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Retraction

Retracted: Nitrogen Inversion Model in a Wetland Environment Based on the Canopy Reflectance of Emergent Plants

Advances in Meteorology

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

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[1] D. Wu, D. Zhao, Y. Zhu, C. Shen, and H. Xue, "Nitrogen Inversion Model in a Wetland Environment Based on the Canopy Reflectance of Emergent Plants," *Advances in Meteorology*, vol. 2022, Article ID 8800371, 9 pages, 2022.

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Research Article

Nitrogen Inversion Model in a Wetland Environment Based on the Canopy Reflectance of Emergent Plants

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Reuse of reclaimed water in constructed wetlands is a promising way to conserve water resources and improve water quality, and it is playing a very important role in wetland restoration and reconstruction. This study utilized reflectance spectra of wetland vegetation to estimate nitrogen content in water in the Beijing Bai River constructed wetland, a typically constructed wetland that uses reclaimed water. Canopy reflectance spectra of two dominant plants in the wetland, including reed and cattail, were acquired using a spectrometer (350–2500 nm). Simultaneously, water samples were collected to measure water quality. To establish the appreciate relationship between total nitrogen content (TN) and reflectance spectra, both simple and multiple regression models, including simple ration spectral index (SR), normalized difference spectral index (ND), stepwise multiple linear regression (SMLR) model, and partial least squares regression (PLSR), were adopted in this study. The results showed that (1) compared with simple regression models (SR and ND), multiple regressions models (SMLR and PLSR) could provide a more accurate estimation of TN concentration in the wetland environment. Among these models, the PLSR model had the highest accuracy and was proven to be the most useful tool to reveal the relationship between the spectral reflectance of wetland plants and the total nitrogen consistency of wetland at the canopy scale. (2) The inversion effect of TN concentration in water is slightly better than that of wetland vegetation, and the reflection spectrum of the reed can predict TN concentration more accurately than that of cattail. The finding not only provides solid evidence for the potential application of remote sensing to detect water eutrophication but also enhances our understanding of the monitoring and management of water quality in urban wetlands using recycled water.

1. Introduction

Water scarcity is one of the primary reasons for wetland loss and degradation in China [1]. At present, as a steady source of water, recycled water plays an important role in alleviating water scarcity in urban areas and restoring wetland functions [2]. However, the chemical characteristics of recycled water might cause many adverse effects to restrict the application of recycled water wetlands [3–5]. With the increasing use of recycled water in urban wetlands, monitoring the status of plant growth and eutrophication in large constructed wetlands is of great significance for wetland management [6]. Currently, remote sensing has become an important technique of environmental monitoring due to its various advantages [7]. Many researchers have successfully used multi-spectral remote sensing images to obtain physiological and biochemical parameters of plants and to monitor and evaluate the status of plant growth [8–10]. However, traditional multi-spectral sensors have a low spectral resolution and they are difficult to identify the diagnostic characteristics of spectral absorption of plants. In contrast, hyperspectral remote sensing has a very narrow electromagnetic spectrum and can obtain more useful information from targeted objects, and has been widely used in monitoring the status of plant growth [11–14]. In addition, some researchers used ground-measured spectra to investigate the relationship between physiological and biochemical parameters and reflection spectral characteristics of plants, and then to establish inversion algorithms of physiological and biochemical parameters to study the status of plant growth [15–18]. However, most of the studies above are focused on open water instead of water covered with surface vegetation. Because the growth status and photosynthetic efficiency of wetland plants are closely related to the wetland environment, some researchers attempted to employ reflectance spectra of wetland plants to monitor environmental changes in wetlands [19].

Nitrogen content is an important indicator to reflect the status of plant growth, and it can be estimated using canopy reflectance spectroscopy with good accuracy [18–22]. Additionally, some previous work suggested that there is a certain relationship between the nitrogen content in wetland plants and the nitrogen concentration in water [23, 24], which implied that the spectral reflectance characteristics of wetland plants can be used to indirectly estimate the nitrogen concentration in water. In this study, to further explore the relationship between spectral characteristics of the wetland plant canopy and environmental TN content (TN content in water and TN content in plants): (1) We collected the reflectance spectra of the plant canopy and measured the total nitrogen (TN) content in water and plants in Beijing Bai River wetland; (2) Several multiple regression models were employed to estimate TN contents in plants (*Phragmites australis* and *Typha angustifolia*) and TN contents in water from the spectral reflectance data; (3) This study is expected to provide scientific evidence for the potential application of remote sensing to monitor nitrogen in wetland and to provide the strategic thinking for wetland restoration and reuse of recycled water in urban wetlands.

1.1. Study Area. The Beijing Bai River constructed wetland is located in Miyun County and is about 50 m away from the outlet of the Miyun wastewater treatment plant that is located on the left bank of the Bai River. The constructed wetland uses reclaimed water as a supplemental water source. The wastewater treatment plant adopts the membrane bioreactor (MBR) treatment process with an initial treatment capacity of up to $1600\,m^3{\cdot}a^{-1}$. The actual processing capacity of sewage treatment reached 9.19 million·m^3. The quality of reclaimed water meets the class I emission standard of "Discharge standard of water pollutants" in China (DB11/307–2005). The reclaimed water is mainly used in landscapes along the Chaobai River and for other municipal use. To eliminate health risks possibly caused by reclaimed water, a surface flow artificial wetland is constructed to improve water quality by removing organic matter and nutrients (such as nitrogen and phosphorus). To form the river landscape, a dam is set up upstream of the drainage outlet in the wetland. A gate dam is also set up in the river landscape located in the wetland downstream. The area of the surface flow constructed wetland is about 21,000 m^2. Wetland vegetations include emergent plants, phytoplankton, and submerged plants. Among them, emergent plants are the dominant vegetation accounting for approximately 70% of the total wetland area. Such plants include Typha, reeds, water lilies, and cress.

2. Experimental Methods

2.1. Collection of Reflectance Spectra of Wetland Vegetation and Environmental Data. Reeds (*Phragmites australis*) and cattails (*Typha angustifolia*) were two main plants found in the wetland and were subjected to the spectral reflectance measurement. Based on the spatial distribution of two plants in the wetland, we set 32 reed spectral sampling points and 26 cattail points. Wetland plant canopy spectral measurements were performed in July 2016 using the ASD Fieldspec®3 portable spectroradiometer (Analytical Spectral Device, Inc., USA). The probe has a 10° field-of-view, and the spectral range is 350–2500 nm. The spectral resolution is 3 nm at 700 nm, 8.5 nm at 1400 nm, and 2100 nm at 6.5 nm, respectively. The spectral sampling interval is 1.4 nm for 350–1000 nm and 2 nm at 1000–2500 nm, respectively. Field measurements were performed under clear calm weather conditions at 10 : 00–14 : 00, which were calibrated using a whiteboard at least once per 20 min. Simultaneously, leaves of two plants were collected and water at ~0.1 m under the water surface was sampled. Next, leaves were fixed at 105°C for 30 min, dried to constant weight at 80°C then digested in H_2SO_4-H_2O_2. TN contents in leaves were measured using the KD method [25]. To determine water quality, TN contents in water were measured using ultraviolet spectrophotometry and ammonium molybdate spectrophotometry, respectively, after alkaline potassium persulfate digestion.

2.2. Data Processing

2.2.1. Pre-Processing of Spectral Data. The reflectance spectra of plants measured at each sampling site were averaged to remove water vapor absorption bands and noisy bands. Spectral resampling was performed to reduce data redundancy (the spectrum resampling resolution of the instrument automatic output was 1 nm), and the sampling interval was 5 nm, and the data were smoothed using the Savitzky–Golay method [26, 27].

2.2.2. Calculation of Hyperspectral Index. Constructing a spectral index can maximize the information derived from the reflectance spectra of plants and minimize the impacts of external factors [28, 29]. In this study, we constructed all of the ratios formed by two-band reflectance values (equation 1) and normalized difference (equation 2) over the wavelength range of 400–2350 nm (except bands that had been removed) and analyzed their relationship with environmental TN concentrations.

$$SR = \frac{\rho_{\lambda 1}}{\rho_{\lambda 2}}, \tag{1}$$

$$N\ D = \frac{\rho_{\lambda 1} - \rho_{\lambda 2}}{\rho_{\lambda 1} + \rho_{\lambda 2}}, \tag{2}$$

where SR is the spectral ratio index, ND is the normalized spectral index, $\rho_{\lambda 1}$ is the band reflectance of $\lambda 1$, and $\rho_{\lambda 2}$ is the band reflectance of $\lambda 2$. $\lambda 1 \neq \lambda 2$.

Table 1: TN contents in water and plants.

TN contents	Species	Number of samples	Mean	Minimum	Maximum	Confidence limit of the mean (95%)
TN in water (mg/L)	Reed	32	1.51	0.64	2.23	0.23
	Cattail	26	1.04	0.52	1.77	0.21
TN in plants (%)	Reed	32	4.47	2.58	5.50	0.22
	Cattail	26	3.23	2.40	5.30	0.25

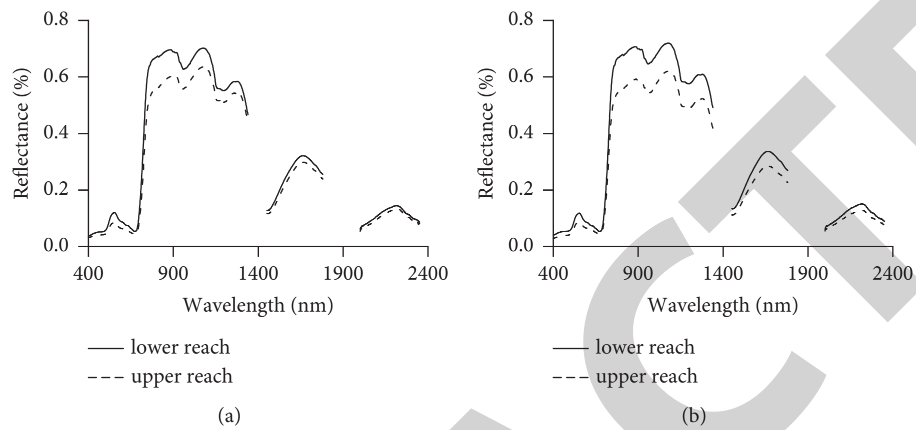

Figure 1: Reflectance of reeds (a) and cattails (b) at upper reach and lower reach of the Bai River.

2.2.3. Model Construction and Accuracy Validation. Models were constructed through three kinds of approaches: (1) regression models of two types of spectral indices and environmental TN content using linear regression, (2) regression models of pretreated spectra and environmental TN content using stepwise multiple linear regression (SMLR) [30–32], and (3) regression models of pretreated spectra and environmental TN content using partial least squares regression (PLSR). The accuracy of these models was examined by a single removal cross-validation validation method [33, 34]. The evaluation indicators were the cross-validation coefficient of the determinant (R_{Cv}^2) and the cross-validation root mean square error ($RMSE_{cv}$). 1 : 1 relationship diagram between measured and estimated values was drawn.

3. Results and Analysis

3.1. Analysis of Biochemical Parameters. TN contents in both water and plants were analyzed (see Table 1). The fluctuation range of TN contents in water at sampling sites where reeds were sampled was 1.51 ± 0.23(mg/L) with the average 95% confidence interval (CL), and the range of TN contents in water at sampling sites where cattails were sampled was 1.04 ± 0.21(mg/L). As for TN contents in plants, the fluctuation range of the reed was 4.47 ± 0.22 (%) and the range of the cattail was 3.23 ± 0.25 (%). These fluctuations provided a good foundation for studying the relationship between reflectance spectra of plants and environmental nitrogen contents. It also showed that TN content in reeds was higher than that in cattails, suggesting that reeds had a higher ability to absorb nitrogen than cattails.

At the same time, in order to explore the difference of vegetation spectra in different wavelength ranges under different eutrophication environments, spectral reflectance data were averaged at sampling sites at the upper reach and lower reach, respectively (see Figure 1). The spectral reflectance of both reeds and cattails at the upper reach, either in the visible light region or in the near-infrared region, was lower than those at the lower reach. This change laid the foundation for studying the relationship between reflectance spectra of plants and wetland environmental nitrogen content.

3.2. Construction of Regression Models and Evaluation of Model Accuracy

3.2.1. The Spectral Index Model. The spectral indices SR and ND of water bodies and plants were constructed (equations 1 and 2), and the correlation coefficients of the spectral indices were calculated (see Figure 2). It was found that ratio indices were almost equivalent to normalized indices in inversion models for both TN in water and TN in plants. Although there was a significantly high correlation ($p < 0.01$), the overall correlation was not high, especially for the spectral index constructed by the reflectance spectra of cattails. Different types of wetland plants had their own specific band combinations to obtain a relatively better correlation. In reeds, the better compositional band of the model for TN in water was the combination of 1085–1115 nm and 965–995 nm, and the better compositional band of the model for TN in the plant was the combination of 775–905 nm and 740–880 nm and the combination of 1285–1300 nm and 1180–1215 nm, respectively. In cattails, the better compositional band of the model for TN in water was the combination of 1690–1705 nm and 1625–1640 nm, and the better compositional band of the model for TN in

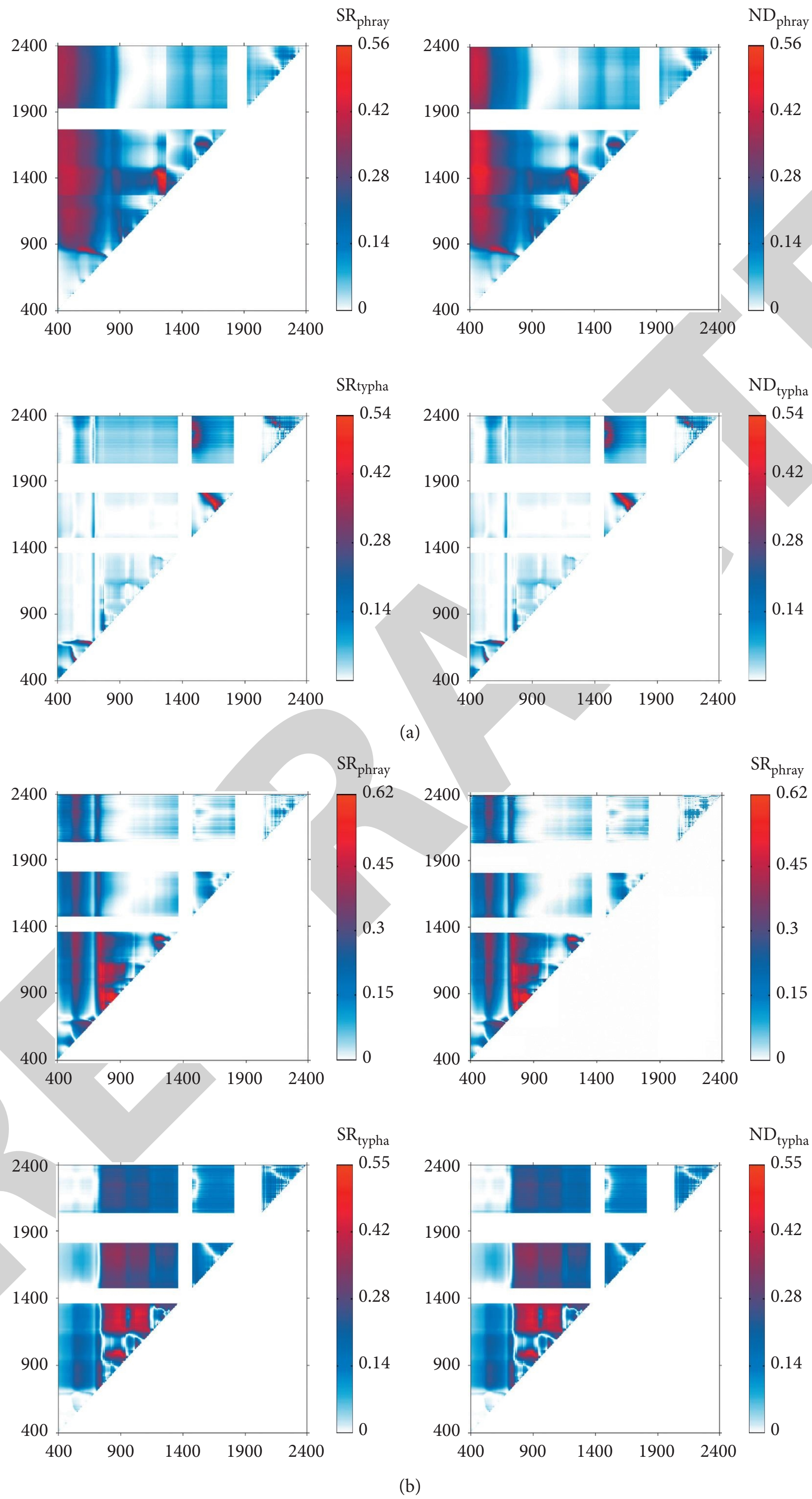

Figure 2: 2-D correlation plots illustrating coefficient of determination between spectral indices and TN contents in water (a) and plants (b).

Table 2: Band position and performance of different models for predicting TN concentration.

TN contents	Species	Models	Selected bands (nm)	R_{Cv}^2	$RMSE_{cv}$
TN in water	Reed	SR	1105/975	0.56	0.27
		ND	1105/975	0.57	0.27
		SMLR	500, 765, 960, 1125	0.75	0.22
		PLSR	—	0.83	0.20
	Cattail	SR	1705/1630	0.54	0.28
		ND	1705/1630	0.54	0.28
		SMLR	405, 520, 615, 1125, 1180	0.75	0.25
		PLSR	—	0.78	0.23
TN in plants	Reed	SR	820/825	0.62	0.33
		ND	820/825	0.62	0.33
		SMLR	580, 715, 1000, 1155, 1295	0.75	0.27
		PLSR	—	0.81	0.24
	Cattail	SR	1130/1120	0.55	0.35
		ND	1105/975	0.56	0.34
		SMLR	420, 720, 865, 900, 935	0.61	0.32
		PLSR	—	0.66	0.28

Note. The higher the R_{Cv}^2 value, the better the fitting effect between the predicted value and the measured value of each model. The lower the $RMSE_{cv}$ value, the higher the accuracy of each model.

the plant was the combination of 975–1000 nm and 885–895 nm and the combination of 1255–1275 nm and 1005–1040 nm, respectively.

For two kinds of parameters composed by reflectance spectra of reeds, the indices for the best correlation with TN contents in water were SR (1105, 755) and ND (1105, 755), while the indices for the best correlation with TN contents in cattails were SR (820, 825) and ND (820, 825), respectively. On the other hand, for two kinds of parameters composed of reflectance spectra of cattails, the indices for the best correlation with TN contents in water were SR (1130, 1120) and ND (1130, 1120), while the indices for the best correlation with TN contents in plants were SR (1705, 1630) and ND (1705, 1630), respectively. Then, a linear regression model was constructed based on optimal spectral indices and environmental TN, and the values of R_{Cv}^2 and $RMSE_{Cv}$ were calculated (see Table 2). It is found that the R_{Cv}^2 values of the SR model and the ND model for TN contents in water constructed by reflectance spectra of reeds were 0.56 and 0.57, respectively, and the $RMSE_{Cv}$ values were 0.27 and 0.27, respectively. Furthermore, the R_{Cv}^2 values of the SR model and the ND model for TN contents in plants were 0.62 and 0.62, respectively, and the $RMSE_{Cv}$ values were 0.33 and 0.33, respectively. However, the R_{Cv}^2 values of the SR model and the ND model for TN contents in water constructed by reflectance spectra of cattails were the same, that is, 0.54, and the $RMSE_{Cv}$ values were 0.28. The R_{Cv}^2 values of the SR model and the ND model for TN contents in plants were 0.55 and 0.56, respectively, and the $RMSE_{Cv}$ values were 0.35 and 0.34, respectively. Therefore, the listed data could show the predictive ability of the models (see Table 2). The estimated nitrogen contents in water and plant by the models based on reflectance spectra of cattails did not fit the measured values as indicated by low R_{Cv}^2 values of <0.57. In contrast, the estimated nitrogen contents in water and plant by the models based on reflectance spectra of reeds did fit the measured values with the high R_{Cv}^2 values of > 0.56. In particular, the ND model had better accuracy than other predictive models.

3.2.2. SMLR Model. For different types of wetland plants, the models were constructed with some bands that were selected from all bands based on pretreated reflectance spectra using the stepwise regression method. However, using a large number of bands when building models easily led to the "multi-collinearity" among different band reflection parameters. To attack this problem, the variance inflation factor was used as a collinearity diagnostic indicator [35]. If the value of the variance inflation factor were higher than 10, which suggested the presence of severe multi-collinearity among the factors. After calculation, since the variance inflation factors of all variables in the models were less than 10, there was no multi-collinearity in this study.

Selected bands were then used to construct the linear models for TN contents in water and TN contents in wetland plants. Compared to the two-band spectral index model, the stepwise multiple linear regression models had higher R_{Cv}^2 values and low $RMSE_{Cv}$ values, suggesting that the model accuracy was improved (see Table 2)). The relationship between measured values and estimated values in cross-validation of the SMLR model was plotted (see Figure 3), and it revealed that the models based on reflectance spectra of reeds had higher accuracy than those based on reflectance spectra of cattails.

3.2.3. PLSR Model. Firstly, TN concentrations in wetlands and pretreated spectral reflectance of plants were mean-centered, and then the relationship between TN content in the wetland and reflectance spectra of different wetland plants was established using the PLSR model. According to the principle of cross-validation, the composition dimensions extracted from reeds and cattails were both 6. Compared to the two-band spectral index model, the PLSR model

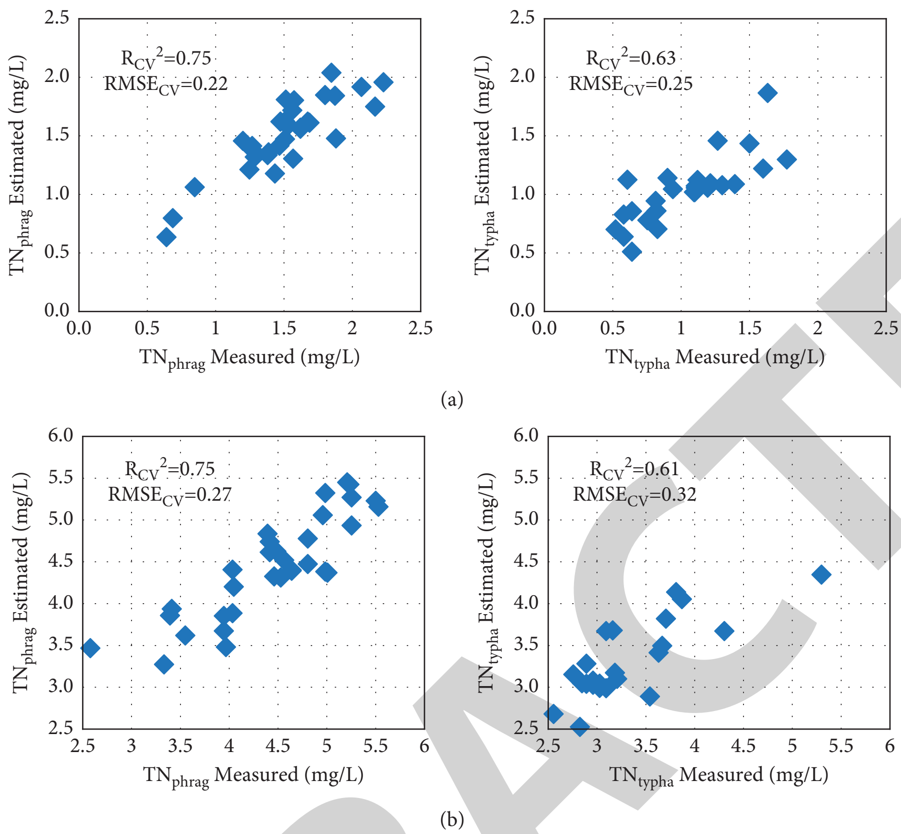

Figure 3: Relationship between measured values and estimated values in cross validation of SMLR model for TN content in water (a) and TN content in plants (b).

established by reflectance spectra of reeds and cattails had an increased R_{Cv}^2 value and decreased $RMSE_{Cv}$ value. For the model of TN in water, the R_{Cv}^2 value was increased by 0.27 and 0.24, respectively, and the $RMSE_{Cv}$ value was reduced by 0.07 and 0.05, respectively; and for the model of TN in plants, the R_{Cv}^2 value was increased by 0.19 and 0.11, respectively, and the $RMSE_{Cv}$ value was reduced by 0.09 and 0.07, respectively. Compared to the SMLR model, the R_{Cv}^2 value of the model for TN in water was increased by 0.08 and 0.03, respectively, and the $RMSE_{Cv}$ value was reduced by 0.02 and 0.02, respectively. The R_{Cv}^2 value of the model for TN in plants was increased by 0.06 and 0.05, respectively, and the $RMSE_{Cv}$ value was reduced by 0.07 and 0.04, respectively. It showed that the model accuracy was greatly improved. The relationship between measured values and estimated values in cross-validation of the PLSR model was plotted (see Figure 4), and it revealed that the model based on reflectance spectra of reeds still had higher accuracy.

4. Discussion and Conclusion

The plant spectrum can not only directly reflect the status of plant growth but also indirectly reflect environmental changes occurring in the field. Many studies showed that monitoring spectral responses of plants to the environment could detect changes in various environmental factors, such as nitrogen contents in soil, salt content, and mineral resources [5, 10, 36]. In addition to the application of plant spectra in crops and minerals, this study also demonstrated that reflectance spectra of wetland plants could be practically used to detect environmental TN contents. Because TN contents of wetland plants have a certain relationship with TN concentrations in water, different models of TN in water and TN in plants have a convergence effect. In contrast to complex laboratory experiments to measure environmental parameters, environmental TN contents can be obtained through a simple band-to-band ratio-oriented calculation of wetland canopy reflectance. The method is timely and rapid; especially, it can complement the disadvantage of remote sensing which is limited to detecting eutrophication in open water. Therefore, it is expected to serve as a useful method to obtain information about water eutrophication in an entire area of water more comprehensively.

This study used three methods to establish regression models for wetland plant reflectance, TN contents in water, and TN contents in plants. After comprehensive comparison of various models, the following conclusions were made: (1) In terms of the model accuracy, the accuracy of the SMLR and PLSR equations was higher than that of the two-band spectral index regression equation. Since the two-band spectral index model only used two bands of the spectra and did not derive rich spectral information from hyperspectral data over the whole spectral range, it likely failed to obtain important information [34, 37]. By comparison, the other

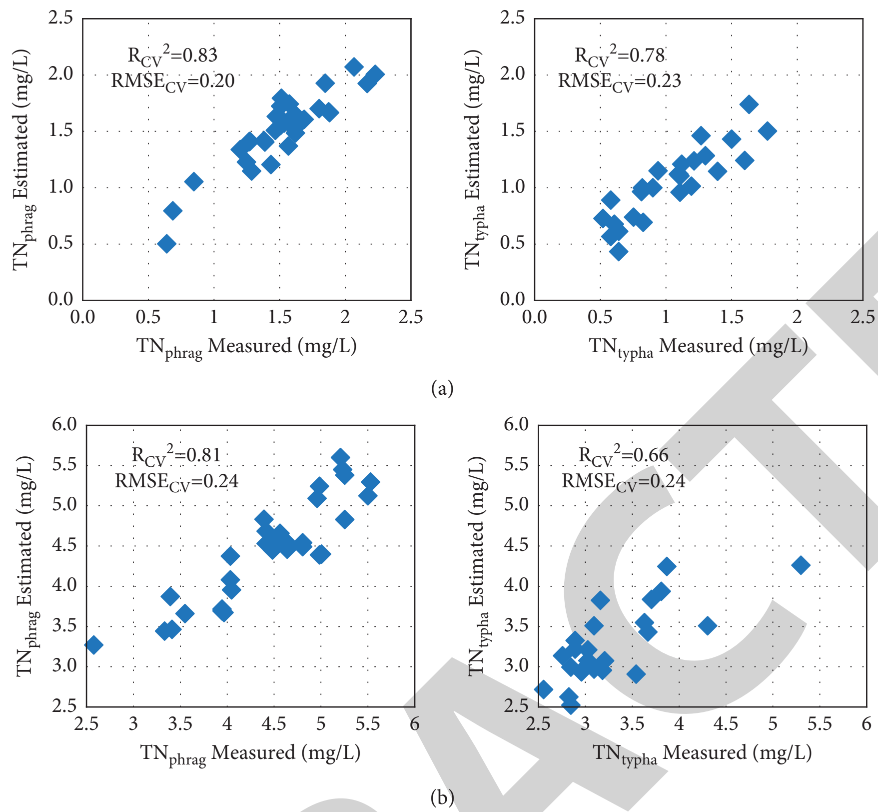

Figure 4: Relationship between measured values and estimated values in cross validation of PLSR model for TN contents in water (a) and TN contents in plants (b).

two models had more spectral parameters, and the accuracy had also been improved to a certain degree. Among them, PLSR considered spectral parameters of each wavelength point over a whole spectrum, solving the problems in multiple linear regressions, such as too many variables and repeated correlation, consequently producing the highest accuracy. So far, many studies have successfully used this method to conduct spectral analysis to estimate elemental contents in soil and physiological parameters of crops and pasture [10, 38, 39]. This study also proved that a more accurate predictive model of environmental TN content can be obtained using this method. (2) In terms of the wetland plant type, different types of wetland plants showed different model accuracies, and the models for reflectance spectra of reeds had generally higher accuracy than those for cattails. It has been reported that reed had a higher nitrogen absorption capacity than cattail [24], indicating that reed can better reflect the characteristics of the environment, which may be the reason for the higher precision of the regression model. Besides, both reed and cattail are plants that are widely distributed in water, and they can survive in eutrophic water, and they are also widely used for water purification in constructed wetlands. It is of practical significance to detect eutrophication by measuring the reflectance spectra of these two wetland plants, and it has the great potential to monitor the water purification performance of wetlands treating reclaimed water.

Since TN concentrations in our study area represent mild and moderate eutrophication, this study only proved that it was feasible to use reflectance spectra of wetland plants to estimate low and middle concentrations of environmental TN. Considering that severe eutrophication may cause saturated absorption of nitrogen in wetland plants, thereby affecting the response of wetland plant spectrum to TN in water to a certain extent, it is needed to further explore the applicability of the methods and models used in this study in severe eutrophicated water.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest.

Acknowledgments

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