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Estimating oceanic primary productivity from ocean color remote sensing: A strategic assessment

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ABSTRACT

It has long been realized that approaches using satellite ocean-color remote sensing are the only feasible means to quantify primary productivity (PP) adequately for the global ocean. Through decades of dedicated efforts and with the help of various satellite ocean-color missions, great progresses have been achieved in obtaining global PP as well as its spatial and temporal variations. However, there still exist wide differences between satellite estimations and *in situ* measurements, as well as large discrepancies among results from different models. The reasons for these large differences are many, which include uncertainties in measurements, errors in satellite-derived products, and limitations in the modeling approaches. Unlike previous round-robin reports on PP modeling where the performance of specific models was evaluated and compared, here we try to provide a candid overview of three primary modeling strategies and the nature of present satellite ocean-color products. We further highlight aspects where efforts should be focused in the coming years, with the overarching goal of reducing the gaps between satellite modeling and *in situ* measurements.

1. Introduction

Photosynthesis is a process that occurs on the illuminated Earth. In a complex light-dependent process, photosynthesis transfers absorbed photon energy to organic compounds (Falkowski and Raven, 2007). Since this process ultimately leads to the conversion of inorganic carbon to organic carbon, photosynthesis not only plays an important role in the global carbon cycle, but also provides the food to support all the heterotrophs. In the ocean, phytoplankton are the primary photosynthesizers, supporting the ocean's food web. As realized ~50 years ago (Goldman, 1965), because of the vast expanse of the oceans, detailed information about the temporal and spatial variation of oceanic photosynthesis is essential for studying and understanding air–sea CO_2 exchange, carbon fixation, and vertical export — the so called “biological pump” (Antoine et al., 1996; Behrenfeld et al., 2002; Bosc et al., 2004; Dunne et al., 2005; Falkowski et al., 2003; Nevison et al., 2012; Platt and Sathyendranath, 1988; Sathyendranath et al., 1995).

The production of organic carbon during photosynthesis is defined as primary productivity (PP, or net primary productivity, NPP; Cullen, 2001; Marra, 2002; Platt and Sathyendranath, 1993). In the ocean, PP provides a measure of inorganic carbon fixed by phytoplankton per unit of water volume per unit of time. Integration of this rate over desired basins and for a given period of time (*e.g.*, a year) provides a measure of carbon transformation for that area for that time period. It has been – and remains – an elusive goal for researchers in biological oceanography to obtain accurate and consistent estimates of PP for the global oceans. Beside limitations in measurement technology (Cullen, 2001; Marra, 2002; Platt and Sathyendranath, 1993), the major limitation is the extreme under sampling of the oceans (Perry, 1986), where the spatial and temporal variations in water properties (including optical, chemical, and biological, *etc.*) cannot be easily scaled-up from a few measurements made at limited space–time grids.

To overcome such spatial–temporal limitations, it has long been recognized that the repetitive measurement by satellite sensors provides the only possible and feasible means for the estimation of PP on basin and global scales (Eppley et al., 1985; Falkowski, 1998; Perry, 1986; Platt, 1986), *i.e.*, to obtain estimates at large scales by linking discrete *in situ* measurements with the synoptic and repetitive satellite observations. The linkage for this scaling-up, as discussed in detail in later sections, is centered on information on phytoplankton (either a biological property such as chlorophyll concentration or an optical property such as phytoplankton absorption coefficient). This is based on the fact that phytoplankton not only plays a key role in photosynthesis, but also alters the appearance of ocean (water) color. Therefore, when a relationship between PP and phytoplankton is developed, the estimation of basin-scale PP becomes possible when the information of

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phytoplankton can be derived from the measurement of ocean color by a satellite sensor. Because of this necessity, the estimation of the global phytoplankton (and then oceanic PP) is a central goal of all ocean-color satellite missions (IOCCG, 1998; McClain, 2009), which include the Sea-Viewing Wide Field-of-View Sensor (SeaWiFS) and the MODerate-resolution Imaging Spectroradiometer (MODIS) supported by NASA, and the Medium Resolution Imaging Spectrometer (MERIS) supported by ESA. In addition, new and advanced ocean color satellites are on the horizon, including the Pre-Aerosol Cloud and Ecosystems (PACE, NASA) mission and the Ocean and Land Colour Instrument (OLCI, ESA). At the same time, in order to properly scale-up the limited field measurements with satellite data, various models have been developed (*e.g.*, Antoine and Morel, 1996; Arrigo et al., 2008; Balch et al., 1989b; Behrenfeld, 1998; Dierssen et al., 2000; Ishizaka, 1998; Kahru et al., 2009; Longhurst et al., 1995; Ondrusek et al., 2001; Sathyendranath and Platt, 1995; Sathyendranath et al., 1989; Sathyendranath et al., 1991) and estimates of global oceanic PP have been achieved (Antoine et al., 1996; Behrenfeld et al., 2002; Longhurst et al., 1995; Platt and Sathyendranath, 1988).

After decades of practice, however, the estimates based on satellite remote sensing are far from satisfactory. For instance, results from the Joint Global Ocean Flux Study (JGOFS) (Ducklow, 2003) have found that, in four of eight oceanic provinces (Longhurst et al., 1995) where data are available for $PP_{\text{basin-year}}$ (basin-scale, annual, depth-integrated primary production) from both *in situ* measurements and from the measurements of the Coastal Zone Color Scanner (CZCS), the satellite estimates were a factor of two or three smaller than the measured values. In only two out of the eight provinces were the CZCS $PP_{\text{basin-year}}$ within 20% of the measured values. If the comparison is made on local-daily instead of basin-year scales regarding the spatial and time ranges, the disagreement could be much larger between measured and ocean color-derived PP_{eu} (daily depth-integrated primary production) as shown in some studies (*e.g.*, Balch et al., 1989a; Behrenfeld and Falkowski, 1997b; Quay et al., 2012), although better results were presented in Platt and Sathyendranath (1988) and Kyewalyanga et al. (1997).

The discrepancies between modeled and measured PP, and among modeled PP, were also highlighted in a series of round-robin experiments (Campbell et al., 2002; Carr et al., 2006; Friedrichs et al., 2009). Even with measured chlorophyll concentration as an input, Campbell et al. (2002) found that PP estimates from the best-performing algorithms were generally within a factor of 2 of measured PP; while Carr et al. (2006) found that global average PP varied by a factor of 2 between models when input parameters (chlorophyll concentration and solar radiation) were derived from SeaWiFS. For a dataset consisting of ~1000 *in situ* measurements in the tropical Pacific, Friedrichs et al. (2009) found that all models underestimated the observed variance of PP, and no models successfully captured a broad-scale shift from low biomass-normalized productivity in the 1980s to a higher biomass-normalized productivity in the 1990s.

Such inconsistent results undermine the confidence of using primary production estimated from satellite ocean color to study the "biological pump" in the oceans, and suggest that there is difficult work ahead in designing the strategy and system for estimating primary production based on remotely sensed data. Here we try to provide a candid overview of the strategies in estimating PP from ocean color remote sensing, discuss the status of "standard" satellite ocean-color products, and highlight areas where efforts should be focused on for improving the estimation of PP from satellite ocean color remote sensing.

2. Principles of ocean color remote sensing

It has been known for centuries that the change of water (ocean) color reflects change of constituents in the water column. To be able to quantitatively, and mechanistically, estimate the constituent concentrations, models have been developed to link ocean color with desired constituents. In ocean color remote sensing, "ocean color" is commonly described with the spectrum of remote-sensing reflectance ($R_{rs}(\lambda)$, sr^{-1}), which is defined as the ratio of water-leaving radiance to downwelling irradiance just above the surface. "Water-leaving radiance" represents photons originating from absorption and scattering processes below the surface and emitting into space, which excludes photons going to space due to sea-surface reflectance, a process having no information of in-water constituents.

Based on the radiative transfer theory, R_{rs} can be expressed as (Gordon et al., 1988; Sathyendranath and Platt, 1997; Zaneveld, 1995)

$$R_{rs} \approx 0.53\left(g_0 + g_1 \frac{b_b}{a+b_b}\right)\frac{b_b}{a+b_b}. \tag{1}$$

Here a and b_b are the total absorption and backscattering coefficients, respectively, and wavelength dependence is omitted for brevity. g_0 and g_1 are model coefficients, which are spectrally independent, although slightly varying with sun-sensor angular geometry (Albert and Mobley, 2003; Lee et al., 2011a; Morel and Gentili, 1993).

a and b_b are bulk inherent optical properties (IOPs) (Preisendorfer and Mobley, 1984), which are sums of the contributions of various constituents (Stramski et al., 2001), with the primary components as water molecules, suspended particulates and dissolved materials (also termed as "gelbstoff", *etc.*). Practically, the bulk IOPs are generally described as

$$\begin{aligned} a &= a_w + a_{ph} + a_{dg}; \\ b_b &= b_{bw} + b_{bp}, \end{aligned} \tag{2}$$

with subscripts "*w*, *ph*, *dg*, *p*" representing water, algae pigments, the combination of detritus and gelbstoff, and particles, respectively. Values of a_w and b_{bw} have been measured or derived from laboratory or field measurements (Morel, 1974; Pope and Fry, 1997; Smith and Baker, 1981), and are considered global constants (vary slightly with temperature and salinity) (Pegau et al., 1997; Sullivan et al., 2006). a_{ph}, a_{dg} and b_{bp}, on the other hand, vary spatially and temporally, and are considered as volatile properties.

For studies in ocean biology and biogeochemistry, traditionally the focus of ocean color remote sensing is on the concentration of chlorophyll, thus the component IOPs are commonly expressed as

$$\begin{aligned} a &= a_w + a_{ph}^* \times Chl + G_{Chl} \times a_{ph}^* \times Chl, \\ b_b &= b_{bw} + b_{bp}^* \times Chl. \end{aligned} \tag{3}$$

Here a_{ph}^* and b_{ph}^* are the chlorophyll-specific (or concentration of chlorophyll normalized) absorption and chlorophyll-specific backscattering coefficients (m^2/mg), respectively, with *Chl* the concentration of chlorophyll (mg/m^3). G_{Chl} is the ratio (at a specific wavelength, such as 440 nm) of a_{dg} to a_{ph}.

Therefore, if values of a_{ph}^*, b_{bp}^* and G_{Chl} are known, or if they co-vary with *Chl*, Eq. (1) is a function of one variable: *Chl*, which can then be solved from known R_{rs}. Because particle backscattering coefficient (b_{bp}) could not be accurately modeled with *Chl* alone (see Stramski et al., 2001), b_{bp}^* encompasses a wide range of variations for a given *Chl* (Babin et al., 2003; Loisel and Morel, 1998). To minimize the impact of this variation on the retrieval of *Chl* from R_{rs}, usually the band ratio of R_{rs} (either blue to green, or red to green; Le et al., 2013) is used as input, with a general form as (Gordon and Morel, 1983; O'Reilly et al., 1998)

$$Chl = f_1\left(R_{rs}(\lambda_i)/R_{rs}(\lambda_j)\right). \tag{4}$$

Here f_1 stands for function number 1. Following Eqs. (2–3), in essence the above ratio algorithm includes (assuming the impact of parameter b_{bp}^* is minimized through the R_{rs} ratio), implicitly, variables other than the ratio of R_{rs} (Carder et al., 1999; Gordon et al., 1988; Sathyendranath and Platt, 1989; Sathyendranath et al., 1994)

$$Chl = f_1\left(a_{\text{ph}}^*, G_{Chl}, R_{rs}(\lambda_i)/R_{rs}(\lambda_j)\right). \tag{5}$$