Remote Estimation of Water Clarity and Suspended Particulate Matter in Qinghai Lake from 2001 to 2020 Using MODIS Images

Zhenyu Tan 1,2, Zhigang Cao 3, Ming Shen 3, Jun Chen 4, Qingjun Song 5,6 and Hongtao Duan 1,2,3,*

1 College of Urban and Environmental Sciences, Northwest University, Xi’an 710127, China; tanzhenyu@nwu.edu.cn
2 Shaanxi Key Laboratory of Earth Surface System and Environmental Carrying Capacity, Northwest University, Xi’an 710127, China
3 Nanjing Institute of Geography and Limnology, Chinese Academy of Sciences, Nanjing 210008, China; zgcao@niglas.ac.cn (Z.C.); mshen@niglas.ac.cn (M.S.)
4 School of Human Settlements and Civil Engineering, Xi’an Jiaotong University, Xi’an 710049, China; chenjun@xjtu.edu.cn
5 National Satellite Ocean Application Service, Ministry of Natural Resources of the People’s Republic of China, Beijing 100081, China; kingdream@mail.nsoas.org.cn
6 Key Laboratory of Space Ocean Remote Sensing and Application, Ministry of Natural Resources of the People’s Republic of China, Beijing 100081, China
* Correspondence: htduan@niglas.ac.cn or htduan@nwu.edu.cn

Abstract: Climate change and human activities have been heavily affecting oceanic and inland waters, and it is critical to have a comprehensive understanding of the aquatic optical properties of lakes. Since many key watercolor parameters of Qinghai Lake are not yet available, this paper aims to study the spatial and temporal variations of the water clarity (i.e., Secchi-disk depth, Z SD) and suspended particulate matter concentration (CS PM) in Qinghai Lake from 2001 to 2020 using MODIS images. First, the four atmospheric correction models, including the NIR–SWIR, MUMM, POLYMER, and C2RCC were tested. The NIR–SWIR with decent accuracy in all bands was chosen for the experiment. Then, four existing models for Z SD and six models for CS PM were evaluated. Two semi-analytical models proposed by Lee (2015) and Jiang (2021) were selected for Z SD (R^2 = 0.74) and CS PM (R^2 = 0.73), respectively. Finally, the distribution and variation of the Z SD and CS PM were derived over the past 20 years. Overall, the water of Qinghai Lake is quite clear: the monthly mean Z SD is 5.34 ± 1.33 m, and CS PM is 2.05 ± 1.22 mg/L. Further analytical results reveal that the Z SD and CS PM are highly correlated, and the relationship can be formulated with Z SD = 8.072 e^−0.212 CS PM (R^2 = 0.65). Moreover, turbid water mainly exists along the edge of Qinghai Lake, especially on the northwestern and northeastern shores. The variation in the lakeshore exhibits some irregularity, while the main area of the lake experiences mild water quality deterioration. Statistically, 81.67% of the total area is dominated by constantly increased CS PM, and the area with decreased CS PM occupies 4.56%. There has been distinct seasonal water quality deterioration in the non-frozen period (from May to October). The water quality broadly deteriorated from 2001 to 2008. The year 2008 witnessed a sudden distinct improvement, and after that, the water quality experienced an extremely inconspicuous degradation. This study can fill the gap regarding the long-time monitoring of water clarity and total suspended matter in Qinghai Lake and is expected to provide a scientific reference for the protection and management of the lake.

Keywords: Qinghai Lake; Secchi disk depth; total suspended matter; MODIS, BFAST; Mann–Kendall test; water color; remote sensing
1. Introduction

Lakes can provide fundamental drinkable water resources for human beings and as an important surface water can extensively affect the surrounding climate and ecological environment and vice versa [1–3]. With rapid industrialization and urbanization, the water quality of lakes has changed considerably in the past decades [4–6]. Increased human activity threatens the water quality of lakes; thus, exploring water quality variation is essential for water security and ecosystem health [7,8]. Qinghai Lake, the largest inland lake and also the largest saline lake in China, is located on the northeastern Tibetan Plateau in Qinghai Province and has a semi-arid and cold climate [9]. Due to its unique geographic location, Qinghai Lake plays a significant role in the climate change of the Tibetan Plateau [10], and climate change on the Tibetan Plateau can heavily affect global climate change [11]. Thus, studies on the ecological environment of Qinghai Lake have drawn much attention in recent years [12–14]. Moreover, with the increasing human activities in the Qinghai Lake Basin, the ecosystem of the lake is also being gradually affected [9,15,16]. Hence, exploring how climate change and human activity are affecting the aquatic environment of the lake and how the water quality varies is truly necessary.

Under the dual influence of climate change and human activity, the physical and biochemical properties of Qinghai Lake and its ecological environment have changed significantly. For example, the area of Qinghai Lake shrank before the 2000s and expanded over the past 20 years [12,13,17], and research suggests that precipitation and evaporation were the main driving forces [18]. It was also discovered that the water surface temperature has maintained an upward trend in the last 50 years, and this tendency accelerated in the past few years [12,19]. The increased water surface temperature of the lake was partially affected by global warming. Accordingly, the frozen period of Qinghai Lake was notably decreased as manifested in the delay of the freeze-up and the advance of the ablation [14,20]. With the global concern regarding the carbon cycle of the Earth, the research on carbon sources and sinks of Qinghai Lake was also conducted [21–23]. It was reported that the carbon storage of the Qinghai Lake Basin decreased before the 2000s and increased over the past two decades [22], which coincidentally conforms with the water level variation of the lake. Evidence also showed that phytoplankton in Qinghai Lake proliferated in recent decades, boosting the primary production of the ecosystem because of the decreased frozen period and the increased sunshine duration and surface temperature [24]. Generally, recent studies on Qinghai Lake have mainly focused on the variations in water level [17], surface temperature [19], ice phenology [20], carbon dynamics [22], etc. These studies usually tend to use remote sensing images to investigate the spatial distribution and temporal variation of Qinghai Lake on its physical, optical, biochemical, and hydrological characteristics because watercolor remote sensing can provide an economical and convenient way to estimate various properties of the water over a long period.

Remote sensing technology has served as a popular way to estimate water quality parameters, such as chlorophyll (Chl), suspended particulate matter (SPM) and colored dissolved organic matter (CDOM) concentrations, from water-leaving radiance ($L_w$) or remote sensing reflectance ($R_{rs}$) [25,26]. Various inversion models have been developed and applied to inland and coastal lakes from clear to turbid water states [27–30]. The modeling process usually involves in situ measured water quality properties for model calibration and validation [26]. However, due to the difficult field sampling conditions and the costs of field survey, limited water samples of Qinghai Lake have been acquired and analyzed for a long time-series estimation of the water quality. For example, Shi used the normalized water-leaving radiance derived from the Visible Infrared Imaging Radiometer Suite (VIIRS) to study the chlorophyll-a (Chl-a) concentration and the water diffuse attenuation coefficient at 490 nm ($K_d(490)$) in Qinghai Lake from 2012 to 2018, but it only revealed the variation trend of the lake properties because there is no actual field measurements of Chl-a and $K_d(490)$ for model validation [31]. Generally, the studies on the long-term monitoring of the water quality, such as water clarity (i.e., Secchi-disk depth, $Z_{SD}$) and SPM concentration ($C_{SPM}$), in Qinghai Lake, are still limited and incomplete.
Moderate Resolution Imaging Spectroradiometer (MODIS) aboard the Terra and Aqua satellites can view the entire Earth every 1 to 2 days with spatial resolution from 250 m to 1000 m [32]. This paper took advantage of the MODIS data to derive the \( Z_{SD} \) and \( C_{SPM} \) quantitatively over the past two decades (from 2001 to 2020) and provide a better understanding of the water quality in Qinghai Lake. To this end, first, the in situ water sampling and field spectral measurement must be collected. Then, the pre-processing routine for remote sensing images needs to be performed to derive the \( R_{rs} \), especially the atmospheric correction (AC). AC is a key step for remote-sensing-based water quality estimation because atmospheric radiation comprises around 90% of satellite-observed radiance at visible wavelengths, and only a small fraction comes from the water body [33,34]. Third, the water quality inversion model should be established with the necessary calibration or validation. At present, empirical, semi-empirical, and semi-analytical models are often employed in remote-sensing-based inversion. The empirical and semi-analytical models are mainly established based on statistical regression between in situ sampled water quality parameters and \( L_w \) or \( R_{rs} \) [35–38]. Empirical or semi-empirical models are simple but effective given sufficient in situ measurements, but the model transferability is usually limited. The semi-analytical model, in contrast, largely relies on the classic radiative transfer theory and is also accompanied by statistical methods [39–41]. Since the semi-analytical model is built based on theoretical physical relations, the estimation accuracy, in practice, may become lower in some complex water bodies with more environmental factors involved.

This paper tested the performance of four commonly-used AC algorithms in Qinghai Lake based on MODIS Level-1 data. The MODIS \( R_{rs} \) images were produced with the optimal AC processor. Some empirical, semi-empirical models, and semi-analytical models from works of literature were compared on \( Z_{SD} \) and \( C_{SPM} \) estimation. Next, the two water parameters in Qinghai Lake were mapped from 2001 to 2020 based on the derived \( R_{rs} \) sequences. The relationship between \( Z_{SD} \) and \( C_{SPM} \) was analyzed using a regression model. In addition, the spatial and temporal variations of the \( C_{SPM} \) were studied using time series analysis models. The rest of this article is organized as follows. The study area and data, including field measurements and MODIS images, are introduced in Section 2. Section 3 delineates the details of the AC and time series analysis models employed in this paper. Sections 4 and 5 present the results and discussion, and the conclusion is summarized in Section 6.

2. Study Area and Data

2.1. Study Area

Qinghai Lake is located in the northeast of Qinghai province in northwestern China. The location of Qinghai Lake (36°32′~37°15′N and 99°36′~100°47′E) is illustrated in Figure 1. Qinghai Lake is at the highest altitude (~3260 m) of the top largest 50 lakes in the world [31]. The area of the lake is about ~4300 km², and it has been getting larger in recent years [12]. The average depth of the lake can reach 21 m [31]. The lake is surrounded by several sub-lakes on the east shore, namely, Haiyan Bay, Shadao Lake, and Gahai Lake, as shown in Figure 1. Qinghai Lake is the largest saline lake in China, and high salinity makes the suspended colloidal particles easily absorb free ions in water to form complexes before settling. Therefore, the lake is often quite clear; moreover, the nutrient level of Qinghai Lake is relatively low [42]. The annual mean precipitation is around 360 mm, and the annual mean temperature is \(-0.7\) °C [24]. It usually enters the freezing period in November and begins thawing in April of the next year [14,20]. In this study, we only investigated the water quality in the ice-free period (i.e., from May to October) in Qinghai Lake.
2.2. Field Data

Two field surveys in Qinghai Lake were conducted in September 2008 and August 2016. The sampling points are marked in Figure 1. The sampling points in 2008 were scattered in the center and southern parts of the lake, while the points in 2016 were mainly distributed in the northwestern section. At each station, water samples were collected at depths of around 0 m, 15 m, and 30 m using a Niskin water sampler before quantitative analysis in the laboratory. The spectra were measured using an ASD FieldSpec spectroradiometer following NASA protocols on the above-water radiance measurement [43]. The $R_{rs}$ can be calculated approximately using Equation (1):

$$R_{rs} = \frac{(S_{sw} - rS_{sky}) \rho_p}{\pi S_p}$$

where $S_{sw}$, $S_{sky}$, and $S_p$ are the total water-leaving radiance, sky radiance, and the radiance of the gray panel, respectively, measured with the spectroradiometer; the constant $r$ and $\rho_p$ are the air–water surface reflectance (a value of 2.5% was used) and the reflectance of the standard reflectance panel, respectively.

There was a total of 29 and 12 valid water samples collected in the surveys of 2008 and 2016. In 2008, only the $C_{SPM}$ was acquired. The SPM was measured by weighing the substance before and after it was filtrated using a Whatman membrane filter with a diameter of 0.45 nm and dried at 105 °C overnight. The SPM was further divided into suspended particulate inorganic matter (SPIM) and suspended particulate organic matter (SPOM) by burning the organic matter out from the SPM at 500 °C for 4 h and reweighing [23]. In 2016, only the water clarity, usually qualified by the Secchi-disk depth, was measured. The $Z_{SD}$ was observed with a 30-cm diameter Secchi disk in the field survey.

2.3. MODIS Data

MODIS Level-1A (L1A) data in the non-frozen period of Lake Qinghai from 2001 to 2020 were downloaded from the NASA ocean color web archives (https://oceancolor.gsfc.nasa.gov/, accessed on 15 March 2021). Since MODIS/Aqua was launched in 2002, MODIS/Terra images in 2001 and MODIS/Aqua images from 2002 to 2020 were collected.
for the 20-year study. The L1A daily product has a spatial resolution of 250 m, 500 m, and 1000 m for different bands. The L1B product was then generated using the NASA SeaDAS software. Next, four atmospheric correction models were comparatively tested, and the $R_{\text{rs}}$ was derived. The generated $R_{\text{rs}}$ was automatically resampled to 1000 m for each band. Finally, strict quality control was performed on the $R_{\text{rs}}$ product to mask pixels that cannot satisfy the quality standard according to the attached l2_flags metadata of each image. For example, pixels labeled as land, sun glint, cloud, ice, or sensor view zenith angle and solar zenith angle exceeding thresholds were all filtered out. The number of $R_{\text{rs}}$ images after processing in each month is distributed as in Figure 2. There is no valid observation in four of the months from 2002 to 2017 due to severe cloud contamination or occasional large-scale missing data in L1A images.

![Figure 2: Heatmap of the data distribution in each month during the whole study period (value in each cell indicates the number of images within the corresponding month).](image)

3. Methods and Models

3.1. Atmospheric Correction Models

Water is highly absorptive, and the effect of atmospheric gasses and particles must be adequately corrected for further quantitative inversion and analysis [33]. Four atmospheric correction models for ocean color remote sensing, including the NIR and SWIR combined method (NIR–SWIR) [44,45], the management unit of the mathematical models of the North Seas (MUMM) [46], the polynomial-based algorithm applied to the MERIS (POLYMER) [47], and the Case 2 regional coast color processor (C2RCC) [48], were selectively tested in the following experiments. The NIR–SWIR method was established based on the black pixel assumption that the water body shows strong absorption in the NIR and SWIR bands, and the water-leaving radiance is neglectable in that spectral range [49]. For MODIS images, the NIR bands at wavelengths of 748 and 869 nm are used for non-turbid water, and the SWIR bands at 1240 and 2130 nm are for turbid water [45,50]. The MUMM assumes a spatial homogeneity of aerosol properties over a region of interest and replaces the black-pixel assumption with the fact that the ratios of two NIR bands for water-leaving reflectance and aerosol reflectance can be regarded as a constant to build the correction model [46,51]. The additional parameters for the MUMM model, such as the water-leaving reflectance ratio, were all set with the default values in the software. The POLYMER employs a per-pixel spectral optimization method based on a polynomial, and it gains the strength to recover the ocean color in the presence of sun glint [47,52]. The output of POLYMER is the water-leaving reflectance ($\rho_w$) instead of $R_{\text{rs}}$. The relation between the two can be simply formulated as $\rho_w(\lambda) = \pi R_{\text{rs}}(\lambda)$ at the wavelength of $\lambda$ [53]. The C2RCC processor is a set of neural networks trained on simulated top-of-atmosphere reflectance [48,54]. As the name suggests, it is usually applied for Case 2 water. The additional environmental parameters for the C2RCC model were set as follows: the ozone
content is 80 DU; the surface air pressure is 801 hPa; the salinity is 12.5 PSU; and the temperature is 20 °C.

3.2. Estimation of $Z_{SD}$

The Secchi disk depth is a common way to measure the clarity of ocean and lake waters. Since limited field data were acquired and the data volume is not sufficient for modeling, we could only test the performance of some existing models and choose the optimal for the following estimation. A semi-analytical model and some empirical or semi-empirical models were comparatively tested and verified. Empirical or semi-empirical models proposed by Wu [55], Kratzer [56], and Binding [57] were tested in the following experiments. These models are both implemented based on the $K_{rs}$ at specific wavelengths. For instance, Wu used the blue (469 nm) and red (645 nm) bands to build an exponential model [55]. Kratzer employed similar blue (470 nm) and red (645 nm) bands with a different regression equation [56]. Binding adopted a cubic polynomial regression with one green (550 nm) band [57].

The $Z_{SD}$ derived using the semi-analytical model has been modeled as a function of the downwelling diffuse attenuation and beam attenuation coefficient [58,59]. However, recent studies suggest that the classic theory of water clarity modeling does not really agree with the physical process of the Secchi disk observed by human eyes [39]. The new model can be simply presented as a function of the reciprocal of the diffuse attenuation coefficient at a specific wavelength [39,60]. This paper tested this novel model based on the new theory. The model can be simply formulated as Equation (2):

$$Z_{SD} = \frac{1}{2.5 \min(K_{tr}^{d}) \ln\left(\frac{0.14 - R_{tr}^{rs}}{C'}\right)}$$

where $\min(K_{tr}^{d})$ is the $K_{d}$ at the transparent window of the water body, namely the wavelength of maximum transmittance [61] corresponding to the minimum $K_{d}$ for the visible spectral wavelengths between 443 nm and 665 nm. $R_{tr}^{rs}$ denotes the remote sensing reflectance at the wavelength corresponding to the transparent window of the water body. $C'$ denotes the contrast threshold of a human eye when measuring the water clarity with a white Secchi disk, and usually it can be regarded as a constant of 0.013 sr$^{-1}$ [62]. The $K_{d}$ can be formulated as a function of the total absorption ($a$) and backscattering coefficients ($bb$) of water from the perspective of radiative transfer modeling [63]. The parameters of $a$ and $bb$ can be derived using the quasi-analytical algorithm (QAA) [40]. Specifically, the latest version of QAA (QAA_v6) was employed in this paper, and the arithmetic details can be found in [64]. This semi-analytical model has been used in coastal waters [60,65] and in the 50 large lakes on the Yangtze Plain, China [66], and demonstrated its effectiveness in practice [66].

3.3. Estimation of $C_{SPM}$

For the same reason, instead of devising a new algorithm from scratch, some existing models on $C_{SPM}$ were comparatively tested, and the optimal was employed. Typical empirical or semi-empirical models in the literature [53], proposed by Mao [67], Dogliotti [68], Han [69], Novoa [70], and Yu [53], were evaluated in this paper. Among these models, some estimate the $C_{SPM}$ based on the $R_{rs}$ and some on the $\rho_{w}$ with single or multiple spectral bands. Mao used the four customized indices most correlated to $C_{SPM}$ to formulate a proxy variable, and then an exponential equation was established based on this proxy [67]. Dogliotti proposed a generic model based on a single band but differentiated for clear and turbid waters with different feature bands. Moreover, a blending scheme was also designed for waters between the definite clear and turbid states [68]. Han revised Dogliotti’s model with different feature bands and an altered blending scheme [69]. Novoa devised a model where the relation between feature bands and $C_{SPM}$ switches among five different condi-
tions based on the value of $\rho_w(671)$ [70]. Yu established a power–law function based on a proposed generalized index involving various feature bands [53].

The semi-analytical model employed in this paper for $C_{SPM}$ estimation is mainly derived from the particulate backscattering coefficients ($b_{bp}$) of water based on the radiative transfer equations [71]. First, the water is classified into four categories: clear, moderately turbid, highly turbid, and extremely turbid, according to the $R_{rs}$ values at the wavelengths of 490, 560, 620, and 754 nm. Second, the radiative transfer equations are used to determine the $b_{bp}$ at the corresponding single wavelength. To be specific, 560 nm for clear water, 665 nm for moderately turbid water, 754 nm for highly turbid water, and 865 nm for extremely turbid water. According to [40], the main process can be formulated as Equation (3):

$$b_{bp}(\lambda) = \mu(\lambda) \cdot a(\lambda) - b_{bw}(\lambda)$$

(3)

where $\mu(\lambda)$ is a function of $R_{rs}$ at the wavelength of $\lambda$, $a$ is the total absorption coefficient, and $b_{bw}$ is the backscattering coefficient of pure water. The calculation of $\mu$ and $a$ can follow the procedures specified in the QAA_v6 [64]. The $b_{bw}$ is a known constant corresponding to each spectral band [40,72]. Finally, the $C_{SPM}$ can be estimated by multiplying the $b_{bp}$ with a coefficient ($b_{bw}^{-1}$) corresponding to each water type at the specific wavelength, as shown in Equation (4):

$$C_{SPM} = b_{bw}^{-1}(\lambda) b_{bp}(\lambda)$$

(4)

where $b_{bw}^*$ denotes the SPM-specific particulate backscattering coefficient. In practice, the $b_{bp}$-based $C_{SPM}$ model has been widely applied in different water areas with various remote sensing data sources and exhibited its superiority in practice [71,73].

3.4. Accuracy Assessment

The model accuracy is assessed and validated by comparing in situ measurements with model estimations in terms of the root mean square error (RMSE), mean absolute percentage error (MAPE), mean normalized bias (MNB), and coefficient of determination ($R^2$). These statistic metrics are calculated as follows:

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (y_i - x_i)^2}$$

(5)

$$\text{MAPE} = \frac{1}{N} \sum_{i=1}^{N} \left| \frac{y_i - x_i}{x_i} \right| \times 100\%$$

(6)

$$\text{MNB} = \frac{1}{N} \sum_{i=1}^{N} \left( \frac{y_i - x_i}{x_i} \right) \times 100\%$$

(7)

$$R^2 = 1 - \frac{\sum_{i=1}^{N} (y_i - x_i)^2}{\sum_{i=1}^{N} (y_i - \bar{x})^2}$$

(8)

where $x_i$ is the $i$-th in situ measurement, $y_i$ is the $i$-th model prediction, $\bar{x}$ is the mean of all in situ measurements, and $N$ is the number of valid samples. RMSE and MAPE represent a model’s accuracy with regard to prediction errors, and smaller RMSE and MAPE indicate higher accuracy. MNB exhibits a degree of deviation, and the sign of the value suggests the deviation direction. $R^2$ measures how the predictions can be explained by the model, and a superior model yields $R^2$ close to one.

3.5. Statistical Analysis

The Breaks for Additive Season and Trend (BFAST) and the Mann–Kendall (M–K) test were employed to comprehensively analyze the spatiotemporal variation of Qinghai Lake over 20 years. The BFAST algorithm can decompose time-series data into fitted seasonal,
trend, and remainder components for change detection [74,75]. It can be formulated as Equation (9):

\[ Y_t = T_t + S_t + e_t \]  

where \( Y_t, T_t, S_t, \) and \( e_t \) are the observed data value, trend component, seasonal component, and noises at the time \( t \). The model iteratively fits piecewise linear trend and seasonal models to a time series. The magnitude and direction of the changes are derived from the intercept and slope of the components, and then they are used to identify the changes in the time series. Changes occurring in the trend component indicate disturbance, while they demonstrate phenological changes in the seasonal component [75]. The BFAST was used to identify the general trend of water quality variation in Qinghai Lake.

The M–K test can be used for time-series data to ascertain whether there is a consistently increasing or decreasing trend [76]. It is a non-parametric test and works for all distributions. The M–K test is based on a test statistic \( S \) under the hypothesis that data are independent and identically distributed [77]. The \( S \) can be formulated as Equation (10):

\[ S = \sum_{j=1}^{n-1} \sum_{i=j+1}^{n} f(x_i - x_j) \]  

where \( n \) is the total number of samples, \( x_i \) and \( x_j \) are the next and previous samples, respectively, and \( f \) is a sign function. A positive value of the normalized \( S \) indicates an upward trend, and a negative value suggests a downward trend. Theil–Sen’s slope [78] is often used in conjunction with the M–K test to quantify the magnitude of the trend. Considering the seasonal variation in the image series, the seasonal M–K test [79] was employed in this paper to eliminate the effect of seasonality. The M–K test was employed to explore the spatial distribution of the temporal variation trend in a pixel-wise manner. The statistical models were implemented with R programming language in the experiments.

4. Results

4.1. General Properties of Qinghai Lake

Generally, the water of Qinghai Lake was quite clear on the days of sampling. Figure 3a shows the derived \( R_{rs} \) curves in the field surveys. Different colors indicate the surveys conducted in different years. Significant reflection peaks at 550 nm, which are usually caused by the weak absorption of chlorophyll, are observed. The \( R_{rs} \) in the red and NIR bands (from 700 to 800 nm) are relatively low, which indicates the water was quite clear. Moreover, the in situ measured \( C_{SPM} \) and \( Z_{SD} \) also confirm that the water quality of Qinghai Lake was in a good condition. The lowest and highest \( C_{SPM} \) of the samples are 0.7 and 12.0 mg/L, respectively, and the average is 3.8 mg/L. The SPIM concentration (\( C_{SPIM} \)) accounts for 50.52% of the \( C_{SPM} \) regarding all the samples, but the proportion varies considerably, ranging from 23.08% to 85.71%. The remaining 49.48% is from the SPOM concentration (\( C_{SPOM} \)). There are 16 samples in which the \( C_{SPM} \) is higher than the \( C_{SPIM} \) among the 29 samples. The Pearson correlation coefficient (\( r \)) between the \( C_{SPM} \) and the \( C_{SPIM} \) was as high as 0.91, and the relation approximates an exponential function with Equation (11) (RMSE = 0.66, MAPE = 34.78%, MNB = −7.65%, \( R^2 = 0.81 \)):

\[ C_{SPIM} = 0.493 e^{0.258 C_{SPM}} \]  

The fit curve is shown in Figure 3b. The symbol \( N \) indicates the valid samples for evaluation. The red line is the regression line, and the bandwidth in translucent green indicates a 95% confidence interval. With respect to the in situ measured \( Z_{SD} \), the shallowest and deepest of the \( Z_{SD} \) are 1.4 and 5.1 m, respectively, and the average is 3.13 m among the 12 valid samples.
4.2. Accuracy of Atmospheric Correction

The performance of atmospheric correction models was evaluated by comparing the in situ measured $R_{rs}$ with the remote sensing derived $R_{rs}$ in a point-to-point manner. The point values extracted from remote sensing images corresponding to in situ stations were averaged with a $3 \times 3$ neighboring window to reduce accidental errors. Because of the severe cloud contamination in the remote sensing images on some days of the filed surveys, only 14 valid matched points were obtained after data filtering. The scatter plots in Figure 4 exhibit the fitness of the four atmospheric correction models on each spectral band. The quantitative metrics of each model are presented in Table 1. The best ones are marked in bold. There is no result produced at the wavelengths of 469 nm, 555 nm, and 645 nm with C2RCC and POLYMER; hence, the corresponding cells remain blank. Several conclusions can be drawn from Figure 4 and Table 1. First, the C2RCC produces the highest uncertainty in all spectral bands (MAPE $\geq 66\%$, MNB $\leq -210\%$). The C2RCC corrected $R_{rs}$ is significantly lower than the in situ measurement. Second, the POLYMER functioned well at the blue and green wavelengths (MAPE $\leq 14\%$, $|\text{MNB}| \leq 6\%$, $R^2 \geq 0.64$), but it showed poor performance at the red wavelengths (MAPE $\geq 24\%$, $|\text{MNB}| \geq 33\%$, $R^2 \leq 0.50$). Third, the NIR–SWIR and MUMM were nearly comparable. The NUMM obtains higher accuracy from the blue to red bands (RMSE $\leq 0.003 \text{ sr}^{-1}$, MAPE $\leq 30\%$, $|\text{MNB}| \leq 6\%$, $R^2 \geq 0.45$), but the MUMM performed defectively at the wavelength of 748 nm with a significantly enlarged outcome (MAPE = 183.21\%, MNB = 58.42\%, $R^2 = 0.07$). The accuracy of NIR–SWIR (RMSE $\leq 0.004 \text{ sr}^{-1}$, MAPE $\leq 41\%$, $|\text{MNB}| \leq 92\%$, $R^2 \geq 0.34$) is slightly lower than MUMM, but it produces averagely acceptable results for all spectral bands. Fourth, the results with NIR–SWIR (MNB less than 0 for 10 bands out of 11) and MUMM (MNB greater than 0 for 9 bands out of 11) were generally a little lower and higher than the in situ measurements, respectively.

Band ratios are often used to measure the system errors induced by the atmospheric correction [5], and some band ratios are also illustrated in Figure 4. The ratios of 443/547 and 488/547 were close to the identity line with the NIR–SWIR, MUMM, and POLYMER. The ratios of 667/547 with the NIR–SWIR and MUMM were slightly lower and higher than the identity line. The NIR–SWIR achieved the best at the ratio of 748/547. In conclusion, the NIR–SWIR and MUMM performed better than the other two models, but considering the MUMM did not perform well in the NIR band (748 nm), and the NIR band is often essential in estimation models of water-quality parameters, the NIR–SWIR was chosen to conduct the atmospheric correction in the following experiment.
Figure 4. Scatter plots of the comparison between MODIS-derived and in situ measured $R_{rs}$.

Table 1. Quantitative metrics for the MODIS-derived $R_{rs}$ with four atmospheric correction models.

| Models  | Metrics | 412 | 443 | 469 | 488 | 531 | 547 | 555 | 645 | 667 | 678 | 748 |
|---------|---------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
|         | RMSE    | 0.0018 | 0.0019 | 0.0022 | 0.0030 | 0.0034 | 0.0036 | 0.0040 | 0.0016 | 0.0016 | 0.0014 | 0.0003 |
| NIR-SWIR| MAPE    | 12.43% | 12.28% | 11.73% | 13.06% | 12.95% | 14.27% | 16.75% | 28.84% | 41.66% | 41.73% | 40.51% |
|         | $R^2$   | 0.39  | 0.71  | 0.69  | 0.74  | 0.76  | 0.76  | 0.75  | 0.50  | 0.35  | 0.34  | 0.40  |
| MUMM    | RMSE    | 0.0025 | 0.0024 | 0.0024 | 0.0027 | 0.0028 | 0.0030 | 0.0011 | 0.0009 | 0.0009 | 0.0009 | 0.0009 |
|         | MAPE    | 23.39% | 21.38% | 17.85% | 14.38% | 14.31% | 15.18% | 15.87% | 29.71% | 28.98% | 29.69% | 183.21% |
|         | MNB     | 17.02% | 15.18% | 11.20% | 3.38% | 1.12% | -1.17% | -6.00% | 10.34% | 6.39% | 8.37% | 58.42% |
|         | $R^2$   | 0.58  | 0.78  | 0.84  | 0.83  | 0.79  | 0.79  | 0.79  | 0.49  | 0.47  | 0.45  | 0.07  |
| C2RCC   | RMSE    | 0.0077 | 0.0076 | 0.0103 | 0.0120 | 0.0116 | 0.0024 | 0.0023 | 0.0005 | 0.0005 | 0.0005 | 0.0005 |
|         | MAPE    | 72.42% | 66.59% | 66.54% | 71.92% | 72.96% | 80.80% | 81.34% | 86.26% | 86.26% | 86.26% | 86.26% |
|         | MNB     | -308.62% | -231.76% | -215.74% | -267.90% | -283.27% | -470.72% | -489.84% | -776.75% | -776.75% | -776.75% | -776.75% |
|         | $R^2$   | 0.00  | 0.00  | 0.16  | 0.57  | 0.59  | 0.34  | 0.32  | 0.08  | 0.08  | 0.08  | 0.08  |
| POLYMER | RMSE    | 0.0010 | 0.0014 | 0.0022 | 0.0028 | 0.0029 | 0.0011 | 0.0010 | 0.0002 | 0.0002 | 0.0002 | 0.0002 |
|         | MAPE    | 8.24%  | 10.86% | 10.77% | 12.18% | 13.23% | 24.56% | 24.23% | 47.70% | 47.70% | 47.70% | 47.70% |
|         | MNB     | 2.25%  | 1.86%  | -4.25% | -4.35% | -5.73% | -32.41% | -31.59% | -4.55% | -4.55% | -4.55% | -4.55% |
|         | $R^2$   | 0.78  | 0.75  | 0.70  | 0.70  | 0.66  | 0.48  | 0.47  | 0.01  | 0.01  | 0.01  | 0.01  |

4.3. Estimation of $Z_{SD}$ and $C_{SPM}$

Several empirical, semi-empirical, and semi-analytical models were tested for the $Z_{SD}$ and $C_{SPM}$ estimation. The model-estimated results were compared with the in situ measurements for validation. The quantitative evaluation of the four models for $Z_{SD}$ and the six models for $C_{SPM}$ are listed in Tables 2 and 3, respectively, in terms of RMSE, MAPE, MNB, and $R^2$. Generally speaking, the empirical and semi-empirical models showed a dreadfully poor performance concerning all the statistical metrics (RMSE $\geq 0.7$ m, MAPE $\geq 26\%$, $|MNB| \geq 36\%$, $R^2 \leq 0.08$ for $Z_{SD}$; RMSE $\geq 2.6$ mg/L, MAPE $\geq 46\%$, $|MNB| \geq 21\%$, $R^2 \leq 0.19$ for $C_{SPM}$). The semi-analytical models, in contrast, exhibited high accuracy (RMSE = 0.54 m, MAPE = 15.71%, MNB = -18.30%, $R^2 = 0.74$ for $Z_{SD}$; RMSE = 0.78 mg/L,
MAPE = 38.24%, MNB = 15.62%, $R^2 = 0.73$ for C$_{SPM}$). The results of semi-analytical models are illustrated in Figure 5. The red line is the regression line, and the translucent green area is the 95% confidence interval. The gray line is the 1:1 line for reference. The $R^2$ can reach 0.7, and the RMSE is less than 0.8 for both the Z$_{SD}$ and C$_{SPM}$ with the limited samples. Basically, the MOSIS-derived Z$_{SD}$ and C$_{SPM}$ are slightly lower and higher than the in situ measurements, respectively. The points in Figure 5a for Z$_{SD}$ are distributed comparatively centralized, while they are more dispersed in Figure 5b for C$_{SPM}$ with a wilder confidence interval. Since there are only 11 valid samples for C$_{SPM}$, we believe the results are acceptable. Hence, the semi-analytical models were adopted for the following long-series water quality estimation.

Table 2. Quantitative evaluation of the inversion models for Z$_{SD}$.

| Models       | RMSE | MAPE    | MNB    | $R^2$ |
|--------------|------|---------|--------|-------|
| Wu (2008)    | 0.73 | 26.27%  | −36.96%| 0.08  |
| Kratzer (2008)| 2.28 | 88.54%  | −958.05%| 0.03  |
| Binding (2015)| 18.10| 717.87% | 87.62% | 0.01  |
| Lee (2015)   | 0.54 | 15.71%  | −18.30%| 0.74  |

Table 3. Quantitative evaluation of the inversion models for C$_{SPM}$.

| Models       | RMSE | MAPE    | MNB    | $R^2$ |
|--------------|------|---------|--------|-------|
| Mao (2012)   | 6.46 | 360.70% | 64.38% | 0.09  |
| Dogliotti (2015)| 2.66 | 46.13%  | −21.28%| 0.12  |
| Han (2016)   | 5.07 | 234.55% | 56.75% | 0.13  |
| Novoa (2017) | 2.89 | 118.21% | 28.74% | 0.13  |
| Yu (2019)    | 3.65 | 64.44%  | −298.64%| 0.19  |
| Jiang (2021) | 0.78 | 38.24%  | 15.62% | 0.73  |

Figure 5. Comparison between the in situ measurements and MODIS-derived Z$_{SD}$ (a) and C$_{SPM}$ (b) with semi-analytical models (the red line is the regression line, and the translucent green indicates a 95% confidence interval).

The daily Z$_{SD}$ and C$_{SPM}$ in non-frozen periods (from May to October) were produced with the MODIS $R_m$ data from 2001 to 2020. Figure 6 illustrates the mean variations of Z$_{SD}$ and C$_{SPM}$ calculated by averaging pixel values of the whole lake on the daily and monthly scales. Statistically, the monthly mean Z$_{SD}$ is 5.34 ± 1.33 m, and C$_{SPM}$ is 2.05 ± 1.22 mg/L. The variation of both Z$_{SD}$ and C$_{SPM}$ exhibits an observable seasonal trend in Figure 6. The Z$_{SD}$ continues decreasing and C$_{SPM}$ keeps increasing throughout the year. Z$_{SD}$ and C$_{SPM}$ are highly correlated parameters manifested in the fact that higher C$_{SPM}$ usually leads to lower Z$_{SD}$ and vice versa. A regression analysis was performed on the monthly averaged Z$_{SD}$ and C$_{SPM}$ to identify the relationship between their quantality. Figure 7 reveals
the two are exponentially correlated with Equation (12) (RMSE = 0.25, MAPE = 4.01%, MNB = −0.8%, $R^2 = 0.65$):

$$Z_{SD} = 8.072e^{-0.212C_{SPM}}$$

The density plot in Figure 7 illustrates the distribution of the corresponding pixel values in the $Z_{SD}$ and $C_{SPM}$ images. The color indicates the number of pixels in the hexagon bin. The red line is the regression line with a satisfactory fitness. Since the relationship between $Z_{SD}$ and $C_{SPM}$ has been qualified, only the $C_{SPM}$ is discussed regarding its spatial and temporal variation for the sake of brevity.

**Figure 6.** Daily and monthly mean variation of the $Z_{SD}$ (a) and $C_{SPM}$ (b) in Qinghai Lake.

**Figure 7.** The relationship between the $Z_{SD}$ and $C_{SPM}$ with remote sensing estimation (the red line is the regression line).

**4.4. Spatial and Temporal Variation of $C_{SPM}$**

Distinct seasonal cycles can be observed in Figure 6. To further explore the seasonal variation, Figure 8 exhibits the monthly spatial variation of $C_{SPM}$. Each of the subfigures demonstrates the spatial distribution of the $C_{SPM}$ where the pixel values were averaged for every corresponding month over the 20 years. The $C_{SPM}$ continues to increase from May to October in a year. The turbid water was mainly distributed along the lake edge every month, specifically on the northwestern and southeastern shores. Because Haiyan Bay is so close to the main Qinghai Lake, there are distinct mixed pixels, sometimes referred to as the land adjacency effect [80], leading to poor water quality on the southeastern shore in Figure 8.
Figure 8. Monthly mean spatial distribution of the $C_{SPM}$ in Qinghai Lake

Figure 9 presents the distribution of the annual mean $C_{SPM}$. Like the monthly distribution, the turbid water was distributed around the shore of the lake, specifically in the northwest and the southeast. The water quality was the best from 2001 to 2004 and reached its peak in 2004. The water turned less clear after 2004, deteriorated severely in 2007, and recovered in 2008 and 2009. From 2010 to 2019, the water quality varied somewhat, and there was not much change observed during this period. In 2020, the lake again experienced a trivial amelioration in water quality. Moreover, the BFAST algorithm was employed on the monthly mean $C_{SPM}$ to explore the seasonal and total trends quantitatively. The result is revealed in Figure 10. The total variation in the month scale is fairly complicated. By decomposing it, the total trend over the 20 years is that the water turned less clear distinctly from 2001 to 2007; it gained sudden distinct recovery in 2008, and after that, the $C_{SPM}$ in the lake has been gradually increasing. By removing noises, the total trend is basically similar to the above conclusion observed in Figure 9. Significant seasonal degradation is observed in Figure 10, confirming the conclusion from Figures 6 and 8. However, the variation of segregated noises is substantially volatile, which shows that temporal change is a complicated process despite the overall decreasing trend.

A seasonal M–K test was employed to determine the spatial variation trend from 2001 to 2020 with the monthly mean data of every year. Figure 11 presents the spatial distribution of the M–K test result and the corresponding Theil–Sen’s Slope to identify the magnitude of the $C_{SPM}$ variation trend. The hypothesis that there is a continuous increasing or decreasing trend is accepted with a significance level of 5%, and the trend is determined to be significant with a significance level of 1%. Generally, the main body of the lake tended to become less clear regarding $C_{SPM}$, and the area showing an increasing trend accounted for 81.67% of the total. The water body near the shore where the water is usually more turbid than the main body showed no trend or had some improvement. The area with decreasing turbidity only accounted for 4.56%. The slope in Figure 11b is generally consistent with the M–K trend in Figure 11a. The biggest magnitude of the trend occurred on the northwestern and southeastern shores regarding the Theil–Sen’s Slope in Figure 11b.
Figure 9. Spatial distribution of the annual mean C_{SPM} from 2001 to 2020.

Figure 10. Temporal variation of monthly mean C_{SPM} with BFAST decomposition.
5. Discussion

AC is a necessary preprocessing step for watercolor remote sensing applications due to the high absorption of water. Since the water in Qinghai Lake is less turbid, some AC algorithms, including NIR–SWIR, MUMM, C2RCC, and POLYMER, designed for oceanic applications over open and coastal waters were tested in this paper. The results of NIR–SWIR were constantly lower than the in situ measurements in the red bands. This might be because the black pixel assumption may not always be valid [51], and the extrapolation process on atmospheric influence from NIR to visible bands might cause some errors to lower the estimation. The MUMM performs the best on nearly all the bands, but it failed for the band at the wavelength of 748 nm with a much higher estimation. This might be because, first, the signals of NIR spectra are extremely weak in Qinghai Lake; second, the in situ average $R_{rs}(748)/R_{rs}(869)$ is $1.870 \pm 1.740$ and the deviation is rather large, not fully satisfying the underlying assumption of MUMM. The POLYMER can compete with the MUMM in the blue and green bands but fails in the red and NIR bands. This malfunction might be ascribable to the low reflectance in the NIR bands. The C2RCC produced the highest uncertainty in Qinghai Lake. Considering the C2RCC is a machine-learning-based model, its transferability in different regions cannot be guaranteed, and further model tuning may be needed. Moreover, the C2RCC needs additional environmental factors as inputs, and the estimated values over the study period are set empirically in the experiments. These less accurate parameters may lead to some unexpected errors.

After assessing various AC algorithms, some available water quality inversion models were evaluated. The water clarity and $C_{SPM}$ are important parameters for water quality monitoring, so the two water parameters were evaluated using inversion models with the acquired in situ water samples. Generally, the semi-analytical models achieve the best performance for the $Z_{SD}$ and $C_{SPM}$ estimation, while the existing empirical and semi-empirical models are not suitable in Qinghai Lake. Nevertheless, this is understandable because empirical and semi-empirical models were established using water samples gathered in a specific region. An empirical model may only fit the relation well in that specific region and does not possess favorable transferability. The semi-analytical model, in contrast, can successfully handle the situation in Qinghai Lake where the water is less turbid. The estimation results for $Z_{SD}$ and $C_{SPM}$ are slightly lower and higher than the in situ measurements. This may be because there are external errors introduced from the AC process, and the semi-empirical model is completely uncalibrated in Qinghai Lake due to the lack of sufficient in situ data. However, overall, the model accuracy is satisfactory for both $Z_{SD}$ and $C_{SPM}$ with $R^2 > 0.7$. The $Z_{SD}$ and $C_{SPM}$ are highly correlated because the phytoplankton abundance in Qinghai Lake is not high [81], and the water clarity is mainly affected by the $C_{SPM}$. The water clarity and $C_{SPM}$ estimated in this paper can only manifest partial optical and chemical characteristics of the water. Some biochemical properties, such as Chl-a and CDOM, still need further investigation. The contribution of this paper is that it
demonstrated a feasible way to conduct long-term water quality monitoring with MODIS images in Qinghai Lake, and it can be applied to other watercolor parameters.

By further analyzing the derived C\textsubscript{SPM} series, the seasonal deterioration of water quality can be found. A similar trend was also disclosed regarding the Chl-a and K\textsubscript{a}(490) in Qinghai Lake [31]. This may be because the lake is often frozen from November to the April, and it is hardly affected by the external environment. Meanwhile, the self-purification of the lake can make the water even more clear. After the thaw in April, the lake is gradually altered by climate changes and human activities. According to studies on the topic [82], we speculate that this may be involved with land use and climate change, but it still remains open to explore. The annual variation is complicated, but the overall trend is that the C\textsubscript{SPM} has been rising over the 20 years, except for the sudden distinct decline in 2008. The government of Qinghai province implemented a plan in 2008 aimed at ecological environment protection and comprehensive management of the Qinghai Lake Basin [83], which may contribute to the water quality improvement in that year. The water quality was degraded significantly before 2008, and it was still experiencing degradation after 2008, but the change was quite slow. The spatial variation mainly happened along the lakeshore, especially in the northwest and the southeast. There were no significant upward or downward trends in the edge areas. Generally, the main body of Qinghai Lake witnessed increased C\textsubscript{SPM} and decreased Z\textsubscript{SD} over the 20 years, but the changes were at an extremely slow and smooth pace. While few studies have looked into the long-term monitoring of Qinghai Lake over recent years, the work in this paper can provide a preliminary estimation of the water quality variation.

6. Conclusions

This paper devotes itself to exploring the spatiotemporal distribution and variation of Qinghai Lake from 2001 to 2020 using MODIS images. First, four atmospheric correction models including NIR–SWIR, MUMM, POLYMER, and C2RCC were evaluated. Generally, the NIR–SWIR and MUMM outperform the POLYMER and C2RCC; the performance of NIR–SWIR and MUMM is comparable: the MUMM shows higher accuracy in blue and green bands, but the NIR–SWIR gains higher accuracy in the NIR bands. Then, the NIR–SWIR algorithm was employed for the atmospheric correction of the MODIS time series. Second, several existing models for Z\textsubscript{SD} and C\textsubscript{SPM} estimation were tested, and the results revealed that the semi-analytical models are superior to the empirical models in Qinghai Lake. Third, he semi-analytical models proposed by Lee (2015) and Jiang (2021) were adopted to map the distribution of daily Z\textsubscript{SD} and C\textsubscript{SPM} in Qinghai Lake over the 20 years. Fourth, the quantitative relationship between Z\textsubscript{SD} and C\textsubscript{SPM} was established, and the BFAST analysis and M–K test were performed to understand the spatiotemporal variation of the C\textsubscript{SPM} during the years.

Several conclusions can be drawn from the distribution and variation of the water quality. First, the C\textsubscript{SPM} and C\textsubscript{SPM} and the Z\textsubscript{SD} and C\textsubscript{SPM} are highly correlated water quality parameters: the C\textsubscript{SPM} shows an exponential relation with C\textsubscript{SPM}, and the Z\textsubscript{SD} is an exponential function of C\textsubscript{SPM}. Second, turbid water mainly existed along the edge of Qinghai Lake, especially on the northwestern and northeastern shores. Third, substantial water quality deterioration can be observed seasonally. In other words, the water became constantly less clear from May to October annually. Fourth, the water quality was declining generally, but the variation was complex. Specifically, the water quality broadly deteriorated from 2001 to 2008; 2008 witnessed a sudden distinct improvement, and after that, the water quality experienced an inconspicuous degradation. Fifth, there is 81.67% of the total area with constantly increased C\textsubscript{SPM}, and the area with decreased C\textsubscript{SPM} occupies 4.56% of the total. This study can fill the gap regarding the long-term monitoring of water clarity and total suspended matter in Qinghai Lake, and hopefully, it can provide a scientific reference for the protection and management of Qinghai Lake.
Author Contributions: Conceptualization, Z.T. and H.D.; methodology and validation, Z.T., Z.C.,
and M.S.; formal analysis, Z.T.; investigation and resources, J.C. and Q.S.; visualization and writing,
Z.T.; revising and editing, Z.T., Z.C. and H.D.; supervision, H.D. All authors have read and agreed to
the published version of the manuscript.

Funding: This research was funded by the National Natural Science Foundation of China (42101342,
U2243205, 41971309), the Third Comprehensive Scientific Expedition to Xinjiang (2021XKK1403),
and the Natural Science Special Project of the Education Department of Shaanxi Province (21JK0928).

Data Availability Statement: MODIS Level-1A (L1A) data can be downloaded from the NASA ocean
color web archives (https://oceancolor.gsfc.nasa.gov/, accessed on 15 March 2021).

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Ma, R.; Duan, H.; Hu, C.; Feng, X.; Li, A.; Ju, W.; Jiang, J.; Yang, G. A half-century of changes in China’s lakes: Global warming or human influence? *Geophys. Res. Lett.* 2010, 37, L24106. [CrossRef]
2. Hou, X.; Feng, L.; Duan, H.; Chen, X.; Sun, D.; Shi, K. Fifteen-year monitoring of the turbidity dynamics in large lakes and reservoirs in the middle and lower basin of the Yangtze River, China. *Remote Sens. Environ.* 2017, 190, 107–121. [CrossRef]
3. Woolway, R.I.; Kraemer, B.M.; Lenters, J.D.; Merchant, C.J.; O’Reilly, C.M.; Sharma, S. Global lake responses to climate change. *Nat. Rev. Earth Environ.* 2020, 1, 388–403. [CrossRef]
4. Bhateria, R.; Jain, D. Water quality assessment of lake water: A review. *Sustain. Water Resour. Manag.* 2016, 2, 161–173. [CrossRef]
5. Shen, M.; Duan, H.; Cao, Z.; Xue, K.; Qi, T.; Ma, J.; Liu, D.; Song, K.; Huang, C.; Song, X. Sentinel-3 OLCI observations of water clarity in large lakes in eastern China: Implications for SDG 6.3.2 evaluation. *Remote Sens. Environ.* 2020, 247, 111950. [CrossRef]
6. Hou, X.; Feng, L.; Dai, Y.; Hu, C.; Gibson, L.; Tang, J.; Lee, Z.; Wang, Y.; Cai, X.; Liu, J.; et al. Global mapping reveals increase in lacustrine algal blooms over the past decade. *Nat. Geosci.* 2015, 15, 130–134. [CrossRef]
7. de Paul Obade, V.; Moore, R. Synthesizing water quality indicators from standardized geospatial information to remedy water security challenges: A review. *Environ. Int.* 2018, 119, 220–231. [CrossRef]
8. Ma, T.; Zhao, N.; Ni, Y.; Yi, J.; Wilson John, P.; He, L.; Du, Y.; Pei, T.; Zhou, C.; Song, C.; et al. China’s improving inland surface water quality since 2003. *Sci. Adv.* 2016, 6, eaau3798. [CrossRef]
9. Ao, H.; Wu, C.; Xiong, X.; Jing, L.; Huang, X.; Zhang, K.; Liu, J. Water and sediment quality in Qinghai Lake, China: A revisit after half a century. *Environ. Monit. Assess.* 2014, 186, 2121–2133. [CrossRef]
10. Ji, S.; Xingqi, L.; Sumin, W.; Matsumoto, R. Palaeoclimatic changes in the Qinghai Lake area during the last 18,000 years. *Quat. Int.* 2005, 136, 131–140. [CrossRef]
11. Colman, S.M.; Yu, S.Y.; An, Z.; Shen, J.; Henderson, A.C.G. Late Cenozoic climate changes in China’s western interior: A review of research on Lake Qinghai and comparison with other records. *Quat. Sci. Rev.* 2007, 26, 2281–2300. [CrossRef]
12. Tang, L.; Duan, X.; Kong, F.; Zhang, F.; Zheng, Y.; Li, Z.; Mei, Y.; Zhao, Y.; Hu, S. Influences of climate change on area variation of Qinghai Lake on Qinghai-Tibetan plateau since 1980s. *Sci. Rep.* 2018, 8, 7331. [CrossRef] [PubMed]
13. Fan, C.; Song, C.; Li, W.; Liu, K.; Cheng, J.; Fu, C.; Chen, T.; Ke, L.; Wang, J. What drives the rapid water-level recovery of the largest lake (Qinghai Lake) of China over the past half century? *J. Hydrol.* 2021, 593, 125921. [CrossRef]
14. Cai, Y.; Ke, C.Q.; Duan, Z. Monitoring ice variations in Qinghai Lake from 1979 to 2016 using passive microwave remote sensing data. *Sci. Total. Environ.* 2017, 607–608, 120–131. [CrossRef]
15. Qi, Y.; Lian, X.; Wang, H.; Zhang, J.; Yang, R. Dynamic mechanism between human activities and ecosystem services: A case study of Qinghai lake watershed, China. *Ecol. Indic.* 2020, 117, 106528. [CrossRef]
16. Dong, H.; Song, Y.; Zhang, M. Hydrological trend of Qinghai Lake over the last 60 years: Driven by climate variations or human activities? *J. Water Clim. Chang.* 2018, 10, 524–534. [CrossRef]
17. Hongmei, D.; Song, Y. Shrinkage history of Lake Qinghai and causes during the last 52 years. In *Proceedings of the 2011 International Symposium on Water Resource and Environmental Protection, Xi’an, China, 20–22 May 2011; Volume 1*, pp. 446–449. [CrossRef]
18. Fang, J.; Li, G.; Rubinato, M.; Ma, G.; Zhou, J.; Jia, G.; Yu, X.; Wang, H. Analysis of Long-Term Water Level Variations in Qinghai Lake in China. *Water* 2019, 11, 2136. [CrossRef]
19. Xiao, F.; Ling, F.; Du, Y.; Feng, Q.; Yan, Y.; Chen, H. Evaluation of spatial-temporal dynamics in surface water temperature of Qinghai Lake from 2001 to 2010 by using MODIS data. *J. Arid Land* 2013, 5, 452–464. [CrossRef]
20. Qi, M.; Yao, X.; Li, X.; Duan, H.; Gao, Y.; Liu, J. Spatiotemporal characteristics of Qinghai Lake ice phenology between 2000 and 2010. *J. Geogr. Sci.* 2019, 29, 115–130. [CrossRef]
21. Li, C.; Li, Q.; Zhao, L.; Ge, S.; Chen, D.; Dong, Q.; Zhao, X. Land-use effects on organic and inorganic carbon patterns in the topsoil around Qinghai Lake basin, Qinghai-Tibetan Plateau. *CATENA* 2016, 147, 345–355. [CrossRef]
22. Li, J.; Gong, J.; Guldmann, J.M.; Li, S.; Zhu, J. Carbon Dynamics in the Northeastern Qinghai-Tibetan Plateau from 1990 to 2030 Using Landsat Land Use/Cover Change Data. *Remote Sens.* 2020, 12, 528. [CrossRef]
23. Cao, S.; Cao, G.; Feng, Q.; Han, G.; Lin, Y.; Yuan, J.; Wu, F.; Cheng, S. Alpine wetland ecosystem carbon sink and its controls at the Qinghai Lake. *Remote Sens. Environ.* 2017, 76, 210. [CrossRef]

24. Feng, L.; Liu, J.; Ali, T.A.; Li, J.; Li, J.; Kuang, X. Impacts of the decreased freeze-up period on primary production in Qinghai Lake. *Int. J. Appl. Earth Obs. Geoinf.* 2019, 83, 101915. [CrossRef]

25. Arabi, B.; Salama, M.S.; Wernand, M.R.; Verhoef, W. Remote sensing of water constituent concentrations using time series of in situ hyperspectral measurements in the Wadden Sea. *Remote Sens. Environ.* 2018, 216, 154–170. [CrossRef]

26. Mouw, C.B.; Greb, S.; Aurin, D.; DiGiacomo, P.M.; Lee, Z.; Twardowski, M.; Binding, C.; Hu, C.; Ma, R.; Moore, T.; et al. Aquatic color radiometry remote sensing of coastal and inland waters: Challenges and recommendations for future satellite missions. *Remote Sens. Environ.* 2015, 160, 15–30. [CrossRef]

27. Wang, X.; Yang, W. Water quality monitoring and evaluation using remote sensing techniques in China: A systematic review. *Ecosyst. Health Sustain.* 2019, 5, 47–56. [CrossRef]

28. Odermatt, D.; Gitelson, A.; Brando, V.E.; Schaepman, M. Review of constituent retrieval in optically deep and complex waters from satellite imagery. *Remote Sens. Environ.* 2012, 118, 116–126. [CrossRef]

29. Rodriguez-López, L.; Duran-Llacer, I.; Gonzalez-Rodriguez, L.; Cardenas, R.; Urrutia, R. Retrieving Water Turbidity in Aruacanan Lakes (South-Central Chile) Based on Multispectral Landsat Imagery. *Remote Sens. 2021*, 13, 3133. [CrossRef]

30. Liu, C.; Zhu, L.; Li, J.; Wang, J.; Ju, J.; Qiao, B.; Ma, Q.; Wang, S. The increasing water clarity of Tibetan lakes over last 20 years according to MODIS data. *Remote Sens. Environ.* 2021, 253, 112199. [CrossRef]

31. Shi, W.; Wang, M.; Li, J. Water property in high-altitude Qinghai Lake in China. *Sci. Remote Sens.* 2020, 2, 100012. [CrossRef]

32. William, L.B.; Vincent, V.S. MODIS: A global imaging spectroradiometer for the Earth Observing System. In *Optical Technologies for Aerospace Sensing: A Critical Review*; SPIE: Bellingham, DC, USA, 1992; Volume 10269, pp. 280–302. [CrossRef]

33. Moses, W.J.; Sterckx, S.; Montes, M.J.; De Keukelaere, L.; Knaeps, E. Atmospheric Correction for Inland Waters. In *Bio-Optical Modeling and Remote Sensing of Inland Waters*; Mishra, D.R., Ogashawara, I., Gitelson, A.A., Eds.; Elsevier: Amsterdam, The Netherlands, 2017; pp. 69–100. [CrossRef]

34. Vidot, J.; Santer, R. Atmospheric correction for inland waters—Application to SeaWiFS. *Int. J. Remote Sens.* 2005, 26, 3663–3682. [CrossRef]

35. Li, H.; He, X.; Shanmugam, P.; Bai, Y.; Wang, D.; Huang, H.; Zhu, Q.; Gong, F. Semi-analytical algorithms of ocean color remote sensing under high solar zenith angles. *Opt. Express 2019*, 27, A800–A817. [CrossRef] [PubMed]

36. Stock, A. Satellite mapping of Baltic Sea Secchi depth with multiple regression models. *Int. J. Appl. Earth Obs. Geoinf. 2015*, 40, 55–64. [CrossRef]

37. Cao, Z.; Duan, H.; Shen, M.; Ma, R.; Xue, K.; Liu, D.; Xiao, Q. Using VIIRS/NPP and MODIS/Aqua data to provide a continuous record of suspended particulate matter in a highly turbid inland lake. *Int. J. Appl. Earth Obs. Geoinf. 2018*, 64, 256–265. [CrossRef]

38. Han, Z.; Gu, X.; Zuo, X.; Bi, K.; Shi, S. Semi-Empirical Models for the Bidirectional Water-Leaving Radiance: An Analysis of a Turbid Inland Lake. *Front. Environ. Sci.* 2022, 9, 557. [CrossRef]

39. Lee, Z.; Shang, S.; Hu, C.; Du, K.; Weidemann, A.; Hou, W.; Lin, J.; Lin, G. Secchi disk depth: A new theory and mechanistic model for underwater visibility. *Remote Sens. Environ.* 2015, 169, 139–149. [CrossRef]

40. Lee, Z.; Carder, K.L.; Arnone, R.A. Deriving inherent optical properties from water color: A multiband quasi-analytical algorithm for optically deep waters. *Appl. Opt.* 2002, 41, 5755–5772. [CrossRef]

41. Lee, Z.P.; Du, K.P.; Arnone, R. A model for the diffuse attenuation coefficient of downwelling irradiance. *J. Geophys. Res. Oceans 2005*, 110, C02016. [CrossRef]

42. Bi, R.; Zhang, H.; Li, H.; Chang, F.; Duan, L.; He, Y.; Zhang, H.; Wen, X.; Zhou, Y. Characteristics and changes of water quality parameters of Qinghai Lake in 2015. *J. Water Resour. Res. 2018*, 7, 74–83. [CrossRef]

43. Mueller, J.L.; Morel, A.; Frouin, R.; Davis, C.; Arnone, R.; Carder, K.; Lee, Z.P.; Steward, R.G.; Hooker, S.; Mobley, C.D.; et al. *Ocean Optics Protocols For Satellite Ocean Color Sensor Validation, Revision 4. Volume III: Radiometric Measurements and Data Analysis Protocols*; Goddard Space Flight Center: Greenbelt, MD, USA, 2003. [CrossRef]

44. Wang, M. Remote sensing of the ocean contributions from ultraviolet to near-infrared using the shortwave infrared bands: simulations. *Appl. Opt.* 2007, 46, 1535–1547. [CrossRef]

45. Wang, M.; Shi, W. The NIR–SWIR combined atmospheric correction approach for MODIS ocean color data processing. *Opt. Express 2007*, 15, 15722–15733. [CrossRef]

46. Ruddick, K.G.; Ovidio, F.; Rijkeboer, M. Atmospheric correction of SeaWiFS imagery for turbid coastal and inland waters. *Appl. Opt.* 2000, 39, 897–912. [CrossRef] [PubMed]

47. Steinmetz, F.; Deschamps, F.Y.; Ramon, D. Atmospheric correction in presence of sun glint: Application to MERIS. *Opt. Express 2011*, 19, 9783–9800. [CrossRef]

48. Brockmann, C.; Doerffer, R.; Peters, M.; Kerstin, S.; Embacher, S.; Ruescas, A. Evolution of the C2RCC Neural Network for Sentinel 2 and 3 for the Retrieval of Ocean Colour Products in Normal and Extreme Optically Complex Waters. In Proceedings of the Living Planet Symposium, Prague, Czech Republic, 9–13 May 2016; Volume 740, p. 54.

49. Siegel, D.A.; Wang, M.; Maritorena, S.; Robinson, W. Atmospheric correction of satellite ocean color imagery: The black-pixel assumption. *Appl. Opt.* 2000, 39, 3582–3591. [CrossRef] [PubMed]

50. Wang, M.; Son, S.; Shi, W. Evaluation of MODIS SWIR and NIR–SWIR atmospheric correction algorithms using SeaBASS data. *Remote Sens. Environ.* 2009, 113, 635–644. [CrossRef]
51. Wang, D.; Ma, R.; Xue, K.; Loiselle, S.A. The Assessment of Landsat-8 OLI Atmospheric Correction Algorithms for Inland Waters. *Remote Sens.* 2019, 11, 169. [CrossRef]
52. Zhang, M.; Hu, C.; Barnes, B.B. Performance of POLYMER Atmospheric Correction of Ocean Color Imagery in the Presence of Absorbing Aerosols. *IEEE Trans. Geosci. Remote Sens.* 2019, 57, 6666–6674. [CrossRef]
53. Yu, X.; Lee, Z.; Shen, F.; Wang, M.; Wei, J.; Jiang, L.; Shang, Z. An empirical algorithm to seamlessly retrieve the concentration of suspended particulate matter from water color across ocean to turbid river mouths. *Remote Sens. Environ.* 2019, 235, 111491. [CrossRef]
54. Warren, M.A.; Simis, S.G.H.; Martinez-Vicente, V.; Poser, K.; Bresciai, M.; Alikas, K.; Spyrrakos, E.; Giardino, C.; Ansper, A. Assessment of atmospheric correction algorithms for the Sentinel-2A MultiSpectral Imager over coastal and inland waters. *Remote Sens. Environ.* 2019, 225, 267–289. [CrossRef]
55. Wu, G.; De Leeuw, J.; Skidmore, A.K.; Frins, H.H.T.; Liu, Y. Comparison of MODIS and Landsat TM5 images for mapping tempo-spatial dynamics of Secchi disk depths in Poyang Lake National Nature Reserve, China. *Int. J. Remote Sens.* 2008, 29, 2183–2198. [CrossRef]
56. Kratzer, S.; Brockmann, C.; Moore, G. Using MERIS full resolution data to monitor coastal waters—A case study from Himmerfjärden, a fjord-like bay in the northwestern Baltic Sea. *Remote Sens. Environ.* 2008, 112, 2284–2300. [CrossRef]
57. Binding, C.E.; Greenberg, T.A.; Watson, S.B.; Rastin, S.; Gould, J. Long term water clarity changes in North America’s Great Lakes from multi-sensor satellite observations. *Limnol. Oceanogr.* 2015, 60, 1976–1995. [CrossRef]
58. Doron, M.; Babin, M.; Hembise, O.; Mangin, A.; Garnesson, P. Ocean transparency from space: Validation of algorithms estimating Secchi depth using MERIS, MODIS and SeaWiFS data. *Remote Sens. Environ.* 2011, 115, 2986–3001. [CrossRef]
59. Preisendorfer, R.W. Secchi disk science: Visual optics of natural waters. *Limnol. Oceanogr.* 1986, 31, 909–926. [CrossRef]
60. Lee, Z.; Shang, S.; Qi, L.; Yan, J.; Lin, G. A semi-analytical scheme to estimate Secchi-disk depth from Landsat-8 measurements. *Remote Sens. Environ.* 2016, 177, 101–106. [CrossRef]
61. Lee, Z.; Shang, S.; Du, K.; Wei, J. Resolving the long-standing puzzles about the observed Secchi depth relationships. *Limnol. Oceanogr.* 2018, 63, 2321–2336. [CrossRef]
62. Blackwell, H.R. Contrast Thresholds of the Human Eye. *J. Opt. Soc. Am.* 1946, 36, 624–643. [CrossRef]
63. Lee, Z.; Hu, C.; Shang, S.; Du, K.; Lewis, M.; Arnone, R.; Brewin, R. Penetration of UV-visible solar radiation in the global oceans: Insights from ocean color remote sensing. *J. Geophys. Res. Ocean.* 2013, 118, 4241–4255. [CrossRef]
64. IOCCG. Update of the Quasi-Analytical Algorithm (QAA_v6). Technical Report, IOCCG Group. 2014. Available online: https://www.ioccg.org/groups/Software_OCA/QAA_v6_2014209.pdf (accessed on 20 April 2021).
65. Warren, M.A.; Simis, S.G.H.; Martinez-Vicente, V.; Poser, K.; Bresciai, M.; Alikas, K.; Spyrrakos, E.; Giardino, C.; Ansper, A. Development of a Semi-Analytical Algorithm for the Retrieval of Suspended Particulate Matter from Remote Sensing over Clear to Very Turbid Waters. *Remote Sens.* 2016, 8, 211. [CrossRef]
66. Feng, L.; Hou, X.; Zheng, Y. Monitoring and understanding the water transparency changes of fifty large lakes on the Yangtze Plain based on long-term MODIS observations. *Remote Sens. Environ.* 2019, 221, 675–686. [CrossRef]
67. Tao, B.; Pan, D.; Zhao, Q. A regional remote sensing algorithm for total suspended matter in the East China Sea. *Remote Sens. Environ.* 2012, 124, 819–831. [CrossRef]
68. Doglioni, A.I.; Ruddick, K.G.; Nechad, B.; Doxaran, D.; Knaeps, E. A single algorithm to retrieve turbidity from remotely-sensed data in all coastal and estuarine waters. *Remote Sens. Environ.* 2015, 156, 157–168. [CrossRef]
69. Han, B.; Loisel, H.; Vantrepotte, V.; Mériaux, X.; Bryère, P.; Ouillón, S.; Dessailly, D.; Xing, Q.; Zhu, J. Development of a Semi-Analytical Algorithm for the Retrieval of Suspended Particulate Matter from Remote Sensing over Clear to Very Turbid Waters. *Remote Sens.* 2016, 8, 211. [CrossRef]
70. Novoa, S.; Doxaran, D.; Odé, A.; Vanhellemont, Q.; Lafon, V.; Lubac, B.; Geniez, P. Atmospheric Corrections and Multi-Conditional Algorithm for Multi-Sensor Remote Sensing of Suspended Particulate Matter in Low-to-High Turbidity Levels Coastal Waters. *Remote Sens.* 2017, 9, 61. [CrossRef]
71. Jiang, D.; Matsushita, B.; Pahelevan, N.; Gurlin, D.; Lehmann, M.K.; Fichot, C.G.; Schalles, J.; Loisel, H.; Binding, C.; Zhang, Y.; et al. Remotely estimating total suspended solids concentration in clear to extremely turbid waters using a novel semi-analytical method. *Remote Sens. Environ.* 2021, 258, 112386. [CrossRef]
72. Hendrik, B.; Hakvoort, J.H.M.; Donze, M. Optical properties of pure water. In *Ocean Optics XII*; SPIE: Bellingham, DC, USA, 1994; Volume 2258. [CrossRef]
73. Balasubramanian, S.V.; Pahelevan, N.; Smith, B.; Binding, C.; Schalles, J.; Loisel, H.; Gurlin, D.; Greb, S.; Alikas, K.; Randla, M.; et al. Robust algorithm for estimating total suspended solids (TSS) in inland and nearshore coastal waters. *Remote Sens. Environ.* 2020, 246, 111768. [CrossRef]
74. Verbessem, J.; Hyndman, R.; Zeileis, A.; Culvenor, D. Phenological change detection while accounting for abrupt and gradual trends in satellite image time series. *Remote Sens. Environ.* 2010, 114, 2970–2980. [CrossRef]
75. Verbessem, J.; Hyndman, R.; Newnham, G.; Culvenor, D. Detecting trend and seasonal changes in satellite image time series. *Remote Sens. Environ.* 2010, 114, 106–115. [CrossRef]
76. Sang, Y.F.; Wang, Z.; Liu, C. Comparison of the MK test and EMD method for trend identification in hydrological time series. *J. Hydrol.* 2014, 510, 293–298. [CrossRef]
77. Hamed, K.H.; Ramachandra Rao, A. A modified Mann-Kendall trend test for autocorrelated data. *J. Hydrol.* 1998, 204, 182–196. [CrossRef]
78. Hipel, K.W.; McLeod, A.I. Time Series Modelling of Water Resources and Environmental Systems; Elsevier: Amsterdam, The Netherlands, 1994.
79. Hirsch, R.M.; Slack, J.R. A Nonparametric Trend Test for Seasonal Data With Serial Dependence. Water Resour. Res. 1984, 20, 727–732. [CrossRef]
80. Feng, L.; Hu, C. Land adjacency effects on MODIS Aqua top-of-atmosphere radiance in the shortwave infrared: Statistical assessment and correction. J. Geophys. Res. Ocean. 2017, 122, 4802–4818. [CrossRef]
81. Jia, J.; Chen, Q.; Ren, H.; Lu, R.; He, H.; Gu, P. Phytoplankton Composition and Their Related Factors in Five Different Lakes in China: Implications for Lake Management. Int. J. Environ. Res. Public Health 2022, 19, 3135. [CrossRef]
82. Wang, H.; Long, H.; Li, X.; Yu, F. Evaluation of changes in ecological security in China’s Qinghai Lake Basin from 2000 to 2013 and the relationship to land use and climate change. Environ. Earth Sci. 2014, 72, 341–354. [CrossRef]
83. Xinhua. China’s Largest Saltwater Lake Sees Water Area Expand. 2021. Available online: http://www.chinadaily.com.cn/a/202110/21/WS617115eea310cdd39bc705fe.html (accessed on 22 April 2022).