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Detecting Spatiotemporal Features of Phosphorus Concentrations Using MODIS Images: A Case Study of Hongze Lake, China

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ABSTRACT. Spatiotemporal tendency of total phosphorus (TP) concentrations in Hongze Lake were estimated using multiple Moderate - Resolution Imaging Spectroradiometer/Aqua images (MODIS) from 2003 to 2017. Considering the non-significant spectral features of phosphorus, this study was designed to primarily link TP with sensitive water quality parameters. Suspended particulate matter (SPM) was identified because SPM contents are sensitive to TP in Hongze Lake and also have notable response wavelengths including red, blue, and green bands. Therefore, a TP estimation model was developed based on the band integration methods suitable for lake SPM. The results showed that: 1) the exponential model of 645 nm and 555 nm is the most suitable model for TP estimation in Hongze Lake, in which the R^2 value for calculation and validation can both reach 0.7; 2) the best TP assessment accuracy always occurred when the SPM values were of a moderate level. The threshold values can be approximately designated as 40 ~ 70 mg/L; 3) the TP concentrations of the entire lake have apparently increased since 2012, and achieved a peak in 2014 because of substantial dredging activities; and 4) the center of the lake showed the highest TP concentrations, while the two bays in the northern and western lake showed the lowest TP concentrations. These spatial variations can be attributed to the integration of several factors including meteorological phenomena, land use change, and human disturbance such as dredging activities. This study further indicates that the Rayleigh-corrected reflectance of red band and green band derived from MODIS can be proposed as the suitable indicators for TP monitoring, especially in SPM-dominated lakes. In addition, more ideal modeling effect can be expected when lake SPM contents kept in a medium level (e.g. 40 ~ 70 mg/L within Hongze Lake).

Keywords: phosphorus, remote sensing, spatial and temporal tendency, lake suspended particulate matter, Hongze Lake basin

1. Introduction

Worldwide, inland aquatic environments have suffered from serious eutrophication during recent decades, leading directly to the proliferation of harmful algal blooms. More than 52% of the lakes in China have high eutrophic conditions, mostly in the Yangtze River Delta region, where the eutrophic degree has increased during the last 20 years. Eutrophication generally results from the accelerated influx of nutrients such as nitrogen (N) and phosphorus (P) (Bricker et al., 1999). P has been regarded as the primary limiting nutrient of eutrophication in large lake ecosystems. Therefore, the efficient and continuous monitoring of the spatiotemporal tendency of lake P is essential for excessive nutrient reduction and lake eutrophication management.

Remote-sensing technology provides a contemporary and quantifiable tool to monitor the spatiotemporal features of several water colors and quality indicators, including chlorophyll-*a* (*Chl-a*), particulate organic carbon (POC), and dissolved organic carbon (DOC) (Miller and McKee, 2004; Le et al., 2013). Specifically, several algorithms have been developed to estimate *Chl-a* in coastal and inland waters using either spectral bands in the green-red, red-near-infrared (NIR), or empirical orthogonal function (EOF) approaches (Erkkila and Kalliola, 2004; Gitelson et al, 2008; Zhang et al., 2016). The selected bands of algorithms are mainly derived from the Rayleigh corrected reflectance (R_{rc}) of Moderate Resolution Imaging Spectroradiometer (MODIS) measurements (Shutler et al., 2007; Shanmugam, 2011). In addition, the lake suspended particulate matter (SPM) concentrations were also used to represent the lake turbidity in some typical optically complex eutrophic lakes (Volpe et al., 2007). Several relative studies had been proved that the lake SPM can be estimated based on multi-satellite remote-sensing data including SeaWiFS, MODIS and VIIRS, etc. The sensitive wavelengths for SPM can ranged from 415 ~ 445 nm, 655 ~ 685 nm and 750 ~ 900 nm, which covered most of the visible spectrum (Wu et al., 2010). Recently, these algorithms have been expanded into the optically complex eutrophic lakes in China, such as Taihu Lake, Chaohu Lake, Hongze Lake

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(Feng, 2014; Shi et al., 2015; Cao et al., 2017).

In spite of these algorithms which were oriented to lake color and lake quality indicators were successfully applied in inland lakes, developing a recognized algorithm for lake TP is still a challenging task. The main reasons lied in that when compared with the lake color parameters previously mentioned the spectral features of TP are not obvious, and the Phosphorus chemistry structure was relatively complex (Malley et al., 1999). Several studies had tried to use statistical relationship to link lake TP to the reflectance of the selected bands of remote sensing images. For instance, Kutser et al. (1995) using three spectral ranges of visible spectrum to assess the lake TP by MODIS images, and the Normalized Trough Depth of spectral reflectance at 675 nm was used by Sun et al. (2014) based on HJ1A /HSI image. These studies provided important basis for the representation of lake nutrients by remote sensing. However, these models were mainly based on the simple mathematical statistics relationship, the mechanism analysis is limited, and the widely recognized algorithms have not been developed due to the suitable bands and wavelengths varied largely among different lakes (Chang et al., 2013).

Recently, a majority of studies proved that lake TP is closely related to some lake color and quality indicators such as SPM and *Chl-a* (Weisberg and Zheng, 2006; Liu and Jiang, 2013). Specially, the SPM is the carrier of watershed P influx and lake P adsorption (Usitalo et al., 2000), as well as the lake P also provides the essential basis for the growth of lake algae and *Chl-a* (Busse et al., 2006). Therefore, the indirect retrieval remote-sensing method can be expected as a feasible tool to capture the spatial and temporal features of lake TP, and the wavelength scales that are sensitive to lake color and quality indicators can be considered as an important intermediate indicator (Chen and Quan, 2012). Therefore, considering the TP dependence on lake color parameters, to propose an indirect inversion method for TP in optically complex turbid and eutrophic lakes is helpful to the digital representation of lake nutrients in long temporal sequence, and it is benefit to the lake environmental management.

Hongze Lake, the fourth largest freshwater lake in China, is located in the northern of Jiangsu Plain. The Hongze Lake is characterized by highly turbid waters and complex optical properties, means that the lake has a relatively higher SPM concentration than that of other nearby turbid and eutrophic lakes such as Taihu and Chaohu. In addition, the lake quality has been degraded drastically since 2010 due to frequent flow exchange and human influence. Therefore, the Hongze Lake watershed can be considered an ideal study site for the lake nutrients and remote sensing study, because of the leading role of lake suspended matter. The present study aimed to i) identify the suitable lake color parameter and sensitive wavelength regions that are sensitive to lake TP and develop an applicable remote-sensing algorithm for lake TP estimation and ii) detect the spatiotemporal features and change tendency of TP concentrations using multiple MODIS/Aqua images.

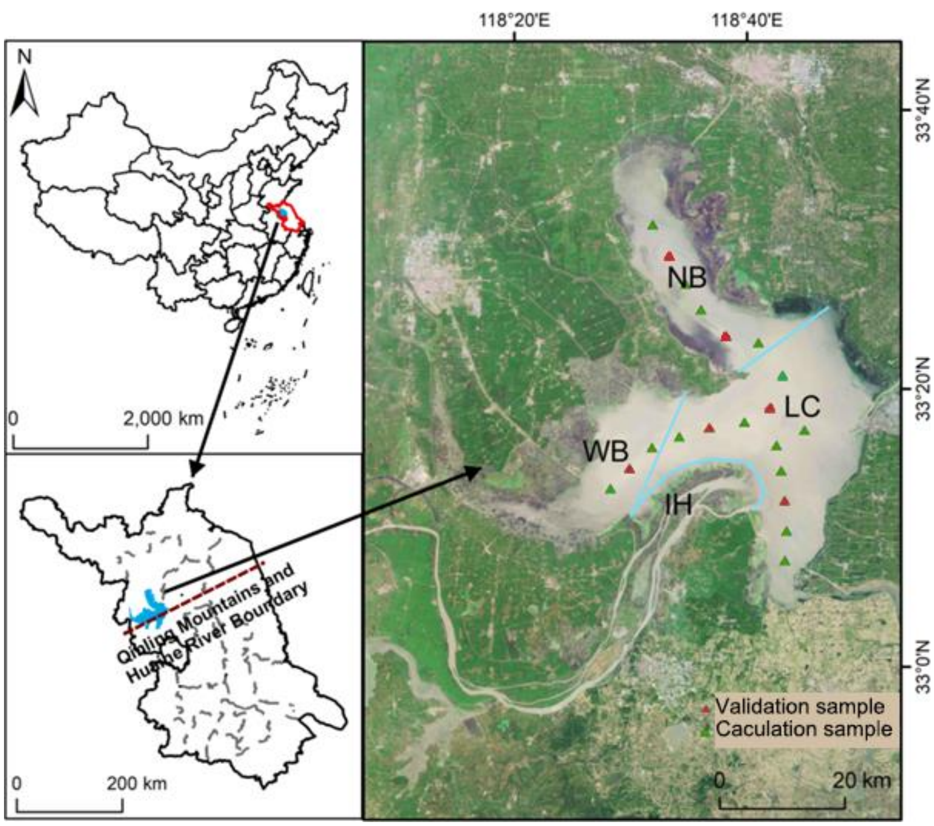

Figure 1. The map of the study site and sampling locations.

2. Material and Methods

2.1. Study Site and Data

Lake Hongze (33°06′ ~ 33°40′N, 118°10′ ~ 118°52′N) is the fourth largest freshwater shallow lake in China. The area covered by Lake Hongze varies with water levels. Specially, the lake's area is 1597 km^2 when then the water level is 12.5 m, and the volume is 3.04 billion m^3. The lake's average water depth is 1.9 m, and its maximum water depth is 4.5 m. The Hongze Lake watershed is subject to subtropical monsoon climate with an annual lake surface temperature of 16.3 ℃ and annual precipitation ranging from 950 ~ 1050 mm in recent 30 years (Zhu and Dou., 1993; Cai et al., 2016).

Lake Hongze is located in a warm temperate zone that belongs to the semi-humid monsoon climate region, resulted in the rainfall occuring primarily during the flood season, and the alternating floods and droughts occuring frequently (Zuo et al., 2012). The rivers that flow into Lake Hongze are concentrated west of the lake, including Huai River, Sui River, Bian River, Xinbian River and An River, etc. Runoff from the Huai River accounts for 70% of all river water runoff into the lake, and approximately 60 ~ 70% of the lake water flows into the Yangtze River through San River Sluice. The water exchange cycle is approximately 35 days, and the frequent flow exchange is characterized by highly turbid waters, the lake total suspended solid (TSS) concentrations also showed apparent seasonal variation. The field observation record from 2012 to 2015 showed that the lake TSS concentrations reached 44.83 mg/L in average, even the highest value can reached 100 mg/L in Dec, 2014 and May, 2015, which indicated that the average TSS concentrations, as well as the spatial-temporal variation degree were much higher than the data of the nearby shallow eutrophic lakes including Taihu Lake and Chao Lake, which are also located in Yangtze River Delta region (Cao et al., 2016).

According to the Environmental Quality Standards for Surface Water promulgated by the Chinese government, the TP concentration was classified as grade III to IV during the last ten years. In specific, the TP concentrations were kept around 0.16 to 0.2 mg/L in most monitoring stations until 2012, while the TP concentrations decreased to 0.12 and 0.10 mg/L in 2014 and 2015. That means the TP concentrations decreased apparently from 2013 ~ 2014, due to the ecological treatment project conducted by Ministry of Environmental Protection of China in 2013 (Cao et al., 2016).

2.2. Field Data Collection and Chemical Analysis

The 18 sample stations were set in Hongze Lake, in which 12 stations were identified as the calibration stations, and the other 6 stations were identified as the calibration stations. Two field trips and sampling works were completed in Hongze Lake in Feb. 18, 2016 and Dec. 16, 2016. During the field sampling process, the 18 sample stations were sampled in order to ensure that one of every three points was a validation sample. Therefore, a total of 36 water samples were collected during the two sampling processes, in which 24 samples belonged to calibration group, and 12 samples belonged to validation group.

The Surface water (depth from 0 ~ 20 cm) was collected using a standard water-sampling instrument. The latitude and longitude data of each sample was located and recorded using GPS with accuracy of 0.3 ~ 3 m. All the samples were stored in the dark and kept cool with ice bags before the laboratory measurements conducted. The chemical analysis of the lake water samples was conducted in The State Key Laboratory of Lake Science and Environment (SKLLSE), Nanjing Institute of Geography and Limnology, Chinese Academy of Sciences (CAS). The TP concentrations, as well as the acknowledged parameters that sensitive to TP including DOC, POC, *Chl-a* and SPM concentrations were reprocessed and determined in SKLLSE. The SPM concentrations were gravimetrically determined from samples collected on pre-combusted and pre-weighed GF/F filters with a diameter of 47 mm that were dried at 105 °C overnight. SPM was differentiated into suspended particular inorganic matter (SPIM) and suspended particular organic matter (SPOM) by burning the organic matter from the filters at 450 °C for 4 h and then re-weighing the filters (Duan et al., 2014). The DOC and POC concentrations (mg/m^3) were measured by combustion of sample filters in an EA3000 elemental analyzer (Parsons et al., 1984; Biddanda and Benner, 1997). The lake TP concentrations were determined by Pbyotassium persulfate oxidation method (Parsons et al., 1984). The *Chl-a* were determined by the standard Spectrophotometer (Shimadzu UV 2700) following extraction using 90% ethanol, in which the absorbance values of 630 nm, 645 nm, 663 nm and 750 nm were measured respectively, as then the *Chl-a* concentrations can be achieved (Strickland and Parsons, 1972).

2.3. Satellite Data and Preprocessing

The MODIS/Aqua Level-1A data at 250 m and 500 m resolutions were used to explore the lake TP spatial features, two senses of remote sensing images for Feb. 18, 2016 and Dec. 16, 2016 were captured to match with the actual sampling time, and the multi images between 2003 ~ 2017 were also used to study the temporal tendency of lake TP concentrations.

All the MODIS data were downloaded from the website of NASA (https://oceandata.sci.gsfc.nasa.gov/). The cloud-free images (the cloud coverage was less than 10%) were obtained for the study area, and totally 672 images were selected and covered the entire temporal series. In addition, at least 4 ~ 5 scenes for each month from 2003 to 2017 were obtained for the purpose of dependable and convincing spatiotemporal analysis.

Level-1A data were first processed using SeaDAS 7.3 to generate Level-1B. Then, a partial atmospheric correction was applied to the MODIS data for the purpose of the correction of Rayleigh scattering effects and gaseous absorption. Moreover, the corrected Rayleigh-corrected reflectance (R_{rc}) was derived and used to model the lake TP, instead using remote sensing reflectance (R_{rs}, sr^{-1}). Because the data loss of R_{rs} resulted from incorrect data were easily to took palce during the masking process (Aurin et al., 2013; Wang and Shi, 2006), and leads to mistake identification of waters and watershed lands (Chang and Nayee, 2011; Hu et al., 2012; Zhang et al., 2014). All of these indicated that the R_{rs} cannot meet the requirements of the long-term MODIS data (Hu et al., 2004). For this case, the R_{rc} was represented as:

$$R_{rc,\lambda} = \pi L_{t,\lambda}^{*} / (F_{0,\lambda} \cdot cos\theta_0) - R_{r,\lambda} \tag{1}$$

where λ is the wavelength of the MODIS spectral band, L_t* is the calibrated at-sensor radiance after correcting for gaseous absorption, F_0 is the extraterrestrial solar irradiance, θ_0 is the solar zenith angle, and R_r is the reflectance due to Rayleigh (molecular) scattering. Lastly, the R_{rc} data were geo-referenced into a cylindrical equidistance (rectangular) projection.

The R_{rc} data at three bands (645, 555 and 469 nm) were simultaneously used to generate the red-green-blue (RGB) “true-color” composite images. The resolution was designated as 250 m, and the 500 m resolution data for 469 and 555 nm were resampled to 250 m resolution using the bi-linear interpolation method in the SeaDAS Reproject module (Pohl and Van Genderen, 1998; Cao et al., 2016). A concurrent dataset of MODIS/Aqua R_{rc} data and in situ TP measurements was constructed using a time window of ±3 h between the MODIS/ Aqua data and the in-situ measurements. A homogeneity test of the 3 × 3-pixel box centered at the in situ station was performed (note that each MODIS pixel is 250 m × 250 m) in order to avoid the potential effects of patchiness on the measurement’s optical properties. When the coefficient of variation (CV) of the 3 × 3 box was less than 0.1, the corresponding matching data pair was used for lake TP assessment (Feng et al., 2012). Finally, the 36 matching data pairs were selected, in which 24 samples were used for modeling, the remaining 12 samples were used for the algorithm validation.

2.4. Bands Selection and Model Calibration

As previously mentioned, the lake TP showed unobvious spectral features, while the TP concentrations are sensitive to *Chl-a*, TSS, DOC, etc. and the relationship varied among different lake regions. Therefore, an indirect remote-sensing estimation algorithm can be used for lake TP representation, in which the primary step was to identify the critical lake color factor that is sensitive to TP concentrations in Hongze Lake.

Table 1. Statistical Data of Correlation Degree between Lake TP and Selected Lake Parameters

	Correlation coefficient (*r*)	Significant level (2 - tailed)	RMSE
Chl-a	-0.342	< 0.05	3.73
DOC	-0.125	--	12.42
POC	-0.121	--	9.72
SPM	0.726	< 0.01	2.12
SPIM	0.606	< 0.01	2.14
SPOM	0.424	< 0.05	4.29

The correlation degree between lake TP and selected lake parameters is provided in Table 1. The most sensitive indicator of lake TP can be unequivocally designated as SPM, in which the *r* value reached 0.726, much higher than that of all the other parameters. This can be partly attributed to the fact that Hongze Lake is dominated by SPM.

The second step is to select the suitable bands, and the wavelength region used for lake TP estimation needed to be consistent with the lake SPM. Importantly, several existing remote sensing models have been widely acknowledged and internationally applied. The four types can be summarized based on different band association methods. i) For the single band method, the selected bands are sensitive to lake SPM concentrations, which cover the spectral regions from the red band to infrared band. This method has been applied and validated by Miller et al. 2004 in Boloxi Lake; Kutser et al. 2007 in Muuga Port; and Shi et al. 2015 in Taihu, China. ii) For the band ratio and band subtraction methods, the spectral ability of the spectral signal can be enhanced by division and subtraction between the two bands that are sensitive to certain lake color parameters. The classical method for lake SPM assessment can be summarized as the ratio or subtraction between the infrared and NIR bands (Doxaran et al. (2002) in Gironde Lake; Feng et al. 2012 in Poyang Lake, China), as well as the ratio or subtraction between the infrared and green bands (Hou et al. (2017) in 58 lakes and reservoirs in the Middle and Lower Yangtze Basin). iii) For the three-band fitting method, mainly used in marine ocean waters, the most important bands for the generation of “true-color” composite images are selected and fitted in the Huanghai Sea (Yellow Sea) and the East China Sea (Zhang et al., 2010). iv) Other multi-band algorithms and enumeration methods can also be attempted when the sensitive band is difficult to identify in the previously discussed methods. All of these methods provided important basis and reference for the Lake TP model building by MODIS images in this study.

Table 2. Statistical Data of the Relationship between R_{rc} and TP Concentrations by Different Bands Fitting Methods

Model	Bands	*r*	RMSE
Single band	R_{rc} 469	0.371	0.371
	R_{rc} 555	0.437*	0.437*
	R_{rc} 645	0.770**	0.770**
	R_{rc} 859	0.690**	0.690**
	R_{rc} 1240	0.294	0.294
Bands ratio	R_{rc} 645/R_{rc} 555	0.854**	0.854**
	R_{rc} 645/R_{rc} 859	-0.364	-0.364
Bands substraction	R_{rc} 645 - R_{rc} 555	0.800**	0.800**
	R_{rc} 645 - R_{rc} 859	0.700**	0.700**
Three bands fitting	(R_{rc} 645 + R_{rc} 555) - (R_{rc} 469/R_{rc} 555)	0.593*	0.593*
Others	(R_{rc} 645 - R_{rc} 555)/ (R_{rc} 645 + R_{rc} 555)	0.810**	0.810**
	(R_{rc} 645 + R_{rc} 859)/ (R_{rc} 645 - R_{rc} 859)	0.702**	0.702**

Note: * represents $p< 0.05$; ** represents $p< 0.01$.

All of these band selection methods showed above were applied simultaneously in order to find the most suitable MODIS bands that can be used for TP assessment in Hongze Lake (Table 2), and the R_{rc} values of each pixel matched with field samples were extracted. The R_{rc} 645 owned with the greatest

Table 3. Calibration and Validation Performances of Different Fitting Functions

R_{rc} 645/R_{rc} 555	Calibration			Validation		
	R^2	RMSE (mg/L)	MRE (%)	R^2	RMSE (mg/L)	MRE (%)
Linear	0.62	0.048	27.82	0.50	0.032	14.14
Exponential	0.79	0.022	17.22	0.70	0.034	12.70
Logarithmic	0.63	0.038	23.72	0.70	0.028	18.03
Power fitting	0.69	0.030	22.82	0.70	0.047	12.42

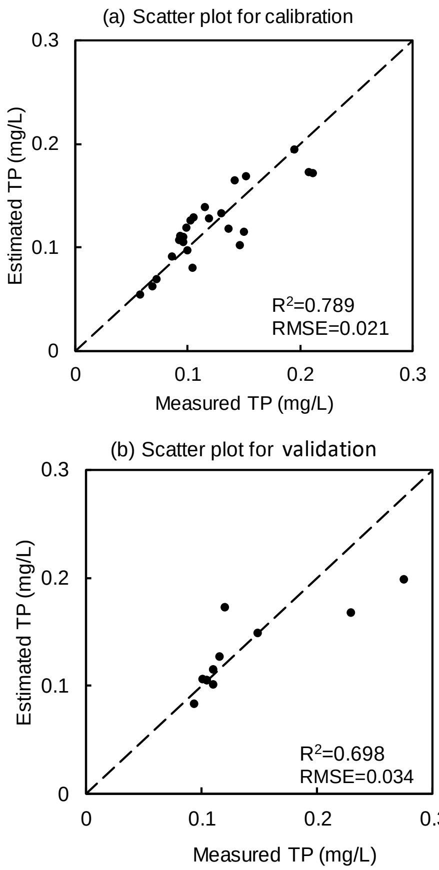

Figure 2. Scatter plot for calibration and validation results of Measured TP VS Estimated TP by using exponential method: (a) calibration; (b) validation.

correlation degree between R_{rc} value and TP concentrations among different bands, which results was consistent with the relative study that focused on SPM inversion in Hongze Lake (Cao et al., 2017). Most importantly, the R_{rc} 645/R_{rc} 555 that means the ratio between the infrared and green band owned with the highest *r* value and lowest RMSE value.

Therefore, the R_{rc} 645/R_{rc} 555 was selected and introduced into the remote sensing algorithms of TP simulation and assessment within Hongze Lake. Moreover, the classical fitting functions including linear, exponential, logarithmic and power fitting function were adopted in the TP simulation model and compared with actual TP concentrations respectively, which was used to determine the ideal TP assessment method that owned with the greatest fitting coefficient (R^2). Lastly, the selected model was used in all the remote images, and the yearly data was generated by averaging the TP estimation data from totally 672 images in each year.

3. Results

3.1. The Appropriate Model in Hongze Lake

The performances of modeling accuracy for different fitting functions were compared by using R_{rc} 645/R_{rc} 555, and the calibration accuracy and validation accuracy were represented in Table 3.

Apparently, the exponential model owned the greatest modeling effect among different fitting functions. The R^2 for calibration dataset and validation dataset were reached 0.7 simultaneously, the RMSE value was only kept around 0.02 mg/L. In contrast, the R^2 for the other functions were rarely exceeded 0.7. Moreover, the scatter points for exponential model were also concentrated nearby the 1:1 line (Figure 2). Therefore, the most suitable model for TP concentrations assessment in Hongze Lake can be designated as:

$$TP = 0.002235\exp(4.181R_{rc}(645) / R_{rc}(555)) \quad (2)$$

3.2. Spatiotemporal Distribution Features of Lake TP

The spatial and temporal features of lake TP concentrations can be mapped pixel by pixel based on all the selected MODIS images within the whole temporal scale. The yearly spatial distributions of TP spanning 2003 to 2017 were constructed and displayed in Figure 3.

The spatial variation features of TP concentrations in Lake Hongze exhibited a consistent tendency over the whole temporal scales. The high TP concentrations were concentrated in the center of lake and southern region of the lake, in which the concentrations could be kept around 0.15 ~ 0.2 mg/L in most years. In contrast, the two lake bays located in northern and western regions owned fewer TP concentrations than the lake center, and the average TP concentrations in these two bays were hardly to exceed 0.1 mg/L within the entire temporal series. The TP values in the southern region of the lake showed an apparent increasing tendency with expectation, and it is also needed to notice that the northern bay of the lake also represented remarkable upwards tendency, which region was once in a low level of TP concentrations from 2003 to 2011.

The inter-annual variability of TP was represented in Figure 4 by box charts. The lake TP concentrations represented a notable fluctuation tendency within the whole temporal scale.

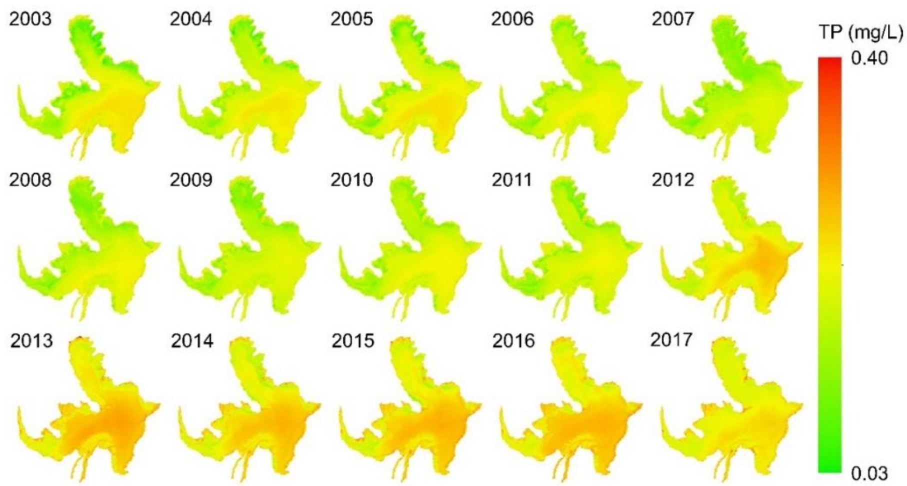

Figure 3. Spatial map of annual mean lake TP distributions derived from MODIS/Aqua data (2003 ~ 2017) for Lake Hongze, China.

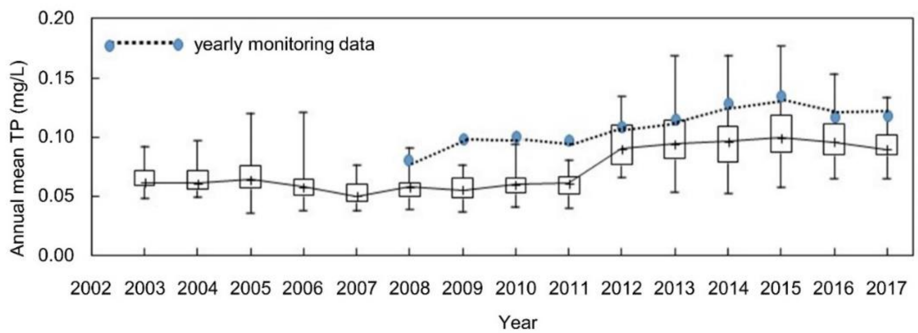

Figure 4. Statistical data of lake TP concentrations in the entire temporal scales.

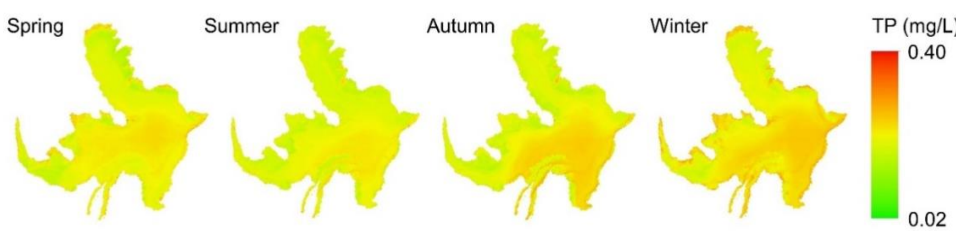

Figure 5. Spatial map of estimated lake TP distributions in different seasons.

In general, the averaged TP concentrations increased from 0.062 ± 0.01 mg/L into 0.09 ± 0.02 mg/L between 2003 and 2017. Furthermore, two phases can be summarized easily from Figure 4. The first phase is ranged from 2003 ~ 2011 clearly, the TP concentrations in the entire lake were relatively low, and also kept relatively consistent variation features in spatial, which concentrations were largely kept around 0.7 mg/L in the years scale. However, a sudden uptrend of TP concentrations occurred since 2012, and the secondly phase can be ranged from 2012 ~ 2017. In specific, the averaged TP concentrations in 2012 reached 0.089 mg/L, which was much higher than that in 2011. The high level of TP concentrations had been maintained in this phase, nevertheless a little decreasing tendency can be found in 2014 and 2015, in which the maximum TP concentrations was even reached 0.16 mg/L.

The intra-annual features of lake TP can also be achieved in seasonal scale, which can be divided into spring season (March to May), summer season (June to August), autumn season (September to November), and winter season (December to February). The estimated seasonal values were acquired by averaging the TP estimation data for the same season within the whole temporal scale. The spatial variation features were shown in Figure 5, which is similar to the trend shown in Figure 3, indicating that the spatial features kept consistent within different seasons. Hence, the statistical data of seasonal changes within the whole temporal series could be represented using box charts

(Figure 6(a)) and histogram charts (Figure 6(b)). The TP concentrations gradually increased from spring to winter, and the average TP values reached 0.081 and 0.083 mg/L during autumn and winter, respectively. The highest value exceeded 0.18 mg/L during winter, whereas the summer season had the lowest TP concentrations, in which the average value was only 0.06 mg/L. These seasonal variations were consistent with the actual change tendency of TP concentrations in Hongze Lake. Moreover, it should be noted that the seasonal change was not significant between 2003 and 2011 because the averaged TP concentrations were kept in a relative low level. In contrast, with the continuous increasing of TP concentration since 2012, the seasonal diversity such as "high in winter and low in summer" has become more and more apparent.

3.3. Reliability of Temporal TP Estimation Using Remote Sensing

The reliability of TP estimation can be assessed at interannual scale. A comparison between the estimated TP vs. actual TP values at long temporal scales was completed as shown in Figure 4. The actual TP was determined by averaging the yearly monitoring data provided by the Jiangsu Environmental Monitoring Center and the Jiangsu Hydrology and Water Resources Survey Bureau (only the yearly data from 2009 to 2017 could be acquired because of the data sharing policy regulations of these two departments). An underestimation of TP results can be found when comparing to the field-monitored TP concentrations. For instance, the actual TP values were kept around 0.08 ~ 0.12 mg/L from 2009 to 2017, while the estimated TP values were almost lower than 0.07 mg/L before 2012. However, the change tendency of the yearly estimated TP was in consistent with the field-monitored TP in general, in which an increasing tendency can be observed (Figure 4). Interestingly, low levels of SPM contents until 2012, as well as the high level of SPM in 2014, had been proven in related studies focused on lake SPM. Therefore, this further indicated that the TP model accuracy is closely related to the variation tendency of lake SPM contents, and a scientific mechanism is needed to show this relationship.

4. Discussion

4.1. Model Accuracy of TP Concentrations in Hongze Lake is Largely Dependent on the SPM Contents

To compare with the relative studies, the modeling results for our study represented a similar accuracy effect with Sun et al. (2013), who also using MODIS data to estimate the TP in a turbid inland lake water, as the R^2 can reached 0.78 for the calibration groups within these two studies simultaneously, and this R^2 were even much better than the other relative studies such as Chang et al. (2013). Moreover, it is also needed to mention that this effect can kept consistently in the whole temporal scales for our study (2013 to 2017). Therefore, the ideal TP inversion results can be obtained through indirect inversion. Among them, SPM is an important intermediate element, because the water body of Hongze Lake is mainly controlled by SPM. And the TP remote sensing inversion model established will largely depend on the characteristic spectrum of SPM (Volpe et al., 2007; Feng et al., 2014). Therefore, a comprehensive analysis of the SPM and TP assessment is necessary, which is helpful for model accuracy and uncertainties control of TP in the SPM-dominated lake.

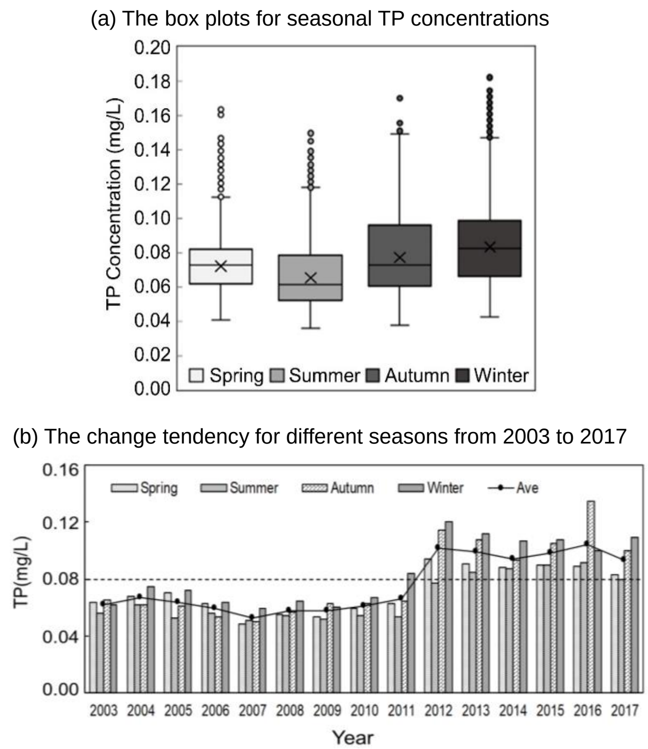

Figure 6. The seasonal diversity of TP concentrations in Hongze Lake: (a) The box plots for seasonal TP concentrations; (b) The change tendency for different seasons from 2003 to 2017.

In spite that a sound correlation can be expected based on the algorithm of R_{rc} (645)/R_{rc} (555), some discrete points apart from the 1:1 line degraded the model accuracy to some extent. Interestingly, these unsatisfactory plots were not related to their actual TP concentrations. Instead, these plots were closely correlated with their measured SPM contents. For instance, the three plots that were far from the 1:1 line had SPM contents of 88 mg/L and 81 mg/L, which are two of the samples with the highest SPM contents. For this case, it can be inferred that the TP assessment accuracy by remote sensing was likely closely related to the level of lake SPM contents. Therefore, all of the 36 data items were divided into 5 classes based on different SPM intervals, and a re-class analysis was completed using the natural-break method.

The threshold of each interval, as well as the relationship between the measured vs. the estimated TP concentrations within these five intervals was analyzed in Figure 7. It apparently shows that the ideal fitting effects were concentrated in the regions having moderate to high SPM contents. For instance, the correlation coefficient (r) value reached 0.81 and 0.77 when the

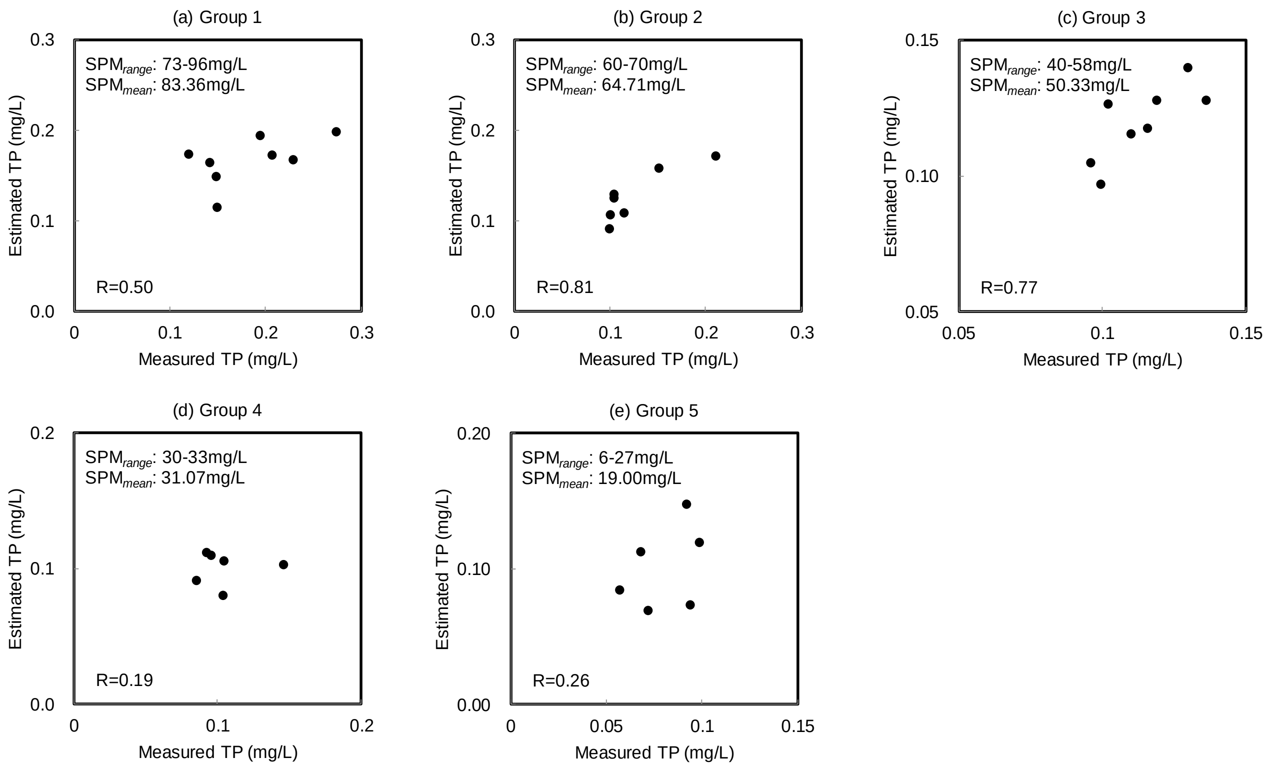

Figure 7. Scatter plots of measured vs estimated TP for different SPM contents groups: (a) Group 1; (b) Group 2; (c) Group 3; (d) Group 4; (e) Group 5.

SPM contents ranged from 40 mg/L to 70 mg/L, respectively, while the fitting effect degraded to some extent as the SPM contents continually increased. In contrast, the poor fitting results unexpectedly appeared when the SPM contents ranged from 6 to 33 mg/L with each sample. Therefore, it can be proved that the assessment accuracy of the lake TP using remote sensing is largely reliant upon lake SPM contents. Good simulation accuracy could be achieved when the lake SPM contents were at a moderate level. From this study, the suitable region of SPM contents in Hongze Lake was approximately designated as 40 ~ 70 mg/L, and the simulation accuracy of TP was severely degraded when the SPM contents were too high and too low, i.e. the value was not within this interval.

The lake nutrient concentrations were positively correlated with SPM contents in general. The scientific truth is that the lake P is involved in various states, and the suspended particles have ability to adsorb inorganic phosphate (Johansson et al., 1998). Moreover, several studies have also indicated that the absorption coefficients decrease significantly, when SPM concentration is at a low level. That is to say, the P is attached on other absorbable substances, including metallic oxides and hydroxides (Hu et al., 2009). This can partly explain the poor assessment accuracy when the SPM contents is smaller than 30 mg/L. Moreover, the *r* value of the modeling accuracy decreased from 0.81 to 0.5 when the SPM contents exceeded 70 mg/L. This issue can be interpreted as a result of the increasing water turbidity and light saturation phenomenon from the remote-sensing signal (Doxaran et al., 2014; Petus et al., 2014). Several studies have showed that light saturation is prone to occur when lake SPM contents are at a high level, which results in a remote-sensing reflectance that is not suitable for lake nutrient assessment, and particularly reflected in short wavelengths of less than 750 nm (Hu et al., 2012; Liu et al., 2013). This region just covered the sensitive bands that were used for lake TP concentration assessment in this study, in which 645 nm and 555 nm were selected.

Therefore, for TP assessment, it is necessary that the lake SPM contents are neither too high nor too low. In addition, the influence of low SPM contents on the modeling accuracy seemed more severe than that of the high SPM content because of the lack of adhesion between the P and SPM.

4.2. The Change Tendency of TP Varied Largely Among Different Lake Districts

The spatial distribution the lake TP concentrations was consistent for all temporal scales, and a sudden increasing tendency appeared during 2012. Particularly, two lake bays in the northern and western lake showed relatively low TP concentrations, the lake center showed higher TP concentrations, and the inlets of the Huai River showed relatively lower TP concentrations than those of the lake center. To more comprehensively analyze the influence mechanism of lake TP distribution, Hongze Lake can be approximately divided into four districts including the Northern Bay (NB), Western Bay (WB), Lake Center (LC) and Huai River Inlet (IH). The geographical characteristics of

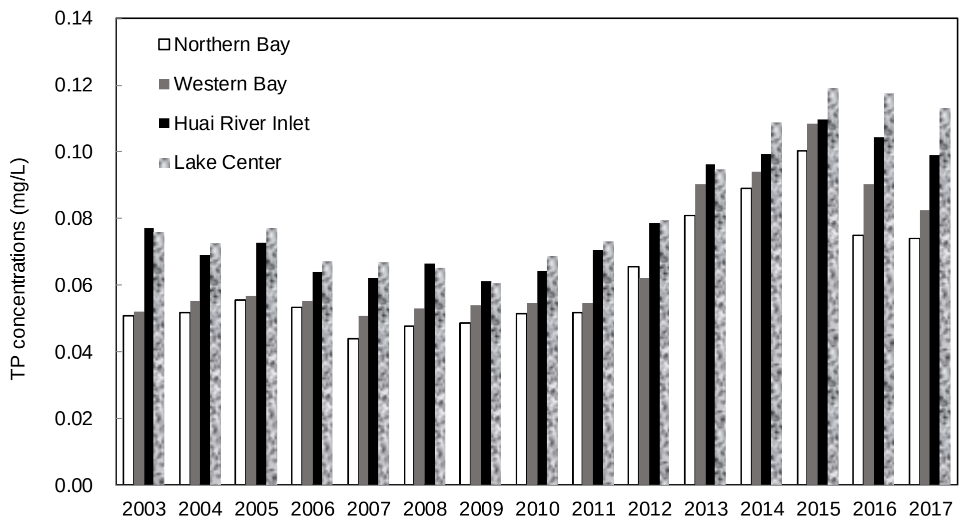

Figure 8. Change tendency of TP concentrations among different lake districts.

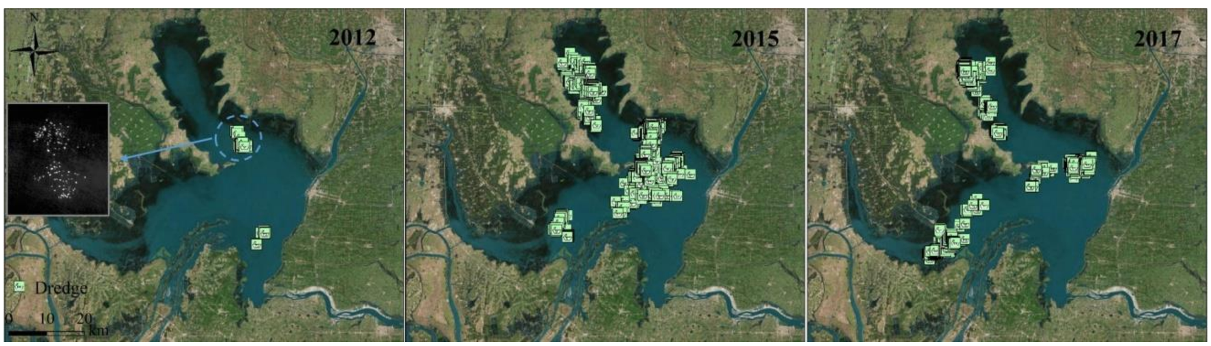

Figure 9. Spatial distributions of dredging activities in Hongze Lake.

the lake, as well as the human activity influence from the watershed, varied within the determined four lake districts. The change tendency of TP within the four lake districts from 2003 to 2017 is shown in Figure 8.

4.2.1. A Sudden Increasing Tendency Occurred Since 2012 in the Entire Lake Region, Due to the Impact of Human Activities Such as Dredging

The TP concentrations remained stable from 2003 to 2011, while a sudden increase occurred during 2012 consistently throughout the lake (Figure 4). This phenomenon was also unexpectedly consistent with Cao et al. (2016), indicating that the SPM concentrations quickly increased from 2012 to 2015 in the whole Hongze Lake (Figure 9). Therefore, these results further proved the interdependency of the spatial variation features of P and SPM. In addition, the explanation for the increaseing tendency of SPM since 2012 can also be found in Cao et al. (2016). Local media reports and onsite surveys indicate that the number of active sand dredges in Lake Hongze has rapidly increased since 2011 (Zuo et al., 2012; Yan et al., 2015), because a yellow sand resource had been discovered in the Huai River Estuary and the entire lake region during recent years, resulting in the high dredging profits (Zuo et al., 2010). The amounts and types of dredging ships were observed from Landsat ETM$^+$ and OLI imagery by Cao et al. (2016), which showed that dredging activities were rarely occurred prior to 2011. Thereafter, approximately 100 ships started to appear in the northeastern bay and southern estuary in 2012, and then the dredges covered the entire lake during 2014. Interestingly, this temporal node is consistent with the change tendency of lake TP. Therefore, it can be inferred that the dredging activities played an important role in the increasing tendency of lake TP since 2012, because the lake substrate sludge agitation caused by the dredging activities led to an increase in sediment TP release, as well as increased turbidity of the surrounding water. Moreover, dredging activities had been prohibited and controlled by local environmental authorities during the recent 2 years for the purpose of lake water quality improvement, which can also partly explain the gradually stabilizing of the lake TP concentrations since 2016.

4.2.2. The NB and WB Had Lower Concentrations Than the Lake Center, and the Increasing Tendency in the WB Was Greater Than That of the NB Since 2012

The TP concentrations of the NB and WB were much lower than those of the lake center. For instance, the average yearly

TP concentrations within the NB and WB never reached 0.1 mg/L from 2003 to 2017, despite the increasing tendency occurring since 2012; even the values of the NB rarely exceeded 0.8 mg/L. The only exception appeared during 2012 and 2013, when the values were 0.085 and 0.080 mg/L, respectively.

The water of the lake bays was isolated from the open water, which means the NB and WB underwent infrequent water exchange compared to the lake center and estuaries. Therefore, the impact of watershed nutrient output on lake TP variations was more apparent than that of endogenous pollutions loads. (Williamson et al., 2008; Schudel et al., 2018). Notably, the watershed nutrient outputs are largely decided by two critical factors, rainfall and land use (Catherine et al., 2013; Maanan et al., 2014).

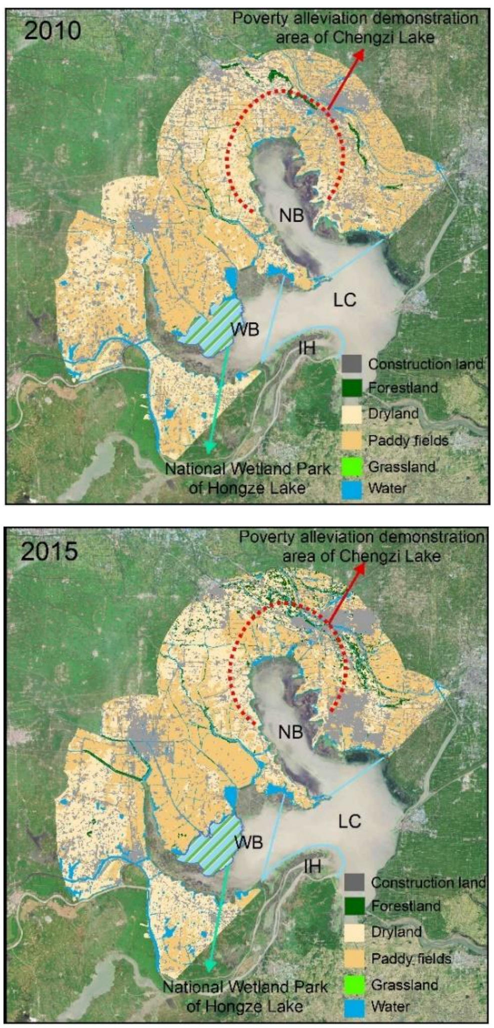

Figure 10. Spatial distribution of major land use patterns within a 20 km buffer region for NB and WB bays.

The NB and WB had lower TP concentrations than the lake center can be partly interpreted as a result of the precipitation factor. The Qinling Mountains and Huaihe River Boundary (QMHR) can be used to approximately divide the ambient meteorological conditions between southern and northern China; the region south of the boundary has much more precipitation than the region to the north (Li and Yan, 2013). The Hongze Lake basin stretches across QMHR, and the major watershed area of the IH and LC are located in the south of QMHR, while the watershed area of the NB and WB bays are located in the north of QMHR. In actuality, there are three national meteorological stations that are distributed around the watershed (Figure 1). According to regional proximity, the Huaiyin City station (HC) and Sihong County station (SH) can represent the rainfall status of the WB and NB region, respectively, and the Xuyu City station (XY) can approximately represent the rainfall status of the IH and LC. Yearly rainfall data covering the entire temporal scale can be obtained from China Meteorological Data Sharing Service Platform (http://data.cma.cn/). The average yearly rainfall of XY station was 1258.7 mm, the maximum value exceeded 1800 mm in 2006. These values were much higher than those of the other stations. These results indicate that the lake center and Huai River estuary always received more rainfall than the lake bays, and the high rainfall intensity not only played an important role in the frequent turbulence of the lake water and sediment, but also led to a large number of watershed pollutants (N and P) entering the lake via soil and sediment (Schallenberg and Burns, 2004). In addition, the national wetland park of Hongze Lake, constructed in 1999, is just located in the estuary of WB region. The wetlands exhibit effective retention ability for N and P pollutants in drainage and are favorable for lake eutrophication inhibition (Coveney et al., 2002), that can also contribute to the relative low level of TP concentrations in WB region.

The more notable increasing tendency of lake TP in the WB compare to that of the NB can be partly explained by the LUCC factor. The excessive development of forestland and farming activities is well known as the main source contributing to watershed nutrient loss (Ahearn et al., 2005). The spatial distribution of major land use patterns within a 20 km buffer region of these two lake bays was compared as shown in Figure 10. The production and validation of 5-year interval land use data since 1990 was provided by the Data Center for Geography and Limnology Science, Chinese Academy of Science, and the data for 2010 and 2015 were used in this study. It is worth mentioning that notable differences can be found in several local regions, despite the land use change features within the two regions seeming similar in general. Specifically, the poverty alleviation demonstration area of Chengzi Lake was near the NB region. This demonstration area was started in 2013, and the main poverty alleviation measures were construction of high standard arable land and comprehensive land remediation. More specifically, more than 500 acres of high-standard farmland were developed between 2014 and 2016, and land fragmentation and groundwater treatment issues were largely resolved, which effectively controlled watershed nutrient loss and input into aquatic ecosystems. Conversely, large areas of fence farming have been established in the peripheral lake regions west of the WB since 2010 (Ban et al., 2010), which has directly resulted in the acceleration of pollutant diffusion such as N and P, particularly reflected during drought periods because of infrequent water exchange (Sarà., 2007; Delpla et al., 2011). Therefore, it can be inferred that the disparate watershed development activities during recent years has resulted in higher TP concentrations in the WB than those in the NB. In addition, a downward trend in the WB in 2016 was also found as shown in Figure 4, which is consistent with the implementation of the "Return polder to the lake" project, in which aquaculture facilities were gradually demolished.

4.2.3. The TP Concentrations in the IH and LC Remained Consistent from 2003 to 2011, while a Sudden Obvious Fluctuation Tendency Has Occurred Since 2012 in the LC Region

The TP concentrations in the lake center and Huai River estuary remained at a relatively high level when compared to the two bays NB and WB. The trend-lines of the LC and IH were nearly coincident until 2012. This means that the difference in the two regions was not notable at this temporal scale; nevertheless, the TP in the LC was slightly higher than that in the IH. However, the difference between the two regions has become more apparent since 2012, and the rising tendency of TP represented more clearly in LC.

Hongze Lake is acknowledged as having high degree of sediment siltation and deposition, and the sediment agitation and water exchange of the LC region occurs more frequently than that of the lake bays and estuaries due to large lake surface and natural features such as "suspended lakes". This means that the bottom of the lake, especially in the lake center, is higher than the surrounding Jiangsu Plain by 4 to 8 m. (Wang and Dou, 1998; Yin et al., 2013). Therefore, the impact of human activities on the increasing lake SPM and TP concentrations are most clearly reflected in the LC region since 2012; nevertheless, dredging activities have occurred throughout the lake. In addition, the TP concentrations have apparently decreased since 2016, which can also be explained by decrease in human activities in the LC region, because dredging activities have been prohibited. In contrast, the IH is in the Huai River estuary, at the junction of the Huai River and Hongze Lake. Therefore, the IH region mostly represents the hydrology features of the Huai River flowing into Hongze Lake (Zuo et al., 2010). Notably, the Huai River has been severely polluted during recent decades, and TP had been designated as among the major pollutants, of which the concentrations have reached 0.10 mg/L in some National Controlled Monitoring Sections (NCMS), belonging to the grade V water (the poorest water quality grade) according to the national standards. In this case, the results of the TP assessment suing remote sensing can be proved, which indicates that the TP in the IH is much higher than that in the NB and WB. Importantly, the State Major Project of Water Pollution Control and Management has been focused on the Huai River since 2008, and some major engineering infrastructure (sluice construction, water diversion, etc.) has been continuously installed over the last 10 years, gradually leading to improved water quality. Several local government reports indicate that the reduction of TP within the Huai River reached 36% on average from 2010 to 2015. Monitoring data acquired from Laozi Mountain Station (LMS), among the NCMSs in the stream outlet of Hongze Lake, also shows that the monitored TP concentrations of LMS remained between 0.06 mg/L and 0.07 mg/L over the last 10 years. These values are lower than the average level of the entire lake region. In this case, the difference in the IH and LC has increased since 2012.

By summarizing the above three aspects, the TP distribution and changes from 2003 to 2017 can be attributed to two major driven forces. First, the contributions of Huai River, which is absolutely the most important input source of exogenous pollutants in the whole Hongze Lake, leading to the high level of TP in Huai River estuary. Second, the dredging activities that were started to spread out in a large area since from 2012 and 2013, which leads to a sudden increase TP throughout the entire lake, especially in lake center.

4.3. Implications

The identification of sensitive lake color parameter and corresponding wavelength region is the primary step of lake TP assessment by remote sensing, due to the non-significant spectral features of TP itself. This study proved that Rayleigh-corrected reflectance of red band and green band derived from MODIS is an ideal TP monitoring index, especially in lakes dominated by SPM. Meanwhile, inversion effect is better when SPM content is medium. Meanwhile, it needs to be acknowledged that only two periods of data have been obtained in this study. In order to further verify and optimize the study, continuous collection of seasonal sample points is necessary. For this case, the regular field sampling tasks are continued in each season since 2016, which are based on the 18 developed sampling locations.

The methods used in this study could be applied to different aquatic ecosystems which are mainly suspended matter dominated. Although it has been found that 645 and 555 nm bands from MODIS are suitable for Hongze lake, other diverse band combinations and variation methods still need to be applied to other satellite sensors (Landsat ETM+/8, Sentinel-2A, SPOT, etc) in order to obtain more accurate results. The fundamental issue is that the red band, blue band and green band are acknowledged as the sensitive wavelength regions to lake SPM. Additionally, the model uncertainty caused by images processing needs to be considered. For instance, the reflectively value derived from remote sensing images are influenced by the edge effect between the junction of lake water region and watershed land surface, and especially represented in high-throughput lakes such as Hongze Lake. Eventually, the universal and reliable remote sensing algorithm for lake TP in SPM dominated lakes can be expected.

5. Conclusion

This study primarily focused on the estimation of lake TP concentrations using a remote-sensing method. Considering the non-significant spectral features of TP itself, an "indirect estimation" method was introduced in this study. SPM was identified as the lake quality parameter that is most sensitive to TP concentration in Hongze Lake, which also showed obvious spectral features. Therefore, a TP estimation model was developed based on band integration methods suitable for lake SPM, and an exponential model of 645 nm and 555 nm for multiple MODIS/Aqua images from 2003 to 2017 was used for lake TP assessment.

The spatial variation features showed a consistent tendency over the whole temporal scale. Specifically, the LC had the highest TP concentrations, while the two lake bays NB and WB had the lowest TP concentrations. These variations for different lake districts can be attributed to the integration of meteorological, land use change, and human disturbance factors. Moreover, substantial dredging activities occurred throughout the entire lake region directly led to frequently occurring sediment resuspension, which play an important role in the increasing SPM and TP concentrations since 2012, and achieving a peak in 2014 and 2015.

The results of the estimated TP concentrations are reliable to reflect the general trend of actual TP concentrations both at inter-annual and intra-annual scales, nevertheless the TP concentrations were sometimes underestimated. The TP model accuracy largely relied on lake SPM contents. In specific, the best estimates occurred when the SPM values were of a moderate level, between 40 and 70 mg/L in Hongze Lake. In general, the remote-sensing methods for lake TP estimation can be applied to different aquatic ecosystems that are mainly dominated by SPM.

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