Identification for the species of aquatic higher plants in the Taihu Lake basin based on hyperspectral remote sensing

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Abstract

Aquatic plants are crucial for an aquatic ecosystem, and their species and distribution reflect aquatic ecosystem health. Remote sensing technology has been used to monitor plant distribution on a large scale. However, the fine identification of aquatic plants is a great challenge due to large temporal-spatial changes in optical properties of water bodies and small spectral differences among plant species. Here, the identification method of each aquatic plant was developed by constructing the decision tree file of the C4.5 algorithm based on the canopy spectra of 8 plants in the Changguangxi Wetland water area measured with hyperspectral remote sensing technology, and then the method was finally used to monitor the distribution of different plants in Changguangxi Wetland water area and two other water areas. The results show that the spectral characteristics of plants is enhanced by calculating the spectral index of aquatic plants, thereby improving the comparability among different species. The total recognition accuracy of the constructed decision tree file for 8 types of plants is 85.02%, among which the recognition accuracy of *Nymphaea tetragona*, *Pontederia cordata*, and *Nymphoides peltatum* is the highest, and the recognition accuracy of *Eichhornia crassipes* is the lowest. The specific species and distribution of aquatic plants are consistent with the water quality in the water area. The results can provide a reference for the accurate identification of aquatic plants in the same type of water area.

Introduction

The development of industry and agriculture not only improves people's living standards, but also discharges a large amount of untreated wastewater into lakes and rivers, which increases pollutants in water bodies, reduces aquatic biodiversity, and finally leads to the degradation of aquatic ecosystems (Chapman, 2015; Khim, Wang, & Snyder, 2017). Recently, the ecological restoration of polluted waters has attracted great attention with the awakening of public awareness of environmental protection. The health status of aquatic ecosystems can screen and predict the potential problems during the development process of whole water (Moiseenko et al., 2006), so it has become an important indicator in preventing aquatic ecosystem from deterioration and evaluating restoration effects of aquatic ecosystem (Wolf, Blahna, Brinkley, & Romolini, 2011).

Ecological indicators are often used to evaluate the health of aquatic ecosystems, including species identification, biomass measurement, and species diversity index of phytoplankton (Feng et al., 2021; Nava & Leoni, 2021), zooplankton (Shao et al., 2019), macroinvertebrate (Hou, Kong, Li, Xi, & Yu, 2020), large aquatic plants (Lacoul & Freedman, 2006), fish (Breine et al., 2010; Martinho, Nyitrai, Crespo, & Pardal, 2015), and other organisms (Aguirre-Rubi et al., 2018; Aguirre & Lutz, 2004; Ciadamidaro, Mancini, & Rivosecchi, 2016). Among them, aquatic plants, as primary producers, are an important part of aquatic ecosystems, and their coverage (Yu, Wang, Liu, & Fan, 2018; Zeng, Wei, Yi, He, & Luo, 2022), plant proportion, and species composition (Rai & Singh, 2020; Shackleton, Shackleton, & Kull, 2019) can reflect the health of aquatic ecosystems and then judge the development trend of aquatic ecosystems. It has been reported that *Trapa natans* covering the water surface in large area will hinder the gas exchange on the water surface, resulting in a sharp drop in the content of dissolved oxygen in the water body (Goodwin, Caraco, & Cole, 2008). In the process of eutrophication, lakes gradually change from “grass lakes” to “algal lakes” (Scheffer, Carpenter, Foley, Folke, & Walker, 2001), and the dominant species of aquatic plants depend on the eutrophic substances in the water body (Y. Chen, Qin, Teubner, & Dokulil, 2003; James, Havens, Zhu, & Qin, 2009). Cyanobacteria, for example, are dominant in water bodies with high-level nitrogen and low-level phosphorus, and green algae are the dominant species in the water bodies with high-level nitrogen and high-level phosphorus (Reavie et al., 2017). Moreover, the process of water restoration is also accompanied by the succession of plant communities (Juttner, Chimonides, & Ormerod, 2010). For example, after the restoration of eutrophic water, the number of cyanobacteria in the water body decrease, and the number of diatoms increase (Oeding & Taffs, 2015; Tan, Sheldon, Bunn, & Zhang, 2013). Therefore, monitoring the species and distribution of aquatic plants in water bodies and establishing an aquatic plant database can provide a basis for the daily maintenance of the ecological environment in the water area and the evaluation for the restoration effect of polluted water.

To accurately obtain the data about the status of plant species and their distribution in entire water area, manual survey methods have exclusively been used in the past, but this method is costly and time-consuming, and it is difficult to investigate the overall status of large-scale habitats (Pimentel, Lach, Zuniga, & Morrison, 2000). The hyperspectral remote sensing technology allows to quickly obtain the status of plant coverages in entire water area (Dierssen et al., 2021; Duffy et al., 2019; Hestir et al., 2008), but the fine identification of aquatic plant species is still in the exploratory stage, and the identification results are affected by various factors, such as water quality, plant species and their phenological stages, and selected characteristic spectral bands (Rowan, Kalacska, Inamdar, Arroyo-Mora, & Soffer, 2021; Villa, Bolpagni, Pinardi, & Toth, 2021). However, to evaluate the health status of aquatic ecosystems and water pollution through aquatic plants, it is necessary to more accurately identify the specific species of plants and their distribution. To improve the method of fine classification and identification of aquatic plant species and establish a spectral database of aquatic plants in water bodies, in the present work, we took Changguangxi Wetland as the research area based on previous studies (Pu, Bell, & English, 2015; Sun, Zhao, Liang, & Zhang, 2012; Tian, Yu, Zimmerman, Flint, & Waldron, 2010), obtained the reflectance of different aquatic plants through ground measurements, analyzed the spectral characteristics of each plant, summarized the identification method of each aquatic plant, and established a fine classification system of aquatic plants. This system is finally applied in monitoring plant species in other water area, which provides a reference for accurately identifying aquatic plants in the same type of water.

Materials And Methods

Study site

The Changguangxi Wetland is located in Taihu New Town, Wuxi City, Jiangsu Province, China, with coordinates at 31°50' N and 120°27' E. It is a national ecological wetland park connecting Taihu Lake and Lihu Lake. The entire wetland is dominated by accumulation plains, with scattered residual hills distributed locally (Xuehua Liu, Liu, Wu, & Tian, 2019). The terrain is flat, with an altitude of 3 ~ 5 m and an area of approximately 2.6 km^2. It is a freshwater river wetland. The soil fertility is high and especially suitable for the growth of wetland plants such as *Phragmites australis* and *Typha angustifolia*.

Acquisition and processing of measured hyperspectral data

By using the Field Spec Pro FR portable ground object spectrometer produced by ASD company in America, the hyperspectral data of the water surface, water bloom, and various species of aquatic plants in the Changguangxi Wetland were collected from 10 a.m. to 2 p.m. on a clear and cloudless day in October 2020 and June 2021. In the process of plant spectrum measurement, plant cluster with single plant, good growth, and high plant coverage was selected to arrange the quadrats, the quadrat size was set to 1 m × 1 m, and the distance between the quadrats was greater than 3 m. To make the data representative, the sampling points were evenly distributed in the study area. During the measurement process, whiteboard optimization was carried out every 20 min. All data were obtained by the vertical observation method, that is, the data were measured at a distance of approximately 1 m above the vegetation canopy, and 10 spectral curves were measured at each sampling point. After the emission spectrum curve was collected, ViewSpecPro software was used with the instrument to eliminate abnormal data and noise bands with large deviations. The 400 ~ 900 nm was taken as the valid data and then the average value of the curves of each ground object was calculated. Finally, the calculated curve was used as the representative curve of the corresponding ground objects. The spectral data measured in June 2021 were used to construct an accurate identification method for aquatic higher plants, and the data in October 2020 were used to verify the accuracy of the constructed method.

Defining the identification index of aquatic plants

The spectral characteristics of the reflectance curves of water bodies, algal blooms, and submerged plants are different, and they have unique reflection peaks and reflection valleys. Moreover, the magnitude and variation trend of the spectral reflectance of each species of emergent plant and floating-leaf plant in specific wavelength bands are also different. Based on these principles, the spectral characteristics and separability of aquatic plants can be enhanced by calculating the band difference or ratio of the reflectance curve to achieve accurate identification of each species of plant.

Chlorophyll spectral index (CSI)

$$\mathrm{CSI}=(\mathrm{R}_{700}\text{-}\mathrm{R}_{675})/(\mathrm{R}_{700}+\mathrm{R}_{675})$$

1

In the formula, R_{700} is the reflectivity of the reflection peak near 700 nm, and R_{675} is the reflectivity of the reflection valley near 675 nm. The CSI is proportional to the chlorophyll content, so algal blooms, aquatic plants and water bodies with high chlorophyll contents have higher CSI values (Z. Zhang et al., 2020). The CSI can be used as a discriminant index to distinguish these three types of ground objects from water bodies with low-level chlorophyll.

Phycocyanin spectral index (PSI)

$$\mathrm{PSI}=(\mathrm{R}_{650}\text{-}\mathrm{R}_{625})/(\mathrm{R}_{650}+\mathrm{R}_{625})$$

2

In the formula, R_{650} is the reflectivity of the reflection peak near 650 nm, and R_{625} is the reflectivity near 625 nm. The PSI is proportional to the density of water algae, and the reflection peak formed near 650 nm is the spectral characteristic of water algae (S. Li & Wang, 2002), so the PSI can be used as a discriminant index to distinguish aquatic plants and algal blooms. Since the density of algae in common waters is lower than that of algal blooms and the PSI value of water is also smaller than that of algal blooms, the PSI can be also used as a discriminant index to distinguish water bodies from algal blooms.

Macrophyte spectral index (MSI)

$$\mathrm{MSI}=(\mathrm{R}_{700}\text{-}\mathrm{R}_{815})/(\mathrm{R}_{700}+\mathrm{R}_{815})$$

3

In the formula, R_{700} is the reflectance at 700 nm, R_{815} is the reflectance at 815 nm, the MSI can characterize the falling speed of the spectral curve at 700 ~ 900 nm band. The chlorophyll of aquatic plants has strong reflectivity in the near-infrared band (J. Li et al., 2009), thus their spectral curve decreases slowly and their MSI value is small, after 700 nm. In addition, the water body has strong absorption in the near-infrared band, and thus its spectral curve decrease rapidly and its MSI value is large, after 700 nm. Therefore, the MSI can be used as a discriminant index to distinguish water bodies and aquatic plants.

Average reflectance in the near-infrared index (ARNI)

$$\mathrm{ARNI}=\mathrm{R}(750\text{~}820)$$

4

In the formula, $R_{(750\sim820)}$ is the mean value of reflectance at 750 ~ 820 nm. Since submerged plants are below the water surface, their spectral reflectance is the mixed spectrum of the water body and plant leaves. The leaves of floating-leaf plants are attached to the water surface, and the leaves of emergent plants are located on the water surface. Therefore, the absorption of water in the near-infrared band has a greater impact on the reflection spectrum of submerged plants (J. Li et al., 2009). Based on this fact, the ARNI can be used to distinguish floating and submerged plants from other aquatic plants.

Spectral reflectance change rate (SRCR)

$$\mathrm{SRCR}=(\mathrm{R_A}\text{-}\mathrm{R_B})/\mathrm{R_B}$$

5

In the formula, R_A is the reflectance at A nm wavelength, R_B is the reflectance at B nm wavelength, and the SRCR can characterize the change rate of the spectral curve at A ~ B nm band. Since each species of plant has its own unique reflectance spectrum, and the magnitude and change trend of the spectral reflectance in a specific interval are also different, so the precise identification of each plant species can be achieved by comparing the SRCR of submerged plants, floating leaf plants and emerging plant species.

Establishment of a decision tree model

Based on the identification index of aquatic plants mentioned above, the node threshold of each identification index is determined, and then the decision tree file of the C4.5 algorithm is constructed to realize the identification of various plant species (L. Chen & Shun, 2018; Jiang, Zhao, Cai, & An, 2012; Yang & Fang, 2016). Finally, the confusion matrix is used to calculate the Kappa coefficient to measure the recognition accuracy (De Raadt, Warrens, Bosker, & Kiers, 2019; Vanbelle, 2019).

Acquisition and processing of airborne hyperspectral images

A six-rotor UAV (DJI M600 Pro, China) equipped with an S185 imaging spectrometer (Cubert, Germany) was used to obtain hyperspectral images of the UAV. The S185 imaging spectrometer has a spectral range of 450 ~ 950 nm and a spectral resolution of 8 nm. It contains 125 channels and can simultaneously obtain a grayscale image of 1000 × 1000 pixels and a hyperspectral image of 50 × 50 pixels. The sampling interval is 4 nm. The flying height of the UAV is fixed at 80 m, the field of view of the imager lens is 15°, and the focal length is 28 mm. The ground resolution of the obtained hyperspectral image is approximately 32.50 cm, and the ground resolution of the grayscale image is approximately 1.53 cm. To ensure the stability of lighting conditions and reduce the influence of sunlight scattering, the collection time is selected from 10:00 am to 2:00 pm, while avoiding the shadow of plants and ground buildings; the wind level when the drone is flying should not be higher than Level 5 to ensure the flight stability of the UAV and reduce the jitter of the airborne hyperspectral measuring instrument.

According to the previous method (P. Chen et al., 2018), the hyperspectral images of the monitoring sections recorded by the airborne hyperspectral measuring instrument were processed as follows: (1) Cube-Pilot 1.5.6 software was used to obtain hyperspectral images with a resolution of 1.53 cm by fusing grayscale images with hyperspectral images; (2) The hyperspectral images obtained by fusion were stitched by Agisoft PhotoScan 1.4.5 software; (3) The ground feature points of the monitoring section were obtained by satellite remote sensing of Wuxi Environmental Monitoring Center Station, using ENVI 5.3 software to perform geometric correction on the acquired hyperspectral images, and finally, the hyperspectral images of the monitoring section were obtained.

Results

Construction of decision trees for the identification of water bodies, algal blooms, and aquatic plants

Before the fine identification and classification of aquatic higher plants, it is necessary to distinguish the three types of ground features: submerged plants, algal blooms, and water bodies, to avoid their spectral confusion with aquatic higher plants. The representative reflection curves of submerged plants, water bodies, and algal blooms are shown in Fig. 1. The results show that the spectral characteristics of submerged plants, algal blooms, and water bodies are significantly different, and the three ground objects have significant reflection peaks and reflection valleys. The three kinds of ground objects appear as reflection peaks near 555 nm, 650 nm, 700 nm, and 850 nm and reflect valleys

near 675 nm. The reflectance of these characteristic wavelengths can reflect the differences in the spectral reflectance of these three ground objects. In addition, algal blooms have the most obvious reflection peaks at approximately 555 nm, 700 nm, and 850 nm, the reflection peaks of water bodies are relatively small around this band, and the reflection peaks of submerged plants are the lowest. The algal blooms and water bodies appear as reflection valleys near 625 nm, and the characteristics of submerged plants are not obvious.

On this basis, four normalized spectral indices, i.e. CSI, PSI, MSI, and ARNI, have been established. The four spectral indices are used to establish a discriminant formula for distinguishing submerged plants, water bodies, and algal blooms. Then, the threshold of the discriminant formula is determined according to the sample data. Finally, a decision tree file is built to identify these three kinds of ground objects. The results are shown in Fig. 2. The obtained hyperspectral data set is imported into the decision tree file. First, the threshold value of the first node is judged. When the CSI value is higher than 0.1, the types of ground objects in the spectrum may be high-chlorophyll water bodies, aquatic plants, and algal blooms; otherwise, it is judged as low-chlorophyll water bodies. The spectral data of high-chlorophyll water bodies, aquatic plants, and algal blooms enter the next node threshold determination. When the PSI value is less than or equal to 0.2, it is judged as high-chlorophyll water bodies and aquatic plants; otherwise, it is judged as algal bloom. Then, the spectral data of high-chlorophyll water bodies and aquatic plants enter the next node threshold judgment. When the MSI value is less than or equal to 0.2, it can be judged as submerged plants, floating leaf plants, and emergent plants; otherwise, it is judged as a water body with high chlorophyll. Finally, the ARNI values of submerged plants, emergent plants, and floating plants are compared. When the ARNI value is higher than or equal to 0.04, it can be considered as emergent and floating-leaf plants; otherwise, it can be considered as submerged plants.

Fine identification of aquatic higher plants

There are 8 species of aquatic higher plants in the Changguangxi Wetland waters, namely, *Nelumbo nucifera*, *Salvinia natans*, *Nymphaea tetragona*, *Nymphoides peltatum*, *Eichhornia crassipes*, *Pontederia cordata*, *Lemna minor*, and *Trapa natans*, of which *Nelumbo nucifera* and *Pontederia cordata* are emergent plants; *Nymphaea tetragona*, *Nymphoides peltatum*, and *Trapa natans* are floating leaf plants; and *Salvinia natans*, *Eichhornia crassipes*, and *Lemna minor* are floating plants, as shown in Fig. 3.

The average spectral reflectance curves of 8 species of aquatic higher plants are shown in Fig. 4. It can be seen that the reflectance of the 8 species of plants in the near-infrared band after 750 nm differs in numerical value and changing trend. First, *Eichhornia crassipes* and *Trapa natans* have the highest ARNI values (0.462 and 0.417, respectively); *Nelumbo nucifera*, *Pontederia cordata*, *Lemna minor*, and *Salvinia natans* have the second highest ARNI values (0.383, 0.360, 0.324 and 0.318); the ARNI values of *Nymphoides peltatum* and *Nymphaea tetragona* are relatively low (0.267 and 0.226, respectively). Therefore, 0.4 and 0.3 are used as the discriminant thresholds of ARNI. Second, the near-infrared reflectance values of *Eichhornia crassipes*, *Lemna minor*, *Salvinia natans*, and

Pontederia cordata increase with increasing wavelength, and the near-infrared reflectance values of *Nelumbo nucifera*, *Trapa natans*, *Nymphaea tetragona*, and *Nymphoides peltatum* decrease with increasing wavelength. Therefore, 780 ~ 900 nm is selected as the characteristic band to calculate and compare the SRCR of 8 species of aquatic plants in this band. The results show that the SRCR values of *Salvinia natans*, *Lemna minor*, *Eichhornia crassipes*, and *Pontederia cordata* are positive, which are 7.42%, 3.8%, 1.7%, and 1.02%, respectively; the values of *Nelumbo nucifera*, *Nymphoides peltatum*, *Trapa natans*, and *Nymphaea tetragona* are negative, which are − 3.93%, -5.09%, -5.73% and − 6.78%, respectively. Therefore, 0 is used as the discriminative threshold of SRCR.

Through the above analysis, a binary decision tree that can distinguish these 8 species of plants can be constructed. As shown in Fig. 5, the spectral data of 8 species of aquatic plants were input into the decision tree file. First, the threshold value of the first node is judged. When the ARNI value is higher than or equal to 0.4, the aquatic plants can be identified as *Eichhornia crassipes* and *Trapa natans*; otherwise, they are identified as other 6 species of aquatic plants. The spectral data of *Eichhornia crassipes* and *Trapa natans* enter the next node. When the SRCR value is higher than or equal to 0, it is judged as *Eichhornia crassipes*; otherwise, it is judged as *Trapa natans*. The spectral data of the remaining 6 species of aquatic plants enter the next node threshold determination. When the ARNI value is higher than or equal to 0.3, it can be determined to be *Nelumbo nucifera*, *Pontederia cordata*, *Lemna minor*, and *Salvinia natans*; otherwise, it is determined to be *Nymphoides peltatum* and *Nymphaea tetragona*. However, the spectral curves of *Nelumbo nucifera*, *Pontederia cordata*, *Lemna minor*, and *Salvinia natans* have a high degree of overlap, so their SRCR can be observed; that is, when the SRCR value is higher than or equal to 0, they can be determined to be *Pontederia cordata*, *Lemna minor* and *Salvinia natans*. The spectral data of these three aquatic plants have a high degree of coincidence and little difference in spectral characteristics; otherwise, they are determined to be *Nelumbo nucifera*.

Analysis of identification results

The spectral data obtained by the field experiment in the Changguangxi Wetland were used to test the accuracy of the constructed decision tree file for the identification of aquatic higher plants. The spectral curves drawn after preprocessing the spectral data of 8 species of aquatic plants collected in the Changguangxi Wetland are shown in Fig. 6. The spectral data of 8 species of aquatic plants are substituted into the established decision tree file, and the confusion matrix is obtained, as shown in Table 1.

Table 1
Identification confusion matrix of reflectance spectra of eight aquatic higher pl

Original category	*Eichhornia crassipes*	*Nelumbo nucifera*	*Pontederia cordata* *Lemna minor* *Salvinia natans*	*Trapa natans*	*Nymphoides peltatum* *Nymphaea tetragona*	Volur
Eichhornia crassipes	21	0	7	0	2	30
Lemna minor	0	0	34	0	6	40
Nelumbo nucifera	0	35	0	3	2	40
Salvinia natans	0	0	30	0	10	40
Trapa natans	0	10	0	30	0	40
Nymphaea tetragona	0	0	0	0	30	40
Pontederia cordata	0	0	40	0	0	40
Nymphoides peltatum	0	0	0	0	40	40
Volume	21	45	111	33	100	300

To measure the accuracy of plant classification, a confusion matrix for the identification accuracy of 8 species of aquatic higher plants is constructed and the Kappa coefficient is 0.8502; that is, the total identification accuracy is 85.02%. The results show that the established decision tree file for identifying 8 species of aquatic higher plants has high identification accuracy. The recognition accuracy of each aquatic plant and which aquatic plant is easily confused can be seen from the mixture matrix. The producer accuracy of *Eichhornia crassipes* identification is 70%, and 2 of them is identified as *Nymphoides peltatum* or *Nymphaea tetragona*, and 7 of them are mistakenly identified as *Pontederia cordata*, *Lemna minor*, or *Salvinia natans*. The producer accuracy of *Lemna minor* identification is 85%, and 6 of them are misidentified as *Nymphoides peltatum* or *Nymphaea tetragona*. The producer accuracy of *Nelumbo nucifera* identification is 87.5%, 2 of them are mistakenly identified as *Nymphoides peltatum* or *Nymphaea tetragona*, and 3 of them are mistakenly identified as *Trapa natans*. The accuracy of the identification of the producers of *Salvinia natans* is 75%, and 10 of them are mistakenly identified as *Nymphoides peltatum* or *Nymphaea tetragona*. The accuracy of the producer identified by *Trapa natans* is 75%, and 10 of them are mistakenly identified as *Nelumbo nucifera*. Due to the influence of external environmental conditions such as climate and sunlight intensity, there are certain errors in the spectral data collected in the field, and the spectral characteristics of aquatic plants are not sufficiently distinguishable, so the final judgment results have certain errors. The producer accuracy of *Nymphaea tetragona*, *Pontederia cordata*, and *Nymphoides peltatum* identification is 100%.

Application of hyperspectral classification and recognition of aquatic plants

The UAV-mounted hyperspectral spectrum combined with the constructed decision tree file was used to identify aquatic higher plants in the Changguangxi Wetland waters, and the hyperspectral image of the Changguangxi Wetland was generated as shown in Fig. 7. Based on the obtained images of the Changguangxi Wetland, the same method was used to identify higher aquatic plants in Xiedaidang and Huochebang in the Wangyu River Basin in Wuxi in September, and the hyperspectral images of Xiedaidang and Huochebang were finally generated, as shown in Fig. 8.

Figure 7 shows that the blue area in the Changguangxi waters is identified as ordinary waters, accounting for 90.83% of the area. The yellow area is identified as *Nelumbo nucifera*, and it can be seen from the figure that the growth area of *Nelumbo nucifera* is small, accounting for 0.21%. The dark green and light green areas are identified as *Nymphaea tetragona* and *Trapa natans*, accounting for 1.93% and 7.04% of the area, respectively. Other aquatic higher plants in the Changguang wetland fail to reach the detection limit of the airborne hyperspectral imager because the growth area is too small, so they could not be identified in the image.

Figure 8 shows that the light blue water in the Xiedaidang waters is low-chlorophyll water, the dark blue is high-chlorophyll water, and the low-chlorophyll water is significantly larger than the high-chlorophyll water. A small number of cyanobacterial blooms have a certain impact on water quality. The rose-red area is judged as *Eichhornia crassipes* by the decision tree, and the yellow, light green and dark green areas are judged as *Pontederia cordata*, *Trapa natans*, and *Lemna minor*, respectively. The growing areas of *Pontederia cordata*, *Trapa natans*, and *Lemna minor* are relatively small. Based on the monitoring of the waters, Huochebang extends the monitoring area to the riparian zone. It can be seen from the figure that the green areas on both sides of the Huochebang waters are identified as terrestrial plants. Due to the large area of plants, the black areas in the waters are blocked during monitoring. It is identified as a shadow part, which has a certain impact on the airborne hyperspectral image. Gray areas are identified as artificial surfaces, i.e., land on bank slopes, etc. The light blue and dark blue areas are identified as low-chlorophyll water and high-chlorophyll water, respectively. It can be seen from the figure that the area of low-pigment water is larger than that of high-chlorophyll water, which proves that the area of low-chlorophyll water is larger than that of high- chlorophyll water. The yellow area is identified as *Eichhornia crassipes*, indicating that a large area of *Eichhornia crassipes* grows on the water surface of Huochebang. The growth area of *Eichhornia crassipes* is too large to prevent sunlight from shining on the water surface, resulting in a significant reduction in dissolved oxygen in the water body, inhibiting the growth of fish and benthic animals and plants, hindering water flow, and damaging the ecological balance of the basin.

Discussion

In a healthy aquatic ecosystem, aquatic plant species are abundant (Fares, Calvão, Torres, Gurgel, & Michelan, 2020). Different species of plants are located in different ecological niches and have different ecological functions. Together, these aquatic plants constitute the primary producers of aquatic ecosystems, providing bait resources and habitats for aquatic animals (W. Li, 2014; Y. Zhang et al., 2017). The factors that affect the growth of aquatic plants include light (Zou & Gao, 2009), nutrition (Scheffer & Nes, 2007), sediment (Atapaththu, Parveen, Asaeda, & Rashid, 2018), water level (Paillisson & Marion, 2011), and stormy waves (Bornette & Puijalon, 2010), and the deterioration of water quality usually changes these factors, resulting in a reduction in the diversity of aquatic plants and a rapid expansion of the distribution of a single species of aquatic plants (Schneider, 2007). This is consistent with the airborne hyperspectral images we obtained. It can be seen from Fig. 8 that the water surface of Huochebang is covered with a large amount of *Eichhornia crassipes*. Combined with the water quality of Huochebang, we found that the water body of Huochebang is seriously eutrophic, and the dissolved oxygen concentration, turbidity and the chlorophyll-a concentration in the water is 4.00 mg/L, 11.37 NTU and 0.68 μg/L, respectively, which is only a normal water body in an oligotrophic state. This is because the Huochebang itself is closed with sufficient light and slow water flow, while the growth of *Eichhornia crassipes* is mainly affected by animal feeding and water flow (Hopper et al., 2021). In addition, there are sufficient nutrients in the waters of Huochebang, and *Eichhornia crassipes* proliferates to become an absolute dominant species. Other floating plants and floating water plants gradually disappear in the competition, and *Eichhornia crassipes* itself secretes allelochemicals to inhibit the growth of algae (Wu, Zhang, & Jin, 2019), which leads to a low content of chlorophyll-a in the waters. *Eichhornia crassipes* grows densely, and its root systems interlace with each other to form a dense layer of grass mat on the water surface, which hinders gas exchange on the water surface of Huochebang and isolates light, resulting in the death of submerged plants (McVea & Boyd, 1975). Submerged plants can release oxygen species into the water through photosynthesis, and their roots can also fix the sediment (Changdong Ye, Yao, Deng, Liu, & Liu, 2018). Therefore, once the concentration of dissolved oxygen in the water body lacking submerged plants decrease significantly, and the turbidity of the water body will increase if bottom sediment is slightly disturbed (J. Zhang et al., 2021). This is also in line with the evolution law of Taihu Lake. Before 1960, the water quality of Taihu Lake was good, and there were 66 species of aquatic plants (NIGL, 1965). In 2006, the total nitrogen in the central area of Taihu Lake had risen to 2.34 mg/L, and there were only 16 species of aquatic plants (G. Zhu, 2008), including 1 species of emergent plants, 7 species of floating plants, with *Nymphoides peltatum* as the dominant species, and 8 species of submerged plants, among which the predominant species was *Potamogeton malaianus*. The original species sensitive to changes in the water environment, such as *Alisma orientalis* and *Ceratopteris thalictroides*, have not been found, while the distribution of adaptable plants, such as *Potamogeton malaianus* and *Nymphoides peltatum*, is still further expanding (Weilong et al., 2007). The single plant community cannot provide a wide and suitable living environment for other aquatic organisms, which will further reduce the diversity of aquatic organisms, thus further aggravating the deterioration of water quality.

With the intensification of water eutrophication, the degradation of aquatic plants in many water areas is obvious, and the waters are facing the transformation from grass-type water bodies to algal-type water bodies (Luo et al., 2020). Therefore, restoring the original aquatic plants in eutrophic water has become the main means to control water eutrophication. Before reconstructing the aquatic plant community in the polluted water body, we should first determine the pioneer species, the proportion among various species, and their respective coverage rate according to local conditions and the growth habit of aquatic plants (K. Zhu, Wu, Li, Xu, & Zhang, 2020). Regarding the sediment in the polluted water body, the research shows that *Lythrum salicaria* is suitable as the pioneer plant for removing nitrogen and phosphorus in water when the salinity of sediment is 0%, while *Typha orientalis* is more suitable as the pioneer plant for removing nitrogen and phosphorus in water when the salinity of sediment is 1% (Xiaochuan Liu, 2013). In terms of the biomass and coverage of aquatic plants, taking *Eichhornia crassipes* as an example, *Eichhornia crassipes* grows rapidly, which can absorb a large amount of nutrients and heavy metals in the water body and stabilize the pH of the water body (Parwin & Paul, 2019; Tabinda et al., 2019). Relevant studies have shown that when *Eichhornia crassipes* doesn't endanger the survival of other animals and plants when its coverage rate is below 25%, but it will shield sunlight and reduce the concentration of dissolved oxygen in the water body once it covers the water surface in a large area (Villamagna & Murphy, 2010). Further research shows that the restoration of aquatic plants must be based on the improvement of the environment (Chun Ye et al., 2011), so the current management ideas are mostly exogenous control and ecological restoration at the same time (Jenny et al., 2020). This is consistent with the Changguangxi wetland we investigated. Since 1980, several reclamations of the lake have caused serious damage to the ecological environment of the whole Changguangxi area. Before the management in 2004 management, the average total nitrogen in the water body was as high as 4.03 mg/L, and the average chemical oxygen demand was 42.70 mg/L. The local government has adopted a combination of artificial management and ecological restoration, setting up a gravity filtration system underground, a clean cloth filtration system on the riverbank, and a sedimentation filtration system on the bank (Lv & Wang, 2013). At the same time, various aquatic plants with different ecological functions are planted throughout the wetland to assist in the restoration. For example, around the sedimentation tank, emerging plants such as *Phragmites australis* and *Typha orientalis* are planted to absorb pollutants in the water body and play a role in isolating tourists. In the places where the water flow rate is relatively fast in the river, *Nymphoides peltatum* with its strong resistance to wind and waves is selected as a plant for phytoremediation (Jin, Yan, & Xu, 2007). In the water body with a slow water flow rate but high turbidity, *Trapa natans*, which can grow normally even in low light conditions, is selected as a plant for phytoremediation; in the area where the sediment is soft and organic matter is thick and most aquatic plants could not germinate, *Nymphaea tetragona* with a developed root system is used as a plant for phytoremediation (Handley & Davy, 2002). In addition, some aquatic plants with good adaptability and absorption capacity to eutrophic water bodies, such as *Cyperus involucratus*, *Vetiveria zizanioides*, *Canna indica*, *Potamogeton crispus*, and *Hydrilla verticillata* are used, to construct a three-dimensional aquatic plant community and achieve good landscape effects while ensuring the improvement of water quality.

In summary, monitoring the species of aquatic plants in healthy waters can identify potential problems in aquatic ecosystems through the number and changes in aquatic plant species, and monitoring aquatic plants in waters during the restoration process can determine the restoration status and evaluate the restoration effect of aquatic ecosystems (Luo et al., 2020). In the process of daily monitoring of aquatic plants, we should pay attention to the coverage rate of aquatic plants in the whole water area. The survey shows that the biomass of aquatic plants in Dianchi Lake is 1363.1 g/m^3 and the biomass of aquatic plants in Liangzi Lake is 1490 g/m^3 when they are not polluted. To maintain a virtuous cycle of aquatic ecosystems, the biomass of aquatic plants should be greater than 1000 g/m^3, and the coverage rate should be higher than 30% (Wang et al., 2007). However, excessive aquatic plants can also cause serious harm. Once, the East Taihu Lake was swamped seriously due to the excessive growth of aquatic plants (Gu et al., 2005). Moreover, when aquatic plants are used to repair polluted water bodies, reasonable harvesting can promote the growth of aquatic plants and avoid secondary pollution to water bodies (Luo et al., 2020; Vereecken, Baetens, Viaene, Mostaert, & Meire, 2006). Studies have shown that 6–9 weeks is the best harvest period for water hyacinth to restore eutrophic water (Jayaweera & Kasturiarachchi, 2004), while emergent plants such as reed cattails need to be harvested twice a year from February to March and August to September. Therefore, to ensure that the aquatic ecosystem remains healthy, it is necessary to regularly and accurately monitor the species and distribution of plants in the entire water area and make appropriate adjustments based on field conditions and vegetation habits. Based on this, the present work uses hyperspectral remote sensing technology to establish a fine classification system of aquatic plants in the Changguangxi Wetland and applies it to actual environmental monitoring to provide a reference for accurately identifying aquatic plants in the same type of waters. However, the results obtained in the present work still have shortcomings, which are mainly manifested in large errors in the identification of *Eichhornia crassipes*; in addition, the field monitoring time selected in the present work is between June and October, and Wuxi is in late spring and early autumn during this period. The temperature is high, and the aquatic plants grow vigorously. The influence of the different phenological stages of aquatic plants on the reflection spectrum has not been fully considered. Therefore, relevant research needs to be improved for practical applications in the future.

Conclusions

This study shows that it is feasible to use hyperspectral remote sensing technology to accurately identify aquatic higher plants. The total recognition accuracy of the recognition method constructed in this paper for 8 species of aquatic higher plants is 85.02%. The application in actual monitoring shows that the recognition system constructed in this study has strong operability and high accuracy in practical applications. The research results of this paper provide a reference for the accurate identification of aquatic higher plants and a new idea for the daily maintenance and management of aquatic ecological environment.

Declarations

Credit authorship contribution statement

Shichen Mu: Formal analysis, Methodology, Data analysis, Writing – original draft preparation. **Kai You:** Methodology, Data curation. **Ting Song:** Methodology. **Yajie Li:** Writing – review & editing. **Lihong Wang:** Conceptualization, Methodology, Supervision, Writing – review & editing. **Junzhe Shi:** Supervision, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

Conflict of interest The authors declare no competing interests.

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References

1. Aguirre-Rubi, J., Luna-Acosta, A., Ortiz-Zarragoitia, M., Zaldibar, B., Izagirre, U., Ahrens, M. J., & Marigomez, I. (2018). Assessment of ecosystem health disturbance in mangrove-lined Caribbean coastal systems using the oyster *Crassostrea rhizophorae* as sentinel species. Science of the Total Environment, *618*, 718–735. https://doi.org/10.1016/j.scitotenv.2017.08.098
2. Aguirre, A. A., & Lutz, P. (2004). Marine turtles as sentinels of ecosystem health: Is *Fibropapillomatosis* an indicator? *EcoHealth, 1*(3), 275–283. https://doi.org/10.1007/s10393-004-0097-3

3. Atapaththu, K. S. S., Parveen, M., Asaeda, T., & Rashid, M. H. (2018). Growth and oxidative stress response of aquatic macrophyte *Myriophyllum spicatum* to sediment anoxia. Fundamental and Applied Limnology, *191*(4), 289–298. https://doi.org/10.1127/fal/2018/1070
4. Bornette, G., & Puijalon, S. (2010). Response of aquatic plants to abiotic factors: A review. Aquatic Sciences, *73*(1), 1–14. https://doi.org/10.1007/s00027-010-0162-7
5. Breine, J., Quataert, P., Stevens, M., Ollevier, F., Volckaert, F. A., Van den Bergh, E., & Maes, J. (2010). A zone-specific fish-based biotic index as a management tool for the Zeeschelde estuary (Belgium). Marine Pollution Bulletin, *60*(7), 1099–1112. https://doi.org/10.1016/j.marpolbul.2010.01.014
6. Chapman, P. M. (2015). Future challenges for marine pollution monitoring and assessment. Marine Pollution Bulletin, *95*(1), 1–2. https://doi.org/10.1016/j.marpolbul.2015.05.043
7. Chen, L., & Shun, Y. (2018). Comparison of object-oriented romote sensing image classification based on different decision trees in forest area. Chinese Journal of Applied Ecology, *29*(12), 3995–4003. https://doi.org/10.13287/j.1001-9332.201812.015
8. Chen, P., Li, G., Shi, Y., Xu, T., Yang, F., & Cao, Q. (2018). Validation of an unmanned aerial vehicle hyperspectral sensor and its application in maize leaf area index estimation. Scientia Agricultura Sinica, *51*(8), 1464–1474. https://doi.org/10.3864/j.issn.0578-1752.2018.08.004
9. Chen, Y., Qin, B., Teubner, K., & Dokulil, M. T. (2003). Long-term dynamics of phytoplankton assemblages: Microcystis-domination in Lake Taihu, a large shallow lake in China. Journal of Plankton Research, *25*(4), 445–453. https://doi.org/10.1093/plankt/25.4.445
10. Ciadamidaro, S., Mancini, L., & Rivosecchi, L. (2016). Black flies (Diptera, Simuliidae) as ecological indicators of stream ecosystem health in an urbanizing area (Rome, Italy). Annali Dellistituto Superiore Di Sanita, *52*(2), 269–276. https://doi.org/10.4415/ANN_16_02_20
11. De Raadt, A., Warrens, M. J., Bosker, R. J., & Kiers, H. A. L. (2019). Kappa coefficients for missing data. Educational Psychological Measurement, *79*(3), 558–576. https://doi.org/10.1177/0013164418823249
12. Dierssen, H. M., Ackleson, S. G., Joyce, K. E., Hestir, E. L., Castagna, A., Lavender, S., & McManus, M. A. (2021). Living up to the hype of hyperspectral aquatic remote sensing: Science, resources and outlook. Frontiers in Environmental Science, *9*, 649528. https://doi.org/10.3389/fenvs.2021.649528
13. Duffy, J. E., Benedetti-Cecchi, L., Trinanes, J., Muller-Karger, F. E., Ambo-Rappe, R., Boström, C., & Yaakub, S. M. (2019). Toward a coordinated global observing system for seagrasses and marine macroalgae. Frontiers in Marine Science, *6*, 317. https://doi.org/10.3389/fmars.2019.00317
14. Fares, A. L. B., Calvão, L. B., Torres, N. R., Gurgel, E. S. C., & Michelan, T. S. (2020). Environmental factors affect macrophyte diversity on Amazonian aquatic ecosystems inserted in an anthropogenic landscape. Ecological Indicators, *113*, 106231. https://doi.org/10.1016/j.ecolind.2020.106231
15. Feng, B., Zhang, M., Chen, J., Xu, J., Xiao, B., Zhou, M., & Zhang, M. (2021). Reduction in the phytoplankton index of biotic integrity in riverine ecosystems driven by industrial activities, dam construction and mining: A case study in the Ganjiang River, China. Ecological Indicators, *120*, 106907. https://doi.org/10.1016/j.ecolind.2020.106907
16. Goodwin, K., Caraco, N., & Cole, J. (2008). Temporal dynamics of dissolved oxygen in a floatingleaved macrophyte bed. Freshwater Biology, *53*(8), 1632–1641. https://doi.org/10.1111/j.1365-2427.2008.01983.x
17. Gu, X., Zhang, S., Bai, X., Hu, W., Hu, Y., & Wang, X. (2005). Evolution of community structure of aquatic macrophytes in East Taihu Lake and its wetlands. Acta Ecologica Sinica, *25*(7), 1541–1548. https://doi.org/10.3321/j.issn:1000-0933.2005.07.002
18. Handley, R. J., & Davy, A. J. (2002). Seedling root establishment may limit *Najas marina* L. to sediments of low cohesive strength. Aquatic Botany, *73*(2), 129–136. https://doi.org/10.1016/S0304-3770(02)00015-3
19. Hestir, E. L., Khanna, S., Andrew, M. E., Santos, M. J., Viers, J. H., Greenberg, J. A., & Ustin, S. L. (2008). Identification of invasive vegetation using hyperspectral remote sensing in the California Delta ecosystem. Remote Sensing of Environment, *112*(11), 4034–4047. https://doi.org/10.1016/j.rse.2008.01.022
20. Hopper, J. V., Pratt, P. D., Reddy, A. M., McCue, K. F., Rivas, S. O., & Grosholz, E. D. (2021). Abiotic and biotic influences on the performance of two biological control agents, *Neochetina bruchi* and *N. eichhorniae*, in the Sacramento-San Joaquin River Delta, California (USA). *Biological Control, 153*, 104495. https://doi.org/10.1016/j.biocontrol.2020.104495
21. Hou, Y., Kong, F., Li, Y., Xi, M., & Yu, Z. (2020). Key factors of the studies on benthic macroinvertebrate in coastal wetlands: Methods and biodiversity. Ecohydrology & Hydrobiology, *20*(3), 424–436. https://doi.org/10.1016/j.ecohyd.2020.02.004
22. James, R. T., Havens, K., Zhu, G., & Qin, B. (2009). Comparative analysis of nutrients, chlorophyll and transparency in two large shallow lakes (Lake Taihu, P.R. China and Lake Okeechobee, USA). *Hydrobiologia, 627*(1), 211–231. https://doi.org/10.1007/s10750-009-9729-5
23. Jayaweera, M. W., & Kasturiarachchi, J. C. (2004). Removal of nitrogen and phosphorus from industrial wastewaters by phytoremediation using water hyacinth (*Eichhornia crassipes* (Mart.) Solms). Water Science and Technology, *50*(6), 217–225. https://doi.org/10.1016/j.watres.2003.10.005
24. Jenny, J.-P., Anneville, O., Arnaud, F., Baulaz, Y., Bouffard, D., Domaizon, I., & Weyhenmeyer, G. A. (2020). Scientists' warning to humanity: Rapid degradation of the world's large lakes. Journal of Great Lakes Research, *46*(4), 686–702. https://doi.org/10.1016/j.jglr.2020.05.006
25. Jiang, H., Zhao, D., Cai, Y., & An, S. (2012). A method for application of classification tree models to map aquatic vegetation using remotely sensed images from different sensors and dates. Sensors, *12*(9), 12437–12454. https://doi.org/10.3390/s120912437
26. Jin, X., Yan, C., & Xu, Q. (2007). The community features of aquatic plants and influence factors of lakeside zone in the north of Lake Taihu. Jouval of Lake Sciences, *19*(2), 151–157. https://doi.org/10.18307/2007.0207
27. Juttner, I., Chimonides, P. J., & Ormerod, S. J. (2010). Using diatoms as quality indicators for a newly-formed urban lake and its catchment. Environmental Monitoring and Assessment, *162*(1–4), 47–65. https://doi.org/10.1007/s10661-009-0775-2
28. Khim, J. S., Wang, T., & Snyder, S. A. (2017). The Yellow Sea ecosystem: Pollution, ecosystem threats, and environmental health. Chemosphere, *182*, 794–796. https://doi.org/10.1016/j.chemosphere.2017.05.052

29. Lacoul, P., & Freedman, B. (2006). Environmental influences on aquatic plants in freshwater ecosystems. Environmental Reviews, *14*(2), 89–136. https://doi.org/10.1139/a06-001
30. Li, J., Wu, D., Wu, Y., Liu, H., Shen, Q., & Zhang, H. (2009). Identification of algae-bloom and aquatic macrophytes in Lake Taihu from in-situ measured spectra data. Journal of Lake Sciences, *21*(2), 215–222. https://doi.org/10.18307/2009.0209
31. Li, S., & Wang, X. (2002). The spectral features analysis and quantitative remote sensing advances of inland water quality parameters. Geography and Territorial Research, *18*(2), 26–30. https://doi.org/10.3969/j.issn.1672-0504.2002.02.008
32. Li, W. (2014). Environmental opportunities and constraints in the reproduction and dispersal of aquatic plants. Aquatic Botany, *118*, 62–70. https://doi.org/10.1016/j.aquabot.2014.07.008
33. Liu, X. (2013). *Effect of screening and water purification of salt tolerance emergent plants.* (Master), Tianjin University, Retrieved from https://d.wanfangdata.com.cn/thesis/ChJUaGVzaXNOZXdTMjAyMjA1MjYSB0Q0ODcyNDUaCG4zOWR3Z3lz
34. Liu, X., Liu, X., Wu, L., & Tian, Z. (2019). Diversity in phytoplankton communities: A field test of the intermediate disturbance hypothesis. Ecological Engineering, *129*, 54–60. https://doi.org/10.1016/j.ecoleng.2018.12.009
35. Luo, J., RuiliangPu, Duan, H., Ma, R., Mao, Z., Zeng, Y., & Xiao, Q. (2020). Evaluating the influences of harvesting activity and eutrophication on loss of aquatic vegetations in Taihu Lake, China. International Journal of Applied Earth Observation and Geoinformation, *87*, 102038. https://doi.org/10.1016/j.jag.2019.102038
36. Lv, N., & Wang, X. (2013). The application of ecological water filtration systems in urban wetland park design taking the landscape design of Changguangxi River National Urban Wetland Park as an example. Landscape Architecture, *5*(5), 92–98. https://doi.org/10.3969/j.issn.1673-1530.2013.05.021
37. Martinho, F., Nyitrai, D., Crespo, D., & Pardal, M. A. (2015). Efficacy of single and multi-metric fish-based indices in tracking anthropogenic pressures in estuaries: An 8-year case study. Marine Pollution Bulletin, *101*(1), 153–162. https://doi.org/10.1016/j.marpolbul.2015.11.004
38. McVea, C., & Boyd, C. E. (1975). Effects of waterhyacinth cover on water chemistry, phytoplankton, and fish in ponds. Journal of Environmental Quality, *4*, 375–378. https://doi.org/10.2134/jeq1975.00472425000400030020x
39. Moiseenko, T. I., Voinov, A. A., Megorsky, V. V., Gashkina, N. A., Kudriavtseva, L. P., Vandish, O. I., & Koroleva, I. N. (2006). Ecosystem and human health assessment to define environmental management strategies: The case of long-term human impacts on an Arctic lake. Science of Total Environment, *369*(1–3), 1–20. https://doi.org/10.1016/j.scitotenv.2006.06.009
40. Nava, V., & Leoni, B. (2021). A critical review of interactions between microplastics, microalgae and aquatic ecosystem function. Water Research, *188*, 116476. https://doi.org/10.1016/j.watres.2020.116476
41. Nanjing Institute of Geography & Limology Chinese Academy of Sciences. (1965). *Preliminary report on comprehensive investigation of Taihu Lake*. Beijin: Science Press.
42. Oeding, S., & Taffs, K. H. (2015). Are diatoms a reliable and valuable bio-indicator to assess sub-tropical river ecosystem health? Hydrobiologia, *758*(1), 151–169. https://doi.org/10.1007/s10750-015-2287-0
43. Paillisson, J.-M., & Marion, L. (2011). Water level fluctuations for managing excessive plant biomass in shallow lakes. Ecological Engineering, *37*(2), 241–247. https://doi.org/10.1016/j.ecoleng.2010.11.017
44. Parwin, R., & Paul, K. K. (2019). Efficiency of *Eichhornia crassipes* in the treatment of raw kitchen wastewater. SN Applied Sciences, *1*(4), 381. https://doi.org/10.1007/s42452-019-0400-0
45. Pimentel, D., Lach, L., Zuniga, R., & Morrison, D. (2000). Environmental and economic costs of nonindigenous species in the United States. BioScience, *50*, 53–65. https://doi.org/10.1641/0006-3568(2000)050[0053:EAECON]2.3.CO;2
46. Pu, R., Bell, S., & English, D. (2015). Developing hyperspectral vegetation indices for identifying seagrass species and cover classes. Journal of Coastal Research, *313*, 595–615. https://doi.org/10.2112/jcoastres-d-12-00272.1
47. Rai, P. K., & Singh, J. S. (2020). Invasive alien plant species: Their impact on environment, ecosystem services and human health. Ecological Indicators, *111*, 106020. https://doi.org/10.1016/j.ecolind.2019.106020
48. Reavie, E. D., Edlund, M. B., Andresen, N. A., Engstrom, D. R., Leavitt, P. R., Schottler, S., & Cai, M. (2017). Paleolimnology of the Lake of the Woods southern basin: continued water quality degradation despite lower nutrient influx. Lake and Reservoir Management, *33*(4), 369–385. https://doi.org/10.1080/10402381.2017.1312648
49. Rowan, G. S. L., Kalacska, M., Inamdar, D., Arroyo-Mora, J. P., & Soffer, R. (2021). Multi-scale spectral separability of submerged aquatic vegetation species in a freshwater ecosystem. Frontiers in Environmental Science, *9*, 760372. https://doi.org/10.3389/fenvs.2021.760372
50. Scheffer, M., Carpenter, S., Foley, J. A., Folke, C., & Walker, B. (2001). Catastrophic shifts in ecosystems. Nature, *413*, 591–596. https://doi.org/10.1038/35098000
51. Scheffer, M., & Nes, E. H. V. (2007). Shallow lakes theory revisited: various alternative regimes driven by climate, nutrients, depth and lake size. Hydrobiologia, *584*(1), 455–466. https://doi.org/10.1007/s10750-007-0616-7
52. Schneider, S. (2007). Macrophyte trophic indicator values from a European perspective. Limnologica-Ecology and Management of Inland Waters, *37*(4), 281–289. https://doi.org/10.1016/j.limno.2007.05.001
53. Shackleton, R. T., Shackleton, C. M., & Kull, C. A. (2019). The role of invasive alien species in shaping local livelihoods and human well-being: A review. Journal of Environmental Management, *229*, 145–157. https://doi.org/10.1016/j.jenvman.2018.05.007
54. Shao, N., Yang, S., Sun, Y., Gai, Y., Zhao, C., Wang, F., & Dong, B. (2019). Assessing aquatic ecosystem health through the analysis of plankton biodiversity. Marine and Freshwater Research, *70*(5), 647–655. https://doi.org/10.1071/mf18342

55. Sun, T., Zhao, Y., Liang, R., & Zhang, X. (2012). Study on the reflected and hyperspectral mixed-pixel character of aquatic plants and water. Spectroscopy and Spectral Analysis, *32*(2), 449–452. https://doi.org/10.3964/j.issn.1000-0593(2012)02-0449-04
56. Tabinda, A. B., Arif, R. A., Yasar, A., Baqir, M., Rasheed, R., Mahmood, A., & Iqbal, A. (2019). Treatment of textile effluents with *Pistia stratiotes*, *Eichhornia crassipes* and *Oedogonium sp*. International Journal of Phytoremediation, *21*(10), 939–943. https://doi.org/10.1080/15226514.2019.1577354
57. Tan, X., Sheldon, F., Bunn, S. E., & Zhang, Q. (2013). Using diatom indices for water quality assessment in a subtropical river, China. Environmental Science and Pollution Research International, *20*(6), 4164–4175. https://doi.org/10.1007/s11356-012-1343-9
58. Tian, Y. Q., Yu, Q., Zimmerman, M. J., Flint, S., & Waldron, M. C. (2010). Differentiating aquatic plant communities in a eutrophic river using hyperspectral and multispectral remote sensing. Freshwater Biology, *55*, 1658–1673. https://doi.org/10.1111/j.1365-2427.2010.02400.x
59. Vanbelle, S. (2019). Asymptotic variability of (multilevel) multirater kappa coefficients. Statistical Methods in Medical Research, *28*(10–11), 3012–3026. https://doi.org/10.1177/0962280218794733
60. Vereecken, H., Baetens, J., Viaene, P., Mostaert, F., & Meire, P. (2006). Ecological management of aquatic plants: Effects in lowland streams. Hydrobiologia, *570*(1), 205–210. https://doi.org/10.1007/s10750-006-0181-5
61. Villa, P., Bolpagni, R., Pinardi, M., & Toth, V. R. (2021). Leaf reflectance can surrogate foliar economics better than physiological traits across macrophyte species. Plant Methods, *17*(1), 115. https://doi.org/10.1186/s13007-021-00816-4
62. Villamagna, A. M., & Murphy, B. R. (2010). Ecological and socio-economic impacts of invasive water hyacinth (*Eichhornia crassipes*): a review. Freshwater Biology, *55*(2), 282–298. https://doi.org/10.1111/j.1365-2427.2009.02294.x
63. Wang, X., Xu, Q., Xin, Y., Jin, X., Ma, G., & Li, J. (2007). Effects of macrophyte on lake ecosystem. Shandong Science, *20*(2), 29–32. https://doi.org/10.3969/j.issn.1002-4026.2007.02.007
64. Weilong, L., Weiping, H., Yonggen, C., Xiaohong., C., Zhixin, H., Yuwei, C., & Jiang, J. (2007). Temporal and spatial variation of aquatic macrophytes in West Taihu Lake. Acta Ecologica Sinica, *27*(1), 159–170. https://doi.org/10.3321/j.issn:1000-0933.2007.01.019
65. Wolf, K. L., Blahna, D. J., Brinkley, W., & Romolini, M. (2011). Environmental stewardship footprint research: linking human agency and ecosystem health in the Puget Sound region. Urban Ecosystems, *16*(1), 13–32. https://doi.org/10.1007/s11252-011-0175-6
66. Wu, X., Zhang, Z., & Jin, Y. (2019). Physiological mechanism of *Eichhornia crassipes* in inhibiting the growth of *Microcytisaeruginosa*. Russian Journal of Plant Physiology, *66*(3), 433–439. https://doi.org/10.1134/s1021443719030178
67. Yang, G., & Fang, S. (2016). Improving remote sensing image classification by exploiting adaptive features and hierarchical hybrid decision trees. Remote Sensing Letters, *8*(2), 156–164. https://doi.org/10.1080/2150704x.2016.1239282
68. Ye, C., Li, C., Yu, H., Song, X., Zou, G., & Liu, J. (2011). Study on ecological restoration in near-shore zone of a eutrophic lake, Wuli Bay, Taihu Lake. Ecological Engineering, *37*(9), 1434–1437. https://doi.org/10.1016/j.ecoleng.2011.03.028
69. Ye, C., Yao, L., Deng, A., Liu, G., & Liu, W. (2018). Spatial and seasonal dynamics of water quality, sediment properties and submerged vegetation in a eutrophic lake after ten years of ecological restoration. Wetlands, *38*(6), 1147–1157. https://doi.org/10.1007/s13157-018-1021-x
70. Yu, H., Wang, L., Liu, C., & Fan, S. (2018). Coverage of native plants is key factor influencing the invasibility of freshwater ecosystems by exotic plants in China. Frontiers in Plant Science, *9*, 250. https://doi.org/10.3389/fpls.2018.00250
71. Zeng, Q., Wei, Z., Yi, C., He, Y., & Luo, M. (2022). The effect of different coverage of aquatic plants on the phytoplankton and zooplankton community structures: a study based on a shallow macrophytic lake. Aquatic Ecology, 1–12. https://doi.org/10.1007/s10452-022-09970-w
72. Zhang, J., Xie, J., Li, Z., Zhang, X., Wang, G., Zhang, K., & Xiao, G. (2021). Phytoplankton community structure in Baiyangdian Lake with different submerged macrophyte coverages. Journal of Hydroecology, *42*(1), 75–83. https://doi.org/10.15928/j.1674-3075.20190515012
73. Zhang, Y., Jeppesen, E., Liu, X., Qin, B., Shi, K., Zhou, Y., & Deng, J. (2017). Global loss of aquatic vegetation in lakes. Earth-Science Reviews, *173*, 259–265. https://doi.org/10.1016/j.earscirev.2017.08.013
74. Zhang, Z., Zhu, Z., Yuan, M., Li, M., You, G., Chen, L., & Zhu, Y. (2020). Predict sample's line positions of absorption peaks in terahertz band with the forced radiation intensity of molecular electric dipoles. Optics Communications, *458*, 124848. https://doi.org/10.1016/j.optcom.2019.124848
75. Zhu, G. (2008). Eutrophic status and causing factors for a large, shallow and subtropical Lake Taihu, China Journal of Lake Science, *20*(1), 21–26. https://doi.org/10.18307/2008.0103
76. Zhu, K., Wu, Y., Li, C., Xu, J., & Zhang, M. (2020). Ecosystem-based restoration to mitigate eutrophication: A case study in a shallow lake. Water, *12*(8), 2141. https://doi.org/10.3390/w12082141
77. Zou, D., & Gao, K. (2009). Photosynthetic acclimation to different light levels in the brown marine macroalga, *Hizikia fusiformis* (Sargassaceae, Phaeophyta). Journal of Applied Phycology, *22*(4), 395–404. https://doi.org/10.1007/s10811-009-9471-4

Figures

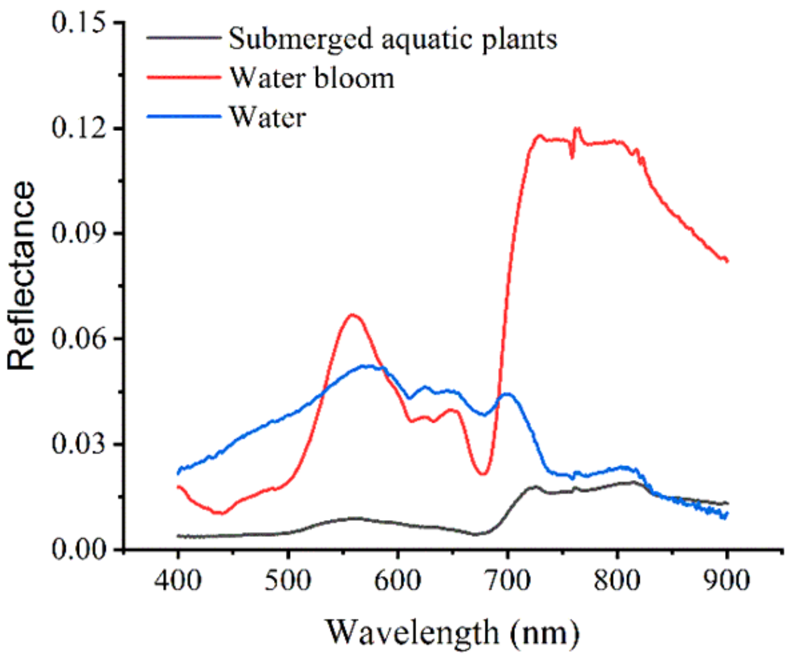

Figure 1

Reflectance spectrum curves of submerged plants, blooms, and water bodies.

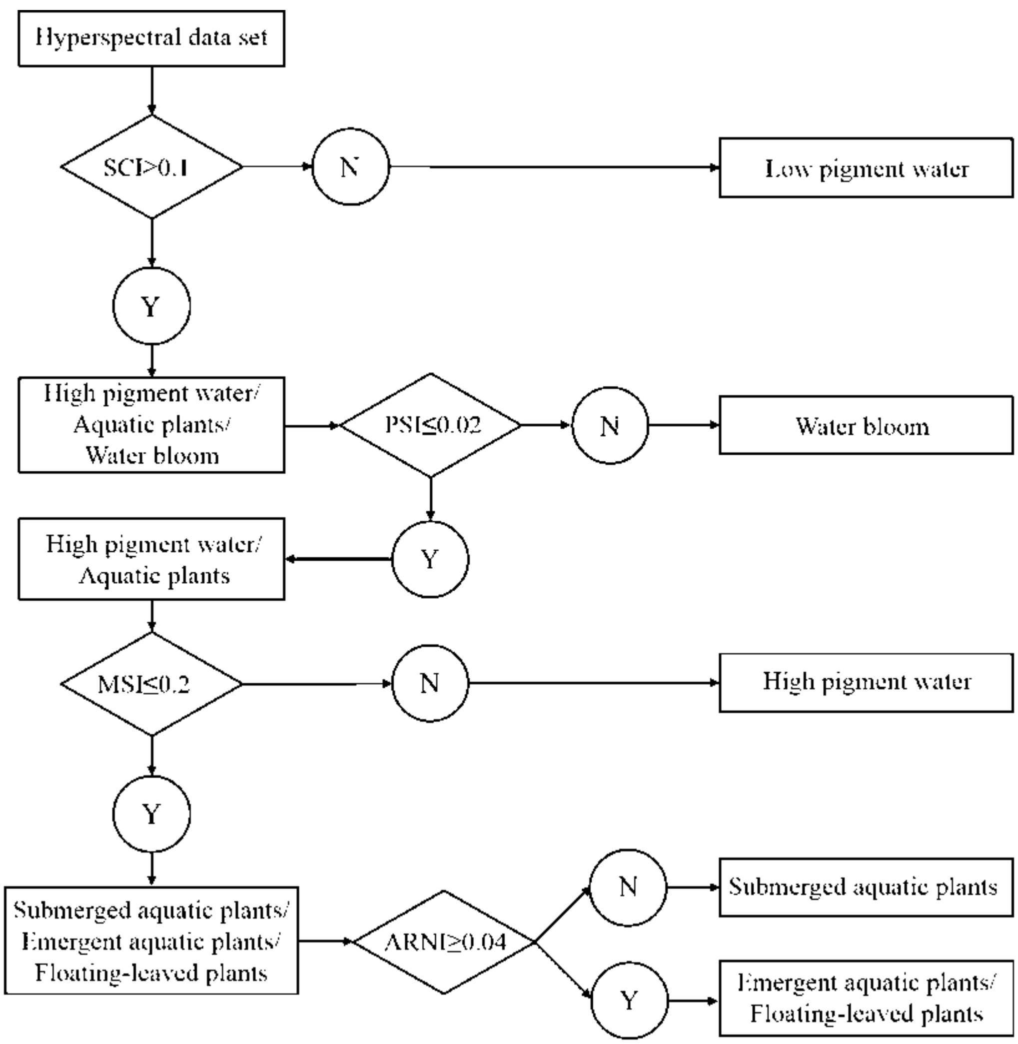

Figure 2

Decision tree classification of aquatic plants, blooms, and water bodies. **Y** means qualified, and **N**means unqualified.

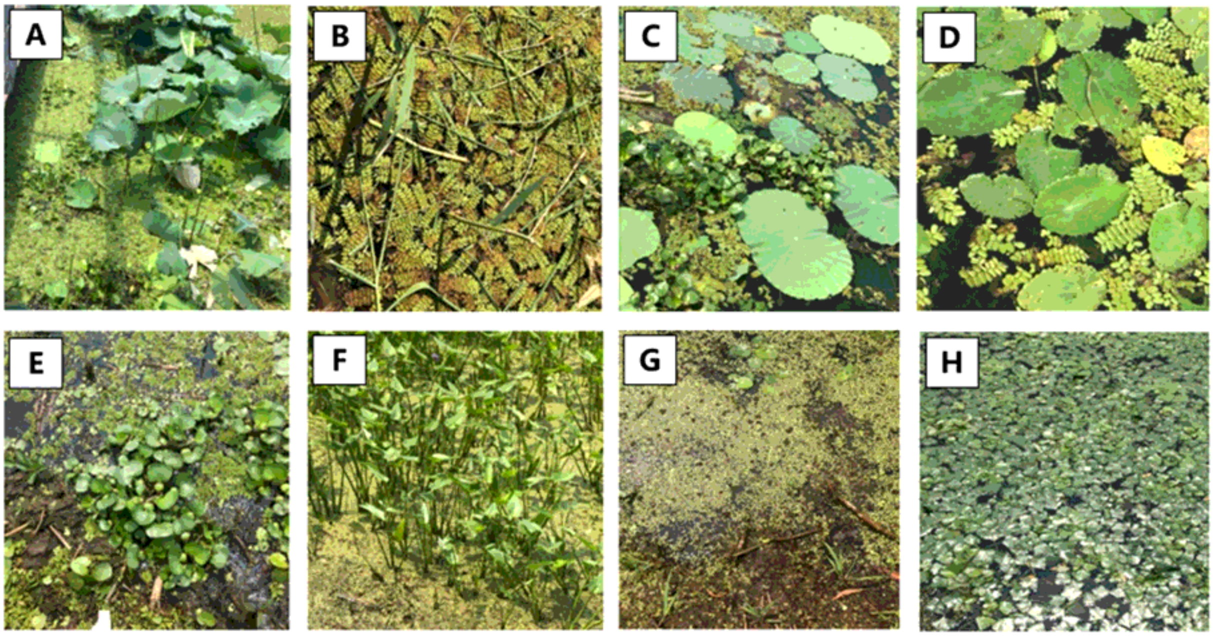

Figure 3

Images of emergent plants and floating-leaf plants. **(A)** *Nelumbo nucifera*, **(B)** *Salvinia natans*, **(C)** *Nymphaea tetragona*, **(D)** *Nymphoides peltatum*, **(E)** *Eichhornia crassipes*, **(F)** *Pontederia cordata*, **(G)** *Lemna minor*, **(H)** *Trapa natans*.

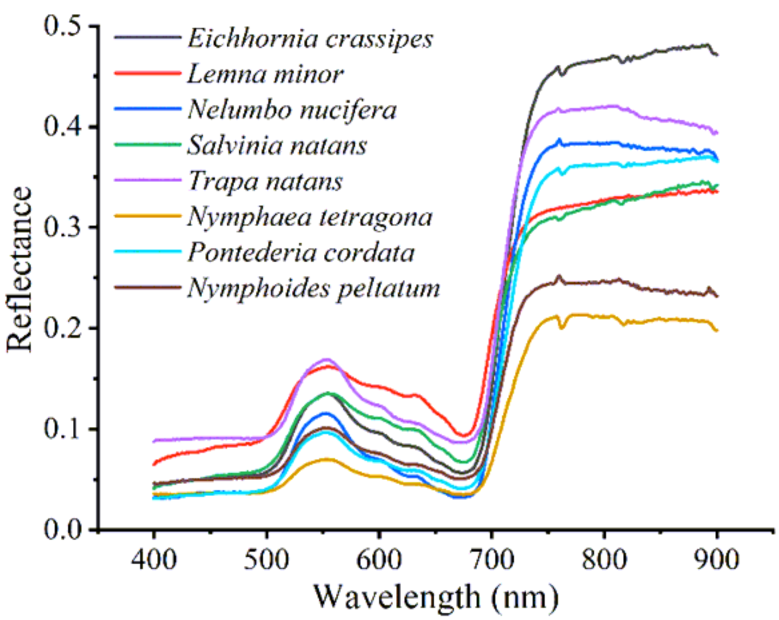

Figure 4

Spectral reflectance of eight emergent and floating leaf plants.

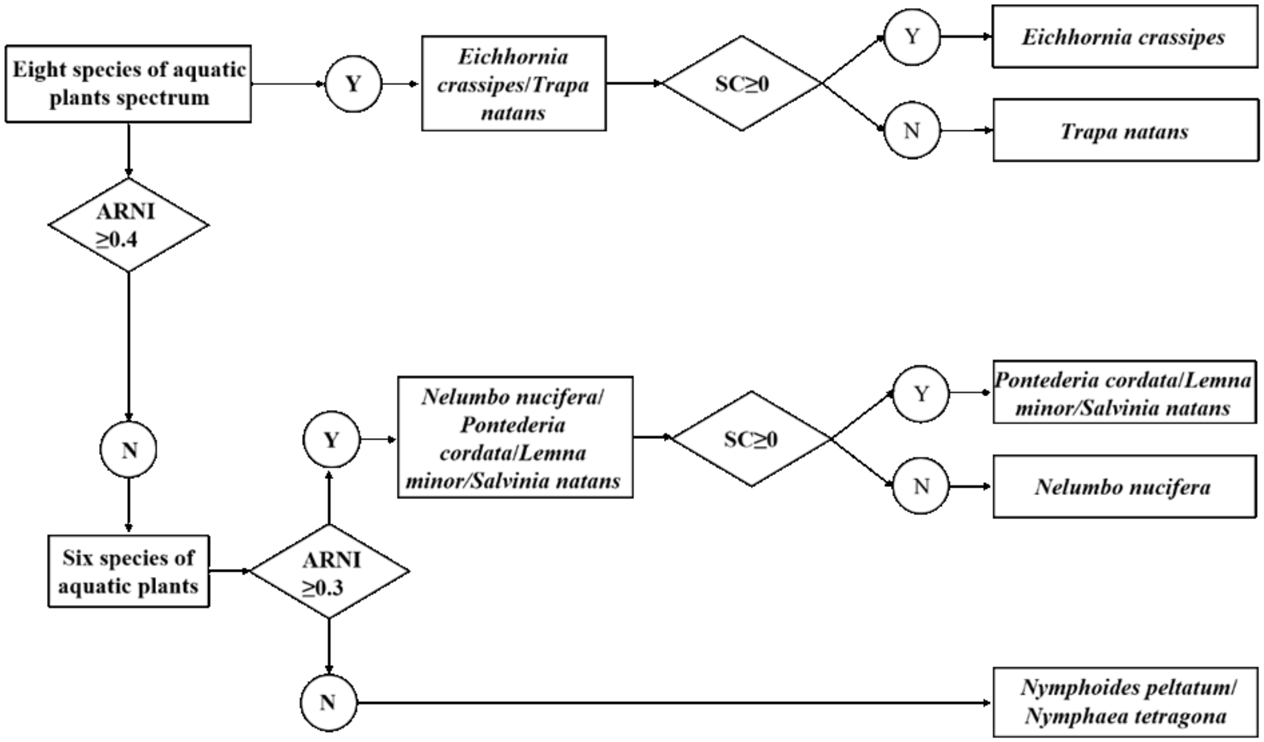

Figure 5

Decision tree for the classification of eight kinds of aquatic plants. Y means qualified, and N means unqualified.

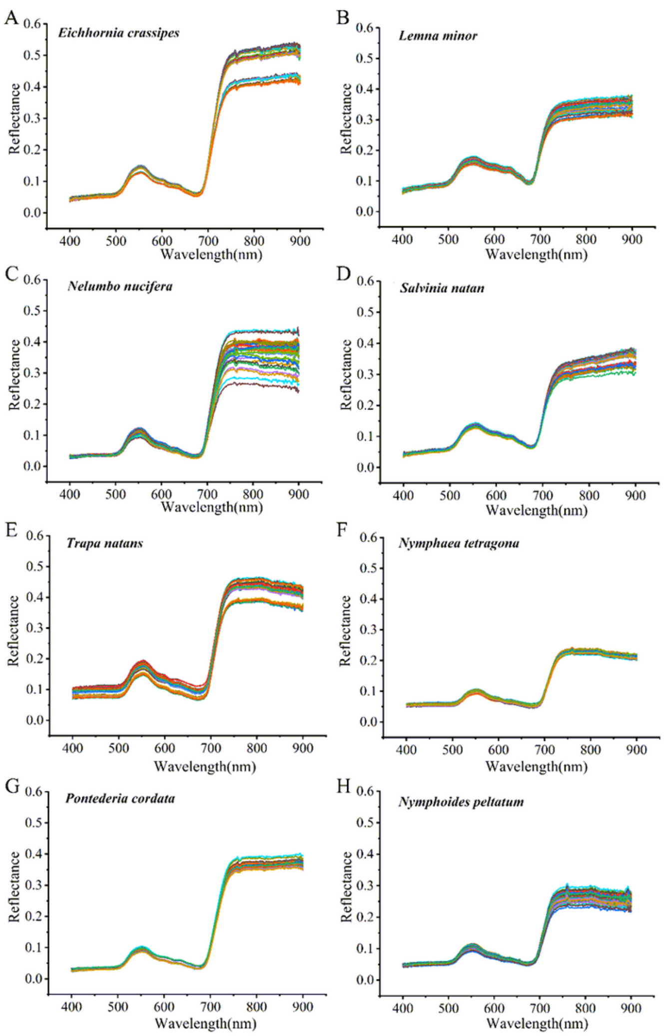

Figure 6

Spectral reflectance of the eight types of higher aquatic plants. **(A)** *Eichhornia crassipes*, 30 curves; **(B)** *Lemna minor*, 40 curves; **(C)** *Nelumbo nucifera*, 40 curves; **(D)** *Salvinia natan*, 40 curves; **(E)** *Trapa natans*, 40 curves; **(F)** *Nymphaea tetragona*, 30 curves; **(G)** *Pontederia cordata*, 40 curves; **(H)** *Nymphoides peltatum*, 40 curves.

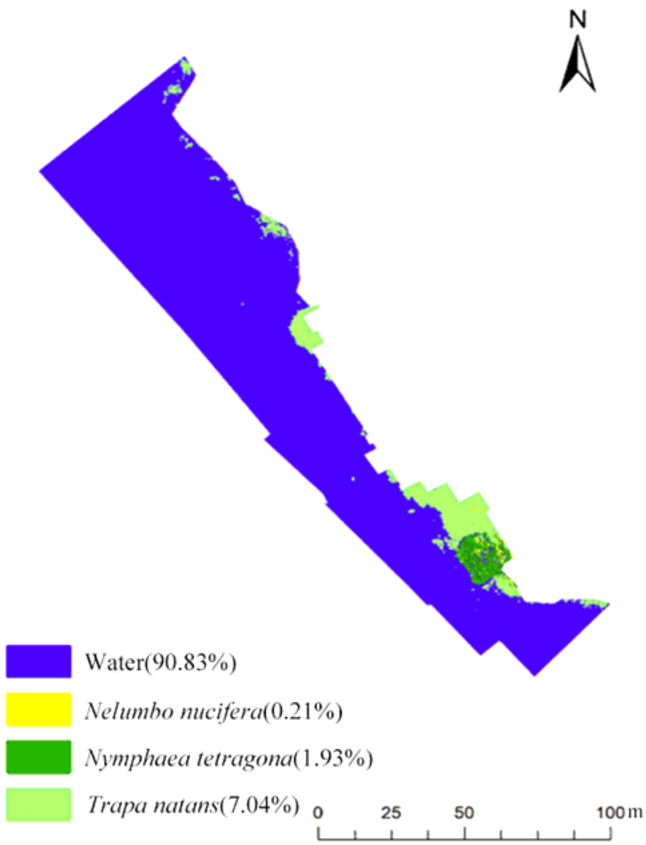

Figure 7

Hyperspectral images of Changguangxi.

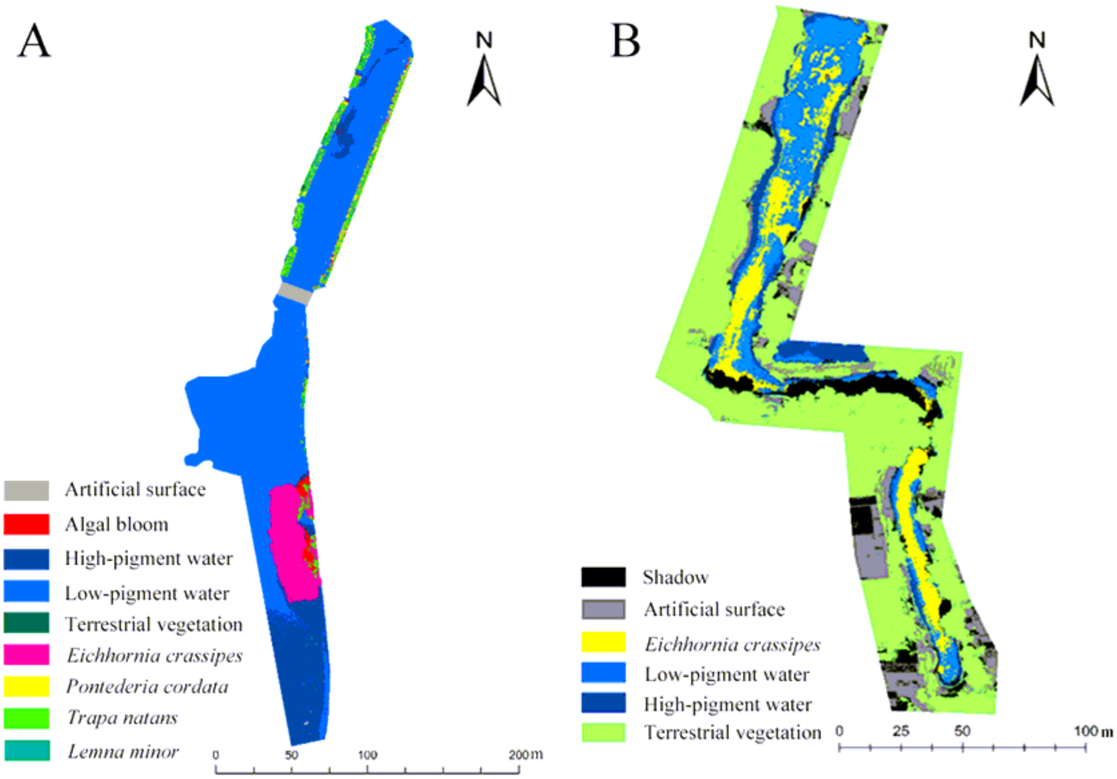

Figure 8

Hyperspectral images of Xiedaidang and Huochebang. **(A)** Xiedaidang, **(B)**Huochebang.