Study on the relationship between inorganic nitrogen or phosphorus and dissolved oxygen in seawater

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Abstract. We analyze the linear correlation between dissolved inorganic nitrogen (DIN), phosphate (PO₄-P) and dissolved oxygen (DO) based on on-site monitoring data at Zhoushan in May 2016, and construct the DIN, PO₄-P and DO related model using neural networks in this paper. Based on the model, we predict the concentration of DIN and PO₄-P in seawater by DO data. From the data analysis, the root-mean-square error of prediction (RMSEP) is less than 0.2, and the predicted values of DIN (including NH₃-N, NO₂-N, and NO₃-N) and PO₄-P are basically consistent with the changes in measured values. The correlation coefficient between NO₂-N and DO is the largest at 0.6247, and the RMSEP is the smallest at 0.1119.

Keywords: Correlation; Dissolved Oxygen; Dissolved Inorganic Nitrogen (DIN); Phosphate (PO₄-P); Relational Model

1. Introduction

In recent years, industrial development and human activities have increased, and rivers have transported a large amount of biogenic elements such as nitrogen and phosphorus, as well as chemical oxygen-consuming substances such as organic matter, which have caused changes in the concentration and structure of nutrients in offshore and estuary water bodies [1]. The nutrients in seawater are important sources of plankton for material absorption and energy metabolism, and one of the important indicators for quantifying seawater eutrophication [2].

Dissolved inorganic nitrogen (DIN) and phosphorus (PO₄-P) are essential nutrients for marine phytoplankton, as well as an important source of material absorption and energy metabolism by plankton, and one of the important indicators to quantify seawater eutrophication [3].

The amount of dissolved oxygen in seawater comes from two sources [4]: One is that the dissolved oxygen in the sea air and the photosynthesis of marine plants make the dissolved oxygen content increase. The other is the degradation of organic matter in seawater. The oxygen consumption of marine organisms reduces dissolved oxygen. If there is more organic matter in seawater, the rate of oxygen consumption exceeds that of oxygen replenishment, the original ecological balance is destroyed, and even eutrophication is caused. Therefore, DIN, PO₄-P and DO have a certain relationship.
Dissolved oxygen in seawater is a routine parameter for ocean monitoring. Judging from the online analytical instruments used in marine field application, DO is more mature and easier to implement than analytical instruments of DIN and PO$_4$-P. Therefore, we study the relationship between the two, and construct a correlation model to provide a basis for predicting the concentration of DIN and PO$_4$-P through conventional parameter data.

At present, many scholars have carried out research on the correlation between DIN, PO$_4$-P and DO. Wang et al. [5] inverted the remote sensing data of nutrients in the estuary of the Yangtze River from the No. 1 satellite and found that there is a correlation between the two, and then derived a linear fitting function, but the method is susceptible to weather, sea conditions and satellite transit time factors affect.

Hou et al. [6] analyzed the influence of Xiaolangdi Reservoir's water and sediment regulation on the downstream channel water quality and found that the correlation between DIN, PO$_4$-P and DO is related to the middle and late stages of water and sediment regulation, and is different in different periods, but the two are always related. Liu [7] analyzed the relationship between the monthly changes of nutrients in the Kuroshio region of the East China Sea and its influencing factors, and concluded that there is a negative correlation between DO and DIN. Long et al. [8] studied the relationship between DIN, PO$_4$-P and DO in autumn in the northern part of the South China Sea and found that DO is positively related to DIN and negatively related to PO$_4$-P. Wu et al. [4] analyzed the distribution characteristics of dissolved oxygen in summer Dalian Bay and the relationship with nutrients and found that DIN, PO$_4$-P and DO have a strong correlation. These studies indicate that there is a two-way internal connection between DIN, PO$_4$-P and DO.

We analyze the correlation between DIN, PO$_4$-P and DO based on the Zhoushan site monitoring data in May 2016 in the paper. From the perspective of artificial intelligence, the BP neural network is used to build a relationship model between the two, and the feasibility of predicting the concentration of DIN and PO$_4$-P through the relationship model is analyzed.

Figure 1. DIN, PO$_4$-P and DO linear correlation diagram.
2. Data and methods

2.1. Experimental data
The experimental data used in the paper were provided by the East China Sea Environmental Monitoring Center of the State Oceanic Administration. In May 2016, a fixed point was selected near the Zhoushan Bansheng Cave tide test station. The data of DO, DIN and PO₄-P were obtained through on-site water sampling laboratory analysis. The collection and analysis methods of water samples are carried out in accordance with "Ocean Monitoring Standards" [9]. After rounding off and normalizing, we obtain 61 sets of measurement data, of which 43 sets of data are used for the prediction model training and 18 sets of data are used for the prediction model predicting.

2.2. Linear correlation analysis of DIN, PO₄-P and DO
Eliminate abnormal data, retain 40 sets of sample data, and obtain the linear correlation between DO and DIN, PO₄-P as shown in Figure 1. DO is negatively correlated with DIN (including NH₃-N, NO₂-N and NO₃-N) and PO₄-P. The correlation coefficient between DO and NO₂-N is the largest at 0.6247, and the correlation coefficient between NO₃-N is the smallest at 0.5252. The correlation coefficients of DO and DIN, PO₄-P are NO₂-N, NH₃-N, PO₄-P, and NO₃-N in the descending order. Correspondingly, the linear correlation between DO and NO₂-N, NH₃-N, PO₄-P, NO₃-N is strong to weak.

2.3. DIN, PO₄-P and DO correlation model
Due to factors such as water area, season and water quality regulation, the linear correlation between DO and DIN, PO₄-P is unstable, and some are positively correlated and some are negatively correlated [4, 6, 8, 10]. In this paper, from the perspective of artificial intelligence, we design DIN, PO₄-P and DO related models based on neural networks. Through learning and training, the model gradually converges until it is stable.

BP neural network is a multi-layer feed forward network trained by error back propagation algorithm [11]. Through learning and training, a nonlinear mapping relationship between input and output is established [12, 13], which is an adaptive Non-linear dynamic system. Therefore, we analyze the data of DIN, PO₄-P and DO, and build a relationship model between the two, as shown in Figure 2. The relationship model is divided into an input layer, a hidden layer, and an output layer. The number of neurons in the input layer is 1, which is DO, and the number of neurons in the output layer is 1, which is one of DIN and PO₄-P. The number of neurons in the hidden layer is different due to different factors; the neuron nodes of each layer are connected to each other, and there is no connection between the neuron nodes of the same layer.

![Figure 2. DIN, PO₄-P and DO relationship model.](image)

3. Experiment
Based on the DIN, PO₄-P and DO relationship model, the DIN, PO₄-P process predicted by DO is as follows.

First, the model is initialized. The number of nodes in the input layer and the output layer is all one, the former is DO, the latter is one of the DIN, PO₄-P. Hidden layer is set, the initial weight matrix and threshold matrix are...
randomly generated, and the learning rate and error accuracy are set. Secondly, the model is trained by training data, the input signal is propagated forward, the network output value is calculated, and compared with the target output value. If the error meets the required accuracy or the training number reaches the set number, the training ends. Conversely, if the error does not meet the required accuracy and the training times have not reached the set number, the error back propagation process is performed, and the new weights and thresholds are obtained by modifying the model weights and thresholds. If the error meets the requirements, the training is ended. Otherwise, the signal forward propagation is continued with the new weight and threshold. Finally, we get a stable training model.

Based on the stable training model, through DO data, the DIN and PO$_4$-P concentrations are predicted as shown in Figure 3. From the perspective of the overall change trend, comparing the predicted value curve and the measured value curve of the DIN, PO$_4$-P concentration in Figure 3, the changes of the two are basically the same.

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4. Analysis and discussion
The root-mean-square error of prediction (RMSEP) is used to evaluate the prediction ability of the model to external samples. The smaller the value is, the better the prediction ability of the model is. In the figure 3(a)–(d), the RMSEP of the NO$_2$-N, NH$_3$-N, NO$_3$-N and PO$_4$-P concentration prediction set is 0.1119, 0.1568, 0.1974 and 0.1678, respectively. The order of RMSEP from low to high is NO$_2$-N, NH$_3$-N, PO$_4$-P, NO$_3$-N, and all are below 0.2.
The correlation coefficient $R$ and the RMSEP of DIN, PO$_4$-P and DO are shown in Table 1. The largest correlation coefficient with DO is NO$_2$-N, which is 0.6247, and the RMSEP is the smallest, which is 0.1119. The smallest correlation coefficient with DO is NO$_3$-N, which is 0.5252, and the RMSEP is the largest, which is 0.1974. The correlation coefficients of DIN, PO$_4$-P and DO from large to small are consistent with the RMSEP from small to large, that is NO$_2$-N, NH$_3$-N, PO$_4$-P and NO$_3$-N. It means that the more relevant it is to DO, the smaller the RMSEP of DIN and PO$_4$-P concentrations is, and vice versa.

In the forecasting process, we should choose strong correlation parameters for prediction based on the model.

5. Conclusion
Through DIN, PO$_4$-P and DO data, we analyze the linear correlation between the two and find a negative correlation between them. From the perspective of artificial intelligence, we build a relationship model of DIN, PO$_4$-P and DO based on the BP neural network in the paper. The DIN and PO$_4$-P concentrations are predicted by the model, the predicted value is consistent with the actual value, and the RMSEP is less than 0.2, which this model is feasible.

Through comparative analysis, it is found that the correlation coefficients of DIN, PO$_4$-P and DO from the largest to the smallest are consistent with the RMSEP from the smallest to the largest, that is NO$_2$-N, NH$_3$-N, PO$_4$-P, NO$_3$-N. This conclusion shows that the higher the correlation coefficient between DIN, PO$_4$-P concentration and DO is, the lower the RMSEP is, and that during the forecasting process, strong correlation parameters should be selected for forecasting.

The correlation model of DIN, PO$_4$-P and DO gradually converge through learning and training until they are stable, and is expected to adapt to the water quality of different environments in the future. It provides a new method for predicting the change trend of seawater nutrients through online monitoring data of conventional water quality parameters.

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