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Estimation of Phytoplankton Primary Productivity in Qinghai Lake Using Ocean Color Satellite Data: Seasonal and Interannual Variations

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Abstract: Estimation of primary production in Qinghai Lake is crucial for the aquatic ecosystem management in the northeastern Qinghai–Tibet Plateau. This study used the Vertically Generalized Production Model (VGPM) with ocean color satellite data to estimate phytoplankton primary productivity (PP) in Qinghai Lake during the non-freezing period from 2002 to 2023. Field data from 2018 and 2023 were used to calibrate and verify the model. The results showed a seasonal trend in chlorophyll-a and PP, with the lowest values in May and peaks from June to September. Qinghai Lake was identified as oligotrophic, with annual mean chlorophyl-a of 0.24–0.40 μg/L and PP of 40–369 mg C/m^2/day. The spatial distribution of PP was low in the center of the lake and high near the shores and estuaries. An interesting periodic increasing trend in PP every 2 to 4 years was observed from 2002 to 2023. This study established a remote sensing method for PP assessment in Qinghai Lake, revealing seasonal and interannual variations and providing a useful example for monitoring large saline mountain lakes.

Keywords: Qinghai Lake; Vertically Generalized Production Model; chlorophyll-a; phytoplankton primary production; remote sensing

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1. Introduction

Aquatic ecosystems are highly dependent on phytoplankton for primary production (PP). In large lakes, phytoplankton often accounts for more than 95% of PP [1]. Qinghai Lake, located in the northeastern part of the Qinghai–Tibet Plateau, is the largest and highest inland saline lake in China. Primary productivity plays a key role in maintaining the balance of the aquatic ecosystem in Qinghai Lake, and its assessment is importance for effective aquatic ecosystem management of the lake [2]. The growth in various aquatic organisms in Qinghai Lake basically depends on the energy accumulated by phytoplankton photosynthesis, so phytoplankton can be regarded as the primary energy for fisheries in Qinghai Lake [3]. Since 2001, Qinghai Province has implemented a comprehensive lake closure and stocking strategy for nearly two decades, with a fishing ban policy to protect a special fish, the naked carp (*Gymnocypris przewalskii*), in Qinghai Lake [4]. PP estimates provide important guidance for the conservation and management of fisheries in Qinghai Lake and for the development of a comprehensive lake closure and no-fishing policy.

The traditional monitoring methods of PP are the light and dark bottle method based on scattered sample points from in situ observation; however, these methods cannot be used to analyze the dynamic monitoring of long time series on a large spatial scale [5]. The area of Qinghai Lake is about 4500 km^2. Most studies on ecological parameters (i.e., chlorophyll-a, dissolved oxygen, temperature, nitrogen, etc.) are mainly based on a small number of field samples from cruise surveys. These methods are time-consuming and labor-intensive, and are also unable to enable spatial distribution estimation over a long time sequence [6–8]. Remote sensing monitoring technology, with its advantages of wide spatial coverage and high temporal continuity, is a powerful tool for monitoring lake environments at large spatial scales [9]. PP monitoring and assessment of Qinghai Lake by remote sensing is currently one of the most efficient methods, but it has not been reported so far [10,11]. Ocean color (OC) inversion products obtain environmental parameters from multiple satellite data (the Sea-viewing Wide Field-of-view Sensor (SeaWiFS) and Moderate Resolution Imaging Spectroradiometer (MODIS)) to obtain long time series (2002–present) of environmental parameters to quantify and analyze global or regional ecological and environmental changes in water bodies. This approach has the advantages of high temporal resolution (revisit period of 1 day), numerous effective data points, and wider coverage than other satellite data [12]. The standard OC algorithm is mainly a set of algorithms developed based on datasets collected from coastal or open ocean waters, including the optical properties of saline alpine lakes [12]. Therefore, OC products are also expected to be applied to the study of the PP assessment of long time series in Qinghai Lake.

Several empirical, analytical, and bio-optical models have been applied to estimate marine PP [13–18]. Among them, empirical models are usually driven by basic remote sensing products, supported by measured data, to estimate the spatial and temporal distribution of biological parameters related to lake ecology [11]. For example, the Vertically Generalized Production Model (VGPM) proposed by Behrenfeld and Falkowski is one of the most-used models to estimate PP based on products such as chlorophyll-a and water temperature from satellite remote sensing inversions [13]. The VGPM is a vertically integrated model that combines empirical relationships with phytoplankton photosynthetic mechanisms and relies on optical principles. It has the advantage of having few input variables and can be driven by satellite remote sensing data products to estimate PP [14]. Due to the intricate challenges posed by the analysis of water quality parameters in inland lakes, encompassing optical complexity, adjacency effects, atmospheric correction issues, and diminished water quality and transparency, accurately estimating phytoplankton productivity (PP) in lakes remains a more daunting task compared to the marine environment [15]. Although we have considerable knowledge of photosynthetic processes and ocean optics, which has been extensively applied in marine research, there are still limitations in using satellite data to monitor primary productivity (PP) in lakes based on observational data [16]. It has been found that re-parameterization of the original inverse relationship based on in situ data can eliminate systematic biases associated with the algorithm [16–18]. Therefore, it is imperative to develop remote sensing estimation models for primary productivity in specific areas. Qinghai Lake is an ideal lake for use of the VGPM method because of its good water quality and high transparency. This study attempts to develop an improved VGPM model applicable to Qinghai Lake using OC products and in situ observational data, and applies this model to estimate chlorophyll-a and PP levels during the non-freezing period of Qinghai Lake over 20 years. This study aims to provide a theoretical basis for the long-term monitoring of PP and dynamic assessment of spatial and temporal variation patterns, and to provide scientific and technological support for the evaluation of ecological restoration effects and fishery management of Qinghai Lake.

2. Materials and Methods

2.1. Study Area

Qinghai Lake is located between 99°36′~100°16′ E longitude and 36°32′~37°15′ N latitude with an elevation of about 3200 m. It has a total area of about 4500 km^2, a perimeter of about 360 km, and an average water depth of about 19 m. It is the largest inland saltwater lake on plateaus in China [2]. The Qinghai Lake region has a highland continental climate with abundant light and low precipitation. The lake region receives little precipitation throughout the year, with most of it falling from May to September. The water temperature varies seasonally. In summer, there is an obvious isothermal layer in the lake, with the highest temperature of 22.3 °C in August. The lower layer of the water has a lower temperature, with an average temperature of 9.5 °C. In autumn, the lake water is stirred up by windy weather, so the phenomenon of water temperature stratification disappears. In winter, the lake water temperature is subject to the isothermal inversion phenomenon. In January, the upper layer of the lake water under the ice is −0.9 °C, while the lower layer is 3.3 °C [19]. The sources of lake water recharge in Qinghai Lake are river water, rainwater, and groundwater. Among the major sources of recharge are five tributary rivers, namely Buha River, Shaliu River, Quanji River, Wuha Alam River, and Hargai River (Figure 1) [20]. In Qinghai Lake, the freezing season typically begins in November and lasts until April of the following year with ice cover, while the non-freezing season lasts from May to October [21,22]. As it is impossible to obtain the water color parameters by remote sensing when the lake surface is frozen, our study period is from May to October in the non-freezing period.

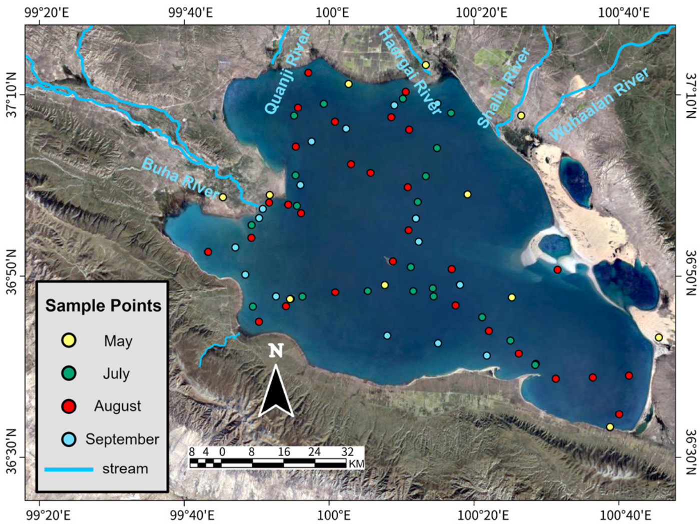

Figure 1. The distribution of sample points and location of the tributary rivers of Qinghai Lake.

2.2. Field Data

Field data were collected from 2018 to 2023, during the non-freezing period. Water temperature and chlorophyll-a were measured at 0.5 m underwater using a portable water quality multi-parameter analyzer (CTD, OCEAN SEVEN310, Idronaut, Brugherio, Italy) (Table 1). Approximately 30 sampling points were measured once throughout the Qinghai Lake, and a total of 257 sample points were measured in this study. The PP was measured with a light–dark bottle device in each sampling site [5].

Table 1. The information of the sampling data in the surface water (<0.5 m underwater) of Qinghai Lake.

Month	Date	Time	Number of Samples	Chlorophyll-a (μg·L^{-1})		Surface Water Temperature (°C)	Average Density of Phytoplankton (ind·L^{-1})	Biomass of Phytoplankton (mg·L^{-1})
				Range	Average	Average	Average	Average
May	14–15 May 2018	7:30~19:50	12	0.030~0.245	0.089	8.8	2400	0.0093
July	1–2 July 2018	8:00~19:38	20	0.070~0.788	0.404	15	21,400	0.0823
August	7–10 August 2018	8:10~19:15	29	0.070~0.730	0.258	17.5	50,730	0.238
September	26–27 September 2018	6:40~19:02	19	0.020~1.229	0.42	13.4	39,470	0.126
August	2–5 August 2019	6:30~18:30	30	0.134~0.594	0.295	13	49,268	0.221
September	19–20 September 2019	7:20~17:50	24	0.196~0.605	0.364	10	38,456	0.119
June	30 June–2 July 2021	8:45~16:20	25	0.198~0.475	0.296	11	14,399	0.044
August	19–23 August 2021	8:50~17:50	24	0.034~0.536	0.266	15	56,687	0.154
June	23–24 June 2022	7:06~17:16	23	0.211~0.719	0.354	15.5	44,106	0.673
May	25–26 May 2023	7:10~17:13	22	0.04~1.642	0.258	8.4	42,061	0.695
August	10–13 August 2023	7:10~18:30	29	0.14~3.23	1.404	17.4	52,693	1.857

A 1 L water sample was collected using a polymethylmethacrylate bottle for analyzing the phytoplankton. Water samples were collected from three layers at each sampling point 0.5 m below the water surface, and 15 mL of Lugol's solution was added to the sample for retention. Species classification and biomass count analysis (wet weight) were performed in the laboratory. A quantity of 1 L of water sample was concentrated to 10–25 mL to count the density and biomass of phytoplankton after standing and precipitation for more than 24 h in the laboratory. The concentrated sample was shaken well and then 0.1 mL was transferred to the phytoplankton counting chamber. Counting was performed under a 10 × 40 microscope, with usually 30–50 fields per slide, and the number of individuals or cells was counted by species. Each sample was counted twice and averaged. The results were valid only if the difference between the two counts and their average were less than 10%; otherwise, the third slide was counted.

The formula for calculating the number of phytoplankton of each water sample is as follows:

$$\mathrm{N} = \frac{A}{a \cdot n} \cdot \frac{\mu}{V} \cdot p$$

where N is the number of phytoplankton in 1 L of water (#. L^{-1}); A is the area of the counting chamber (mm^2); a is the area of each visual field (mm^2); n is the number of individuals counted in each slide; μ is the volume of the concentrated water sample (mL); V is the volume of the counting chamber (mL); and p is the number of phytoplankton counted by each slide.

The counting results were converted into biomass (wet weight) by the cell volume method. The average of the counting results from the three layers of each sampling point was taken as the result of that sampling point.

2.3. Vertically Generalized Production Model (VGPM)

The VGPM model was developed to estimate marine primary productivity based on parameters such as temperature and chlorophyll-a samples in water quality classes I and II of the Environmental Quality Standards for Surface Water of China (GB3838-2002) [13,23]. The water quality of Qinghai Lake was classified as class I with high transparency, which is suitable for the use of this model to calculate PP. The parameters can be obtained using remote sensing monitoring and other resources, and the equation is:

$$PP = 0.66125 \times P^{B}_{ept} \times \frac{E_0}{E_0 + 4.1} \times Z_{eu} \times C_{opt} \times D_{irr} \tag{1}$$

where PP is the primary productivity (mg C/m^2/day) integrated from the surface layer to the euphotic layer; P^{B}_{ept} is the maximum rate of carbon fixation in the water column (mg C/mg Chl·h); E_0 is the photosynthetically available radiation (PAR) at the water surface (μmol/m^2/day); Z_{eu} is the depth of the true photosphere (m); D_{irr} is the photoperiod (h); and C_{opt} is the chlorophyll-a concentration (Chl-a) (μg/L) at the water surface.

2.3.1. Calculation of the Maximum Rate of Carbon Fixation in the Water Column

P^B_{ept} can be considered as a function of the temperature in the water column and is calculated as follows [15]:

$$P^B_{ept} = \left\{ \begin{array}{c} 1.13(T \leq -1.0) \\ 4.00(T \geq 28.5) \\ P^B_{ept}(-1.0 < T < 28.5) \end{array} \right\} \quad (2)$$

T (°C) is the surface temperature.

$$P^B_{ept} = 1.2956 + 2.749 \times 10^{-1}\mathrm{T} + 6.17 \times 10^{-2}\mathrm{T}^2 - 2.05 \times 10^{-2}\mathrm{T}^3 + 2.462 \times 10^{-3}\mathrm{T}^4 - 1.348 \times 10^{-4}\mathrm{T}^5 + 3.4132 \times 10^{-6}\mathrm{T}^6 - 3.27 \times 10^{-8}\mathrm{T}^7$$

2.3.2. Estimation of Photoperiod and Photosynthetically Available Radiation

The photoperiod D_{irr} is calculated from the average monthly sunshine hours from national weather station websites (http://data.cma.cn/ (accessed on 31 December 2023)). The spectral component of solar radiation that is effective for plant photosynthesis is called PAR, and has a wavelength range of 380–710 nm and largely coincides with visible light [24]. The photosynthetically available radiation E_0 is derived from remotely sensed products from the ocean color satellite MODIS.

2.3.3. Calculation of Euphotic Zone

The euphotic zone (Z_{eu}) is obtained from the diffuse attenuation coefficient Kd_{PAR} of photosynthetically available radiation obtained from OC products, which is calculated by the equation [24,25] below:

$$Z_{eu} = \frac{4.605}{Kd_{PAR}} \quad (3)$$

$$Kd_{PAR} = 0.896Kd_{490}^{0.873}, (r^2 = 0.98, n = 81, P < 0.001) \quad (4)$$

Since the diffuse attenuation coefficient of irradiance at a wavelength of 490 nm correlates well with the diffuse attenuation coefficient of photosynthetically available radiation Kd_{PAR}, Kd_{PAR} can be calculated from Kd_{490} [24,25].

2.4. Estimating Phytoplankton Primary Productivity in Qinghai Lake

2.4.1. Setting up the Model and Data Sources

In this study, an improved VGPM model was constructed to estimate the PP of Qinghai Lake. The model construction involved the following two steps: (1) Extracting the MODIS satellite data from the OC Level-2 products of NASA Goddard Space Flight Center (GSFC, https://Oceancolor.gsfc.nasa.gov/ (accessed on 31 December 2023)) in the non-freezing period (May to October) of Qinghai Lake from 2002 to 2023, with a total of 32,120 images at a spatial resolution of 1 km and a temporal resolution of daily satellite revisits. The data were pre-processed, specifically including batch clipping, matching, and reprojection in ArcGIS using a Python scripting program with a uniform WGS 84 coordinate system and UTM projection. (2) The relevant parameters required for the VGPM model to calculate PP (Equation (1)) were extracted from the above data products. The chlorophyll-a concentration (Copt) product was obtained using the standard blue-to-green band ratio algorithm in the NASA OC4 Algorithm products [26]. Surface water temperature (T) is a product obtained from MODIS mid- and far-infrared bands, inverted using the proto-algorithm algorithm, and validated by AVHRR satellite sensors and situ data. The photosynthetically available radiation (E_0) and the diffuse attenuation coefficient of photosynthetically available radiation at a wavelength of 490 nm ($Kd_{(490)}$) were OC data products from the Visible Infrared Imaging Radiometer Suite (VIIRS) [26]. Photoperiod was obtained from the nearest Republican National Reference Weather Station closest to Qinghai Lake (http://data.cma.cn (accessed on 31 December 2023)). These parameters were used as input parameters to the VGPM model shown in Equations (1)–(4) for the estimation of PP.

2.4.2. Calibration and Validation of VGPM Model

In this study, the survey data from 2018 to 2023 (mainly including chlorophyll-a concentration (C_{opt}) and surface water temperature (T)) were compared with the spatio-temporal synchronized data products extracted by OC to verify the accuracy of the model and calibrate the model. The final model-estimated PP values from the model can be compared with the measured mean phytoplankton densities, and the reasonableness of the model-estimated PP values can be verified by analyzing their correlations. First, the applicability of the OC data products in Qinghai Lake was verified by comparing the errors between the simulated and measured values of water temperature and chlorophyll-a from the model inversion. A total of 179 out of 256 samples in Qinghai Lake were selected to establish a regression equation with the temperature products of OC. The remaining 77 samples were used to validate the temperature values. The comparative analysis of the measured water temperature and the OC data product showed a correlation coefficient of 0.88, indicating that the OC water temperature data product could explain 88% of the measured data, with an average relative error of 5% and an absolute error range of −1.76~1.64 °C (Figure 2a). The water temperature error was within an acceptable range, so the OC water temperature data products could be directly substituted into the VGPM model for PP estimation.

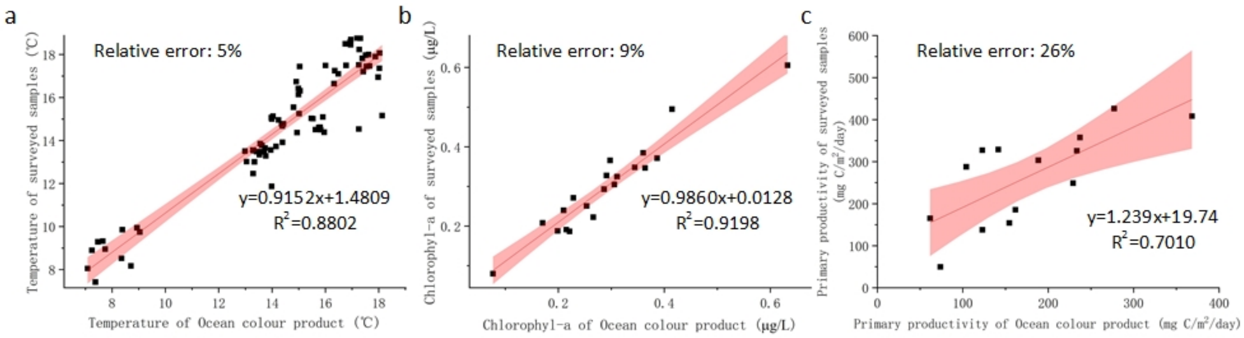

Figure 2. The comparison of the measured and ocean color remote sensing data in Qinghai Lake. (**a**) is the comparative analysis of the measured and the OC derived water temperature; (**b**) is the comparative analysis of the measured and the OC derived rectified chlorophyll-a; (**c**) is the comparative analysis of the measured and VGPM modelled primary productivity.

The results of the comparative analysis between the chlorophyll-a data products of OC and the measured values showed the chlorophyll-a product values of OC are much higher than the measured values and the correlation is low, so the chlorophyll-a products of OC cannot be directly used to calculate the PP values, and the chlorophyll-a values from the OC products need to be rectified with measured data before applying the VGPM model of Qinghai Lake (Figure 2b). The rectification process is as follows: (1) A total of 193 out of 256 samples were selected to establish a regression equation with chlorophyll-a products of OC; 43 measured samples collected between 2018 and 2023 were selected to rectify the chlorophyll-a products; and the remaining 20 samples were used to validate the rectified chlorophyll-a values. The validation results showed that the correlation coefficient between the calibrated chlorophyll-a and the measured values was 0.92, with a relative error of 9% and an absolute error range of −0.07 to 0.04 μg/L (Figure 2b), and the error of the calibrated chlorophyll-a values was within an acceptable range. A total of 14 matched pairs of PP from the surveyed data were compared with simultaneous VGPM-modeled PP results; the correlation coefficient was 0.70, with a relative error of 26% (Figure 2c), indicating that the VGPM model for Qinghai Lake has a good accuracy for predicting PP.

3. Results

3.1. Seasonal Variation of Chlorophyll-a during the Non-Freeze Period in Qinghai Lake

The 2019 results were used as an example to analyze the spatial distribution of chlorophyll-a in Qinghai Lake. The center of the lake had a low concentration of chlorophyll-a, while there was a much higher concentration near the lakeshore and in the estuary regions (Figure 3). From 2002 to 2023, the seasonal variation of chlorophyll-a showed a fluctuating trend with the low values occurring in May and the high values occurring in June, then decreasing from July to October (Figure 4). In May, the aquatic plants begin to proliferate as the thaw occurs after the freezing period. Meanwhile, the chlorophyll-a shows a lower value in the box plots with an interquartile distance of 0.07 g/L, indicating that chlorophyll-a concentration fluctuated less from year to year than other months of the year (interquartile range was 0.17–0.23 µg/L). Regarding the medians, the lowest median chlorophyll-a was 0.18 µg/L in May; from June to September, chlorophyll-a showed a gradual increase from 0.20 µg/L in June to 0.39 µg/L in September, and started to decrease to 0.32 µg/L in October. Concerning the minima, the minima of chlorophyll-a varied little from May to September, ranging from 0.11 to 0.16 µg/L, and the lowest minima occurred in October, at 0.06 µg/L. In terms of maxima, the lowest maxima chlorophyll-a was 0.79 µg/L in May, the maxima from June to October showed a trend of decreasing and then increasing, and the highest maxima also occurred in October, at 0.91 µg/L. The maximum value of 0.91 µg/L in October indicates that October is the month with the largest interannual fluctuation of chlorophyll-a. The multi-year monthly mean values of chlorophyll-a concentration during the non-freezing period of Qinghai Lake from 2002 to 2023 ranged from 0.24 to 0.40 µg/L, which is typical for an oligotrophic lake.

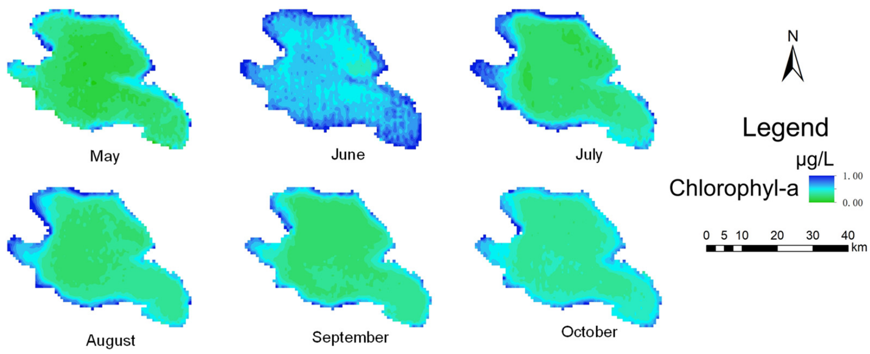

Figure 3. The spatial distribution of chlorophyll-a (MODIS Aqua) in Qinghai Lake from May to October, 2019.

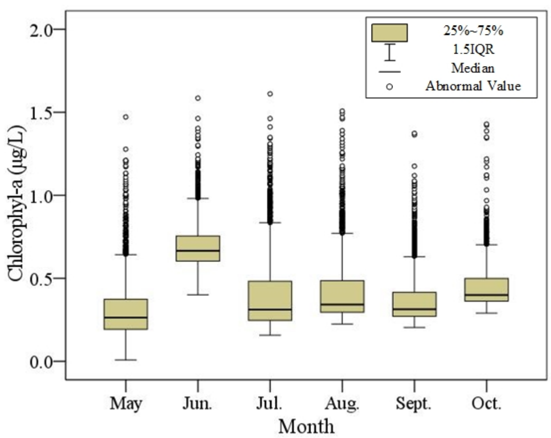

Figure 4. The boxplots of chlorophyll-a (MODIS Aqua) in Qinghai Lake from 2002 to 2023 in the non-freezing period. The five lines from the bottom to the top of the box plot represent the minimum, lower quartile, median, upper quartile, and maximum values, respectively.

3.2. Seasonal Changes in PP during the Non-Freezing Period of Qinghai Lake

The results estimated by MODIS Aqua data source were used to analyze the seasonal variation pattern of PP during the non-freezing period of Qinghai Lake. The spatial distribution of PP was basically consistent with chlorophyll-a, and the spatial distribution showed a small value in the center of the lake and a large value near the lakeshore and estuary areas (Figure 5, taking 2019 as an example). The seasonal variation trend also showed a fluctuation of first increasing and then decreasing, with the low value occurring in May and October and the high value occurring in July to September (Figure 6). The box plots of PP values were smaller in May and September, with interquartile distances of 87.37 mg C/m^2/day and 94.86 mg C/m^2/day, respectively, indicating that the PP values fluctuated less annually in May and September than in other months. With regard to the median, the mean PP was lowest in May at 16.76 mg C/m^2/day, and the PP from June to September showed a gradual increase from 92.77 mg C/m^2/day in June to 135.27 mg C/m^2/day in September, and then started to decrease to 119.38 mg C/m^2/day in October. The minimum value of PP also increased first and then decreased from May to October, ranging from 10.07 mg C/m^2/day to 28.30 mg C/m^2/day. The maximum value in May was the smallest among all the months, being 223.83 mg C/m^2/day. The maximum value from June to October showed a trend of first decreasing and then increasing, and the maximum value also appeared in July, which was 397.50 mg C/m^2/day. This indicates that July is the month with the highest seasonal value of PP, and it is also the month with the largest interannual variation in PP. The multi-year monthly average values of PP during the non-freezing period of Qinghai Lake from 2002 to 2023 ranged from 40 to 369 mg C/m^2/day.

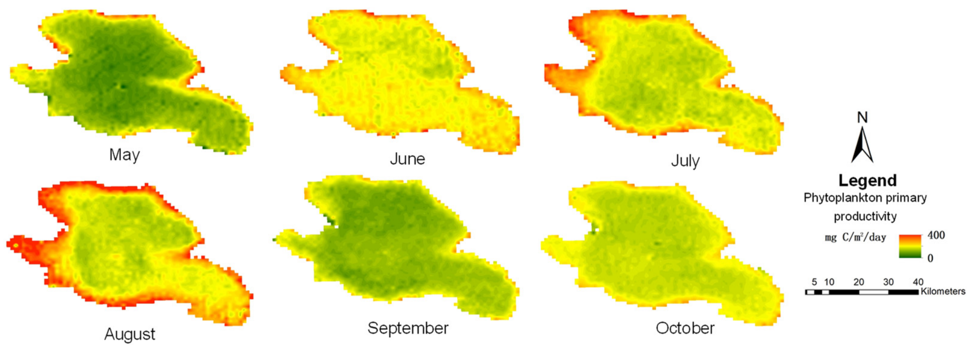

Figure 5. The spatial distribution of phytoplankton primary productivity in Qinghai Lake from May to October, 2019.

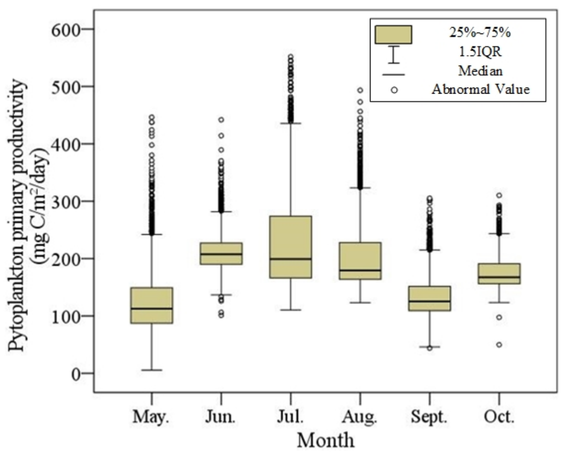

Figure 6. The boxplots of phytoplankton primary productivity (MODIS Aqua) in Qinghai Lake from 2002 to 2023 in the non-freezing period. The five lines from the bottom to the top of the box plot represent the minimum, lower quartile, median, upper quartile, and maximum values, respectively.

3.3. Interannual Variation of PP during the Non-Freezing Period of Qinghai Lake

The PP value of Qinghai Lake in the non-freezing period from 2002 to 2023, which is in the period of "closed lake for breeding fish", was estimated in our study. Estimated PP values in August are most representative for analysis of the interannual variation trend of PP values in Qinghai Lake from 2002 to 2023. This is because the only months in which the OC data product had no missing data records for Qinghai Lake were August and October; the month of August also coincides with a critical life stage for naked carp, and the PP could be related to fish resources through the food web [27]. The results show that the PP values near the lakeshore are larger than those near the center of the lake in all years in terms of spatial distribution. In particular, the PP values near the mouth of Buha River and Quanji River in the western region are significantly larger than those in other regions (Figure 7). The PP values showed a very significant interannual fluctuation trend, with values ranging from about 20 to 400 mg C/m^2/day. Among them, the PP values were less than 100 mg C/m^2/day from 2002 to 2004, which were smaller than those of other years (the green area in Figure 7). While the PP values increased significantly to 200–400 mg C/m^2/day from 2005 to 2007 (the color changes from green to yellow in the graph), the PP values decreased again to less than 100 mg C/m^2/day from 2008 to 2009. The PP values increased significantly in 2010, especially in the northwest area near the Buha and Quanji River regions. From 2011 to 2014, PP values began to decrease again, and most areas of the lake fluctuated in the range of 100 to 200 mg C/m^2/day. The PP values of the whole lake increased significantly again to about 300 mg C/m^2/day in 2015; in particular, the value for the area near the river estuary was larger than that for other areas. PP then decreased to below 200 mg C/m^2/day in 2016~2018, and PP increased to the highest value of about 400 mg C/m^2/day in 2019. Overall, the range of PP values in Qinghai Lake from 2002 to August 2019 seems to be from about 20 to 400 mg C/m^2/day, showing a cyclical fluctuating upward trend, with PP values decreasing and then increasing significantly at intervals of 2–4 years, reaching the highest value in 2019, then decreasing from 2020 to 2023 (Figure 8).

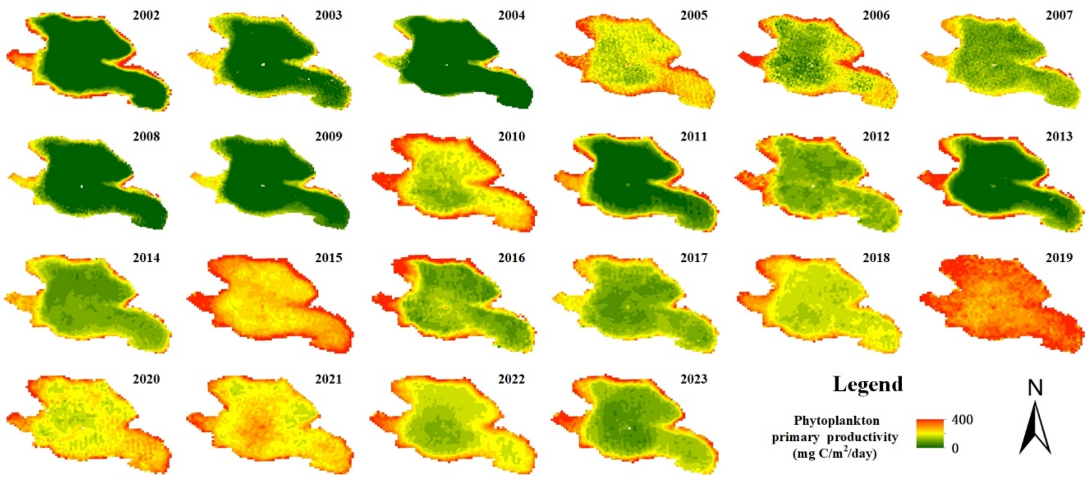

Figure 7. Spatial and temporal distribution map of phytoplankton primary productivity (PP) in Qinghai Lake from 2002 to 2023 (August).

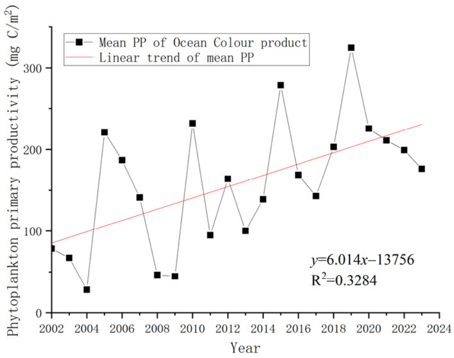

Figure 8. Trend of mean of phytoplankton primary productivity (PP) in Qinghai Lake from 2002 to 2023 in August.

4. Discussion

4.1. Limitation and Improvement of Remote Sensing Estimation Method for Phytoplankton Primary Productivity in Qinghai Lake

Due to the large difference between chlorophyll-a from OC products and in situ samples, the chlorophyll-a from OC products cannot be directly used for calculation in the VGPM model; therefore, we used the measured data to rectify the OC products. After rectification, the relative error between the calibrated chlorophyll-a and the measured value was less than 9%, which could be substituted into the VGPM formula to calculate the PP value of Qinghai Lake. The reason for this error is, on the one hand, that the measured sample points do not coincide with the time of the remote sensing satellite products. The time period of the sampling point measurement is from about 6:30 a.m. to 19:30 p.m., while the MODIS satellite transit time is 6:00 a.m. and 15:00 p.m. Due to the large area of Qinghai Lake (about 4500 km^2), the measurement work required several days to obtain a large amount of sample data for the average distribution of the whole lake. Therefore, it is impossible to collect the sample points of the whole lake within the satellite transit time period, and only the satellite data products close to the sampling time point were selected for verification. On the other hand, because the spatial resolution of the MODIS satellite OC product is 1 km, the actual sampling point value and the remote sensing satellite extraction value have a spatial error of 1 km. However, because the MODIS satellite has a long time series and high-temporal-resolution data, combined with the large area of Qinghai Lake, enough sampling points (more than 4000 data points) can be extracted for interpolation, and the error caused by the spatial resolution is within the acceptable range. In contrast, other satellites (Landsat, Sentinel series satellites, etc.) have high spatial resolution, but low temporal resolution because of their long revisit period; thus, they have few images per month (cloudy weather above Qinghai Lake), and it is impossible to obtain enough valid sample points to cover the whole lake. Therefore, in order to estimate the PP results over a long time series for each month of the whole Qinghai Lake, MODIS satellite imagery is the most suitable for use in PP estimation.

Although the error is caused by the time and space issues described above, it is an absolute error, and does not affect the relative value from the same satellite data source. Therefore, the results of the spatial and temporal variation trend of chlorophyll-a and PP values reflected by the model results are credible. In addition, due to the limitations of remote sensing satellite products, there are many dates without effective data. In this study, the number of days with effective data of chlorophyll-a in each month of the OC data products from 2002 to 2023 was counted (if the data points of the obtained remote sensing data products can cover more than 50% of the lake area, this day is considered as providing effective remote sensing data) (Figure 9). The results show that the number of days with effective data is higher in August and October than in May and July, so the accuracy of the remote sensing data products is higher in August and October than in other months. The PAR in the OC data product cannot be compared with the results of the VGPM model because it was not measured in our study. In the future, this parameter will be measured synchronously to better verify the model.

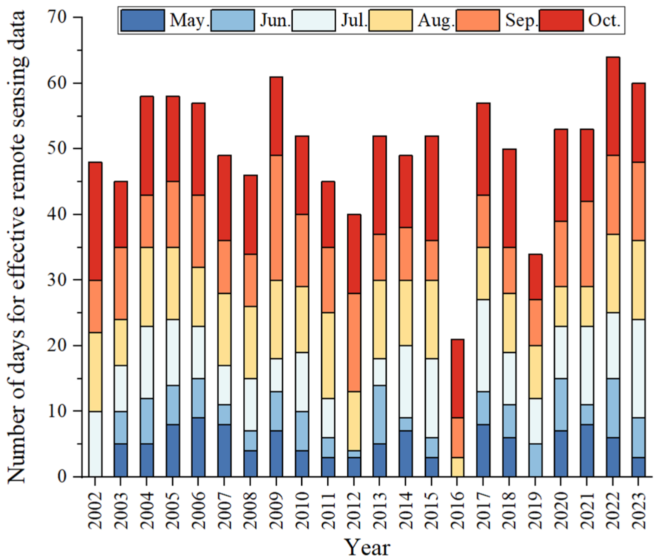

Figure 9. Statistical results of the effective days of chlorophyll-a in OC data products in each month from 2002 to 2023.

4.2. Validation Analysis of Estimation Results of Phytoplankton Primary Productivity in Qinghai Lake

In other lakes at a high altitude and having high salinity, water quality and transparency are similar to those of Qinghai Lake, and these lakes thus highly suitable for the assessment of their long-term and large-scale primary productivity of plankton using the method proposed in this study. Other results show that chlorophyll-a and PP are relatively low in these similar ecosystems, which are oligotrophic lakes [28–30]. Studies have shown that the primary productivity of phytoplankton is mainly affected by temperature, salinity, sunshine duration, nutrients, wind, and the growth cycle of phytoplankton [28–30]. Factors such as water temperature and light cycle have been considered in this model. Therefore, comparison of the measured phytoplankton with the PP trend simulated by this model was considered to verify the reliability of the model (taking 2018 as an example). The average biomass and density of phytoplankton at 20 sampling sites monitored from May to October in 2018 were compared with the simulated PP. The results showed that the average density of phytoplankton in May is the smallest in the surveyed months, and has a similar trend to the simulated PP values in Haixin Mountain, Sankuaishi, and Heima Estuary (Figure 10). In August, the average density of phytoplankton in Heimahekou, Haixinshan, and Erlangjian is largest among the surveyed months, and the simulated PP values also had a similar trend [31]. The results of the VGPM model showed that the PP values reached their peak in July, and the measured average density of phytoplankton was the highest in August and September. Since the PP is also affected by light and temperature, and the average temperature of Qinghai Lake from May to October is highest in July, temperature has the greatest impact on PP [32]. The variation trend and distribution of the average density of phytoplankton is basically consistent with the simulated PP; therefore, the simulated PP from the VGPM model can well reflect the spatial and temporal distribution of phytoplankton primary productivity in Qinghai Lake.

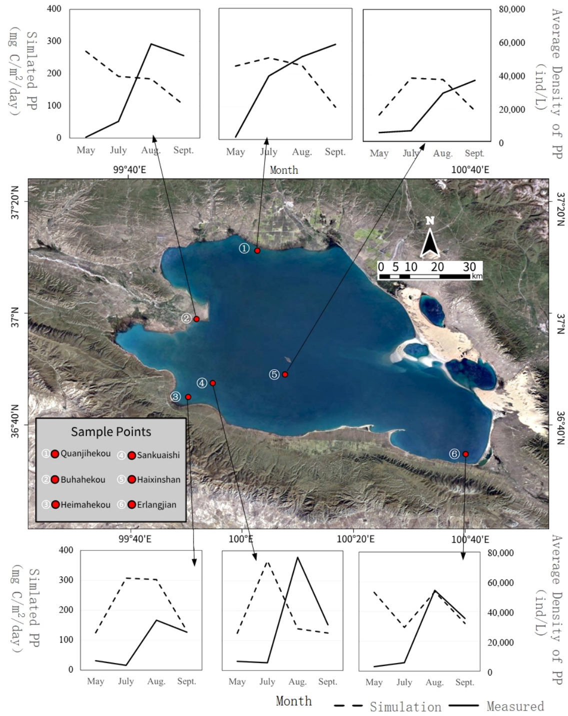

Figure 10. Contrast of average density of the phytoplankton and simulated PP in Qinghai Lake.

4.3. The Change Trend of Chlorophyll-a and PP in Qinghai Lake in the Past Twenty Years and Its Causes

The seasonal variation in chlorophyll-a and PP values from 2002 to 2023 showed a trend of first increasing and then decreasing in most years. This phenomenon may be caused by the life stage of phytoplankton and the feeding of naked carp in Qinghai Lake. Naked carp is an anadromous spawning fish that migrates from the lake to the tributaries of Qinghai Lake to spawn. Its peak spawning period is around mid-June, and adult fish mostly migrate to the tributaries. Thus, fewer adults remain in the lake, which is one of the reasons for the increase in PP in July and August [2,27]. During this period, the phytoplankton just start to grow from May to September, and there are fewer fish in the lake to feed on it, causing the PP value to peak in August. After August, the adult naked carp and their larvae migrate into the lake and start to feed on the plankton in Qinghai Lake, causing the PP value to decrease. In September and October, due to the feeding of naked carp, and because the phytoplankton gradually enter a dormant period, the density of phytoplankton begins to decrease, while the PP also begins to decrease [13,28]. The spatial distribution of PP values shows a low value in the center of the lake and a high value near the lakeshore and estuary, where more nutrients can be received from the lakeshore drainage or tributary streams for phytoplankton growth [29].

The interannual fluctuation trend in the PP value from 2002 to 2023 is consistent with the research results of other scholars on the primary productivity of Qinghai Lake. The reasons for the fluctuation are mainly the nutrient input and water temperature [33–35]. The results of this study show that the PP value shows a trend of periodic fluctuation and increase from 2002 to 2023. It is speculated that this may be related to the significant increase in the average temperature of Qinghai Lake in the past 50 years [36]. According to this study, the average temperature of Qinghai Lake shows interannual fluctuation with a gradual upward trend [37]. It is speculated that the fluctuating trend in water temperature affects the interannual fluctuation in PP. In addition, the increased precipitation in the Qinghai Lake basin caused the increase in runoff in the Buha River estuary [38], which resulted in more nutrients being imported into Qinghai Lake. Increased chlorophyll-a and PP will increase the food supply for fish resources in Qinghai Lake [32].

5. Conclusions

The model of phytoplankton primary productivity of Qinghai Lake established in this study can estimate the monthly mean value of phytoplankton primary productivity of Qinghai Lake during the non-freezing period (May to October), and can be used to analyze the interannual spatial and temporal distribution trends of phytoplankton primary productivity of a long time series. The spatial distribution of chlorophyll-a and PP generally showed a small value in the center of the lake, and a large value in the lakeshore and estuary area. Seasonal changes showed an increasing and then decreasing trend. Chlorophyll-a and PP were lowest in the early stages of thawing (May), increased with increasing water temperature, and decreased to a low value in October. The multiannual monthly mean values ranged from 0.24 to 0.40 μg/L and 40 to 369 mg C/m^2/day, characteristic of oligotrophic lakes. The interannual fluctuation trend in PP showed a fluctuating upward trend with a period of 2~4 years, and the range of its value was about 20~400 mg C/m^2/day. The results can be explained by the growth cycles of phytoplankton and naked carp. Compared with traditional measurement methods, the PP estimation method of Qinghai Lake based on satellite remote sensing established in this study not only has the advantages of wide monitoring coverage and strong monitoring timeliness, but also significantly reduces the cost of field sampling and avoids the risks of field work. It can also enable continuous systematic observation and historical inversion of phytoplankton productivity in Qinghai Lake. In the future, it could provide important support for the dynamic monitoring of the ecological environment, and the conservation and management of fish resources, by linking it with analysis of the trophic food chain in Qinghai Lake.

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