EVALUATION METHOD OF WATER QUALITY FOR RIVER BASED ON MULTI-SPECTRAL REMOTE SENSING DATA

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KEY WORDS: Han River, Multi-Spectral Data, Retrieval, Water Quality Evaluation, Neural Network, ZY-3, HJ-1A

ABSTRACT:

With the rapid development of the regional economy, water pollution has gradually become an environmental problem that cannot be ignored. As an important water source in central China, the Han River should strengthen water quality monitoring and management in order to ensure the sustainable development of watershed and related areas. Taking typical sections of middle and lower reaches of the Han River as the study area, this paper focuses on rapid river water quality assessment using multispectral remote sensing images. Based on measured water quality data and synchronous spatial high and medium-resolution remote sensing data (multi-spectral data of ZY3 and HJ1A) in 2013, neural network algorithm is used to establish water quality index retrieval model for the study area, and then water quality status is assessed accordingly. The results show that BP neural network retrieval model of water quality index that is established based on multispectral data of ZY3 satellite has higher accuracy and that its assessment results are of high credibility and strong applicability, which can really reflect changes in water quality and better achieve water quality assessment for the study area. In addition, water quality assessment results show that major excessive factors in the study area are total nitrogen and total phosphorus; the polluting type is organic pollution; water quality varies greatly with seasons.

1. INTRODUCTION

Water quality evaluation is a fundamental link in water environment management and monitoring. Only through water quality monitoring can water quality be reasonably evaluated and targeted water environment management planning and scheme be developed. In terms of water quality evaluation, traditional methods like water sample collection, indicator analysis and grade evaluation can only provide water quality status at the sampling point instead of large area of waters, while large-scale field sampling will consume a large amount of manpower, materials and financial resources. In recent years, with the rapid development of remote sensing technique, more and more researchers carried out fast, continuous and dynamic monitoring on waters by means of remote sensing technique. Further, this technique has been adopted by lots of domestic and foreign scholars on water quality evaluation (Wu, 2012, Gu, 2014, Zhu, 2013, Bitelli, 2010, Markogianni , 2014, Syahreza ,2012, Alparslan, 2007, Thiemann , 2000), and most of these studies used remote-sensing data to quantitatively retrieve concentration of water quality parameter and then establish a water quality evaluation model on this basis. The difficulty of this method mainly lies in the establishment of a definite linear relationship between remote sensing data and water quality parameter. Existing studies have shown that neural networks can better simulate the complex nonlinear relationship between remote sensing signal and water quality parameter concentration and have significantly higher retrieval accuracy than empirical models (Keiner,1998, Buckton, 1999, Schiller,1999, Gross,1999, Karul,2000, Zhang, 2002, Wang,2003, Lv,2006, Zhao,2009). Among numerous neural networks, BP neural network is mainly used for function approximation and is thus involved in the establishment of remote sensing retrieval model of water quality parameter (Reynolds, 2002, Li, 2009, Reynolds, 2002, Kuo,2007).

Although remote sensing technique exhibits many advantages in terms of water quality evaluation, current studies mostly adopt medium-resolution remote sensing images. Due to their time advantage (for instance, the HJ-1A/1B developed by China independently has a revisiting cycle of 4 days), water quality status can be monitored in a real-time manner and water quality evaluation can be updated rapidly. Yet, as these images have relatively low resolution, their application to lakes with smaller inland area, narrow rivers or reservoirs are largely limited. On January 9, 2012, a civilian high-resolution stereo mapping satellite "ZY-3", the first one of its kind in China, was successfully launched of which the multispectral data's resolution is 5m and the revisiting cycle is 5 days. Through the satellite, nationwide multispectral images can be obtained in a continuous, stable and rapid manner over a long period of time. With typical section of middle and lower reaches of Han River as the study area, based on BP neural network algorithm, this paper makes use of the measured water quality monitoring data acquired in summer and autumn in 2013 as well as the multispectral data of the satellites ZY-3 and HJ-1A to establish a water quality parameter retrieval model of the study area, conduct water quality evaluation of the Han River and draw a water quality map of the study area.

2. DATA AND METHODS

2.1. Study Area

The middle and lower reaches of Han River is not only an important water source for cities along the River but also serves as a water body with important water environment functions. According to Environmental Status Bulletins reported by Hubei Provincial Environmental Protection Bureau in 2000-2012, water quality of Han River tends to be improved year by year as a whole. Historical monitoring data show that the pollution type of Han River is organic pollution and that the main excess items are total phosphorus (TP) and ammonia nitrogen (TN) (Environmental Protection Bureau of Hubei Province, 2000-2012).

2.2. Relevant Data and Water Quality Evaluation Methods

Based on field investigation, with Xiantao section of Han River as the study area, the author determined 9 monitoring sections, conducted field experiments in summer and autumn of 2013

and obtained the multispectral data of the satellites HJ-1A and ZY-3 in the same period. According to Environmental Quality Standards for Surface Water (GB3838-2002), Class III water is regarded as the control objective. Although a lot of methods can be used for water quality evaluation, the previous study considers (Xiao, 2013a, Xu, 2005) that single factor water quality identification indicator (SFWQII) is most suitable for this study area, so this method is also applied in this research. The evaluation results show that major excessive substances of the monitoring sections are total nitrogen (TN) and total phosphorus (TP). Both these two items exceed certain limits to varying degrees in summertime. Among them, TN indicator exceeds the Class III water limits and gets close to Class IV water limits in summer; as for autumn, this indicator is a bit improved but is still above the Class III water limits for some monitoring sections. TP indicator in summer also goes above the Class III water limits and gets close to Class III water limits for some monitoring sections, while it gets better in autumn, living up to the limits of Class III water (Figure1).
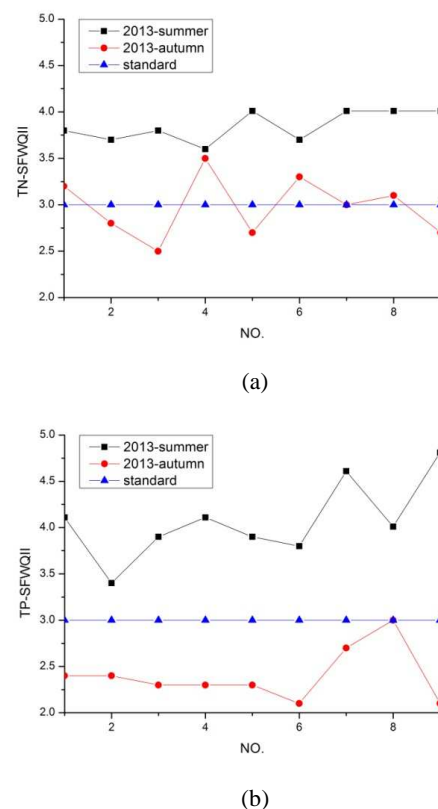

(a)

(b)

Figure1. Statistical results of SFWQII of TN and TP in the study area, (a) TN-SFWQII,(b)TP-SFWQII

2.3. Image Data

As for remote sensing images, multispectral data of HJ-1A and

ZY-3 are adopted. Image data consistent with field sampling time are acquired and preprocessed, including geometric correction, radiometric calibration and atmospheric correction (Xiao, 2013b, Yang.2013).

"HJ-1" Satellite System is an earth observation system specifically designed by China for environment and disaster monitoring, which consists of two optical satellites (HJ-1A and HJ-1B) and one radar satellite (HJ-1C). By means of optical, infrared and hyperspectral detection methods, this system can dynamically monitor environment and disasters on a large-scale, all-weather, and 24-hour basis. Among them, HJ-1A is characterized by four-band multispectral data, a spatial resolution of 30m and a revisiting cycle of 4 days.

"ZY-3" Satellite is the first civilian high-resolution optical stereo mapping satellite independently developed and successfully launched by China, whose main task is to obtain nationwide high-resolution stereo images and multispectral images continuously, steadily and quickly over a long period of time (Zhao, 2014). These images can be then used for land resources investigation and detection, disaster prevention and mitigation, agriculture, forestry and water conservancy as well as ecological environment. This satellite has been equipped with four linear push-broom optical cameras, including three full-color cameras and one multispectral camera. Among them, the multispectral camera includes four bands: red, green, blue and infrared and has a ground resolution of 5m and a revisiting cycle of 5 days. ZY-3 owns higher image quality and has stronger information extraction ability than SPOT5 in terms of water elements except for vegetation (Li, 2014). It can basically replace similar satellites like SPOT-5, P5 and ALOS in China (Fu, 2013).

3. MODELS

BP neural network model (back-propagation) is the most common one among neural network classifiers. One of its most important applications is function approximation. It can create any non-linear non-significant function mapping relationship from input to output for the training set and is suitable for the quantitative remote sensing retrieval study of water quality parameters. As a result, BP neural network is used in this paper to establish a retrieval model for concentrations of TN and TP on the basis of multispectral data from HJ-1A and ZY-3.

Further, the root mean square error ($RMSE$) and the absolute value of relative error ($|RE|$) are employed to evaluate the retrieval accuracy.

To accelerate the establishment of the model, the samples are normalized before modeling so that the input and the target value are between -1 and 1. As the samples for experiments are not in great numbers, K-fold cross-training method is used to get more stable simulation results. According to the existing research results (Xiao, 2013a, 2013b), the bands which are most correlated with the concentration of target parameters are selected to participate in the establishment of the model. That is to say, four bands in the multispectral data of the two satellites are chosen as the inputs (for TP, the inputs are B3 and B4). The concentration of TN (TP) are taken as the expected outputs; the initial learning rate is set as 0.05, the display cycle 1000, the number of iterations 2500 and the error performance target 0.0005. Based on the comparisons of different training algorithms of different BP neural networks (the selection for the optimal training algorithm of BP neural network is published in another paper), after several adjustments of the numbers of learning iterations and neurons in the hidden layer, in consideration of fitting speed and accuracy, S-type function is adopted for the neurons in the hidden layer, while a linear function is adopted for the output layer; the number of the neurons in the hidden layer is 6 and the network structure is 4-6-1(for TP, the structure is 2-6-1).

4. RESULTS

4.1. Comparisons Results

Based on the multispectral data of ZY-3 and HJ-1A, the concentration of water quality parameter in the study area is retrieved, and then the water quality evaluation results are obtained from the retrieval results. $|RE|$ and $RMSE$ are adopted to compare the water quality evaluation accuracies of these two kinds of multispectral data. See details in Figure2.
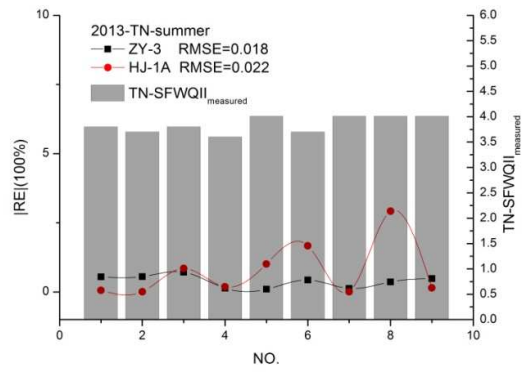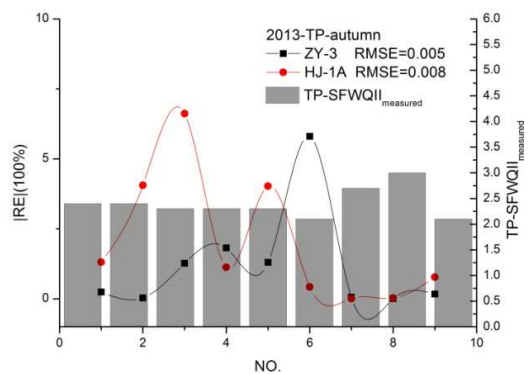
(a)
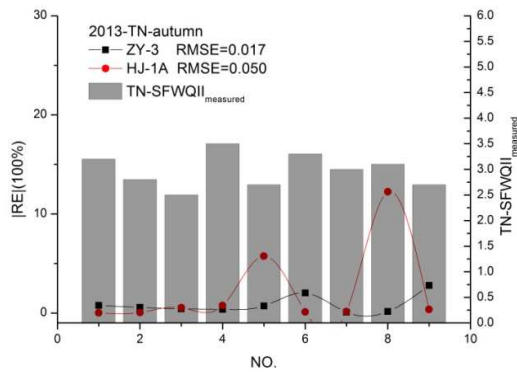
(b)
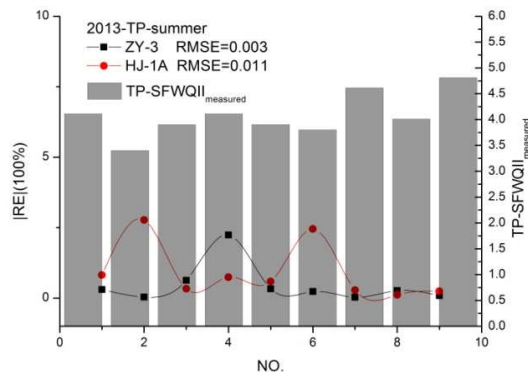
(c)

(d)

Figure2. Comparisons of accuracies of SFWQII for TN and TP

in the study area based on different image data

(a) 2013-TN-summer, (b) 2013-TN-autumn,

(c) 2013-TP-summer, (d) 2013-TP-autumn

It can be seen from Figure 2 that, for TN, two evaluation standards $|RE|$ and $RMSE$ should be taken into account. No matter in the summer or autumn of 2013, the evaluation results obtained through multispectral data of ZY-3 are closer to those of measured data. In addition, when TN indicator gets better (namely, TN concentration decreases), the retrieval results obtained based on multispectral data of ZY-3 still maintain a low error, while in the similar case, the fitting results from multispectral data of HJ-1A experience increased error and enhanced volatility, and a large gap can be identified between the simulation evaluation results of some samples and the measured evaluation results (for instance in autumn, $|RE|$ of Sample 8 is 12%).

TP indicator also shares some similarities with TN indicator. The evaluation results obtained from ZY-3's multispectral data are more in line with the actual situation. In the summertime of 2013, the simulation evaluation results of individual monitoring sections based on HJ-1A's multispectral data have larger errors, while other sections are not; in the autumn of the same year, this indicator gets better (the concentration goes down) and the evaluation accuracy still reduces.

4.2. Water Quality Evaluation

By means of BP neural network (resilient BP algorithm), based on the multispectral data of ZY-3 and HJ-1A, the spatial distribution map of single factor water quality identification index for TN and TP in the study area is made in the ENVI and MATLAB2013a environment, as shown in Figure 3.
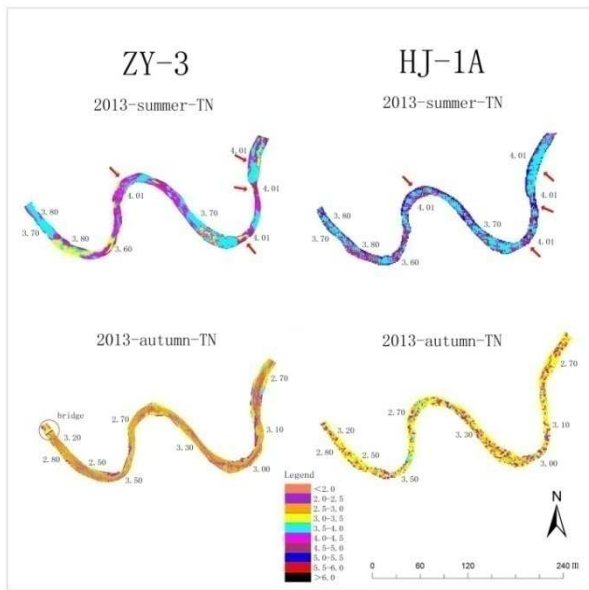
(a)
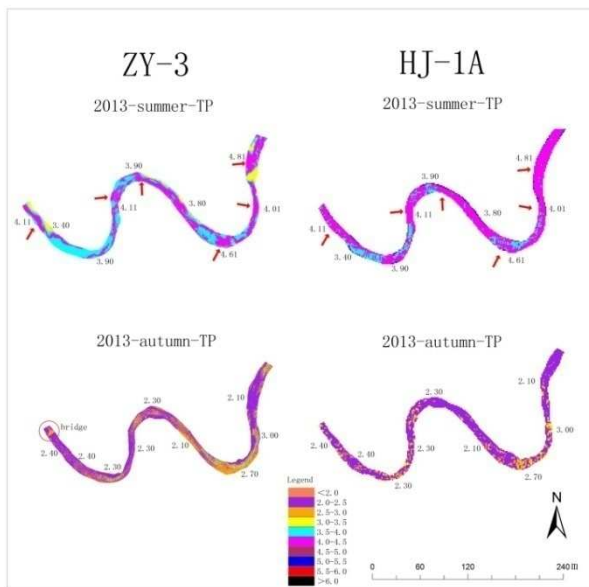
(b)

Figure 3. Spatial distribution of SFWQII for TN and TP in the study area, (a)SFWQII-TN,(b)SFWQII-TP

It can be seen from this map that, compared with SFWQII based on measured data (the figures marked on the map reflect the SFWQII obtained from measured data), both these two kinds of multispectral data can get the evaluation results similar to measured data. However, the comparisons indicate that, the spatial distribution map for SFWQII from ZY-3's multispectral data has a higher accuracy, which not only accurately reflect the level of distribution of water quality indicators in the study area (the arrow points out the high value area), but also precisely identify non-water parts (as shown by the circles in Figure 3. (a) and Figure 3. (b)); Yet, as for the spatial

distribution map for SFWQII from HJ-1A's multispectral data, although it is able to reflect the overall water quality status of the study area, the levels of distribution of water quality indicators can only be roughly expressed; when we need to know the upstream and downstream statuses of a certain section with high indicator value, the specific evaluation results acquired are less reliable than those results from ZY-3's multispectral data, which is mainly attributed to the low spatial resolution (30m) of these data.

5. CONCLUSIONS

The water quality evaluation conducted based on remote sensing data supplements the traditional evaluation work. In this paper, the multispectral data from two domestic satellites (ZY-3 and HJ-1A) are used to establish a remote-sensing retrieval model of concentrations of TN and TP through BP neural network (resilient BP algorithm) and conduct water quality evaluations on typical section of middle and lower reaches of the Han River. Comparisons reveal that, ZY-3 s' multispectral data can get more reliable water quality evaluation results and higher-resolution spatial distribution map of these results. Besides, the evaluation results based on ZY-3 s' multispectral images not only reflect the overall water quality status of the study area, but also reveal the upstream and downstream water quality statuses of a certain section with high indicator value and precisely identify non-water parts. From the perspective of research results, the multi-spectral data from ZY-3 and HJ-1A are good sources for remote sensing data of retrieval models of concentration of water quality parameter, and the researchers may selectively make use of their advantages to conduct water quality evaluation work of inland rivers. Based on the data obtained in summer and winter of 2013, the advantage of ZY-3's short revisiting cycle is not reflected, and future studies should focus on this point more; in the meantime, the data from ZY-3 and HJ-1A can be further used for the dynamic monitoring and simulated forecasting of water quality in inland waters.

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