Inversion of Water Quality Parameters of Maozhou River by Hyperspectral Technology

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ABSTRACT: Maozhou river is the largest and the most representative pollution urban river in Shenzhen. The pollution sources of Maozhou river mainly come from the upstream and domestic or industrial water, which has a serious impact on residents' life and urban ecological environment. Therefore, water quality monitoring of Maozhou river is extremely significant, not only for sustainable construction of water environment in Shenzhen, but also for urban river water quality research. Most of the current studies focus on large lakes and reservoirs, few on urban rivers. In this paper, the water quality parameters and in-situ reflectance of 15 sampling points were simultaneously measured. The monitoring model were established by measured spectral data, the inversion accuracy of chl-a, TSS, COD, total phosphorus, total nitrogen and ammonia nitrogen ratio index is above 0.55. The results showed that hyperspectral technology can provide data source and method for urban river water quality monitoring.

1. Introduction

With the rapid development of economy, water pollution is becoming a serious problem, restricting the sustainable development of the city(Chen et al. 2018). Therefore, it is very important for people's production and life to obtain the water quality of rivers and lakes quickly(Han et al. 2014; Zhou et al. 2013). According to the traditional method of water quality monitoring, artificial monitoring stations are set up in the water area, and water samples were taken back to the laboratory for testing by chemical reagents or professional instruments. This method has a higher precision, while it is easy to cause secondary pollution for water.

Remote sensing technology has been widely used to monitor water quality because of its wide range and multi temporal(Feng et al. 2015; Harvey et al. 2015; Palmer et al. 2015; Salem et al. 2017). Several researchers have attempted to monitor the water quality using remote sensing approaches. For example, Moderate Resolution Imaging Spectroradiometer (MODIS) data were used to estimate coastal Chl-a concentration(Manzar Abbas et al. 2019). A unified algorithm of eutrophic and ultra-turbid waters were developed and Chl-a and turbidity in different regions were evaluated (Sakuno et al. 2018). A multi-linear regression between Rrs of each wavelength and the in-situ chl-a were used to observe coastal environment of the west coast of South Korea (Baek et al. 2019). While due to the limitation of temporal and spatial resolution of satellite images, satellite remote sensing technology is often used in large area water monitoring, there is little research on urban river.

This study aimed to explore the method of urban river water quality monitoring, consisted of two steps: (1) analyze in situ water reflectance spectra and relationship of different water parameters. (2) establish the ratio index model and evaluate the accuracy by correlation coefficient(R) and coefficient of determination(R^2).

2. DATA AND METHODS

2.1 Study Area

Maozhou river originates from the northern foot of Yangtai mountain, and distributes in most areas of Shenzhen and some areas of Dongguan. As the largest river in Shenzhen, it has 1 main stream and 45 tributaries, whose main stream is 41.61km and the drainage area is 398.13km^2. As an urban river, Maozhou river is also the most representative pollution river of Shenzhen, whose pollution mainly comes from the upstream and domestic or industrial water, serious impacting on residents' life and urban ecological environment.

2.2 Data Source

Field data were obtained from Maozhou river in January 2018(from January 22 to 29), with a total of 15 sample points. Figure 1 shows the locations of the sampling sites. For each sampling site, water were collected from a depth of 50cm. All of the samples were placed in incubators for subsequent measurements in the laboratory.

Figure 1. Remote sensing image and sampling points distribution of Maozhou river.

Field data were measured by PSR-3500 spectrometer, which covers the spectral range from 350 to 2500nm and provides a spectral resolution of 3.5nm, 10nm and 7nm at the wavelengths of 700nm, 1500nm and 2100nm. The radiances of water, sky, and a reference panel were measured at each sampling site. A total of 400 bands(400-1000nm) were selected to do research, the remote sensing reflectance spectra of sampling sites are shown in Figure 2.

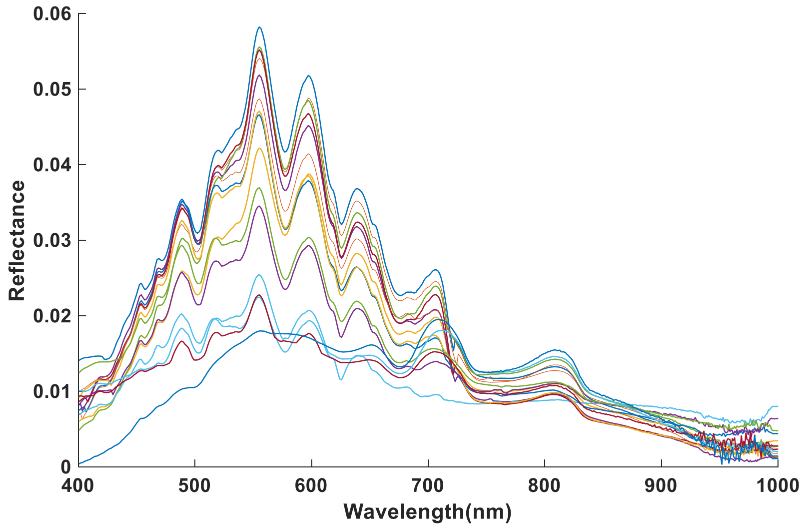


Figure 2. In-situ reflectance spectra of Maozhou river.

Figure 2 shows the absorption characteristics of chl-a and phycocyanin in Maozhou river are obviously weak. In addition, it also shows strong phycoerythrin absorption characteristics at 566nm, and the absorption characteristics at 502 nm may be the absorption characteristics of lycopene or organic dyes. The remote sensing reflectance spectra of Maozhou river shows a combined spectral characteristics of low chl-a and high organic matter.

3. EXPERIMENTS AND RESULTS

3.1 In-Situ Data

The sample statistics of water quality parameters are shown in the Table 1. It mainly includes the maximum value, minimum value, mean value, standard deviation and coefficient of variation of each parameter.

Table 1. Statistics analysis of water quality parameters of Maozhou river.

	TSS (mg/L)	COD (mg/L)	NH3-N (mg/L)	TP (mg/L)	TN (mg/L)	Chl-a (mg/m^3)
Max	116.00	185.00	46.40	4.42	53.90	8.76
Min	30.00	24.00	1.09	0.29	2.56	2.64
Mean	73.60	51.67	6.97	1.00	10.70	5.97
SD	30.09	53.95	14.01	1.23	15.27	1.88
C.V.	0.41	1.04	2.01	1.24	1.43	0.32

The results of calculate the correlation coefficient between the water quality parameters are shown in Table 2. There is a strong correlation among COD, TP, TN and NH3-N, and all correlation coefficients are above 0.97. The correlation between TSS and other parameters is low, not more than 0.5. Chl-a has a similar correlation with TP, TN and NH3-N.

Table 2. Correlation of water quality parameters.

	TSS	COD	NH3-N	TP	TN	Chl-a
TSS	1	0.199052	0.240798	0.325148	0.307699	0.423562
COD		1	0.97897	0.978645	0.973865	-0.31253
NH3N			1	0.992879	0.994264	-0.56629
TP				1	0.994938	-0.52316
TN					1	-0.51835
Chl-a						1

3.2 Inversion Model

Figure 3 shows the Pearson correlation between in-situ remote sensing reflectance and each water quality parameters. The correlation varied at different wavelengths for different water quality parameters. The change trend of TP, TN, COD and NH3-N is consistent, which is consistent with those in Table 2. The maximum negative correlation of TP, TN, COD and NH3-N is at 712 nm. The maximum positive correlation of Chl-a is at 709 nm, the sensitive band of Chl-a. The negative correlation of TSS is at 717 nm, close to the sensitive band of Chl-a. The Figure 3 shows that the strong correlation of water quality parameters appear at about 700~720 nm and 1000~1100 nm, while the correlation curve in 1000~1100nm is not smooth, because there are some noises after 900 nm(Figure2).

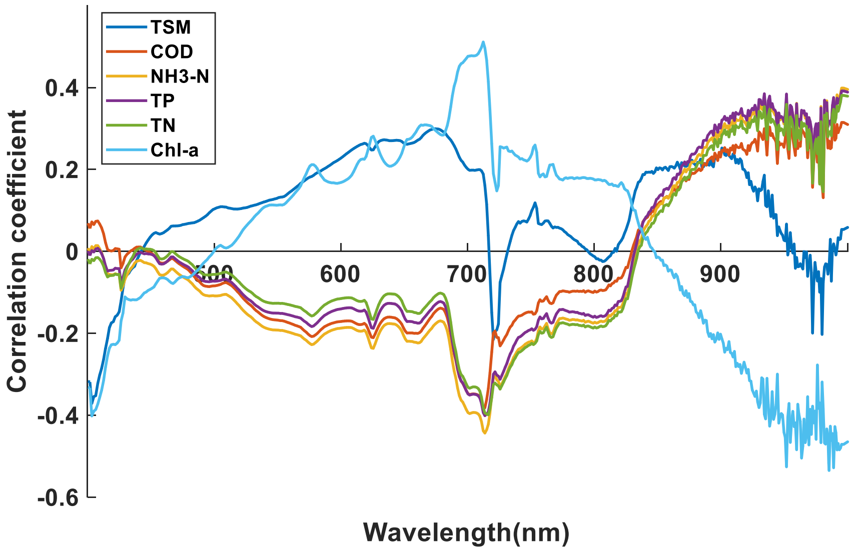


Figure 3. Correlation coefficient curve between water quality parameters and in-situ reflectance.

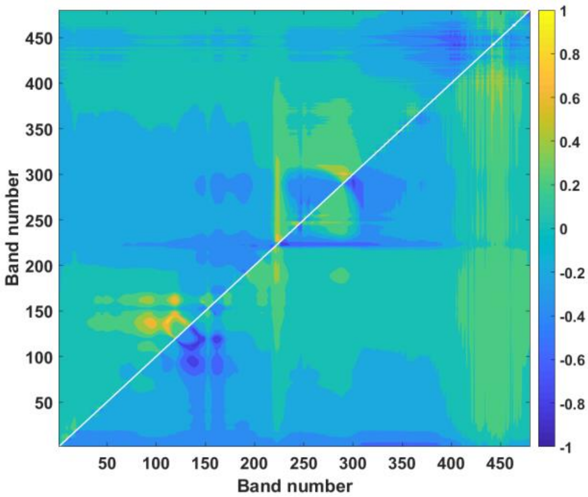
The correlation coefficient of ratio index and difference index are shown in Table 3. In general, the correlation coefficient of all water quality parameters is above 0.74. TP, TN, COD and NH3-N have the same characteristic band in difference indexs.

In this paper, empirical model were used for estimating the concentrations of water quality parameters by sensitive indices. The accuracy of single band water quality monitoring model is not as high as that of dual band model. The ratio index and difference index are constructed from the reflectance of all bands, and then the correlation analysis between these indexes and each water quality parameter is carried out.

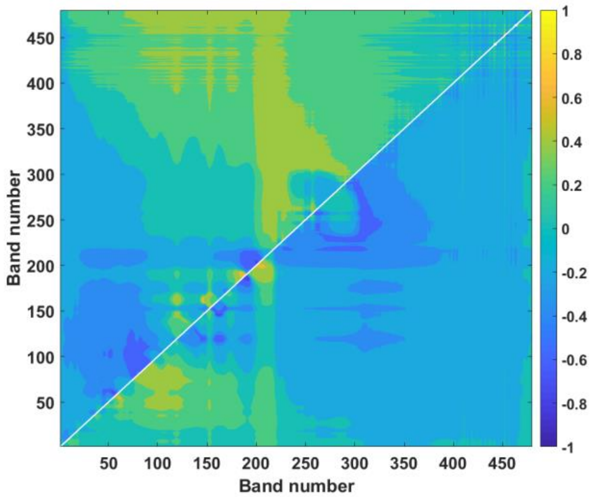
Table 3. Spectral response characteristic of different indexs.

	Ratio index(B1/ B2)				Difference index(B1- B2)			
	B1	B2	R	R^2	B1	B2	R	R^2
TSS	113	140	-0.84834	0.72	137	112	0.863239	0.65
COD	191	186	0.760652	0.58	454	453	0.808456	0.52
NH3N	162	145	0.754395	0.57	454	453	0.788924	0.43
TP	160	146	0.764513	0.58	454	453	0.7933	0.44
TN	160	146	0.742559	0.55	454	453	0.796997	0.42
Chl-a	192	187	-0.83162	0.69	192	186	-0.78498	0.68

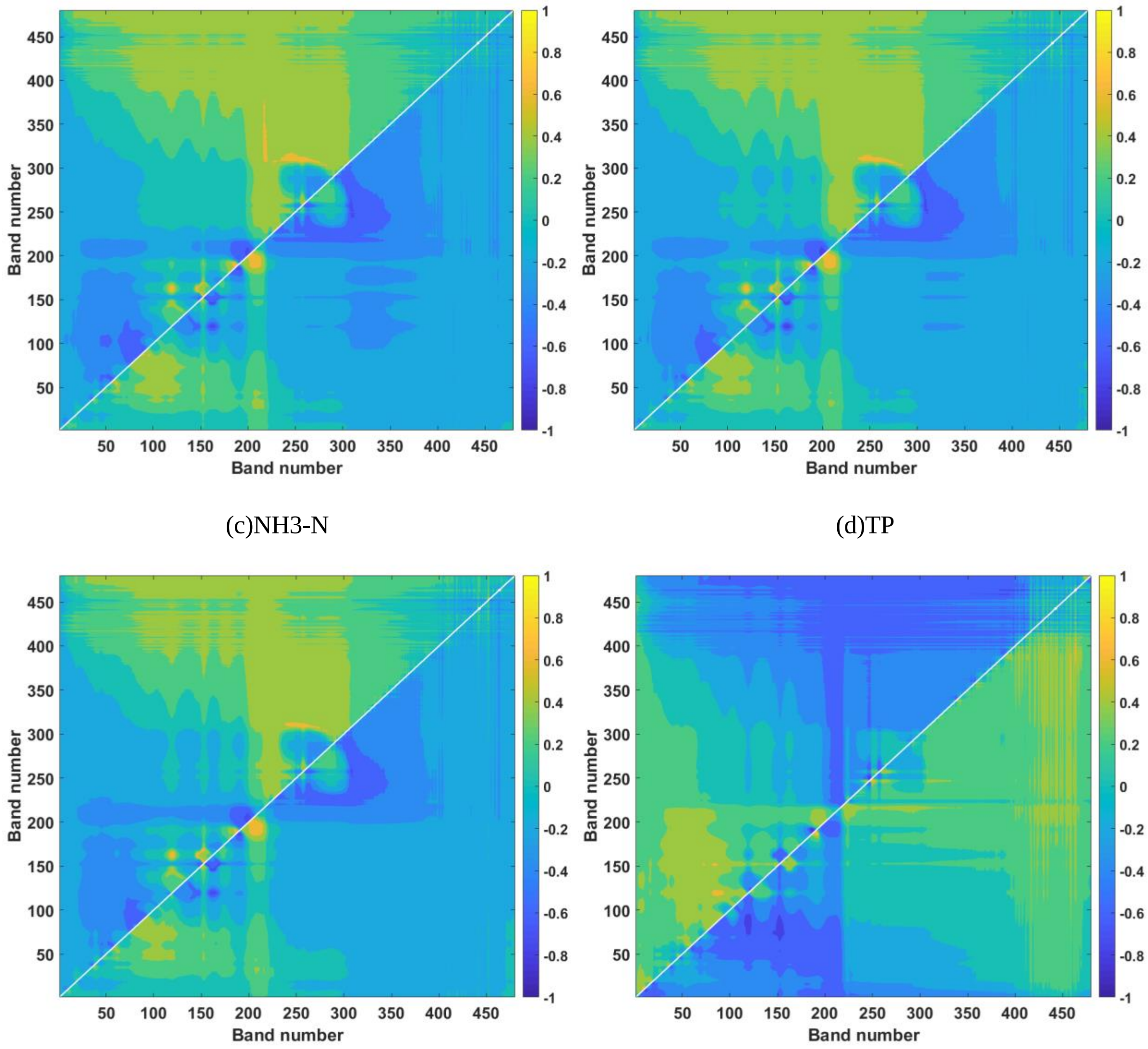
Through the band combination calculated, the linear regression model was established between each water parameter and index. The accuracy of the model was evaluated by the coefficient of determination(R^2). Table 3 shows that the accuracy of ratio model is better than that of difference model for each water parameter. The R^2 of the ratio model are all above 0.55, Tur is the highest, reaching 0.77, and TSS is 0.7, the two water parameters have a high correlation(Table 2).



(a)TSS



(b)COD



(c)NH3-N (d)TP

(e)TN (f)Chl-a

Figure 4. Correlation coefficients between the ratio index and water quality parameters.

Figure 4 shows the coefficients between the ratio index and water quality parameters. The coefficients are relatively high in 740-750 nm (band 240-250) for TP, TN, COD and NH3-N. Table 4 shows the details of the models for the inversion of different water parameters.

Table 4. Details of the inversion models for water parameter.

Water parameter	X	Model Expression
TSS	$Ref_{565.3}$/ $Ref_{607.1}$	Y = -771.65X + 891.64
COD	$Ref_{678.5}$/$Ref_{671.6}$	Y = 5670.1X - 5572.4
NH3N	$Ref_{638.2}$/ $Ref_{614.2}$	Y = 952.8X - 912.28
TP	$Ref_{635.4}$/ $Ref_{615.6}$	Y = 101.7X - 97.507
TN	$Ref_{635.4}$/ $Ref_{615.6}$	Y = 1224.9X - 1175.7
Chl-a	$Ref_{679.9}$/ Ref_{673}	Y = -307.93X + 316.13

4. CONCLUSIONS

In this paper, as a typical urban polluted river, Maozhou river was choosed as study area. We established index model according to the in-situ data, the accuracy of the model is above 0.55 for all water parameters. In the future research, the higher spatial resolution image data is considered, such as UAV hyperspectral image, to obtain the distribution of water quality parameters, aiming to provide a new data source and technical means for urban river water quality monitoring, as well as water environment protection and management.

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