Front. Environ. Sci. Engin. China (2008) 1:
DOI
Verso: Water quality monitoring in slightly-polluted inland water body through remote sensing
Recto: Weiqi HE, et al.
RESEARCH ARTICLE

Water quality monitoring in slightly-polluted inland water body through remote sensing —A case study in Guanting Reservoir, Beijing, China

Weiqi HE [1], Shan CHEN [1,2], Xuehua LIU (✉)[1], Jining CHEN [1]

1. Department of Environmental Science and Engineering, Tsinghua University, Beijing 100084, China;
2. Research Center for Eco-environmental Science, Chinese Academy of Sciences, Beijing 100085, China.

Abstract This study focused on water quality for Guanting Reservoir, the possible auxiliary drinking water source of Beijing. Through remote sensing (RS) approach, water quality retrieval models were established and analyzed for eight common concerned water quality variables, including algae content, turbidity, and concentrations of chemical oxygen demand, total nitrogen, ammonia nitrogen, nitrate nitrogen, total phosphorus, and dissolved phosphorus, by using Landsat 5 Thematic Mapper (TM) data. The results showed that there existed a statistical significant correlation between each water quality variable and remote sensing data in the slightly-polluted inland water body with fairly weak spectral radiation. With appropriate method of sampling pixel digital numbers and multiple regression algorithms, algae content, turbidity, and nitrate nitrogen concentration could be retrieved within 10% mean relative error, concentrations of total nitrogen and dissolved phosphorus within 20%, concentrations of ammonia nitrogen and total phosphorus within 30% while chemical oxygen demand had no effective retrieval method. These accuracies were acceptable for the practical applications of routine monitoring and early warning on water quality safety with some support of precise traditional monitoring. The results showed that it was possible and effective to perform most traditional routine monitoring tasks of water quality on relatively clean inland water bodies by RS.

Keywords Guanting Reservoir, Landsat Thematic Mapper (TM), remote sensing (RS), water quality, retrieval algorithm, drinking water source, linear regression

1 Introduction

The quality of surface water has deteriorated in many countries in the past few decades. As a result of the growing population, increasing industry, agriculture, and urbanization, the inland water bodies are confronted with the increasing water demand, as facing with extensive anthropogenic inputs of nutrients and sediments, especially the lakes and reservoirs [1]. To handle this problem, it is necessary to carry out water quality assessment, planning, and management, in which water quality monitoring plays an important role [2].

The current *in situ* techniques for measuring water quality variables are time-consuming and do not give a synoptic view of a water body or, more significantly, a synoptic view of different water bodies across the landscape [3]. It requires excessive traveling, sampling, and expensive laboratory analysis, especially for a large area; thus it is very difficult to report and predict the water quality situation in time [4]. Fortunately, while with the development of remote sensing (RS) techniques, water quality monitoring based on RS methods becomes accessible and very efficient.

As the pollutants scatter and absorb the incoming solar radiation, the water quality is significantly correlated with the water column’s optical characteristics, such as color and transparency, which can be obtained from RS data [5]. Therefore, investigations suggest that optical data can provide an alternative

Received: September 10, 2007; accepted: October 20, 2007
E-mail: xuehua-hjx@tsinghua.edu.cn

means for obtaining relatively low-cost, simultaneous information on surface water quality conditions from numerous lakes, coastal, and oceanic areas [6, 7]. Although the methods to retrieve water quality from RS data might not be as precise as traditional methods, they are time and cost efficient over the large area and can provide the opportunity for regular observation of even very remote regions [2]. Therefore, remote sensing techniques have been widely used in estimating the pollution situation of surface water [8-10].

Today, many satellites with high enough resolution have been used in water quality monitoring studies. For instance, Thiemann and Kaufmann [11] found that a linear spectral unmixing method using IRS-1C satellite data yielded a good estimation of chlorophyll-a content in lakes. Blumberg and Lehahn [12] used the Chinese Fenyeng 1C (FY-1C) multi-spectral sensor to map chlorophyll (Chl)-a concentration in the Southeastern Mediterranean Sea. Chen et al. [13] investigated the relationship between chlorophyll concentration and spectral parameters of SPOT sensor data. Lavery et al. [9] developed regression models for predicting surface water quality parameters from TM data, and demonstrated that Landsat TM data have the potential on resolution and accuracy to be a very useful tool for water quality monitoring in estuarine waters. So this paper specifically addresses the Landsat-5 TM data that have been the primary source of satellite images used for lake monitoring, particularly in Europe due to the data's spatial resolution and spectral characteristics [7,14-16].

With studies on pollutants' spectral features and improvement of retrieval algorithms, it is possible to perform water quality monitoring through RS on more water quality variables and with higher precisions. But they still could not meet all the needs of water quality management. Most of them focused on only a few water quality variables which were usually considered as optically active variables, such as chlorophyll-a (chl-a) [8], total suspended solids (TSS) [3], and turbidity [17]. And the previous studies were mostly carried out on the seriously polluted inland water body. However, the slightly polluted water bodies, especially those drinking water sources, have not been taken into consideration. The main reason is that they are of weak optical characteristics and low signal noise ratio. Anyway, they are practically the most important part of water quality management. Consequently, this is the challenging part of our research.

This study focused on the Guanting Reservoir which would be the auxiliary drinking water source of Beijing, established and analyzed the remote sensing methods to retrieve water quality with eight variables including algae content, turbidity, and concentrations of chemical oxygen demand (COD), total nitrogen (TN), ammonia nitrogen (NH_3-N), nitrate nitrogen (NO_3^--N), total phosphorus (TP), and dissolved phosphorus (DP). This study aimed to find out the appropriate retrieval algorithms, to tell the different procurabilities of these water quality variables and to show the possibility of performing routine water quality monitoring on slightly-polluted inland water bodies by Landsat-5 TM data.

2 Study area

The Guanting Reservoir is located in the northwest Beijing between 40°13′46″ N—40°25′42″ N and 115°34′2″ E—115°49′30″ E. As a controlling project for the Yongding River, it covers an area of 253 km^2, encapsulates about 2.3 billion m^3 of fresh water and provides around 300 to 400 million m^3 water each year.

It has been the water source for urban, industry, and agriculture in Beijing. Due to the increase of the polluted inflow of the developing upriver region, the reservoir was dropped out of the list of the drinking water sources in 1997 and only served as an industrial water source in the western Beijing. Since then, great efforts have been made to improve its water quality. As the continuous drought from 2001 to 2005 resulted in a serious shortage of drinking water supply, the government banned fishing from 2005 to 2006 in order to recover the water quality and made it reach the Level III specified by the *Environmental Quality Standards for Surface Water* [18]; therefore, the reservoir was adopted as an auxiliary drinking water source for Beijing in future.

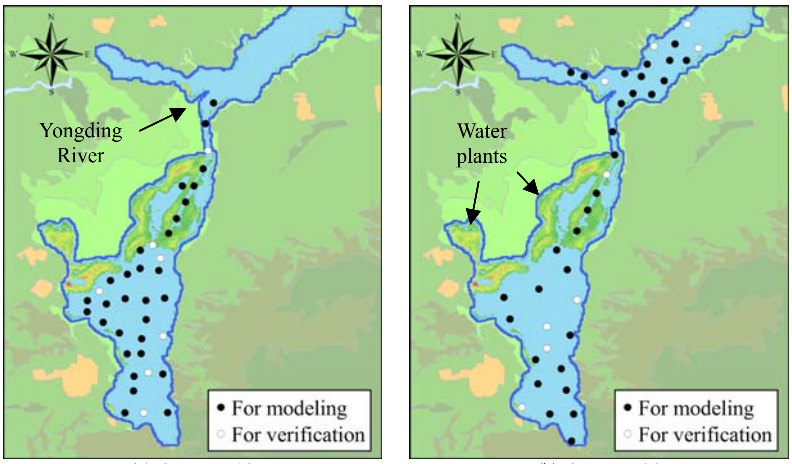
This study mainly focused on the western part of the reservoir which is the entrance of the Yongding River, and it has a remarkable diversification of water quality.

3 Methods

In this study, the concurrent ground truth data and remote sensing data were used to establish the appropriate algorithms to retrieve water quality variables from RS data.

3.1 Ground truth data and water quality variables

The 76 representative water samples were collected on May 13 and 29, 2005. These samples evenly distributed in the study area except the western part where grows the flourish water plants (**Fig. 1**). In order to carry out the study efficiently, the sampling position on the reservoir should be as close as possible to the part which satellite observes directly [4]. Thus these water samples were collected for each site just beneath the surface. Traditional chemical analyses were applied to eight common water quality variables, including algae content, turbidity, and concentrations of COD, TN, NH_3-N, NO_3^--N, TP, and DP. Because of the low concentration of chlorophyll, algae content was used to replace chlorophyll.



(a) On May 13 (b) On May 29

Fig. 1 Location of 76 samples collected on May 13 and 29, 2005 in the Guanting Reservoir (at the northwest Beijing, China). These samples evenly distributed in the study area except the western part where grows the flourish water plants. There were 60 samples randomly selected for modeling (the black circles) and 16 left for verification (the white circles)

The sampling and chemical analyses were based on the standard methodology [19]. The laboratorial precision and limitation of each variable were given in **Table 1**. The 60 samples were randomly selected from 76 total samples for modeling and the remaining 16 samples for verification.

Table 1 Precision and control level of water quality variables in chemical analysis based on the standard methodology in China

Variables	Concentrations							
	Algae	Turbidity	COD	TN	NH_3-N	NO_3-N	TP	DP
	$10^7 \cdot L^{-1}$	NTU	$mg \cdot L^{-1}$	$mg \cdot L^{-1}$	$mg \cdot L^{-1}$	$mg \cdot L^{-1}$	$mg \cdot L^{-1}$	$mg \cdot L^{-1}$
Precision	2.5	0.01	0.01	0.001	0.01	0.001	0.001	0.001
Control level	2.5	0.01	5	0.02	0.05	0.02	0.005	0.005

3.2 Remote sensing data

The used Landsat 5 TM data have 7 bands with a spectral resolution of 30 by 30 m and a repeating period of 16 d. TM images acquired on May 13 and June 7, 2005 were used to match the sampling data. The first TM image exactly matched the first sampling date, but the second one was 9 d later than the second sampling date, i.e., on May 29. It was because that the TM image on May 29 was with lots of clouds and could not be used for this study. The closest TM image to May 29 was the one on June 7.

During those 9 d, there was only one rainfall of 1.3 mm and the water quality was stable according to the site monitoring. Thus the image acquired on June 7 could be used to replace the image on May 29.

The necessary image pro-processing included radiation correction, atmospheric correction, and geometric correction. Correction contained a register into a reference coordinate system with a resampling method [20,21]. Eight ground control points were used to rectify images.

The pixel digital numbers (DNs) were obtained from TM images for all water samples based on the GPS locations. Since the spatial resolution of 6th band is different from others, the image of this band was re-sampled to unify the resolution to 30 by 30 m.

3.3 Retrieval algorithms

Three groups of algorithms were applied for water quality retrieval from RS data, i.e., empirical algorithms, theoretic algorithms, and their combinations. Due to the complexity of the theory and the difficulty of calculation, many people were still using empirical algorithms. This study used multiple linear regression algorithm, the most famous empirical one, to establish the correlation between RS data and water quality variables. Stepwise multiple linear regression was applied to find the best correlation with the entry significance at a level of 0.05 and the removal significance at a level of 0.10. Finally the regressive model should pass the F test at the confidence level of 95%.

In order to find the best sampling method of pixel DNs for water quality retrieval, three different ways were tried to use pixel DNs, which are the original single pixel DN, the average and median values of a 3×3 pixel window.

Eight water quality variables and their natural logarithms were all selected to be the dependent variables for regression. For the independent variables, besides DNs, the DN’s reciprocals, squares, square roots, powers of *e* and the ratio of each two bands’ DNs were also considered, totally 92 variables defined in

Table **2**.

Table 2 Definition of independent variables in retrieval algorithms, where $TM_{i/j}$ is for DNs of each band, i.e., TM_1—TM_7, which is extracted by certain DNs sampling method.

Variable index	Definition	Variable index	Definition
1—7	TM_i	29—35	$Ln(TM_i)$
8—14	$Exp(TM_i/100)$	36—42	TM_i^2
15—21	$Exp(TM_i/10)$	43—49	$Sqrt(TM_i)$
22—28	$1/TM_i$	50—92	TM_i / TM_j

4 Results

4.1 Descriptive statistics of water quality variables for samples

Descriptive statistics of eight water quality variables calculated from all water sample data were shown in

Table 3, including maximum (MAX), minimum (MIN), average (AVG), standard deviation (STD), and the goal of surface water quality in Level III specified by the *Environmental Quality Standards for Surface Water* [18] as drinking water source.

Table 3 Descriptive statistics of eight water quality variables for 76 water samples collected on May 13 and 29, 2005 in the Guanting Reservoir (at the northwest of Beijing, China).

Statistics	Concentrations							
	Algae	Turbidity	COD	TN	NH_3-N	NO_3-N	TP	DP
	$10^7\cdot L^{-1}$	NTU	$mg\cdot L^{-1}$	$mg\cdot L^{-1}$	$mg\cdot L^{-1}$	$mg\cdot L^{-1}$	$mg\cdot L^{-1}$	$mg\cdot L^{-1}$
MAX	1035.0	142.00	46.01	7.255	10.85	2.638	0.176	0.139
MIN	37.5	2.13	6.03	2.225	0.37	1.728	< 0.005	< 0.005
AVG	266.0	25.45	25.04	3.274	1.10	2.267	0.026	0.012
STD	253.1	27.36	9.84	0.753	1.61	0.254	0.036	0.019
Goal*	—	—	≤ 20	≤ 1.0	≤ 1.0	≤ 10	≤ 0.05	—

* The goal of surface water quality in Level III specified by the *Environmental Quality Standards for Surface Water* [18], which

is used as drinking water source.

4.2 Comparison of DNs sampling methods

Stepwise multiple linear regression was carried out with three different DNs: the original single DN of the exact sample position, the average DN and the median DN of the 3×3 pixel window. Significance was used to evaluate the performance of different DN sampling methods. Because all the significances (Sig.) were very small, their minus natural logarithms, i.e., –Ln(Sig.) were used instead and shown in **Fig. 2**.

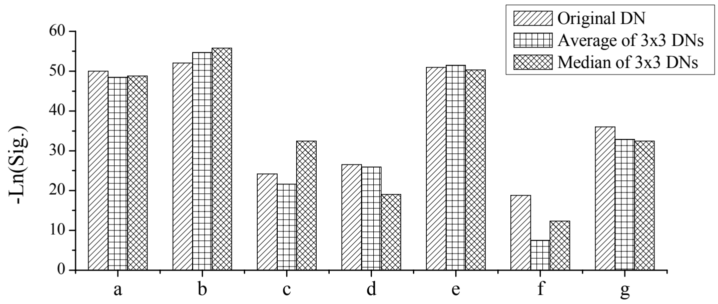


Fig. 2 Significances of correlations of seven common water quality variables calculated from different sampling methods: the original DN, the mean, and median DN of the 3×3 pixel window

4.3 Regressive retrieval models

With stepwise multiple linear regression using original DNs, seven water quality variables can get satisfied regressive correlations except COD. In this study, COD could not be retrieved under a degree of confidence at 90%. The best retrieval models evaluated by their significances were described in **Table 4** with their significances (Sig.), correlation coefficients (R), and mean relative errors (MRE), where TM1 to TM7 represented the original DNs of 7 TM bands. MRE is the mean relative errors between the model results and those 16 independent site sampling data. It represents the precisions of the model results, especially for application.

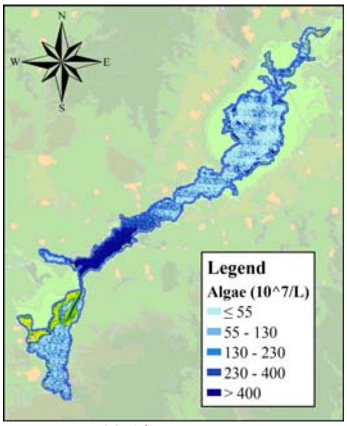
Table 4 Retrieval models of seven common water quality variables from Landsat TM data for the Guanting Reservoir, Beijing and their regression statistics including significances (Sig.), correlation coefficients (R), and mean relative errors (MRE)

Water quality variables	Models	Sig.	R	Mean relative error /%
Algae/ ($10^7 \cdot L^{-1}$)	$C_{\text{Algae}} = 44903.44 + 755.3791\frac{\text{TM}_3}{\text{TM}_5} + 0.031446 \times e^{\text{TM}_3/10} + 0.002773 \times e^{\text{TM}_6/10} - 10888.1\frac{\text{TM}_1}{\text{TM}_2} - 49160.3\frac{\text{TM}_2}{\text{TM}_1}$	8.87×10^{-22}	0.927	9.00
Turbidity/ (NTU)	$\text{Ln}(C_{\text{Turb}}) = 34.92214 - 3497.32/\text{TM}_6 + 0.000874\text{TM}_2^{\ 2} + 12.13469\frac{\text{TM}_3}{\text{TM}_6} - 3.821\text{LnTM}_7$	1.83×10^{-24}	0.937	10
TN/ ($mg \cdot L^{-1}$)	$\text{Ln}(C_{\text{TN}}) = 4.3907 - 177.9298/\text{TM}_6 - 0.1362\frac{\text{TM}_6}{\text{TM}_7} - 1.211\frac{\text{TM}_3}{\text{TM}_6}$	4.06×10^{-10}	0.75	11
NO_3-N/ ($mg \cdot L^{-1}$)	$C_{\text{NO}_3\text{-N}} = 21.9888 - 0.70578\frac{\text{TM}_2}{\text{TM}_5} - 3.688\text{LnTM}_6 - 0.0186\text{TM}_3$	4.33×10^{-23}	0.922	4.40

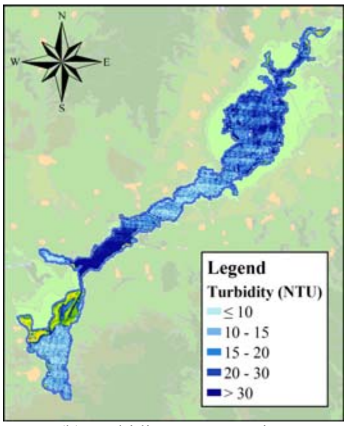
NH_3-N/ (mg·L^{-1})	$\mathrm{Ln}(C_{\mathrm{NH_3\text{-}N}}) = -7.177 + 1.93\mathrm{LnTM}_7 + 0.1323\mathrm{TM}_6 - 2.185\dfrac{\mathrm{TM}_6}{\mathrm{TM}_3} - 0.07648\mathrm{TM}_1$	5.35×10^{-12}	0.806	28
TP/ (mg·L^{-1})	$\mathrm{Ln}(C_{\mathrm{TP}}) = 4.334 - 4.594\dfrac{\mathrm{TM}_1}{\mathrm{TM}_2} + 1.103\dfrac{\mathrm{TM}_4}{\mathrm{TM}_7}$	5.38×10^{-4}	0.613	30
DP/ (mg·L^{-1})	$C_{\mathrm{DP}} = -0.0698 + 1.9\times10^{-5}\times e^{\mathrm{TM}_3/10} + 0.0855\dfrac{\mathrm{TM}_3}{\mathrm{TM}_2}$	5.36×10^{-15}	0.955	15

4.4 Retrieval results of water quality in Guanting Reservoir

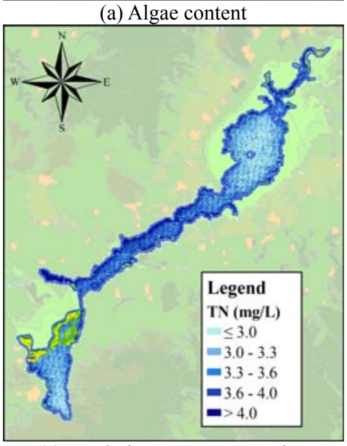
Based on the TM image on June 7, 2005, the retrieval models were applied to predict the spatial distributions of water qualities over the whole Guanting Reservoir, except those areas with flourish water plants. The modelling results for seven water quality variables are shown in **Fig. 3**, including algae content, turbidity, and concentrations of total nitrogen, nitrate nitrogen, ammonia nitrogen, total phosphorous, and dissolved phosphorus. Although these results were inevitably affected by the scan strip noise from Landsat-5 TM data, they still clearly showed that different water quality variables had various spatial distribution patterns over the reservoir.



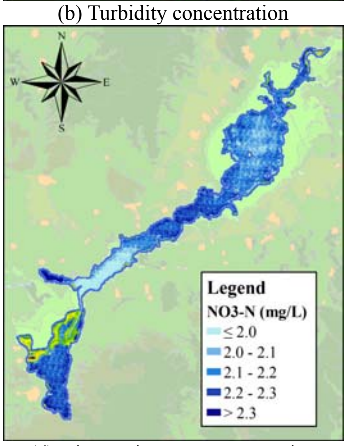
(a) Algae content



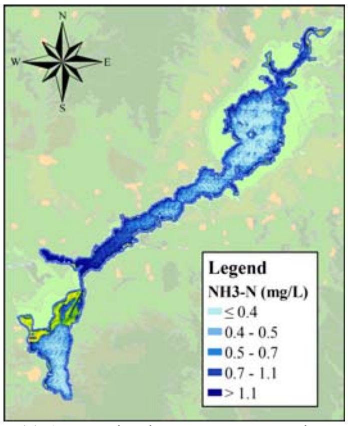
(b) Turbidity concentration



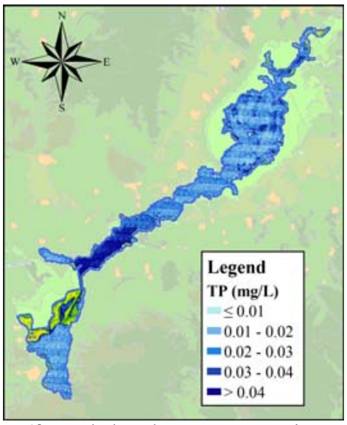
(c) Total nitrogen concentration



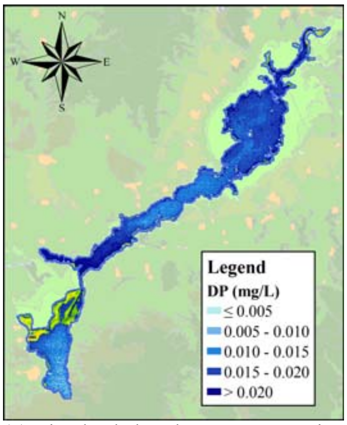
(d) Nitrate nitrogen concentration



(e) Ammonia nitrogen concentration



(f) Total phosphorus concentration



(g) Dissolved phosphorus concentration

Fig. 3 Spatial distributions of model retrieval results with TM image of June 7, 2005 for 7 water quality variables in Guanting Reservoir

Upon the spatial distributions of water quality variables, it is possible to consider the water quality over the whole reservoir instead of only several sampling points. The overall statistics results of the water quality variables are shown in **Table 5**, including the minimum, maximum, and average concentrations, standard deviation, and average load ratio which is the proportion of the pollutant concentration to its goal. Comparing standard deviation to the average showed that concentrations of TN, NO_3^--N, and DP all had less spatial variance, while other variables were significantly spatial heterogeneous. According to the average load ratio, TN was the most serious pollutant with an average load ratio up to 347% and its minimum concentration was still higher than its goal. Concentrations of NH_3-N and TP could reach the goal on average, as their average load ratios were less than 100%. But they still could not reach the goal over the whole reservoir because their maximum concentrations were still higher than their goals. NO_3^--N concentration was the only one water quality variable that could fully reach its goal, as its maximum concentration was still much lower than its goal.

Table 5 Statistics of water quality retrieval results over the whole Guanting Reservoir, including the minimum concentration, maximum concentration, average concentration, standard deviation, and average load ratio, which is the proportion of the pollutant concentration to its goal

Statistics	Concentrations						
	Algae (10^7·L^{-1})	Turbidity (NTU)	TN (mg·L^{-1})	NO_3-N (mg·L^{-1})	NH_3-N (mg·L^{-1})	TP (mg·L^{-1})	DP (mg·L^{-1})
Minimum	0.00	1.38	1.51	1.47	0.14	0.00	0.00
Maximum	1171.97	380.15	7.44	2.62	12.73	0.27	0.04
Average	166.05	24.69	3.47	2.15	0.79	0.03	0.02
Standard deviation	195.21	20.99	0.60	0.13	0.65	0.02	0.005
Goal	–	–	1.0	10	1.0	0.05	–
Average load ratio/%	–	–	347	21	79	53	–

5 Discussion

5.1 Statistic analysis of water samples

With regard to the average values of 76 samples, though the water quality still could not reach the goal as drinking water source [18], the gap was small and indicated that the reservoir was not polluted seriously. Therefore, it was believed that the Guanting Reservoir could be used as the auxiliary drinking water source of Beijing under the government's great efforts.

In

Table 3, the maximum values showed very high comparing to the average. It was due to that the water samples were collected near the mouth of the Yongding River. While the minimum values were fairly small, most of which were distributed in the central part of the study area. These samples were very valuable for modeling as they could extend the confidence interval of model and can ensure the significance of statistical regression algorithms.

5.2 Analysis of DNs sampling methods

In order to reduce the noise in the RS data, researchers usually extract data values by averaging or other low pass filtering algorithms within a certain window, such as 3×3 or 5×5 pixel [22,23]. But these methods will make RS data less precise, especially for those RS data with lower spatial resolution. Thus there is no best DNs sampling method for all RS data and all applications.

According to the existing similar applications on ocean water, coastal water, and inland polluted water bodies with Landsat data, three typical kinds of DNs sampling methods were selected in this study. Stepwise multiple linear regression was run by using the three different ways to get model input DNs. The significance evaluation result (**Fig. 2**) showed that the original DN had better performance in for water quality variables while NO_3^--N concentration seems not sensitive to the various sampling schemes. The upscaling in sampling methods would cause information loss rather than noise removal. Therefore, the sampling method using the original DN was proposed for water quality retrieval with TM data.

For the cases of TN concentration and Turbidity, the median DN of the 3×3 pixel window has the best performance, implying that these two water quality variables have specific characteristics and need further studies.

5.3 Analysis of regressive retrieval models

The significances of the regressive retrieval models (**Table 4**) indicated that there existed a statistical perfect correlation for water quality variables including algae content, turbidity, and concentrations of TN, NH_3-N, NO_3^--N, TP, and DP to Landsat-5 TM data, while COD could not be retrieved within an acceptable error in this study. The correlation coefficients of the seven regressive equations (**Table 4**) were fairly high, among which four coefficients were higher than 0.9, only those of TN and TP were lower than 0.8.

Our results showed that all seven water quality variables had satisfied retrieval results according to the mean relative error, which is one of the most important indicators for practical application of water quality monitoring through remote sensing. Concentrations of algae, turbidity, and NO_3^--N could be retrieved within a mean relative error (MRE) of 10%; concentrations of TN and DP within 20%; concentrations of NH_3-N and TP within 30%. These accuracies could be acceptable for the early warning on water quality safety and routine water quality monitoring with supports of a few additional precise traditional monitoring.

Our results also proved that Landsat-5 TM has capabilities in modeling of lake water quality as Brivio et al. did [24], and can even be used in relatively clean water body which has low reflective spectral radiation, although TM sensors were mainly designed to study land surfaces and have several limitations for characterizing water bodies. For the purpose of surface water quality retrievals from Landsat-5 TM data, the parameters used in this study were significantly estimated using the multiple regression algorithm. Therefore, the study also demonstrated that remote sensing is a valuable tool in obtaining information on the processes taking place in surface water quality monitoring [17].

Our study showed that inland water quality monitoring through RS data could be just based on simple retrieval methods; for this case, regression can be used to model well for linear or known nonlinear transfer functions in Guanting Reservoir. As there are many hidden but useful relationships between the input and output data, which may not be recognized by the analyst, some researchers found that statistical regression is poor to characterize the relationship between both the digital data of TM and SAR and the water quality parameters in some studies [17]. And Keiner et al. ascribed the main reason to the poor ability of regression analysis to model the unknown nonlinear transfer function in surface waters [25]. But in our study, the highly significant and predictive algorithms were obtained for seven common water quality variables merely by linear regression.

Our study showed that inland water quality monitoring through RS data could cover many water quality variables; for this case, seven common water quality variables in Guanting Reservoir had been derived within an applicable error. It is generally accepted that inland lake and coastal waters have three main classes of constituents: inorganic suspended sediment, phytoplankton pigment, and dissolved organic material (DOM) [26]. And it was considered that the number of surface water quality parameters that can be derived from optical satellite data is limited [17]. However, Mattikalli suggested a model for estimating losses of nitrogen reasonably satisfactorily [27], and more and more researchers try to cover more water quality variables. It seems that it is possible to establish models between water quality variables and RS data though the mechanisms of those models require more research.

Our study demonstrated that all the bands of TM data contribute to the water quality variables deriving, including the thermal data (TM_6). Single band data have been widely used in water quality study. However, attempts have been made to find combinations of Landsat TM bands which would provide more information about water quality variables than were available in single band [9]. The results of our study also indicated that it was essential to select feasible combinations of bands in the correlation analysis. Although algorithms were quite different in the selected bands when compared with those used in other studies [3,4,9]. But correlation coefficients of relevant water quality variable models in our study were higher or at least comparable to other studies. Wang et al. has pointed that TM_4 has no correlation with other bands and water quality variables in their study [4]. In our study, it was interesting for us to find this band only presented in the model of TP concentration with relatively low R value, as shown in **Table 4**, which was in agreement with previous study. Studies in the literature have mainly concentrated on the trends in nitrate concentrations because of the increasing concerns over health impacts, and the gradual increase in legislative control of the nitrate content of drinking water and drinking water sources [27]. In addition, although TM_6 is measuring the emitted thermal radiance of the water body and not the reflected sun light, or the thermal band can be considered having no or very little effect on optical measurements when they are relatively less correlated to the surface properties, it was pointed that surface roughness has an effect on thermal radiance [17]. Thus the thermal data (TM_6) of Landsat TM was still included, and results demonstrated that the TM_6 does have some effects on algae content, turbidity, and concentrations of TN, NO_3^--N, and NH_3-N.

Natural waters can be divided into two classes, clear oceanic zone and inland/marine coastal zone (i.e., Case I and Case II) waters [28]. In Case II waters, light attenuation is greater due to optical complexity in the form of inorganic particulates, and also due to a greater variety and higher concentration of dissolved and particulate organic matter that result from significant quantities of terrigenous materials [29]. Furthermore, the temporal and spatial variations of water surface roughness are actually factors that disturb the interpretation of optical data [30]. As a result, before applying the remote sensing method to more water quality variables (e.g., COD or BOD), some parameters for a given site or, alternatively, some inherent optical properties (IOPs) must be known [31]. For instance, radar data are only affected by water surface properties other than those in the case of optical/IR observations [17]. Moreover, due to the very low values of the water-leaving radiance, the signal-to-noise ratio for a water resource sensor should be higher than for a land resource sensor. Data products' validation and quality considerations will continue to be important for operational uses of remote sensing technology [24] and multi-temporal as well as data fusion use of satellite remote sensing for the estimation of major water quality variables in surface waters will permit to determine seasonal and yearly cycles and trends in inland waters to be integrated into the future.

6 Conclusions

This study showed that there existed a statistical significant correlation between each selected water quality variable and remote sensing data in the slightly-polluted inland water body with weak radiation. Among eight water quality variables considered in the Guanting Reservoir (i.e., algae content, turbidity, and concentrations of COD, TN, NH_3-N, NO_3^--N, TP, and DP), seven of them obtained the correlation with acceptable accuracies except COD. And the original pixel DNs were tested to be the best sampling method for water quality retrieval with TM data, compared to the average and median values of 3×3 pixel window.

Several important environmental variables such as concentrations of NH_3-N, NO_3^--N, and DP, which were neglected before, were approved applicable in the routine monitoring through RS. It also showed that the retrieval models with Landsat-5 TM data could meet the accuracy requirements of routine water quality monitoring on reservoir for algae content, turbidity, and concentrations of NO_3^--N, TN, and DP, as they could be retrieved within a mean relative error (MRE) of 20%. Furthermore, the accuracies of water quality retrieval could be greatly improved under a support of new remote sensing data with higher spectral and spatial resolutions. In this case, the selection of DN sampling methods would become much more important.

Remote sensing was further confirmed to be very useful on establishing a time-cost effective method for the routine monitoring of slightly-polluted inland water body. More attentions should be paid to the rapidly developing RS techniques and the theoretic studies on water quality retrieval, especially for the slightly polluted inland water body and those water quality variables concerned by environmental management.

Acknowledgements

This research was supported by the Key Innovation Projection of Chinese Academy of Sciences of China (Grant No. KZCX3-SW-338-1). The authors would like to thank Prof. Huang Xia and Prof. Zhou Lv for their laboratory supports, and we are very grateful to Miss Li Shuyuan, Mr. Bu Dehua, Mr. Huang Yunhui, Mr. Yang Naipeng, Miss Du Yuan, Miss Wang Yajun, Miss Zheng Chaohui, Miss Wang Di and Miss Zhang Xuehui for their great helps in chemical analysis of water samples.

References

1. Kondratyev K, Pozdnyakov D V. Water quality remote sensing in the visible spectrum. International Journal of Remote Sensing, 1998, 19(5): 957－979
2. Seker D Z, Goksel C, Kabdasli S, Musaoglu N, Kaya S. Investigation of coastal morphological changes due to river basin characteristics by means of remote sensing and GIS techniques. Water Science and Technology, 2003, 48(10): 135－142
3. Bilge F, Yazici B, Dogeroglu T, Ayday C. Statistical evaluation of remotely sensed data for water quality monitoring. International Journal of Remote Sensing, 2003, 24(24): 5317－5326
4. Wang X J, Ma T. Application of remote sensing techniques in monitoring and assessing the water quality of Taihu Lake. Bulletin of Environmental Contamination and Toxicology, 2001, 67(2): 863－870
5. Dor I, Ben-Yosef N. Monitoring effluent quality in hypertrophic wastewater reservoirs using remote sensing. Water Science and Technology, 1996, 33(8): 23－29
6. Braga C Z F, Setzer A W, de Lacerda L D. Water quality assessment with simultaneous Landsat-5 TM data at Guanabara Bay, Rio de Janeiro, Brazil. Remote Sensing of Environment, 1993, 45(2): 95－106
7. Dekker A G, Peters S W M. The use of the Thematic Mapper for the analysis of eutrophic lakes: A case study in the Netherlands. International Journal of Remote Sensing, 1993, 14(5): 799－821
8. Ekstrand S. Landsat TM based quantification of chlorophyll-a during algae blooms in coastal waters. International Journal of Remote Sensing, 1992, 13(10): 1913－1926
9. Lavery P, Pattiaratchi C. Water quality monitoring in estuarine waters using the Landsat Thematic Mapper. Remote Sensing of Environment, 1993, 46(33): 268－280
10. Gitelson A, Garbuzov G, Szilagy F, Mittenzwey K H, Karnieli A, Kaiser A. Quantitative remote sensing methods for real-time monitoring of inland waters quality. International Journal of Remote Sensing, 1993, 14(7): 1269－1295
11. Thiemann S, Kaufmann H. Determination of chlorophyll content and trophic state of lakes using field spectrometer and IRS-1C satellite data in the Mecklenburg Lake District, Germany. Remote Sensing of Environment, 2000, 73(3): 227－235
12. Blumberg D, Lehahn G. Utilizing Fenyeng 1C (FY-1C) to monitor ocean colour and water quality: A demonstration experiment in the eastern Mediterranean. International Journal of Remote Sensing, 2003, 24(6): 1393－1399

13. Chen L. A study of applying genetic programming to reservoir trophic state evaluation using remote sensor data. International Journal of Remote Sensing, 2003, 24(11): 2265－2275
14. Zilioli E, Brivio P A, Gomarasca M A. A correlation between optical properties from satellite data and some indicators of eutrophication in Lake Garda (Italy). Science of the Total Environment. 1994, 158: 127－133
15. Schneider K, Mauser W. Processing and accuracy of Landsat Thematic Mapper for lake surface temperature measurement. International Journal of Remote Sensing, 1996, 17(11): 2027－2041
16. Zilioli E, Brivio P A. The satellite derived optical information for the comparative assessment of lacustrine water quality. Science of the Total Environment, 1997, 196(3): 229－245
17. Zhang Y Z. Application of an empirical neural network to surface water quality estimation in the Gulf of Finland using combined optical data and microwave data. Remote Sensing of Environment, 2002, 81(2): 327－336
18. GB 3838-2002. Environmental Quality Standards for Surface Water. Beijing: State Environmental Protection Administration, 2002 (in Chinese)
19. China Standard Press. The Compilation of National Environmental Protection Standards: Environmental Quality and Pollution Discharge in 2003. Beijing: China Standard Press, 2003 (in Chinese)
20. Janssen L L F, van der Wel F J M. Accuracy assessment of satellite derived land-cover data: A review. Photogrametric Engineering and Remote Sensing, 1994, 60(4): 419－426
21. Goksel C. Monitoring of water basin area in Istanbul using remote sensing data. Water Science and Technology, 1998, 38(11): 209－216
22. Östlund C, Flink P, Strömbeck N, Pierson D, Lindell T. Mapping of the water quality of Lake Erken, Sweden, from Imaging Spectrometry and Landsat Thematic Mapper. Science of the Total Environment, 2001, 268(1-3): 139－154
23. Chen X, Li Y S, Liu Z, Yin K, Li Z, Wai O W, King B. Integration of multi-source data for water quality classification in the Pearl River estuary and its adjacent coastal waters of Hong Kong. Continental Shelf Research, 2004, 24(16): 1827－1843
24. Brivio P A, Giardino C, Zilioli E. Validation of satellite data for quality assurance in lake monitoring applications. Science of the Total Environment, 2001, 268: 3－18
25. Keiner L E, Yan X. A neural network model for estimating sea surface chlorophyll and sediments from Thematic Mapper Imagery. Remote Sensing of Environment, 1998, 66(2): 153－165
26. Lathrop R G, Lillesand T M. Monitoring water quality and river plume transport in Green Bay, Lake Michigan with SPOT-1 Imagery. Photogrammetric Engineering and Remote Sensing, 1989, 55(3): 349－354
27. Mattikalli N M, Richards K S. Estimation of surface water quality changes in response to land use change: Application of the export coefficient model using remote sensing and geographical information system. Journal of Environmental Management, 1996, 48(3): 263－282
28. Morel A, Prieur L. Analysis of variations in ocean color. Limnology and Oceanography, 1977, 22(4): 709－722
29. Woodruff D L, Stumpf R P, Scope J A, Paerl H W. Remote estimation of water clarity in optically complex estuarine waters. Remote Sensing of Environment, 1999, 68(1): 41－52
30. Lindell T, Pierson D, Premazzi G, Zilioli E. Manual for monitoring European lakes using remote sensing techniques. Luxembourg: Official Publications of the European Communities, 1999: 161
31. Lahet F, Ouillon S, Forget P. A three-component model of ocean color and its application in the Ebro River mouth area. Remote Sensing of Environment, 2000, 72(2): 181－190