Desalination and Water Treatment
www.deswater.com

doi: 10.5004/dwt.2020.25310

187 (2020) 133–143
May

Multi-parameter water quality testing model for marine environmental pollution emergency response

Ye Chen[a,b,*], Qingyun Ma[a,b], Chao Liu[a,b], Qiang Shu[a,b]

[a]*College of Marine Science and Engineering, Nanjing Normal University, Nanjing 210023, China, email: chenyensd@163.com (Y. Chen)*
[b]*Jiangsu Center for Collaborative Innovation in Geographical Information Resource Development and Application, Nanjing Normal University, Nanjing 210023, China*

Received 29 June 2019; Accepted 18 December 2019

ABSTRACT

When building a multi-parameter water quality testing model for marine environmental pollution emergency response, the characteristics of marine environmental data are analyzed based on the method of a data-driven model artificial neural network, and the mapping relationship between state variables of the marine environment is established by taking state variables of the marine environment as input-output parameters of the model. The method of emergency multi-parameter inversion of the combined unit model is used to optimize the inversion of emergency parameters (chemistry and biology) of a data-driven model with regional variation, and to invert the near-optimal solution. Based on the inversion results, a non-conservative water quality testing model of marine environmental pollution is constructed from the two emergency parameters of chemistry and biology. This model mainly studies the decomposition rate of nitrogen and phosphorus and the effects of phytoplankton growth, respiration, withering and sedimentation on the nutrient value from the two aspects of chemical decomposition speed and biological process which affect the change of the nutrient value of marine environmental pollution. The water quality concentration of the marine environment is determined according to nutrient value, and the ocean ring is realized. The test results of the water quality test model are as follows: the predicted values of chlorophyll and inorganic nitrogen content in Liaodong Bay and Bohai Bay, China is in good agreement with the measured values, and the predicted values of inorganic nitrogen, chlorophyll current and water level in the nutrient salts of Liaodong Bay and Bohai Bay are in good agreement with the measured values. The test results are of high accuracy.

Keywords: Marine Environment; Pollution; Parameter Inversion; Emergency Multi-Parameter; Water Quality; Test Model; Nutrients

1. Introduction

In recent years, with the rapid development of the domestic economy, the problem of marine pollution has become more and more serious. Some factories directly discharged pollutants into the sea, which not only caused great damage to the marine environment but also brought a certain degree of potential safety hazards to people's health [1]. Since the 1990s, the area of coastal water quality in China which is inferior to that of a class of seawater quality standards has risen from 100,000 square kilometers in 1992 to 220,000 square kilometers in 1999, with an average annual growth rate of 14.6%. Since 1999, China's marine environmental protection work has achieved initial results, the overall pollution situation has been improved [2], the momentum of pollution aggravation has been curbed, and the area of the whole sea area that does not meet the water quality standards of clean sea areas has decreased from 220,000 square kilometers in 1999 to 169,000 square kilometers in 2003, a decrease of 16.3%. The environmental pollution situation has been preliminarily improved [3–5]. However, the data of 2004 show that the area of the whole sea area which fails to meet the water quality standard

* Corresponding author.

of clean sea area is about 196,000 square kilometers, which is about 27,000 square kilometers more than that of 2003, and the area of moderate and seriously polluted coastal waters in China has increased [6].

Marine environmental pollution hinders the development of the domestic economy to a certain extent, so it is particularly important to monitor marine environmental pollution in an emergency way, which requires relevant personnel to strengthen emergency multi-parameter testing of water quality. The uncertainty of marine environmental pollution parameters is a major problem in research and application [7]. Many foreign scholars have done a lot of research in the field of marine environmental pollution emergency multi-parameter water quality testing. The influence of metal concentration in the Black Sea Bay on the marine environment and the changing trend of water quality in Kamchia River are analyzed by the regression method. The method only considers the change of chemical element content in seawater, but not the biological effect of biological content in seawater on water quality.

In this paper, a multi-parameter water quality testing model for marine environmental pollution emergency is constructed. Considering several emergency parameters, the changes of chemical substances and plankton contents in the marine environment are studied, and the effects of the changes of chemical substances and plankton contents on marine environmental water quality are analyzed [8,9]. The measured water quality results are basically consistent with the measured values. Therefore, the multi-parameter water quality testing model for marine environmental pollution emergency is of great significance for monitoring the marine environment.

2. Materials and methods

2.1. Emergency multi-parameter inversion

2.1.1. Artificial neural network method of a data-driven model

Different from the traditional engineering numerical model, the data-driven model is based on limited knowledge of marine environment physics. It only takes the state variables of the marine environment as input-output parameters of the model, analyses the characteristics of the marine environment data [10], and establishes the mapping relationship between the state variables of the marine environment (reference formula (1)). It is realized by an artificial neural network, fuzzy logic, expert system and machine learning. The neural network BP algorithm can approximate any non-linear continuous function based on training samples. By learning input-output sample data, the functional relationship between them is fitted. In this paper, an artificial neural network BP algorithm model is proposed. Only when the weight is adjusted, and additional momentum term with an assignment of 0.5 is introduced, and the learning rate is 0.05.

$$\left(y_1,\ldots,y_i,\ldots,y_m\right)=F\left(x_1,\ldots,x_i,\ldots,x_n\right) \tag{1}$$

In Eq. (1), $(x_1,\ldots,x_i,\ldots,x_n)$ and $(y_1,\ldots,y_i,\ldots,y_m)$ are input-output variables of the state of marine environment respectively, and F is a function reflecting the relationship between input-output variables.

2.1.2. Emergency multi-parameter inversion method and steps of the combined unit model

In this paper, the study area is divided into several units. The concentration of pollutants in each unit is calculated by the numerical calculation of the design conditions of the water quality test model. The relationship between state variables and control variables (F in the same Eq. (1) is established by the method of a data-driven model artificial neural network, $(x_1,\ldots,x_i,\ldots,x_n)$ represents the concentration of pollutants at the observation points in the domain, and $(y_1,\ldots,y_i,\ldots,y_m)$ represents the model parameter, is inverted with the measured data [11]. The specific implementation steps are as follows:

- *Step 1*: Selection of control variables:

  The seawater quality testing model includes a large number of parameters. If all the parameters are used as control variables, there will be great uncertainty. Therefore, emergency parameters (chemical parameters and biological parameters) should be selected as control variables.
- *Step 2*: Study the division of units in the sea area:

  According to the distribution of geographic location and measured location, the study area is divided into N units, and an emergency parameter a in the model is set to $(a_1,\ldots,a_i,\ldots,a_n)$.
- *Step 3*: The numerical calculation of seawater quality test model:

  For m control variables, n points are selected for each control variable in the range of values, to fully reflect the response of the marine environment to the change of parameters combination, the principle of multi-parameter matching design is adopted, and the $\prod_{i=m}\left[c_n^1\right]_i=n^m$ operating conditions are obtained through combination. The multi-parameter matching design conditions are calculated by using the seawater quality model, and the pollutant concentration results of the observation points in each unit are output.
- *Step 4*: Emergency multi-parameter combination unit inversion based on the data-driven model:

  Considering the dynamic changes of model parameters among different units in the study area, the results of pollutant concentration at the internal observation points and the corresponding control variables are used as sample data to learn the data-driven model, and the relationship formula between them is obtained.

$$\begin{bmatrix}\left(a_1,\ldots,b_1,\ldots,z_1\right)\\\left(a_2,\ldots,b_2,\ldots,z_2\right)\\\cdots\\\left(a_N,\ldots,b_N,\ldots,z_N\right)\end{bmatrix}=F\begin{bmatrix}\left(\mathrm{St}_1^1,\ldots,\mathrm{St}_1^2,\ldots,\mathrm{St}_1^k\right)\\\left(\mathrm{St}_2^1,\ldots,\mathrm{St}_2^2,\ldots,\mathrm{St}_2^k\right)\\\cdots\\\left(\mathrm{St}_N^1,\ldots,\mathrm{St}_N^2,\ldots,\mathrm{St}_N^k\right)\end{bmatrix} \tag{2}$$

In Eq. (2), $(a,b,\ldots,z)$ is the model parameter, St is the state variable of water quality model, superscript k represents different state variables, and N is the number of divided sea area units.

The measured data of the observation points in the sea area are taken as input samples and substituted into the relationship established in Eq. (2) to invert the near-optimal solution $\left[\left(a_1^{'},b_1^{'},\ldots,z_1^{'}\right),\left(a_2^{'},b_2^{'},\ldots,z_2^{'}\right),\ldots,\left(a_N^{'},b_N^{'},\ldots,z_N^{'}\right)\right]$ of the model parameters.

- *Step 5*: inversion results test:

The near-optimal solution of the model parameters is introduced into the water quality model of the sea area, and the quality of the calibration results is verified [12]. Fig. 1 is a schematic diagram of the parameter inversion process of the data-driven model.

Fig. 1 represents the sequence of the whole process. It mainly includes parameter inversion module and water quality calculation module. The water quality calculation module calculates the design conditions and verifies the optimal solution. The parameter inversion module analyses the results of the water quality module and concludes the relationship between model parameters and observation points in the sea area, to invert the near-optimal solution. *A* and *B* are the links of two modules. Fig. 2 is a schematic diagram of the data-driven model neural network architecture for emergency multi-parameter inversion of combined units.

The data-driven model neural network for emergency multi-parameter inversion of combined units in Fig. 2 consists of three layers, that is, input layer, intermediate layer and output layer. The input layer is the pollutant concentration test results of observation points in the sea area with a total of *N* units, and the output layer is the model parameter $\left[\left(a_1',b_1',...,z_1'\right),\left(a_2',b_2',...,z_2'\right),...,\left(a_N',b_N',...,z_N'\right)\right]$ of *N* units.

Taking the measured data above into the non-linear relationship, the optimal inversion of model emergency parameters (chemistry and biology) with regional variations is studied. The relationship between model parameters and observation points in the sea area is summarized, and the near-optimal solution is inverted. Based on the inversion results, the non-conservative multi-parameter water quality for an emergency is constructed.

Because phytoplankton is the indicator organism to measure water quality [13], the quality of marine environment water is closely related to the abundance of phytoplankton and community composition. The decrease or overbreeding of phytoplankton will indicate that the marine environment is tending to deteriorate. As a nutrient element in marine water quality, nutrients consumed by phytoplankton through photosynthesis and nutrient production by phytoplankton through respiration, extracellular dissolution, and decomposition of organic debris are analyzed below. From the point of view of chemistry and biology, the nutrient content in the marine water quality can be measured to measure the water pollution in the marine environment.

2.2. Construction of emergency multi-parameter water quality testing model

The income and expenditure of nutrients mainly include three parts: one is the process of physical income and expenditure; the other is the process of the influence of the transformation of chemical forms on the income and expenditure; the third is the process of biological income and expenditure. The main form of physical revenue and expenditure process is the input of terrestrial pollution sources, which will bring a large number of organic substances such as nitrogen and phosphorus into the water body. Chemical effects mainly refer to the decomposition of pollutants under the action of marine microorganisms, forming various inorganic salts and becoming an important source of nutrients in seawater. In this paper, the chemical transformation between different forms of nutrients is mainly reflected in the decomposition of nitrogen and phosphorus. There are many forms of nitrogen in seawater. In addition to NO_3^-, NO_2^- and NH_4^+, there are gaseous compounds such as N_2, N_2O and NH_3, and there are nitrification and denitrification among different forms of nitrogen compounds. The decomposition rate of phosphorus can be obtained from the literature experiment [14]. The specific values are shown in Table 1. Biological revenue and expenditure can be divided into biological absorption and nutrient regeneration. This paper mainly considers that phytoplankton consumes a certain amount of nutrients through

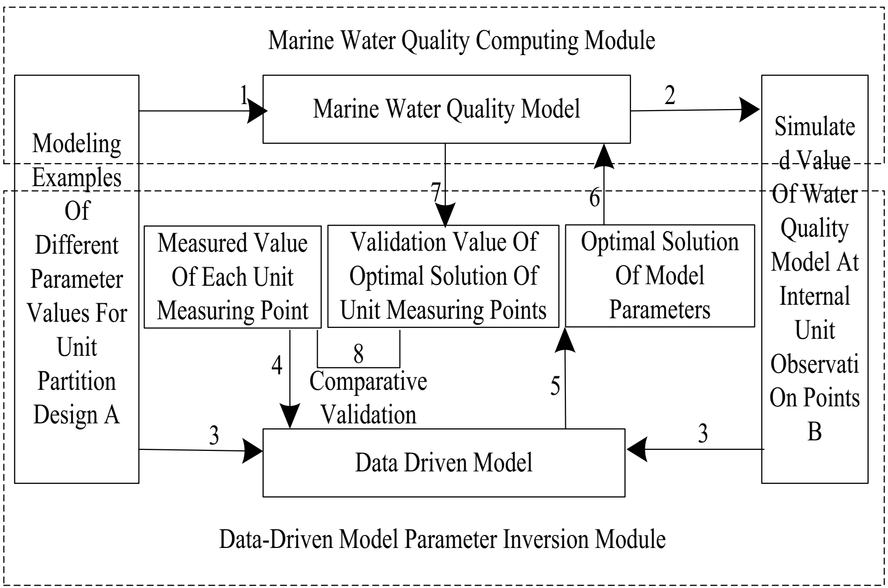


Fig. 1. Data-driven model parameter inversion process diagram.

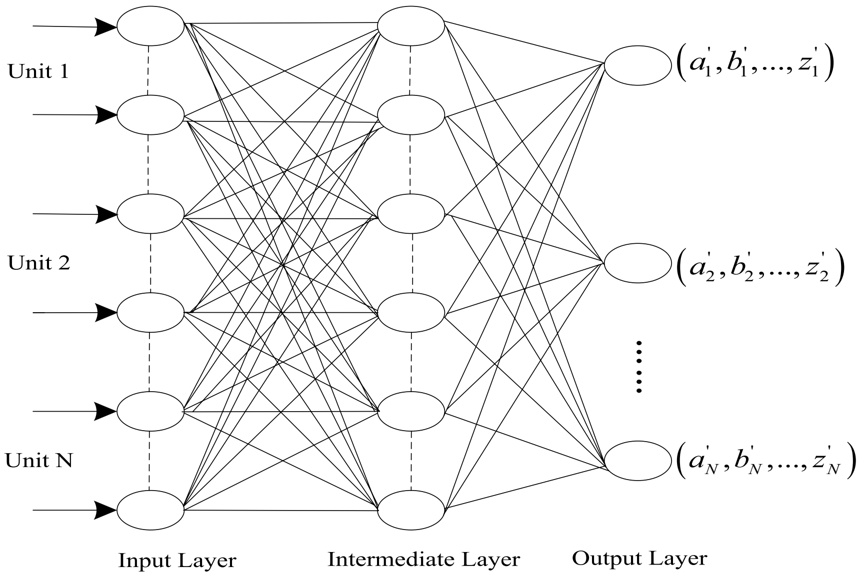


Fig. 2. Schematic diagram of the data-driven model neural network architecture for parameter inversion of combined units.

Table 1
Main parameter values required for calculation

Influencing process	Parameter	Value
Phytoplankton	Maximum growth rate	2.0 d
	Semisaturated constant (DIN)	3.0 μmol/L
	Semisaturated constant (DIP)	0.15 μmol/L
	Optimum light intensity	0.07 cal/cm^2/min
	Respiratory velocity at 0°C	0.03 d
	Temperature dependence coefficient of respiration	0.0519°C
	Dead speed (20°C)	0.0281 L μmol-N/d
	Dead temperature coefficient (20°C)	0.069°C
	Settlement velocity	0.173 m d
Decomposition process of nitrogen	Decomposition speed from PON to NH_4 (20°C)	0.030 d
	Decomposition speed from PON to NH_4 (20°C)	0.0693°C
	Decomposition speed from PON to DON (20°C)	0.030 d
	Decomposition speed from PON to DON (20°C)	0.0693°C
	Decomposition speed from DON to NH_4 (20°C)	0.030 d
	Decomposition speed from DON to NH_4 (20°C)	0.0693°C
	Nitrification coefficient	0.05 d
	Decomposition velocity temperature coefficient	0.0693°C
Decomposition process of phosphorus	Decomposition velocity of P(20°C)	0.012 d
	Temperature coefficient of decomposition velocity	0.0691°C

photosynthesis, and phytoplankton generates nutrients through respiratory release, extracellular dissolution, and decomposition of organic debris.

2.2.1. Conservative water quality model

The Conservative water quality model is the basis of the non-conservative water quality model. The Conservative concentration equation is also the basis of the non-conservative concentration equation. Conservative pollutant transport equation based on concentration C is given as follows:

$$\frac{\partial C}{\partial t}+\frac{\partial (uC)}{\partial x}+\frac{\partial (vC)}{\partial y}+\frac{\partial \left(w-w^S\right)C}{\partial z}=\frac{\partial}{\partial x}\left(k^h\frac{\partial C}{\partial x}\right)+\frac{\partial}{\partial y}\left(k^h\frac{\partial C}{\partial y}\right)+\frac{\partial}{\partial x}\left(k^v\frac{\partial C}{\partial z}\right)+M_0 \quad (3)$$

In Eq. (3), u, v, w, and η are the velocity and water level values calculated by hydrodynamic equation respectively; C is the concentration; M_0 is the physical source term, which is the source strength of removing convective diffusion effect caused by physical action, mainly referring to the point source strength of input from sewage outlet; k^h and k^v are horizontal and vertical pollutant diffusion respectively; w^S is the settling velocity of pollutants.

2.2.2. Non-conservative water quality model

The difference between the non-conservative equation and the conservative equation is mainly reflected in the source term, that is, the source strength of the conservative water quality model mainly introduces the source strength of pollutants, while the source strength of the non-conservative model equation also includes the source strength of chemical and biological effects. Namely:

$$M = M_0 + M_h + M_s \tag{4}$$

In Eq. (4), M_h is the source term of inorganic nitrogen (DIN) and inorganic phosphorus (DIP), which is caused by chemical decomposition. The expression is $M_h = kc$, k is the decomposition rate, and M_s is the source term reflecting the absorption and consumption of nutrients by various changes of phytoplankton.

To quantitatively calculate the effects of chemical and biological actions on the concentration of nutrient elements, the following Eqs. (5) and (6) are used to describe the changes in nutrient values:

$$\frac{d(\mathrm{DIN})}{dt} = (\mathrm{PON} + \mathrm{DON})_{\mathrm{FJ}} - N_{\mathrm{SW}} \times \left(1 - R_{\mathrm{NO_3}}\right) + N_{\mathrm{XH}} \tag{5}$$

$$\frac{d(\mathrm{DIP})}{dt} = (\mathrm{POP} + \mathrm{DOP})_{\mathrm{FJ}} - P_{\mathrm{SW}} \tag{6}$$

PON represents suspended DIN; DON represents dissolved DIN; FJ represents chemical decomposition; SW represents the consumption of nutrients by biological processes; $R_{\mathrm{NO_3}}$ is the coefficient of nitrification; $(1 - R_{\mathrm{NO_3}})$ represents denitrification; XH represents nitrification.

Chemical decomposition rate:

The decomposition rate of nitrogen can be expressed as:

$$K_N = K_{N20} \cdot \theta_{\mathrm{KN}}^{T-20} \tag{7}$$

In Eq. (7), K_N is the decomposition rate of abiotic nitrogen; K_{N20} is the decomposition rate of abiotic nitrogen at 20°C; θ_{KN} is the temperature coefficient of the abiotic nitrogen decomposition rate.

The decomposition rate of phosphorus can be expressed as:

$$K_P = K_{P20} \cdot \theta_{\mathrm{KP}}^{T-20} \tag{8}$$

In Eq. (8), K_P is the decomposition rate of abiotic phosphorus; K_{P20} is the decomposition rate of abiotic phosphorus at 20°C; θ_{KP} is the temperature coefficient of abiotic phosphorus decomposition rate.

In this paper, the dissolved and suspended nutrients in Eqs. (5) and (6) are combined for calculation.

Biological process equation:

Biological effects are mainly reflected in the impact of phytoplankton on nutrients [15], so the nutrient variables caused by phytoplankton are closely related to the amount of phytoplankton:

$$\frac{d(\mathrm{DIN})}{dt} = N(\mathrm{Withered} + \mathrm{Settlement} - \mathrm{Breathing} - \mathrm{Grow})_{\mathrm{fz}} \tag{9}$$

$$\frac{d(\mathrm{DIP})}{dt} = P(\mathrm{Withered} + \mathrm{Settlement} - \mathrm{Breathing} - \mathrm{Grow})_{\mathrm{fz}} \tag{10}$$

In Eqs. (9) and (10), fz represents phytoplankton; the right end of the equation can be described by the following four phytoplankton processes, respectively:

- *Phytoplankton withering process*:

$$D_P = D_{P20} \cdot \theta_{D_P}^{T-20} \tag{11}$$

In Eq. (11), D_P is the dead rate of phytoplankton; D_{P20} is the dead rate of phytoplankton at 20°C; θ_{D_P} is the temperature coefficient of the dead rate of phytoplankton.

- *Deposition rate of phytoplankton*:

$$D_{\mathrm{PP}} = \mathrm{const} \tag{12}$$

- *Respiratory processes of phytoplankton*:

The respiratory process of phytoplankton can be treated according to Eq. (13):

$$R_P = g_p \cdot g_p(T) \tag{13}$$

In Eq. (13), R_P is the respiration rate of phytoplankton; g_p is the respiration rate at 0°C; $g_p(T)$ is the temperature control function, where $g_p(T) = e^{rT}$ is taken, and r is the temperature-dependent coefficient.

- *Phytoplankton growth process*:

The growth process of phytoplankton is related to temperature, light condition and nutrient supply [22,23].

The effect of temperature:

$$F_T = \frac{T}{T_S} \cdot \exp\left[1 - \frac{T}{T_S}\right] \tag{14}$$

In Eq. (14), F_T is the influence of temperature on the reproductive rate, T_S is the most suitable growth temperature for plants, and its value is related to the optimum light intensity of different phytoplankton species. The optimum growth temperature of general phytoplankton is higher than the average annual temperature of the waters they live in. The effect of temperature on the primary production process is exponential, which indicates that the growth activity of phytoplankton will increase rapidly with the increase of temperature at a suitable temperature [16,24,25], but it will be inhibited when the temperature is too high or too low.

Effects of illumination conditions:

$$F_I = \frac{I}{I_S} \cdot \alpha^{I - \frac{I}{I_S}} \tag{15}$$

In Eq. (15), F_I is the influence of light conditions on reproduction; I_S is the most suitable light intensity; I is the effective solar radiation of water body, which is related to the water area and species; α is the semi-saturated constant of light effects.

Nutrient limitation effects:

$$F_{\mathrm{NP}} = \min\left(\frac{\mathrm{DIP}}{K_{\mathrm{DIP}} + \mathrm{DIP}}; \frac{\mathrm{DIN}}{K_{\mathrm{DIN}} + \mathrm{DIN}}\right) \tag{16}$$

In Eq. (16), F_{NP} is the effect of nutrients on the reproductive rate of phytoplankton; DIP is the concentration of inorganic phosphorus; DIN is the concentration of inorganic nitrogen; K_{DIP} is the absorption semi-saturation constant of inorganic phosphorus; K_{DIP} is the absorption semi-saturation constant of inorganic nitrogen.

Because the growth process of phytoplankton is affected by the above three factors: temperature, light condition, and nutrient supply, the amount of nutrient consumed in the growth process of phytoplankton can be calculated as follows:

$$G_P = \mu_{\max} \cdot F_I \cdot F_T \cdot F_{\mathrm{NP}} \tag{17}$$

In Eq. (17), G_P is the growth rate of phytoplankton, $\mu_{\max}$ is the maximum growth rate of phytoplankton, F_I is the light quantity dependence of reproductive speed, and F_T is the temperature dependence of reproductive speed.

It should be noted [17–19] that the amount of residual nutrients needed to be converted by the amount of phytoplankton after the withering and sedimentation processes occur, in which the reduction of phytoplankton is obtained by multiplying the withering rate, sedimentation rate and time. Similarly, nutrients consumed by respiration and growth processes can also be obtained according to this principle, in which respiration rate, growth rate and time multiply to increase phytoplankton production. The parameters required for the above calculation are shown in Table 1.

2.2.3. Conditions for calculating concentration field

Initial condition: interpolation of C_0 = 2006 annual sampling detection scatter concentration. Boundary conditions: They are also divided into the fixed coastal and open coastal boundaries. There is no diffusion term at the coastal solid boundary, sea surface and seabed, and the normal gradient of each state variable is 0. At the open boundary of the [18], the state variables are treated according to the inflow and outflow computational domains: when inflow into the computational domain, the state variables at the open boundary are measured offshore; when outflow, the state variables at the open boundary only consider the convection effect.

2.2.4. Moving boundary treatment

Because the Bohai Sea is submerged and dried up from time to time according to the different topography, the dynamic boundary is used to simulate the environmental dynamic conditions of the sea area. Therefore, in the material transport model, only the wet and drypoints determined by power flow calculation need to be treated as follows: if *n*–1 time is a wet point and *n* time is a dry point, then the continuing calculation of the wet point into wet point time only needs to be substituted by the concentration value of *n*–1 time; otherwise, if *n*–1 time is a dry point and *n* time is a wet point [19], then *n*–1 time is the wet point. The concentration value of time is *n*–2 is substituted for the calculation.

3. Results

Taking the Bohai Sea as the research object, the validity of the multi-parameter water quality testing model for environmental pollution emergencies in this paper is verified. The Bohai Sea includes Liaodong Bay, Bohai Bay, and Laizhou Bay. This paper mainly studies Liaodong Bay and Bohai Bay. Firstly, DIN and chlorophyll state variables are selected to verify the inversion effect of the multi-parameter combination unit of the water quality testing model in this paper. Then, based on the inversion results, the real-time distribution of DIN and Chl in Liaodong Bay and Bohai Bay is tested by the water quality testing model in this paper.

3.1. Multiparameter inversion test of pollution emergency response in Liaodong Bay and Bohai Bay

- Monte Carlo method was used to select the emergency parameters of state variables with a coefficient of variation as control variables, Table 2 as state variables and the selection of emergency parameters, and Table 3 as emergency parameters.
- The Bohai Sea is divided into three main units: Liaodong Bay, Bohai Bay, and Laizhou Bay. However, only two main units are observed in this paper. Therefore, the expression of the data-driven model for emergency multi-parameter inversion of combined units should be as follows:

$$\begin{bmatrix} (\mathrm{VMMAX}_1, \mathrm{TEMPS}_1, \mathrm{VKDN}_1) \\ (\mathrm{VMMAX}_2, \mathrm{TEMPS}_2, \mathrm{VKDN}_2) \end{bmatrix} = F \begin{bmatrix} (\mathrm{Chl}_1, \mathrm{DIN}_1) \\ (\mathrm{Chl}_2, \mathrm{DIN}_2) \end{bmatrix} \tag{18}$$

In Eq. (18), subscripts 1 and 2 represent Liaodong Bay and Bohai Bay respectively.

Table 2
State variables and their emergency parameters

State variable	Emergency parameters
Inorganic nitrogen (DIN)	Phytoplankton growth rate (VMMAX)
	Growth temperature of phytoplankton (TEMPS)
	Decomposition rate of inorganic nitrogen (VKDN)
Chlorophyll (Chl)	Phytoplankton growth rate (VMMAX)
	Growth temperature of phytoplankton (TEMPS)

- From Table 2, we can see that DIN has three emergency parameters, Chl has the same two emergency parameters as DIN. The range of parameters is set and three points are selected among them. As shown in Table 2, 27 design conditions are obtained by matching the three emergency parameters. The concentration changes of DIN and Chl in each of the two units are calculated by the water quality test model.
- Two element concentration data and their corresponding model parameters in two units are taken as sample input data driving model. Combining with the network structure of Fig. 2, the relationship between state variables and control variables Eq. (18) is established, that is, combined inversion.
- Table 4 takes the average of the three emergency parameters in Table 3. According to the emergency parameters, the experiment is designed and the DIN and Chl concentration data are calculated as "pseudo" observation data. By inputting the "pseudo" observation data obtained in this paper into the established relationship, the near-optimal solution of the control variable can be obtained, as shown in Table 5.
- According to the combined inversion method, the emergency multi-parameter inversion results of the combined unit in Table 5 are brought into the multi-parameter water quality test model for a marine pollution emergency. The results of the chlorophyll and DIN test are compared with the measured results (Figs. 3 and 4, Table 6).

Table 3
Emergency parameters

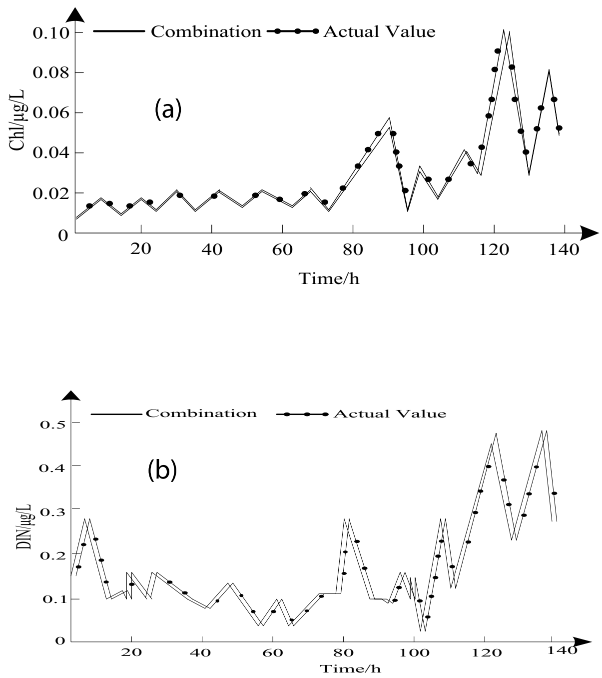
State variable	Emergency parameters	Parameter value		
DIN	VMMAX	1.44	2.5	3.36
Chl	TEMPS	15	26	35
	VKDN	0.012	0.018	0.026

Table 4
Experimental design of this paper

State variable	Emergency parameters	Parameter value
DIN	VMMAX	2.4
Chl	TEMPS	25
	VKDN	0.02

From Figs. 3 and 4 and Table 6, we can see that the average absolute error of chlorophyll in Liaodong Bay and Bohai Bay is 0.0033, the average relative error is 0.0188, the error is very small, the linear correlation coefficient is higher than 0.99; the average absolute error of DIN in Liaodong Bay and Bohai Bay is 0.0175, the average relative error is 0.0488, and the linear correlation is 0.0175. The coefficients are higher than 0.99. After comparing the results of the emergency multi-parameter calibration, the predicted results of the Liaodong Bay combined inversion method are in good agreement with the measured values, and the predicted results of the Bohai Bay combined inversion method are in good agreement with the trend of the measured values.

The results show that the absolute error and relative error between the predicted results and the actual results are low, and the linear relationship between the predicted results and the actual results is higher than 0.99. The high correlation indicates that the prediction of environmental water quality in the Bohai Sea by using two emergency parameters has high accuracy.



Comparison of emergency multi-parameter calibration results for (a) chlorophyll retrieval and (b) inorganic nitrogen inversion in Liaodong Bay.

Table 5
Near-optimal solutions to control variables

Inversion method	Unit	Emergency parameters		
Combination inversion	Liaodong Bay	$VMMAX_1$	$TEMPS_1$	$VKDN_1$
		2.54429385	25.368715	0.019675208
	Bohai Bay	$VMMAX_2$	$TEMPS_2$	$VKDN_2$
		2.4485965	25.037195	0.018655743

3.2. Real-time distribution test of nutrient DIN and Chl in Liaodong Bay and Bohai Bay

Based on the influence of Liaodong Bay and Bohai Bay as mainland source sewage outlets on the real-time distribution of nutrient DIN and Chl in marine water quality, the real-time distribution of nutrient DIN and Chl in water quality of the two regions was tested by using the emergency multi-parameter water quality testing model constructed in this paper, and the measured results were compared with the measured current and water level values. The difference is shown in Figs. 6–9, Fig. 5 is the distribution map of Liaodong Bay and Bohai Bay stations and sewage outlets, and Table 7 is the sewage discharge from key sewage outlets.

From Figs. 6–9, we can see that the real-time distribution results of DIN and Chl of nutrients in Liaodong Bay and Bohai Bay are tested by using the water quality testing model in this paper. Compared with the measured current and water level values, the results are in good agreement, which

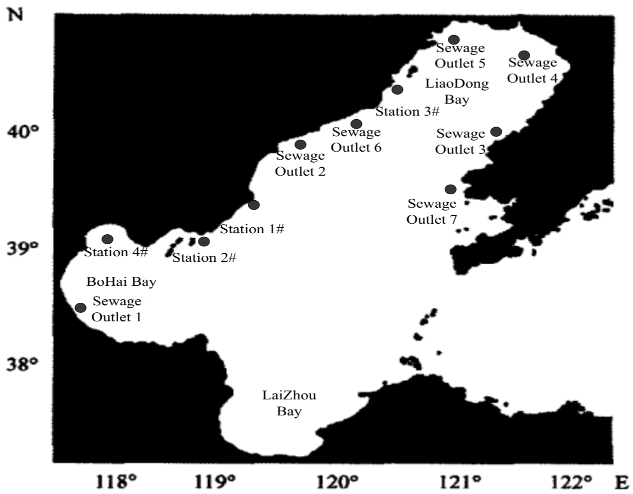


Fig. 5. Distribution of measuring stations and sewage outlets.

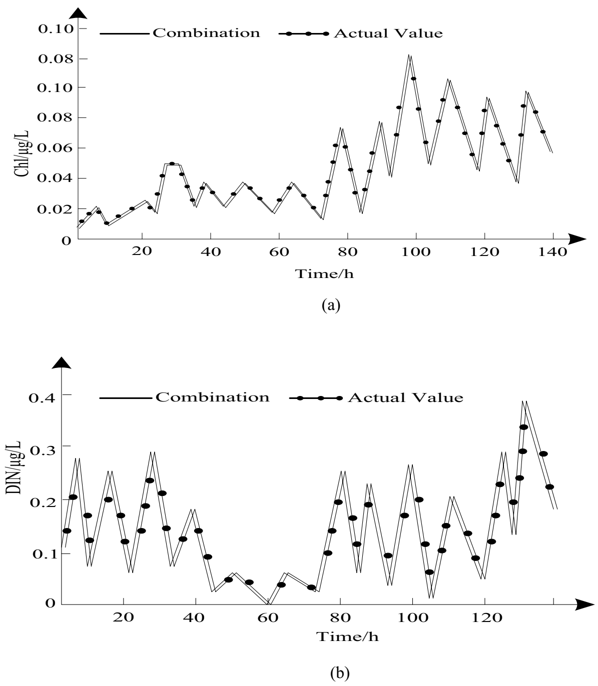


Fig. 4. Comparison of emergency multi-parameter calibration results for (a) chlorophyll retrieval and (b) inorganic nitrogen inversion in Bohai Bay.

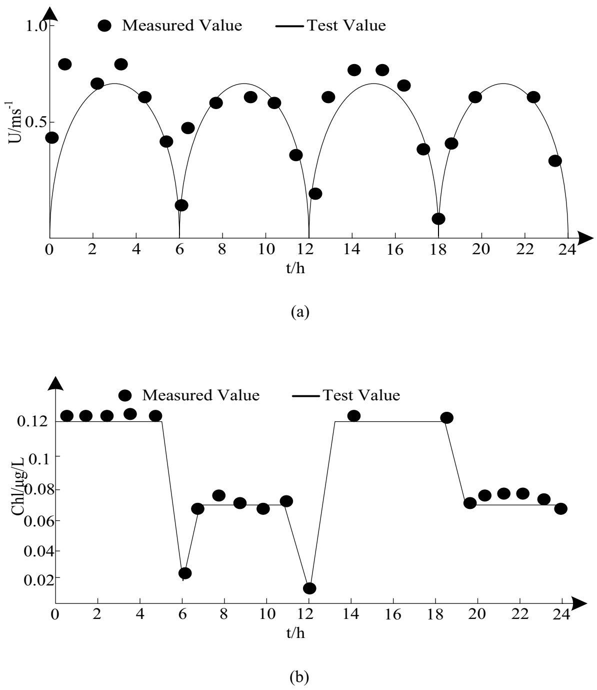


Fig. 6. Comparisons between observed and calculated (a) flow velocities and (b) flow directions (Station 1#).

Table 6
Comparisons of combined inversion errors

State variable	Error	Inversion method	Liaodong Bay	Bohai Bay
Chl	Absolute error	Combination	0.0005	0.0016
	Relative error	Combination	0.0068	0.0241
	Correlation coefficient	Combination	0.9999	0.9999
DIN	Absolute error	Combination	0.0161	0.0188
	Relative error	Combination	0.0773	0.0204
	Correlation coefficient	Combination	0.9996	0.9991

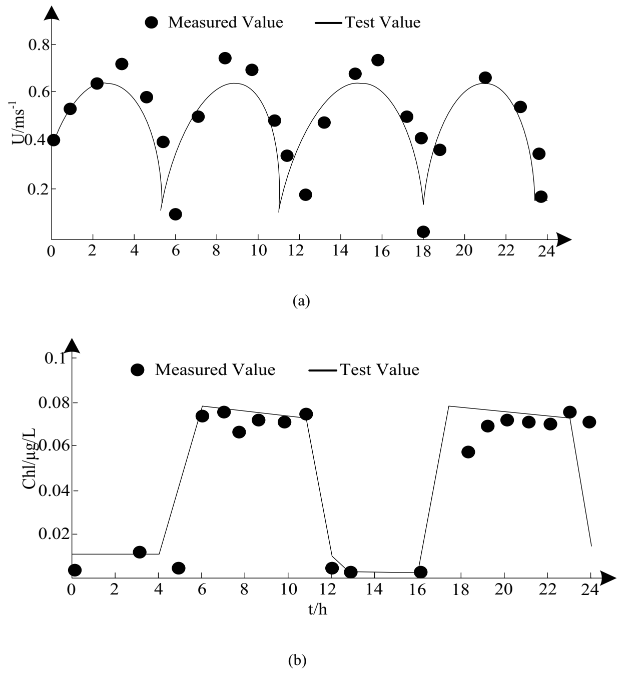


Fig. 7. Comparisons between observed and calculated (a) flow velocities and (b) flow directions (Station 2#).

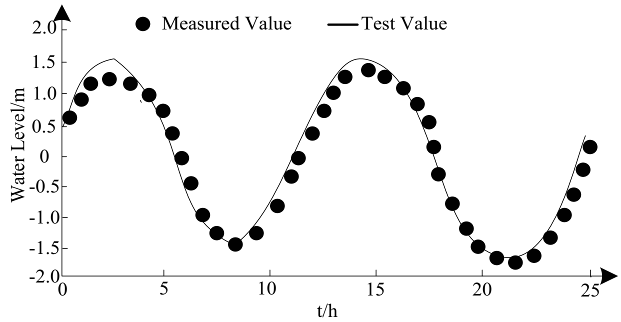


Fig. 8. Variation of water level (Station 3#).

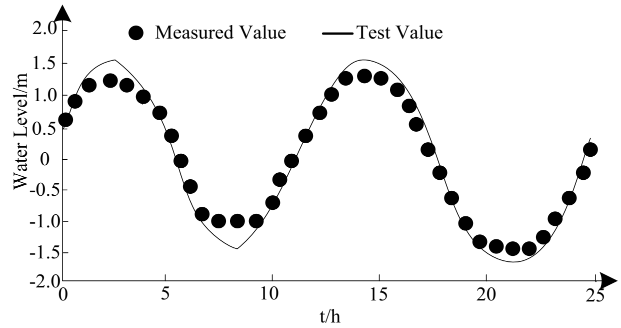


Fig. 9. Variation of water level (Station 4#).

Table 7
Emissions from key outlets

Sewage outlet number	Average daily discharge (t/d)
Sewage outlet 1	475
Sewage outlet 2	100,000
Sewage outlet 3	162.5
Sewage outlet 4	89,500
Sewage outlet 5	22,800
Sewage outlet 6	127,100
Sewage outlet 6	70,352

shows that the water quality conclusion of the emergency multi-parameter water quality testing model constructed in this paper is tested. The results are in good agreement with the actual values, with high accuracy, and can well test the horizontal diffusion of pollutants in the sea area, which can provide the correct flow field for the test process of pollutant migration and transformation.

4. Discussions

Marine environmental water quality testing model not only plays an important role in water quality simulation, pollutant control, and water resources planning but also provides strong technical support for water quality early warning. With the vigorous development of new technologies, the water quality testing model is innovative based on the original, and its applicability and simulation ability is also available. There have been new improvements. With the development of the ocean water quality testing model in an application, the water quality testing model has a wider application field. A more comprehensive and more diverse biochemical model has been established, which is conducive to a more accurate description of the biochemical process in the ocean area and makes the simulation results have higher reference value. This paper studies a multi-parameter water quality testing model for marine environmental pollution emergencies. The model can not only test the marine water quality but also test the results with high accuracy and a good linear correlation coefficient. It can well test the horizontal diffusion of pollutants in the sea area and provide the correct flow field for the test process of pollutant migration and transformation. The model in this paper is of great significance in the treatment of marine environmental pollution. While applying the water quality testing model in this paper, we should also pay attention to the problems faced by the water quality testing model in its development.

- The lack of real-time observation data. The ocean water quality testing model needs complete, continuous and systematic hydrological and water quality data, which is the basis of establishing the model. Observation data can provide the initial field, boundary condition and forced field for the model, and can also be used to verify the accuracy of the calculation results of the model. Now, cruise observation and buoy observation are based on time. Continuity and data quality needs to be improved. It is suggested that buoys should be placed at representative locations along the coast instead of setting up observation points for a certain project. Observation variables include basic physical variables and water quality state variables, data transmission and processing automatically, and data sharing at the same time.

- The mechanism of water pollution is not fully clear, and it is difficult to express it in detail with mathematical formulas, and there are many hypotheses in the model, which are inevitably different from the reality. It is suggested that we should pay attention to the study of basic theory, verify the rationality of hypothesis by experiment when necessary, combine with observation data and confirm the condition of the hypothesis.
- Water quality changes in coastal waters are affected by many factors, including biology, physics, chemistry and other disciplines. How to improve the intersection and collaboration between disciplines, and how to build a multi-disciplinary and multi-media marine ecosystem model based on water quality testing model are more conducive to the objective simulation of marine water quality. Marine water quality testing model has been widely used since its inception, and its universality has been increasing. It has gradually become a powerful tool for decision-makers. Based on the marine water quality testing model, a perfect and systematic coastal water quality early warning system has been established to predict and forecast the trend of eutrophication, and to improve the simulation ability of marine water quality testing model. It is a hotspot in the application of ocean water quality testing model.

5. Conclusions

In this paper, a multi-parameter water quality testing model for marine environmental pollution emergency is studied. Based on inducting the relationship between the parameters of the model and the observation points in the sea area, and inverting the two near-optimal solutions of chemical and biological aspects of marine environmental pollution water quality, a non-conservative water quality testing model for marine environmental pollution is constructed from the two parameters. The validity of the multi-parameter water quality test model for marine environmental pollution emergency is studied from two aspects: the inversion of DIN and Chl emergency parameters in Liaodong Bay and Bohai Bay, and the real-time distribution test of DIN and Chl nutrients in water quality in Liaodong Bay and Bohai Bay.

- The parameters inversion results of environmental pollution emergency in Liaodong Bay and Bohai Bay: After comparing the results of multi-parameter calibration, the combined inversion of chlorophyll and DIN emergency parameters was carried out in Liaodong Bay and Bohai Bay. The relative errors and absolute errors between the predicted results of the two parameters and the actual measured values were both obtained. The correlation coefficient between the predicted value and the measured value is higher than 0.99, which indicates that the inversion effect of the two parameters is high, and the accuracy of the two parameters for marine environmental pollution water quality testing is high.
- The real-time distribution test results of nutrient DIN and Chl in Liaodong Bay and Bohai Bay are obtained by using the water quality test model in this paper. The results of DIN, Chl current and water level measured by the water quality model in Liaodong Bay are in good agreement with the measured values, which shows that the accuracy of the water quality test model in this paper is high.

Acknowledgement

This research was supported by a study on carbon burial record and influence mechanism of marine-terrestrial facies deposits in the Subei basin since Holocene (No. 41671195) and the study on peat deposition process and paleoclimate since MIS 3 in Shennongjia (41373011).

References

[1] W.H. Qin, Y.T. Fu, Water quality abnormity inspection and detection via the vector autoregressive model, J. Saf. Environ., 18 (2018) 31–32.
[2] R.R. Dong, H.C. Chen, J.B. Wang, Study on prediction model of accidental water pollution in the middle and lower reaches of Hanjiang River, Water-Power, 43 (2017) 1–5.
[3] D.H. Liu, N. Zhao, W.H. Zou, Multi-period reputation effect model of governmental emergency strategy in environmental pollution incidents, Manage. Rev., 30 (2018) 241–247.
[4] H. Wang, H. Zhong, G. Bo, Existing forms and changes of nitrogen inside of horizontal subsurface constructed wetlands, Environ. Sci. Pollut. Res., 25 (2018) 771–781.
[5] Z. Liu, W. Peng, M. Motahari-Nezhad, Circulating fluidized bed gasification of biomass for flexible end-use of syngas: a micro and nanoscale study for production of bio-methanol, J. Cleaner Prod., 129 (2016) 249–255.
[6] Z. Liu, Economic analysis of energy production from coal/biomass upgrading; part 1: hydrogen production, Energy Sources Part B, 13 (2018) 132–136.
[7] F.H. Sun, J.Q. Shen, Study on the construction of ABMS model for the impact of unexpected water environmental pollution events on urban residents' life quality, Social Sci. Nanjing, 19 (2017) 90–96.
[8] A. Daunaraviciene, D. Jasaitis, Assessment of the external exposure dose to humans from (CS)-C-137 and (SR)-S-90 in the coastal waters of the Baltic Sea near Lithuania, Appl. Ecol. Environ. Res., 15 (2017) 779–785.
[9] S. Wang, A.Q. Ma, J. Hu, Comparative study on remote seining inversional model of Chlorophyll-*a* concentration in semi-closed Bay—a case study in the Jiaozhou Bay, Mar. Environ. Res., 38 (2019) 78–86.
[10] M. Hertzberg, A. Siddons, H. Schreuder, Role of greenhouse gases in climate change, Energy Environ., 28 (2017) 530–539.
[11] Z.X. Xing, L.H. Zhang, Y. Ji, Study on water quality simulation and eutrophication assessment in Wudalianchi based on EFDC model, J. Northeast Agric. Univ., 49 (2018) 91–101.
[12] Y.P. Zheng, H.W. Yao, H. Wang, A renovated comprehensive assessment method for CFD models for atmospheric dispersion, J. Saf. Environ., 17 (2017) 1053–1057.
[13] Z.D. Wu, G.F. Lin, M.F. Zhang, A dynamic planning model of emergency resource scheduling for sudden river pollution incident, J. Geo-Inf. Sci., 20 (2018) 799–806.
[14] Y. Liang, Z.B. Li, C.Q. Liu, Effects of different phosphorus sources on the growth and interspecific competition in three marine *microalgal* sp., Trans. Oceanol Limn., 33 (2017) 132–140.
[15] J.W. Lai, J.T. Cen, Water quality testing unmanned ship based on internet of things communication technology, Chin. J. Power Sources, 16 (2018) 14–18.
[16] D.J. Zhu, X.S. Pi, X.C. Yue, A method on direct arrival wave suppression for high-frequency hybrid sky-surface wave radar, J. China Acad. Electron. Inf. Technol., 12 (2017) 31–36.
[17] H. Wu, B. Zhao, W. Gao, Analysis of gradient descent ontology iterative algorithm for geological setting, Geol. Ecol. Landscapes, 1 (2017) 41–46.

[18] W.H. Zhang, H.P. Zhang, M. Zhang, Tail gas treatment system of marine diesel engine based on SCR technology, Autom. Instrum., 33 (2018) 112–114.

[19] C.C. Okpoli, D.O. Iselowo, Hydrogeochemistry of Lekki, Ajah and Ikorodu water resources, Southwestern Nigeria, J. Clean WAS, 3 (2019) 20–24.

[20] X.M. Li, S.J. Sun, P. Cui, Effects of water environmental chemical characteristics on difference of phytoplankton community structure in Xianghai and Chagan Lake wetlands, J. Jilin Univ. (Sci. Ed.), 55 (2017) 739–750.

[21] Y.C. Tan, H.H. Fan, M.L. Liu, Signal reconstruction of underwater wireless sensor networks based on blind source separation, Comput. Simul., 35 (2018) 173–176.

[22] F.O. Ogbemudia, R.E. Ita, O. Kekere, Distributional patterns of *Flora* sp. in response to salinity gradients in a Palustrine wetland, Environ. Ecosyst. Sci., 3 (2019) 20–25.

[23] F. Jing, L.W. Zhou, W.G. Lu, Design of power quality monitoring terminal based on ADALINE neural, J. Power Supply, 15 (2017) 118–125.

[24] C.S. Orji, E.D. Uko, I. Tamunobereton-ari, Permeability-porosity trends in Cawc reservoir sands in the Niger Delta Nigeria, Using well-log data, Malaysian J. Geosci., 3 (2019) 33–42.

[25] G.G. Mahmood, H. Rashid, S. Anwar, A. Nasir, Evaluation of climate change impacts on rainfall patterns in Pothohar region of Pakistan, Water Conserv. Manage., 3 (2019) 01–06.