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RESEARCH ARTICLE

Water quality monitoring in a slightly-polluted inland water body through remote sensing — Case study of the Guanting Reservoir in 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 the water quality of the Guanting Reservoir, a possible auxiliary drinking water source for Beijing. Through a remote sensing (RS) approach and using Landsat 5 Thematic Mapper (TM) data, water quality retrieval models were established and analyzed for eight common water quality variables, including algae content, turbidity, and concentrations of chemical oxygen demand, total nitrogen, ammonia nitrogen, nitrate nitrogen, total phosphorus, and dissolved phosphorus. The results show that there exists a statistically significant correlation between each water quality variable and remote sensing data in a slightly-polluted inland water body with fairly weak spectral radiation. With an appropriate method of sampling pixel digital numbers and multiple regression algorithms, retrieval of the algae content, turbidity, and nitrate nitrogen concentration was achieved within 10% mean relative error, concentrations of total nitrogen and dissolved phosphorus within 20%, and concentrations of ammonia nitrogen and total phosphorus within 30%. On the other hand, no effective retrieval method for chemical oxygen demand was found. These accuracies were acceptable for the practical application of routine monitoring and early warning on water quality safety with the support of precise traditional monitoring. The results show that performing the most traditional routine monitoring of water quality by RS in relatively clean inland water bodies is possible and effective.

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

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E-mail: xuehua-hjx@tsinghua.edu.cn

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, inland water bodies are confronted with increasing water demand and are facing 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, with the development of remote sensing (RS) techniques, water quality monitoring based on RS methods has become accessible and very efficient.

As the pollutants scatter and absorb 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 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 information from RS data might not be as precise as traditional methods, they are time and cost efficient over a 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 in terms of 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].

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

The focus of this study is the Guanting Reservoir, which is set to be the auxiliary drinking water source of Beijing. The study established and analyzed remote sensing methods to retrieve water quality data 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). It aims to determine appropriate retrieval algorithms, to ascertain 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 using Landsat-5 TM data.

2 Study area

The Guanting Reservoir is located in 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 areas, industries, and agriculture in Beijing. Due to the increase in the polluted inflow of the developing upriver region, the reservoir was taken out of the list of drinking water sources in 1997 and served only as an industrial water source in 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 a bid to recover water quality and make it reach the Level III standard specified by the *Environmental Quality Standards for Surface Water* [18]. As a result of these efforts, the reservoir has been adopted as a possible auxiliary drinking water source for Beijing in the future.

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

3 Methods

In this study, 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 were evenly distributed in the study area except for the western part where water plants flourished (Fig. 1). In order to carry out the study efficiently, it was deemed necessary for the sampling positions on the reservoir to be as close as possible to the part which the 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.

The sampling and chemical analyses were based on the standard methodology [19]. The laboratory precision and limitation of each variable are shown in Table 1. From 76 total samples, 60 samples were randomly selected for modeling and the remaining 16 samples were used for verification.

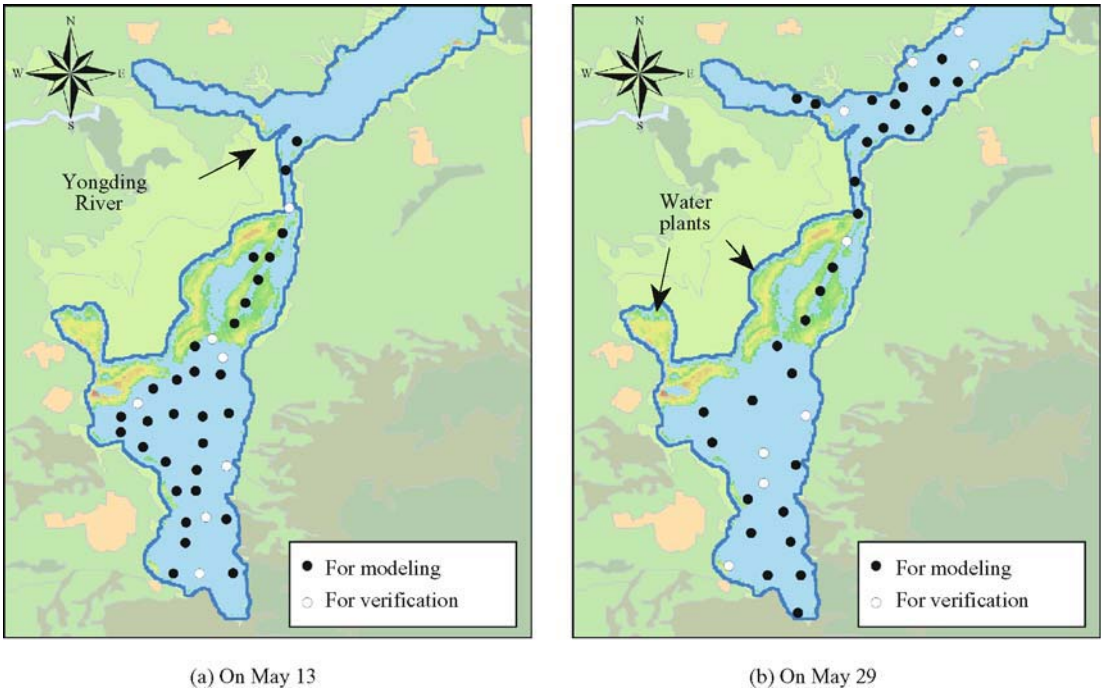

Fig. 1 Location of 76 samples collected on May 13 and 29, 2005 in the Guanting Reservoir (at the northwest Beijing, China). These samples were evenly distributed in the study area except the western part where water plants flourished. There were 60 samples randomly selected for modeling (the black circles)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

3.2 Remote sensing data

The Landsat 5 TM data that was used had 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 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 was considered suitable to replace the image on May 29.

The necessary image pre-processing included radiation correction, atmospheric correction, and geometric correction. Correction involved registration into a reference coordinate system with a resampling method [20,21]. Eight ground control points were used to rectify the 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 the 6th band was different from the 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 the retrieval of water quality information from RS data. These included empirical algorithms, theoretic algorithms, and their combinations. Due to the complexity of the theory and the difficulty of calculation, many researchers still use empirical algorithms. This study used multiple linear regression algorithms, the most well known of the empirical algorithms, 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 was made to pass the F test at the confidence level of 95%.

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

variables	concentrations							
	algae/ $10^7 \cdot L^{-1}$	turbidity/ NTU	COD/ $mg \cdot L^{-1}$	TN/ $mg \cdot L^{-1}$	NH_3–N/ $mg \cdot L^{-1}$	NO_3–N/ $mg \cdot L^{-1}$	TP/ $mg \cdot L^{-1}$	DP/ $mg \cdot L^{-1}$
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

In order to find the best method of sampling pixel DNs for water quality data retrieval, three different methods of using pixel DNs were tried. These include the original single pixel DN as well as 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 the DNs, the DNs' reciprocals, squares, square roots, powers of *e* and the ratio of each of the two bands' DNs were also considered. In total, 92 variables were considered, as defined in Table 2.

Table 2 Definition of independent variables in the retrieval algorithms, where $TM_{i/j}$ is for DNs of each band, i.e., TM_1–TM_7, which were extracted by a 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 the samples

Descriptive statistics of eight water quality variables calculated from all water sample data are shown in Table 3, including maximum (MAX), minimum (MIN), average (AVG), standard deviation (STD), and the goal of surface water quality specified in Level III of the *Environmental Quality Standards for Surface Water* [18] for drinking water sources.

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, as well as 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, as shown in Fig. 2.

4.3 Regressive retrieval models

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

4.4 Results of the retrieval of water quality data in the 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 flourishing 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.

Using 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 statistical 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

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/ $10^7 \cdot L^{-1}$	turbidity/ NTU	COD/ $mg \cdot L^{-1}$	TN/ $mg \cdot L^{-1}$	NH_3–N/ $mg \cdot L^{-1}$	NO_3–N/ $mg \cdot L^{-1}$	TP/ $mg \cdot L^{-1}$	DP/ $mg \cdot L^{-1}$
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*	–	–	$\leqslant 20$	$\leqslant 1.0$	$\leqslant 1.0$	$\leqslant 10$	$\leqslant 0.05$	–

* The goal of surface water quality specified in Level III of the *Environmental Quality Standards for Surface Water* [18] for drinking water sources.

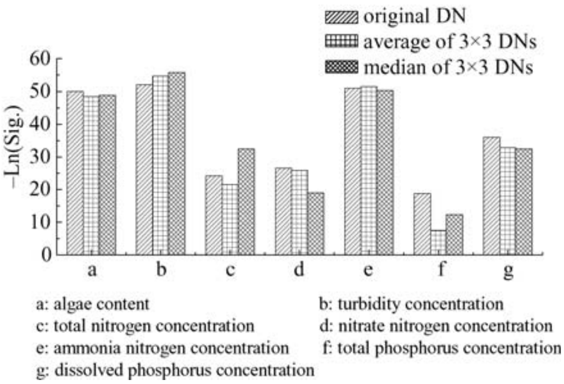

Fig. 2 Significances of the correlations of seven common water quality variables calculated from different sampling methods: the original DN, the mean, and the median DN of the 3 × 3 pixel window

to the average showed that concentrations of TN, NO_3^-–N, and DP all had less spatial variance, while other variables were significantly spatially heterogeneous. According to the average load ratio, TN was the most serious pollutant with an average load ratio of 347% and a minimum concentration that 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 water quality variable that could fully reach its goal, as its maximum concentration was still much lower than its goal.

5 Discussion

5.1 Statistical analysis of water samples

With regard to the average values of 76 samples, although 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 is believed that the Guanting Reservoir could be used as an auxiliary drinking water source for Beijing with the government's great efforts.

In Table 3, it can be seen that the maximum values are very high compared to the average. This is due to the fact that the water samples were collected near the mouth of the Yongding River. On the other hand, the minimum values are fairly small, most of which were retrieved from samples distributed in the central part of the study area. These samples were very valuable for modeling as they were useful in extending the confidence interval of the model and ensuring the significance of statistical regression algorithms.

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/$10^7 \cdot L^{-1}$	$C_{\mathrm{Algae}} = 44903.44 + 755.3791\dfrac{TM_3}{TM_5} + 0.031446 \times e^{TM_3/10} + 0.002773 \times e^{TM_6/10} - 10888.1\dfrac{TM_1}{TM_2} - 49160.3\dfrac{TM_2}{TM_1}$	8.87×10^{-22}	0.927	9.0
turbidity/NTU	$\mathrm{Ln}(C_{\mathrm{Turb}}) = 34.92214 - 3497.32/TM_6 + 0.000874TM_2^2 + 12.13469\dfrac{TM_3}{TM_6} - 3.821\mathrm{Ln}TM_7$	1.83×10^{-24}	0.937	10
TN/$mg \cdot L^{-1}$	$\mathrm{Ln}(C_{\mathrm{TN}}) = 4.3907 - 177.9298/TM_6 - 0.1362\dfrac{TM_6}{TM_7} - 1.211\dfrac{TM_3}{TM_6}$	4.06×10^{-10}	0.75	11
NO_3–N/$mg \cdot L^{-1}$	$C_{NO_3-N} = 21.9888 - 0.70578\dfrac{TM_2}{TM_5} - 3.688\mathrm{Ln}TM_6 - 0.0186TM_3$	4.33×10^{-23}	0.922	4.4
NH_3–N/$mg \cdot L^{-1}$	$\mathrm{Ln}(C_{NH_3-N}) = -7.177 + 1.93\mathrm{Ln}TM_7 + 0.1323TM_6 - 2.185\dfrac{TM_6}{TM_3} - 0.07648TM_1$	5.35×10^{-12}	0.806	28
TP/$mg \cdot L^{-1}$	$\mathrm{Ln}(C_{\mathrm{TP}}) = 4.334 - 4.594\dfrac{TM_1}{TM_2} + 1.103\dfrac{TM_4}{TM_7}$	5.38×10^{-4}	0.613	30
DP/$mg \cdot L^{-1}$	$C_{\mathrm{DP}} = -0.0698 + 1.9 \times 10^{-5} \times e^{TM_3/10} + 0.0855\dfrac{TM_3}{TM_2}$	5.36×10^{-15}	0.955	15

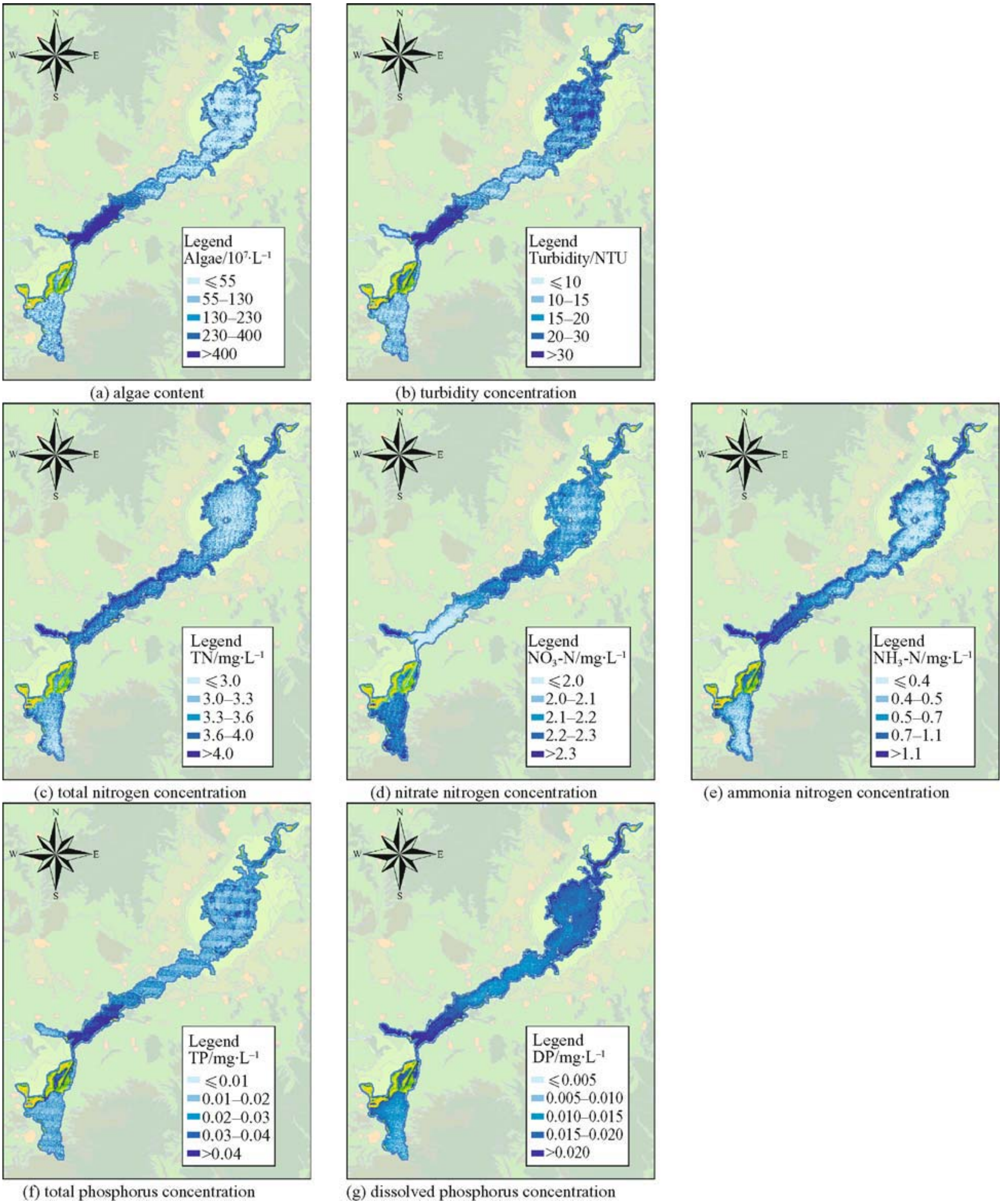

Fig. 3 Spatial distributions of model retrieval results with TM image of June 7, 2005 for 7 water quality variables in Guanting Reservoir

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 using 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.

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/$10^7 \cdot L^{-1}$	turbidity/NTU	TN/$mg \cdot L^{-1}$	NO_3–N/$mg \cdot L^{-1}$	NH_3–N/$mg \cdot L^{-1}$	TP/$mg \cdot L^{-1}$	DP/$mg \cdot L^{-1}$
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	–

According to similar applications of Landsat data on ocean water, coastal water, and inland polluted water bodies, three typical kinds of DNs sampling methods were selected for this study. Stepwise multiple linear regression was run using the three different ways to get model input DNs. The significance evaluation results (Fig. 2) show that the original DN had better performance for water quality variables, while NO_3^-–N concentration did not seem 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 the retrieval of water quality information with TM data.

For the cases of TN concentration and turbidity, the median DN of the 3 × 3 pixel window was found to have 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) indicate that there exists a statistically 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 a correlation for COD could not be retrieved within an acceptable error margin 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, and only those of TN and TP were lower than 0.8.

Our results showed that all seven water quality variables had satisfactory retrieval results according to the mean relative error, which is one of the most important indicators for the 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%; and concentrations of NH_3–N and TP within 30%. These accuracies could be acceptable for early warning on water quality safety and routine water quality monitoring with the support of a few additional precise traditional monitoring methods.

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

In addition, our study showed that inland water quality monitoring through RS data could be just based on simple retrieval methods; for this case, regression was used to effectively model linear or known nonlinear transfer functions in the 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 have found that statistical regression has poor ability to characterize the relationship between both the digital data of TM and SAR and water quality parameters [17]. Keiner et al. has ascribed it to the poor ability of regression analysis to model the unknown nonlinear transfer function in surface waters [25]. But in our study, 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 the Guanting Reservoir were derived within an acceptable error margin. 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]. Also taken into consideration was the reality that the number of surface water quality parameters that can be derived from optical satellite data is limited [17]. However, Mattikalli has suggested a model for estimating losses of nitrogen reasonably satisfactorily [27], and more and more researchers have tried 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 derivation of water quality variables, including thermal data (TM_6). Single band data have been widely used in water quality studies. However, attempts have been made to find combinations of Landsat TM bands that would provide more information about water quality variables than single band [9]. The results of our study also indicate that it is essential to select feasible combinations of bands in correlation analysis. Although algorithms were quite different in the selected bands when compared with those used in other studies [3,4,9], 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 out 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 present only in the model of TP concentration with relatively low R value, as shown in **Table 4**, which was in agreement with previous studies. Studies in the literature have mainly concentrated on 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 measures the emitted thermal radiance of a body of water and not the reflected sunlight and since the thermal band can be considered as having no or very little effect on optical measurements when it is relatively less correlated to the surface properties, it was pointed out that surface roughness has an effect on thermal radiance [17]. Thus the thermal data (TM_6) of Landsat TM was still included, and the 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 multitemporal as well as data fusion use of satellite remote sensing for the estimation of major water quality variables in surface waters will allow the determination of seasonal and yearly cycles and trends in inland waters to be integrated in the future.

6 Conclusions

This study showed that there exists a statistically significant correlation between each selected water quality variable and remote sensing data in a 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), correlation was obtained for seven of them with acceptable accuracies, except for COD. Furthermore, the original pixel DNs were found to be the best sampling method for water quality retrieval with TM data, compared to the average and median values of the 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 proved applicable in routine monitoring through RS. The study also showed that retrieval models made with Landsat-5 TM data could meet the accuracy requirements of routine water quality monitoring on the reservoir for the variables of 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 data retrieval could be greatly improved with the 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 in establishing a time-cost effective method for the routine monitoring of slightly-polluted inland water bodies. More attention should be paid to rapidly developing RS techniques and theoretical studies on water quality data retrieval, especially for slightly polluted inland water bodies and those water quality variables that are key to environmental management.

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