Contents lists available at ScienceDirect







journal homepage: www.elsevier.com/locate/dsri

Particulate organic carbon in the global ocean derived from SeaWiFS ocean color

Malgorzata Stramska*

Center for Hydro-Optics & Remote Sensing (CHORS), San Diego State University, 6505 Alvarado Rd., Ste. 206, San Diego, CA 92120, USA

ARTICLE INFO

Article history: Received 29 October 2008 Received in revised form 9 April 2009 Accepted 21 April 2009 Available online 6 May 2009

Keywords: Ocean color Particulate organic carbon SeaWiFS

ABSTRACT

Satellite remote sensing offers new means of quantifying particulate organic carbon, POC, concentration over large oceanic areas. From SeaWiFS ocean color, we derived 10-year data of POC concentration in the surface waters of the global ocean. The 10-year time series of the global and basin scale average surface POC concentration do not display any significant long-term trends. The annual mean surface POC concentration and its seasonal amplitude are highest in the North Atlantic and lowest in the South Pacific, when compared to other ocean basins. POC anomalies in the North Atlantic, North Pacific, and global concentrations seem to be inversely correlated with El Niño index, but longer time series are needed to confirm this relationship. Quantitative estimates of POC reservoir in the oceanic surface layer depend on the choice of what should represent this layer. Global average POC biomass is 1.34 g m^{-2} if integrated over one optical depth, 3.62 g m⁻² if integrated over mixed layer depth, and up to 6.41 g m⁻² if integrated over 200-m layer depth (when assumed POC concentration below MLD is 20 mg m^{-3}). The global estimate of total POC reservoir in the surface 200-m layer of the ocean is 228.61 \times 10¹³ g. We expect that future estimates of POC reservoir may be even larger, when more precise calculations account for deep-water organic-matter maxima in oligotrophic regions, and POC biomass located just below the seasonal mixed layer in spring and summer in the temperate regions.

© 2009 Elsevier Ltd. All rights reserved.

1. Introduction

The past decade has witnessed a significant increase in appreciation of the role of biology in shaping biogeochemical fluxes in the ocean and its potential responses to global climate change. The production of particulate organic carbon, POC, during photosynthesis is one of the pathways for the drawdown of carbon from the surface ocean and its removal into deep ocean waters. During photosynthesis, dissolved inorganic carbon, DIC, is used together with nutrients to form POC, in that way decreasing the partial pressure of carbon dioxide, pCO₂, of surface ocean waters. The production is eventually followed by the sinking of the POC particles out of surface waters, and a fraction of them becomes incorporated into the bottom sediments. These processes are referred to as "the biological pump" (Ducklow et al., 2001).

Oceanic POC particles include the autotrophic and heterotrophic microorganisms and biologically derived detrital particles suspended in seawater. Although POC represents only a small fraction of the total carbon present in the global ocean, its importance results from high turnover rates. It has been estimated that the living phytoplankton component of POC contributes about 50% of global primary production on Earth (Behrenfeld et al., 2005). Total POC biomass in ocean surface waters has been estimated at around 4-5 Gt C (Gardner et al., 2006), while the flux from the dissolved inorganic phase to the particulate organic reservoir (carbon uptake through

^{*} Tel.: +16195942229; fax: +16195948670.

E-mail addresses: mstramska@chors.sdsu.edu, mstramska@ucsd.edu (M. Stramska).

^{0967-0637/\$ -} see front matter @ 2009 Elsevier Ltd. All rights reserved. doi:10.1016/j.dsr.2009.04.009

primary production) has been projected at around 50 GtCyr⁻¹ (Behrenfeld et al., 2006; Carr et al., 2006). Thus, the oceanic POC reservoir is much smaller than the fluxes controlling this reservoir. This implies that even small changes in POC reservoir can be a sign of substantial changes in the related fluxes. In addition, the importance of POC for biogeochemical processes in the ocean results from the fact that POC can sink in the water across isopycnals, scavenging other particles and transporting carbon and associated elements to deep waters until they settle as sediments or are remineralized. Therefore, the analysis of the distribution and magnitude of the oceanic pool of POC is important for understanding the role of the marine biosphere in the global carbon cycle.

One of the major difficulties in quantifying POC reservoirs and fluxes is the fact that the temporal and spatial variations of POC concentration in the upper ocean cover a broad range of scales. It has been extremely difficult to characterize this variability using only measurements taken from ships or other *in situ* observing platforms. Recently, development of ocean color POC algorithms (Stramski et al., 1999; Loisel et al. 2002; Stramska and Stramski, 2005; Pabi and Arrigo, 2006; Stramski et al., 2008) and the availability of satellite ocean color data has dramatically improved this situation by providing the capabilities for long-term monitoring of the ocean with global coverage.

In this paper, algorithms described by Stramski et al. (2008) were used to derive, from SeaWiFS data, the 10-year time series of POC concentration in the surface waters of the global ocean. Our main goal is to develop a better understanding of the large-scale geographical variability of POC concentration in the ocean, and to investigate long-term trends. In addition, we attempt to derive global and basin scale estimates of POC biomass contained in the oceanic surface waters. Evaluation of the global marine POC reservoir provided in this paper can be used for comparisons with ocean ecosystem and biogeochemical models. We believe that our assessment of POC reservoir will benefit studies on ocean carbon cycle and the role of POC in this cycle.

2. Data sources and methods

In this section, the input data and methods used to estimate POC are briefly described. Ocean surface POC concentrations were derived from normalized waterleaving radiances, $L_{wn}(\lambda)$, available from the Sea-viewing Wide Field-of-view Sensor (SeaWiFS) mission on the OrbView-2 satellite (e.g., Hooker and McClain, 2000). SeaWiFS collects radiometric data at eight spectral bands in the visible and near-infrared spectral region and provides global coverage approximately every two days. The standard data processing procedures used to derive $L_{wn}(\lambda)$ from recorded data involve atmospheric correction and removal of pixels with land, ice, cloud, or heavy aerosol load (O'Reilly et al., 1998, 2000). In this study, the daily normalized water-leaving radiances at 443, 490, and 555 nm were used. These data were obtained from the NASA Ocean Color FTP site (http://oceancolor.gsfc.nasa.

gov/ftp.html) as the Level 3 standard mapped images (SMI), which are projections of the Global-Area-Coverage data onto a global, equal-angle grid with a nominal 9 km \times 9 km resolution (reprocessing version 5.2).

We have converted the $L_{wn}(\lambda)$ data to remote sensing reflectances, $R_{rs}(\lambda)$, using the following relationship (e.g. Mobley, 1994):

$$R_{\rm rs}(\lambda) = L_{\rm wn}(\lambda) / F_0(\lambda) \tag{1}$$

where λ indicates the spectral waveband, $R_{rs}(\lambda)$ is the spectral remote-sensing reflectance in sr^{-1} , $L_{wn}(\lambda)$ is the normalized water leaving radiance in μ W cm⁻² nm⁻¹ sr⁻¹, and F_0 is the extraterrestrial solar irradiance taken as $F_0(443) = 190.154$, $F_0(490) = 196.473$, and $F_0(555) = 183.010$ in μ W cm⁻² nm⁻¹. These F_0 values, derived by averaging the Thullier spectrum at the nominal wavelengths of SeaWiFS, were taken from the table of SeaWiFS bandpass averaged quantities made available by NASA (http://oceancolor.gsfc.nasa.gov/DOCS/RSR_tables.html).

In the next step of data processing, we have transformed the remote sensing reflectances to daily surface POC concentrations using two algorithms developed by Stramski et al. (2008) and summarized in Table 1. Note that Stramski et al. discussed several POC algorithms, and reported that the two algorithms listed in Table 1 had the best error statistics. Instead of selecting one of these algorithms, we have decided to apply both of them, which allowed us to quantify a range of divergence between the algorithms. Our calculations show that algorithm 2 (based on $R_{rs}(490)/R_{rs}(555)$) leads to somewhat higher POC estimates in the euthrophic waters and lower POC estimates in the oligotrophic waters in comparison to POC concentrations derived using algorithm 1 (based on $R_{\rm rs}(443)/R_{\rm rs}(555)$). For example, yearly average global POC concentration estimates are on average about 2.5% higher, and POC estimates in the eutrophic waters of the North Atlantic are about 14% higher when algorithm 2 is used in comparison to algorithm 1. At the present time, we do not have sufficient evidence to decide which of the two algorithms leads to more precise POC estimates; therefore, our final results reported in this paper are based on

Table 1
Summary of the POC band-ratio algorithms used in this paper.

$POC = A_i [R_{rs}(\lambda)/R_{rs}(555)]^{-Bi}$											
$R_{\rm rs}(\lambda)/R_{\rm rs}(555)$	A _i	B _i	<i>R</i> ²	RMSE (mg m ⁻³)	MNB (%)	NRMS (%)	Ν				
$R_{\rm rs}(443)/R_{\rm rs}(555)$ $R_{\rm rs}(490)/R_{\rm rs}(555)$	203.2 308.3	1.034 1.639	0.871 0.906	21.29 18.38	2.26 2.28	21.68 21.71	53 52				

The $R_{rs}(\lambda)/R_{rs}(555)$ is the blue-to-green band ratio of remote sensing reflectance, POC is in mg m⁻³, and A_i and B_i are regression coefficients, fitted by least-squares linear regression analysis using \log_{10} -transformed data of POC and $R_{rs}(\lambda)/R_{rs}(555)$. All regression coefficients and statistical parameters have been recalculated to represent the non-transformed data. The light wavelength λ is either 443 or 490, R^2 is the determination coefficient, *RMSE* the root mean square error, *MNB* the mean normalized bias, *NRMS* the normalized root mean square error, and *N* the number of observations (see Stramski et al., 2008 for more details).

averaging the POC estimates derived using the two algorithms. We hope that with more *in situ* data collected in the future, it will be possible to further improve and document the performance of ocean color POC algorithms.

Note that both POC algorithms are nonlinear. In order to minimize the biases, which could be accrued if calculations were completed on temporal averages (such as monthly composites) of satellite radiometric data, our calculations always started with the daily fields of remote sensing reflectances to estimate daily fields of POC concentrations. The derived set of daily POC concentrations (in mgCm⁻³) covers 10 successive years (1998-2007) of SeaWiFS data. From daily POC imagery, we have calculated 21-day moving averages to fill in the missing data. We have also calculated monthly averages and 10-year averaged monthly mean surface POC concentrations, which are presented in this paper (Fig. 1). Finally, from 21-day moving average imagery, we have calculated time series of large area mean surface POC concentrations.



Fig. 1. Maps of the 10-year averaged (1998-2007) monthly mean surface POC concentration derived in this study for the months of February, July, and September.

This spatial averaging provides POC estimates representative of mean conditions over relatively large sections of the ocean, removes the small and mesoscale features, and reduces (but does not eliminate) gaps in the time series due to missing data. Gaps, which were left unfilled, were still present after this spatial averaging in the polar regions in winter.

Other data sets used in this study include two SeaWiFS standard data products, surface chlorophyll a concentration, Chl, and diffuse attenuation coefficient, K(490). Chl and K(490) data were also downloaded from the NASA Ocean Color FTP site (http://oceancolor.gsfc.nasa.gov/ ftp.html). POC and Chl data were used to derive bulk POC/Chl ratios. The diffuse attenuation coefficient was used to obtain estimates of the optical attenuation depth, z_{opt} , and POC biomass integrated in one attenuation depth, POC_{opt}. One optical attenuation depth of the ocean is the maximum depth from which a remotely sensed signal is radiated. In our calculations, one optical attenuation depth was estimated as $z_{opt} = 1/K(490)$ (Gordon and McCluney, 1975), while POC_{opt} was calculated as POC_{opt} = POC/K(490) (Campbell et al., 1995; Gardner et al., 2006).

Another estimate of POC reservoir derived in this paper is based on the mixed layer depth, MLD, climatology available from the Laboratoire d'Océanographie Dynamique et de Climatologie, Université Pierre et Marie Curie in Paris (de Boyer Montégut et al., 2004). The mixed layer, ML, of the ocean is defined as the layer near the ocean surface with vertically guasi-uniform oceanic tracers (temperature, salinity, density) above a layer of more rapid vertical changes (e.g., Lorbacher et al., 2006). The intense vertical turbulent mixing near the ocean surface is the cause of the observed vertical uniformity. We have assumed that, similarly to other water properties, POC concentration within the ML is also nearly homogenous. This assumption allowed us to estimate the geographic distribution of POC reservoir located in the oceanic mixed layer, POC_{MLD} . The estimated POC_{MLD} at a given location was taken as a product of the surface POC concentrations derived from ocean color and MLD. Note that in comparison with older MLD estimates (Kara et al., 2003; Monterey and Levitus, 1997), the newer MLD climatology that we have chosen to use (de Boyer Montégut et al., 2004) is based on larger hydrographic data sets. In addition, these newer MLD estimates were established with 0.2 °C temperature criterion applied to the individual unsmoothed profiles, while the 0.5 °C or 0.8 °C threshold values were applied to already averaged profiles in earlier MLD estimates (Kara et al., 2003; Monterey and Levitus, 1997). We have decided to use the more recent MLD estimates, as it seems that the older (larger) temperature criteria tend to represent changes of the main thermocline rather than changes in the depth of the mixed top water column. Nevertheless, it is important to understand that our final estimates of POC_{MLD} depend on the choice of the MLD estimates used in such calculations. For example, the newer climatology yields somewhat lower MLD estimates in the northern North Atlantic than the older climatology, which means that our derived POC_{MLD} would be higher if we used older MLD climatology.

The third approach to estimate the POC reservoir in the oceanic surface waters is based on using a layer with a constant depth of water. This approach is more complicated as the assumption about a constant POC concentration within the layer is invalid when the assumed water depth is greater than the MLD. Nevertheless, we have explored this approach briefly. In our simplified approach we have used an oceanic surface layer that is 200-m deep and estimated POC biomass, POC₂₀₀, in this layer. In our calculations, we have assumed that POC concentration is homogenous throughout the mixed layer and equals surface POC concentrations derived from ocean color. If the MLD is less than 200-m deep, the POC concentration below ML is assumed to reach a background concentration of 10 or 20 mg m^{-3} (both scenarios are examined). This background POC concentration is in agreement with in situ data (see, for example, BATS POC data at bats,bios, edu/bats form bottle.html). Note however, that in this approach we do not account for a possibility of increased POC concentration above the background concentration below MLD, which can, for example, accompany a deepwater phytoplankton maximum.

The Oceanic El Niño Index, calculated as the 3-month running mean of Extended Reconstructed Sea Surface Temperature (ERSST.v3) SST anomalies in the Niño 3.4 region (5°N-5°S, 120°-170°W) has been used for comparison with POC data. This index has been made available by the NOAA Climate Prediction Center (www.cpc.noaa.gov/ products/_monitoring/ensostuff/ensoyears.shtml).

3. Results and discussion

Example, 10-year averaged (1998-2007) monthly mean surface POC concentration maps in the global ocean are presented in Fig. 1. These examples include POC maps for the months of February, July, and September. The seasonal changes in the POC distributions are quite distinct in Fig. 1. In the global ocean, the highest values of surface POC concentration are observed in summer of the northern hemisphere in the northern North Atlantic. Low 10-year averaged monthly means of POC concentrations are present in the oligotrophic subtropical gyres (with the lowest values in the South Pacific at 10-30°S). Between the gyres, there is a zone of somewhat higher POC concentration located in the region of equatorial divergence. Note that many major patterns of global POC concentration in the open ocean are oriented zonally. This is not true in coastal regions. The coastal upwelling regions (western coasts of Americas and Africa) show consistently higher POC concentrations than adjacent waters, and the seasonal changes in POC concentrations are evident in the upwelling regions as well. Notice, however, that in some coastal areas characterized by high concentrations of suspended solids which originate, for example, from continental runoff (e. g., Amazone and Orinoco Rivers plumes), our algorithm may produce erroneous POC concentrations. The well-known problems of ocean color algorithms (including Chl algorithms) in case 2 waters remains a difficult issue that requires additional work. In the future, this problem can be minimized when we have

more information about optical relationships in different geographic regions and optical properties of various water components.

In the past, the concentration of chlorophyll *a* was the basic data product derived from ocean color, and it was often used as a metric for phytoplankton biomass in the ocean. If POC concentration was needed, it was estimated from Chl by assuming certain POC/Chl ratios. In Fig. 2, we have plotted example maps of POC/Chl ratio as estimated from ocean color. In these estimates, we have used our daily POC concentrations derived in this study and daily Chl SeaWiFS data product. The daily POC/Chl ratios were then binned into monthly means and averaged for the 10-year time period (1998-2007). As can be seen, estimated POC/Chl ratio varies broadly in the global ocean in spite of the fact that averaging applied to the daily data somewhat decreased the range of overall variability. The highest values of POC/Chl ratio are observed between November and March in the oligotrophic waters of the South Pacific (10-30°S), while low values are present in the northern eutrophic waters during summer of the northern hemisphere. Spatial and temporal variability of POC/Chl ratio is the reason why it is more practical to determine POC concentrations directly from ocean color using POC algorithms than to try to estimate POC from Chl.

In Fig. 3, we have plotted time series of the average surface POC concentrations for different ocean basins and for the global ocean. These time series have been obtained from 21 day moving-average spatial POC maps for which all pixels were averaged over the entire area of each ocean region. The geographical boundaries of the ocean basins used in our calculations are the same as in Antoine et al.



Fig. 2. Example maps of POC/Chl ratio.



Fig. 3. Time series of the spatially averaged surface POC concentrations for different ocean basins and for the global ocean.



Fig. 3. (Continued)

(1996). In particular, we have assumed that the Southern Ocean is delimited by the parallel of 50°S, which is approximately the average latitude for the Antarctic convergence. We have also assumed that the North Atlantic and North Pacific are restricted by the latitude of 70°N, where the Arctic zone starts. We do not present separate estimates of average POC concentration for the Arctic because of the significant problem with ice and cloud free pixels in this region. This problem is also encountered in the Southern Ocean, but because of the larger ocean area, the problem of missing data seems to be less significant here except during austral winter, when there were not enough ice and cloud free pixels to create the time series. In the surface POC concentration time series for the global ocean, all ocean pixels in SeaWiFS images that were not removed by atmospheric correction algorithms have been averaged. The most striking observation (Fig. 3) is that there are large differences between average POC concentrations in different ocean basins. The South Pacific is characterized by the lowest yearly average of POC concentration and consistently low POC concentrations throughout the year. The North Atlantic, North Pacific, and Southern Ocean waters are characterized by relatively high surface POC concentrations in comparison to the other oceans. Note also that even if significant interannual variability in the spatial distribution of POC concentration is evident in daily and monthly POC images in every year for a given location (not shown), the time series of large area averaged surface POC concentration for each of the ocean regions (Fig. 3) display quite consistent annual patterns in different years (i.e. annual amplitude and timing of the seasonal increase of averaged surface POC concentration are guite similar in different years). The North Atlantic region is characterized by the largest seasonal amplitude of POC concentration, with a prominent spring/summer maximum of about 120 mg m^{-3} (+/-10 mg m⁻³) present on day 140-150 and corresponding to the development of seasonal phytoplankton blooms in the northern North Atlantic. The timing of the seasonal maximum in regional average POC concentration in the North Pacific is similar, but the amplitude is significantly lower than in the North Atlantic. The Southern Ocean is characterized by significant increase in the surface POC concentration during the productive season in austral spring/summer months. It also seems that the Southern Ocean is characterized by a somewhat stronger interannual variability of the average POC concentration than the other regions. Because of the large area covered by the North Pacific and North Atlantic waters and relatively high amplitude in the seasonal patterns of POC concentration in these regions, the average POC concentration for the global ocean is highest at the time of spring/summer season in the northern hemisphere. The highest values in the global average time series are observed in May - July. However, the seasonal variability of the globally averaged surface POC concentration is relatively weak, and the 10-year mean time series of the globally averaged POC are in the range of 60 - 75 mg m^{-3} . Note that there is also relatively little interannual variability in the annual pattern of the globally averaged surface POC concentration.

To better visualize the long-term trends in POC concentrations, we have plotted in Fig. 4 the 10-year time series of POC anomalies for each of the ocean basins. These anomalies were calculated as the difference between the regional time series of surface POC concentration in a given year and the 10-year averaged time series. The anomalies have the highest values in the North Atlantic and Southern Ocean (with standard deviations of 3.2 and 3.4 mg m⁻³, respectively), and the lowest values in the Southern Pacific (standard deviation of 1.3 mg m⁻³). The global and regional POC anomalies do not reveal any significant long-term trend in POC concentrations. Patterns of interannual variability are documented in Fig. 4 and appear to be more pronounced in the North Atlantic, North Pacific, and Southern Ocean than in other regions. It

seems that the anomalies in the North Atlantic and North Pacific are inversely correlated with the Oceanic El Niño Index, ONI, which is also shown in Fig. 4. Longer ocean color time series than are available presently will be needed in order to investigate the issue of long-term POC variability more thoroughly.

The information about global and basin scale POC concentrations gains particular significance if we can use it to estimate POC biomass contained within the surface ocean waters. Global and regional mass balances for all compartments of ocean carbon reservoir are necessary in order to quantify the role of the ocean as a source and sink for atmospheric CO_2 and its impact on earth's climate. For that reason we have attempted to assess a standing stock of POC in oceanic surface waters and to calculate contributions by different oceans. We have derived three estimates of POC biomass. The first estimate, POC_{opt} , is based on the optical attenuation depth, z_{opt} . The second estimate, POC_{MLD} , utilizes the mixed layer concept. The third estimate, POC_{200} , is based on a water layer with constant 200-m depth.

Note that using MLD provides a sensible link to the physical structure of the water column, while there is no sound physical rationale for applying the optical depth for estimating POC reservoir. Nevertheless, POCopt is presented here for comparisons with previously published assessment of oceanic POC reservoirs (Gardner et al., 2006). Notice that, according to our calculations, z_{opt} varies between a few meters in the eutrophic waters to less than sixty meters in the extremely oligotrophic waters. In contrast, MLD can reach a few hundred meters. for example, in the winter season in the North Atlantic. These large differences between z_{opt} and MLD are illustrated in Fig. 5, which shows examples of z_{opt} and MLD maps. The fact that MLD is on average significantly deeper than z_{opt} implies that POC_{MLD} represents POC biomass integrated over a deeper water layer than POC_{opt}. Therefore, POC_{MLD} usually includes greater biomass of POC than POC_{opt}. Example maps of POC_{opt} and POC_{MLD} are shown in Fig. 6. The estimates of POC_{opt} for the month of February shown in Fig. 6 are within the range $1 - 2 \text{ g m}^{-2}$. In contrast the values of $\mathsf{POC}_\mathsf{MLD}$ can be as high as 10 g m^{-2} . Thus, POC_{MLD} accounts for a larger portion of the total POC biomass present in the oceanic surface waters than POC_{opt}.

Note that even if the estimates of POC_{MLD} are significantly higher than POC_{opt}, POC_{MLD} should still be considered as an underestimate of the total POC biomass present in the oceanic surface layer. There are a few reasons for this. First, in our calculations we disregard deep algal biomass maxima and assume uniform POC concentrations with depth. Second, we do not account for POC biomass that can be produced and reside under the mixed layer if the critical depth is greater than the MLD. The critical depth is defined as the depth for which 24-hour vertically integrated water column productivity is equal to water column integrated losses (Sverdrup, 1953; Siegel et al., 2002; Marra, 2004). These community loss processes include autotrophic and heterotrophic respiration, grazing, and vertical export by sinking particles. Finally, in our calculations we do not account for the POC



Day

Fig. 4. The 10-year time series of surface POC concentration anomalies. Anomalies were calculated as the difference between the time series of regionally averaged surface POC concentration in a given year and the 10-year averaged POC time series. The Oceanic El Niño Index (ONI) has been made available by the NOAA Climate Prediction Center (www.cpc.noaa.gov/products/_monitoring/ensostuff/ensoyears.shtml).

biomass, which can be separated from the ML during the process of seasonal decrease of the MLD with increasing stratification of the ocean in the spring/summer season. An example of *in situ* data, showing that increased biomass is present under a shoaling ML when the phytoplankton bloom develops in the North Atlantic has been described, for example, by Stramska et al. (1995). Our current methods do not allow us to properly account for the organic matter located just below ML in such situations.

Global distributions of POC_{MLD} shown in Fig. 6 (middle and bottom panels) indicate that seasonal trends in POC_{MLD} are controlled by seasonal trends in MLD. For

example, in the regions where seasonal amplitude of the MLD is large (North Atlantic and Southern Ocean) the seasonal maximum POC_{MLD} is observed at the same time when the MLD is deepest. This indicates that the seasonal increase of surface POC concentration does not compensate for the decrease of POC biomass contained within the ML caused by the decrease of the MLD. This observation supports the notion that future improved estimates of POC biomass in the surface ocean should account not only for the POC_{MLD} but also for the POC biomass, which is located just below the ML.

The third estimate of POC biomass, POC_{200} , is expected to be smaller than POC_{MLD} if the MLD is greater than



Fig. 5. Example maps of one optical attenuation depth (top panel) and mixed layer depth (middle and bottom panels). Note that the range of values is larger for MLD than for z_{opt} , and that MLD undergoes significant seasonal changes.

200-meters, because POC biomass located within the ML below 200-m depth is not taken into account in the POC₂₀₀ estimate. If the MLD is less than 200-meters, POC₂₀₀ is larger than POC_{MLD}, since, in this case, accounting for the background POC concentration below the MLD increases integrated POC biomass. Recall that in our calculations of POC₂₀₀, we have assumed that background POC concentration is 10 or 20 mg m⁻³.

A summary of the global and regional estimates of the POC_{opt} , POC_{MLD} , and POC_{200} is provided in Table 2. Our estimate of global POC reservoir based on POC_{opt} is 48.10×10^{13} g, which is about 12% higher than similar estimate reported before by Gardner et al. (2006). The difference between the two estimates can be most likely attributed to differences in the remote sensing POC algorithms used in each study (see Stramski et al. 2008 for the discussion of POC algorithms). While inspecting data in Table 2, we observe that estimates of POC_{opt} are quite similar in different regions. One of the reasons for



Fig. 6. Maps of the POC biomass integrated over the depths shown in Fig. 5. These maps were obtained as monthly averages of the daily POC_{opt} (top panel) and POC_{MID} (middle and bottom panels).

this similarity is the fact that z_{opt} decreases with the increase of concentration of organic matter in surface waters. This means that an increase in POC concentration is accompanied by a parallel decrease of z_{opt} . In consequence, with increasing POC concentration, POC_{opt} represents biomass integrated over shallower water layers, and this is why POC_{opt} does not vary significantly. In contrast, POC_{MLD} and POC_{200} show considerable regional differences. The highest POC_{MLD} and POC₂₀₀ estimates are for the Southern Ocean and North Atlantic, the regions were POC concentration is high and MLD is deep. The greatest contribution to total global POC stock integrated over MLD are made by the Southern Ocean (31%) and North Pacific (17%). Our calculations show that global average POC_{opt} is about 32% of the global average POC_{MLD} and about 27 or 21% of the global POC₂₀₀ (assuming background POC concentration below MLD of 10 or 20 mg m⁻³, respectively). However, as noted before, POC_{MLD} and POC₂₀₀ probably also underestimate total POC

Table 2

Global and regional estimates of the average POC biomass (in g m^{-2}) integrated down to one attenuation depth (POC_{opt}), mixed layer depth (POC_{MLD}), and 200-m depth (POC₂₀₀).

Region	$POC_{opt} \left(g m^{-2}\right)$	POC_{MLD} (g m ⁻²)	POC _{MLD} stock (10 ¹³ g)	POC _{MLD} stock (%)	$POC_{200} (g m^{-2})$	POC_{200} stock $(10^{13} g)$	POC ₂₀₀ stock (%)
Global	1.34	3.62	130.68	100	6.41 (5.0)	228.61 (178.36)	100 (100)
N. Atlantic	1.38	4.09	19.63	15	7.10 (5.61)	34.09 (26.95)	15 (15)
S. Atlantic	1.35	3.53	10.90	8	6.43 (4.98)	20.07 (15.54)	9 (9)
N. Pacific	1.32	2.98	22.38	17	6.06 (4.53)	46.13 (34.51)	20 (19)
S. Pacific	1.28	2.73	17.75	13	5.60 (4.16)	37.01 (27.52)	16 (15)
Indian	1.34	3.46	18.30	14	6.29 (4.85)	33.81 (26.06)	15 (15)
S. Ocean	1.38	5.79	40.50	31	7.78 (6.74)	54.55 (47.27)	24 (26)

POC stock (global and regional) was calculated as the annual average POC_{MLD} and POC_{200} biomass multiplied by the regional area. The contribution (in %) of each region to global POC stock is also shown. Note that the two numbers shown in columns for POC_{200} represent estimates of POC_{200} assuming that POC concentration below MLD is 20 or 10 mg m⁻³ (the later estimates are shown in brackets).

biomass contained in oceanic surface waters. In the future, improved estimates of POC biomass should account for POC biomass residing in some geographical regions under the seasonal thermocline, which may lead to somewhat higher POC biomass estimates.

One possible (but difficult and laborious) approach to improving POC biomass estimates could be based on a development of regional relationships for which surface concentrations and detailed vertical POC profiles are known. The application of such regional relationships in combination with a knowledge of the typical vertical structure of the water column for a given region and season could then yield the best possible satellite-derived POC reservoir in the oceanic surface layer. (A similar approach has been used by Antoine et al., 1996 for integrating Chl biomass and PP modeling.) Improved estimates of POC reservoir could be also obtained with the application of ocean models which would resolve vertical profiles of POC concentration. More in situ data is needed for better understanding of regional relationships before information about vertical POC profiles can be incorporated into the estimates of POC reservoirs from remote sensing. Until such data are available, our preliminary estimates of POC reservoir in the oceanic surface waters presented in this paper can be treated as a first approximation of this reservoir.

Zonally averaged 10-year mean surface POC concentration, POC_{opt}, POC_{MLD}, and POC₂₀₀ plotted as a function of latitude are shown in Fig. 7. Zonally averaged primary productivity, PP, and export, PE, estimates are displayed for comparison in Fig. 8. These PP and PE are obtained from data published by Dunne et al. (2007), and have been derived from the 7 years of SeaWiFS data (1998-2004). As can be seen in Figs. 7 and 8, POC concentrations, integrated POC biomass estimates, PP, and PE have the highest values in the north $(70 - 50^{\circ}N)$ and the lowest values in the oligotrophic regions around 30°N and 30°S. In the equatorial zone, PP is almost as high as in the zone of 70 – 50°N, but POC concentration, POC biomass, and PE do not reach such high values. More to the south all the estimates increase from low values at around 30°S to higher values at 40°S, but these increased values are more evident in POC concentration and POC biomass (in particular POC_{MLD} and POC_{200}) and extend in broader zonal area than PP and PE.

Ocean color data are an invaluable source of information about global biogeochemical processes, but one needs to be aware of potential errors. Recall, that space-borne ocean color instruments quantify water leaving radiance at selected visible and near-infrared wavebands. These radiance spectra are than used to estimate geophysical parameters, such as Chl or POC via application of biooptical algorithms. Therefore, errors in the final biogeochemical estimates can be conceptually divided into two categories. In the first category are errors in the primary measurement of satellite-based sensors (spectral radiances). These errors propagate in bio-optical algorithms, which use spectral radiances as input. In the second category are errors caused by the limitations of the bio-optical algorithms.

Errors in the first category result from the fact that an ocean color satellite sensor such as SeaWiFS receives about 90% of its signal from the atmosphere, while only 10% comes from the ocean (e.g., Gordon and Morel, 1983). In order to derive radiance leaving the water, the atmospheric contribution must be accurately estimated and subtracted from the total radiance recorded at the top of the atmosphere. One of the problems is that current atmospheric correction algorithms do not correct adequately for absorbing aerosols (e.g., Kahru and Mitchell 1999; Schollaert et al., 2003; Nobileau and Antoine, 2005; Hyde et al., 2007; Wang et al., 2009). Another difficulty is a possible failure of the black pixel assumption in highly scattering waters (e.g., Siegel et al., 2000; Morel and Bélanger, 2006; Morel and Gentili, 2008). The analyses carried out by the NASA Ocean Biology Processing Group (OBPG) indicate that SeaWiFS radiance accuracy is within 9-19% in a global data set and within 6-12% in the deepwater (>1000 m) subset (Werdell and Bailey, 2005; Bailey and Werdell, 2006; Bryan et al., 2007).

Errors in the second category are due to imperfection of the bio-optical algorithms. For example, in the case of SeaWiFS Chl algorithm (OC4v4), the normalized root mean square error (*NRMS*) was estimated to be 24% (O'Reilly et al., 2000). As noted above, final errors in secondary derived ocean color products are also impacted



Fig. 7. Average surface POC concentration, POC_{opt} , POC_{MLD} , and POC_{200} plotted as a function of latitude. POC_{200} is shown as solid line when POC concentration below MLD is assumed to be 20 mg m^{-3} and as dashed line when POC concentration below MLD is assumed to be 10 mg m^{-3} . All estimates are based on SeaWiFS data from 1998-2007.

by errors in the input data (spectral radiances). Thus, the secondary product accuracy may be lower than the accuracy of the algorithm from which the product is derived. Nevertheless, the NRMS documented by the OBPG during global SeaWiFS Chl validation activity was very similar to the NRMS documented before for the Chl algorithm itself (Bailey and Werdell, 2006). Independent evaluation of the global SeaWiFS Chl data product carried out by Gregg and Casey (2004) showed the normalized root mean square (NRMS) error of 27.7% in the open ocean (water depth > 200 m) and 33% in the coastal regions. In comparison, the NRMS for the POC algorithms estimated by Stramski et al. (2008) are approximately 22% (see Table 1). This estimate is based on a relatively small data set. It is vital to collect more in situ POC data in the future in order to further validate the performance of the POC algorithms. Nevertheless, evaluation of POC algorithms based on comparisons with our own and historical data sets (Stramska and Stramski, 2005; Stramski et al., 2008) allows us to assume that the overall performance of POC algorithms is similar to the performance of Chl algorithms. As is the case with Chl algorithms, it is anticipated that the performance of POC algorithms is less dependable in the coastal regions than in the open ocean regions. Note however, that the respective area of the ocean with depth < 1000 m is less than 12% and coastal waters (depth < 200 m) are only about 7.5% of the global ocean. Because of the small percentage area of the coastal regions, potentially inferior performance of POC algorithms in optically complex coastal waters should not significantly affect global trends discussed in this paper.

4. Summary and conclusions

Analysis of spatial distribution of POC concentration and integrated biomass is important for understanding



Fig. 8. Primary productivity (PP) and export (PE) estimates plotted as a function of latitude (as derived from the 1998-2004 SeaWiFS data by Dunne et al., 2007).

the potential of the marine biosphere to affect the global carbon cycle. The development of the ocean color POC algorithms provides a new capability to obtain long term spatially resolved time series of POC data for detecting real trends in ocean and global carbon cycling. In this paper we have used 10 years of SeaWiFS data to derive global surface POC concentration time series and estimates of POC biomass in oceanic surface waters.

Our results indicate that the 10-year time series of the global and basin scale average surface POC concentrations do not exhibit significant long term trends. There are considerable differences between ocean basins. The mean POC concentration and the seasonal amplitude are highest in the North Atlantic and lowest in the South Pacific, when compared to other ocean basins. Surface POC concentration anomalies in the North Atlantic, North Pacific, and global ocean seem to be inversely correlated with El Niño index, but longer time series are needed to confirm this relationship. Quantitative estimates of the POC reservoir in the oceanic surface layer depend on the choice of what should represent this layer (Table 2). The global estimate of POC reservoir contained within the optical depth is the lowest, while the estimates of POC reservoir embedded within the MLD and the 200-m surface water lavers are much higher. Global average POC biomass is 1.34 g m^{-2} if integrated over one optical depth, 3.62 g m^{-2} if integrated over mixed layer depth, and up to 6.41 if integrated over 200-m layer depth (if the background POC concentration below MLD is assumed to be 20 mg m^{-3}). This means that the estimate of global POC reservoir in surface waters is as high as 228.61×10^{13} g of carbon, if calculations are based on POC integrated over the 200-m surface water layer.

Our calculations may underestimate the total POC reservoir present in oceanic surface waters because we did not account for the elevated POC concentrations that in some situations can be present in the water column below MLD. For example, we did not account for POC located in the organic matter maxima in the oligotrophic ocean regions or below ML in temperate regions during the development of spring phytoplankton blooms (when MLD is shoaling). More effort is needed in the future to improve POC reservoir estimates. These should include work on validation and improvements of the ocean color remote sensing POC algorithms, development of regional approaches, which would take into account regional features of vertical POC distribution in specific regions and seasons, and work on merging surface POC data derived from ocean color with ocean models.

Acknowledgments

Financial support for this research was provided by NASA Ocean Biology and Biogeochemistry Program (Grant NNX08AG02G) and NSF Chemical Oceanography Program (Grants OCE-0324346 and OCE-0324680). SeaWiFS data were made available by NASA's Goddard DAAC and the SeaWiFS Science Project. The Oceanic El Niño Index (ONI) data have been made available by NOAA Climate Prediction Center. I would like to thank C. de Boyer Montégut for mixed layer depth climatology data and John Dunne for PP and PE estimates. I am also grateful to Dr. Michael P. Bacon and two anonymous reviewers for their detailed comments and suggestions.

References

- Antoine, D., Andre, J.-M., Morel, A., 1996. Oceanic primary production 2. Estimation at global scale from satellite (coastal zone color scanner) chlorophyll. Global Biogeochemical Cycles 10, 57–69.
- Bailey, S.W., Werdell, P.J., 2006. A multi-sensor approach for the on-orbit validation of ocean color satellite data products. Remote Sensing of Environment 102, 12–23.
- Behrenfeld, M.J., Boss, E., Siegel, D.A., Shea, D.M., 2005. Carbon-based ocean productivity and phytoplankton physiology from space. Global Biogeochemical Cycles 19, GB1006.
- Behrenfeld, M.J., O'Malley, R.T., Siegel, D.A., McClain, C.R., Sarmiento, J.L., Feldman, G.C., Milligan, A.J., Falkowski, P.G., Letelier, R.M., Boss, E.S., 2006. Climate-driven trends in contemporary ocean productivity. Nature 444, 752–755.
- Bryan, A.F., Bailey, S.W., Werdell, P.J., McClain, C.R., 2007. Sensorindependent approach to the vicarious calibration of satellite ocean color radiometry. Applied Optics 46, 5068–5082.
- Campbell, J.W., Blaisdell, J.M., Darzi, M., 1995. Level-3 SeaWiFS data products: spatial and temporal binning algorithms. SeaWiFS Technical Report Series 32, 73.
- Carr, M.-E., Friedrichs, M.A.M., Schmeltz, M., Aita, M.N., Antoine, D., Arrigo, K.R., Asanuma, I., Aumont, O., Barber, R., Behrenfeld, M., Bidigare, R., Buitenhuis, E.T., Campbell, J., Ciotti, A., Dierssen, H., Dowell, M., Dunne, J., Esaias, W., Gentili, B., Gregg, W., Groom, S., Hoepffner, N., Ishizaka, J., Kameda, T., Quéré, C.L., Lohrenz, S., Marra, J., Melin, F., Moore, K., Morel, A., Reddy, T.E., Ryan, J., Scardi, M., Smyth, T., Turpie, K., Tilstone, G., Waters, K., Yamanaka, Y., 2006. A comparison of global estimates of marine primary production from ocean color. Deep-Sea Research II 53, 741–770.
- de Boyer Montégut, C., Madec, G., Fischer, A.S., Lazar, A., Iudicone, D., 2004. Mixed layer depth over the global ocean: an examination of profile data and a profile-based climatology. Journal of Geophysical Research 109, C12003.
- Ducklow, H.W., Steinberg, D.K., Buesseler, K.O., 2001. Upper ocean carbon export and the biological pump. Oceanography 14 (4), 50–58.
- Dunne, J., Sarmiento, J.L., Gnanadesikan, A., 2007. A synthesis of global particle export from the surface ocean and cycling through ocean interior and seafloor. Global Biogeochemical Cycles 21.
- Gardner, W.D., Mishonov, A.V., Richardson, M.J., 2006. Global POC concentrations from in-situ and satellite data. Deep-Sea Research II 53, 718–740.
- Gordon, H.R., McCluney, W.R., 1975. Estimation of the depth of sunlight penetration in the sea for remote sensing. Applied Optics 14, 413–416.
- Gordon, H.R., Morel, A., 1983. Remote Assessment of Ocean Color for Interpretation of Satellite Visible Imagery—A Review, Lecture Notes on Coastal and Estuarine Studies. Springer, Berlin, 114 pp.
- Gregg, W.W., Casey, N.W., 2004. Global and regional evaluation of the SeaWiFS chlorophyll data set. Remote Sensing of Environment 93, 463–479.
- Hooker, S.B., McClain, C.R., 2000. The calibration and validation of SeaWiFS data. Progress in Oceanography 45, 427–465.
- Hyde, K.J.W., O'Reilly, J.E., Oviatt, C.A., 2007. Validation of SeaWiFS chlorophyll a in Massachusetts Bay. Continental Shelf Research 27, 1677–1691.
- Kahru, M., Mitchell, B.G., 1999. Empirical chlorophyll algorithm and preliminary SeaWiFS validation for the California Current. International Journal of Remote Sensing 20, 3423–3429.
- Kara, A.B., Wallcraft, A.J., Hurlburt, H.E., 2003. Climatological SST and MLD predictions from a global layered ocean model with an embedded mixed layer. Journal of Atmospheric and Oceanic Technology 20, 1616–1632.
- Loisel, H., Nicolas, J.-M., Deschapms, P.-Y., Frouin, R., 2002. Seasonal and inter-annual variability of particulate organic matter in the global ocean. Geophysical Research Letters 29 (24), 2196.

- Lorbacher, K., Dommenget, D., Niiler, P.P., Köhl, A., 2006. Ocean mixed layer depth: a subsurface proxy of ocean-atmosphere variability. Journal of Geophysical Research 111, C07010.
- Marra, J., 2004. The compensation irradiance for phytoplankton in nature. Geophysical Research Letters 31, L06305.
- Mobley, C.D., 1994. Light and Water: Radiative Transfer in Natural Waters. Academic Press, New York.
- Monterey, G., Levitus, S., 1997. Seasonal Variability of Mixed Layer Depth for the World Ocean, NOAA Atlas NESDIS, vol. 14. Natl. Oceanic and Atmos. Admin., Silver Spring, MD, 100 pp.
- Morel, A., Bélanger, S., 2006. Improved detection of turbid waters from ocean color sensors information. Remote Sensing of Environment 102, 237–249.
- Morel, A., Gentili, B., 2008. Practical application of the "turbid water" flag in ocean color imagery: interference with sun-glint contaminated pixels in open ocean. Remote Sensing of Environment 112, 934–938.
- Nobileau, D., Antoine, D., 2005. Detection of blue-absorbing aerosols using near infrared and visible (ocean color) remote sensing observations. Remote Sensing of Environment 95, 368–387.
- O'Reilly, J., Maritorena, E.S., Mitchell, B.G., Siegel, D.A., Carder, K.L., Garver, S.A., Kahru, M., McClain, C.R., 1998. Ocean color chlorophyll algorithms for SeaWiFS. Journal of Geophysical Research 103, 24,937–24,953.
- O'Reilly, J.E., Maritorena, S., Siegel, D.A., O'Brien, M.C., Toole, D., Mitchell, B.G., Kahru, M., Chavez, F.P., Strutton, P., Cota, G.F., Hooker, S.B., McClain, C.R., Carder, K.L., Müller-Karger, F., Harding, L., Magnuson, A., Phinney, D., Moore, G.F., Aiken, J., Arrigo, K.R., Letelier, R., Culver, M., 2000. Ocean color chlorophyll a algorithms for SeaWiFS, OC2 and OC4: Version 4, NASA Tech. Memo, 2000-206892, vol. 11, pp. 9–27.
- Pabi, S., Arrigo, K.R., 2006. Satellite estimation of marine particulate carbon in waters dominated by different phytoplankton taxa. Journal of Geophysical Research 110, C10018.
- Schollaert, S.E., Yoder, J.A., O'Reilly, J.E., Westphal, D.L., 2003. Influence of dust and sulfate aerosols on ocean color spectra and chlorophyll a concentrations derived from SeaWiFS off the US east coast. Journal of Geophysical Research 108, 3191.
- Siegel, D.A., Wang, M., Maritorena, S., Robinson, W., 2000. Atmospheric correction of satellite ocean color imagery: the black pixel assumption. Applied Optics 39, 3582–3591.
- Siegel, D.A., Doney, S.C., Yoder, J.A., 2002. The North Atlantic spring bloom and Sverdrup's critical depth hypothesis. Science 296, 730–733.
- Stramska, M., Dickey, T.D., Plueddemann, A., Weller, R., Langdon, C., Marra, J., 1995. Bio-optical variability associated with phytoplankton dynamics in the North Atlantic Ocean during spring and summer of 1991. Journal of Geophysical Research 100, 6621–6632.
- Stramska, M., Stramski, D., 2005. Variability of particulate organic carbon concentration in the north polar Atlantic based on SeaWiFS ocean color observations. Journal of Geophysical Research 110, C10018.
- Stramski, D., Reynolds, R.A., Kahru, M., Mitchell, B.G., 1999. Estimation of particulate organic carbon in the ocean from satellite remote sensing. Science 285, 239–242.
- Stramski, D., Reynolds, R.A., Babin, M., Kaczmarek, S., Lewis, M.R., Röttgers, R., Sciandra, A., Stramska, M., Twardowski, M.S., Franz, B.A., Claustre, H., 2008. Relationships between the surface concentration of particulate organic carbon and optical properties in the eastern South Pacific and eastern Atlantic Oceans. Biogeosciences 5, 171–201.
- Sverdrup, H.U., 1953. On conditions for the vernal blooming of phytoplankton. Journal du Conseil, Permanent International pour l'Exploration de la Mer 18, 287–295.
- Wang, M., Son, S., Shi, W., 2009. Evaluation of MODIS SWIR and NIR-SWIR atmospheric correction algorithms using SeaBASS data. Remote Sensing of Environment 113, 635–644.
- Werdell, P.J., Bailey, S.W., 2005. An improved in-situ bio-optical data set for ocean color algorithm development and satellite data product validation. Remote Sensing of Environment 98, 122–140.