Application of SeaWiFS data for assessment of eutrophication in the Pearl River estuary

Chuqun CHEN, Xiaobin LI
(LED, South China Sea Institute of Oceanography, Chinese Academy of Sciences,
164 West Xingang Road, Guangzhou 510300, China. cqchen@scsio.ac.cn)

Abstract In this paper a method for remotely-sensed assessment of eutrophication was experimented. The water samples were collected for analysis of COD (chemical oxygen demand) and nutrients concentration, and the remote sensing reflectance data at the sampling points were synchronously measured using above-water method in two cruises, which were conducted in the Pearl River Estuary in January 2003 and January 2004 respectively. Based on the in-situ data the local algorithms for estimation of concentration of nutrients (P and N) and COD were developed by Partial Least Squares (PLS) regression. The algorithms were then applied to atmospheric-corrected SeaWiFS data and the COD and nutrients concentration in Pearl River Estuary were estimated. And then the assessment of eutrophication was carried out by comparison of the estimated nutrients and COD value with the water quality standard. The results show that the whole estuary is seriously in eutrophication.

KEY WORDS: entrophication; Pearl River estuary; Ocean color remote sensing; SeaWiFS data.

1. INTRODUCTION

With of population growth and rapid industrialization and urbanization, more and more solid, liquid and gas wastes (known as the "three wastes") have been emitted to the environment in China, especially in the Pearl River Delta area, the environmental pressure has increased during the last two decades. The environmental conditions have become a major limiting factor for the progress of society and for the economical development. Many serious red tide or harmful algae blooms have occurred in the estuary area or its adjacent coastal areas since the 1980s, and caused huge economic losses. It is believed that the algae bloom or red tides is related with the eutrophication in the estuary, and eutrophication has become one of most serious problems of water quality in the Pearl River estuary.

To detect the nutrients concentration is important for water quality assessment and for red tides monitoring. The conventional mothed for investigation on distribution of nutrients concentration in coastal waters is to collect water samples from the field and analyse the nutrients concentration of the water samples in laboratory. This kind measurement is expensive and time-consuming. As it is hard to synchronously to collect water samples from different stations, in return, it is hard to get accurate distributions of the nutrients concentration, which will be changeful due to the effect of tides and advection.

The satellite remote sensing technique is complemental to the conventional measuring method, and has advantage for its wide-view field, synchronous and high frequency repeatable measurement, and low cost. Remote sensing is expected to play a role on water quality monitoring. With the development of remote sensing technique, many studies on application of satellite data for water quality monitoring have been reported (e.g., Oron and Gitelson, 1996; Brivio et al., 2001; Ostlund et al., 2001; Hu et al., 2004; Wang et al. 2004). However, most remotely sensed monitoring investigations focused on determining single water quality variables, such as suspended sediment, turbidity, transparency or Secchi disc depth, chlorophyll, dissolved organic matters (yellow substance), COD, and BOD (Tassan 1994; Doerffer and Fischer 1994; Allee and Johnson 1999; Arenz et al 1996; Chen et al 2003; Wang et al. 2004).

In this paper, the Partial Least Squares (PLS) regression is employed for analysis of the measured remote sensing reflectance data and nutrients concentration data, and the local algorithms for estimation of nutrients concentration were developed. And the nutrients concentration distribution in the Pearl River estuary were retrieved from the atmospheric-corrected SeaWiFS images. And then the eutrophication was assessed according to the nutrients concentration retrieved from SeaWiFS data with reference concentraion. The eutrophication extents and their distribution patterns in the Pearl River estuary were obtained from ocean colour satellite data.

2. STUDY AREA

The Pearl River is 2214 km long and has a catchment area of 453,690 km^2 (Zhao, 1990). It has a mean annual runoff of 326 billion m^3. The annual discharge depends on the amount of rainfall received in its catchment. From Oct. to Apr. the weather is dominated by the northeast monsoon, and the mean rainfall is relatively low with about 30-40 mm/month (Zhao, 1990; Larson et al. 2005). From May to Sep. the humid air is brought up from lower latitudes causing larger amounts of rainfall (300-400 mm/month). The discharge into the Pearl River estuary during the dry season is about 1,500 m^3/s but the flow rate can increase up to 20,000 m^3/s during the wet season. The annual discharge of suspended sediments is about 87 million tons. The warm-humid climate results in strong chemical weathering and about 30 million tons of dissolved matters are discharged yearly (Zhao, 1990). The water is discharged to the South China Sea through a delta with eight river branches, which results in a complicated spatial distribution of the water components. There are several major cities in the delta, including Guangzhou, Foshan, Shenzhen, and Zhuhai. The delta area has experienced rapid industrialization and urbanization. The economic expansion has adversely impacted the water quality in the downstream areas of the Pearl River system because of an increasing discharge of industrial and domestic wastewater (Jayawardena and Lai, 1989). Water quality in the estuary has become progressively worse in the last 20 years.

The serious environmental crisis in the Pearl River estuary is eutrophication. Since the nutrients mostly originate from the discharge, the concentration of nutrients is higher in the surface layer than in bottom layer, displaying a seasonal variation (Yin, 2003). The concentrations of total inorganic nitrogen (TIN) can be very high (up to 126 μM, and generally >70 μM), however the PO4 concentrations are generally low (maximum 1.5 μM, and mostly <1 μM). The nutrient ratios of N:P (N = TIN, P = PO4) is typically >50:1, however, it can be >100:1, which is much higher than 16:1, the standard nutrient ratio for phytoplankton ingestion. The nutrient ratio shows that P is the main limitation factor in controlling phytoplankton biomass production. The eutrophication has produced serious red tide events or harmful algal blooms in the estuary and its adjacent coastal waters since the 1980s and caused huge economic loss. Thus, the environmental condition of the area is a serious concern for the local societies. Recovery programs for water quality are in operation and the water quality in the estuary will hopefully be improved in the near future. The remote sensing technique is expected to monitor the effects of the recovery programs for the water quality.

3. DATA EMPLOYED and METHODOLOGY

3.1. Data Collection

The in-situ data were collected during 2 cruises conducted in the Pearl River Estuary, respectively in the period of 25-26 January 2003 and 5-6 January 2004. The in-situ measurements were taken at 18 stations in each cruise; Fig.1 shows the positions of the stations.The variables determined in this study include temperature, salinity, chlorophyll-a, total suspended matters (TSM), nutrients (TIN TP), chemical oxgen demand (COD), dissolved organic carbon (DOC), gelbstoff absorption coefficient (Ag), and remote sensing reflectance (Rrs). The nutrients (TIN, TP) and COD were analyzed in laboratory of the institute with China Standard Method, the GB Method (GB/T 17378-1998). An above-water method was used for the measurement of remote sensing reflectance (R_λ).

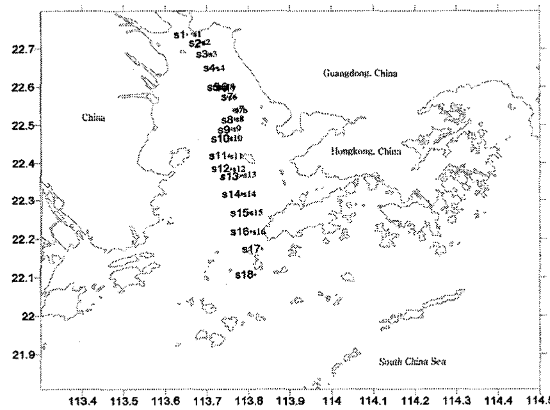

Figure 1 The sampling position of cruises January 2003 and 2004

The water-leaving radiance, radiance reflected by a reference panel with 25% reflectance and sky radiance were measured 3 times in rapid succession at each station using the Ocean Optics USB2000 spectrometer (wavelength range from 200 to 850 nm with a spectral resolution of 0.37 nm) with fibre-optic extension cables, and pistol-like grips. The R_λ data were averaged for the 3 radiance measurements. The average R_λ values over SeaWiFS bands 1 to 6 were calculated. The R_λ increased with increasing wavelength from SeaWiFS bands 1 to 5, with the R_λ at band 6 being lower compared with band 5 (Table 1).

Table 1. In-situ reflectance data in the Pearl River Estuary

cruise	2003			2004		
R(%)	Min	Max	Mean	Min	Max	Mean
R_{412}	0.9373	3.2489	1.8000	0.9376	3.1007	1.9831
R_{443}	1.0581	4.2323	2.2139	0.9429	3.2595	2.2014
R_{490}	1.3246	5.3007	2.7858	1.1360	3.6110	2.6267
R_{510}	1.4234	5.9766	3.0714	1.3343	3.7982	2.8869
R_{555}	1.7044	7.4515	3.7229	2.0276	4.6781	3.5901
R_{670}	0.6300	7.1935	2.3352	0.8777	3.3283	2.0537

3.2 The Partial Least Squares (PLS) regression algorithms

As a relative newer multivariate statistics approach, PLS allows evaluation of the latent variables in a multivariate space (Andren et al.,1998; Eriksson et al.,1995). The basic theory of PLS regression and its application on algorithm development can be found in references (Helland 2001; Ehsani et al. 1999, Yang 2005). Being similar to PCA (Principal Component Analysis) , PLS regression can detect the maximum variance that is called principal component in a data set. PLS regression can also maximize the covariance between the predictor (independent X-matrix) and the response matrix (dependent Y-matrix). In addition, PLS regression can simultaneously project the independent X-variables and dependent Y-variables onto the same subspace based on the optimal relationship between the observation position in the X and the Y plane. Comparing with many other regression methods, PLSR is better for dealing with such data sets that have fewer observations than variables and a high degree of intercorrelation among the independent variables (Sonesten,2001; Zhang et al.,1998).

PLS regression can find out latent structures successively with component projection. In most cases, this procedure can reduce spectral variables to a few independent Principal Components. The final algorithm predicted y_i was expressed as

$$y_i=a_0+a_1t_{1i}^*+a_2t_{2i}^*+\ldots+a_nt_{ni}^* \qquad (1)$$

where t_{1i}^* to t_{ni}^* were the scores from principal component (PC) 1 to n for variable i. The scores were calculated on the basis of mean-centered data. And a_n was the regression coefficient obtained by linear regression of t versus y in the calibration iteration process. a_0 was the centered mean parameter.

PLS uses prediction residual sum of squares (PRESS) for checkout. The PRESS will be calculated in the following ways:

$$\text{PRESS}=\sum_{i=1}^{n}(y_i-y_{i,-i})^2 \qquad (2)$$

The lower the value of PRESS is, the better the predicted ability of algorithm is. The model will be set up when the value of PRESS is infinitesimal.

4. RESULTS

The measured reflectance data were first processed to reflectance ratio, and 6 ratio cases were considered, that is the reflectance of each band was divided by band 1 t oband 6. Then with the reflectance data of 6 band, five reflectance ratio can be obtained for each case. The series of principal components (from first to fifth PC) were analysed for different reflectance ratio cases, and used for algorithm development. Totally 30 algorithms were developed for different reflectance ratio cases with the different PC series, and the algorithms were assessed with their PRESS. And the algorithm with lowest PRESS was choosed for estimation of nutrients concentrations. The algorithm for TIN estimation is:

$$\text{Log(TIN)}=0.5776-0.2156*(R_{1/6})-0.2513*(R_{2/6})-0.4166*(R_{3/6})-0.0065(R_{4/6})+0.2545(R_{5/6}) \qquad (3)$$

Here R is the reflectance ratio, which band combination is shown with the subscript. The algorithm shown in Eq.(3) was developed using the first 2 PCs, its PRESS is 0.0502, its average relative eroor is 9.06%. And the algorithm for TP estimation is:

$$\text{Log(TP)}=-1.3259-0.752*(R_{1/6})-0.0213*(R_{2/6})+0.243*(R_{3/6})+0.3003*(R_{4/6})-0.1222*(R_{5/6}) \qquad (4)$$

similar to Eq. (3), R in Eq.(4) is the reflectance ratio, which band combination is shown with the subscript. The algorithm for TP estimation was also developed using the first 2 PCs, its PRESS is 0.7802, its average relative eroor is 32.64%. And the algorithm for COD estimation is

$$\text{Log(COD)}=0.6075-0.3011*(R_{2/1})-0.1469*(R_{3/1})-0.0658*(R_{4/1})+0.0874*(R_{5/1})+0.1104*(R_{6/1}) \qquad (5)$$

Then the three algorithms were applied to atmospheric-corrected SeaWiFS data, the concentration of TIN, TP and COD can be retrieved for the whole Pearl River estuary.

The eutrophication was assessed with the nutrients quality index (NQI), which is calculated from Eq.(6):

$$NQI=\frac{C_{COD}}{C'_{COD}}+\frac{C_{TIN}}{C'_{TIN}}+\frac{C_{TP}}{C'_{TP}} \qquad (6)$$

Where C_{COD}、C_{TIN}、C_{TP} are the satellite-retrieved concentration of COD, TIN and TP respectively, and C'_{COD}、C'_{TIN}、C'_{TP} are reference concentration for assessment of COD, TIN and TP, respectively. The reference concentration are set as: C'_{COD} =3.0mg/L; C'_{TIN} =0.3mg/L; C'_{TP} =0.03mg/L。

Then the eutrophication was divided into three levels based on the NQI values: the Oligotrophication level for NQI<2, middle eutrophication level for 2<=NQI>3, and eutriohication level for NQI>=3. The eutrophication levels were assessed and their distribution patterns were revealed from the SeaWiFS data. Fig. 2 shows the distribution of eutrophication in the Pearl River estuary and its adjacent waters, retrieved from SeaWiFS data of January 10, 2003.

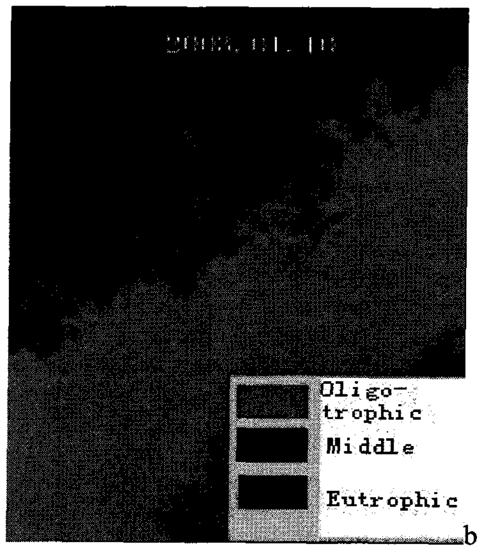

Fig. 2 Eutrophication distribution retrieved from SeaWiFS data of Dec.31,1998 (a) and Jan. 10, 2003 (b) respectively.

5. DISCUSSION and CONCLUSION

The PLS regression results showed that ratio in case of reflectance divided by band 6 is better than other ratio cases for both of TIN and TP concentration estimation. While the ratio in case of reflectance divided by band 1 is better for COD estimation. COD is the index for oganic pollution, and the coloured dissolved organic matters (CDOM) or yellow substance has strong absorption at short wavelength, and the higher yellow substance, the higher COD, so the blue band (band 1) is important for COD.

Our previous works showed that the Band 6 with central wavelength of 670 nm is very important for coastal waters (chen et al. 2003; Chen et al. 2005). The remote sensing reflectance at 670 nm is very low in case 1 waters, and significantly increases in case 2 coastal waters because of scattering from the suspended sediments. SeaWiFS band 6 (670nm) is therefore an important band for the retrieval of water components with terrestrial origine such as the suspended sediments and nutrients in estuarine waters. The optical properties of TIN and TP and their impacts on remote sensing reflectance is not well-known, but both of sediments and nutrients have similar terrestrial origine, and encounter similar transfer processes. It makes the nutrients have indirect relationship with reflectance.

The data used for algorithm development were collected in winter time (local dry season). In order to improve the algorithms, the dataset needs to be expanded to include data collected in other seasons (including wet season).

ACKNOWLEDGMENT

The research work was jointly supported by China national 973 project 2001CB409708, national 863 project 2002AA639130, project from National Natural Science Foundation of China(NSFC, 40276049) and the China-UK scientific foundation project E2. Many thanks to the SeaWiFS project within NASA GSFC, for providing the SeaWiFS data and SeaDAS software.

REFERENCES

Allee, R.J., and Johnson, J.E.,. Use of satellite imagery to estimate surface chlorophyll-a and Secchi disc depth of Bull Shoals, Arkansas, USA. International Journal of Remote Sensing, 1999, vol.20, p.1057-1072

Andren, C., Eklund, B., Gravefors, E., Kukulska, Z., Tarkpea, M. (1998), A multivariate biological and chemical characterization of industrial effluents connected to municipal sewage treatment plants. *Environmental Toxicology and Chemistry, 17*, 228-233.

Arenz, R., F.,Jr, Lewis W. M. Jr and Saunders J.F. Determination of chlorophyll and dissolved organic carbon from reflectance data for Colorado reservoirs, International Journal of Remote Sensing, 1996, 17(8), 1547-1566.

Brivio PA, Giardino C, Zilioli E. Validation of satellite data for quality assurance in lake monitoring applications. The Science of the Total Environment. 2001,Vol.268, p.3-18.

Catherine Ostlund , Peter Flink , Niklas Strombeck , Don Pierson ,Tommy Lindella. Mapping of the water quality of Lake Erken, Sweden, from Imaging Spectrometry and Landsat Thematic Mapper. The Science of the Total Environment. 2001, Vol.268, p.139-154.

Chuanmin Hu, Zhiqiang Chen, Tonya D. Clayton, Peter Swarzenski, John C. Brock, Frank E. Muller-Karger. Assessment of estuarine water-quality indicators using MODIS medium-resolution bands: Initial results from Tampa Bay, FL. Remote Sensing of Environment, 2004,vol.93, p.423–441.

Chuqun Chen, Ping Shi, HaiGang Zhan, A local algorithm for estimation of yellow substance (gellbstoff) in coastal waters from Sea WiFS data: Pearl River estuary, China. Int. J. Remote Sensing, 2003a, 24(5), p.1171-1176.

Chuqun Chen, Jun Wei, Ping Shi, Atmospheric correction of SeaWiFS imagery for turbid waters in Southern China coastal aeas, proceedings of SPIE, 《Ocean Remote Sensing and Applications》, 2003b, Vol.4892, p.80-86

Doerffer, R., and Fischer, J.,. Concentrations of chlorophyll, suspended matter, and gelbstoff in case II waters derived from satellite coastal zone color scanner data with inverse modeling methods, Journal of Geophysics Research, 1994, C4, 99, 7457-7466.

Ehsani, M.R., Upadhyaya, S.K., Slaughter, D., Shafii, S., & Pelletier, M. (1999), A NIR technique determination of soil mineral nitrogen. *Precision Agriculture, 1*, 217-234.

Eriksson, L., Hermens, J.L.M., Johansson, E., Verhaar, H.J.M., Wold, S. (1995), Multivariate analysis of aquatic toxicity data with PLS. *Aquatic Sciences, 57*, 217-241

Gideon Oron, and Anatoly Gitelson. Real-time quality monitoring by remote sensing of contaminated water-bodies: Waste stabilization pond effluent. Water Research 1996,vol.30(12), p.3106-3114.

Helland, I.S. (2001b). Some theoretical aspects of partial least squares regression. *Chemometrics and Intelligent Laboratory* Systems, **58**, 97-107.

Jayawardena, A.W. and Lai, F. "Time Series Analysis of Water Quality Data in Pearl River, China," Journal of Environmental Engineering, 1989,Vol.115(3), p.590-607.

Magnus Larson, Raffaella Bellanca, Lennart Jeonsson, Chuqun Chen and Ping Shi. Modeling the 3D Circulation, Salinity Distribution,and Transport Pattern in the Pearl River Estuary, China. Journal of Coastal Research, 21 (5): 896-908 SEP 2005

Sonesten, L. (2001), Mercury content in roach (Rutilus rutilus L.) in circumneutral lakes-effects of catchment area and water chemistry. *Environmental Pollution, 112*, 471-481

S. Tassan. Local algorithms using SeaWiFS data for the retrieval of phytoplankton, pigments, suspended sediment, and yellow substances in coastal waters. Applied Optics, 1994,vol.33(12), 2369~2378.

Yunpeng Wang, Hao Xia, Jiamo Fu, Guoying Sheng. Water quality change in reservoirs of Shenzhen, China: detection using LANDSATyTM data. The Science of the Total Environment. 2004,Vol.328, p.195-206.

Yang Y M, Liu Z W, Chen B Q, Tang J W. (2005), Retrieval of Oceanic Color Constituents from Case II water Reflectance by Partial Least Squares Regression. *Journal of Remote Sensing, 3(9)*, 123-130. (In chinese)

Yin Kedong. Influence of Monsoons and Oceanographic Processes on Red Tides in Hong Kong Water Marine Ecology Progress Series, 2003,vol. 262, p.27-41.

Zhang, Y.X., Malmqvist, B., Englund, G (1998), Ecological processes affecting community structure of blackfly larvae in regulated and unregulated rivers: a regional study. *Journal of Applied Ecology, 35*, 673-686.

Zhao Huanting (1990). The Evolution of the Zhujiang River Estuary. China Ocean Press. Beijing, China.