyzed. The results showed that parameters had a considerable influence on simulation and three groups of parameters related to algal kinetics (i.e. PMc, BMRc and PRRc), light (KeChl) and temperature (KTG1c) were very sensitive. For shallow lakes with frequent algal blooms, light extinction due to Chlorophyll-a is also a sensitive parameter. While the temperature effect coefficient for algal growth is sensitive for lakes with seasonal temperature variation. Sensitive parameters and their relevant uncertainty varied spatially. For high nutrients and algae concentration subareas, temperature was more likely to be a limiting factor, whereas sensitive factors could be light in lower concentration subareas. Since most sensitive parameters were related to algae, uncertainty in simulation increased with increasing algal kinetic processes over time and varied in different subareas. Lower nutrients and algae concentration subareas were more easily influenced by model parameters while nearshore areas were highly influenced by boundary conditions. For better simulation of water quality, variable stoichiometry phytoplankton models should be considered and zooplankton need to be integrated into the model explicitly rather than a fixed predation rate.

Key words Lake Taihu; Sensitivity analysis; Uncertainty analysis; Water quality models;

1 Introduction

Water quality models (WQMs), valuable tools of supporting water quality predictions, have been widely applied in environmental management in recent years (Arhonditsis and Brett 2005; Li and Zhang et al. 2015; Xu et al. 2013; Cerco and Cole 1993). However, the inherent uncertainty of these models is greatly influenced by factors including model-structure uncertainty, model-input uncertainty, model-parameter uncertainty and measurement errors (Radwan et al. 2002). With the development and application of performance computing technology, many water quality models with good structure and complex parameters have been developed (Wang, Li and Jia et al. 2013). However, an increasing number of parameters has resulted in a sharp increase in computational requirements and thus exacerbated the complexity of these models. Highly interactive parameter spaces and the nonlinear, non-monotonous objective spaces have increased the difficulty of calibration. (Gupta et al. 2000; Herman et al. 2013; Yi et al. 2016).

In order to improve the accuracy and rationality of model predictions and study the parametric uncertainty and sensitivity of models, we conducted several uncertainty and sensitivity studies in different water bodies such as rivers, lakes, reservoirs, estuaries and coasts to identify subsets of important model parameters that significantly influence model outputs have been carried out (Muleta et al. 2005; Neumann 2012; Yi et al. 2016). Amongst these studies, large shallow lakes are often accompanied with complex hydrodynamic and eutrophication problems. The simulation of water quality is difficult and few studies were conducted on parameters under different situations.

The hydrodynamic conditions in large shallow lakes are highly influenced by wind-wave. They are not like other deep lakes or reservoirs which may be driven by thermal stratification. Parameters related to wind and wave like wind drag coefficient were supposed to be sensitive parameters in simulation (Li and Tang et al. 2015). Some large shallow lakes also face serious eutrophication and algal bloom problems like Lake Taihu. Parametric uncertainty is considerable with parameters related to growth, respiration and death of algae and zooplankton generally sensitive in lake eutrophication models (Omlin et al. 2001; Missaghi et al. 2013). Three factors (i.e. nutrients, temperature and light) are considered to control the algal growth but the limitation factors are normally not so clear in many cases. For example, phosphorus was thought to be the limitation factors in Lake Taihu before but the influence of nitrogen is also quite important by recent researches (Tang et al. 2016; Paerl et al. 2011). Some typical large shallow lake models, which have been analyzed with different methods, showed that parameters related to light and temperature were significant, for example in the Venician Lagoon (Pastres and Ciavatta 2005; Pastres et al. 1997), and Dian Lake, China (Yi et al. 2016). Parameters related to limitation factors will change according to real situation and sensitivities of these parameters need to be investigated. Sediment is also an important source of pollution, and parameters related to settling velocity and mineralization were found to be sensitive in some models (Missaghi et al. 2013). Researches on different models of shallow lakes suggested that the adsorption constant was relatively important in the simulation of total nitrogen, whereas mineralization and settling rates were sensitive to total phosphorus (Janse et al. 2010).

Meteorological and hydrodynamic situations, pollutant inflow and bathymetric variance in lakes and reservoirs results in inherent temporal and spatial variability in water quality (Missaghi et al. 2013). In a multi-dimensional model formulated by physical, chemical, and biological processes, model behavior may vary across the spatial domain whilst time-dependency should also be considered because of time-varying sensitivities (Herman et al. 2013; Wang, Li and Lu et al. 2013; Herman et al. 2013). However, few studies involving complex water quality models of multi-dimensional lakes or reservoirs have been conducted on this problem.

In this research, we choose Lake Taihu, a large shallow lake, the third largest freshwater lake in China, as an example to make relevant analysis. The water quality module of the Environmental Fluid Dynamic Code (EFDC) was chosen for the simulation, and water quality indicators such as ammonia nitrogen, nitrate nitrogen phosphate and chlorophyll-a as model outputs. The objectives of this study were thus to: (1) quantify the sensitivity of parameters in simulation of water quality model and evaluate uncertainty caused by it; (2) analyze the spatial-temporal variability of uncertainty and sensitivity; and (3) compare with other lakes and extend the result to a larger modelling community. The results can be utilized in the design of a reasonable water quality model for large shallow lakes and improve the efficiency of calibration of such models.

2 Methods and materials

2.1 Study area

Lake Taihu (longitude 119°08′–122°55′E, latitude 30°05′–32°08′N) is the third largest shallow freshwater lake in China, with a surface area of 2,338 km^2 and a catchment area of 36,500 km^2 (Zhu et al. 2007). The average depth of the lake is 1.9m and the maximum depth is 2.6m, corresponding to an elevation of 3.0m a.s.l. (Qin 2009). The floor of the lake features flat terrain with an average topographic gradient of 0°0′19.66″. Lake Taihu has complex shoreline geometry and is connected to 172 rivers or channels (Qin 2009), and the mean hydraulic retention time is about 300d. The water quality of the lake is seriously deteriorated. Nuisance algal blooms often occur in summer and early fall in most lake areas, especially Meiliang Bay and Zhushan Bay. The blooms are considered to be the result of a combination of high nutrient loading and weak hydrodynamics (Mao et al. 2008). For the convenience of management and monitoring, Lake Taihu have been divided into eight subareas (Liu et al. 2014; Zhang et al. 2010). Three subareas (i.e. Meiliang Bay, Central Zone and Southwest Zone) represent bay, central and nearshore zones respectively, and represent different hydrodynamic and water quality situations for uncertainty and sensitivity analysis in the water quality model (Fig. 1).

2.2 Model set-up and calibration

The Environmental Fluid Dynamic Code, a three-dimensional hydrodynamic model originally developed by John Hamrick (Hamrick 1996), is utilized to simulate water quality in Lake Taihu. The model is one of the most widely applied advanced modeling frameworks for simulating hydrodynamics, water quality, eutrophication, and dynamic changes and interactions in sediment transportation in lakes, rivers and estuaries (Park et al. 2012; Kim et al. 2011; Li et al. 2011). A large number of applications have demonstrated that the model has considerable generality, convenient operation, and faster calculation times (Wu and Xu 2011; Youngteck and Jinhyeog 2009).

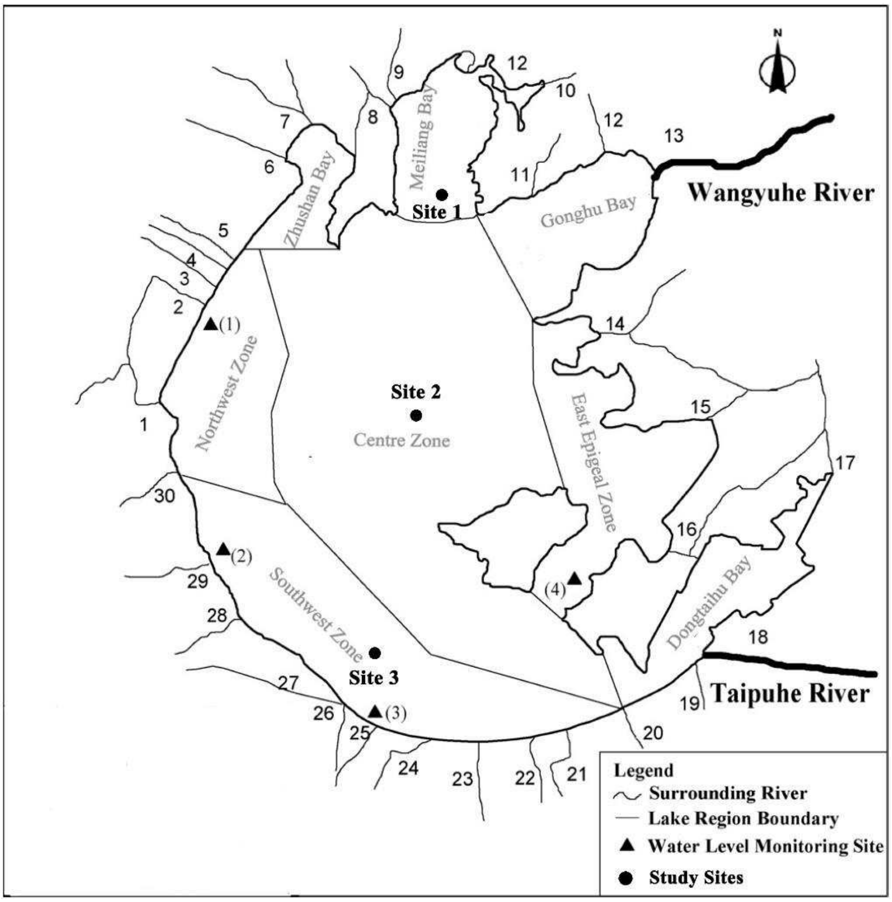


Fig.1 Location of the study area, surrounding rivers and monitoring stations in and around Lake Taihu, China. Water level monitoring stations (1) - (4) represent Dapukou, Jiapu, Xiaomeikou and Xishan respectively.

Uniform rectangular grids were utilized to set-up the model for Lake Taihu in the horizontal plane. In the vertical direction, vertical sigma coordinates with an evenly distributed three-layer system were adopted as a trade-off between resolution and stability issues (Li and Tang et al. 2015). The effect of temperature stratification was ignored because the lake was shallow. The model was driven by atmospheric forcing, surface wind stress, tributary inflow/outflow, and benthic fluxes (Fig. 2). Inflow/outflow tributaries were generalized into 30 primary rivers (Fig. 1). Atmospheric precipitation data was obtained by averaging data from eight monitoring stations near the lake (Fig. 1). The wind data was collected from previous field monitoring (Li and Tang et al. 2015). Benthic fluxes were set zonally by field experiment and previous research (Pang and Wang 1994), and the dry/wet atmospheric deposition was set by field experiment (Song et al. 2005; Yang et al. 2007). We try to run the model for several days with an assumption that the lake surface was level and then the initial hydrodynamic conditions was set by the average value of simulation on the first day. It is also applied in our previous study and can help alleviate the influence of initial conditions on the simulation results. The initial condition of water quality was set by the monitoring data in the first few days of January from the 30 monitoring sites in Lake Taihu, including water temperature and the concentrations of DO, COD, NO_3^--N, NH_4^+-N, TN, $PO4^-$, TP and Chl-a. The simulated time lasted for one year (From 1 Jan to 31 Dec), and a 10-s time step was used as a trade-off between computational speed and stability issues.

Parameters concerned with the hydrodynamic processes were the same as those used in previous studies (Li and Tang et al. 2015), and the results of current calibrations have been presented in previous research (Li et al. 2011). Annual monitoring data of water quality variables from 2005 was used to calibrate the water quality module, and relative errors were less than 30% on the whole. The amount of error remained significant after calibration, and therefore parametric uncertainty was estimated and the most sensitive parameter(s) was investigated in order to improve the model.

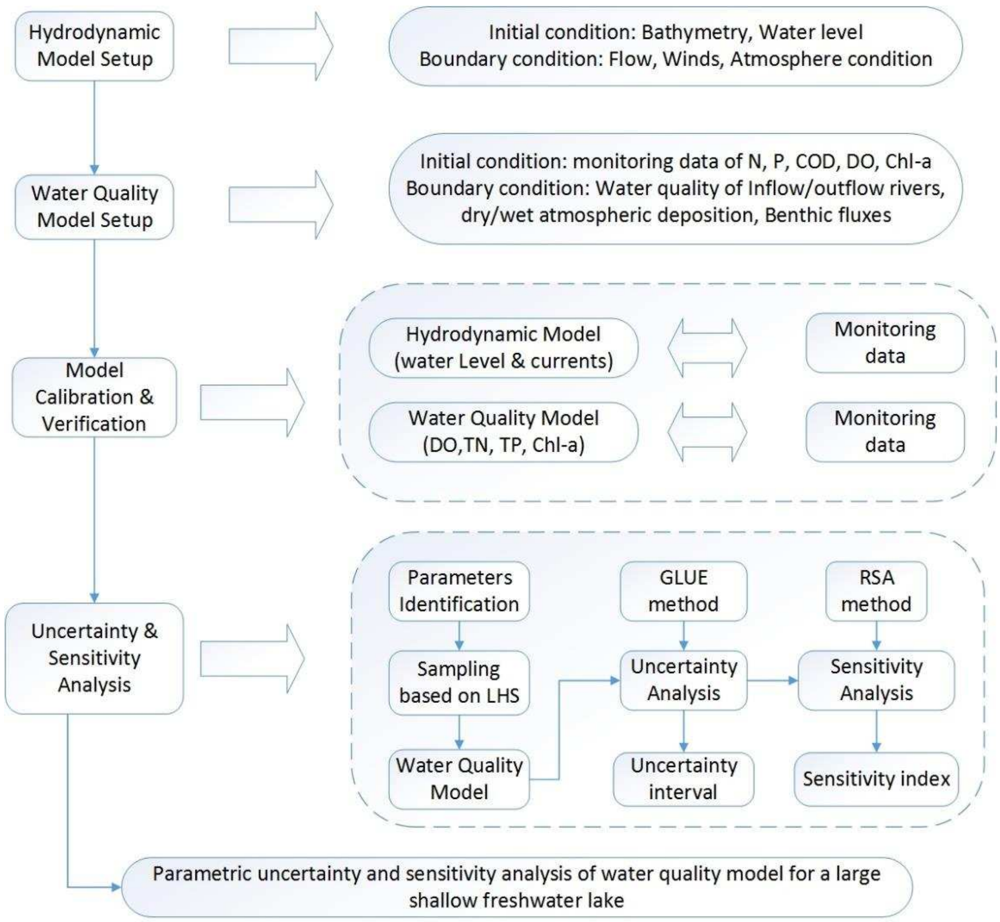


Fig.2 Methodology flowchart of uncertainty and sensitivity analysis.

2.3 Methods of uncertainty and sensitivity analysis

Uncertainty and sensitivity analysis for the water quality module in EFDC for Lake Taihu was conducted based on the GLUE and RSA methods. The main analysis procedure is shown as follows.

2.3.1 Parameter identification

The simulation of water quality with EFDC involves a large number of parameters. It was not feasible or necessary to take all parameters into consideration (Muleta et al. 2005), so a reduction in the number of parameters based on the actual simulations was performed. Taking into account that the predominant type of algae in Lake Taihu is cyanobacteria, especially when algal blooms happened (Feng et al. 2016; Lu et al. 2016; Yue et al. 2014), we excluded all parameters relating to other algal species, i.e. macroalgae, diatoms, and greens. The competitive relationships between algal groups were omitted to reduce the number of parameters. Sediment is another factor that can have a great impact on the simulation result. The sediments module and water quality module were separated in EFDC model. It is difficult to calibrate the simulation results and the sampling quantity will increase exponentially if we include the sediments part. In our previous research, field observations with using of advanced devices were conducted on the lake to find behaviours of sediments settling and resuspension (Gao et al. 2017). Diffusive exchange of dissolved phase nutrients between water column and interstitial waters was investigated in many studies as well (Yu et al. 2016; Huang et al. 2015; Qiu et al. 2015; Kaiming et al. 2014). Thus, we set the model with fixed benthic flux rates spatially by recent researches to simulate the processes of sediment instead (i.e. phosphate, ammonia-nitrogen, nitrate nitrogen, chemical oxygen demand, sediment oxygen demand). Since these processes were highly influenced by the hydrodynamic conditions driven by wind-wave in the lake, we set flux rates with considering about the influence of wind (Yu et al. 2016; Huang et al. 2015; Qiu et al. 2015; Kaiming et al. 2014). In addition, parameters about reference temperature, optimal depth for algal growth, and other parameters not likely to be modified in most cases were set to default values. Finally, 40 parameters were determined for further study and their descriptions are summarised in Table 1. The ranges of these parameters for uncertainty and sensitivity analysis were determined through a detailed investigation of the literature (He et al. 2011; Seo and Kim 2011; Wang and Zou et al. 2014; Wang and Jiang et al. 2014; Arhonditsis and Brett 2005).

Table 1 Statistical features of the water quality module parameters for sampling.

Parameters groups	Parameters	Description	Units	Distribution	Min	Max
Algal Kinetic	PMc	Maximum growth Rate for Cyanobacteria	1/day	Uniform	2	5
	BMRc	Basal Metabolism Rate for Cyanobacteria	1/day	Uniform	0.01	0.06
	PRRc	Predation Rate on Cyanobacteria	1/day	Uniform	0.01	0.06
Nitrification	rNitM	Maximum Nitrification Rate	1/day	Normal	0.04	0.2
Dissolved Oxygen	KRO	Reaeration Rate Constant	-	Uniform	1.5	5.32
Chemical Oxygen Demand	KCD	COD Decay Rate	1/day	Uniform	0.01	0.15
Dissolution and Mineralization	KRN	Minimum Hydrolysis Rate of RPON	1/day	Normal	0.001	0.01

	KLN	Minimum Hydrolysis Rate of LPON	1/day	Normal	0.01	0.1
	KDN	Minimum Mineralization Rate of DON	1/day	Normal	0.01	0.08
	KRC	Minimum Dissolution Rate of RPOC	1/day	Normal	0.001	0.01
	KLC	Minimum Dissolution Rate of LPOC	1/day	Normal	0.01	0.1
	KDC	Minimum Dissolution Rate of DOC	1/day	Normal	0.005	0.15
	KRP	Minimum Hydrolysis Rate of RPOP	1/day	Normal	0.001	0.01
	KLP	Minimum Hydrolysis Rate of LPOP	1/day	Normal	0.01	0.1
	KDP	Minimum Mineralization Rate of DOP	1/day	Normal	0.01	0.3
Light	Keb	Background Light Extinction Coefficient	1/m	Uniform	0.45	0.55
	KeTSS	Light Extinction due to TSS	1/m per mg/l	Uniform	0.01	0.1
	KeChl	Light Extinction due to Chlorophyll a	1/m per mg/l	Uniform	0.01	0.07
	IsMIN	Minimum Optimum Solar Radiation	Langley /day	Uniform	40	60
Half-Sat Constant	KHNitDO	Oxygen Half-Sat Constant for Nitrification	gO_2/m^3	Uniform	0.5	1
	KHNitN	NH4 Half-Sat Constant for Nitrification	gN/m^3	Uniform	0.5	1
	KHCOD	Oxygen Half-Saturation Constant for COD Decay	mg/L O_2	Uniform	1	1.5
	KHNc	Nitrogen Half-Saturation for Cyanobacteria	mg/L	Normal	0.01	0.25
	KHPc	Phosphorus Half-Saturation for Cyanobacteria	mg/L	Normal	0.001	0.05
	KHDNN	Half-Sat Constant for Denitrification	gN/m^3	Uniform	0.05	0.2
	KHORDO	Oxygen Half-Sat Constant for Algal Respiration	gO_2/m^3	Uniform	0.5	2
Temperature	KTHDR	Temperature Effect Coefficient for Dissolution	-	Normal	0.05	0.1
	KTMNL	Temperature Effect Coefficient for Mineralization	-	Normal	0.05	0.1
	KTCOD	Temperature Rate Constant for COD Decay	-	Uniform	0.03	0.05
	KNit1	Suboptimal Temperature Coefficient for Nitrification	-	Normal	0.002	0.006
	KNit2	Superoptimal Temperature Coefficient for Nitrification	-	Normal	0.002	0.006
	KTG1c	Suboptimal Temperature Effect Coefficient for Growth, Cyanobacteria	-	Uniform	0.001	0.01
	KTG2c	Superoptimal Temperature Effect Coefficient for Growth, Cyanobacteria	-	Uniform	0.001	0.01
	TMc1	Lower Optimal Temperature for Growth, Cyanobacteria	degC	Uniform	20	27
	TMc2	Upper Optimal Temperature for Growth, Cyanobacteria	degC	Uniform	27	30
	KTR	Reaeration Temperature Rate Constant	-	Normal	1	1.05
	KTBc	Temperature Effect Coefficient for Basal Metabolism, Cyanobacteria	-	Uniform	0.05	0.08
Settling Velocity	WSc	Settling velocity for cyanobacteria	m/day	Uniform	0.05	0.3
	WSrp	Settling velocity for refractory POM	m/day	Uniform	0.2	1
	WSlp	Settling velocity for labile POM	m/day	Uniform	0.2	1

2.3.2 Sampling of input parameters with the LHS method

Input parameters were sampled by using the Latin Hypercube Sampling (LHS) method, a random sampling method which is commonly used for uncertainty and sensitivity analysis (Manache and Melching 2008). The LHS method works by taking the range of each independent parameter, dividing the range by the selected realizations, rearranging the values into a random distribution, and then combining the distributions for each independent parameter (Xu and Gertner 2008). As the variable space was sampled with relatively few samples in LHS, the number of model runs could be less compared with Monte Carlo sampling. In the study, 100, 300, 500, 1000 and 2000 realizations were generated by using LHS and were tested in order to obtain their optimal realizations for analyzing model uncertainty and sensitivity.

Using the robustness test, we found that the results of the sensitivity analysis were nearly stable when the sampling quantity was greater than 500. Therefore, taking into consideration the computational cost and the stability of the result, we chose 500 Latin hypercube samples for uncertainty and sensitivity analysis.

2.3.3 Uncertainty analysis with the GLUE method

The GLUE methodology (Beven and Binley 1992) was utilized to quantify the uncertainty of the model. The method, which avoided the optimal partial solution, was suitable for the water quality model with equifinality of different parameter sets and. It is commonly used in river, lake, and rainfall-runoff models (Blasone et al. 2008).

500 sets of parameters obtained from random sampling using the LHS method were used in this model, and 500 sets of simulation results were obtained. The following formula was used to calculate the likelihood measure of the simulated results:

$$L(\theta_i/Y) = 1 - \alpha_i^2/\alpha_0^2 \tag{1}$$

Where $L(\theta_i/Y)$ is the likelihood measure for the *ith* model conditioned on the observations, α_i^2 is the error variance for the *ith* model (i.e. the combination of the model and the *ith* parameter set), and α_0^2 is the variance of the observations.

To ensure that the group of parameters can represent the functional characteristics of the model, a threshold was set to exclude these groups from the results and normalized likelihood measure by using the linear function:

$$l(\theta_i/Y) = \frac{L(\theta_i/Y) - L_{min}(\theta_i/Y)}{L_{max}(\theta_i/Y) - L_{min}(\theta_i/Y)} \quad (2)$$

Where $L(\theta_i/Y)$ is the likelihood measure calculated by using formula (1), $l(\theta_i/Y)$ is the likelihood measure that has been normalized, $L_{min}(\theta_i/Y)$ and $L_{max}(\theta_i/Y)$ are the minimum and maximum likelihood measures respectively.

The normalized likelihood measure was sorted by value and the $97.5th$ and $2.5th$ percentiles were chosen as the upper and lower bounds of confidence intervals. Proportion of observations in uncertainty interval and ratio of uncertainty interval to mean concentration were calculated to evaluate the uncertainty of the model.

2.3.4 Parametric sensitivity analysis with the RSA method

The RSA methodology is utilized to analyze the sensitivity of parameters. The method overcomes the constraints of single factor analysis in traditional sensitivity analysis, and complex assumptions were not necessary.

Marginal cumulative distributions were calculated by likelihood measure, and sensitivity can be assessed qualitatively by examining differences between 10 distributions of the parameter. The degree of dispersion of the lines is the visual measure of a model's sensitivity to an input parameter. To acquire the sensitivity accurately, the sensitivity indices (SI) of parameters in the three subareas were then calculated by adopting the Kolmogorov-Smirnov (K-S) test (Kottegoda and Rosso 1997). The K-S test is a non-parametric test which can be used to compare different samples. The method is one of the most useful and general nonparametric methods for comparing the difference of samples and it is sensitive to differences in both location and shape of the empirical cumulative distribution functions of samples.

First, 500 sets of simulation results were divide into ten groups by the likelihood measure and the empirical distribution function F_n for n iid observations X_i in each group is defined as

$$F_n(x) = \frac{1}{n}\sum_{i=1}^{n} I_{[-\infty,x]}(X_i) \quad (3)$$

where $I_{[-\infty,x]}(X_i)$ is the indicator function, equal to 1 if $X_i \leq x$ and equal to 0 otherwise. The Kolmogorov–Smirnov statistic used to quantify a distance between the empirical distribution functions of different groups is:

$$D_{i,j} = sup\left|F_{i,n}(x) - F_{j,m}(x)\right| \tag{4}$$

where $F_{i,n}(x)$ and $F_{j,m}(x)$ are the empirical distribution functions of two samples respectively (i, j were the number of groups) and *sup* is the supremum of the set of distances. The maximum vertical distances (MVD) were then calculated as Sensitivity Indices (SI) to quantify the sensitivity.

$$MVD = SI = max\left(D_{i,j}\right) \tag{5}$$

The parameters were divided into three levels by the sensitivity indices: very sensitive parameters (SI⩾0.25, P<0.05), sensitive parameters (0.1<SI<0.25, P⩽0.05), and insensitive parameters (SI⩽0.1, P>0.05). The interval range of these parameters was divided into 10 groups. Finally, the posterior distributions of these parameters were calculated to discover suitable ranges in simulation.

In this research, a matlab toolbox for global sensitivity analysis (Pianosi et al. 2015) was utilized to analyze the output data.

3 Results

3.1 Model uncertainty analysis

The reliability and uncertainty of the model was studied by setting the threshold of the Nash-Sutcliffe efficiency coefficient (NSE) to 0.5. The 2.5th percentile and the 97.5th percentile of the NSE were chosen to determine the lower and upper bounds of likelihood measure. The simulated results with 95 percent confidence in the three subareas of Lake Taihu are shown in Fig. 3 and Fig. 4.

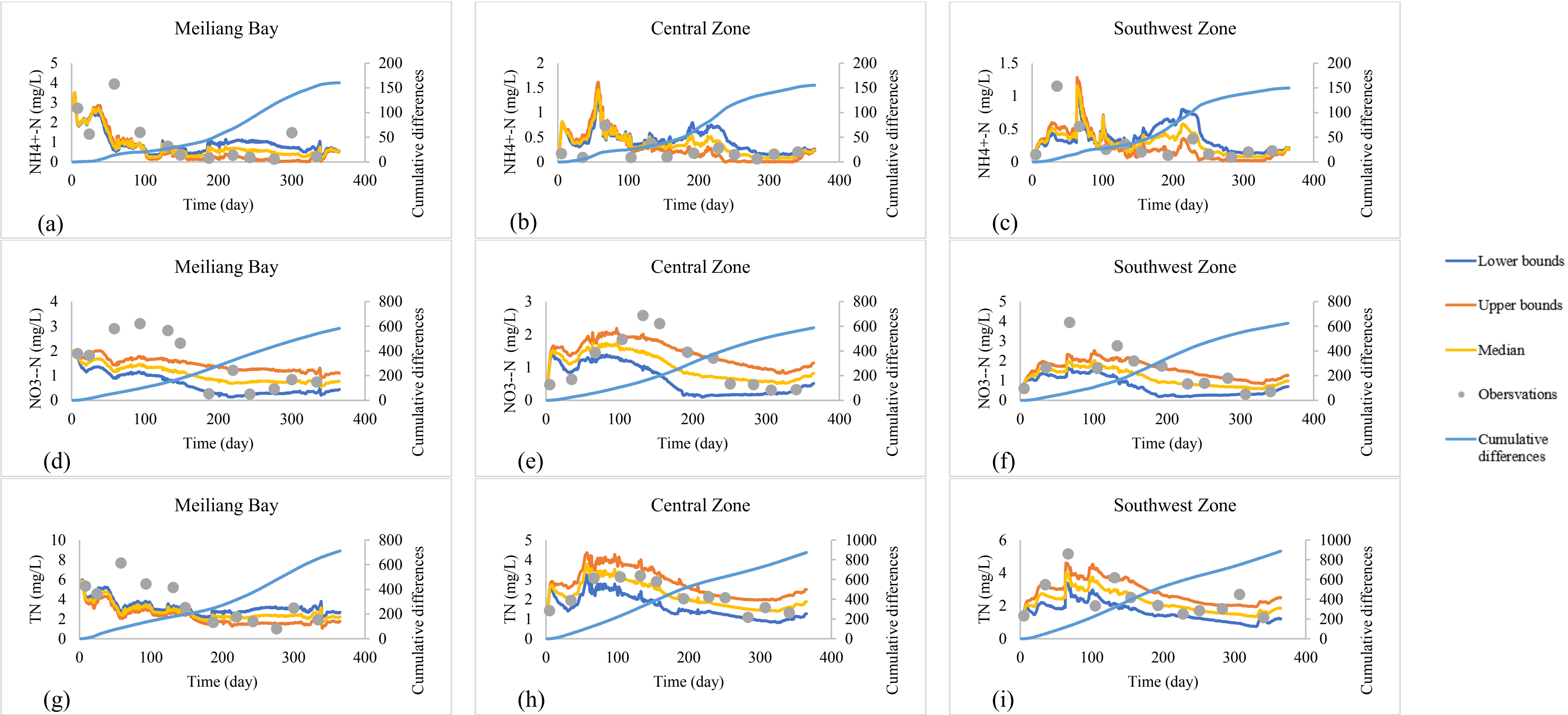
Trends in simulated results were basically consistent with field observations in the three subareas (Fig. 3 and Fig. 4), and the proportion of observations in uncertainty interval (CR) was mostly higher than 66.7% (Table 2) meant that most observations were within the confidence interval. The model was therefore deemed feasible to be utilized in the simulation of water quality in Lake Taihu. The CR was also distinguished between the three subareas. The average CR in Central Zone was the highest (84.7%) and higher than that of Southwest Zone (76.4%). The average CR in Meiliang Bay with a higher indicator concentration was the lowest (66.7%), which indicated that it is difficult to get accurate simulations in Meiliang Bay.

Table 2 Statistics of simulated values and monitoring values for uncertainty analysis.

Indicators	**Meiliang Bay**				**Central Zone**				**Southwest Zone**			
	CR	UI	MC	RI	CR	UI	MC	RI	CR	UI	MC	RI
Ammonia nitrogen (mg/L)	66.7%	0.222	1.113	19.9%	75.0%	0.108	0.217	49.8%	75.0%	0.104	0.281	37.0%
Nitrate nitrogen (mg/L)	58.3%	0.407	1.554	26.2%	75.0%	0.411	1.138	36.1%	83.3%	0.435	1.492	29.2%
Total nitrogen (mg/L)	66.7%	0.497	3.593	13.8%	100.0%	0.610	2.153	28.3%	75.0%	0.620	2.420	25.6%
Phosphate (mg/L)	66.7%	0.014	0.050	27.0%	91.7%	0.010	0.019	52.6%	83.3%	0.011	0.019	57.9%
Total phosphorus (mg/L)	66.7%	0.027	0.108	24.5%	75.0%	0.025	0.084	29.2%	66.7%	0.025	0.085	28.8%
Chlorophyll-a (μg/L)	75.0%	15.59	41.75	37.3%	91.7%	12.28	23.76	46.1%	75.0%	13.00	28.80	45.1%

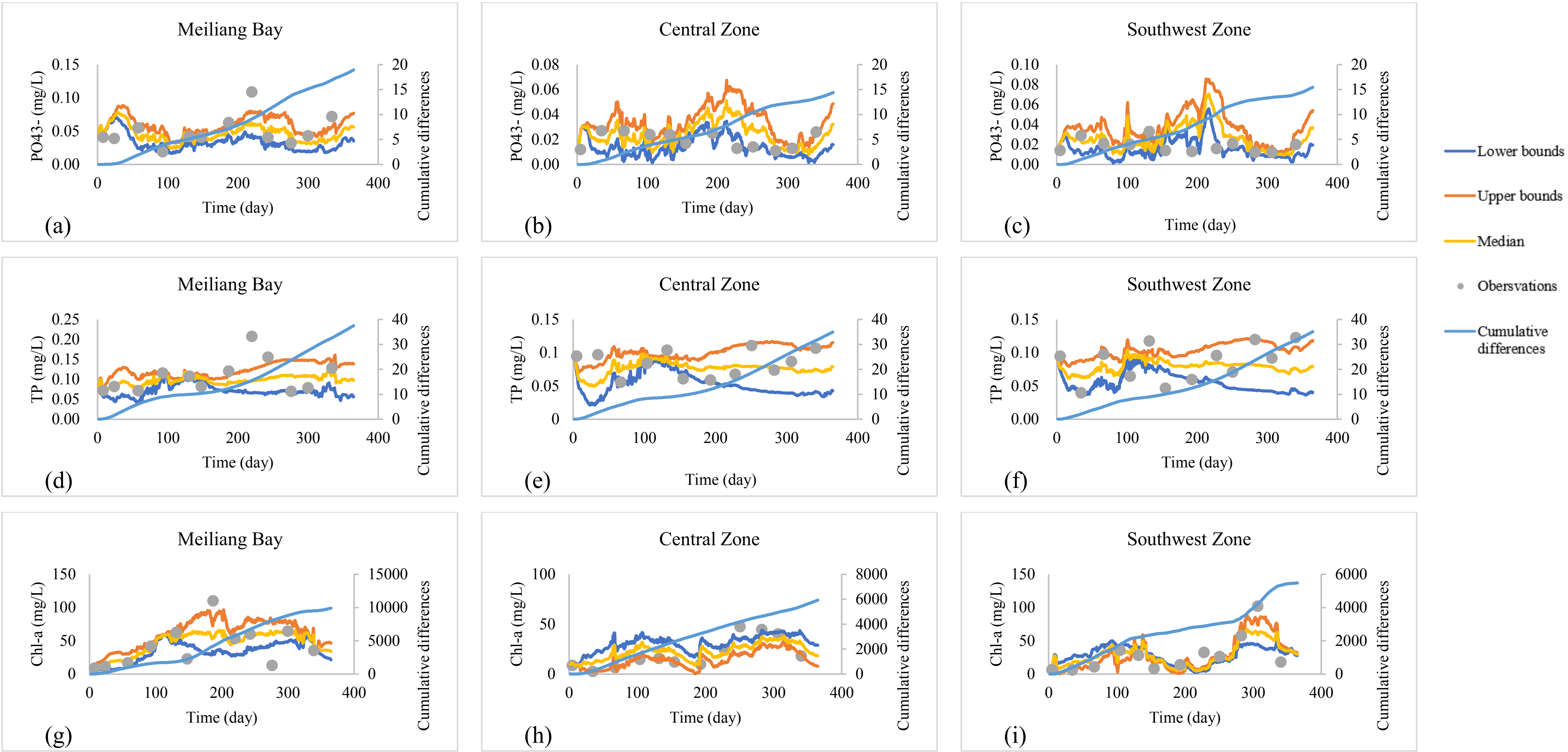
CR, Proportion of observations in uncertainty interval; UI, uncertainty interval between median and lower bounds; MC, Mean concentration of observations; RI, ratio of uncertainty interval to mean concentration.

The uncertainty intervals between the median and lower bounds (UI) were significant, with some of them even accounted for more than half of the mean concentrations from field observations (MC). Therefore, uncertainty resulting from these parameters could not be ignored. The ratio of uncertainty to mean concentration (RI) increased basically with decreased concentration of observations, although the UI decreased at the same time. For example, the RI of Chlorophyll-a simulation in Southwest Zone was 45.1%, higher than that of Meiliang Bay (37.3%, Table 2), although UI decreased from 15.59 to 13.00 μg/L. The UI of different indicators were also variable in simulation of nitrogen. The UI of nitrate nitrogen was greater than that of ammonia nitrogen, especially in the Southwest Zone which showed that the accuracy of nitrate nitrogen simulation was highly important in the simulation of total nitrogen.



304 **Fig.3** Uncertainty interval related to nitrogen in three subareas. (a), (b), and (c) are the simulations for ammonia nitrogen; (d), (e), and (f) are the simulations for

305 nitrate nitrogen; (g), (h), and (i) are the simulations of total nitrogen.



306 **Fig. 4** Uncertainty interval related to phosphorus and chlorophyll-a in three subareas. (a), (b), and (c) are the simulations for phosphate; (d), (e), and (f) are the
307 simulations for total phosphorus; (g), (h), and (i) are the simulations of chlorophyll-a.

In simulation of nitrogen and chlorophyll-a, the cumulative differences between the lower and upper bounds (CD) increased slowly at the beginning, but more rapidly after half of the simulation time. This indicated that the uncertainty of some parameters was strongly related to model simulation time. For example, the CD of ammonia nitrogen in the Central Zone (Fig. 3(b)) increased slowly before 150 days, but more rapidly after that time. In simulation of phosphorus, the CD were founded to be highly related to chlorophyll-a. Especially for phosphate, for example, the uncertainties in Central Zone were lowest when simulation time was about 120 and 300 days, with highest concentrations of chlorophyll-a (Fig. 4(b) (h)).

Some observations were found not to be within the confidence intervals. For example, the simulation of nitrate nitrogen in Meiliang Bay (Fig. 3(d)) did not conform to field observations, and the median of the simulated results underestimated the concentration. In this case, only 58.33% of the monitoring data was within the confidence interval. The model appears to be missing several important nutrients peaks, as it can be easily in Figs. 3 & 4. This result most likely stems from some other uncertainty factors such as inflow rivers, monitoring data and so on, which could also be significant factors and not be ignored when the water quality model is modified.

3.2 Sensitive parameters in the simulation

The maximum vertical distance (MVD), calculated by using the Kolmogorov-Smirnov test (Eq.5), was used to represent sensitivity indices (SI) of parameters. Sensitive parameters with an SI greater than 0.1 are shown in Fig. 5.

The maximum growth rate (PMc), basal metabolism rate (BMRc), predation rate (PRRc), light extinction due to Chlorophyll A (KeChl), and suboptimal temperature effect coefficient for growth (KTG1c) were all found to be sensitive parameters in simulations of all indicators. All of these sensitive parameters are connected with algal growth kinetics which indicated that water quality simulations were influenced by algae.

Sensitive parameters distinguished between different indicators. In the simulation of ammonia nitrogen and nitrate nitrogen, PMc, KeChl and KTG1c were very sensitive parameters. PRRc was found to be the most sensitive parameter in the simulation of total nitrogen but it was not a sensitive parameter in the simulation of ammonia nitrogen and nitrate nitrogen. This may indicate that PRRc is a significant parameter in the simulation of organic nitrogen. KDC, a parameter representing the minimum dissolution rate of DOC, was also a sensitive parameter in the simulation of nitrate nitrogen and total nitrogen which influenced simulations through denitrification. The settling velocity of cyanobacteria (WSc) was the most sensitive parameter in the simulation of phosphate since settling of algae with absorbed phosphate is one way for soluble phosphate to be removed from the aquatic system (Fig. 5(d)). WSc was also a sensitive parameter in the simulation of phosphorus and algae although the sensitivity was lower than that of other parameters such as three important parameters related to algal kinetics (i.e. PMc, PRRc and BMRc). Two parameters related to light and temperature (i.e. KeChl and KTG1c, respectively) were the most important parameters in simulation of algae. TMc1, optimal temperature for algal growth, was also a significant parameter for simulating algae.

Sensitive parameters also varied spatially and were influenced primarily by concentration. The bar charts (Fig. 5), showing six indicators, indicated that some parameters are clearly distinguished between the three subareas such as KTG1c, KeChl and PMc. In the simulation of nitrate nitrogen and algae, the SI of KTG1c in Meiliang Bay was higher than that of the Central Zone and Southwest Zone. For ammonia nitrogen and total nitrogen, the SI of KTG1c in Meiliang Bay was almost two times higher than that of the other two subareas. In simulation of almost all indicators except for phosphate, the SI of KeChl in Meiliang Bay were lower than that of the other two subareas, which demonstrated KeChl was a more sensitive parameter in the Central Zone and Southwest Zone. In the simulation of phosphate, the SI of KeChl and PMc in Meiliang Bay was obviously higher than that of the

Central Zone and Southwest Zone, which became lowest in the simulation of total phosphorus and algae. It indicated that the sensitivities of these two parameters were influenced by both indicators and locations. The SI of other indicators in the three subareas was almost identical which means the parametric sensitivity of these indicators was less affected by location. Although sensitive parameters were distinguished in the three subareas, the situations in the Central Zone and Southwest Zone were similar probably due to the close concentrations in these two subareas. We suggest that sensitivities of these parameters are highly influenced by concentrations of indicators (Fig. 5).

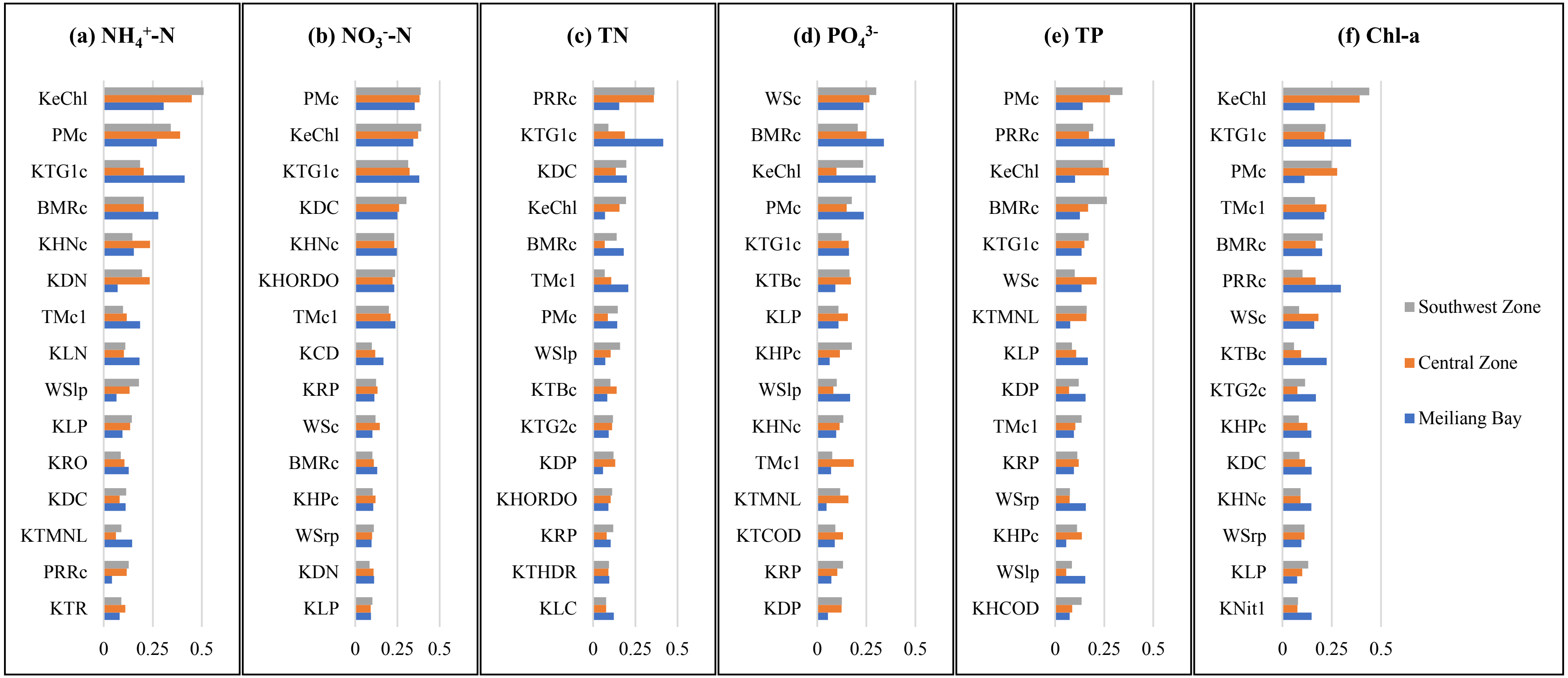


Fig. 5 Sensitive indices in the simulation of water quality.

The cumulative distribution functions (CDFs) of likelihood measures within each group were calculated to be the posterior distributions of parameters (Fig. 6). The sensitivity and the proper range of parameters can be found directly by the deviation of the posterior distribution.

For example, the probability of cumulative distribution functions increased obviously when BMRc>0.04, which mean that the simulation with BMRc>0.04 are more likely to have high likelihood measures. Therefore, the probably suitable range of BMRc was from 0.04 to 0.06/day. Other speculative ranges of sensitive parameters are also shown in Table 3. The CDFs were useful not only for setting parameter ranges, but also for specifying more informative distributions than the uniform or normal distributions used in this analysis. PMc fits a normal or gamma distribution well, which PRRc should probably use a triangle distribution, with suitable values at 0.05.

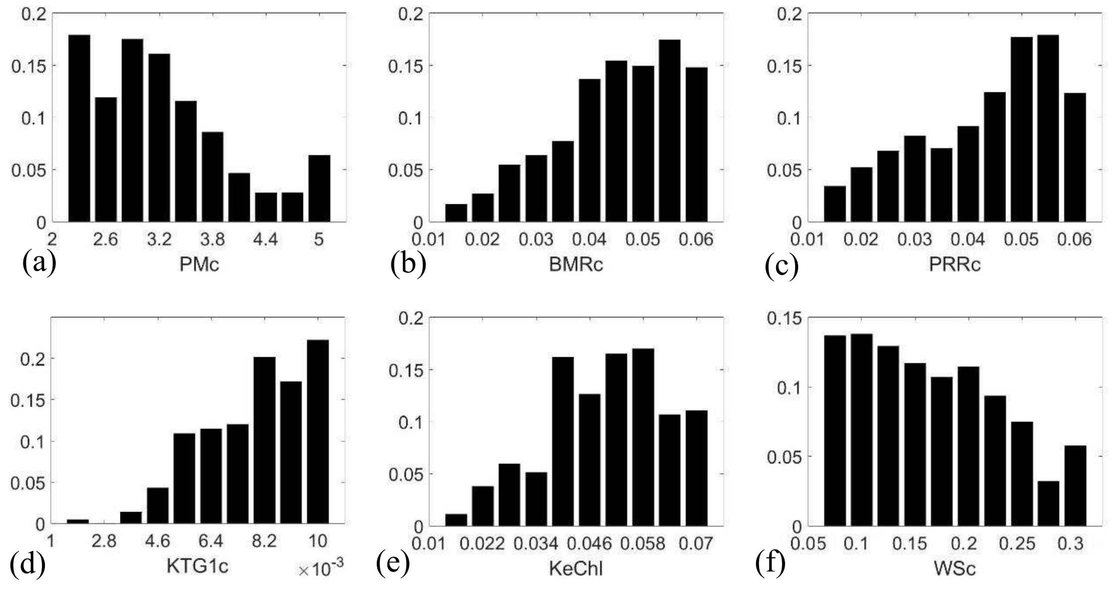


Fig. 6 Posterior distributions of sensitive parameters. X axis is the range of parameters and Y axis is the probability of cumulative distribution functions.

Table 3 Possible range of sensitive parameters.

Parameters	PMc (1/day)	BMRc (1/day)	PRRc (1/day)	KTG1c (--l)	KeChl (1/m per mg/l)	WSc (m/day)
Min	2	0.04	0.04	0.0046	0.034	0.05
Max	3.8	0.06	0.06	0.01	0.058	0.2

4 Discussion

4.1 Influence of algae on parameter sensitivity

Biological activity was found to be an important mechanism in influencing the simulation of water quality, particularly in lakes with higher concentrations of algae. As shown in Fig. 7, most of the sensitive parameters were found to be related to algal growth kinetics, such as PMc, BMRc and PRRc. In the three-dimensional nutrients-algal dynamic model built using EFDC in Lake Dianchi, which is a large shallow lake similar to Lake Taihu and also suffers from algae blooms, the global sensitivity analysis also showed the maximum growth rate and basal metabolism rate were sensitive parameters in the simulation of TN and TP (Yi et al. 2016). In the Venetian Lagoon, a large shallow lake with average depth of 1.1m, maximum growth rate of phytoplankton and zooplankton, also had significant impacts on simulation results (Pastres and Ciavatta 2005; Pastres et al. 1997). We suggest that parameters related to algal growth kinetics are significant parameters for large shallow lakes with high concentrations of algae.

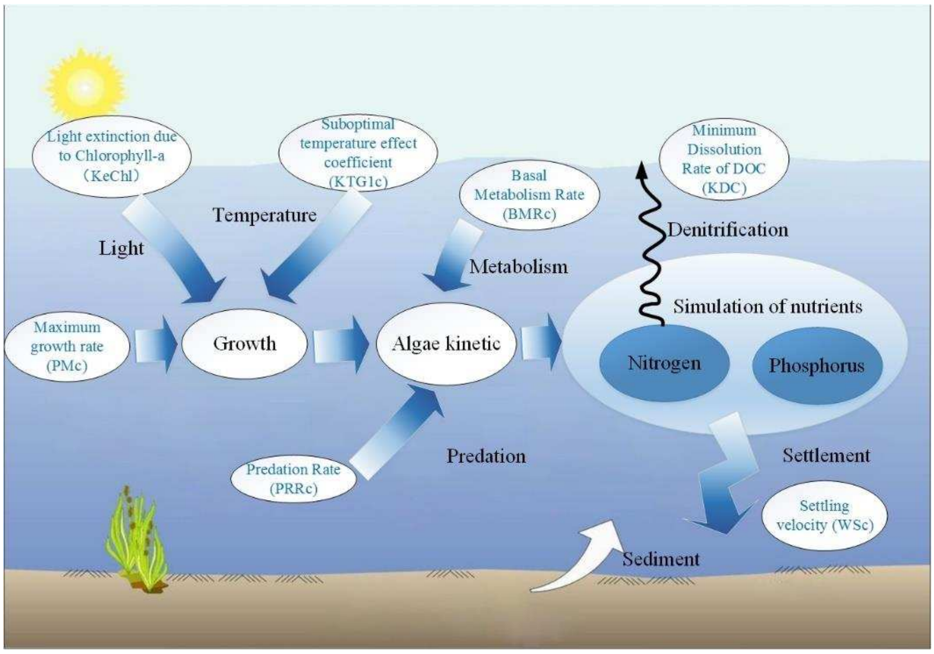


Fig. 7 Relation schema of sensitive parameters in the simulation of water quality. Sensitive parameters in the study were marked in blue.

In this study, the minimum value for PMc was set to 2/day which may be a little higher than the value in ever research (Hoogenhout and Amesz 1965; Edwards et al. 2015; Kruk et al. 2010). From measured values reported in literatures, a mean value for Microcystis (which is common in Taihu) was 0.53/day (temperature-adjusted), or 0.7/day without temperature correction (Robson et al. 2018; Edwards et al. 2015). However, we checked the real time growth rate in our model when PMc was set to 3/day and found the values varied from 0.15/day to 0.6/day which was close to the range reported in literatures. We have conducted several pre-researches with a wider range of PMc and the results showed that the concentration of algae will be quite low if we set the PMc lower than 2. We attributed the difference to the overestimation of settling of algae, which lead to a lower rate of algal increase. Cyanobacterial settling (WSc) was found in this study to be a sensitive parameter, especially in the simulation of phosphorus, in part because it is one of ways for soluble phosphate to be removed from the aquatic system. Another P removal processes is adsorption to suspended or benthic sediment surfaces and it may be compensated for in part by high cyanobacterial settling. Therefore, a higher PMc used would then be needed to compensate for the effect of high cyanobacterial settling on chlorophyll-a concentration and the possible range of PMc would be lower than the speculative range we provided.

Light and temperature impacts on algal growth also have significant influence on models (Benke et al. 2008; Confalonieri 2010). In Meiliang Bay, parameters related to energy such as light and temperature were found to be more sensitive than parameters concerned with nutrients (Li and Chen et al. 2015). In marine biological models, the result of sensitivity analysis also suggested that light limitation was a sensitive parameter on phytoplankton growth (Chu et al. 2007). In our research, light extinction due to Chlorophyll-A (KeChl) was a very sensitive parameter in simulations of all water quality indicators and similar phenomenon was also found in Lake Dianchi (Yi et al. 2016). In these eutrophic lakes, algae concentration is very high and play an important role in light extinction, which in return lead to a great impact on algal growth and then affect the simulation of nutrients. Temperature was also a significant factor in algal growth, and the suboptimal temperature effect coefficient (KTG1c) was a very sensitive parameter in the limitation of temperature in our research. Due to the great change of temperature seasonally in Lake Taihu, temperature effect coefficient was sensitive, which was not found in lakes with little difference in temperature over time like Dianchi (Yi et al. 2016).

4.2 Spatial variability of sensitivity and uncertainty

Sensitive parameters were apparently related to concentrations of water quality indicators in the three subareas. In the Central Zone and Southwest Zone with lower concentrations, the rank of very sensitive parameters was almost identical, while they changed significantly in Meiliang Bay (Table 4). In simulations of phosphorus, for example, BMRc and PRRc were more sensitive in Meilang Bay, while WSc and PMc were very sensitive in other two subareas with lower nutrients concentrations. In Meiliang Bay, KTG1c was the most sensitive parameter in simulations of most indicators, which meant that temperature was the most significant factor in this subarea. In subareas with lower concentrations (i.e. Central Zone and Southwest Zone), KeChl were the most important parameters (Table 4). Thus, influence of light should be given greater attention. We attribute the phenomenon to the difference in limiting factors in three subareas. In subareas with lower algae concentration, algae play an important role in light extinction, which in return lead to a great impact on algal growth and then affect the simulation of nutrients. However, influence of light decreases in subareas with too high algae concentration because algae on the water surface has already intercepted most light. Temperature then became a limiting factor in these subareas.

Not only light and temperature have great impact in simulation, but also other boundary conditions could also be responsible for the spatial variability of sensitivity. For example, wind speed was found to have the largest impact on simulation between in/out flow, wind speed, wind direction and initial water level (Li et al. 2014). Thus, some parameters concerned with wind like wind drag coefficient were found to be very sensitive in our previous research on hydrodynamic conditions (Li and Tang et al. 2015). The effects of external nutrients reductions on algal blooms were investigated to evaluate the influence of boundary conditions on the model and results showed that Chlorophyll a (Chl-a) concentrations only decreased a little when implementing high nutrients reduction scenario (Tang et al. 2016). It is consistent with our results that little parameters related to nutrients were sensitive.

Table 4 Sensitivity ranks of parameters in the three lake subareas.

Subarea	Rank	Ammonia nitrogen	Nitrate nitrogen	Total nitrogen	Phosphate	Total phosphorus	Chlorophyll-A
Meiliang Bay	1	KTG1c	KTG1c	KTG1c	BMRc	PRRc	KTG1c
	2	KeChl	PMc	-	KeChl	-	PRRc
	3	BMRc	KeChl	-	-	-	-
	4	PMc	-	-	-	-	-
Central Zone	1	KeChl	PMc	PRRc	WSc	PMc	KeChl
	2	PMc	KeChl	-	BMRc	KeChl	PMc
	3	-	KTG1c	-	-	-	-
	4	-	KDC	-	-	-	-
Southwest Zone	1	KeChl	KeChl	PRRc	WSc	PMc	KeChl
	2	PMc	PMc	-	-	BMRc	PMc
	3	-	KTG1c	-	-	-	-
	4	-	KDC	-	-	-	-

Uncertainty of simulation also had a close relationship with indicators' concentration in different subareas. Meiliang Bay is connected to some inflow rivers with high concentrations of nutrients and greater benthic fluxes due to thick sediment deposits (Luo et al. 2004). The simulation in this subareas was therefore less influenced by model parameters, and lower concentration subareas should be given much attention when modifying parameters. In addition, currents and waves were weak in this bay area where the impact of wind is expected to be less than other two subareas. The calculation of water quality variables was based on hydrodynamic conditions, strong currents and waves will accelerate transportation and transformation of nutrients, which results in higher relative uncertainty in the Central Zone and Southwest Zone.

Uncertainty of simulation was related to the simulation time as well. According to the results, the uncertainty in the three subareas increased rapidly when the simulation time was over 150 days, while the concentration of algae began to rise and algae blooms frequently occurred at the same time. With increasing temperature and light intensity, algal growth, basal metabolism and some other algal kinetic processes became more active. From the results of the sensitivity analysis that most sensitivity parameters were related to algal kinetics, we infer that the increased uncertainty over time mostly resulted from enhanced algal kinetic processes.

Finally, it was hard to simulate all water quality indicators through modification of model parameters since other uncertain factors also showed significant impact on simulation results. Several important nutrients peaks were missed in Figs. 3 & 4. Almost all of the missed peaks were located in offshore areas (i.e. Meiliang Bay and Southwest Zone) which were highly influenced by boundary conditions. We attributed the result to the uncertainty of nutrients loading data, especially for the non-point source pollution. We checked the rainfall data and found that there is a strong relationship between missed peaks and the intensity of rainfall. We suggested that the non-point source pollution resulted from rainfall was underestimated which caused reduce in nutrients loading.

4.3 Generalization for a larger modelling community and future work

Except external input from rivers and internal input from sediment beds, biological activity is a significant part for nutrients simulation in these models, with more sensitive parameters than that in hydrolysis, mineralization and settlement. Since net algal production can be divided into five phases: algal growth, metabolism, predation, settling, and external sources (Ji 2007), maximum growth rate, basal metabolism rate and predation rate were sensitive apparently, which was found both in our study and other places like Lake Kinneret (based on a DYRESM–CAEDYM model) (Bruce et al. 2006). Light was an important limitation on algae growth and light extinction due to Chlorophyll-A was a very sensitive parameter in this study. However, for some deep lakes like Lake Washington, background light extinction was more sensitive (Arhonditsis and Brett 2005). Thus, light extinction due to Chlorophyll-A in shallow lakes with serious algal blooms were more sensitive than that in deep lakes where background light extinction was more sensitive. Temperature was also a significant factor in algal growth and the optimal temperature effect coefficient was a very sensitive parameter in the limitation of temperature in our research. Seasonal temperature, varying widely in Lake Taihu, was mostly lower than the optimal temperature for cyanobacterial growth. In contrast, the temperature of Lake Dianchi was higher than that of Lake Taihu, and temperature effect coefficient was not a sensitive parameter in the Dianchi Model (Yi et al. 2016). Hence, we infer that the temperature effect coefficient might turn out to be a sensitive parameter in lakes with an obvious seasonal temperature variation. Some water quality models used widely are based on similar theory which contains dissolved oxygen, algae, nutrients and so on. Some modern models are only subtle variations on model structures established in the 1970s or earlier (Franks 2009). The governing equations in these models such as EFDC, WASP and DYRESM are similar as well (Park et al. 2005; Cerco and Cole 1993), which encourage us to extend the results in this study to a larger modelling community.

Producing a believable output requires not only a realistic growth rate response to limiting nutrients but also a realistic consumption of non’ or lesser limiting nutrients (Flynn 2003; Flynn 2005). For the future work, variable stoichiometry phytoplankton models like Caperon-Meyer quota model need to be considered for non-steady state applications rather than some traditional models like Michaelis-Menten nutrient kinetics (Flynn 2008, 2005; Flynn and Mitra 2016). Though this requires better statistical comparisons of models and data, it can make planktonic ecosystem models much more powerful tools (Franks 2009). Redfield–Monod models often use nutrient limitation as a significant factor controlling phytoplankton growth, and yet biologically such nutrient limitation is associated with significant variation in elemental stoichiometry (Flynn 2010) such as the variable stoichiometry (C:N:P and in some models C:Chl) of phytoplankton cells (Jackson et al. 2017; Butenschön et al. 2016; Robson 2014; Baird et al. 2013; Flynn 2001; Droop 1975). It can demonstrate the behavior of the dynamic Chl parameterization over a range of light- and nutrient-limiting environments for phytoplankton of different sizes and growth rates (Baird et al. 2013). The appropriate description of the control of the transport of the non-limiting nutrient is also important and a fixed algal N:P should not be assumed (Flynn 2008).

Including zooplankton explicitly rather than a fixed predation rate leads to much more realistic plankton dynamics. Due to the complexity of zooplankton model, there are no advanced module in EFDC currently. Current knowledge of plankton ecology ascribes a large proportion of zooplankton losses to zooplankton cannibalism and carnivory, rather than via the activity of higher trophic levels beyond the plankton. Planktonic ecosystem models typically represent all zooplankton losses by mathematically (rather than biologically) justified closure functions. Even these closure functions include zooplanktonic cannibalism and carnivory, these processes are not explicitly implemented within the grazing function. While the biomass outputs may appear similar, the fate of annual primary production and f-ratios vary widely (Mitra 2009).

5 Conclusions

In this research, nutrients were chosen as output indicators and 40 parameters were sampled. GLUE and RSA methods were applied to analyze the parametric uncertainty and sensitivity of the EFDC model in Lake Taihu, a typical large shallow lake. Three parameters related to algal kinetics (i.e. PMc, BMRc and PRRc) were sensitive parameters in the simulation of water quality in the eutrophic waterbody. For shallow lakes with frequent algal blooms light extinction due to Chlorophyll-a is also a sensitive parameter, while background light extinction has also been shown to be sensitive for deep lakes. For lakes with seasonal temperature variation, the temperature effect coefficient for algal growth is sensitive. Sensitive parameters also varied in different lake subareas. For high nutrients and algae concentration subareas, temperature was more likely to be a limiting factor, whereas sensitive factors could be light in lower concentration subareas. Since most sensitive parameters were related to algae, uncertainty of simulation results increased with increase in algal kinetic processes over time. It also varied in different subareas. Lower nutrients and algae concentration subareas were more easily influenced by model parameters and nearshore areas were highly influenced by boundary conditions. For the future work, variable stoichiometry phytoplankton models will be considered and zooplankton will be integrated into the model explicitly rather than a fixed predation rate.

Acknowledgement

The authors wish to express their great gratitude to the toolbox developed by Pianosi et al. and thank the Chinese National Science Foundation (No.51579071, No.51379061), National Science Funds for Creative Research Groups of China (No. 51421006), Innovative Research Team in Jiangsu Province and a Project Funded by the Priority Academic Program Development of Jiangsu Higher Education Institutions for their financial support.

References:

Arhonditsis, George B., and Michael T. Brett. 2005. Eutrophication model for Lake Washington (USA). *Ecological Modelling* 187 (2-3):140-178.

Baird, Mark E., Peter J. Ralph, Farhan Rizwi, Karen Wild-Allen, and Andrew D. L. Steven. 2013. A dynamic model of the cellular carbon to chlorophyll ratio applied to a batch culture and a continental shelf ecosystem. *Limnology and Oceanography* 58 (4):1215-1226.

Benke, Kurt K., Kim E. Lowell, and Andrew J. Hamilton. 2008. Parameter uncertainty, sensitivity analysis and prediction error in a water-balance hydrological model. *Mathematical and Computer Modelling* 47 (11 – 12):1134 – 1149.

Beven, Keith, and Andrew Binley. 1992. The Future Of Distributed Models—Model Calibration And Uncertainty Prediction. *Hydrological Processes* 6 (3):279 – 298.

Blasone, Roberta Serena, Jasper A. Vrugt, Henrik Madsen, Rosbjerg Dan, Bruce A. Robinson, and George A. Zyvoloski. 2008. Generalized likelihood uncertainty estimation (GLUE) using adaptive Markov Chain Monte Carlo sampling. *Advances in Water Resources* 31 (4):630-648.

Bruce, Louise C., David Hamilton, Jörg Imberger, Gideon Gal, Moshe Gophen, Tamar Zohary, and K. David Hambright. 2006. A numerical simulation of the role of zooplankton in C, N and P cycling in

Lake Kinneret, Israel. *Ecological Modelling* 193 (3-4):412-436.

Butenschön, Momme, James Clark, John N. Aldridge, Julian Icarus Allen, Yuri Artioli, Jeremy Blackford, Jorn Bruggeman, Pierre Cazenave, Stefano Ciavatta, Susan Kay, Gennadi Lessin, Sonja van Leeuwen, Johan van der Molen, Lee de Mora, Luca Polimene, Sevrine Sailley, Nicholas Stephens, and Ricardo Torres. 2016. ERSEM 15.06: a generic model for marine biogeochemistry and the ecosystem dynamics of the lower trophic levels. *Geoscientific Model Development* 9 (4):1293-1339.

Cerco, Carl F., and Thomas Cole. 1993. Three-dimensional eutrophication model of Chesapeake Bay. *Journal of Environmental Engineering* 119 (119):1006-1025.

Chu, Peter C., Leonid M. Ivanov, and Tetyana M. Margolina. 2007. On non-linear sensitivity of marine biological models to parameter variations. *Ecological Modelling* 206 (3):369-382.

Confalonieri, Roberto. 2010. Monte Carlo based sensitivity analysis of two crop simulators and considerations on model balance. *European Journal of Agronomy* 33 (2):89-93.

Droop, M. R. 1975. nutrient status of algal cells in batch culture. *Journal of the Marine Biological Association of the United Kingdom* 55 (3):541-555.

Edwards, Kyle F., Christopher A. Klausmeier, and Elena Litchman. 2015. Nutrient utilization traits of phytoplankton. *Ecology* 96 (8):2311-2311.

Flynn, K. J. 2005. Castles built on sand: dysfunctionality in plankton models and the inadequacy of dialogue between biologists and modellers. *Journal of Plankton Research* 27 (12):1205-1210.

Flynn, K. J. 2008. The importance of the form of the quota curve and control of non-limiting nutrient transport in phytoplankton models. *Journal of Plankton Research* 30 (4):423-438.

Flynn, Kevin J. 2001. A mechanistic model for describing dynamic multi-nutrient, light, temperature interactions in phytoplankton. *Journal of Plankton Research* 23 (9):977-997.

Flynn, Kevin J. 2003. Modelling multi-nutrient interactions in phytoplankton; balancing simplicity and realism. *Progress in Oceanography* 56 (2):249-279.

Flynn, Kevin J. 2010. Ecological modelling in a sea of variable stoichiometry: Dysfunctionality and the legacy of Redfield and Monod. *Progress in Oceanography* 84 (1-2):52-65.

Flynn, Kevin J., and Aditee Mitra. 2016. Why Plankton Modelers Should Reconsider Using Rectangular Hyperbolic (Michaelis-Menten, Monod) Descriptions of Predator-Prey Interactions. *Frontiers in Marine Science* 3.

Franks, P. J. S. 2009. Planktonic ecosystem models: perplexing parameterizations and a failure to fail. *Journal of Plankton Research* 31 (11):1299-1306.

Gao, XiaoMeng, Yiping Li, Chunyan Tang, Kumud Acharya, Wei Du, Jianwei Wang, Liancong Luo, Huiyun Li, Shujun Dai, Zhongbo Yu, Jalil Abdul, Wenfei Yu, Shuangshuang Zhang, Robert Bofah-Buoh, Mercy Jepkirui, Xuchuan Lu, and Baozhu Pan. 2017. Using ADV for suspended sediment concentration and settling velocity measurements in large shallow lakes. *Environmental Science and Pollution Research* 24 (3):2675-2684.

Gupta, Hoshin Vijai, Soroosh Sorooshian, and Patrice Ogou Yapo. 2000. Toward improved calibration of hydrologic models: Multiple and noncommensurable measures of information. *Water Resources Research* 34 (4):3663-3674.

Hamrick, J. M. 1996. User's Manual For the Environmental Fluid Dynamics Computer Code. *Aquatic Ecosystem Health & Management*.

He, Guojian, Hongwei Fang, Sen Bai, Xiaobo Liu, Minghong Chen, and Jing Bai. 2011. Application of a three-dimensional eutrophication model for the Beijing Guanting Reservoir, China. *Ecological Modelling* 222 (8):1491-1501.

Herman, J. D., J. B. Kollat, P. M. Reed, and T. Wagener. 2013. From maps to movies: high resolution time-varying sensitivity analysis for spatially distributed watershed models. *Hydrology & Earth System Sciences* 17 (12):5109-5125.

Herman, J. D., J. B. Kollat, P. M. Reed, and T. Wagener. 2013. Technical note: Method of Morris effectively reduces the computational demands of global sensitivity analysis for distributed watershed models. *Hydrology & Earth System Sciences Discussions* 10 (4):4275-4299.

Hoogenhout, H., and J. Amesz. 1965. Growth rates of photosynthetic microorganisms in laboratory cultures. *Archiv für Mikrobiologie* 50 (1):10－25.

Huang, Jian, Qiujin Xu, Beidou Xi, Xixi Wang, Weiping Li, Guang Gao, Shouliang Huo, Xunfeng Xia, Tiantian Jiang, and Danfeng Ji. 2015. Impacts of hydrodynamic disturbance on sediment resuspension, phosphorus and phosphatase release, and cyanobacterial growth in Lake Tai. *Environmental Earth Sciences* 74 (5):3945-3954.

Jackson, Thomas, Shubha Sathyendranath, and Trevor Platt. 2017. An Exact Solution For Modeling Photoacclimation of the Carbon-to-Chlorophyll Ratio in Phytoplankton. *Frontiers in Marine Science* 4.

Janse, J. H., M. Scheffer, L. Lijklema, L. Van Liere, J. S. Sloot, and W. M. Mooij. 2010. Estimating the critical phosphorus loading of shallow lakes with the ecosystem model PCLake: Sensitivity, calibration and uncertainty. *Ecological Modelling* 221 (4):654-665.

Ji, Zhen Gang. 2007. *Hydrodynamics and water quality : modeling rivers, lakes, and estuaries*: Wiley-Interscience.

Kaiming, H. U., Shui Wang, and Yong Pang. 2014. Suspension-sedimentation of sediment and release amount of internal load in Lake Taihu. *Journal of Lake Sciences* 26 (2):191-199.

Kim, Seon Joo, Dong Il Seo, and Ki Hong Ahn. 2011. Estimation of Proper EFDC Parameters to Improve the Reproductability of Thermal Stratification in Korea Reservoir. *Journal of Korea Water Resources Association* 44 (9):741-751.

Kottegoda, N. T., and Renzo Rosso. 1997. Statistics, probability, and reliability for civil and environmental engineers. *Journal of America Chemistry Society* 10 (2):501-503.

Kruk, Carla, Vera L. M. Huszar, Edwin T. H. M. Peeters, Sylvia Bonilla, Luciana Costa, Miquel Lurling, Colin S. Reynolds, and Marten Scheffer. 2010. A morphological classification capturing functional variation in phytoplankton. *Freshwater Biology* 55 (3):614-627.

Li, K., L. Zhang, Y. Li, L. Zhang, and X. Wang. 2015. A three-dimensional water quality model to evaluate the environmental capacity of nitrogen and phosphorus in Jiaozhou Bay, China. *Marine Pollution Bulletin* 91 (1):306.

Li, Yiping, Chunyan Tang, Jianting Zhu, Baozhu Pan, Desmond O. Anim, Yong Ji, Zhongbo Yu, and Kumud Acharya. 2015. Parametric uncertainty and sensitivity analysis of hydrodynamic processes for a large shallow freshwater lake. *Hydrological Sciences Journal/Journal des Sciences Hydrologiques* 60 (6):1078-1095.

Li, Yiping, Kumud Acharya, and Zhongbo Yu. 2011. Modeling impacts of Yangtze River water transfer on water ages in Lake Taihu, China. *Ecological Engineering* 37 (2):325-334.

Li, Yiping, Kumud Acharya, and Zhongbo Yu. 2011. Modeling impacts of Yangtze River water transfer on water ages in Lake Taihu, China. *Ecological Engineering* 37 (2):325-334.

Li, YiPing, Li Qiu, Tang ChunYan, MinSheng Bu, Wei Tian, ZhongBo Yu, and Acharya Kumud. 2014. Uncertainty and sensitivity analysis of input conditions in large shallow lake hydrodynamic model. *China Environmental Science* 34 (2):410-416.

Li, Zhijie, Qiuwen Chen, and Qiang Xu. 2015. Modeling algae dynamics in Meiliang Bay of Taihu Lake and parameter sensitivity analysis. *Journal of Hydro-environment Research* 9 (2):216-225.

Liu, Jiajia, Peifang Wang, Chao Wang, Jin Qian, J. Hou, and Bin Hu. 2014. The macrobenthic community and its relationship to the contents of heavy metals in the surface sediments of Taihu Lake, China. *Fresenius Environmental Bulletin* 23 (7):1697-1707.

Luo, Lian Cong, Bo Qiang Qin, and Guang Wei Zhu. 2004. CALCULATION OF TOTAL AND RESUSPENDABLE SEDIMENT VOLUME IN LAKE TAIHU. *Oceanologia Et Limnologia Sinica*.

Manache, Gemma, and Charles S. Melching. 2008. Identification of reliable regression- and correlation-based sensitivity measures for importance ranking of water-quality model parameters. *Environmental Modelling & Software* 23 (5):549-562.

Mao, J., Q. Chen, and Y. Chen. 2008. Three-dimensional eutrophication model and application to Taihu Lake, China. *Journal of Environmental Sciences* 20 (3):278-84.

Missaghi, Shahram, Miki Hondzo, and Charles Melching. 2013. Three-Dimensional Lake Water Quality Modeling: Sensitivity and Uncertainty Analyses. *Journal of Environmental Quality* 42 (6):1684-1698.

Mitra, Aditee. 2009. Are closure terms appropriate or necessary descriptors of zooplankton loss in nutrient－phytoplankton－zooplankton type models? *Ecological Modelling* 220 (5):611-620.

Muleta, Misgana K., John W. Nicklow, Misgana K. Muleta, and John W. Nicklow. 2005. Sensitivity and uncertainty analysis coupled with automatic calibration for a distributed watershed model. *Journal of Hydrology* 306 (1-4):127-145.

Neumann, M. B. 2012. Comparison of sensitivity analysis methods for pollutant degradation modelling: a case study from drinking water treatment. *Science of the Total Environment* 433 (433):530-537.

Omlin, Martin, Roland Brun, and Peter Reichert. 2001. Biogeochemical model of Lake Zürich: sensitivity, identifiability and uncertainty analysis. *Ecological Modelling* 141 (1-3):105-123.

Paerl, H. W., H. Xu, M. J. Mccarthy, G. Zhu, B. Qin, Y. Li, and W. S. Gardner. 2011. Controlling harmful cyanobacterial blooms in a hyper-eutrophic lake (Lake Taihu, China): the need for a dual nutrient (N & P) management strategy. *Water Research* 45 (5):1973.

Pang, Yong, and Qianqian Wang. 1994. NUMERICAL SIMULATIONS AND THEIR VERIFICATION WITH UNUNIFORM WIND STRESS IN TAIHU LAKE. *Transaction of Oceanology & Limnology*.

Park, K., H. S. Jung, H. S. Kim, and S. M. Ahn. 2005. Three-dimensional hydrodynamic-eutrophication model (HEM-3D): application to Kwang-Yang Bay, Korea. *Marine Environmental Research* 60 (2):171-93.

Park, No Suk, Seong Su Kim, Sun A. Chong, Jong Oh Kim, Do Hwan Kim, and Moon Sun Kang. 2012. Modelling the Dispersion Behavior of Conservative Pollutants within Daechung Dam using EFDC-Hydro. *Journal of Korean Society of Water and Wastewater* 26 (5):705-712.

Pastres, R., D. Franco, G. Pecenik, C. Solidoro, and C. Dejak. 1997. Local sensitivity analysis of a distributed parameters water quality model. *Reliability Engineering and System Safety* 57 (1):21-30.

Pastres, Roberto, and Stefano Ciavatta. 2005. A comparison between the uncertainties in model parameters and in forcing functions: its application to a 3D water-quality model. *Environmental Modelling & Software* 20 (8):981 – 989.

Pianosi, Francesca, Fanny Sarrazin, and Thorsten Wagener. 2015. A Matlab toolbox for Global Sensitivity Analysis. *Environmental Modelling & Software* 70:80-85.

Qin, Boqiang. 2009. Progress and prospect on the eco-environmental research of Lake Taihu. *Journal of Lake Sciences* 21 (4):445-455.

Qiu, H., J. Geng, H. Ren, and Z. Xu. 2015. Phosphite flux at the sediment-water interface in northern Lake Taihu. *Science of the Total Environment* 543 (Pt A):67.

Radwan, Mona, Patrick Willems, and Jean Berlamont. 2002. Sensitivity and uncertainty analysis of river water quality modelling. *Journal of Hydroinformatics* 6 (2):83-99.

Robson, Barbara J. 2014. State of the art in modelling of phosphorus in aquatic systems: Review, criticisms and commentary. *Environmental Modelling & Software* 61:339-359.

Robson, Barbara J., George B. Arhonditsis, Mark E. Baird, Jerome Brebion, Kyle F. Edwards, Leonie Geoffroy, Marie-Pier Hébert, Virginie van Dongen-Vogels, Emlyn M. Jones, Carla Kruk, Mathieu Mongin, Yuko Shimoda, Jennifer H. Skerratt, Stacey M. Trevathan-Tackett, Karen Wild-Allen, Xiangzhen Kong, and Andy Steven. 2018. Towards evidence-based parameter values and priors for aquatic ecosystem modelling. *Environmental Modelling & Software* 100 (Supplement C):74-81.

Seo, Dong Il, and Min Ae Kim. 2011. Application of EFDC and WASP7 in Series for Water Quality Modeling of the Yongdam Lake, Korea. *Journal of Korea Water Resources Association* 44 (6):439-447.

Song, Yuzhi, Boqiang Qin, Longyuan Yang, and H. U. Weiping. 2005. Primary Estimation of Atmospheric Wet Deposition of Nitrogen to Aquatic Ecosystem of Lake Taihu. *Journal of Lake Science*.

Tang, Chunyan, Yiping Li, and Kumud Acharya. 2016. Modeling the effects of external nutrient reductions on algal blooms in hyper-eutrophic Lake Taihu, China. *Ecological Engineering* 94:164-173.

Wang, Jing, Xin Li, Ling Lu, and Feng Fang. 2013. Parameter sensitivity analysis of crop growth models based on the extended Fourier Amplitude Sensitivity Test method. *Environmental Modelling & Software* 48 (5):171-182.

Wang, Q., S. Li, P. Jia, C. Qi, and F. Ding. 2013. A review of surface water quality models. *The Scientific World Journal* 2013 (3):231768.

Wang, Yuhui, Yunzhong Jiang, Weihong Liao, Pin Gao, Xiaomin Huang, Hao Wang, Xinshan Song, and Xiaohui Lei. 2014. 3-D hydro-environmental simulation of Miyun reservoir, Beijin. *Journal of Hydro-environment Research* 8 (4):383-395.

Wang, Z., R. Zou, X. Zhu, B. He, G. Yuan, L. Zhao, and Y. Liu. 2014. Predicting lake water quality responses to load reduction: a three-dimensional modeling approach for total maximum daily load. *International Journal of Environmental Science and Technology* 11 (2):423-436.

Wu, Guozheng, and Zongxue Xu. 2011. Prediction of algal blooming using EFDC model: Case study in the Daoxiang Lake. *Ecological Modelling* 222 (6):1245-1252.

Xu, Chonggang, and George Zdzislaw Gertner. 2008. Uncertainty and sensitivity analysis for models with correlated parameters. *Reliability Engineering & System Safety* 93 (10):1563-1573.

Xu, J., Y. Li, and G. Huang. 2013. A Hybrid Interval-Robust Optimization Model for Water Quality Management. *Environmental Engineering Science* 30 (5):248-263.

Yang, L. Y., B. Q. Qin, W. P. Hu, L. C. Luo, and Y. Z. Song. 2007. The atmospheric deposition of nitrogen and phosphorus nutrients in Taihu Lake. *Oceanologia Et Limnologia Sinica* 38:104-110.

Yi, Xuan, Rui Zou, and Huaicheng Guo. 2016. Global sensitivity analysis of a three-dimensional nutrients-algae dynamic model for a large shallow lake. *Ecological Modelling* 327:74-84.

Youngteck, Hur, and Park Jinhyeog. 2009. Assessment of EFDC model for hydrodynamic analysis in the Nakdong River. *Journal of Korea Water Resources Association* 42 (4):309-317.

Yu, J., C. Fan, J. Zhong, Y. Zhang, C. Wang, and L. Zhang. 2016. Evaluation of in situ simulated dredging to reduce internal nitrogen flux across the sediment-water interface in Lake Taihu, China. *Environmental Pollution* 214:866.

Zhang, Yuchao, Lin Shan, Jianping Liu, Qian Xin, and Ge Yi. 2010. Time-series MODIS Image-based Retrieval and Distribution Analysis of Total Suspended Matter Concentrations in Lake Taihu (China). *International Journal of Environmental Research & Public Health* 7 (9):3545-3560.

Zhu, Guangwei, Boqiang Qin, Guang Gao, Lu Zhang, Liancong Luo, and Yunlin Zhang. 2007. Effects of hydrodynamics on phosphorus concentrations in water of Lake Taihu, a large, shallow, eutrophic lake of China. *Hydrobiologia* 581 (1):53-61.