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Remote Sensing Estimation of Chlorophyll-a Content in Nearshore Aquaculture Areas Based on Sentinel 2 Data

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Abstract: Accurate monitoring of chlorophyll-a concentration in offshore aquaculture areas is of great significance for ecological assessment and fisheries management. In this paper, a semi-analytical inversion model of chlorophyll-a concentration was constructed based on field-measured spectral reflectance data of the water column in the Zhelin Bay aquaculture area of Guangdong Province as a research object. The study validated the model using Sentinel-2 satellite data, revealing the spatial and temporal distribution characteristics of chlorophyll-a concentration in Zhelin Bay. The results showed that the inversion model constructed by the sensitive band ratio method had a high estimation accuracy, with a relative error of 13.25% and a coefficient of determination of R^2 of 0.891. It was found that the distribution of chlorophyll-a concentration in the aquaculture area of Zhelin Bay showed obvious regional differences, with the highest chlorophyll-a concentration in the pond culture area in the north and the west, and the relatively low chlorophyll-a concentration in the nets and shell-fisheries culture area. summer and fall were significantly higher than those in spring and winter, showing seasonal fluctuations. This study provides a scientific basis for pollution monitoring and aquaculture management in near-shore waters.

1. Introduction

In recent years, as the impacts of human activities and climate change on coastal ecosystems continue to intensify, the problem of eutrophication in nearshore waters, especially in coastal aquaculture area, has become increasingly serious, posing a direct threat to the aquaculture industry and marine ecosystems[1,2]. Nearshore mariculture plays a crucial role in the global fishery industry. Its scale has been continuously expanding, and its impact on the marine ecological environment has become increasingly significan[3,4]. Since the 1990s, China's aquaculture industry has developed rapidly, and China has become one of the countries with the largest aquaculture output in the world[5]. While bringing huge economic benefits, mariculture has caused serious damage to the offshore ecological environment, resulting in a series of water pollution problems[6]. Chlorophyll-a (Chl-a) , as a key bioindicator of water eutrophication, reflects changes in the concentration of phytoplankton and can effectively indicate the degree of eutrophication in the water column, which is an important parameter for assessing the health of marine ecosystems[7]. Accurate monitoring of Chl-a concentrations in aquaculture areas is important for developing scientific fisheries management strategies, assessing water quality and improving ecosystem health; however, traditional discrete sampling methods are time-consuming, labor-intensive and have limited spatial coverage, which makes it difficult to meet the real-time monitoring needs of large aquaculture areas[8]. In contrast, remote sensing technology has the advantages of rapid, large-scale and periodic acquisition of surface information, and is able to efficiently collect water quality data in large-scale waters, which provides the possibility of long-term spatial and temporal dynamic monitoring of Chl-a concentration[9].

In the field of remote sensing estimation of Chl-a content in water bodies, the development of inverse modeling has become a significant advancement for water quality monitoring, particularly in dynamic aquatic environments. Traditional methods commonly utilize reflectance spectra to infer the concentration of water body constituents by examining the absorption and scattering properties of optical elements within the water[10,11]. These models, while valuable, often depend on empirical and semi-analytical approaches that have been widely implemented for quantitative Chl-a estimation across diverse water types[12,13]. However, the adaptability of these models is limited by their assumptions, which tend to be overly idealized concerning water body optical properties, thus reducing their generalizability in complex and variable water quality conditions[14,15].

Machine learning approaches, including support vector machines, neural networks, and random forests, are increasingly applied to water quality parameter inversion and have demonstrated strong non-linear fitting capabilities alongside greater accuracy[16]. Unlike traditional models, machine learning-based inversion techniques are better suited for handling complex interactions between variables such as phytoplankton, suspended sediments, and colored dissolved organic matter, all of which significantly influence Chl-a concentration[17-19]. These models have shown to enhance the accuracy of Chl-a concentration estimation markedly, providing higher robustness in varied water conditions. However, they remain highly dependent on large datasets and substantial computational resources, necessitating further optimization to improve practical usability and reduce computational load.

In terms of remote sensing platforms, a range of satellite data sources has been utilized for Chl-a concentration inversion, with notable success achieved across various platforms. Data from satellites such as Landsat TM, OLI, MODIS, and SeaWiFS have been employed effectively in water quality assessments[20]. MODIS and SeaWiFS, owing to their high temporal resolution, facilitate extensive, long-term monitoring of water quality on a large scale; however, their lower spatial resolution constrains their applicability in smaller, more intricate water bodies[21]. TM and OLI provide improved spatial resolution suitable for medium-scale water quality monitoring but still lack the detail required for capturing the complexities of nearshore environments[22].

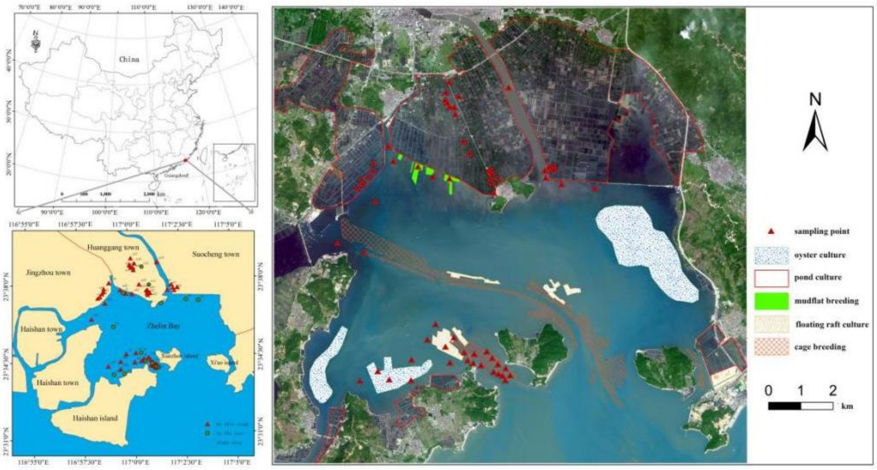
In addition, in order to improve the inversion accuracy, researchers have recently introduced multi-band combination and spectral analysis methods to enhance the ability of the model to recognize different water quality features[23].Gitelson et al. (2003) proposed a three-band combination method, which improved the estimation accuracy of the Chl-a concentration by combining the reflectance of different bands, especially for turbid water bodies containing a large amount of suspended solids. The analysis based on the red-edge band further improves the sensitivity and applicability of the model to Chl-a changes, especially for aquaculture-intensive areas[24,25]. Based on such improvements, remote sensing technology is becoming an indispensable tool in water quality monitoring, which can quickly and effectively provide ecological information on water bodies at large scales and over long periods of time, providing important support for fisheries management and environmental protection.

In conclusion, although certain achievements have been made in the remote sensing monitoring of chlorophyll-a in offshore aquaculture areas, there are still many deficiencies in model universality, consideration of environmental factors and data processing. Further in-depth research and improvement are needed to enhance the monitoring and management ability of the offshore aquaculture ecological environment. In the context of the many challenges faced by the global offshore ecological environment, it is crucial to accurately monitor the water quality of offshore aquaculture areas. This study takes the aquaculture area of Zhelin Bay in Guangdong as the object, focuses on the remote sensing estimation of chlorophyll a content, deeply analyzes its spatio-temporal distribution characteristics and influencing factors, and provides a valuable reference basis for offshore aquaculture pollution monitoring and management.

2. Data and methods

2.1 Study sites

Zhelin Bay is located in the southern part of Raoping County, Chaozhou, Guangdong, with a unique geographical location. Its longitude and latitude range from 116°55′E - 117°05′E and 23°31′N - 23°38′N (see Fig. 1). It is adjacent to multiple towns and islands. The average water depth is 4.8 meters, and the tidal type is an irregular semi - diurnal tide with an average tidal range of 1.69 meters. After years of development, it has become an important cage - culture area in the southern coastal area and is also facing serious eutrophication problems.



*Drawing No. GS (2019) 1822

Figure 1 Location of Zhelin Bay

2.2 Data Collection

60 sampling points were carefully set up in the oyster - culture area, pond - culture area, tidal - flat - culture area, floating - raft - culture area, cage - culture area and near - shore sea area of Zhelin Bay. These sampling points were representative and could fully cover the typical water - quality - change characteristics of different culture types and areas. During the joint field surveys on May 3, June 11, August 10 and September 3, 2018, the FieldSpec4 spectrometer of ASD Company was used to collect the water - body spectral data in the spectral range of 350nm - 2500nm with a sampling interval of 1.5nm. The water - surface measurement technology was adopted to measure the spectral curves of the standard plate, water body and skylight in turn at each sampling point. The water - body remote - sensing inversion rate data were obtained by using the ViewSpecPro software. The chlorophyll - a concentration was determined by using the UV - 2550 UV

spectrophotometer in the laboratory according to national standards. Among them, 45 samples were used to construct the model and 15 samples were used for model - error testing.

The Sentinel - 2 satellite 1C data with cloud cover less than 10% and synchronous with ground measurement in 2018 (from January to December) were downloaded from the European Space Agency Data Center. The Sen2Cor module of the SNAP software was used for atmospheric correction. The cirrus clouds were removed through a semi - empirical algorithm and the remote - sensing reflectance data were obtained. Then, the water - body area of Zhelin Bay was extracted by using the Normalized Difference Water Index (NDWI) combined with multi - scale segmentation and spectral, geometric and texture features to lay a foundation for subsequent research.

2.3 Methods

In this study, the three - band model and the Normalized Difference Chlorophyll Index (NDCI) model in the semi - empirical analysis model were used for remote - sensing estimation of the chlorophyll - a content in water bodies. The three - band model reasonably selected the band combination according to specific physical principles to minimize the interference of other water - body components on the chlorophyll - a estimation and ensured the applicability of the model to a certain extent. The NDCI model was constructed based on the absorption peak of chlorophyll - a near 665 - 675nm and the reflection peak near 700 - 710nm, which could effectively avoid the influence of suspended solids in water on short - wave spectra and had high sensitivity to chlorophyll - a in turbid water bodies. In terms of model evaluation, the Root - Mean - Square Error (RMSE) and the Mean Absolute Percentage Error (MAPE) were introduced as measurement standards to accurately quantify the estimation error of the model and ensure the scientific and reliable evaluation of the model accuracy.

3. Results

3.1 Analysis of Water - body Spectral Characteristics

The in - depth analysis of the 350 - 1000nm spectra of the water body in Zhelin Bay revealed its rich spectral characteristics (see Fig. 2). In the 400 - 500nm band, due to the strong absorption of short - wave blue - violet light by chlorophyll a and yellow substances, although the water - body reflectance increased with the increase of wavelength, it was at a relatively low level as a whole. The spectral characteristics in this band were closely related to the distribution of phytoplankton and provided important clues for the identification of phytoplankton concentration. The first reflection peak in the 550 - 580nm band was attributed to the weak absorption of carotenoids and chlorophyll in this band and the strong scattering of non - algal substances in the water body. This reflection peak not only reflected the characteristics of non - algal suspended particulate matter but also could assist in the analysis of water - quality composition. The reflectance trough near 670nm was the result of the strong absorption of chlorophyll a by high - density algae and was often used to monitor the change of algae concentration. The reflection peak in the 690 - 710nm band was due to the local minimum of the total absorption coefficient of water and chlorophyll here, and its peak height and position provided a key basis for the quantitative evaluation of the eutrophication degree of water bodies. The reflectance curve in the 750 - 780nm band tended to be stable, indicating that the spectral characteristics of the water body changed little in this interval and were mainly affected by the absorption and scattering of the water body itself. The small reflection peak near 800nm might be related to the increase of water - body scattering particles, and the continuous decrease of the reflectance in the 820 - 1000nm band was closely related to the absorption characteristics of the water body for long - wavelength light.

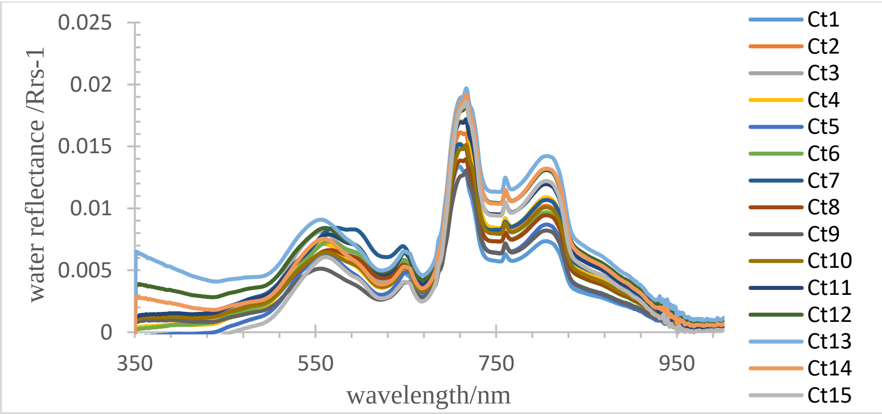


Fig. 2 The curve of sample measured spectral reflectance

3.2 Construction and Validation of Chl - a Inversion Model

To improve the data quality and the significance of spectral characteristics, the water - body reflectance data were standardized and the first - order differential spectral analysis was carried out. The results showed that the correlation between the standardized 510nm and 710nm bands and the chlorophyll - a concentration reached 0.83, and the correlation between the first - order differential spectra of 560nm, 675nm and 700nm bands and the chlorophyll - a concentration was close to 0.9, indicating that these bands were sensitive to the change of chlorophyll - a concentration and suitable for modeling. Through the comparative analysis of different models, it was found that the quadratic model constructed with Rrs(700nm)/Rrs(675nm) had the highest fitting accuracy, with the determination coefficient R^2 reaching 0.891 and the significance level of 0.002 (see Table 1). At the same time, combined with the Sentinel - 2 satellite band settings, it was determined that the B5 (705nm), B4 (665nm) and B3 (560nm) bands performed outstandingly in the model. The quadratic model with Rrs(B5)-Rrs(B4)/Rrs(B5)+Rrs(B4) as the inversion factor and the linear model of Rrs(B5)/Rrs(B4) both had high fitting degrees, further verifying the validity and stability of the model .

According to the validation results of the optimal model, the scatter plot of chlorophyll-a measured values and predicted values was plotted (see Fig. 3). From the figure, the coefficient of determination of the model reaches 0.817, which indicates that the model has good stability and applicability in the inversion of chlorophyll-a concentration in the near-shore sea area, and basically meets the requirements of water quality monitoring in the near-shore sea area.

Table 1 Accuracy comparison of different chlorophyll-a inversion models

Model Types	Linear Equation	X variable	r^2	*F*	*P*
Ratio method	y=38.461x-3.267	Rrs (700) / Rrs (675)	0.896	18.32	0.002
	y=53.079x-16.303	Rrs (B5) /Rrs (B4)	0.812	15.75	0.004
Three-band	y=58.903x-18.536	[1/Rrs (675) -1/Rrs (700)]×Rrs (560)	0.807	9.78	0.003
	y=-89.438x+93.723	[1/Rrs (B4) -1/Rrs (B5)]×B3	0.754	12.08	0.008
NDCI	y=-10.465x+8.35	Rrs (700) -Rrs (675nm) / Rrs (700nm) +Rrs (675)	0.901	17.54	0.001
	Y=53.162x-13.07	Rrs (B5) -Rrs (B4) /Rrs (B5) +Rrs (B4)	0.891	13.64	0.002

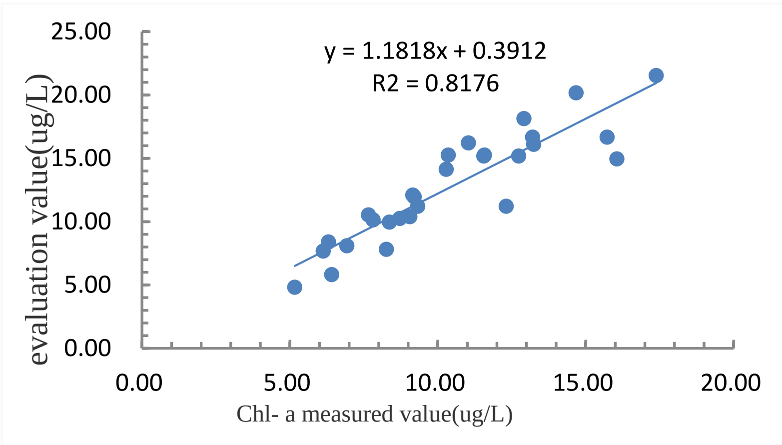


Fig. 3 Comparison of measured and predicted errors

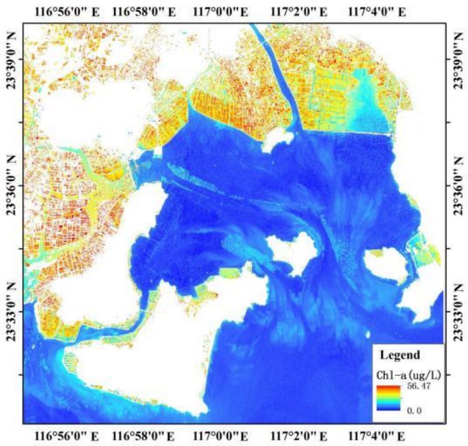


Fig. 4 chlorophyll-a concentration inversion map

3.3 Estimate of chlorophyll-a Concentration

Based on the optimal inversion model of chlorophyll-a content, combined with the quasi-simultaneous acquisition of Sentinel - 2A satellite data, the spatial distribution map of chlorophyll-a content in Zhelin Bay was generated (see Fig. 4). The results showed that the chlorophyll-a concentration in the aquaculture area was significantly higher than that in the non-farming area, especially in the western and northern reclamation areas. The highest chlorophyll-a concentration was found in the net-pen culture area in the middle of the bay, and the second highest was found in the shellfish culture area, where some water bodies showed high concentration aggregation, reaching the level of the phenomenon of water bloom.

3.4 Seasonal Variation Characteristics of chlorophyll-a

There were significant temporal and spatial differences in the chlorophyll-a content in the marine aquaculture area of Zhelin Bay, and the overall trend of the aquaculture area in the bay increased first and then decreased, while the overall trend of the pond aquaculture area in the bay increased first, then decreased and increased (see Fig. 5).

First, from an annual perspective, the chlorophyll-a concentration in Zhelin Bay showed more significant cyclic fluctuations in different seasons. Spring and fall were usually the peak periods of chlorophyll-a concentration, while the concentration was relatively low in summer and winter. This phenomenon is closely related to the seasonality of aquaculture activities. Warmer water temperatures and increased aquaculture densities in spring led to an increase in chlorophyll-a concentrations. In fall, chlorophyll-a concentrations rose again due to the peak of aquaculture activities.

Secondly, in terms of monthly changes, the analysis results showed that the chlorophyll-a concentration in Zhelin Bay increased gradually between January and September, reached a peak and then decreased gradually from October to December. In particular, during the summer months of June to August, the chlorophyll-a concentration, although higher than that in winter, showed a small overall trend of decreasing and then increasing. This may be related to the management measures of culture activities (e.g., water change and use of oxygenation equipment), which were frequent in the culture area during the high temperature period in summer and reduced the accumulation of some chlorophyll-a concentrations.

In addition, combining the distribution maps drawn from the long time series data, spatial differences in the variation of chlorophyll-a concentrations in different regions could be observed.

For example, chlorophyll-a concentrations were higher in pond culture areas in the north and west, while lower concentrations were observed in net-pen culture areas and shellfish culture areas. This difference in spatial distribution reflects the different effects of different types of aquaculture activities on chlorophyll-a concentrations. In particular, chlorophyll-a concentrations tended to be higher in the paddock and pond aquaculture areas than in the more mobile net box aquaculture areas due to poor water mobility and inconvenient water exchange.

In summary, the long time series characterization of chlorophyll-a concentration in Zhelin Bay revealed its seasonal change pattern and the concentration differences in different aquaculture areas. The results of this long-time observation provide a scientific basis for the management of eutrophication in aquaculture areas, pointing out that the breeding density should be reasonably controlled in high-density aquaculture areas, and effective water quality management measures should be taken to reduce the impact of eutrophication on the ecological environment.

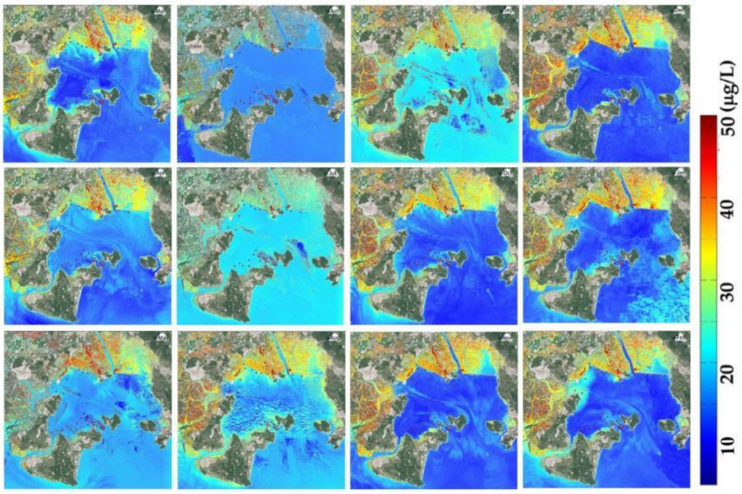


Fig. 5 Temporal and spatial distribution map of chlorophyll-a content in Zhelin Bay

3.5 Long time series characteristics of chlorophyll-a

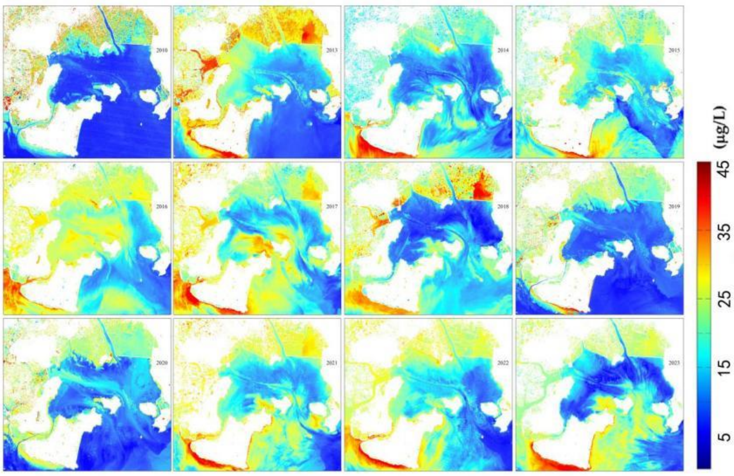


Fig 6. Spatial distribution map of chlorophyll-a content from 2010 to 2023 in Zhelin Bay

In order to reveal the long-term trend of chlorophyll-a concentration in the aquaculture area of Zhelin Bay, this study used Sentinel-2 satellite data from 2010 to 2023, combined with long time series observations. Annual trend were explored by mapping the changes in chlorophyll-a concentration over different time periods (see Fig. 6). There is a significant interannual variation in Zhelin Bay breeding area. The content of chlorophyll-a in the water body in the bay showed an increasing trend from 2010 to 2017, but decreased from 2018 to 2023. Meanwhile, in the western coastal waters of Seamount Island, chlorophyll-a was perennial high, which is a eutrophication sensitive area. The content of chlorophyll-a in the water breeding area increased first and then decreased from 2010 to 2023. Among them, the content of chlorophyll-a was higher in 2013 and 2018, while was lower in 2014-2015 and 2019-2020.

4. Discussion

The aquaculture mode and density have a significant impact on the spatial distribution of chlorophyll-a concentration. In pond aquaculture areas, due to poor water mobility and high aquaculture density, nutrients are difficult to be diluted and diffused. As a result, the chlorophyll-a concentration is significantly higher than that in cage aquaculture areas and other areas with better water mobility. This is consistent with the results of other related studies and fully demonstrates the crucial role of the water exchange rate in the process of eutrophication.

The climatic conditions of high temperature and heavy rainfall in summer have an important impact on the eutrophication of aquaculture water bodies. High temperature promotes the growth of phytoplankton and accelerates the accumulation of chlorophyll-a. Heavy rainfall increases surface runoff, carrying a large amount of nutrients into water bodies, further exacerbating the degree of eutrophication. On this basis, this study further emphasizes the enhancing effect of the synergistic action of temperature and rainfall on the spatio-temporal fluctuations of chlorophyll-a concentration, revealing the complex mechanism of climatic factors in the process of eutrophication more comprehensively compared with previous studies.

Tidal activities are one of the important factors affecting the chlorophyll-a concentration in nearshore water bodies. They not only directly change water mobility but also affect the diffusion range of aquaculture waste. In ponds and reclamation areas with weak tidal activities, nutrients are prone to accumulate and the chlorophyll-a concentration is relatively high. In areas with strong tidal activities, frequent water exchange helps to dilute nutrients and slow down the eutrophication process, which is in line with the research conclusions of other studies on the impact of tides on the water quality of aquaculture areas, reconfirming the important ecological function of tides in the offshore ecosystem.

5. Conclusions

This study constructed and verified the chlorophyll-a inversion model through the analysis of ground - sampling data and satellite remote - sensing data. The spectral characteristics of the water body in Zhelin Bay were analyzed, and the spatial - temporal distribution characteristics of chlorophyll-a concentration were explored. The chlorophyll-a concentration in the aquaculture areas of Zhelin Bay showed significant spatial differences, with the concentration in ponds and polder areas higher than that in nets and shellfish aquaculture areas, which was mainly due to the poor mobility of the water body in the former area, which made it easy for nutrients to accumulate. In addition, chlorophyll-a concentrations showed seasonal fluctuations in time, with peaks in spring and fall, and relatively low levels in summer and winter, indicating that culture density and climatic conditions jointly affected the spatial and temporal dynamics of chlorophyll-a. Further analysis showed that culture density, water body mobility, tides and climatic conditions (especially high temperature and heavy rainfall in summer) had important effects on chlorophyll-a concentration. High summer temperatures promoted phytoplankton growth, while surface runoff from rainfall significantly exacerbated the eutrophication process by inputting large amounts of nutrients into the water body. The results provided a scientific basis for the remote - sensing monitoring of water quality and the prevention and control of eutrophication in Zhelin Bay and other similar mariculture - affected areas. However, there were still some limitations in this study. For example, the influence of other factors such as different types of aquaculture organisms and changes in weather conditions on the accuracy of the model was not fully considered. In addition, at present, a perfect offshore aquaculture pollution assessment and monitoring system has not been established, which is difficult to meet the urgent needs for fine-grained and dynamic monitoring of water quality in actual fishery management and environmental protection. Future research could focus on further improving the accuracy of the model and exploring more effective remote - sensing monitoring methods, effectively deal with environmental problems such as eutrophication and promote the sustainable development of offshore aquaculture.

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