Ocean primary productivity estimation of China Sea by remote sensing*

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Abstract Ocean primary productivity is a key parameter in the research of global carbon cycle, ocean biological resources, and in evaluation of the feature and quality of ocean biological environment. Traditional shipboard measurement which is costly and time-consuming is impossible to obtain the spatial and temporal information on primary productivity on a large scale in a short period of time. Satellite remote sensing is an effective strategy to acquire the ocean information in near real time. Here we propose a model special for China Sea based on the concept of primary productivity using *in situ* primary productivity and environmental data from 1984 to 1990, and discuss every modeling parameter which can be retrieved by remote sensing in detail. The reliability of this model is tested by *in situ* data, and the comparison of other primary productivity models is made. We also analyze the temporal and spatial distribution of China Sea primary productivity in 2000. From our analysis the satellite remote sensing data have been proved very useful for ocean primary productivity study.

Keywords: ***remote sensing, ocean primary productivity.***

Ocean primary productivity is a key parameter to estimate the feature and quality of ocean bio-environment. It is doubtless that the knowledge of ocean primary productivity is very important for many studies, such as the global carbon cycle, climate change, ocean ecosystem and potential fishery productivity. Many ocean ecological and environmental data—chlorophyll concentration, sea surface temperature, water transparency, and so on—are assessable fast on large scale by satellite remote sensing, with sufficient spatial resolution, high accuracy, and the ability to show spatial and temporal fluctuation of primary productivity dynamically. Satellite remote sensing, therefore, will be one of the important methods to retrieve ocean primary productivity.

There are generally two kinds of algorithms for ocean primary productivity, namely, empirical approaches, and analytical approaches. The empirical approach is based on the statistical relationship between ocean environmental parameters and primary productivity obtained by *in situ* measurements, e.g. Eppley developed experimental relationships with chlorophyll concentration, temperature and the length of the day to calculate ocean primary productivity[1]. Without physiological implication, however, the accuracy of empirical approach is subject to the specialties of area and time. With the increasing knowledge of phytoplankton physiology, as well as the couple relationship between physiological parameters and environmental parameters, physiological analysis is involved in algorithm development, which is called the analytical approach. Whereas, obtaining physiological parameters still relies on empirical statistics, e.g. an analysis approach developed by Platt et al. in 1986 based on the light intensity and chlorophyll concentration[2]; optic-biological models in general sense proposed by Platt[3,4] and Morel[5]; and the vertical general productivity model (VGPM) by Behrenfeld and Falkowski[6].

Ocean primary productivity researches in China are mainly focused on shipboard measurements, and studies concerned about remote sensing data are less documented[7—20]. Due to the specific bio-optical behaviors, the models for other conditions are not suitable for China Sea. In this paper, we develop a remote sensing model special for China Sea and make an attempt to estimate ocean primary productivity.

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1 A satellite-based model for primary productivity in China Sea

1.1 Data

Our research areas are South Yellow Sea, East China Sea, and the area on the east of Taiwan island (18.29°N—34°N, 120.4°E—129.0°E), China, including both oligotrophic and eutrophic sea, and they are typical hydrological areas. The data sets of ocean primary productivity and environmental parameters of South Yellow Sea and North East China Sea (28°N—34°N, on the west of 127°E, Aug. & Nov. 1984, Feb. & May 1985)[7,8] were used; some are from the investigation in East China Sea (from 1986 to autumn 1991) and Changjiang River in 1986 (a cooperative project of China and France); some are from island investigation project of Zhejiang Province in 1990[9], and some from references, e.g. the data from Taiwan Strait[10], from the sea on the east of Taiwan island[11], from Bohai Sea[12], and from South China Sea[13]. For those data sets without temperature and radiance records, monthly mean meteorological data were used instead.

1.2 Modeling and parameter analysis

1.2.1 Modeling

According to the basic concept of ocean primary productivity, ocean primary productivity estimation is often based on the PvsE (photosynthesis-irradiance) curve[5]. Our research used the simplified light-inhibition PvsE model developed by Morel[5], and the primary productivity at a certain depth can be expressed as:

$$OPP(z) = PAR(z) \times \overline{\alpha(z)} \times chla(z) \times \phi(z) \times 12000, \qquad (1)$$

where OPP is the primary productivity at the depth of z, with the unit of mg $C \cdot m^{-3} \cdot d^{-1}$; PAR, in $Ein \cdot m^{-2} \cdot d^{-1}$, stands for the photosynthesis available radiance in all directions; $\bar{a}$ is the average absorption coefficient, in $m^{-1}/(mg\ chla \cdot m^{-3})$; $chla$ means chlorophyll concentration ($mg\ chla \cdot m^{-3}$); $PAR \times \bar{a} \times chla$ represents the total quantum number harvested by phytoplankton. ϕ is the utility efficiency which means molar carbon synthesized by per molar quantum; and the factor 12000 is used for conversing the unit from per molar carbon to per microgram of carbon.

The column daily-average primary productivity in the whole euphotic layer, then, can be modeled by rewriting Eq. (1) as follows, with daily-averaged PAR, $chla$ and ϕ in the whole euphotic layer represented by the subscript eu, and H_d means the length of the day:

$$OPP = \overline{PAR} \times \bar{a} \times \overline{chla_{eu}} \times Z_{eu} \times \bar{\phi} \times 12000 \times H_d. \qquad (2)$$

1.2.2 Discussion on parameters in Eq. (2)

$\overline{PAR}$ is the daily average PAR which can be obtained either from *in situ* measurement, or retrieved by remote sensing data with the correction by relevant day time coefficient[6,21].

$\overline{chla_{eu}}$ is the daily average column chlorophyll concentration in the whole euphotic layer, which can be calculated by *in situ* $chla(z)$ at different depths, and expressed as[6]:

$$\overline{chla_{eu}} = \frac{\int_0^{z_{eu}} chla(z)dz}{z_{eu}}. \qquad (3)$$

$\overline{chla_{eu}}$ can also be obtained by the sea surface chlorophyll, $chla_{sat}$, from ocean color satellite data. We developed a regressive relationship ($r = 0.91$) by the $chla_{sat}$ from CZCS data as:

$$\overline{chla_{eu}} = 0.9899 \times chla_{sat}^{0.734}. \qquad (4)$$

Z_{eu} stands for the depth of euphotic layer, retrieved from water transparency (sd): $z_{eu} = 2.53sd$; sd can be obtained either by *in situ* measurement or by remote sensing[22].

$\bar{\phi}$ is the daily-average photon utility efficiency, also named the daily average quantum productivity which reflects sophisticated internal and external environments, and is affected by the light intensity, temperature and nutrient concentration. Even in the same sea area, $\bar{\phi}$ still has a ten-order range, e.g. 0.005—0.063 (molC/Ein) in a factor of 12, found by Babin et al.[23]; or 0.00189—0.06019 (molC/Ein) in a factor up to 31, from Lu et al.'s report on Sanggou Bay[24]. An adjusted coefficient of daily average light utility is, therefore, essential in the regressive model. In our research, we found that there is a relationship between *in situ* $\bar{\phi}$ and satellite-retrieved $\overline{PAR}$, and between sea surface temperature SST and chlorophyll concentration $chla_{sat}$, namely

$$\bar{\phi} = (0.11 - 0.037\lg(\overline{PAR})) \times Fx \times \frac{Chla_{sat}}{Chla_{sat} + X} \times \beta. \qquad (5)$$

when $chla_{sat}$ retrieved by satellite model is less than 1.5 mg/m^3, X is 0.3; and when $chla_{sat}$ is higher than 10 mg/m^3, X has the value of 2.5; and the data between these two extremes are obtained by the means of interpolation. $F_x = 0.0183SST^{1.3773}$, where SST is the sea surface temperature from either *in situ* measurement or remote sensing. β is the regressive adjusted coefficient of daily-average quantum utility special for China Sea, with the value of 0.16. $\bar{\alpha}$ is the average cross-section absorption coefficient of chlorophyll; here, we take its value of 0.016 m^2/(mg chl)[4]. H_d is the length of the day.

According to the above discussion, Eq. (2) can be rewritten as:

$$
\begin{aligned}
OPP = & \overline{PAR} \times \bar{\alpha} \times \overline{chla_{eu}} \times Sd \\
& \times (0.11 - 0.037\lg(\overline{PAR})) \times Fx \\
& \times \frac{chla_{sat}}{chla_{sat} + X} \times H_d \times 5 \times 10^4. \qquad (6)
\end{aligned}
$$

1.3 Result analysis and discussion

1.3.1 Model validation

The *in situ* data from the field investigation in South Yellow Sea and North East China Sea (Aug. & Nov., 1984 and Feb. & May, 1985) were integrated into Eqs. (3) and (6) for modeled primary productivity, which was then compared with *in situ* primary productivity (shown in Fig. 1). The result illustrates a good consistency, with $r = 0.95$, $RRMS = 0.35$ ($n = 242$). Because the information on the synchronous satellite-retrieved radiance, sea surface temperature, and water transparency was not available for the above mentioned periods, we could only use the satellite data of chlorophyll concentration from CZCS data. In order to test the reliability of chlorophyll concentration data, we also use Eq. (4) to estimate the depth-integrated chlorophyll concentration (Fig. 1). Although it is a little more dispersed than that in Fig. 2, the result of $r = 0.92$, $RRMS = 0.45$ ($n = 242$) is still satisfactory.

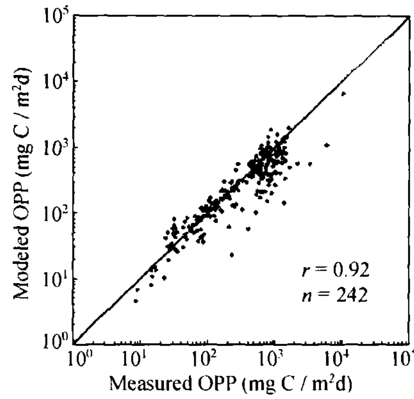

Fig. 1. Comparison of measured and model daily depth-integrated primary productivity from the average chlorophyll concentration within the surface layer by satellite.

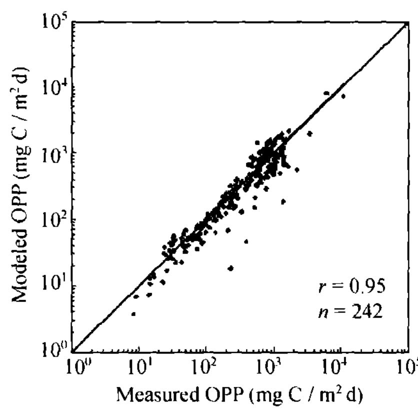

Fig. 2. Comparison of measured and modeled daily depth-integrated primary productivity from *in situ* chlorophyll concentration within the euphotic layer.

1.3.2 Model comparison

The data set of 1442 stations from VGPM model provided by NASA was used for model comparison. Fig. 3 displays the comparison of different models. In Fig. 3(a), modeled values are the results of our research, called as the SIO-1 model, and the values in Fig. 3(b) also come from our model calculation (Eq. (6)) but with the VGPM temperature function instead, called as the SIO-2 model. Fig. 3(c) and 3(d) show the results from Campbell's model[25] and Behrenfeld's VGPM model[6], respectively, for comparison.

From the above comparison, we may see that the results illustrated in Fig. 3 (b) and (d) are better, but when China Sea investigated data (Aug. & Nov., 1984 and Feb. & May, 1985) were used as *in situ* data for comparison, our developed SIO-1 and SIO-2 models show better results. This suggests that the primary productivity models depend heavily on the data sets used and the region studied. In terms of global primary productivity, it is very difficult to adopt one model to achieve fairly good results. To standardize a general model, however, with regional parameters is effective for primary productivity estimation from remote sensing.

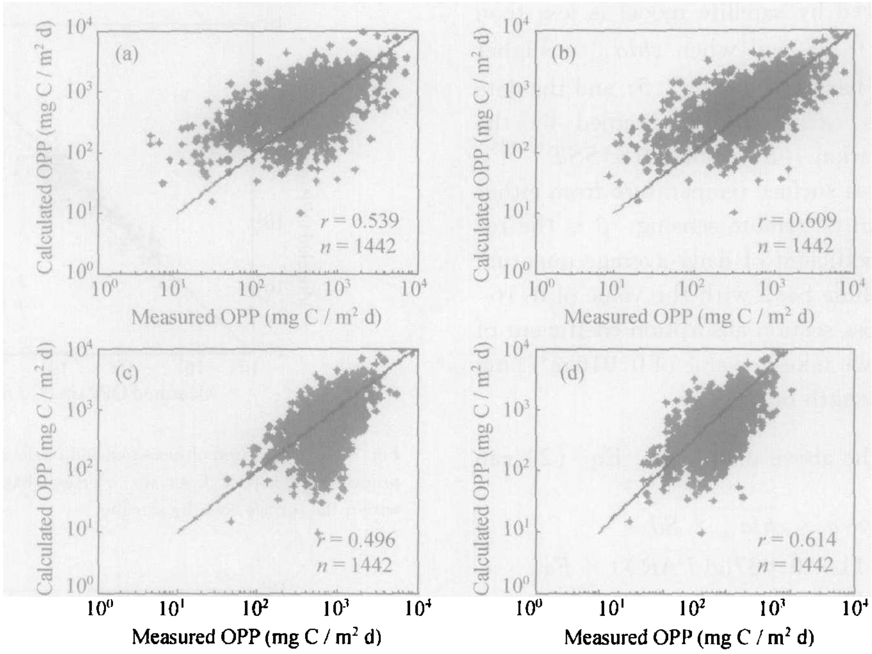

Fig. 3. Comparison of measured and modeled daily depth-integrated primary productivity with different models. (a)—(d) see text.

2 Model applications

In order to prove the efficiency of our model, we calculated the primary productivity of China Sea in year 2000 using monthly averaged (Jan.-Dec., 2000) chlorophyll concentration[22], water transparency retrieved from SeaWiFS data[22], and sea surface temperature from AVHRR data[26] (see Fig. 4).

We divided China Sea into 5 sub-areas: Bohai Sea, North Yellow Sea, South Yellow Sea, the north of East China Sea, and the north sea area on the east of Taiwan island. Bohai Sea is on the east of Bohai Strait; the North Yellow Sea means the area on the north of 34°N; South Yellow Sea is on the north of the line from Changjiang estuary to Jizhou Island; and on the south of that line is North East China Sea (north to 30°N, west to 126.62°E). The East Taiwan Sea is confined within the rectangle of points 122°E 24°N, 122°E 18.10°N, 128.26°E 18.10°N, 128.26°E 24°N, excluding lands.

The primary productivity of these sub-areas shows the seasonal variation (Figs. 4 and 5). In Bohai Sea, the lowest mean primary productivity is in February, and the value begins to rise in March and April, reaching the second highest in May, then has some decrease in the following June, and then rises again in July, reaching the peak of the whole year. In September and October, it has a declining trend but rises slightly in November. This feature of variation is similar to the descriptions of Zun et al.[12].

As for the Yellow Sea and North East China Sea, primary productivity is generally low in winter (February), which is mainly affected by low sea surface temperature and low transparency. In spring (May), high productivity areas present in South Yellow Sea and some parts of North East China Sea. Spring is the highest productive season in North East China Sea, but sea temperature in North Yellow Sea in spring remains low, therefore, with a low primary productivity. In summer, the primary productivity of Yellow Sea rises and reaches its highest value of a year. Primary productivity of North East China Sea in summer decreases a little compared with that in May (spring), ranking the second highest. In both Yellow Sea and North East China Sea, primary productivity decreases gradually in the following September and October, and then it decreases generally in autumn (November), but is still higher than that of October, and even the second highest in some area.

High productivity areas are significantly south-east-ward with water depth increasing, which may be related with low temperature of alongshore current and low water transparency. The productivity in estuarine areas of Bohai Sea, Yellow Sea and East China Sea is generally low in a whole year because of their high suspended material concentration and low water transparency, as well as low water temperature.

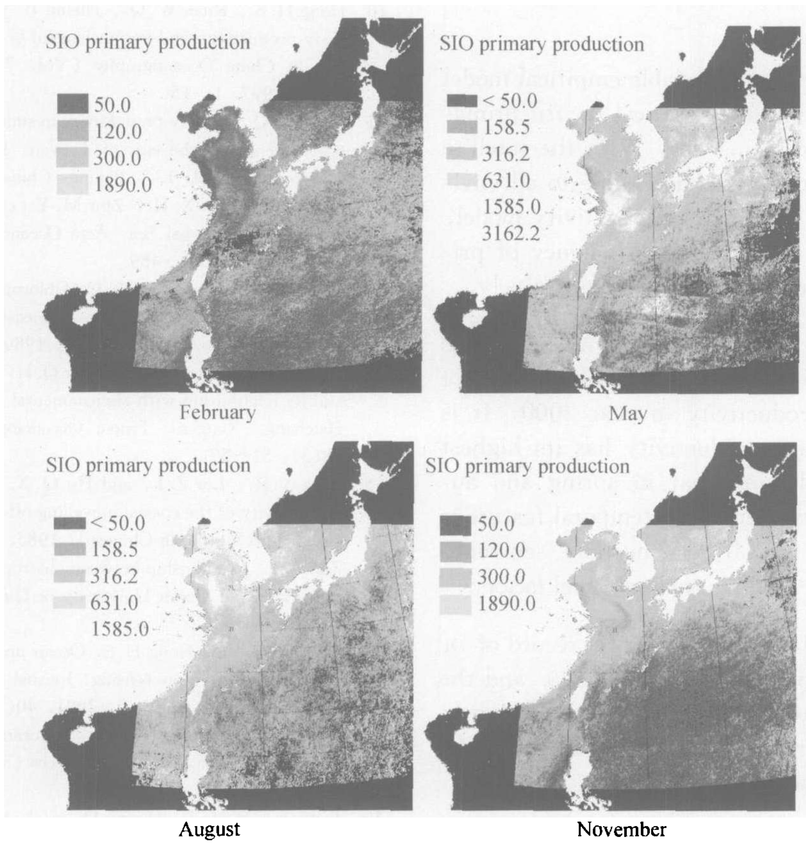

Fig. 4. Distribution of estimated oceanic primary productivity of China Sea in 2000 (mg C/m^{2}d).

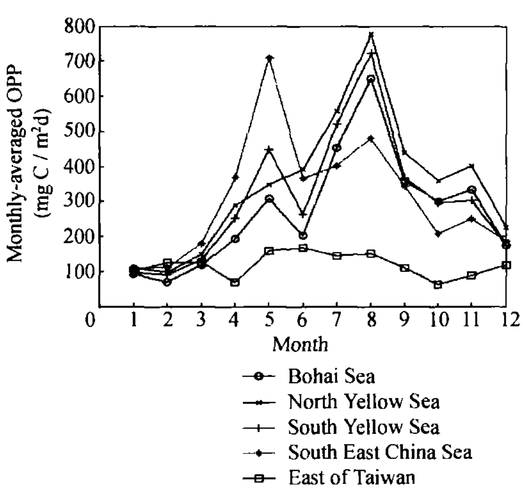

Fig. 5. The daily-integrated primary productivity averaged monthly in 2000.

Comparing with documented contour graphics of primary productivity in Bohai Sea, North Yellow Sea, and East China Sea[7,9], we found that modeled primary productivity from remote sensing can tell the truth of distribution and fluctuation to some extent. Because high chlorophyll concentrations in lower euphotic layer can not be detected by satellite sensor[21,27], primary productivity may be underestimated in North East China Sea and South Yellow Sea. In general, the tendency of China Sea primary productivity can be shown well in Figs. 4 and 5. With respect of time series, the primary productivity is highest in summer (July-August), following that in spring (April-June) and autumn (September-November), and lowest in winter (December-March).

Moreover, remote sensing images also contain the information that primary productivity of China Sea is impacted by the interaction of river runoff (eutrophic water, low temperature, and high suspended material), alongshore current (eutrophic water, low temperature, and low salinity), Kuroshio (oligotrophic water, high temperature, and high salinity), and the other currents. Features and scope of various water mass, and their generating, developing and disappearing are impacted by alongshore current and other currents like Kuroshio and so on, which thus forms the consequent temporal and spatial fluctuation of primary productivity.

3 Conclusions

(i) We have developed a reliable empirical model of primary productivity using historical *in situ* primary productivity data of China Sea. With the satellite remote sensing technique, it is accessible to all environmental parameters in primary productivity model, which then improves the detecting efficiency of primary productivity dramatically and cost-effectively.

(ii) Our satellite primary productivity model has been applied to the temporal and spatial research of China Sea primary productivity in year 2000. It is shown that the primary productivity has its highest level in summer, following that in spring and autumn, and lowest in winter. This temporal feature is impacted by river runoff, alongshore current, Kuroshio and the other dynamic environmental factors.

(iii) Due to the lacking of historical record of *in situ* primary productivity data in China Sea, and the wide variation of water optical feature in this area, our model is a primary one, and more sophisticated models need to be established.

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