Remote sensing inversion modeling of chlorophyll-a concentration in Wuliangsuhai Lake based on BP neural network

Xueliang Fu*, Wenyao Liu and Hua Hu

1,2,3College of computer and Information Engineering, Inner Mongolia Agricultural University, Hohhot, 010018, China
*Corresponding author’s e-mail: fuxl@imau.edu.cn

Abstract. Monitoring chlorophyll-a concentration in Wuliangsuhai Lake can effectively grasp the primary production of Wuliangsuhai Lake. The traditional manual sampling monitoring method is time-consuming and laborious, compared with the monitoring method, the monitoring range of chlorophyll-a in lake water by remote sensing is not only wide, long time sequence, but also lower than that of the original. Based on the Landsat 8 remote sensing image data of Wuliangsuhai Lake and the measured data of chlorophyll-a concentration sampling points in Wuliangsuhai Lake, the spectral reflectance of each sampling point was extracted through the longitude and latitude coordinates of each sampling point, the first to fifth band spectral reflectance combination of Landsat 8 remote sensing image data is used as input, and the measured chlorophyll-a concentration is used as output, 26 BP neural network models were constructed to Retrieve Chlorophyll-a Concentration in Wuliangsuhai Lake. Through the verification and analysis of all the models, it is found that the inversion model with spectral reflectance of band 1, 2, 3, 4 and 5 as input has the best performance.

1. Introduction
Wuliangsuhai Lake is an important part of "one lake and two seas" in Inner Mongolia, and the stability of its ecological environment is of great significance to the ecological balance of local areasments[1]. Photosynthesis and chlorophyll-a can reflect the degree of eutrophication and algae biomass in lake waters to a certain extent, and chlorophyll-a can effectively represent the ebb and flow of bloom in lake waters[2]. Therefore, it is very necessary to monitor the concentration of chlorophyll-a in Wuliangsuhai Lake, which can provide some basis and reference for the control of water quality deterioration and improvement of water quality of Wuliangsuhai Lake.

The traditional method for monitoring chlorophyll-a concentration in lake waters is to divide the lake area according to the grid and set sampling points, and conduct chemical analysis after field sampling[3], although this method can accurately measure the concentration of chlorophyll-a in local water bodies within the sampling range, sampling tests are time-consuming and laborious, and can not cope with sudden and large-scale water pollution. Monitoring the concentration of chlorophyll a in lake waters by remote sensing technology has the advantages of wide monitoring range, long time series, and low cost, it is an economical and effective method for monitoring the concentration of chlorophyll a in lake waters[4]. Reflection spectra of secondary water bodies such as inland lakes are usually very complex[5] and changes in the earth's atmosphere will interfere with the inversion output values of the model[6], however, machine learning has great advantages in nonlinear information
processing. Machine learning method is not a fixed model framework, but an effective method to solve nonlinear regression problems by continuously "learning" the laws through historical data, finding out the hidden patterns in the data and making predictions[7].

With the rapid development of machine learning theory and practice, the research on remote sensing retrieval of lake water environment elements (chlorophyll-a, suspended matter, total phosphorus, minerals, etc.) has been continuously promoted. Teng Zhang et al. used Pearson correlation analysis to analyze the correlation between the measured chlorophyll a concentration and the band reflectance of Landsat 8 remote sensing image data, and used the sensitive band of chlorophyll-a to build a support vector machine (SVM) model to invert the concentration of chlorophyll-a. The model verification results showed that the model had high accuracy[8]. Fan Guangli et al. used the Gaofen-1 remote sensing image data of Taihu Lake to construct the ELM model to predict the concentration of chlorophyll-a in the water of Taihu Lake, and the results showed that this model could effectively predict the concentration of chlorophyll-a in the water of Taihu Lake[9].

Based on the Landsat 8 remote sensing image data of Wuliangsuhai Lake and the measured chlorophyll-a concentration data of Wuliangsuhai Lake in the same period, this paper uses BP neural network to construct 26 remote sensing inversion models of chlorophyll-a, verifies and analyzes these 26 inversion models, and analyzes the influence of different band input combinations on the models.

2. Data and experimental methods

2.1. Remote sensing image data

Landsat8 satellite remote sensing image data comes from USGS official website, to ensure that the imaging date is close to the field measurement time, and the cloud of selected image data is less than 20%. The remote sensing image data obtained directly in this paper need necessary data preprocessing, including radiometric calibration and atmospheric correction.

The initial acquired Landsat 8 satellite remote sensing data recorded the grayscale value (DN value) of the ground object, but the input of constructing BP neural network model must use the absolute radiance value. The purpose of image radiance calibration is to convert DN value into absolute radiance value according to the calibration formula[10]. In this paper, Envi 5.2 was used to complete the radiation calibration of Landsat 8 remote sensing image data.

Atmospheric correction refers to the error caused by the scattering of atmospheric molecules and aerosols, which is not reflected by the actual ground object information of the total radiance value of the target measured by satellite sensor. Atmospheric correction is the process of eliminating these radiation errors caused by atmospheric influence and inverting the real surface spectral reflectance of ground objects[11]. In this paper, the Flaash model of Envi 5.2 was used to complete the atmospheric correction work, and the real spectral reflectance images of the atmospheric correction from Landsat 8 remote sensing images were obtained.

2.2. Measured data of chlorophyll-a

The measured data of chlorophyll-a were provided by Water Conservancy and Civil Engineering College of Inner Mongolia Agricultural University, and the sampling points were all located in the clear water area of Wulangsuhai Lake (see Figure 1 for the sampling points). In this paper, the sampling time of chlorophyll-a measured data for BP neural network inversion model training and testing is May, June, July and August 2017, May, June and October 2018, June, July and September 2019, a total of 100, the lowest concentration of chlorophyll-a was 0.32 μg·L⁻¹, the highest value was 44.16 μg·L⁻¹, the average value was 8.63 μg·L⁻¹.
Table 1. Chlorophyll-a concentration in the measured data.

| Number | Chlorophyll a concentration ($\mu$g L$^{-1}$) |
|--------|---------------------------------------------|
| 1      | 0.32                                        |
| 2      | 0.32                                        |
| 3      | 0.34                                        |
| ...    | ...                                         |
| 98     | 28.84                                       |
| 99     | 30.28                                       |
| 100    | 44.16                                       |

2.3. Design and training of BP neural network inversion model

BP (back propagation) neural network is a concept put forward by scientists headed by Rumelhart and McClelland in 1986. It is a kind of learning method of multi-layer network according to the error "backstepping"[12]. It is the most widely used neural network at present.

2.3.1. Division of training and testing data sets. In this paper, the division of training set and testing set of BP neural network in this paper refers to the idea of stratified random sampling method[13]. Stratified random sampling method is that the measured data of chlorophyll a (100 in total) are arranged in descending order from high to low, and four of them are divided into a group. One measured data from each group (25 in total) is randomly selected as the test set for the test and evaluation of BP neural network model (25 in total). The remaining 75 measured data are the most training set for the training of BP neural network model.
2.3.2. Input layer, output layer, hidden layer and model training. The remote sensing reflectance of the water body in Wuliangsuhai Lake is higher within the wavelength range of 440-800nm[14]. The wavelength is consistent with the wavelength range of the first five bands of landsat8 satellite. Therefore, the input layer of BP neural network is set as 5 nodes, and the input data is the spectral reflectance of Landsat 8 remote sensing image data 1-5. The output layer is set as a node to output chlorophyll-a concentration. At present, there is no unified and clear regulation on the number of hidden layer nodes, which is generally completed by repeated attempts. After testing, this paper finally takes 4 layers with 5000 nodes per layer as the best. In the process of model training, MSE is used as the loss function, and the random gradient descent method is used to optimize the weight, and tanh() function is selected as the activation function. Before learning and training the BP neural network model, it is necessary to normalize the measured values of band reflectance and chlorophyll-a concentration of Landsat 8 remote sensing image data.

![Neural network structure](image)

2.3.3. Model performance evaluation. In this paper, the root mean square error (RMSE) and determination coefficient ($R^2$) of BP neural network inversion model test are used as the evaluation index of the inversion model, and the best model is selected. Root mean square error (RMSE) is used to measure the deviation between the inversion value and the measured value, determination coefficient ($R^2$), also known as goodness of fit, can be used to measure the quality of the model, the range of $R^2$ is from negative infinity to 1, the smaller the $R^2$ value is, the worse the fitting degree of the model is.

\[
RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (y_i - pre_i)^2}
\]

\[
R^2 = 1 - \frac{\sum_{i=1}^{N} (pre_i - \bar{y})^2}{\sum_{i=1}^{N} (y_i - \bar{y})^2}
\]

\[
\bar{y} = \frac{1}{N} \sum_{i=1}^{N} y_i
\]

Note: $i$ is the number, $N$ is the total number of samples, $y_i$ is the measured value, $pre_i$ is the inversion value, $\bar{y}$ is the average of the measured value.

3. Analysis of experimental results
In the 26 inversion models, the top three input band combinations of $R^2$ are 1+2+3+4+5,
1+2+3+5 and 1+2+3+4, the $R^2$ and RMSE of the three inversion models are 0.736 and 2.371, 0.728 and 2.409, 0.703 and 2.515. With the increase of the input band, the accuracy of the model is improved gradually. The results show that the BP neural network inversion model with 1+2+3+4+5 input band has the best performance.

### Table 2. Verification results of 26 inversion models.

| Band combination | $R^2$  | RMSE(μg·L$^{-1}$) |
|------------------|--------|-------------------|
| 1+2              | 0.338  | 3.758             |
| 1+3              | 0.170  | 5.781             |
| 1+5              | 0.218  | 4.083             |
| 2+3              | 0.373  | 3.656             |
| 2+4              | 0.462  | 3.387             |
| 2+5              | 0.247  | 4.009             |
| 3+4              | 0.448  | 3.431             |
| 3+5              | 0.156  | 4.969             |
| 4+5              | 0.302  | 3.859             |
| 1+2+3            | 0.689  | 2.574             |
| 1+2+4            | 0.434  | 3.475             |
| 1+2+5            | 0.412  | 3.543             |
| 2+3+4            | 0.369  | 3.660             |
| 2+3+5            | 0.409  | 3.552             |
| 3+4+5            | 0.451  | 3.421             |
| 1+3+4            | 0.499  | 3.270             |
| 1+3+5            | 0.580  | 2.991             |
| 1+4+5            | 0.598  | 2.929             |
| 2+4+5            | 0.469  | 3.364             |
| 1+2+3+4          | 0.703  | 2.515             |
| 1+2+3+5          | 0.728  | 2.409             |
| 1+2+4+5          | 0.540  | 3.310             |
| 1+3+4+5          | 0.657  | 2.705             |
| 2+3+4+5          | 0.493  | 3.290             |
| 1+2+3+4+5        | 0.736  | 2.371             |

### 4. Conclusion

The first five bands of Landsat 8 remote sensing image data were combined as input, and the measured chlorophyll-a values of Wuliangsuhai Lake in the same period were taken as output. The BP neural network inversion models of chlorophyll-a concentration of 26 Wuliangsuhai Lake were constructed, it is found that the BP neural network inversion model based on the first, second, third, fourth and fifth bands of Landsat 8 remote sensing image data has the best performance, with $R^2$ value of 0.736 and RMSE value of 2.371.

### Acknowledgments

This work was supported by National Key R & D Plan of China(grant no. 2019YFC049205), National Natural Science Foundation of China(grant no. 61962047), Inner Mongolia Natural Science Foundation(grant no. 2019MS06015).

### References

[1] Tian W, Jia K, Shi X et al. (2016)The characteristics of water quality changes in Wuliangsuhai Lake from 2005 to 2014[J]. Lake Science, 2016,28(06):1226-1234.
[2] Wu A, Zhu M, Tang L et al. (2011) Analysis of chlorophyll a dynamics and related environmental factors during the high-occurrence period of cyanobacteria bloom in Dianshan Lake[J]. Lake Science, 2011, 23(01):67-72.

[3] Jiang X, Li Changyou, Shi Xiaohong et al. The temporal and spatial distribution of chlorophyll a in Wuliangsuhai Lake and its relationship with environmental factors[J]. Acta Eco-Environmental Sciences, 2019, 28(05):964-973.

[4] Zhang B, Li J, Shen Q et al. (2021) Research progress of long time series and large-scale inland water optical remote sensing[J]. Journal of Remote Sensing, 2021, 25(01):37-52.

[5] Mishra S, Mishra D, Schluchter W. (2009) A Novel Algorithm for Predicting Phycocyanin Concentrations in Cyanobacteria: A Proximal Hyperspectral Remote Sensing Approach[J]. Remote Sensing.

[6] Feng L. (2021) Discussion on Several Key Issues of Interpretation of Lake Cyanobacteria Bloom by Satellite Remote Sensing[J/OL]. Lake Science, 1-7.

[7] Bandi K., Nagaraju R. (2020) Comparison of different deep learning frameworks[J]. Materials Today: Proceedings, 2020 (prepublish).

[8] Zhang T, Huang M, Wang Z. (2020) Estimation of chlorophyll-a Concentration of lakes based on SVM algorithm and Landsat 8 OLI images[J]. Environmental Science and Pollution Research, 2020, 27(13).

[9] Fan G, Cao H, Xu J. (2020) Prediction of chlorophyll a in Taihu Lake based on HJ-1A CCD image and ELM model[J]. Journal of Water Resources and Water Engineering, 2020, 31(05):16-22.

[10] Shi Y, Jiang Y, Li L et al. (2020) Research on the normalized relative radiometric calibration method of optical satellite[J]. Journal of Geo-Information Science, 2020, 22(12):2410-2424.

[11] Zhang X, Li L, Wang Y et al. (2020) Atmospheric correction of Gaofen-1 data using Landsat8 product algorithm process[J]. Transactions of the Chinese Society of Agricultural Engineering, 2020, 36(01):182-192.

[12] Hu J, Zhen J. (2010) A fast and globally convergent BP neural network learning algorithm[J]. System Science and Mathematics, 2010, 30(05):604-610.

[13] Wong, Fung. (2014) Combining EO-1 Hyperion and Envisat ASAR data for mangrove species classification in Mai Po Ramsar Site, Hong Kong[J]. International Journal of Remote Sensing, 2014, 35(23).

[14] Qing S, Bao Y, Hao Y. (2017) Atmospheric correction based on Wuliangsuhai Landsat-8 OLI data in the shortwave infrared band[J]. Infrared, 2017, 38(03):21-30.