ABSTRACT
Water transparency is an important parameter to characterize water quality of rivers, lakes and wetlands. We measured the water quality data such as water transparency and the water spectral data of Shahu Lake. GF-1 image data were preprocessed to assure that the measured data were consistent with the reflectance curve of the remote sensing image data, and then selected an empirical method and semi-empirical/semi-analysis method of water transparency for remote sensing estimation of water transparency and constructed a remote sensing estimation model suitable for studying the water transparency of Shahu Lake. The new model was combined with GF-1 image data to analyze the total temporal and spatial variation characteristics of the water. The results showed that the empirical model based on the measured band 1/B4 of the spectral data was the best model for water transparency remote sensing estimation of Shahu Lake. The model was expression: 
\[ SD = 0.3336 \times \left( \frac{1}{B1} \right) + 27.94. \]
The coefficient of determination of the verification model was 0.7454. The estimation of the water transparency model showed that the water in Shahu Lake has the transparency of the central lake and intake was higher and the transparency of the Third Drainage, Bird Island and Old Wharf were lower compared to each region. These findings were consistent with the measured numerical characteristics. The transparency of Shahu Lake is mainly affected by the water quality index, tourism activities, ecological hydration and distribution of reeds.
1. Introduction

Water transparency is a parameter that intuitively reflects water quality. It is an important indicator of eutrophication (Lysiak-Pastuszak et al. 2014), and it is affected by solar radiation (Li 2006), optical attenuation (Vantrepotte et al. 2007), suspended particulate matter and phytoplankton (Zhang et al. 2006). Suspended matter is the main factor affecting the transparency of water, mainly by reducing the amount of light radiation and reducing water visibility. In addition, organisms such as planktonic algae in water absorb and scatter light, which affects water transparency (Chellappa et al. 2009).

Measurement of water transparency is mainly accomplished by optical sensors and the SecchiDisk (Lewis et al. 1988). The SecchiDisk is easy to use and economical (Prasad et al. 2000). However, when using the SecchiDisk for water transparency measurement, the transparency value often deviates from the actual value due to the influence of surrounding environment background and the subjective input of the user. The SecchiDisk value only reflects the water transparency at the selected target point and it is inappropriate for measuring the water transparency in other areas (Wu et al. 2007). Remote sensing technology is now commonly used for water transparency monitoring because of its wide observation area, timeliness, high resolution and ability to obtain data from remote areas (Katja and Oppelt 2016). The Coastal Zone Color Scanner (CZCS) in the 1970s, marine satellites, and MODIS and MERIS in the 1990s were sensors with several narrow bands (~20 nm) in the visible region. They measured the radiance of these bands and provided quantitative information on water components. Examples include chlorophyll or suspended particulate matter concentration and water transparency (Parslow et al. 2010; Maeva et al. 2011; Vilas et al. 2013). These sensors are useful in coastal areas and large lakes (Miller and Mckee 2004), but spatial resolution, radiation resolution and atmospheric correction accuracy were limited. Errors occurred in the estimation of water transparency. The remote sensing monitoring of water transparency in small lakes requires highly accurate hyperspectral data or high spatial resolution satellite imagery data, and most sensors do not provide high spatial resolution measurements for smaller areas such as bays, estuaries and lakes. Landsat series satellite data features of time, space and spectral resolution combinations enable it to be used for monitoring lake water quality (Cox et al. 1998). The United States government has considered adoption of a charging policy for the Landsat series of satellite data (Popkin 2018). If the changes are implemented, they could increase the difficulty of data acquisition and lead to higher costs.

Domestic satellite data could be useful for water quality research. The GF-1 satellite developed by China has high spatial and temporal resolution. It can be used to detect local environmental pollution and for macroscopic monitoring and evaluation of water, atmosphere and environment quality. The signal strength of the GF-1 PMS2 sensor is greater than the Landsat-8 OLI in the visible light band and it has advantages in the remote sensing analysis of small lakes (Wu et al. 2019). The resolution of hyperspectral data is 10 nm, which can reflect the complex spectral features and subtle changes of the ground spectrum of inland water. These data are widely used in transparency estimation. Hyperspectral data are divided into imaging and non-imaging. The imaging hyperspectral technique combines a traditional image with the ground spectrum to achieve syncretic combination of image and spectrum, and produces a continuous spectral curve while acquiring the image of the object space (Yu et al. 2015). Koponen combined hyperspectral data and water transparency data obtained from four measurements of lake water quality in southern Finland (Koponen et al. 2002). They found that the model with the 521 and 700 nm reflectance estimation transparency had the highest coefficient of determination.
The nine bands of MERIS are required for detecting Chlorophyll a in the surface waters of southern Finland and the Baltic coast (Härmä et al. 2001).

This study established a model for measuring water quality based on field data combined with GF-1 remote sensing images, which was used to analyze the temporal and spatial variation characteristics of water transparency in small- and medium-sized lakes, providing dynamic water transparency monitoring data and more model selection for transparency monitoring of inland small- and medium-sized lakes. Finally confirmed the model improved the water quality monitoring model for evaluation of lakes and reservoirs, and provides a better method of water quality analysis.

2. Materials and methods

2.1. Sample layout and data acquisition

Shahu Lake (106°19′6″E-106°24′10″E, 38°45′17″-38°49′42″N) is a typical oasis-sedimentary structured depression lake (Figure 1). The sample layout was divided into two series. Series one was based on differences in environmental conditions. Shahu Lake was divided into seven areas and seven sampling points including Old Wharf (S1), No. 5 Bridge Farm (S2), intake (S3), Bird Island (S4), Central Lake (S5), New Docklands (S6) and Third Drainage (S7). Series two included two cross-shaped strips that were evenly distributed over the entire lake surface with 22 sampling points (1–22) and a total of 29 sampling points. GPS on-site positioning during sampling was used to ensure that the sampling points were consistent (Figure 2).

Water samples were collected every two months (synchronously using the Field-SpecProFR-2500 portable field spectrometer from ASD (Boulder, CO, USA) to collect spectral data of correspond points) from June to October of 2017. The sample time span corresponds to the acquisition times of GF-1 remote sensing images, which were June 22, August 11 and October 26. In addition, we obtained 17 GF-1 remote sensing images during 2017 (Table 1), and collected 2 L water samples below the water surface 50 cm using a plexiglass water collector. Samples were put into polyethylene bottles, returned to the laboratory and stored inside a dark refrigerator at 4°C.

2.2. Methods

2.2.1. Sample determination method

Index determination of water samples was carried out in two parts. Water temperature, water depth, dissolve oxygen and transparency were measured on-site, by a YSI handheld multi-parameter measuring rod and a SecchiDisk. The laboratory water sample was divided into three parts. One part about 0.6 L was filtered with a 0.45 μm microporous membrane for extraction and determination of the Chl-a. A sample about 0.3 L, filtered with a 0.45 μm microporous membrane, was used to determine the TSS. A sample about 0.5 L was used to determine water quality parameters such as COD_{Mn}, TP, TN and NH_3–N. According to the research needs and work progress, the spectral data, SD, TSS and Chl-a were measured in water taken from the 29 sampling points mentioned previously. Other water quality indicators were measured from S1–S7 sampling points.

2.2.2. Data processing

We used IBM SPSS Statistics 2017 (Chicago, IL, USA), Origin and Excel software for descriptive statistics and correlation analysis of the Shahu water quality data. According
to the environmental quality standards for surface water of China (GB3838-2002), the limit value of the class III water standard was used as the evaluation basis. The Nemero Water Pollution Index Method was used to evaluate the water quality of Shahu Lake.
The measured point spectral curve data were exported in ASDViewSpecPro software and the curves of numerical and shape anomalies were eliminated. The spectral curves of the sample points were averaged by software. We used the following formulas to calculate the water remote sensing spectral reflectance (Figure 3) and equivalent reflectance (Figure 4) of Shahu Lake. The measured data were consistent with the reflectance curve of the remote sensing image data:

\[
R_{rs}(\lambda_i) = \frac{(L_{sw}(\lambda_i) - 0.025 \times L_{sky}(\lambda_i))R_p}{(\pi \times L_p(\lambda_i))}
\]

where the \(R_{rs}\), \(L_{sw}\), \(L_{sky}\), \(R_p\) and \(L_p\) represent remote sensing spectral reflectance, total radiance value, sky scatter radiation, gray plate reflectivity and the radiance measured by

| The data source                              | Data acquisition time                |
|----------------------------------------------|--------------------------------------|
| Field measured spectral data                 | 6.22, 8.11, 10.26                    |
| GF-1 remote sensing image data               | 3.26, 4.02, 4.27, 5.06, 5.26, 6.08, 6.16, 7.01, 7.18, 8.04, 9.02, 9.23, 10.04, 10.12, 10.28, 11.07, 11.14 |

Figure 3. Spectral reflectance of partial measurement point.

Figure 4. Spectral resampling reflectance curve of partial measurement point.
standard plates, the fresnel reflection coefficient of the water–air surface to the sky light is \( r \) (taking into account the meteorological and hydrological characteristics of the Shahu Lake, \( r = 0.025 \))

\[
\text{Equivalent reflectivity} : q_s(\lambda) = \frac{\int_{\lambda_{\text{min}}}^{\lambda_{\text{max}}} \rho_s(\lambda_i) \Psi(\lambda_i) d\lambda}{\int_{\lambda_{\text{min}}}^{\lambda_{\text{max}}} \Psi(\lambda_i) d\lambda}
\]

where the \( \rho_s(\lambda_i) \), \( \lambda_{\text{max}} \), \( \lambda_{\text{min}} \), \( \rho_s(\lambda_i) \) and \( \Psi(\lambda_i) \) represent the simulated reflectivity of satellite sensor bands, the minimum and maximum wavelengths of the wavelength range, the reflectance of the \( i \)th wavelength response point of the field measured spectrum, and the spectral response function value of the \( i \)th wavelength response point of the satellite sensor.

We used ENVI software for geometric correction, radiometric calibration and atmospheric correction processing of the downloaded GF-1 image data. At the same time, we adopt the normalized water index to extract the water of Shahu Lake to better study the water of Shahu Lake. For data processing, samples with large errors due to floating garbage on the water surface were removed and 45 samples were randomly selected from the effective 66 samples for model construction. The remaining 21 points were used for model verification.

3. Results and analysis

3.1. Correlation between water transparency and water quality parameters

For each sampling point, measured transparency and water quality parameters were studied using correlation analysis (Table 2). The pH, Chl-a and TSS were negatively correlated with transparency (\( p < .01 \)), and the correlation coefficients, respectively, were \(-0.509\), \(-0.342\) and \(-0.628\). NH\(_3\)-N was negatively correlated with transparency (\( p < .05 \)). DO was positively correlated with transparency (\( p < .01 \)). COD\(_{\text{Mn}}\) was positively correlated with transparency (\( p < .05 \)), and correlation coefficients, respectively, were 0.685 and 0.585. The transparency of Shahu Lake water was mainly affected by water quality indicators such as pH, DO, COD\(_{\text{Mn}}\), Chl-a and TSS.

3.2. Spatial distribution of TSS and Chl-a and their effects on water transparency (SD)

Correlation analysis showed that TSS and Chl-a are the main factors affecting the transparency of Shahu Lake (Figure 5). The transparency, TSS and Chl-a data measured by three samples were interpolated by inverse distance weight method (IDW), and the relationship between TSS and Chl-a with water transparency was analyzed from the spatial distribution and time variation.

The water concentration of TSS was higher in northwest of the Intake area, Old Wharf area and New Docklands on June 22, and the corresponding spatial distribution of transparency was generally consistent. The concentration of TSS was higher but the
corresponding water transparency was low in the Bird Island area on August 11. On October 26, the concentration of TSS was higher in the Bird Island area and the water transparency was also higher in the Bird Island area.

The water concentration of Chl-a was higher in the farming area on June 22, but the corresponding transparency value was lower. On August 11 and October 26, the spatial distribution of Chl-a was similar. Both concentrations were high, and the corresponding transparency value was low in the Bird Island area. On June 22, August 11 and October 26, the concentration of Chl-a tended to deteriorate on the whole, and only in local waters showed a trend of improvement, and the water transparency in the corresponding period was variable, and the spatial heterogeneity was large.

From the perspective of time change, the water transparency on June 22 was higher in Old Wharf, Bird Island and the Third Drainage area, while the concentration of Chl-a was lower in this area and this period, that indicated it was mainly affected by the
concentration of CH1-a. On August 11 and October 26, the spatial distribution of water transparency was opposite to that of suspended matter, and the coincidence degree was very high, indicating that suspended matter was the main factor affecting water transparency in this period. The TSS, water transparency and Ch1-a presented a point family distribution in this area of bird island on October 26 and August 11, that was mainly because the area of bird island growth lots of water plants such as reeds, underwater plankton, microorganisms and birds, fish also gather here, causing disturbance and plant purification to occur frequently in local areas.

Above analysis shows that: the spatial heterogeneity of water transparency is large, which indicates that water transparency is driven by multiple factors, and the change of a single index is difficult to drive the change of water transparency.

### 3.3. Construction and verification of water transparency estimation model

Remote sensing monitoring of water transparency is needed to establish a transparent remote sensing estimation model. The study mainly explored remote sensing estimation of empirical models and semi-analytical models for water transparency readings.

#### 3.3.1. Empirical models

We selected the established four ($1/B4$, $1/B3$, $B2/B3$ and $B1/B2$) sensitive band combination estimation factors according to the correlation size to construct a water transparency estimation line model. The linear models were: $SD = 0.3336(1/B4) + 27.94$, $SD = 2.378(1/B3) + 16.718$, $SD = 64.428(B2/B3) - 49.452$ and $SD = -190.36(B1/B2) + 160.68$, and the determination coefficients of the four models respectively were 0.6661, 0.6249, 0.6256 and 0.5921.

#### 3.3.2. Verification of the estimation models

Used the verification samples to verify the linear models (Figure 6), we found that the estimated and measured values of the root mean square error were 6.82, 7.23, 7.22 and 7.54 cm. The average relative errors were 12.59%, 13.73%, 10.56% and 14.46%. The decision coefficients of the verification models were 0.7454, 0.6453, 0.6239 and 0.4992. Comparing the stability and accuracy of the four models, we found that the empirical model constructed by the combined reflectance of the $1/B4$ band had the highest accuracy.

#### 3.3.3. Semi-analytical model

Based on relevant research (Zhu et al. 2010, 2015; Xu et al. 2011; She et al. 2017), we selected the semi-analytical model of transparency estimation. The model calculation formula is:

$$C_{TSS} = 119.62 \times \left(\frac{B3}{B2}\right)^{0.0823}$$

$$SD = 284.15 \times C_{TSS}^{-0.67}$$

#### 3.3.4. Verification of the models

We used all samples to verify the semi-analytical model. The estimated and measured values of the root mean square error were 15.81 cm, the average relative error was 23.3% and the coefficient of determination of the semi-analytical model was 0.5727 (Figure 7).
3.3.5. Models selection

Comparing the accuracy and determination coefficient of the best empirical model and semi-analytical model, the 1/B4 empirical model verifies of the overall predicted and measured values about the root mean square error was 6.82 cm, the average relative error was 12.59% and the coefficient of determination of the verification model was 0.7454. The estimated and measured values of the semi-analytical model verified about the root mean square error were 15.81 cm, the average relative error was 23.3%, and the coefficient of

Figure 6. Contrast between estimated and measured values of SD.

Figure 7. Contrast between estimated and measured values of SD.
The determination of the verification model was 0.5727. Comprehensive the stability and accuracy of models, and finally select the empirical model constructed by the band ratio 1/B4. The model formula is:

$$SD = 0.3336 \times \left( \frac{1}{B4} \right) + 27.94$$

### 3.4. Temporal and spatial variation characteristics of water transparency

We applied the empirical model to the 2017 GF-1 remote sensing image during the time span of March–November of 2017 (December–March of the following year is the lake icing period, so the transparency estimated value of March–November represents the whole year). We used ArcGIS software to plot the transparency spatial distribution map, calculate the variation in overall time and variation in time for each area and analyze the spatial variation characteristics of water transparency.

The estimation results were used to extract the transparency values of 85 points covering the lake surface over different seasons. The water transparency was more obvious with the seasonal changes (Figure 8). The period of March–May showed an initial drop, transparency varied from May to the beginning of October but was generally low (≤30 cm). In late June, water transparency reached its lowest value and transparency gradually increased from June until November.

In the seasonal distribution (Table 3), spring (March–May) the transparency value ranged from 4.76 to 82.7 cm. The average value was 37.81 cm, and the median value was 42.39 cm. During summer (June–August) the transparency value ranged from 6.04 to 41.66 cm, with an average value of 20.64 cm, and a median value of 23.16 cm. In autumn (September–November) the transparency value ranged from 6.21 to 72.73 cm, with a mean value of 31.09 cm. The water transparency is lower in summer and higher in spring and autumn.

![Figure 8. Time distribution of water transparency estimation.](image)

Table 3. Water transparency estimation data from Shahu Lake.

| Season       | Minimum | Maximum | Mean   | Median | Standard deviation |
|--------------|---------|---------|--------|--------|--------------------|
| Spring \( (n = 6) \) | 4.76    | 82.7    | 37.81  | 42.39  | 18.2               |
| Summer \( (n = 10) \) | 6.04    | 41.66   | 20.64  | 23.16  | 7.98               |
| Autumn \( (n = 14) \) | 6.21    | 72.73   | 31.09  | 30.47  | 14.32              |
Figure 9. Spatial distribution of water transparency.
Figure 9. Continued.
Figure 9. Continued.
We used the estimation results of water transparency to execute the spatial interpolation and analyze its characteristics (Figure 9). From March to May, the transparency values of the Central Lake district, Intake area and the No. 5 Bridge Farming area were higher than other areas. The transparency showed an initial decreasing trend followed by a rise and then a fall. This was consistent with the analysis of time variation. From June to August, the spatial distributions of water transparency were similar. The low value transparency area was in the New Docklands and Third Drainage and the high transparency value areas were Lake Central and the Bird Island. The spatial distribution boundary of water transparency was more obvious from September to November. The spatial distribution characteristics of water transparency were generally consistent from September to October and the transparency was lower in the New Docklands and Third Drainage. The Bird Island district had a higher transparency value. The range of high transparency areas in November increased. The No. 5 Bridge Farming area, Central Lake district, Intake area and the Old Wharf area were all higher and the Bird Island area and Third Drainage area were relatively lower.

Statistical analysis of the transparency values of the 30-view estimation product, the Intake area, the No. 5 Bridge Farming area, the Bird Island district, the Central Lake district, the New Docklands area and the Third Drainage area (Figure 10) showed the following.

The estimated value of transparency in the Old Wharf area initially decreased and then rose during the remainder of the year. The transparency value reached lows of 12.64 and 13 cm on June 28 and August 4, respectively, and reached a peak of 44.41 cm on March 25.
26. The transparency value of the intake area also initially decreased and then rose. It reached a low value of 8.24 cm on June 28 and reached peaks of 44.73 and 42.29 cm, respectively, on March 26 and April 27. The transparency value fluctuations during the whole year were relatively large in the No. 5 Bridge Farming area, and had a trend of initial decline followed by an overall rise. The transparency value reached a bottom value of 9.28 cm on June 28, and reached a peak of 52.70 cm on March 26. The estimated transparency in Central Lake had low values of 11 and 15.74 cm on June 28 and July 6, and then peaked at 54.45 and 56.36 cm on March 26 and April 27. The annual trend of the New Docklands was consistent with Central Lake, reaching a 60.91 cm peak on March 26 and a low value of 10.43 cm on June 28. The annual variation trends of Bird Island and the Third Drainage were different from other areas. The trend was an initial rise followed by a decrease. This trend possessed the characteristics of a high summer and autumn and a low spring.

4. Discussion

4.1. Influence of water quality parameters to the water transparency

The water quality parameters is a visual representation of water quality and it comprehensively reflects the impact of factors such as internal, external, point, surface source pollutants and wind or wave disturbances on the water environment. The composition and level of TSS are the main factors influencing transparency and they have a direct influence on water transparency (Zhang et al. 2003). Chl-a indirectly affects water transparency through the amount of algae (Zhang et al. 2009). An increased concentration of nutrient
leads to an increase of phytoplankton biomass. This decreases light conditions underwater (water transparency decreases) and affects the underwater light field distribution. The primary productivity of the water is decreased resulting in the water quality deterioration. The pH determines the form of the inorganic carbon source in the water which in turn affects the photosynthetic rate (Brettum 1996).

We used linear regression to fit the pH, DO, Chl-a and TSS with measured data of SD (Figure 11). Water transparency decreased with the increase of pH, Chl-a and TSS. Shahu Lake is a shallow water lake with a relatively high annual wind speed. It is also a tourist attraction, and boats and yachts commonly move around the lake, agitating the sediment particulate matter and reducing the water transparency. The pH was negatively correlated with water transparency. The pH can influence the species composition and distribution of phytoplankton. Higher pH is more favorable to cyanobacteria growth (Qiu et al. 2012), the monitoring data showed that the pH of Shahu Lake is >8 which favors the growth of cyanobacteria. Cyanobacteria can directly reduce the transparency of water and also increase the level of Chl-a. The water transparency increased with the increase of DO, and these factors had a significant positive correlation. Higher levels of dissolved oxygen in water foster the photosynthesis of aquatic plants and increase plant growth. The aquatic plants are mainly reeds in Shahu Lake and the reeds consolidate sediment and increase water quality (Liang et al. 2013).

4.2. Effect of artificial water replenishment on water transparency

We found that, in 2017, the total lake water was replenished six times, and the replenishment water volume was 2017.3 cubic in 2017 (Table 4). In the supply water, the content of COD$_{\text{Mn}}$ was greatest, reaching 40.346 t. The contents of NH$_3$–N and TP were lower.

![Figure 11. Correlation between major water quality indicators and water transparency.](image-url)
Comparing the time change of water transparency, we found that the peak of water transparency is roughly consistent with the water replenishment time, indicating the artificial water replenishment improved the water transparency. The replenishment water source is mainly Yellow River water. Considering the impact of water quality on the ecosystem and the tourism industry, the Yellow River water was replenished after purification (Luo & Qu 2011).

### 4.3. Influence of tourism activities to the water transparency

The number of tourists and the correlation analysis with water transparency of Shahu Lake (Figure 12) indicates that water transparency is inversely related to the number of tourists. From April to October is the tourist season on Shahu Lake, and holidays concentrate tourist numbers in May, August and October. We found that transparency had corresponding low values in May, August and October compared with the time variation characteristics of water transparency.

The pollutants generated by tourism activities mainly include boat fuel, tourist garbage solid waste, wade tourism, etc. There are more than 200 restaurants, hotels, entertainment venues and shops around the Shahu Lake, and the wastewater generated by these accommodations and catering service facilities is only partially treated. Wastewater enters the lake directly and affects water transparency.

### 4.4. Influence of reed to the water transparency

The water purification effect of aquatic plants is obvious, and it can play an important role in the ecological environment protection and the restoration of degraded water

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**Table 4.** Main pollutant index content of artificial recharge water in 2017.

| Date of water replenishment | Water replenishment (10^4 cubic meters) | Pollutant flux (t) |
|-----------------------------|----------------------------------------|--------------------|
|                             |                                        | COD<sub>Mn</sub>  | NH<sub>3</sub>-N  | TP   |
| April                       | 452.46                                 | 9.052              | 1.0455            | 0.5884 |
| May                         | 496.2                                  | 9.924              | 1.1462            | 0.6451 |
| July                        | 393.6                                  | 7.872              | 0.9092            | 0.5117 |
| August                      | 330.3                                  | 6.606              | 0.763             | 0.4294 |
| October                     | 293.1                                  | 5.862              | 0.6771            | 0.3811 |
| November                    | 51.5                                   | 1.03               | 0.119             | 0.067  |
| Total                       | 2017.3                                 | 40.346             | 4.66              | 2.6225 |

**Figure 12.** Relationship between water transparency and the number of tourists.
ecosystems of lake and wetlands (Wu et al. 2018). Reeds can reduce the water waves fluctuation of lake surface, inhibit the agitation of suspended particles in sediment, absorb the pollutants and nutrients of water, inhibit the growth of algae, reduce the load of sediment pollution, purify the water and improve the water transparency (Li 2010). The reeds are mainly distributed in the Bird Island and the Third Drainage of Shahu Lake (Figure 13). Compared with the change characteristics of water transparency value, it is found that the transparency of Bird Island and Third Drainage is different from other areas and present a trend is first rising and then decreasing overall. The transparency was higher than other months from June to September and the transparency began to decline after October. The reeds entered the vegetative period from June to September, and the purification power was strong, which lead to the water transparency in this period was higher than other months in Bird Island and the Third Drainage. After October, the reeds entered a recession and the plants began to wither, and the purification effect was weakened of the reeds to the water (Qiao et al. 2017).

5. Conclusions
This research according to the spring, summer and autumn three times and more water quality monitoring of point, measured data of water spectrum in combination with the same period GF-1 image data, to analysis in time and space distribution characteristics of water transparency and correlation with other water quality parameters in Shahu Lake.
(oasis in middle and small lakes), found that both Chl-a and TSS could affect the transparency of water. The empirical model was built based on the sensitive band, and compared with the semi-analytical model suitable for remote sensing monitoring of lake water transparency, it was found that the empirical model constructed by band combination 1/B4 had a better remote sensing effect on water transparency estimation. The empirical model was applied to GF-1 remote sensing image to estimate the water transparency parameters of Shahu Lake, found that the transparency was the lowest in summer, followed by autumn and the highest in spring, and the Central Lake and Intake areas of high transparency, and Third Drainage, Bird Island and Old Wharf of low transparency. The factors affecting the water transparency of Shahu Lake were mainly by the water quality indicators, tourism activities, water replenishment and the distribution of reeds.

**Disclosure statement**

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