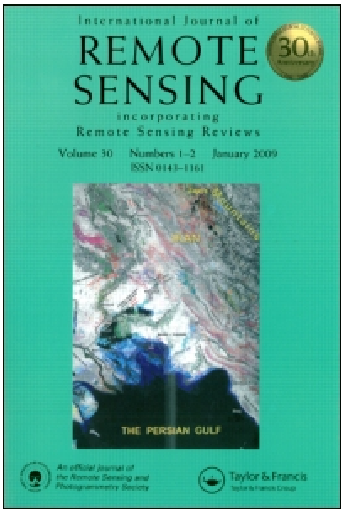

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Empirical estimation of total phosphorus concentration in the mainstream of the Qiantang River in China using Landsat TM data

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Eutrophication is a serious environmental problem in Qiantang River, the largest river in the Zhejiang Province of southeast China. Increased phosphorus concentration is thought to be the major cause of water eutrophication. The objective of this study was to develop an empirical remote sensing model using Landsat Thematic Mapper (TM) data to estimate phosphorus concentration and characterize the spatial variability of the phosphorus concentration in the mainstream of Qiantang River. Field water quality data were collected across a spatial gradient along the river and geospatially overlaid with Landsat satellite images. Various statistical regression models were tested to correlate phosphorus concentration with a combination of other water quality indicators and remotely sensed spectral reflectance, including Secchi depth (SD) and chlorophyll-*a* (Chl-*a*) concentration. The optimal regression model was subsequently used to map and characterize the spatial variability of the total phosphorus (TP) concentration in the mainstream of Qiantang River. The results suggest that spectral reflectance from the Landsat satellite is spatially and implicitly correlated with phosphorus concentration ($R^2 = 0.77$). The approach proved to be effective and has the potential to be applied over large areas for water quality monitoring.

1. Introduction

Nutrient (nitrate, phosphate) enrichment in lakes, rivers and streams is the major cause of water eutrophication (Gulati and van Donk 2002). Many freshwater lakes and rivers in China (e.g. Dianchi Lake, Donghu Lake, Taihu Lake and Yangtze River) have become eutrophic because of nutrient discharge from agricultural fields, industrial sectors and untreated residential waste. Poor water quality has become one of the major environmental and human health issues in China. Qiantang River, the largest river in Zhejiang Province, is currently undergoing rapid eutrophication. Algal blooms have occurred several times over the past few years, with the most serious case

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occurring from late July to early August in 2004 (Environmental Monitoring Stations of Zhejiang Province 2004). Recent studies have shown very high nitrogen and phosphorus concentrations in lakes and rivers in China (e.g. Wen *et al*. 2005, Tong *et al*. 2006) that are associated with the high eutrophication and algal blooms in rivers and lakes of the region.

Numerous studies suggest that nitrogen (N) is the limiting nutrient of primary productivity (Ryther and Dunstan 1971) in marine waters, and that phosphorus (P) is the limiting nutrient of eutrophication in lake/river ecosystems (e.g. Edmondson 1970, Dillon and Rigler 1974, Vollenweider 1976, Schindler 1977, Guildford and Hecky 2000). A ratio of total nitrogen (TN) to total phosphorus (TP) of 15:1 is generally regarded as the dividing point between nitrogen and phosphorus limitation (USEPA 1980). Ratios of nitrogen to phosphorus < 10 often indicate nitrogen deficiency, and ratios > 20 indicate phosphorus deficiency. Past research efforts have focused on nitrogen concentration as a gauge of water quality while, in reality, phosphorus is the determining factor of algal blooms, eutrophication and the primary productivity of aquatic ecosystems (Tyrrell 1999). Efforts to limit eutrophication, therefore, often focus on reducing phosphorus inputs to lakes and streams.

To measure and monitor phosphorus concentrations in rivers and lakes is challenging because of the spatial heterogeneity and the labour-intensive collection and testing of field samples. Remote sensing may provide a tool for phosphorus monitoring, as it has already been used successfully to monitor other water quality variables over large areas. For example, remote sensing methods have been developed for operational large-scale monitoring of chlorophyll concentration and suspended materials (Kloiber *et al*. 2000, 2002, Harma *et al*. 2001, Wiangwang *et al*. 2006). Several studies have shown that imagery from Landsat sensors can be used in the estimation of Secchi depth (SD), chlorophyll-*a* (Chl-*a*) concentration, turbidity and total suspended solids (Tassan 1987, Harrington *et al*. 1992, Dekker and Peters 1993, Pattiaratchi *et al*. 1994, Keiner and Yan 1998, Nellis *et al*. 1998, Allee and Johnson 1999, Roelfsema *et al*. 2001). These remote sensing methods were shown to be effective in reducing the experimental cost and labour (Khorram and Cheshire 1985, Lathrop 1992). Other studies (e.g. Li *et al*. 2007) have used Sea-viewing Wide Field-of-view Sensor (SeaWiFS) satellite images to retrieve the total inorganic nitrogen concentration of Pearl River estuaries in China and found that the remote sensing model was effective and provided consistent estimation results.

So far, attempts to estimate phosphorus concentrations in rivers and lakes have met with limited success. Theoretical phosphorus models based on mass balance have been developed (e.g. Vollenweider 1976, Imboden and Gächter 1978, Jorgensen *et al*. 1986, Chapra and Canale 1991) to predict phosphorus concentration of rivers and lakes, although each of them has some degree of limitation (Malmaeus and Hakanson 2004). The Vollenweider approach to predicting phosphorus concentration using basic mass-balance modelling and regression analysis has been tested by many others (e.g. Meeuwig and Peters 1996). These methods, although successful in some cases, are difficult to generalize and, more importantly, lack spatial explicitness as they are mass balance-based approaches. Although remote sensing has the potential to estimate water quality variables in general, it presents a challenge in estimating phosphorus concentration. In theory, it is difficult to correlate remote sensing spectral features directly to phosphorus concentration of water bodies. Many studies, however, have shown that Chl-*a* concentration has a general tendency to increase with TP concentration (e.g. Vollenweider 1976, McQueen *et al*. 1986, Chen *et al*. 2003, Dörthe *et al.* 2003) because nitrate and phosphorus are the two most important nutrients of Chl-*a* growth. The study by Schindler (1977) showed that 74% of the variability in chlorophyll concentration among lakes could be explained by the variation of phosphorus concentration. This finding suggests that chlorophyll concentration may serve as a proxy of phosphorus concentration. In a similar study (Heiskary and Wilson 2005), the SD was shown to decrease with increasing water TP concentration in some systems. This was attributed to the fact that a large proportion of phosphorus in the water was attached to suspended materials (from soil erosion), and we know that suspended materials reduce the water transparency or visibility that SD measures. These studies suggest that both chlorophyll concentration and SD are closely correlated with TP concentration (Carlson 1977) and therefore there is the potential to predict TP concentration empirically and indirectly from the estimation of Chl-*a* concentration and/or SD measurements. These latter water quality variables have been strongly correlated with surface reflectances as observed from satellite images. The logical deduction, which is the assumption of this study, is that there is a correlation between remote sensing observations and TP concentration in a water body, in the form of reflectance = f[Chl-a(TP), SD(TP)].

Although there is a possibility that TP may be indirectly correlated to remote sensing measurements, few studies have been conducted to estimate TP concentration using remotely sensed imagery. The overall aim of this study was to develop a spatial modelling technique to estimate TP concentration of lakes and rivers from satellite imagery. Our specific objectives were to: (1) develop an empirical remote sensing model using Landsat Thematic Mapper (TM) data to estimate TP concentration, (2) characterize the spatial variability of the concentration and (3) identify potential sources of the phosphorus related to agricultural activities in the mainstream of Qiantang River.

2. Study area

Qiantang River, originating in Xiuning City, Anhui Province, China, passes through Anhui, Jiangxi, Fujian and Zhejiang Provinces (28° 10′–30° 29′ N, 117° 37′–121° 52′ E). The total length of the river is 605 km, and its watershed covers 55 558 km^2, 86% of which is within Zhejiang Province. Qiantang River is the largest inland river in Zhejiang Province. The river passes through Hangzhou City, the capital of Zhejiang Province, before entering the East China Sea through Hangzhou Bay. Hangzhou, with a population of about 6 million, is the most developed city in the Qiantang River watershed and about 85% of its surface water supplies come from the river. The Hangzhou segment of the Qiantang River is 308 km long. Its watershed area occupies 14 067 km^2 with a water surface of about 700 km^2. The geomorphology of the Qiantang watershed is complex, with basins, mountains and valleys interlaced. Upriver, Qiandao Lake is a huge reservoir covering an area of 580 km^2 with a storage capacity of 17.8 km^3. It was a basin before the completion of a dam in 1958. Following Qiandao Lake to Jiande City, the average gradient of the riverbed is 0.1‰, and the width is 150–300 m. The width near Jiande City is about 500 m. Approximately 5 km downstream away from Jiande City, the river enters into a canyon 24 km long and 320–470 m wide with an average gradient of 0.3‰. As the river enters Fuyang City, the width of the waterbed increases to 4000–5000 m and then to 7000–8000 m. Its average gradient in this area is 0.03‰ (figure 1).

Water pollution and eutrophication of the Hangzhou segment of the watershed is becoming worse because of an increase in human activities, including agricultural

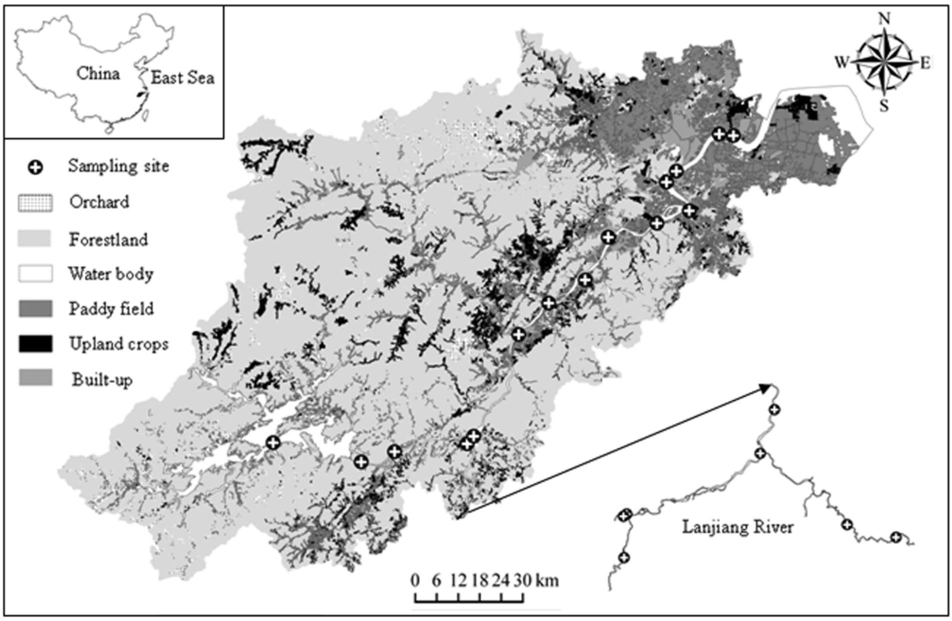

Figure 1. A map of Qiantang River (Hangzhou segment), showing the general location, land use/cover types, sampling sites of 15 mixed water samples within the study area and sampling sites of seven mixed water samples for validation of the models from Lanjiang River.

production and residential and industrial discharges (Lin 2001, Lü *et al.* 2003, Wu *et al.* 2003, Tong *et al.* 2006). In 2001 the annual mean concentrations of TN and TP of this segment were 2.52 and 0.112 mg kg^{-1}, respectively, with a high TN/TP ratio of 22.5:1 (Wu *et al.* 2003). The sub-watershed of the Hangzhou segment is at the interface between the land and the ocean. The mean annual temperature is 16.2°C and the annual rainfall is approximately 1500 mm. The topography of the sub-watershed is characterized by mountains in the southwest and flood plains in the northeast sections of the watershed. The land use/land cover (LULC) pattern is very complicated, including primarily forestland, paddy fields, water bodies, orchards, built-up areas (urban land, residential land, public facilities and industrial sectors) and upland crops. Forestland is the dominant LULC by area, accounting for about 65%, and upland crops are the least LULC by area, accounting for only 3.25% (figure 2).

3. Data acquisition and processing

3.1 In situ *data*

In this study, the *in situ* water quality data were collected between 15 and 19 July 2004, and their corresponding images was acquired on 26 July 2004. Fifteen mixed water samples within this study area (figure 1) and seven from the Lanjiang River, the largest sub-branch adjacent to the Hangzhou segment of the Qiantang River, were collected and analysed. At each site, water was sampled at the central portion of a river cross-section to be a representative water quality profile of the rivers. During the experimental period, a serious algal bloom occurred in some river segments; the water quality was the worst in the year.

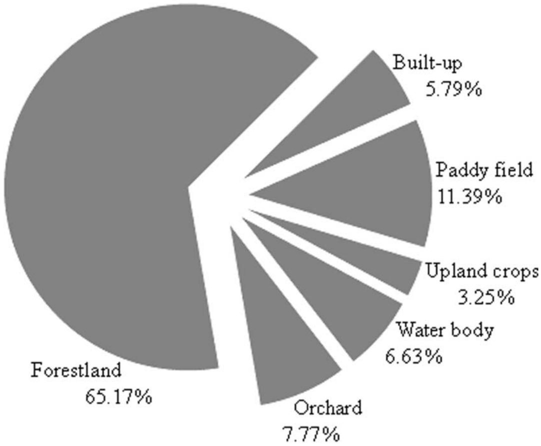

Figure 2. Proportion of LULC types interpreted from the four scenes of Landsat TM images as listed in table 1 in the study area.

Water samples were collected in the upper 2 m profile of the river using a PVC tube 2 m long with an internal diameter of 1¼ inches (integrated samplers). We collected 5–8 water samples in a grid of about 30 m $\times$ 30 m, and mixed them together to produce a mixed water sample. The central geographical location of each mixed sample was recorded with a global positioning system (GPS), to be colocated later on satellite images. Water samples were acid preserved immediately after sampling. TP concentration was determined using the second-derivative method after persulfate oxidation (Crumpton *et al*. 1992) and the ascorbic acid method (Prepas and Rigler 1982).

Considering external factors such as tidal and temporal variations that might affect the water quality data, an effort was made to ensure that all water samples were collected during a non-tidal period. We also designed the experiment in such a way that the water quality was more or less stable during the experimental period, as normally in the region there are few agricultural activities during the time of the experiment due to crop seasonality. Additionally, we examined data from an experiment station, including pH, turbidity, dissolved oxygen (DO) and chemical oxygen demand (COD), for an extended period of time. Analysis of this data set (not included in this paper) showed little change in water quality during the experimental period of this study. This led us to believe that the approximately 10-day separation between satellite overpasses and the *in situ* water samplings should not pose a major problem in the analysis. We proceeded from the assumption that the two data sets (satellite imagery and *in situ* water quality measurements) can be treated as simultaneous data pairs.

The *in situ* measurements of TP concentration, Chl-*a* concentration and SD were collected from 30 stations along the Qiantang River in 2004 by the staff at the Environmental Monitoring Stations of Zhejiang Province. In total, there were 86 paired TP and Chl-*a* and 181 paired TP and SD measurements throughout 2004. These data were used to examine the relationships between the TP, Chl-*a* concentration and SD.

3.2 *Satellite images and processing*

Landsat TM images were used in this study, and the spectral characteristics of the satellite sensor are provided in table 1. Four images were needed to cover the entire

Table 1. Acquisition parameters of the four Landsat-5 Thematic Mapper (TM) images used in the study and spectral characteristics of the first three Landsat 5 TM bands.

Path/Row	Acquired date	Sun elevation (°)	Sun azimuth (°)
119/39	26 July 2004	63	107
119/40	26 July 2004	64	104
120/39	19 October 2003	45	147
120/40	1 July 2004	65	97
Band	Spectral region (μm)	Bandwidth (μm)	Centre wavelength (μm)
1	0.45 – 0.52	0.07	0.485
2	0.52 – 0.60	0.08	0.56
3	0.63 – 0.69	0.06	0.66

Hangzhou segment of the Qiantang River (table 1) and relevant portions of the Lanjiang River where validation samples were collected. Because of the frequent cloud coverage in the region, it was not possible to acquire four images on the same date and therefore images from different dates were used in this study (table 1). Only a fraction (8%) of the 2003 image, once mosaicked, was within the study area. Although possible errors due to differences in acquisition dates exist, these images were the best we could get for this study. We also believe that the magnitudes of errors introduced will depend on the temporal variability of the Qiantang River, and will certainly vary from lake to lake. However, as noted earlier, there is little variation in water quality during the experiment period of this study.

Atmospheric correction of satellite imagery is very important in aquatic remote sensing, as a considerable amount ($>$ 90% in many cases) of radiation detected by satellite sensors is backscattered from the atmosphere without ever penetrating the water (Kutser *et al.* 2005). For multiple scenes of different dates, it is especially important to normalize atmospheric effects. Because of a lack of atmospheric measurements at the time of the satellite overpasses, in this study a semiempirical procedure based on the improved dark object subtraction technique by Chavez (1996) was used to remove the haze contribution. Although the procedure does not completely remove atmospheric effects on satellite images, it normalizes the four scenes to the extent that there is no significant discontinuity across scene boundaries. The procedure can be considered as an approximation of atmospheric normalization/correction and consists of the following steps:

Step 1. Convert the raw digital number (DN) to at-satellite radiance (L_{sat}). The following equation was applied based on the Landsat imagery calibration equation:

$$L_{\text{sat}\lambda} = \text{DN}_\lambda \times \text{Gain} \times \text{Offset} \tag{1}$$

where λ indicates wavelength, and Gain and Offset are gain and offset factors, respectively, provided in the header file.

Step 2. Determine the minimum radiance for each reflective band ($L_{\lambda,\min}$). This minimum radiance of a scene, which can be obtained from imagery histograms, is dependent on the atmospheric condition during the satellite overpasses and needs to be normalized. Its value was computed using:

$$L_{\lambda,\min} = L_{\min\lambda} + \mathrm{QCAL}(L_{\max\lambda} - L_{\min\lambda})/255 \quad (2)$$

where QCAL is the minimum DN obtained from histogram, and constants $L_{\min\lambda}$ and $L_{\max\lambda}$ are provided in the header file or listed in various studies (e.g. Markham and Barker 1986, Moran *et al*. 1992).

Step 3. Determine the radiance of dark objects as the contribution from atmospheric scattering ($L_{\lambda,1\%}$). For each band, the radiance value of a dark object (assumed to have a reflectance of 1% in this study) based on Chavez (1996) was computed using:

$$L_{\lambda,1\%} = 0.01(\mathrm{ESUN}_\lambda) \times \cos^2\theta/(\pi \mathrm{d}^2) \quad (3)$$

where ESUN_λ is the mean solar exoatmospheric spectral irradiance, θ is the solar zenith angle (provided in the header file) and d is the Earth–Sun distance in astronomical units.

Step 4. Compute the radiance from the atmospheric haze ($L_{\mathrm{haze}\lambda}$). This is a simple subtraction of the radiance from dark objects calculated in step 3 from the sensor's observed minimum radiance using:

$$L_{\mathrm{haze}\lambda} = L_{\lambda,\min} - L_{\lambda,1\%} \quad (4)$$

Step 5. The normalized (for haze) reflectance (ρ) is finally computed using the modified reflectance equation:

$$\rho = \pi \mathrm{d}^2 \times (L_{\mathrm{sat}\lambda} - L_{\mathrm{haze}\lambda})/(\mathrm{ESUN}_\lambda \times \cos^2\theta) \quad (5)$$

These steps were used in an attempt to normalize the atmospheric discrepancies among the selected satellite overpass dates. Note that the absolute atmospheric correction may not be as important as atmospheric consistency because the regression analysis approach used in this study (described later) is more sensitive to the slope of a linear regression, and the intercept can be calibrated with *in situ* measurements.

4. Statistical approach and validation

Several studies have explored the possibility of using Landsat TM data for the determination of Chl-*a* concentration and SD, with varying degrees of success (Khorram and Cheshire 1985, Lathrop and Lillesand 1986, Allee and Johnson 1999, Koponen *et al*. 2001, Kloiber *et al*. 2002). These studies found the TM3/TM2 ratio to be the best predictor of Chl-*a* concentration (Allee and Johnson 1999, Koponen *et al*. 2001), and the combination of TM1/TM3 ratios and TM1 to be the best predictor of SD (Kloiber *et al*. 2002). As TP concentration is closely related to Chl-*a* and SD, we can empirically predict TP concentration by using the indicators of Chl-*a* concentration and SD measurements and the hypothesis that a combination of TM3/TM2, TM1/TM3 and TM1 is also a good indicator of TP concentration. The spectral bands centred on the blue–green (0.45–0.52 μm), green (0.52–0.60 μm) and red (0.63–0.69 μm) spectral regions (see table 1) are more sensitive to water quality than the other spectral bands at longer wavelengths.

In this study, a combination of these spectral bands and the respective ratios was used to correlate empirically with the *in situ* TP measurements. To reduce possible effects of geometric misregistration, the average reflectance from a 3 × 3 pixel window (about 90 m $\times$ 90 m) was computed for each sampling location. This averaging technique has been shown to be effective in removing geometric errors in other studies (Almanza and Melack 1985, Yacobi *et al*. 1995, Allee and Johnson 1999).

All regression analyses were performed using the statistical program SPSS 13.0 for Windows. Image processing, area statistics and mapping were carried out using ERDAS IMAGE 8.7. To establish the relationship between TP concentration and the remotely sensed variables, we set the *in situ* TP concentration as the dependent variable and various band ratios and their linear combinations as independent variables. A total of 15 water samples collected within the study area were used to build the regression models, from which the best fit was selected and further validated with an additional, independent data set of smaller size. Seven additional mixed water samples from Lanjiang River, upstream of Qiantang River, were used for model validation. These mixed water samples represented a very dynamic range of water quality as the TP values ranged from 20 to 177 μg l^{-1} and comprise a good data set for validation of the regression model. Once validated, the selected regression model was then applied to the satellite images to empirically estimate the spatial distribution of TP concentration in the mainstream of Qiantang River. The estimated map was further classified according to the eutrophication classification systems (table 2) of the Organization for Economic Cooperation and Development (OECD 1982) to allow spatial representation of the water quality.

5. Results

5.1 *Relationship between TP and remotely sensed variables*

We found a relationship between TP and Chl-*a* and between TP and SD in the study area. The correlation coefficient (r) between TP and Chl-*a* was 0.45 ($p < 0.05$), and r between TP and SD was 0.76 ($p < 0.01$), based on a statistical analysis of the *in situ* TP, Chl-*a* and SD data. This finding confirmed the assumption that TP was correlated with Chl-*a* and SD, the latter of which has been shown to be strongly correlated to remotely sensed variables. Analysis of the relationships between various spectral bands of the Landsat TM image and TP data showed correlation. The correlation coefficient between the natural logarithmic TP concentration and TM1, TM1/TM3 and TM3/TM2 was found to be 0.65, –0.81 and 0.70, respectively, at the $p < 0.01$ significance level. The correlations between the various spectral bands and TP concentrations allowed us to develop a regression model to link the remotely sensed imagery to TP concentrations.

Table 2. The Organization for Economic Cooperation and Development eutrophication classification system (OECD 1982).

	Ultraoligotrophic	Oligotrophic	Mesotrophic	Eutrophic	Hypertrophic
Total phosphorus (μg l^{-1})	≤ 4	≤ 10	≤ 35	≤ 100	> 100
Chlorophyll (μg l^{-1})	≤ 1	≤ 2.5	≤ 8	≤ 25	> 25
Secchi disc depth (m)	≥ 12	≥ 6	≥ 3	≥ 1.5	< 1.5

Numerous regression models were tested to correlate TP with different spectral band combinations. The regression equation based on both SD (TM1 and TM1/TM3) and Chl-*a* (TM3/TM2) had the highest regression coefficient ($R^2 = 0.77$) and was of the form:

$$\ln(\mathrm{TP}) = -21.45(\mathrm{TM3}/\mathrm{TM2}) - 14.42(\mathrm{TM1}/\mathrm{TM3}) + 42.99(\mathrm{TM1}) + 27.1 \quad (6)$$

where ln(TP) is the natural logarithmic TP concentration in μg l^{-1} and TM is the corresponding Landsat TM spectral reflectance value. We determined a coefficient of determination (R^2) of 0.77, root mean squared error (RMSE) of 0.77, mean error of TP (ME_{TP}) of 6.6, and the significance probability of the F statistic test for the equation (p) < 0.001. The high coefficient of determination ($R^2 = 0.77$), relatively low RMSE for ln(TP) and low ME_{TP} for TP estimation all indicate that it is possible to use Landsat TM data as an alternative to estimate the TP concentration in Qiantang River. Although it may vary in equation forms, we expect that this statistical regression approach is applicable to other geographical areas of similar environment type. Therefore, satellite images may have the potential to estimate TP concentration over large areas of similar river systems. When applied with frequent and repeated satellite images, the TP status of Qiantang River can be effectively monitored.

5.2 *Model validation*

To validate the empirical model, we used the seven independent *in situ* mixed water samples from Lanjiang River (figure 1) and the results are presented in figure 3. No significant outliers were found; all measured values in the data sets for both model building and model validation were within the 95% confidence interval of the model prediction; and the inspection of residuals showed that the empirical model adequately explained the variation in phosphorus concentration. This suggests the feasibility of extending the model to the entire area of the Qiantang River when the TP concentrations are beyond the ability of the model to adequately or reliably predict them (6–233 μg l^{-1}).

5.3 *Spatial patterns of total phosphorus*

Equation (6) was subsequently used to predict the TP concentration empirically for the Hangzhou segment of the Qiantang River (figure 4). The resulting predictions were consistent with previous studies (e.g. Wen *et al.* 2005, Tong *et al.* 2006). The TP concentration in the study area showed a clear spatial variability. For example, in Qiandao Lake, the TP concentration was mostly in the range of 10–50 μg l^{-1}, but in the northwest and northeast corners it exceeded 200 μg l^{-1}. Within the lake, the TP concentration in the northwest was higher than in the southeast. The TP concentration in the vicinity of Jiande City was much higher than in its neighbouring areas, exceeding 200 μg l^{-1}. The concentration close to Fuyang City was lower than its neighbourhood, in the range 50–100 μg l^{-1}. Near Hangzhou City, the TP concentration was mostly within the range 20–50 μg l^{-1}. Along Qiantang River estuaries, the TP concentration varied from 10 to 20 μg l^{-1}, while in the other areas the TP values were in the range 100–200 μg l^{-1}.

Throughout the entire study area, the TP concentration varied widely, from 1.0 μg l^{-1} to more than 200 μg l^{-1}, and the associated eutrophication ranged from ultraoligotrophic to hypertrophic conditions. According to the OECD eutrophication

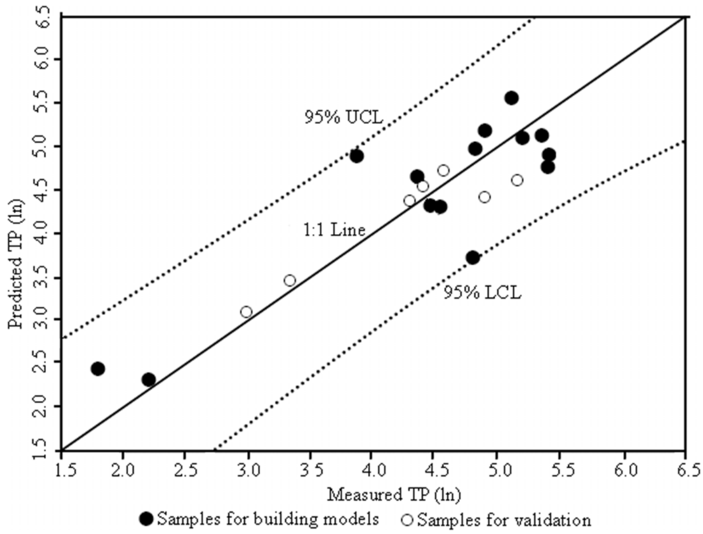

Figure 3. The natural logarithm of measured total phosphorus (TP) concentrations ($\mu g\ l^{-1}$) versus the natural logarithm of predicted TP concentrations from Landsat TM data using equation (6): $\ln(TP) = -21.45(TM3/TM2) - 14.42(TM1/TM3) + 42.99(TM1) + 27.1$. The solid line is the 1:1 line, while the two dashed lines correspond to the prediction interval of the 95% upper confidence limit (UCL) and the 95% lower confidence limit (LCL).

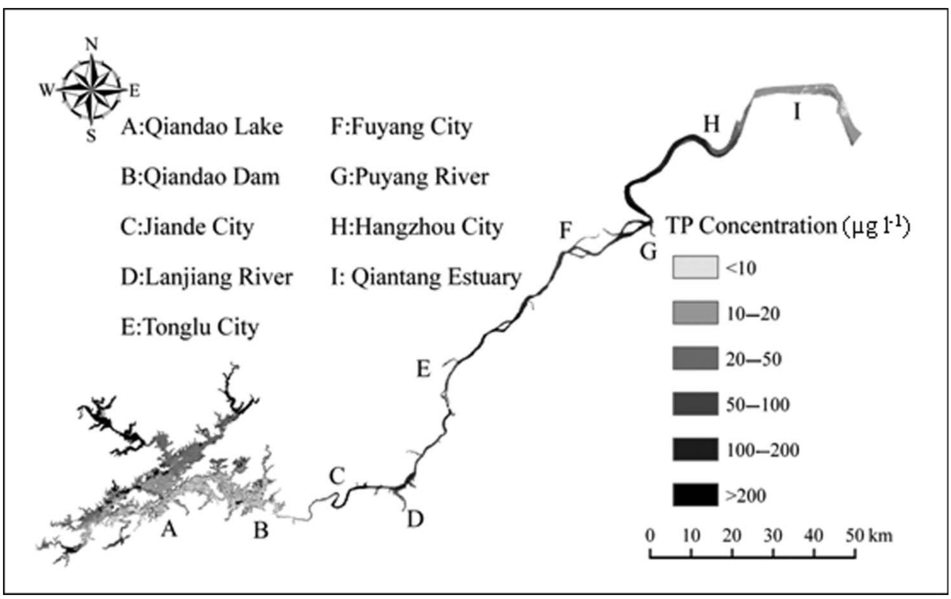

Figure 4. Estimated total phosphorus (TP) concentration from Landsat TM images in the mainstream of Qiantang River.

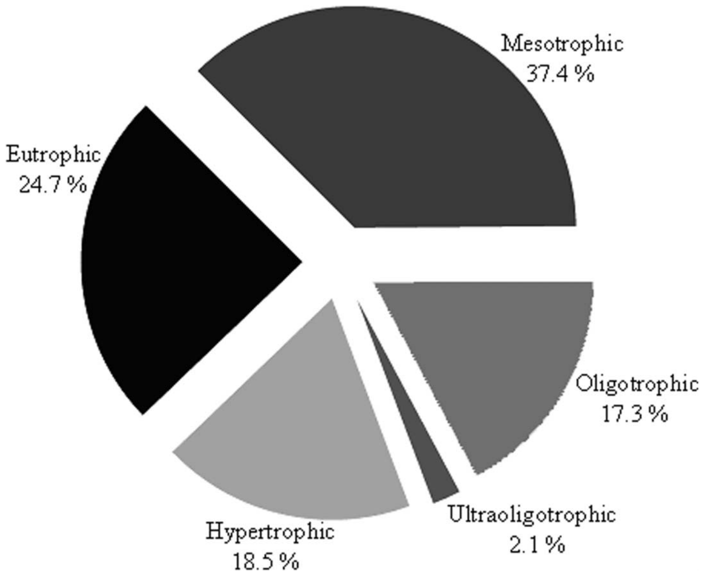

Figure 5. Proportion of total phosphorus (TP) concentration and pollution status in the mainstream of Qiantang River according to the Organization for Economic Cooperation and Development eutrophication classification system (OECD 1982).

classification standards, approximately 2.1% of the Qiantang River water is in the ultraoligotrophic state, about 17.3% is in the oligotrophic state, and about 37.4% is in the mesotrophic state (figure 5). A total of 43.2% (18.4% + 24.8%) of the water area exceeded the threshold eutrophication level in July 2004, when the eutrophication was the worst in the history of the study area.

6. Discussion

The empirical model for predicting TP concentration was developed for the mainstream of Qiantang River. Although the developed model performed satisfactorily as the validation shows, there are some shortcomings and limitations.

The *in situ* measurements used in the model construction and validation were sampled from locations with deep water, either in Qiandao Lake away from the lakeshore or in the midstream of the cross-section of the river. In shallow water, light reflection from the bottom was not accounted for, which may contribute significantly to the above-water remotely sensed reflectance spectra. Therefore, the TP concentration estimated in shallow water may not be very reliable, such as in the northwest and northeast corners of Qiandao Lake where the TP concentration exceeded 200 μg l^{-1}. These areas have unusually high concentrations of TP and validation needs to be carried out. Under these circumstances, it is better to incorporate additional information about the water depth, such as bathymetric data, in the modelling activities to avoid any misinterpretation of the results.

All of the *in situ* TP concentration measurements in this study were in the range 6–233 μg l^{-1}. As in any other statistical approach, the developed equation has a relatively narrow confidence interval of prediction within the range of the measured TP concentrations. Outside the range, the confidence interval of prediction increases dramatically, which means that large uncertainty may occur in the prediction. In addition, a natural logarithmic transformation was applied to all TP concentrations before regression analyses. To understand better the physical meaning of the transformation, a back-transformation (exponential of logarithmic values) was applied. This back-transformation procedure was especially sensitive to uncertainties and may magnify the prediction error (Deutsch and Journel 1998). Therefore, caution must be exercised with any estimation outside the range of *in situ* measurements (6–233 $\mu g\ l^{-1}$).

The empirical estimation model of TP concentration was based on the underlying assumption that there is a direct relationship between TP concentration, Chl-*a* concentration and SD, not based on the TP/radiometric spectra relationship for lacking spectral study of TP in surface water. Thus, the model has spatial and temporal limits of applicability. The assumption may not be true if other nutrients, such as nitrogen, are the main limiting factors of eutrophication. Examples are water bodies where nitrogen is limited, thereby preventing algal growth even in the presence of excess phosphorus. Previous studies indicated that Chl-*a* had a positive correlation with nitrogen when nitrogen was the limiting nutrient (Lesen 2006, Smith 2006). Chl-*a* concentration will be less than the normal concentration when the TP concentration is very high and nitrogen is the limiting nutrient. Our regression model was developed on the assumption that TP is the sole limiting nutrient of eutrophication and therefore it is most likely to be applicable in areas where nitrogen is high.

The empirical model developed in this study was intended to estimate TP concentration, which is the major cause of water eutrophication. This study, however, did not consider the dynamic processes of the fate of phosphorus, such as sedimentation, burial, resuspension, diffusion, biouptake and mixing.

The spatial pattern of the TP concentration along Qiangtang River suggests that the sources of phosphorus must also have a spatial pattern. Previous studies (Lin 2001, Tong *et al.* 2006) showed that the surface run-off from agricultural fields and industry sites and the discharge of untreated residential waste were the main sources of phosphorus inputs to the Qiantang River. The water quality of Qiandao Lake in the upstream of Qiantang River is among the best because of its limited source of TP inputs from agricultural and industrial activities. As Qiandao is a deep lake, it also has some degree of self-purification capability (Lü *et al.* 2003). The LULC surrounding Qiandao Lake was primarily forestland (figure 1), which introduces low or no phosphorus inputs into the lake. Other LULC types in the Qiandao Lake area, including agricultural fields (e.g. rice paddies and upland crops), occupy only a fraction of the land. Numerous studies (e.g. Chen *et al.* 1999, Liu 2001) have shown that only 10–15% of agricultural phosphorus fertilizer was taken up by crops, and 4–5% of the phosphorus was lost through either surface run-off or infiltration processes to lakes and streams, while the rest was fixed by soil materials and remained inactive in the soil system. High fertilizer application rates (reported to be about 290, 86 and 90 kg ha^{-1} of nitrogen, phosphorus pentoxide and potassium oxide, respectively, in 2000; see Liu 2001) and possibly improper ratios of nitrogen/phosphorus/potassium have caused major phosphorus losses from agricultural fields to aquatic ecosystems for crops uptake. A good example is that the TP concentration near the stream input was much higher than in the centre of Qiandao Lake.

The higher TP concentration in the vicinity of Jiande City indicates that urban land uses may have an important but adverse influence on water quality. The run-off from industries and the discharge of untreated residential waste were thought to be the main factors that cause a higher TP concentration near Jiande City. A serious algal bloom occurred in this segment of the Qiantang River in July 2004. A recent field survey confirmed that the area of serious algal bloom corresponded to high TP concentration, as estimated in this study. This again suggests that phosphorus may be the main limiting factor of water eutrophication in the study area. The results from this study agree with previous studies, which confirm that phosphorus concentration may be the limiting nutrient in freshwater systems for eutrophication (Gilliom 1984, Gamini 1997, Young *et al*. 1999) and algal growth (Villessot *et al*. 1985).

The Qiantang River tide near the East China Sea is thought to be the major reason for the low TP concentration in the estuaries of the river, as the sea water dilutes the TP concentration because of the frequent mixing of sea and river waters. The fact that high TP concentration areas along the river tended to correspond to agriculture-intensive areas suggests that the phosphorus losses from agricultural fields were a dominant TP source for the Qiantang River system.

Phosphorus is known to be an important factor contributing to the process of eutrophication and, as our findings suggest, the detection of elevated TP in the study area is probably associated with the observed eutrophication of Qiantang River. Therefore, efforts to mitigate algal blooms should focus on the reduction of phosphorus inputs to the river systems. Furthermore, this study suggests that agricultural fields might be the major source of phosphorus inputs, as well as a key common non-point source of pollution in many other areas. Therefore, the optimal investment in water quality control (particularly eutrophication) may be the improvement of agricultural practices in the region.

7. Conclusions

In this study, the TP concentration, which is closely related to Chl-*a* concentration and SD in the Qiantang River, was shown to be correlated indirectly to reflectance values observed from satellite sensors. A statistical model was developed to estimate TP concentration using spectral bands of Landsat imagery. The model was successfully used to map the spatial pattern of TP concentration in Qiantang River. The estimated TP concentration in the Qiantang River seemed to agree well with the actual situation and with results from other reports. Therefore, the results of this study indicate that there is the potential to monitor phosphorus concentration at large scales using satellite images such as Landsat TM. It should be pointed out, however, that calibration and validation using *in situ* measurements are needed to generalize this approach to other geographical areas.

Based on the mapping results for Qiantang River in July 2004, the TP concentrations in most regions were very high: about 43.2% of the river was in the eutrophication or hypertrophication category and 37.4% in the mesotrophication category. The high TP concentration areas appeared to be related to local agriculture and other land uses, but further validation is needed to quantitatively examine the causal–response relationships.

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