VIP-BP model for retrieving chlorophyll a concentration in the river by using remote sensing data
Xiao Xiao, Biyu Song, Xiongfei Wen, Dengzhong Zhao, Xuejun Cheng, Chengfang Hu, Jian Xu and Zhaohui Wang

ABSTRACT
Chlorophyll a (Chla) is an important indicator of phytoplankton biomass in waters, and its concentration can reflect the degree of eutrophication. This paper is aimed to develop a highly accurate and universally applicable retrieval model for the concentration of Chla in rivers using remote sensing data. Taking the middle and lower reaches of the Han River as the study area, the Chla retrieval model (VIP-BP model) is established by combining the Variable Importance Projection Index and BP neural algorithm and then calibrated by the measured data from 2012 to 2013. This model uses the VIP index for selection of the appropriate spectrum transformation form and input bands. Then, the BP neural network algorithm is integrated to estimate Chla concentration. After validation and comparison with the three-band model, the results suggest that the VIP-BP model could more accurately and really reflect the changes in Chla concentration than the three-band model in the study area. When Chla concentration decreases, the retrieval error of both models increases, while the error of the VIP-BP model is significantly lower than that of the three-band model, which indicates that the VIP-BP model is more stable and preferred.

Key words | chlorophyll a, Han River, hyperspectral data, neural network, retrieval model

LIST OF ACRONYMS
Chla Chlorophyll a
TSM Total suspended matter
CV Coefficient of variation
VIP Variable Importance Projection index
RMSE Root mean square error
RE Relative error

INTRODUCTION
As one of the major environmental problems, eutrophication has become a global concern, especially in developing countries. Chlorophyll a (Chla) is an important indicator of phytoplankton biomass in waters, and its concentration can reflect the degree of eutrophication. Conventional Chla concentration monitoring relies on water surface sampling and physical and chemical analyses in laboratories, which wastes a lot of time and labour. Previous studies have shown that Chla is somewhat correlated with spectral reflectance of visible and near-infrared bands (Gitelson 1992; Gitelson et al. 1993; Li et al. 2002; Zhou et al. 2004); thus, based on this correlation, remote sensing data are incorporated to establish the retrieval model for Chla concentration. Then, conventional monitoring methods can be combined to achieve the goal of real-time dynamic monitoring and evaluation of water conditions in critical waters.

According to the current studies, Chla concentration retrieval models can be generally divided into three
categories: empirical model, semi-empirical model and analytical model. Among them, the analytical model is considered to be the most stable and universal retrieval model (Li et al. 2006; Ma et al. 2006; Lei 2013). However, since the inherent spectral properties of the waters studied are difficult to obtain, its wide application is hindered. Comparatively, the empirical model can better reflect the relationship between the water spectral signal and the Chla concentration; in addition, it can be easily constructed, so it is quite popular. Yet, as it is overly dependent on measured data, the empirical model is restricted by time and region and is not so universal. In contrast, the semi-empirical model also uses simple algebraic expressions to establish the functional relationship between remote sensing data and Chla; furthermore, it is constructed based on the spectral characteristics of some water colour substances, thus reducing dependence on measured ground data and improving the model applicability. As a result, it will be more and more frequently used. Here is a classical study on Chla concentration retrieval: phytoplankton’s absorption peaks in red bands and fluorescence peaks in near-infrared bands are used to establish single band or band ratio models of Chla concentration (Gitelson et al. 1985). From the practical application effect, band ratio models are generally more accurate than single band models (Gitelson & Kondratyev 1991; Gons 1999; Li et al. 2002; Liu et al. 2005; Ma & Dai 2005; Hunter et al. 2010), which is mainly due to the fact that the adoption of the ratio of these two characteristic bands can partially eliminate the interference of water surface smoothness, microwave and other environmental factors and reduce the influence of other non-target substances, thereby improving water quality parameter retrieval accuracy. However, in turbid waters, some non-target substances will have great impact on water reflectance, and the spectral signal of waters is weak, so the simple ratio method does not easily highlight the changes in Chla concentration. In order to further improve the Chla retrieval accuracy of turbid inland waters, researchers (Dall’Olmo & Gitelson 2005; Le et al. 2009; Yang et al. 2010) propose a three-band model and then develop a four-band model and enhanced three-band model. These models mainly consider the absorption and backscatter features of waters and partially eliminate the influence of yellow substances and non-pigmented particles, thereby enhancing Chla concentration retrieval accuracy of turbid inland waters.

However, according to the existing studies, Chla concentration retrieval models are mostly linear ones (Ma & Dai 2005; Xu et al. 2007; Y. E. Li et al. 2009; Y. L. Li et al. 2009; Yu et al. 2009; Ma et al. 2013). Compared to ocean waters, inland waters have more complex compositions and their spectral characteristics are subject to the mutual influence of phytoplankton pigments, suspended particles and yellow substances. In the meantime, components of the water body also interact on each other, and a nonlinear relationship can be found between spectral reflectance and these components. To solve this problem, researchers introduce machine learning algorithms like the neural network, genetic algorithm and support vector machine to the retrieval of Chla concentration. These models can better simulate the complex nonlinear relationship between the remote sensing signal and Chla, and their accuracies are generally higher than those of regression models (Schiller & Doerffer 1999; Wang et al. 2005, 2013; Zhang et al. 2005; Zhan et al. 2004; Lv et al. 2006; Li et al. 2010).

Yet, in the establishment of Chla retrieval models based on machine learning algorithms, most researchers choose all bands or highly-correlated single bands and band combinations as the spectrum input (Zhang & He 2002; Zhan et al. 2004; Li et al. 2010; Jiang 2011; Song et al. 2012; Wang et al. 2013). In the case that measured hyperspectral data are used to establish the Chla retrieval model, as the measured spectral data generally contain hundreds or even thousands of wavelength variables, not only will redundant variables (noise) unrelated to Chla be introduced to complicate the model, but also the model will produce large errors or be trapped into a local optimal solution if the model is just established based on a simple correlation. As a result, before the measured hyperspectral data are used to establish a Chla retrieval model, effective variables must be selected to improve the accuracy and stability of the retrieval model.

Currently, most studies in domestic and foreign countries that use remote sensing technology to monitor the water quality in inland waters have focused on lakes or reservoirs, and the studies on inland rivers are not in great numbers, which is primarily attributed to the following facts: strong liquidity of river water, rapid diffusion of water pollutants, higher requirements for temporal and spatial
resolutions of remote sensing data and difficulty in the use of the quantitative remote sensing retrieval technique to monitor the water quality of rivers due to their long and narrow shapes. However, as sensors have developed, sensors with high spatial and temporal resolutions have been gradually put into use, which has greatly promoted the quantitative remote sensing retrieval study of water quality parameters for inland rivers.

Consequently, with the middle and lower reaches of the Han River as the area of interest, this paper aims to establish a highly reliable and universal Chla retrieval model for turbid rivers, laying the foundation for the development and application of machine learning models of Chla concentration for turbid rivers and promoting the development of water quality remote-sensing monitoring technology for rivers.

**STUDY AREA AND DATA**

**Study area**

This paper focused on the middle and lower reaches of the Han River, originating in Danjiangkou and running deep into the hinterland of Hubei Province. The middle and lower reaches of the Han River are not only an important water source for cities along the River, but also a water body with an important water environment function. With the increasing degree of industrialization and use of pesticide, the middle and lower reaches of the Han River are subjected to different degrees of pollution. During the last decade, algal blooms have frequently occurred in that region, which have greatly affected the normal production and life of people along the River (Li et al. 2007; Yin et al. 2011; Liang et al. 2012). Therefore, strengthening the monitoring and management of water quality in the Han River would contribute to the sustainable development of the basin and related areas. Selection of the middle and lower reaches of the Han River as the study area is of typical significance.

**Data collection**

The reaches from Qianjiang to Xiantao City are typical middle and lower reaches of the Han River, as well as an important water source for cities along the River. Twenty monitoring sections were identified in accordance with field investigation, and six sampling experiments were conducted in spring, summer and autumn from 2012 to 2013.

A Hydrolab_DS5X_DS5 portable water quality detector manufactured by Hach Company (USA) was used to obtain the Chla concentration at various sampling points; the concentration of the total suspended matter (TSM) was determined through laboratory analysis (water quality–determination of suspended matter–gravimetric method (GB11901-89), People’s Republic of China National Standard). See the statistics for concentrations of Chla and TSM in Table 1.

**Chla and TSM**

It can be seen from Table 1 that the overall Chla concentration in the study area is relatively low (0.67–9.07 μg/L) and changes significantly with the seasons, which is consistent with the algae growth characteristics. For example, the Chla concentrations are low in autumn (0.67–2.15 μg/L) and high in summer (4.86–9.07 μg/L). The concentration of TSM is relatively high (with a maximum of 187 mg/L) and the concentration in autumn is significantly higher than those in spring and summer, which can be attributed to the low water level and small water flow of the river in autumn. In addition, except for spring 2013, the discrete

<table>
<thead>
<tr>
<th>Datasets</th>
<th>Water quality parameter</th>
<th>Maximum</th>
<th>Minimum</th>
<th>Mean</th>
<th>CV (%)</th>
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<tr>
<td>2012 Spring</td>
<td>chla (μg/L)</td>
<td>7.99</td>
<td>2.88</td>
<td>4.67</td>
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<td>–</td>
<td>–</td>
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<td>chla (μg/L)</td>
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<td>5.73</td>
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<tr>
<td></td>
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<td>chla (μg/L)</td>
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<td>2.08</td>
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<td></td>
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<tr>
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<td>4.32</td>
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<td>84.60</td>
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<td>All</td>
<td>chla (μg/L)</td>
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<td>0.67</td>
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<td>63</td>
</tr>
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<td></td>
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<td>18.80</td>
<td>75.43</td>
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</table>
levels of concentrations of Chla and TSM in other sampling periods are not high (coefficient of variation [CV] <30%).

**Measured hyperspectral data**

The spectral acquisition instrument used is an ASD-fieldspec3 portable spectrum measuring instrument manufactured by ASD Corporation (USA), whose waveband ranges from 350 nm to 1,050 nm. Spectral measurement adopts the surface-above measurement method (Tang et al. 2004). The angle between the observation plane and the sunshine incident plane is set as 135° and the angle between the instrument and the surface normal direction as 40°.

Figure 1 presents the spectral curves of the measured hyperspectral remote-sensing reflectance within the range of 350–900 nm for various sampling sites under different seasons. In this paper, the Savitzky-Golay smoothing method is employed to de-noise the reflectance, whose measurement interval is 1 nm to eliminate the difference or instrument noise due to the band response; then, the spectral characteristics in the study area are analysed through first-order and second-order differentials (Tsai & Philpot 1998; Ruffin et al. 2008; Shen et al. 2011). In the latter part, \( R_{rs} \) refers to the spectral reflectance after Savitzky-Golay pre-processing, and various spectral forms transform on the basis of \( R_{rs} \).

It can be seen from Figure 1 that the spectral reflectance in the study area shows general characteristics of inland waters: reflection valleys (or shoulder shape) with low reflectance in 400–500 nm (Gitelson 1992; Kirk 1994), 620 nm (Gitelson 1992; Dekker 1993; Kirk 1994; Gitelson et al. 1995), 680 nm (Gitelson et al. 1993, 1994a, 1994b; Yacobi et al. 1995); and obvious reflection peaks around 560 nm (Schalles et al. 1998), 700 nm (Fischer & Kronfeld 1990) and 810 nm (Song et al. 2008). In addition, the water reflectance varies obviously with season, but the characteristics of the reflectance are similar under different seasons, namely, the positions of the high and low values of the reflectance almost remain unchanged. The distinction is the reflection valley around 675 nm and the reflection peak at 700 nm in summer are more apparent in depth and height due to the high content of algae. However, in autumn there is a relatively apparent reflection peak around 580 nm and 810 nm, but no significant reflection valley (peak) around other bands.

According to the statistics, the remote sensing reflectance in the study area has nine characteristic wavelengths, including four valleys and five peaks (Table 2). Compared with typical characteristic wavelengths of remote sensing reflectance in lakes, as the concentrations of Chla and carotenoids in the study area are relatively low, the water reflectance does not have significant characteristic peaks (valleys) at 440 nm, 470 nm and 490 nm that are mainly caused by Chla and carotenoids (Gordon & Morel 1985; Gitelson et al. 1993; Yacobi et al. 1995; Iluz et al. 2003).

**METHODS**

**Data processing**

As the spectral information of the water is weak, \( R_{rs} \) must be pre-processed prior to the establishment of the retrieval model to enhance the spectral information in the study area. This paper adopts the following commonly used spectral transformation forms to pre-process \( R_{rs} \): logarithmic transformation, reciprocal transformation, square root transformation, first-order derivative transformation and normalization processing. By combination of these
transformation modes, 13 changing modes including \( R_{ts} \) are introduced. It was found that after \( R_{ts} \) goes through logarithmic transformation, reciprocal transformation, square root transformation and normalization processing, the overall trend of the spectral curve changes, but no significant changes are found in various small bands. After the first-order derivative transformation, the spectral curve presents relatively obvious ups and downs, which better highlight the subtle changes in spectral information. Especially, after the first-order derivative transformation, the logarithmic first-order derivative transformation and the reciprocal logarithmic first-order derivative transformation, local reflectance is greatly enlarged and multiple obvious bands with peaks occur. In the meantime, the correlation analysis also shows that (Figure 2), compared to the reciprocal logarithmic transform, its effectance has the same correlation analysis results after \( R_{ts} \) and other transformation forms, the correlation between \( R_{ts} \) transformed based on first-order derivative and Chla concentration is significantly improved. The reflectance has the same correlation analysis results after logarithmic first-order derivative transformation and reciprocal logarithmic first-order derivative transformation, so only \( R_{ts}, R_{ts}', (1/R_{ts})', (\log R_{ts})', (\sqrt{R_{ts}})' \) and \((1/(\log R_{ts}))'\) are introduced in the subsequent analysis. The spectral curves and correlation curves transformed are shown in Figure 2.

### VIP-BP model

The key to the construction of retrieval models of Chla concentration is to determine appropriate input bands. Therefore, the useful bands reflecting the changes in Chla concentration must be extracted to establish a simple but practical retrieval model, which involves the selection of informative variables. The correlation coefficient method is commonly employed, namely, extracting the variable greater than a certain standard as the spectrum input for model construction. However, as this method is based on a single-point searching algorithm, the information variables obtained are few, and the simulation results always mislead to local optimal solutions. Besides, when extracting the information variables, the influence of collinearity between variables is also neglected.

The VIP index (Variable Importance Projection index), an input variable selection index based on partial least squares regression, selects input variables by measuring the importance of variable to dependent variable. The VIP index reflects the importance of independent variables in explaining the dependent variable (Wold et al. 1993; Wang et al. 2006). For the \( i_h \) independent variable, its VIP index is defined as:

\[
\text{VIP}_i = \sqrt{\frac{p \sum_{h=1}^{m} R(Y, t_h) w_{hi}^2}{\sum_{h=1}^{m} R(Y, t_h)}}
\]

where \( p \) is the number of independent variables; \( m \) is the number of components extracted from the original variables by the partial least squares method; \( t_h \) represents the \( h_{th} \) component; \( R(Y, t_h) \) represents the explanatory ability of the component \( t_h \) for the dependent variable \( Y \), which is the squared correlation coefficient; \( w_{hi} \) is the \( j_{th} \) weight on the axis \( w_h \). A variable with a very big VIP index (\( VIP > 1 \)), plays a more important role in explaining the dependent variable \( Y \) (Chong & Jun 2005).

Inland turbid waters are characterized by complex spectral characteristics, and strong mutual influence can be found between water components. Thus, the relationship between reflectance and Chla cannot be easily described by a simple linear relationship. Due to its self-learning, self-adaptability, self-organization, large memory capacity, fault tolerance and nonlinear mapping, the neural network boasts strong vitality and superiority in
expressing the nonlinear relationship between Chla and reflectance. The BP neural network (back-propagation network) is the most common one among artificial neural networks, and its network features are very suitable for simulation of this kind of complex relationship. The neurons in the BP network are arranged hierarchically, including input layer, output layer and at least one hidden layer; the neuron output in each layer is transmitted to the next layer. During the transmission, the output can be strengthened, weakened or suppressed by connective weight. Except for the neurons in the input layer, the net input of neurons in the other two layers is the weighted
sum of the outputs of neurons in the previous layer. The activation of each neuron is decided by its input, activation function and weight threshold.

Combining the VIP index and BP neural network algorithm, $R_{ss}, R_0, (1/R_{ss})', (\text{lg} R_{ss})', (\sqrt{R_{ss}})'$ and $(1/(\text{lg} R_{ss}))'$ are considered as the variable input layer. Before modelling, the VIP index can be determined to improve the spectral transformation forms of the estimation capacity of water reflectance for Chla concentration and screen effective spectral variables. Then, the screening results and Chla concentrations of their corresponding samples are taken as the input and output layer neurons of the BP neural network, respectively, so as to establish the Chla concentration retrieval model for the study area. The VIP-BP model is established through Matlab R2013a.

**Figure 2** Continued.
Three-band model

Based on the optical transmission mechanism of vegetation, soil and other substances, Gitelson & Merzlyak (2003) propose a three-band semi-analytical model, which is then introduced by Dall’Olmo & Gitelson (2005) and Zimba & Gitelson (2006) into the retrieval study of Chla concentration. It considers the absorption and backscattering features of the water, and improves the retrieval accuracy by partially eliminating the influence of yellow substances and de-pigmented particles. The model form is as follows:

\[
\text{Chla} \approx \frac{a_w(\lambda_3)}{a_{\text{Chla}}(\lambda_1)} \left( R_{\alpha}(\lambda_1)^{-1} - R_{\alpha}(\lambda_2)^{-1} \right) \times R_{\alpha}(\lambda_3) + \frac{a_w(\lambda_2) - a_w(\lambda_3)}{a_{\text{Chla}}(\lambda_1)}.
\]

(2)
RESULTS

Two models were used to estimate Chla concentration for the study area. A total of 84 samples randomly selected in various sampling periods were used for calibration; the remaining 20 samples were taken as test ones to compare the accuracy and validation of these two models.

Simulation results were evaluated by root-mean-square error and relative error (RE) and an optimal model was selected to estimate the Chla concentration in the study area. $C_{imea}$ is the measured value; $C_{imod}$ is the simulation value; $n$ is the number of samples.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (C_{imea} - C_{imod})^2}{n}}$$ (3)

$$RE = \left(\frac{C_{imod} - C_{imea}}{C_{imea}}\right) \times 100\% \quad (4)$$

In addition to combining the existing studies (Han & Rundquist 1994) and the results of the study area spectral characteristic analysis, we utilized the reflectance within 350–750 nm.

Model calibration

After the screening of the VIP index, taking into account the waveband coverage and VIP index, $(\log R_{rs})^\prime$ is considered to be able to improve the estimation capability of water reflectance for Chla concentration, so it is taken as the input spectrum of subsequent modelling (Table 3). The bands for spectral input of the neural network model are finally identified as $\lambda_1 = 510$ nm, $\lambda_2 = 546$ nm, $\lambda_3 = 638$ nm, $\lambda_4 = 677$ nm, $\lambda_5 = 747$ nm. In the experiment, the initial learning rate is set as 0.05, the incremental factor of the learning rate is 1.05 (the reduction factor of the learning rate is 0.7), number of display cycles is 1,000, number of iterations is 3,000 and the error performance is 0.0005. After repeated iterations of learning and adjustment of neurons in the hidden layer, the three-layer BP neural network is adopted: the number of neurons in the hidden layer is 7 and the network structure is 6-7-1. The neurons in the hidden layer adopt an S-type function (tansig), while the neurons in the output layer utilize a linear function (purelin). The training function adopts the steepest descent algorithm (traingdx), whose learning rate is variable.

The fitting accuracy ($R^2$) of the retrieval results from the VIP-BP model and three-band model (after multiple iterations, we get $\lambda_1 = 660$ nm, $\lambda_2 = 700$ nm and $\lambda_3 = 749$ nm) are 0.98 and 0.83, respectively (Figure 3); the VIP-BP model has a higher accuracy. From the perspective of different levels of Chla concentration, for both the VIP-BP model and three-band model, errors increase with the decrease of Chla concentration. However, whether the Chla concentration is low or high, the error of the VIP-BP model is significantly lower than that of the three-band model; while the Chla concentration is low (<2 $\mu$g/L), the fitting results for the three-band model are unacceptable (Table 4).

Model validation

The remaining 20 samples are taken as validation ones to test the accuracy and applicability of these two models. The fitting formula for the three-band model is:

$$Chla = -1.63 \times (Diff(R_{rs}(660))^{-1} - Diff(R_{rs}(700))^{-1}) \times Diff(R_{rs}(749)) + 2.78$$ (5)
Table 3 | Statistics of VIP index

<table>
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<tr>
<th>Spectra form</th>
<th>Waveband ranges (nm) and VIP (&gt;1)</th>
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<tr>
<td>$R_{rs}$</td>
<td>Waveband ranges (nm) 350–390 657–750</td>
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<td></td>
<td>VIP 1.00–1.13 1.02–1.70</td>
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<tr>
<td>$R'_{rs}$</td>
<td>Waveband ranges (nm) 413–440 478–490 577–604 621–643 657–707 750</td>
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<td>VIP 1.02–1.34 1.01–1.20 1.03–1.32 1.00–1.77 1.07–1.89 1.02</td>
</tr>
<tr>
<td>$(1/R_{rs})'$</td>
<td>Waveband ranges (nm) 357 502–566 571–598 636–641 657–750</td>
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<td></td>
<td>VIP 1.04 1.00–1.23 1.01–1.17 1.15–1.38 1.00–1.85</td>
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<td>$(\lg R_{rs})'$</td>
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<td></td>
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<tr>
<td>$(\sqrt{R_{rs}})$'</td>
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<td>$(1/(\lg R_{rs}))'$</td>
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<td>VIP 1.01–1.08 1.01–1.16 1.02–1.51 1.02–1.63 1.02–1.86 1.05–1.19</td>
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Figure 3 | Scatter plots of measured vs predicted values of Chla and error values: (a) and (c) for VIP-BP model, (b) and (d) for three-band model.
It can be seen from the fitting curve of predicted and measured values that the VIP-BP model still boasts better retrieval results and the RE also increases with the decrease of Chla concentration (Figure 4 and Table 5).

<table>
<thead>
<tr>
<th>C\text{chla} (\mu g/L)</th>
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<th>2-5</th>
<th>5-7</th>
<th>7-10</th>
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<tbody>
<tr>
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<td>19-95</td>
<td>20-85</td>
<td>41-78</td>
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<td><strong>Accuracy</strong></td>
<td><strong>RE(100%)</strong></td>
<td><strong>RMSE</strong></td>
<td><strong>RE(100%)</strong></td>
<td><strong>RMSE</strong></td>
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<td>130.90</td>
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<td>63.28</td>
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</table>

**DISCUSSION**

It can be seen from the retrieval results that the VIP-BP model boasts a higher accuracy and that the retrieval accuracies of these two models both decrease with the
The decrease of Chla concentration. By comparison, the retrieval error of the three-band model increases far more than that of the VIP-BP model. This could be explained by the establishing rules of the three-band model, which takes into account the water’s absorption and backscattering characteristics and introduces the three band sections to eliminate the influence of yellow substances and non-pigmented granules to improve the inversion accuracy. According to the existing findings (Xiao et al., 2013), when establishing the three-band inversion model for Chla under different seasons, with low concentration of Chla and high concentration of TSM (autumn), the model slope transforms with a large magnitude. Under this circumstance, due to the limitations of the three-band model, the changes in model slope are less affected by the specific absorption of pigment particles, which are mainly caused by the changes in the backscattering coefficient (Huang et al., 2013). However, when the change in water temperature is small and Chla concentration is low, the backscattering from pure water and Chla can be neglected (Buitenveld et al., 1994; Zhang et al., 2012), so it can be considered that the backscattering coefficient mainly comes from suspended matter at this time, and the three-band model is unable to completely eliminate the influence of suspended matter on the near-infrared band. Therefore, the inversion accuracy of the three-band model decreases in the case of a high concentration of suspended matter in the study area. In contrast, the VIP-BP retrieval model is established on the basis of advantages of the VIP index and BP neural network. It first selects effective variables from several bands by the VIP method and the selected bands can accurately reflect the changes in Chla concentration in the study area. After that, the model integrates the advantages of the BP neural network, weakens the influence of backscattering of suspended matter on spectral characteristics of the water, and solves the data transmission and exchange problems in the complex nonlinear calculation process reflected in establishment of the model. After the model is applied, we can know that, in the case where Chla concentration is greater than 2 μg/L, the RE(100%) of the VIP-BP model is 7.23%, significantly lower than that (44.92%) of the three-band model; even if the Chla concentration is very low and the TSM concentration is very high (C_{chla} < 2 μg/L, C_{TSM} > 70 mg/L), its RE is also much lower than that of the three-band model (Table 4).

In terms of the VIP-BP model, effective spectral variables are screened out before the modelling, and considering the complex spectral characteristics of the water body in the study area, benefiting from the advantages of the neural network model, the influence of the backscattering of the suspended matter on the spectral characteristics of the water body is weakened. In terms of the three-band model, the Chla inversion model is established only by partially eliminating the influence of yellow substances and de-pigmented particles on the spectral characteristics of the water body. Therefore, under the circumstance of low Chla concentration and high TSM concentration, the VIP-BP model is still applicable, but the fitting results of the three-band model are unacceptable. In addition, when the Chla concentration is relatively high, the VIP-BP model still has higher accuracy than the three-band model. Based on the above discussions and analyses, it is considered that the VIP-BP model is superior to the three-band model from the perspectives of applicability and inversion accuracy.

### CONCLUSIONS

As the study area is a river, its spectral characteristics are a bit different from those of inland lakes that contain similar Chla concentration. The derivation method is adopted to analyse the measured spectral data under different seasons and to obtain the season-based spectral characteristics of the study area. Due to the backscattering impact of suspended matter, in autumn with high content of TSM and low concentration of Chla, the spectral characteristics reflecting changes in Chla concentration are partially concealed. The VIP-BP retrieval model first identifies the optimal spectral transformation form of the measured hyperspectral spectral signal and determines that first-order derivative transformation can strengthen the subtle

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Table 5 | Accuracy analysis for two models

<table>
<thead>
<tr>
<th>Model</th>
<th>RE(100%)</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>VIP-BP</td>
<td>9.73</td>
<td>0.59</td>
</tr>
<tr>
<td>Three-band</td>
<td>43.3</td>
<td>1.39</td>
</tr>
</tbody>
</table>

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information of water reflectance in the study area; then, the characteristic bands that can accurately reflect the changes in Chla concentration are selected; finally, the BP neural network is combined to establish the Chla retrieval model for the study area. By comparison, it is found that the VIP-BP model boasts higher accuracy than the three-band model; even in the case of low Chla concentration, it can still accurately reflect the changes in the concentration, indicating that the VIP-BP model is highly reliable and universal.

Quantitative study by remote sensing inversion to monitor water quality parameters in the river is rarely reported. The VIP-BP model established in this paper for Chla concentration retrieval has high retrieval accuracy and can be used to facilitate the study of Chla retrieval for long and narrow rivers, providing a reference for the application of quantitative remote sensing technology in the monitoring of water quality in rivers.

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**REFERENCES**


Han, L. & Rundquist, D. C. 1994 The response of both surface reflectance and the underwater light field to various levels of suspended sediments: preliminary results. Photogrammetric Engineering and Remote Sensing 60 (12), 1463–1471.


