

1 **Remote sensing of the absorption coefficients and chlorophyll *a* concentration in the**  
2 **U.S. southern Middle Atlantic Bight from SeaWiFS and MODIS-Aqua**

3 Xiaoju Pan<sup>1</sup>, Antonio Mannino<sup>1</sup>, Mary E. Russ<sup>1,2</sup>, Stanford B. Hooker<sup>1</sup>

4 <sup>1</sup>NASA Goddard Space Flight Center, Greenbelt, Maryland, USA

5 <sup>2</sup>University of Maryland, Baltimore County, Goddard Earth Sciences and Technology  
6 Center

7  
8 *Accepted by the Journal of Geophysical Research – Oceans* September 2008

9  
10 Index terms:

11 0480 Remote sensing

12 0422 Bio-optics

13 4219 Continental shelf and slope processes

14 4805 Biogeochemical cycles, processes, and modeling

15 Key Words: absorption, chlorophyll, remote sensing, SMAB, SeaWiFS, MODIS

16

17 Corresponding Author:

18 Xiaoju Pan

19 NASA Goddard Space Flight Center, Mail Code 614.7, Build 22 Room 248

20 Greenbelt, Maryland 20771, USA

21 Phone: +1 301 286 8966

22 FAX: +1 301 286 5337

23 E-mail: [xpan@neptune-web.gsfc.nasa.gov](mailto:xpan@neptune-web.gsfc.nasa.gov)

1 Abstract

2           At present, satellite remote sensing of coastal water quality and constituent  
3 concentration is subject to large errors as compared to the capability of satellite sensors in  
4 oceanic waters. In this study, field measurements collected on a series of cruises within  
5 U.S. southern Middle Atlantic Bight (SMAB) were applied to improve retrievals of  
6 satellite ocean color products in order to examine the factors that regulate the bio-optical  
7 properties within the continental shelf waters of the SMAB. The first objective was to  
8 develop improvements in satellite retrievals of absorption coefficients of phytoplankton  
9 ( $a_{ph}$ ), colored dissolved organic matter (CDOM) ( $a_g$ ), non-pigmented particles ( $a_d$ ), and  
10 non-pigmented particles plus CDOM ( $a_{dg}$ ), and chlorophyll *a* concentration ([Chl\_a]).  
11 Several algorithms were compared to derive constituent absorption coefficients from  
12 remote sensing reflectance ( $R_{rs}$ ) ratios. The validation match-ups showed that the mean  
13 absolute percent differences (MAPD) were typically <35%, although higher errors were  
14 found for  $a_d$  retrievals. Seasonal and spatial variability of satellite-derived absorption  
15 coefficients and [Chl\_a] was apparent and consistent with field data. CDOM is a major  
16 contributor to the bio-optical properties of the SMAB, accounting for 35-70% of total  
17 light absorption by particles plus CDOM at 443 nm, as compared to 30-45% for  
18 phytoplankton and 0-20% for non-pigmented particles. The overestimation of [Chl\_a]  
19 from the operational satellite algorithms may be attributed to the strong CDOM  
20 absorption in this region. River discharge is important in controlling the bio-optical  
21 environment, but cannot explain all of the regional and seasonal variability of  
22 biogeochemical constituents in the SMAB.

1 1. Introduction

2           Satellites such as the Sea-viewing Wide Field-of-view Sensor (SeaWiFS) and the  
3 MODERate-resolution Imaging Spectrometer (MODIS) have been widely applied to the  
4 study of biogeochemical processes [*IOCCG*, 1999; *McClain et al.*, 2004]. Based on bio-  
5 optical theory, the satellite measurement, here remote sensing reflectance ( $R_{rs}$ ), is often  
6 related to inherent optical properties (IOPs) such as the absorption coefficient ( $a$ ) and  
7 scattering coefficient ( $b$ ) [*Garver and Siegel*, 1997; *Gordon et al.*, 1988; *Kirk*, 1994;  
8 *Maritorena et al.*, 2002; *Mobley*, 1994]. IOPs are often related to relevant  
9 biogeochemical constituents such as chlorophyll  $a$  concentration ([Chl\_  $a$ ]), dissolved  
10 organic carbon (DOC), particulate organic carbon (POC), and suspended sediment  
11 [*Ferrari et al.*, 2003; *Mannino et al.*, 2008; *Rochelle-Newall and Fisher*, 2002; *Siegel et*  
12 *al.*, 2002].

13           Although chlorophyll  $a$  pigment plays a critical role in understanding the bio-  
14 optical properties in oceanic waters, it is insufficient to fully characterize the  
15 biogeochemical properties, especially in coastal waters where colored dissolved organic  
16 matter (CDOM) and sedimentary resuspended matter often overwhelm phytoplankton in  
17 the contribution to bio-optical properties [*Gordon and Morel*, 1983; *IOCCG*, 2006; *Kirk*,  
18 1994; *Mobley*, 1994]. In general, IOPs are composed of four components: pure water,  
19 phytoplankton, CDOM, and non-pigmented particles [*Kirk*, 1994; *Mobley*, 1994].  
20 Absorption from components other than pure water is often considered to be strongly  
21 correlated to [Chl\_  $a$ ] in oceanic Case 1 waters, while such an assumption often breaks  
22 down in Case 2 waters (e.g. coastal and inland waters) [*Gordon and Morel*, 1983;  
23 *IOCCG*, 2000; *Kirk*, 1994; *Mobley*, 1994].

1           In theory semi-analytic (SA) models, which apply spectral deconvolution, are  
2 applicable to retrieve constituent IOPs from  $R_{rs}$  [IOCCG, 2006]. For instance, the GSM01  
3 model [Garver and Siegel, 1997; Maritorena et al., 2002] produces [Chl\_a], absorption  
4 coefficient of CDOM and non-pigmented particles ( $a_{dg}$ ), and particulate backscattering  
5 coefficient ( $b_{bp}$ ). Unfortunately there are at least two problems with SA models applied to  
6 coastal waters. First, SA models require detailed knowledge of IOP relationships, which  
7 vary regionally or seasonally in coastal waters and in fact are regionally specific or  
8 empirically derived [Babin et al., 2003a, 2003b; Magnuson et al., 2004]. Second, SA  
9 models are equally sensitive to signals at all wavelengths and require them to be equally  
10 accurate. In coastal waters the satellite-derived water-leaving radiances ( $L_w$ ) at shorter  
11 wavelengths (e.g. 412 and 443 nm) often contain some error. Incorrect atmospheric  
12 correction due to inadequate information on aerosol absorption and the selection of  
13 inappropriate aerosol model, along with the weak signal-to-noise ratio due to strong  
14 CDOM absorption, often causes errors on  $L_w$  derivation in coastal waters [Bailey and  
15 Werdell, 2006; IOCCG, 2000; Siegel et al., 2000, 2005]. Consequently, the application of  
16 SA models in coastal waters faces a significant challenge because of the requirement of  
17 highly accurate  $L_w$  at all wavelengths.

18           Empirical algorithms do not require a full understanding of fundamental bio-  
19 optical theory. For example, they provide a direct link between satellite-sensed radiance  
20 and relevant bio-optical parameters such as [Chl\_a] and diffuse attenuation coefficient  
21 ( $K_d$ ) on global and regional scales [Harding et al., 2005; Mueller, 2000; O'Reilly et al.,  
22 1998, 2000; Signorini et al., 2005]. The creation of empirical algorithms, however,  
23 requires a sufficient size of highly accurate field measurements spanning all seasons and

1 adequate spatial coverage for the regions of interest. Thus, empirical algorithms are  
2 subject to updates as the dataset increases in size. In the work presented here, a set of  
3 self-consistent field  $R_{rs}$  data is applied to derive absorption coefficients of oceanic  
4 constituents in the U.S. southern Middle Atlantic Bight (SMAB). Absorption coefficients  
5 are very important bio-optical properties in the study of radiative transfer modeling and  
6 heat budget [Mobley, 1994], carbon flux (e.g. [Chl\_a], primary production, DOC, and  
7 POC) [Arrigo and Brown, 1996; Behrenfeld et al., 2005; IOCCG, 2006; Mannino et al.,  
8 2008; Marra et al., 2007; Rochelle-Newall and Fisher, 2002], water quality (e.g. diffuse  
9 attenuation coefficient) [Mueller, 2000], and oceanic physical processes (e.g. salinity  
10 distribution) [Rochelle-Newall and Fisher, 2002]. The objectives of this work were: 1) to  
11 develop and validate satellite algorithms in deriving constituent absorption coefficients  
12 for phytoplankton, non-pigmented particles, and CDOM and [Chl\_a] near the ocean  
13 surface within the SMAB to within  $\pm 35\%$  uncertainty, 2) to determine the relative  
14 importance of phytoplankton, CDOM, and detritus in sunlight absorption, and 3) to  
15 evaluate the seasonal and regional impacts of river discharge on biogeochemical  
16 constituents in the SMAB.

17

## 18 2. Methods

### 19 2.1. Study region and field experiments

20 This study focuses on the SMAB from the Delaware Bay (DB) mouth to the  
21 region south of the Chesapeake Bay (CB) mouth (Figure 1). This region is well  
22 recognized for the significant impacts by riverine discharge from the Delaware and  
23 Chesapeake Bays, which account for most of the salinity variability of the SMAB [Acker

1 *et al.*, 2005; *Austin*, 2002; *Harding*, 1994]. The magnitude of freshwater run-off, along  
2 with wind and tidal forcing, generates periodic outflow plumes (e.g. winter-spring plume  
3 and fall sub-plume) for this region, and enhances the bio-optical complexity of the  
4 SMAB compared to pelagic regions of the Atlantic Ocean [*Acker et al.*, 2005; *Harding*,  
5 1994; *Johnson*, 2001; *O'Reilly and Zetlin*, 1998; *Rennie et al.*, 1999].

6 Multiple cruises were conducted in this region during 2004-2006, including the  
7 Bio-physical Interactions in Ocean Margin Ecosystems cruises (BIOME) during 30  
8 March to 1 April 2005 (BIOME1), 26 to 30 July 2005 (BIOME2), 9 to 12 May 2006  
9 (BIOME3), and 2 to 6 July 2006 (BIOME4), and the Chesapeake Bay Plume cruises  
10 (CBP) during 27 May and 3 November 2005, and 6 September and 28 November 2006,  
11 and the Chesapeake Bay Hydrological survey (CBH) during 5 May, 5 July, 1 September,  
12 15 October, and 15 November 2004, and 10 January, 26 May, 21 June, 19 August, and 23  
13 September 2005 (Figure 1). The collected bio-optical data included, but not limited to,  
14 phytoplankton pigments, IOPs (absorption), and  $R_{rs}$  (only on BIOME and CBP cruises in  
15 2005). Water samples were collected at multiple depths with Niskin bottles.

16

## 17 2.2. Pigments and absorption coefficient

18 Pigment samples were collected on 25 mm GF/F filters under a gentle vacuum  
19 (<5 in Hg) and stored in liquid nitrogen in the field before transfer to a -80°C freezer in  
20 the laboratory. Pigments were analyzed at Horn Point Laboratory by reverse-phase high-  
21 performance liquid chromatography (HPLC) with a C8 column on the HPLC system  
22 equipped with photodiode array detector [*Van Heukelem and Thomas*, 2001]. [Chl\_a]

1 was calculated as the sum of concentration from monovinyl Chl\_a, divinyl Chl\_a, and  
2 chlorophyllide *a*.

3 Absorption coefficients of particles ( $a_p$ ) and non-pigmented particles ( $a_d$ ) were  
4 determined by the quantitative “filter pad” method following the recommendations of  
5 *Mitchell et al.* [2002]. Particulate samples were collected on 25 mm GF/F filters under a  
6 gentle vacuum (<5 in Hg) and stored in liquid nitrogen in the field before transfer to a -  
7 80°C freezer in the laboratory. Non-pigmented particulate samples were defined as the  
8 detritus component of particulate samples after two cold methanol extractions (first 5 ml  
9 for 10 minutes, then 10 ml for 1 hour) [*Kishino et al.*, 1985]. Artificial seawater pre-  
10 filtered through 0.2 µm Whatman Nuclepore filters was used to rinse off methanol and to  
11 hydrate the GF/F filters of both blanks and samples. CDOM samples were collected by  
12 filtering seawater through pre-combusted (6 hours at 450°C) GF/F filters and stored  
13 under refrigeration (4 to 8 °C). In the laboratory, CDOM samples were warmed to room  
14 temperature and filtered through 0.2 µm Whatman Nuclepore (polycarbonate) or Gelman  
15 Supor (polyethersulfone) filters prior to analysis [*Mannino et al.*, 2008].

16 Absorbance spectra were measured using a double-beam Cary 100 Bio  
17 Ultraviolet-Visible scanning spectrophotometer through 250-800 nm (CDOM in Suprasil  
18 quartz 10 cm pathlength cells) or 300-800 nm (particles) in 1 nm intervals. Blank GF/F  
19 filters hydrated with 0.2 µm pre-filtered artificial seawater and ultraviolet (UV) oxidized  
20 Milli-Q water were used as the blank and reference for particulate absorbance and  
21 CDOM absorbance, respectively. Null correction was made by subtracting the mean of  
22 absorbance at 790 to 800 nm for particulate samples for each spectrum. No null  
23 correction for CDOM absorption was made since the raw absorbance of seawater samples

1 at 690-700 nm was within the noise level of the instrument [Mannino *et al.*, 2008]. The  
2 multiple-scattering effect for calculating particulate absorption coefficient ( $a_p$ ) and non-  
3 pigmented particulate absorption coefficient ( $a_d$ ) was corrected following the method of  
4 Mitchell [1990], from which non-pigmented particulate samples were assumed to have  
5 the same multiple-scattering amplification factor to total particulate samples [Mitchell *et*  
6 *al.*, 2002]. Phytoplankton absorption coefficient ( $a_{ph}$ ) was calculated as  $a_{ph} = a_p - a_d$ .  
7 The absorption coefficient by CDOM and non-pigmented particles ( $a_{dg}$ ) was calculated as  
8 the sum of  $a_d$  and CDOM absorption coefficient ( $a_g$ ). Total absorption coefficient ( $a$ ) was  
9 calculated as  $a = a_w + a_p + a_g$ , where pure water absorption coefficient ( $a_w$ ) was adopted  
10 from Pope and Fry [1997].

11 The absorption coefficient from non-pigmented particles, CDOM, or their sum  
12 ( $a_x$ ) was fitted to an exponential function as:

13

$$14 \quad a_x(\lambda) = a_x(\lambda_0) \exp[-S_x(\lambda - \lambda_0)] \quad (1)$$

15

16 Here,  $S_x$  represents the exponential slope for absorption coefficient from non-pigmented  
17 particles ( $S_d$ ), CDOM ( $S_g$ ), or their sum ( $S_{dg}$ ). We selected the reference wavelength,  $\lambda_0$ ,  
18 equal to 380 nm. In Equation (1), the wavelengths analyzed were 350 to 600 nm for  $a_g(\lambda)$ ,  
19 and 380 to 730 nm for  $a_d(\lambda)$  but excluding 400 to 480 nm and 620 to 710 nm to avoid the  
20 chlorophyll pigment peaks due to methanol's incapability to extract some pigments as  
21 discussed by Jeffrey *et al.* [1997], and 380 to 600 nm (but excluding 400 to 480 nm) for  
22  $a_{dg}(\lambda)$  [Babin *et al.*, 2003b].



1 The phytoplankton absorption coefficient ( $a_{ph}$ ) is typically related to [Chl\_a] as a  
2 power function [Bricaud *et al.*, 1995, 1998; Prieur and Sathyendranath, 1981]:

$$3 \quad a_{ph}(\lambda) = A_0(\lambda)[Chl\_a]^{A_1(\lambda)} \quad (2)$$

4  
5  
6 The modification of Equation (2) provides an expression of  $a_{ph}$  from its value at a  
7 reference wavelength (here 670 nm):

$$8 \quad a_{ph}(\lambda) = B_0(\lambda)[a_{ph}(670)]^{B_1(\lambda)} \quad (3)$$

9  
10  
11  $A_i(\lambda)$  and  $B_i(\lambda)$  are derived coefficients. [Chl\_a] can also be determined from  $a_{ph}(670)$  by  
12 a power function similar to Equation (3).

### 13 14 2.3. Apparent optical properties from *in situ* measurements

15 The remote sensing reflectance ( $R_{rs}$ ) spectra (bands centered at 320, 340, 380,  
16 395, 412, 443, 465, 490, 510, 532, 555, 560, 625, 665, 670, 683, 710, 780, and 860 nm,  
17 and each band is 10 nm wide at full-width half max) were determined with a BioPro in-  
18 water profiling spectroradiometer (Biospherical Instruments, Inc., San Diego, CA), as  
19 described in detail by *Mannino et al.* [2008]. The instrument was deployed multiple times  
20 for each station, and the absolute uncertainty was less than 5%. The  $R_{rs}$  at 551 nm was  
21 calculated from a linear interpolation of values at 532, 555, and 560 nm [*Mannino et al.*,  
22 2008]. The  $R_{rs}$  at 488 nm was assumed to be equivalent to the value at 490 nm.  $R_{rs}$   
23 measured at 6 stations during BIOME1 cruise, 19 stations during BIOME2 cruise, and 3

1 and 6 stations during CBP cruises on 27 May and 3 November 2005 were included for  
2 analysis in this paper.

3

#### 4 2.4. Satellite ocean color validation

5 The method to process satellite images was described in *Mannino et al.* [2008]  
6 following *Bailey and Werdell* [2006] protocols. SeaWiFS and MODIS-Aqua observations  
7 were processed from Level 1 to Level 2 using the SeaWiFS Data Analysis System  
8 software (SeaDAS version 5.1.1 and ms12 version 5.6.3). The pixels were masked after  
9 atmospheric correction by any of the following flags: land, cloud or ice, high top-of-  
10 atmosphere radiance, low normalized water-leaving radiance at 551 or 555 nm, stray  
11 light, sun glint, or atmospheric correction failure) [*Bailey and Werdell*, 2006]. Pixels with  
12  $L_w(412) < 0.2 \text{ mW cm}^{-2} \mu\text{m}^{-1} \text{ sr}^{-1}$  were excluded to minimize the impacts from atmospheric  
13 over-correction in causing negative or significantly reduced water-leaving radiance  
14 [*Siegel et al.*, 2002]. The 3x3 pixel arrays centered on the field stations, each with ~1 km  
15 resolution (sensor native), were analyzed. The satellite observations which occurred  
16 within  $\pm 8$  hours and  $\pm 32$  hours of in situ measurements were considered for match-up  
17 analysis to allow for inclusion of sufficient data points.

18

#### 19 2.5. Analysis and validation methods

20 Three curve-fitting functions, linear function (Model II regression) after log-  
21 transformation (log\_linear\_model; Equation 4), fourth-order polynomial function after  
22 log-transformation similar to OC4V4 [*O'Reilly et al.*, 1998, 2000]  
23 (log\_polynomial\_model; Equation 5), and one-phase exponential decay function

1 (exponential\_model; Equation 6), were developed to correlate  $R_{rs}$  band ratio to the  
 2 relevant absorption products:

3

$$4 \quad \log[a_i(\lambda)] = C_0(\lambda) + C_1(\lambda)R \quad (4)$$

5

$$6 \quad \log[a_i(\lambda)] = D_0(\lambda) + D_1(\lambda)R + D_2(\lambda)R^2 + D_3(\lambda)R^3 + D_4(\lambda)R^4 \quad (5)$$

7

$$8 \quad a_i(\lambda) = G_0(\lambda) + G_1(\lambda) \exp\left[-G_2(\lambda) \frac{R_{rs}(\lambda_1)}{R_{rs}(\lambda_2)}\right] \quad (6)$$

9

10 Here,  $R = \log[R_{rs}(\lambda_1)/R_{rs}(\lambda_2)]$ , and  $\lambda_1$  and  $\lambda_2$  represent the various bands evaluated, and  
 11  $C_i$ ,  $D_i$  and  $G_i$  are wavelength-specific derived coefficients, and  $a_i$  is the analyzed  
 12 absorption coefficient as  $a_{ph}$ ,  $a_d$ ,  $a_g$ , or  $a_{dg}$ . In addition, a one-phase exponential function  
 13 to determine  $R_{rs}$  from  $a_i$  similar to *Mannino et al.* [2008] was also developed, and  $a_i$  was  
 14 then calculated by its reverse function (reverse\_exponential\_model; Equation 7):

15

$$16 \quad \frac{R_{rs}(\lambda_1)}{R_{rs}(\lambda_2)} = H_0(\lambda) + H_1(\lambda) \exp[-H_2(\lambda)a_i(\lambda)] \quad (7)$$

17

18 Four products,  $a_{ph}(670)$ ,  $a_d(380)$ ,  $a_g(380)$ , and  $a_{dg}(380)$ , whose surface measurements  
 19 were represented as the site values, were analyzed with the above equations. The mean  
 20 absolute percent difference (MAPD) and root mean square error (RMSE) between the  
 21 modeled products ( $C_{alg}$ ) and field measurements ( $C_{field}$ ) were calculated.

1

2

$$MAPD = \frac{\sum |C_{alg} - C_{field}|}{N} \times 100\% \quad (8)$$

3

4

$$RMSE = \sqrt{\sum (C_{alg} - C_{field})^2 / N} \quad (9)$$

5

## 6 2.6. Monthly time series analysis

7

Monthly Level 3 mapped MODIS-Aqua images (4 km resolution) from July 2002

8

to December 2006 were downloaded from the NASA ocean color website

9

(<http://oceancolor.gsfc.nasa.gov>) on 8 January 2008. Empirical algorithms developed

10

from this paper were applied to calculate products such as [Chl\_a],  $a_{ph}$ ,  $a_d$ , and  $a_g$ . Three

11

stations—Location A (75.90W, 36.93N), B (75.30W, 36.93N), and C (74.77W, 36.93N)

12

representing a transect from the Chesapeake Bay mouth to an outer shelf location—were

13

selected and plotted to demonstrate a monthly time series.

14

## 15 3. Results and Discussion

16

### 3.1. Absorption spectra

17

We observed seasonal transitions in phytoplankton absorption coefficients in

18

April-May and October-November periods. Therefore, at least two seasonal algorithms

19

(May-October and November-April) are required to describe phytoplankton absorption

20

relationships (Figure 2a and Table 1). In general, the phytoplankton absorption ratio

21

$[a_{ph}(\lambda)/a_{ph}(670)]$  in May-October is higher than that in November-April (Figure 2a). This

22

coincides with historical observations that the dominant phytoplankton taxa are diatoms

1 in winter and spring, but the phytoplankton assemblage transitions to a greater proportion  
 2 of dinoflagellates, cryptophytes, and cyanobacteria in summer and fall [Adolf *et al.*, 2006;  
 3 Marshall and Alden, 1993]. Although phytoplankton absorption coefficients are subject  
 4 to seasonal variation, the relationship between  $a_{ph}(670)$  and [Chl\_a] ( $r^2=0.964$ ,  $N=230$ ;  
 5 Figure 2b) is relatively constant seasonally due to the dominant contribution from Chl\_a  
 6 to  $a_{ph}(670)$  [Jeffrey *et al.*, 1997]:

7

$$8 \quad [Chl\_a] = 70.632 \times [a_{ph}(670)]^{1.184} \quad (10)$$

9

10 Seasonal variability of riverine discharge, along with other factors such as wind forcing  
 11 and direction, may cause the seasonal variability of phytoplankton taxonomic  
 12 composition, pigment package effect, and therefore normalized phytoplankton absorption  
 13 spectra (Figure 2a) [Babin *et al.*, 2003b; Bricaud *et al.*, 1995, 1998; Trees *et al.*, 2000].  
 14 The pigment package effect refers to a consequence of the fact that in the natural waters  
 15 pigment molecules are not uniformly distributed but are contained within discrete  
 16 packages such as chloroplasts, cells, and cell colonies, which causes a flattening of the  
 17 phytoplankton absorption peak due to self-shading wherever pigments are localized  
 18 within cell membranes [Duysens, 1956].

19 Equation (1) described the exponential decay characteristics of  $a_d$ ,  $a_g$ , and  $a_{dg}$   
 20 rather well with coefficients of determination ( $r^2$ ) of  $>0.95$  for  $a_d$ , and  $>0.99$  for  $a_g$  and  $a_{dg}$ .  
 21 The exponential slopes ( $S$ ) covered a wide range with mean  $\pm 1$  standard deviation of  
 22  $0.0122 \pm 0.0023$  ( $N=247$ , ranging from 0.0084 to 0.0260) for  $a_d$ ,  $0.0170 \pm 0.0011$  ( $N=300$ ,  
 23 ranging from 0.0137 to 0.0221) for  $a_g$ , and  $0.0148 \pm 0.0014$  ( $N=222$ , ranging from 0.0122

1 to 0.0205) for  $a_{dg}$ . However, the general exponential decay relationships of  $S$  (ordinate)  
2 versus absorption coefficients (abscissa) for coastal regions that are significantly  
3 impacted by freshwater discharge as suggested by *Carder et al.* [1989] was not apparent  
4 for the SMAB dataset. Part of the reason was that the dataset presented in this paper  
5 (Figure 1) did not extend far into the estuaries to cover the full range of water types from  
6 freshwater to oceanic waters. The observations above suggest that using mean  $S$  values  
7 may cause significant errors in predicting  $a_x$  spectra. Multiple algorithms to retrieve  $a_d$ ,  $a_g$ ,  
8 and  $a_{dg}$  at multiple wavelengths may be required, as discussed in the next section.

9

### 10 3.2. Algorithm development and validation

11 Three  $R_{rs}$  band ratios (412/555, 443/555, and 490/555 for SeaWiFS, and 412/551,  
12 443/551, and 488/551 for MODIS-Aqua) were compared to determine the best algorithm  
13 performance. No matter which of the curve-fitting models from Equations (4)-(7) was  
14 selected, algorithms based on  $R_{rs}$  band ratio at 490/555 or 488/551 performed similar to,  
15 or better than, the other two band ratios. Figure 3 shows examples of model performance  
16 on predicting  $a_{ph}(670)$ ,  $a_d(380)$ ,  $a_g(380)$ , and  $a_{dg}(380)$  from Equations (4)-(7),  
17 respectively. Performance from other models, i.e. Equation (4) on predicting  $a_d(380)$ ,  
18  $a_g(380)$ , and  $a_{dg}(380)$ , showed similar results to Figure 3 (data not shown). Due to the  
19 possibly poor quality of satellite water-leaving radiance at shorter wavelengths (e.g. 412  
20 and 443 nm) in coastal waters [*Bailey and Werdell, 2006; Siegel et al., 2002*], we selected  
21  $R_{rs}$  band ratios at 490/555 or 488/551 for further analysis. Although the selection of only  
22 two bands will cause interdependence of satellite-derived products, it still provides

1 valuable information on bio-optical properties of the SMAB in the absence of appropriate  
2 semi-analytic algorithms based on more bands.

3 The log\_linear\_model (Equation 4) proved suitable to validate satellite-derived  
4  $a_{ph}$ ,  $a_d$ , and  $a_{dg}$  with relatively high  $r^2$  and relatively low MAPD and RMSE (Figures 4-5  
5 and Table 2). The  $r^2$  for the log\_linear\_model ranged from 0.92 to 0.93 for all three  
6 products of  $a_{ph}(670)$ ,  $a_d(380)$ , and  $a_{dg}(380)$ , while 0.84 to 0.95 for the other three models.  
7 The MAPD for the log\_linear\_model was typically similar to, or lower than, the other  
8 three models, regardless of the satellite sensor (SeaWiFS or MODIS-Aqua) and overpass  
9 satellite/in situ time window selected ( $\pm 8$  hours or  $\pm 32$  hours) (Figures 4a-b and 5a-b).  
10 This was also supported by the validation results from the RMSE comparisons (Figures  
11 4c-d and 5c-d). The exponential\_model may provide lower MAPD and RMSE in some  
12 cases (Figures 4-5), but was not selected due to its relatively low  $r^2$  (0.84 to 0.87). In  
13 contrast, the reverse\_exponential\_model yielded the best validation results for  $a_g(380)$   
14 with the highest  $r^2$  (0.90 versus 0.77-0.86) and typically lowest MAPD and RMSE  
15 (Figures 4-5 and Table 4) as compared to the other models. *Mannino et al.* [2008]  
16 showed the same model for  $a_g$  but did not include the CBH stations in their validation  
17 analysis. The selected  $R_{rs}$  band ratio models can also be applied to derive  $a_d$ ,  $a_g$ , and  $a_{dg}$  at  
18 multiple wavelengths (Tables 2-3). Except for the higher MAPD for  $a_d$  (34.8-57.5% for  
19 SeaWiFS and 41.9-65.3% for MODIS-Aqua), the selected regression methods typically  
20 limited MAPD for  $a_g$  and  $a_{dg}$  to within 30% for wavelengths between 350 and 555 nm  
21 (Table 4). The exponential decay slopes ( $S$ ) for  $a_d$ ,  $a_g$ , and  $a_{dg}$  can be derived from non-  
22 linear regression methods with  $R_{rs}$  band ratio models at multiple wavelengths (e.g. 355,  
23 380, 400, 412, 443, 490, 510, 531, and 555), and agree reasonably well with field

1 derivations (Table 4). The GSM01 [Garver and Siegel, 1997; Maritorena et al., 2002]  
2 and its regional version (GSM01-CB) [Magnuson et al., 2004] resulted in relatively high  
3 MAPD and RMSE when compared with the field measurements (Figures 4-5). The  
4 GSM01 model was developed for global ocean application, and thus is not optimized for  
5 the variability of in-water constituents observed in near-shore coastal regions, such as  
6 variable or region-specific  $S$  values. However, even the optimized GSM01 model for this  
7 coastal region (GSM01-CB; primarily Chesapeake Bay and near-shore coastal ocean)  
8 developed by Magnuson et al. [2004] did not perform significantly better than GSM01,  
9 e.g. MAPD=42.6% and 46.0% for  $a_{ph}(670)$  and  $a_{dg}(380)$  from GSM01-CB, versus 43.3%  
10 and 40.7% from GSM01 for SeaWiFS  $\pm 8$  hour overpass window (Figures 4-5). The lack  
11 of adequate knowledge of backscattering coefficients, as well as the higher uncertainty of  
12  $R_{rs}$  at shorter wavelengths (e.g. 412 and 443 nm) from satellite measurements, may  
13 account for the performance of GSM01 and GSM01-CB for this region [Bailey and  
14 Werdell, 2006; IOCCG, 2000; Magnuson et al., 2004; Siegel et al., 2000, 2005].

15 By applying the regression results shown in Table 1, phytoplankton absorption  
16 coefficients at other visible wavelengths can also be derived from  $a_{ph}(670)$ , which can be  
17 derived from satellite radiance observations as shown in Table 2. The validation match-  
18 ups based on this approach yielded similar MAPD accuracy levels for  $a_{ph}(\lambda)$  at 412, 443,  
19 488, 490, 510, 667, and 678 nm to  $a_{ph}(670)$  (21.5-26.1% versus 25.7% for SeaWiFS and  
20 19.0-28.1% versus 21.2% for MODIS-Aqua), but relatively higher MAPD at 531, 551,  
21 and 555 nm (27.2-30.9% for SeaWiFS and 33.1-43.1% for MODIS-Aqua) due to the  
22 relatively higher measurement errors from weaker absorption at these wavelengths (Table  
23 4). If we exclude those stations with extremely low  $a_{ph}$  (e.g.  $<0.003 \text{ m}^{-1}$  at 555 nm), the



1 MAPD for  $a_{ph}(\lambda)$  was at the same accuracy level for all visible wavelengths evaluated.  
2 The satellite derivation of [Chl\_a] from Equation (10) had slightly lower but still  
3 reasonable accuracy level compared to that for  $a_{ph}(670)$  with MAPD of  $32.3 \pm 28.2\%$   
4 (N=29) for SeaWiFS and  $28.8 \pm 20.6\%$  (N=14) for MODIS-Aqua (Table 4).

5 The validation match-ups between field measurements of absorption constituents  
6 and satellite derivations within  $\pm 8$  hours demonstrated reasonable agreement (Figures 6-  
7 7). The SeaWiFS and MODIS-Aqua match-ups have similar  $r^2$  varying from 0.80-0.97,  
8 and show slope values from 0.52 to 0.73 and from 0.46 to 0.80, respectively. Including  
9 the stations applied to develop the algorithms, which increases dataset size by 10-12  
10 points for SeaWiFS and 5-6 points for MODIS-Aqua, yielded improvements in all the  
11 slopes (e.g. 0.73-0.87 for SeaWiFS and 0.57-0.64 for MODIS-Aqua). When extending  
12 the match-up dataset from  $\pm 8$  hours to  $\pm 32$  hours of the satellite overpass window, similar  
13 improvements were also found due to significant increase of dataset size by 50% to 140%  
14 (data not shown). The validation match-ups between field measurements of [Chl\_a] and  
15 satellite derivations after log-transformation agreed well with  $r^2=0.86$  to 0.95, slope=0.87  
16 to 0.96, and RMSE=0.20 to 0.24 (Figure 7). Similar statistical results were found for  
17  $a_{ph}(670)$  when including those stations used to develop the algorithms (data not shown).  
18 It implies that these empirical algorithms are relatively successful and should improve as  
19 the size of the dataset increases.

20 Above all, the satellite-derived absorption coefficients from selected functions  
21 (log\_linear\_model for  $a_{ph}$ ,  $a_d$ , and  $a_{dg}$ , and reverse\_exponential\_model for  $a_g$ ) yielded  
22 relatively good results for the SMAB. Since the dataset used for algorithm development  
23 did not include stations from the CBH cruises (because AOP data was not collected at

1 those stations), the validation analyses should improve after excluding those CBH  
2 stations. For example, MAPD improved from 25.7% to 21.9% for  $a_{ph}(670)$ , from 35.3%  
3 to 29.5% for  $a_d(380)$ , from 25.2% to 20.9% for  $a_g(380)$ , from 26.5% to 23.8% for  
4  $a_{dg}(380)$ , and from 32.3% to 24.2% for [Chl\_a] for SeaWiFS  $\pm 8$  hours overpass time  
5 window. Therefore, in the future the addition of complete datasets from the lower bay  
6 locations will expand the dynamic range of the algorithms and may significantly improve  
7 the model capability in more turbid areas of the SMAB.

8

### 9 3.3. Seasonal variability

10 These empirical algorithms can be applied to study the spatial and seasonal  
11 variability of coastal ocean constituents. Figure 8 shows typical examples of the spatial  
12 distribution of the absorption coefficients within the SMAB during four seasons: summer  
13 (June-August), fall (September-November), winter (December-February), and spring  
14 (March-May). The satellite images clearly show the gradients from high to low  
15 constituent concentration between the coast and the open ocean as well as the  
16 riverine/estuarine outflow impact along the coast (Figure 8). The seasonal variability of  
17 phytoplankton absorption [e.g.  $a_{ph}(443)$ ] may be due primarily to the river discharge rate  
18 from the bay mouths [Acker *et al.*, 2005; Adolf *et al.*, 2006; Marshall and Alden, 1993;  
19 Marshall *et al.*, 2006]. The monthly mean flow rates out of the Chesapeake Bay for these  
20 selected images were 510, 1648, 2983, and 1463  $\text{m}^3 \text{s}^{-1}$  for August 2005, November 2005,  
21 February 2006, and May 2006, respectively (Data sources:  
22 <http://waterdata.usgs.gov/nwis/>; written communication from Gary Fisher, U.S.  
23 Geological Survey, 17 July 2007). Consequently, lower phytoplankton abundance

1 occurred during the dry season in summer 2005 compared to the other three seasons. The  
2 seasonal variability of detritus absorption [e.g.  $a_d(443)$ ] is complex. At least two primary  
3 sources of detritus from riverine/estuarine outflow and sedimentary resuspension  
4 controlled  $a_d$  in the SMAB. The significant contribution from storm-driven sedimentary  
5 resuspension in autumn may explain the higher detritus content in November 2005. The  
6 seasonal variability of CDOM absorption [e.g.  $a_g(443)$ ] may be controlled primarily by  
7 the degree of riverine inputs of degraded terrestrial vegetation to the SMAB [*Del Vecchio*  
8 *and Blough, 2004; Mannino et al., 2008*].

9 CDOM plays a critical role in contributing to sunlight absorption and thus impacts  
10 primary production in the SMAB by reducing the amount of photosynthetically active  
11 radiation (PAR) available for phytoplankton growth [*Arrigo and Brown, 1996*]. At 443  
12 nm, CDOM accounted for 35-70% of total light absorption excluding water absorption  
13 ( $a_{pg}$ ), as compared to 0-20% for non-pigmented particles, and 30-45% for phytoplankton  
14 (Figures 9-10). Pure seawater absorption [ $a_w(443) \approx 0.007 \text{ m}^{-1}$ ; *Pope and Fry, 1997*]  
15 typically accounts for a negligible fraction ( $\sim 3.0\%$ ) of  $a(443)$  in the SMAB. The  
16 relatively low contribution of detritus absorption within coastal ocean regions was also  
17 reported by *Siegel et al. [2002]* and may explain the performance of the satellite-derived  
18  $a_d(\lambda)$  in the validation analysis (Table 4, and Figures 4-6). The satellite-derived  $a_d(\lambda)$   
19 underestimates  $a_d(\lambda)$  with respect to field samples collected in the near-shore ocean  
20 region ( $< 20 \text{ m}$  bottom depth) and overestimates  $a_d(\lambda)$  in water with very low  $a_d(\lambda)$   
21 (Figures 6, 8, and 10). The gradients of high to low percentages of  $a_{ph}$  and  $a_d$ , and low to  
22 high percentage of  $a_g$  from the coast to the open ocean were consistent with field  
23 measurements (Figure 10). During the dry season (e.g. August 2005), CDOM accounts

1 for a higher percentage of total absorption than during the wet season (e.g. February 2006)  
2 (Figure 9). Such a phenomenon may be explained by the impact of river discharge in  
3 contributing nutrients to support phytoplankton growth as well as the export of terrestrial  
4 CDOM. During the wet season, CDOM and phytoplankton abundance are both elevated,  
5 but phytoplankton blooms increase the relative percentage of phytoplankton absorption  
6 compared to CDOM absorption. During the dry season, CDOM and phytoplankton are  
7 both low, but the reported higher primary productivity and mature grazer community may  
8 result in a higher percentage of phytoplankton to be grazed and degraded which in turn  
9 reduces the relative percentage of phytoplankton absorption [*Adolf et al.*, 2006; *Marshall*  
10 *and Nesius*, 1996; *Marshall et al.*, 2006] and increase CDOM through grazer and  
11 microbial processing of organic matter [*Nelson et al.*, 2004; *Steinberg et al.*, 2004]. Since  
12 phytoplankton pigments have a much weaker relationship with CDOM absorption than  
13 with phytoplankton absorption, the significant contribution of CDOM absorption may  
14 pose complications for applying global operational algorithms (e.g. OC4V4 and OC3M)  
15 [*O'Reilly et al.*, 1998, 2000] to coastal regions. For CDOM-rich Case 2 waters such as  
16 the Chesapeake Bay, OC4V4 has been found to significantly overestimate [Chl\_a],  
17 especially for offshore regions of the SMAB [*Harding et al.*, 2005; *Magnuson et al.*,  
18 2004]. Our results also support this conclusion. For example, match-ups within  $\pm 8$  hours  
19 showed that OC4V4 performed better for the lower CB region (e.g. CBH stations) with  
20 MAPD of 33.8% as compared to 79.6% for whole SMAB region (data not shown). It  
21 implies that the relative difference between our approach and operational algorithms  
22 would be relatively small in near-shore regions but high in offshore regions. The spatial  
23 distribution and the seasonal variability of [Chl\_a] based on our approach displayed

1 similar trends as those from OC4V4 and OC3M algorithms, but significantly reduced the  
2 overestimation by operational Chl\_a algorithms in the offshore region of the SMAB  
3 (Figure 11). In general, the ratios of [Chl\_a] based on operational Chl\_a algorithms to our  
4 approach increase with the increase of CDOM contribution to light absorption (Figures 9  
5 and 11). OC4V4 and OC3M [Chl\_a] were higher by 0-0.5 times for the inner-shelf  
6 region, 0.4-1.2 times for the middle shelf region, and 1-2 times for the outer shelf region  
7 (Figure 11). This higher ratio trend toward offshore demonstrates the impact of CDOM  
8 on ocean color products in the SMAB.

9         The satellite derivations of absorption coefficients provide tools to study  
10 biogeochemical processes and radiative transfer. For examples, DOC and salinity can be  
11 strongly correlated to CDOM absorption [*Del Vecchio and Blough, 2004; Mannino et al.,*  
12 *2008; Rochelle-Newall and Fisher, 2002*], and primary productivity is correlated to  
13 phytoplankton absorption [*Behrenfeld et al., 2005; Marra et al., 2007*]. The knowledge of  
14 absorption also provides methods to study other IOPs from space. For example, the  
15 expression of  $R_{rs}$  from absorption and backscattering [*Garver and Siegel, 1997; Gordon*  
16 *et al., 1988; Maritorena et al., 2002*] and the empirical expression of absorption from  $R_{rs}$   
17 ratio make it possible to express backscattering into  $R_{rs}$ . The knowledge of backscattering  
18 might significantly improve the capability of semi-analytical models in deriving ocean  
19 color products from space [*Magnuson et al., 2004*].

20         Although we have shown the significant impact of river discharge on  
21 biogeochemical constituents in the SMAB, the direct link between them should be  
22 interpreted with caution. First, the impact of river discharge on the coastal region of  
23 Chesapeake Bay is different from Delaware Bay. The lower Chesapeake Bay is subject to

1 nutrient limitation for phytoplankton growth, in contrast to light availability in the  
2 Delaware Bay [Harding *et al.*, 1986; Marshall and Alden, 1993]. Therefore, an increase  
3 in river discharge is more likely to cause a phytoplankton bloom in the lower Chesapeake  
4 Bay by driving more nutrients downstream, while an increase in turbidity from higher  
5 river discharge may decrease primary production in the lower Delaware Bay. Second, the  
6 impact of river discharge is subject to seasonal variability and distance from the bay  
7 mouths, as shown in the following for the coastal region of Chesapeake Bay. In the inner-  
8 shelf region, the correlation coefficients ( $r$ ) between river discharge rate and  
9 biogeochemical products are low (e.g.  $r=0.05-0.12$  for [Chl\_a] and  $-0.01-0.14$  for  $a_g$ ) for  
10 all seasons except for summer (Figure 12). The poor correlation may be due to averaging  
11 out the higher frequency responses (less than one week) for the export of nutrients and  
12 CDOM, respectively, from the bays. During summer, the vertical stratification is well  
13 developed [Verity *et al.*, 2002], and the strength of river discharge represents the flux of  
14 nutrients for phytoplankton growth. Thus, the correlation between biogeochemical  
15 products and river discharge improves for summer (e.g.  $r=0.48$  for [Chl\_a] and  $a_g$ )  
16 (Figure 12). In the middle shelf region, however, river discharge is significantly  
17 correlated to biogeochemical products in winter but poorly correlated during other  
18 seasons (e.g.  $r=0.79$  for [Chl\_a] and  $a_g$  in winter and  $r=0.09-0.36$  in other seasons)  
19 (Figure 12). During winter, low water temperature and a less mature grazer community  
20 may cause the phytoplankton biomass to be linked directly to nutrient availability, which  
21 is driven primarily by river discharge and by wind-induced vertical mixing of nutrients  
22 from depth [Adolf *et al.*, 2006; Marshall and Alden, 1993]. As the zooplankton and  
23 bacterial communities develop into spring and summer, lower phytoplankton biomass

1 and higher primary productivity are expected [Adolf *et al.*, 2006] and the direct response  
2 of the biological system to river discharge dissipates. The outer shelf region shows a  
3 similar pattern but a lower correlation coefficient (e.g.  $r=0.49$  for [Chl\_a] and  $a_g$  in  
4 winter, and  $-0.13$ - $0.31$  in other seasons) with river discharge than the middle shelf region  
5 (data not shown).

6 Other physical factors than river discharge, such as water temperature and wind  
7 forcing, anthropogenic activities, and even climate change, can also impact  
8 phytoplankton abundance, productivity, and carbon distributions in the SMAB. For  
9 example, the direction and distribution of the Chesapeake Bay plume is highly dependent  
10 on the wind stress direction. During winter and early spring northerly winds  
11 (downwelling favorable) and the along-shore southward current force the Chesapeake  
12 Bay [Rennie *et al.*, 1999; Verity *et al.*, 2002] and Delaware Bay [Sanders and Garvine,  
13 2001] plumes to flow southward along the coast. As winds reverse later in spring the  
14 southerly along-shore flow weakens, and the Chesapeake Bay plume broadens and flows  
15 offshore, primarily to the south and east. Upwelling-favorable conditions can initiate  
16 local phytoplankton blooms and contribute additional particles to surface waters [Johnson  
17 *et al.*, 2001]. The Chesapeake Bay estuarine ecosystem has experienced a large increase  
18 in anthropogenic nutrient loading and reductions in the past half century which have  
19 affected the floral composition and biomass [Harding, 1994; Paerl *et al.*, 2006].  
20 Furthermore, climate forcing (e.g. hurricanes, drought, etc.) significantly influences  
21 phytoplankton dynamics (e.g. by reducing vertical stratification, increasing sedimentary  
22 resuspension, and redistributing particles from hurricane forcing) [Miller and Harding,  
23 2005; Paerl *et al.*, 2006].

1 Above all, the impacts from physical factors (e.g. river discharge, wind forcing,  
2 and bathymetry) on bio-optical constituents (e.g. [Chl\_a] and  $a_g$ ) are complicated and  
3 cannot be explained by a single factor [Harding, 1994]. Nevertheless, we found that the  
4 variability of an optical property, the diffuse attenuation coefficient at 490 nm (K490),  
5 represents the variability of multiple bio-optical constituents. In the Chesapeake Bay  
6 inner-shelf site, the correlation coefficient ( $r$ ) of [Chl\_a],  $a_{ph}$ ,  $a_d$ ,  $a_g$ , and  $a_{dg}$  to K490 was  
7 0.66-0.74, while 0.94-0.99 in the middle shelf location, and 0.93-0.98 in the outer shelf  
8 locations. These results also imply that absorption is the dominant contributor to the  
9 diffuse attenuation coefficient at offshore locations but scattering contributes  
10 significantly at near-shore locations.

11

#### 12 4. Conclusions

13 Several important conclusions can be made from the present analyses of  
14 absorption coefficients and [Chl\_a] derived from ocean color remote sensing. The  
15 empirical algorithms demonstrate successful retrieval of absorption coefficients and  
16 [Chl\_a] within a reasonable uncertainty (e.g.  $\pm 35\%$ ), and demonstrate significant  
17 improvements from the standard semi-analytic model (e.g. GSM01 and GSM01-CB) and  
18 operational algorithms (e.g. OC4V4 and OC3M). Field observations and satellite  
19 derivations both demonstrate that CDOM is the major contributor to water-column light  
20 absorption at shorter wavelengths (e.g.  $< 500$  nm), especially during the dry seasons and  
21 on the outer shelf where it can account for 35-70% of absorption by particles plus CDOM  
22 at 443 nm. River discharge plays a principal role in controlling the distribution of  
23 biogeochemical constituents, but is subject to seasonal and regional variability.



1 Acknowledgements

2 This research was supported by an appointment to the NASA Postdoctoral Program at the  
3 Goddard Space Flight Center, administered by Oak Ridge Associated Universities  
4 through a contract with NASA. This work was funded with support from the NASA New  
5 Investigator Program, Interdisciplinary Science, and Earth Observing System programs  
6 and by NOAA through a grant in support of the Coastal Observatories program  
7 (NA03NOS4730220). We thank the captains and crews of R/V *Cape Henlopen*, *Hugh R.*  
8 *Sharp*, and *Fay Slover*. H. Throckmorton, P. Bernhardt, K. C. Filippino, C. Makinen, and  
9 M. Linksweiler provided assistance in collecting particulate samples. We are grateful to  
10 J. Morrow, J. Brown, D. D'Alimonte, and J.-N. Druon for deploying the profiling  
11 radiometer, and L. Van Heukelem and C. Thomas for analyzing HPLC pigments, and the  
12 Ocean Biology Processing Group at GSFC. J. O'Reilly kindly provided the high-  
13 resolution bathymetry data.

1 References

- 2 Acker, J.G., L.W. Harding, G. Leptoukh, T. Zhu, and S. Shen (2005), Remotely-sensed  
3 chl *a* at the Chesapeake Bay mouth is correlated with annual freshwater flow to  
4 the Chesapeake Bay, *Geophys. Res. Lett.*, 32(L05061), doi: 10.1029/2004GL  
5 021852.
- 6 Adolf, J.E., C.L. Yeager, W.D. Miller, M.E. Mallonee, and L.W. Harding (2006),  
7 Environmental forcing of phytoplankton floral composition, biomass, and primary  
8 productivity in Chesapeake Bay, USA, *Estuar. Coast. Shelf Sci.*, 67, 108-122.
- 9 Arrigo, K.R. and C.W. Brown (1996), Impact of chromophoric dissolved organic matter  
10 on UV inhibition of primary productivity in the sea, *Mar Ecol Prog Ser.*, 140,  
11 207-216.
- 12 Austin, J. (2002), Estimating the mean ocean-bay exchange rate of the Chesapeake Bay, *J.*  
13 *Geophys. Res.*, 107(C11), 3192, doi: 10.1029/2001JC001246.
- 14 Babin, M., A. Morel, V. Fournier-Sicre, F. Fell, and D. Stramski (2003a), Light scattering  
15 properties of marine particles in coastal and open ocean waters as related to the  
16 particle mass concentration, *Limnol. Oceanogr.*, 48(2), 843-859.
- 17 Babin, M., D. Stramski, G.M. Ferrari, H. Claustre, A. Bricaud, G. Obolensky, and N.  
18 Hoepffner (2003b), Variations in the light absorption coefficients of  
19 phytoplankton, nonalgal particles, and dissolved organic matter in coastal waters  
20 around Europe, *J. Geophys. Res.*, 108(C7), 3211, doi: 10.1029/2001JC000882.
- 21 Bailey, S.W., and P.J. Werdell (2006), A multi-sensor approach for the on-orbit  
22 validation of ocean color satellite data products, *Remote Sens. Environ.*, 102, 12-  
23 23.

1 Behrenfeld, M.J., E. Boss, D.A. Siegel, and D.M. Shea (2005), Carbon-based ocean  
2 productivity and phytoplankton physiology from space, *Global Biogeochem.*  
3 *Cycles*, 19(GB1006), doi:10.1029/2004GB002299

4 Bricaud, A., M. Babin, A. Morel, and H. Claustre (1995), Variability in the chlorophyll-  
5 specific absorption coefficients in natural phytoplankton: analysis and  
6 parameterization, *J. Geophys. Res.*, 100(C7), 13321-13332.

7 Bricaud, A., A. Morel, M. Babin, K. Allali, and H. Claustre (1998), Variations of light  
8 absorption by suspended particles with chlorophyll a concentration in oceanic  
9 (case 1) waters: analysis and implications for bio-optical models, *J. Geophys. Res.*,  
10 103(C13), 31033-31044.

11 Carder, K.L., R.G. Steward, G.R. Harvey, and P.B. Ortner (1989), Marine humic and  
12 fulvic acids: Their effect on remote sensing of ocean chlorophyll, *Limnol.*  
13 *Oceanogr.*, 34(1), 68-81.

14 Del Vecchio, R., and N.V. Blough (2004), Spatial and seasonal distribution of  
15 chromophoric dissolved organic matter (CDOM) and dissolved organic carbon  
16 (DOC) in the Middle Atlantic Bight, *Mar. Chem.*, 89, 169-187.

17 Duysens, L.N.M. (1956), The flattening of the absorption spectrum of suspensions as  
18 compared to that of solutions, *Biochim. Biophys. Acta*, 19, 1-12.

19 Ferrari, G.M., F.G. Bo, and M. Babin (2003), Geo-chemical and optical characterizations  
20 of suspended matter in European coastal waters, *Estuar. Coast. Shelf Sci.*, 57, 17-  
21 24.

- 1 Garver, S.A., and D.A. Siegel (1997), Inherent optical property inversion of ocean color  
2 spectra and its biogeochemical interpretation: 1. Time series from the Sargasso  
3 Sea, *J. Geophys. Res.*, 102(C8), 18607-18625.
- 4 Gordon, H.R., and A. Morel (1983), *Remote assessment of ocean color for interpretation*  
5 *of satellite visible imagery*, 114 pp., Springer-Verlag, New York.
- 6 Gordon, H.R., O.B. Brown, R.H. Evans, J.W. Brown, R.C. Smith, K.S. Baker, and D. K.  
7 Clark (1988), A semianalytic radiance model of ocean color, *J. Geophys. Res.*,  
8 93(D9), 10909-10924.
- 9 Harding, L.W. (1994), Long-term trends in the distribution of phytoplankton in  
10 Chesapeake Bay: roles of light, nutrients, and streamflow, *Mar. Ecol. Prog. Ser.*,  
11 104, 267-291.
- 12 Harding, L., B. Messon, and T. Fisher (1986), Phytoplankton production in two east coast  
13 estuaries: photosynthesis-light functions and patterns of carbon assimilation in  
14 Chesapeake and Delaware Bays, *Estuar. Coast. Shelf Sci.*, 23, 773-806.
- 15 Harding, L.W., A. Magnuson, M.E. Mallonee (2005), SeaWiFS retrievals of chlorophyll  
16 in Chesapeake Bay and the mid-Atlantic bight, *Estuar. Coast. Shelf Sci.*, 62, 75-  
17 94.
- 18 IOCCG (1999), Status and plans for satellite ocean-colour missions: considerations for  
19 complementary missions, in *Reports of the International Ocean-Color*  
20 *Coordinating Group*, no. 2, edited by J. Yoder, pp. 43, Dartmouth, Nova Scotia.
- 21 IOCCG (2000), Remote sensing of ocean color in coastal, and optically-complex waters,  
22 in *Reports of the International Ocean-Color Coordinating Group*, no. 3, edited by  
23 S. Sathyendranath, pp. 140, Dartmouth, Nova Scotia.

1 IOCCG (2006), Remote sensing of inherent optical properties: Fundamentals, tests of  
2 algorithms and applicaitons, in *Reports of the International Ocean-Color*  
3 *Coordinating Group*, no. 5, edited by Z. Lee, pp. 126, Dartmouth, Nova Scotia.

4 Jeffrey, S.W., R.F.C. Mantoura, and S.W. Wright (1997), *Phytoplankton pigments in*  
5 *oceanography*, UNESCO Publishing.

6 Johnson, D.R., A. Weidemann, R. Arnone, and C.O. Davis (2001), Chesapeake Bay  
7 outflow plume and coastal upwelling events: physical and optical properties, *J.*  
8 *Geophys. Res.*, 106(C6), 11613-11622.

9 Kirk, J.T.O. (1994), *Light and phytosynthesis in aquatic ecosystems*, 2<sup>nd</sup> ed., Cambridge  
10 University Press, New York.

11 Kishino, M., N. Takahashi, N. Okami, and S. Ichimura (1985), Estimation of the spectral  
12 absorption coefficient of phytoplankton in the sea, *Bull. Mar. Sci.*, 37, 634-642.

13 Magnuson, A., L.W. Harding, M.E. Mallonee, and J.E. Adolf (2004), Bio-optical model  
14 for Chesapeake Bay and Middle Atlantic Bight, *Estuar. Coast. Shelf Sci.*, 61, 403-  
15 424.

16 Mannino, A., M.E. Russ, and S.B. Hooker (2008), Algorithm development and validation  
17 for satellite-derived distributions of DOC and CDOM in the U.S. Middle Atlantic  
18 Bight, *J. Geophys. Res.*, doi: 10.1029/2007JC004493, in press.

19 Maritorena, S., D.A. Siegel, and A.R. Peterson (2002), Optimization of a semianalytical  
20 ocean color model for global-scale applications, *Appl. Opt.*, 41, 2705-2714.

21 Marra J., C.C. Trees, and J.E. O'Reilly (2007), Phytoplankton pigment absorption: A  
22 strong predictor of primary productivity in the surface ocean, *Deep Sea Res., Part*  
23 *I*, 54, 155-163.

- 1 Marshall, H.G., and R.W. Alden (1993), A comparison of phytoplankton assemblages in  
2 the Chesapeake and Delaware estuaries (USA), with emphasis on diatoms,  
3 *Hydrobiologia*, 269/270, 251-261.
- 4 Marshall, H.G., and K.K. Nesius (1996), Phytoplankton composition in relation to  
5 primary production in Chesapeake Bay, *Mar. Bio.*, 125, 611-617.
- 6 Marshall, H.G., R.V. Lacouture, C. Buchanan, and J.M. Johnson (2006), Phytoplankton  
7 assemblages associated with water quality and salinity regions in Chesapeake  
8 Bay, USA, *Estuar. Coast. Shelf Sci.*, 69, 10-18.
- 9 McClain, C.R., G.C. Feldman, and S.B. Hooker (2004), An overview of the SeaWiFS  
10 project and strategies for producing a climate research quality global ocean bio-  
11 optical time series, *Deep Sea Res., Part II*, 51, 5-42.
- 12 Miller, W.D., and L.W. Harding (2007), Climate forcing of the spring bloom in  
13 Chesapeake Bay, *Mar. Ecol. Prog. Ser.*, 331, 11-22.
- 14 Mitchell, B.G. (1990), Algorithms for determining the absorption coefficient of aquatic  
15 particulates using the quantitative filter technique (QFT), *Ocean Optics X*, 137-  
16 148.
- 17 Mitchell, B.G., M. Kahru, J. Wieland, and M. Stramska (2002), Determination of spectral  
18 absorption coefficients of particles, dissolved material and phytoplankton for  
19 discrete water samples, in *Ocean optics protocols for satellite ocean color sensor*  
20 *validation, Revision 3*, Vol. 2, edited by J.L. Mueller and G.S. Fargion, pp. 231-  
21 257, NASA Goddard Space Flight Center, Greenbelt, Maryland.
- 22 Mobley, C. (1994), *Light and Water: Radiative Transfer in Natural Waters*, 592 pp.,  
23 Academic Press, San Diego, California.

1 Mueller, J.L. (2000), SeaWiFS algorithm for the diffuse attenuation coefficient, K(490),  
2 using water-leaving radiances at 490 and 555 nm, in O'Reilly, J.E. and co-authors:  
3 *SeaWiFS Postlaunch Calibration and Validation Analyses*, Part 3, edited by S.B.  
4 Hooker and E.R. Firestone, NASA/TM-2000-206892, Vol. 11, NASA Goddard  
5 Space Flight Center, Greenbelt, Maryland, 24-27.

6 Nelson, N.B., C.A. Carlson, and D.K. Steinberg (2004), Production of chromophoric  
7 dissolved organic matter by Sargasso Sea microbes, *Mar. Chem.*, 89, 273-289.

8 O'Reilly, J.E., and C. Zetlin (1998), Seasonal, horizontal, and vertical distribution of  
9 phytoplankton chlorophyll a in the northeast U.S. continental shelf ecosystem,  
10 *NOAA Technical Report NMFS 139*, 120 pp., U.S. Department of Commerce,  
11 Seattle, Washington.

12 O'Reilly, J.E., S. Maritorea, B.G. Mitchell, D.A. Siegel, K.L. Carder, S.A. Garver, M.  
13 Kahru, and C. McClain (1998), Ocean color algorithms for SeaWiFS. *J. Geophys.*  
14 *Res.*, 103, 24937-24953.

15 O'Reilly, J.E., et al. (2000), SeaWiFS Postlaunch Calibration and Validation Analyses,  
16 Part 3, in Hooker, S.B., Firestone, E.R. (Eds.), *SeaWiFS Post-launch Technical*  
17 *Report Series*. NASA Tech. Memo. 2000-206892, vol. 11, NASA Goddard Space  
18 Flight Center, Greenbelt, Maryland.

19 Paerl, H.W., L.M. Valdes, B.L. Peierls, J.E. Adolf, and L.W. Harding (2006),  
20 Anthropogenic and climatic influences on the eutrophication of large estuarine  
21 ecosystems, *Limnol. Oceanogr.*, 51(1, part 2), 448-462.

22 Pope, R.M., and E.S. Fry (1997), Absorption spectrum (380-700nm) of pure water, II,  
23 Integrating cavity measurements, *Appl. Opt.*, 36, 8710-8723.

1 Prieur, L., and S. Sathyendranath (1981), An optical classification of coastal and oceanic  
2 waters based on the specific spectral absorption curves of phytoplankton  
3 pigments, dissolved organic-matter, and other particulate materials, *Limnol.*  
4 *Oceanogr.*, 26, 671-689.

5 Rennie, S.E., J.L. Largier, and S.J. Lentz (1999), Observation of a pulsed buoyancy  
6 current downstream of Chesapeake Bay, *J. Geophys. Res.*, 104(C8), 18227-18240.

7 Rochelle-Newall, E.J., and T.R. Fisher (2002), Production of chromophoric dissolved  
8 organic matter fluorescence in marine and estuarine environments: an  
9 investigation into the role of phytoplankton, *Mar. Chem.*, 77, 7-21.

10 Sanders, T.M., and R.W. Garvine (2001), Fresh water delivery to the continental shelf  
11 and subsequent mixing: An observational study, *J. Geophys. Res.*, 106(C11),  
12 27087-27101.

13 Siegel, D.A., M. Wang, S. Maritorena, and W.D. Robinson (2000), Atmospheric  
14 correction of satellite ocean-color imagery: the black pixel assumption, *Appl. Opt.*,  
15 39, 3582-3591.

16 Siegel, D.A., S. Maritorena, N.B. Nelson, D.A. Hansell, and M. Lorenzi-Kayser (2002),  
17 Global distribution and dynamics of colored dissolved and detrital organic  
18 materials, *J. Geophys. Res.* 107(C12), 3228, doi:10.1029/2001JC000965.

19 Siegel, D.A., S. Maritorena., N.B. Nelson, and M.J. Behrenfeld (2005), Independence and  
20 interdependencies among global ocean color properties: Reassessing the bio-  
21 optical assumption, *J. Geophys. Res.*, 110(C07011), doi:10.1029/2004JC002527.

22 Signorini, S.R., C.R. McClain, A. Mannino, and S. Bailey (2005), *Report on ocean color*  
23 *and carbon study for the south Atlantic Bight and Chesapeake Bay regions,*



1           NASA/TM-2005-212787, NASA Goddard Space Flight Center, Greenbelt,  
2           Maryland.

3   Steinberg, D.K., N.B. Nelson, C.A. Carlson, and A.C. Prusak (2004), Production of  
4           chromophoric dissolved organic matter (CDOM) in the open ocean by  
5           zooplankton and the colonial cyanobacterium *Trichodesmium* spp., *Mar. Ecol.*  
6           *Prog. Ser.*, 267, 45-56.

7   Trees, C.C., D.K. Clark, R.R. Bidigare, M.E. Ondrusek, and J.L. Mueller (2000),  
8           Accessory pigments versus chlorophyll a concentration with the euphotic zone: A  
9           ubiquitous relationship, *Limnol. Oceanogr.* 45(5), 1190-1143.

10   Van Heukelem, L., and C.S. Thomas (2001), Computer-assisted high-performance liquid  
11           chromatography method development with applications to the isolation and  
12           analysis of phytoplankton pigments, *J. Chrom. A*, 910, 31-49.

13   Verity, P.G., J.E. Bauer, C.N. Flagg, D.J. DeMaster, and D. J. Repeta (2002), The Ocean  
14           Margins Program: an interdisciplinary study of carbon sources, transformations,  
15           and sinks in a temperate continental margin system, *Deep Sea Res., Part II*, 49,  
16           4273-4295.

1 Figure captions

2

3 Figure 1. Map of the study area within the southern Middle Atlantic Bight (SMAB).

4 Symbols representing the sampling stations from the following cruises are:  $\triangle$  – BIOME1

5 (30 March to 1 April 2005),  $\nabla$  – BIOME2 (26 to 30 July 2005),  $\circ$  – BIOME3 (5 to 9

6 May 2006),  $\times$  – BIOME4 (2 to 6 July 2006),  $\square$  – CBP (four daily cruises), and  $\blacksquare$  –

7 CBH (ten daily cruises).

8

9 Figure 2. Log-transformed linear regression of phytoplankton absorption coefficient at

10 670 nm [ $a_{ph}(670)$ ] to a)  $a_{ph}(443)$ , and b) chlorophyll *a* concentration [Chl *a*]. The solid

11 and dashed lines in the upper figure represent the regression for summer-fall season (May

12 to October) and winter-spring season (November to April), respectively.

13

14 Figure 3. Absorption algorithms derived from field observations of remote sensing

15 reflectance ( $R_{rs}$ ) from a) log\_linear\_model for  $a_{ph}(670)$ :  $\log[a_{ph}(\lambda)] = C_0(\lambda) + C_1(\lambda)R$ ,

16 where  $R = \log[R_{rs}(\lambda_1)/R_{rs}(\lambda_2)]$ ; and b) log\_polynomial\_model for non-pigmented

17 particulate absorption coefficient at 380 nm [ $a_d(380)$ ]:

18  $\log[a_d(\lambda)] = D_0(\lambda) + D_1(\lambda)R + D_2(\lambda)R^2 + D_3(\lambda)R^3 + D_4(\lambda)R^4$ ; and c)

19 exponential\_model for CDOM absorption coefficient at 380 nm [ $a_g(380)$ ]:

20  $a_g(\lambda) = G_0(\lambda) + G_1(\lambda)\exp[-G_2(\lambda)\frac{R_{rs}(\lambda_1)}{R_{rs}(\lambda_2)}]$ ; and d) reverse\_exponential\_model for

21 absorption coefficient by non-pigmented particles plus CDOM at 380 nm [ $a_{dg}(380)$ ]

1  $\frac{R_{rs}(\lambda_1)}{R_{rs}(\lambda_2)} = H_0(\lambda) + H_1(\lambda)\exp[-H_2(\lambda)a_{dg}(\lambda)]$ . Regression lines from  $R_{rs}$  band ratios of  
2 412/555, 443/555, and 490/555 are represented as solid, dotted, and dashed lines,  
3 respectively.

4  
5 Figure 4. Validation results comparing SeaWiFS observations with field measurements of  
6  $a_{ph}(670)$ ,  $a_d(380)$ ,  $a_g(380)$ , and  $a_{dg}(380)$  from multiple models (log\_linear\_model,  
7 log\_polynomial\_model, exponential\_model, reverse\_exponential\_model). Figures a) and  
8 b) show the mean absolute percent difference (MAPD), while c) and d) show the root  
9 mean square error (RMSE) of the validation results within 8 hours and 32 hours of the  
10 satellite overpass, respectively. The data from stations applied to develop the algorithms  
11 were not included in this analysis. The satellite derived  $a_{ph}(670)$  and  $a_{dg}(380)$  from  
12 GSM01 model [Maritorena et al., 2002] and GSM01-CB model [Magnuson et al., 2004]  
13 are also shown for comparison.

14  
15 Figure 5. Validation results comparing MODIS-Aqua observations with field  
16 measurements of  $a_{ph}(670)$ ,  $a_d(380)$ ,  $a_g(380)$ , and  $a_{dg}(380)$  from multiple models. See  
17 Figure 4 for details.

18  
19 Figure 6. Comparisons of SeaWiFS and MODIS-Aqua and field observations of the  
20 absorption coefficients of a)  $a_{ph}(670)$ , b)  $a_d(380)$ , c)  $a_g(380)$ , and d)  $a_{dg}(380)$ . The values  
21 are plotted on log scale. The satellite derivations of  $a_{ph}(670)$ ,  $a_d(380)$ , and  $a_{dg}(380)$  were  
22 from the log\_linear\_model, while  $a_g(380)$  from the reverse\_exponential\_model. The  
23 match-ups procedure is limited to within  $\pm 8$  hours, and the data from stations used to

1 develop algorithms are excluded for validation analyses. The statistical results are based  
2 on log-transformation of the data and shown on upper left for SeaWiFS and lower right  
3 for MODIS-Aqua. The solid lines represent the 1:1 lines, while dashed lines and dotted  
4 lines represent the regression for SeaWiFS and MODIS-Aqua respectively.

5  
6 Figure 7. Comparisons of SeaWiFS and MODIS-Aqua and field observations of [Chl\_a]  
7 for satellite overpass window of a)  $\pm 8$  hours and b)  $\pm 32$  hours. The data from stations  
8 used to develop algorithms of  $a_{ph}$  are excluded for this analysis. The solid lines represent  
9 the 1:1 lines, while dashed lines and dotted lines represent the regression for SeaWiFS  
10 and MODIS-Aqua respectively. See Figure 6 for detail.

11  
12 Figure 8. The distribution of  $a_{ph}$ ,  $a_d$ , and  $a_g$  at 443 nm within the SMAB for 5 August and  
13 3 November 2005, and 15 February and 12 May 2006 representing four seasons. The  
14 derived images for 5 August 2005 and 15 February 2006 were from MODIS-Aqua, while  
15 the other two were from SeaWiFS.

16  
17 Figure 9. The distribution of the relative percentage of  $a_{ph}$ ,  $a_d$ , and  $a_g$  to their sum at 443  
18 nm within the SMAB. See Figure 8 for detail.

19  
20 Figure 10. The relative percentage of  $a_{ph}$ ,  $a_d$ , and  $a_g$  to their sum at 443 nm from field  
21 measurements grouped into two regions (near shore region with bottom depth  $< 20$  m, and  
22 offshore region with bottom depth  $\geq 20$  m) within the SMAB.

23

1 Figure 11. The distribution of [Chl\_a] calculated from operational ocean color algorithms  
2 (OC4V4 for SeaWiFS and OC3M for MODIS-Aqua) and from the empirical method  
3 described in this paper (OC\_SMAB;  $[Chl\_a] = 70.632 \times [a_{ph}(670)]^{1.184}$ ), and their ratio  
4  $[(OC4V4 \text{ or } OC3M)/OC\_SMAB]$  within the SMAB. See Figure 8 for detail. The  
5 responding scales of the color bar are in log units for [Chl\_a] and in linear units for the  
6 ratio.

7  
8 Figure 12. Monthly time series of a) [Chl\_a], b)  $a_g(443)$ , and c) diffuse attenuation  
9 coefficient at 490 nm (K490) from MODIS-Aqua Level-3 images (4x4 km resolution) for  
10 a near shore location (75.90W, 36.93N; solid circle) and a middle shelf location (75.30W,  
11 36.93N; open circle). [Chl\_a] and  $a_g(443)$  are calculated from algorithms developed in  
12 this paper, while K490 is a direct product from the Level-3 images. Monthly river  
13 discharge rates at the mouth of Chesapeake Bay (open triangle; Data sources:  
14 <http://waterdata.usgs.gov/nwis/>; written communication from Gary Fisher, U.S.  
15 Geological Survey, 17 July 2007) are also shown for comparison.

Table 1. Regression results of phytoplankton absorption coefficient ( $a_{ph}$ ) to  $a_{ph}(670)$  from Equation (3):  $a_{ph}(\lambda) = B_0(\lambda)[a_{ph}(670)]^{B_1(\lambda)}$ . Log-transformation was applied to the data and Model II linear regression was adopted to calculate  $\log[B_0(\lambda)]$  and  $B_1(\lambda)$ . The selected wavelengths for  $a_{ph}$  analysis were the visible bands for SeaWiFS and MODIS-Aqua.

$\lambda$ (nm)	May-October			November-April		
	(N=196)			(N=51)		
	$B_0$	$B_1$	$r^2$	$B_0$	$B_1$	$r^2$
412	1.296	0.835	0.986	1.131	0.849	0.987
443	1.525	0.843	0.989	1.290	0.848	0.979
488	1.023	0.846	0.983	0.806	0.821	0.961
490	1.015	0.851	0.983	0.800	0.825	0.963
510	0.842	0.911	0.983	0.637	0.856	0.975
531	0.694	0.983	0.970	0.489	0.875	0.974
551	0.603	1.047	0.945	0.378	0.893	0.956
555	0.587	1.067	0.938	0.347	0.895	0.948
667	0.899	1.005	1.000	0.923	1.012	1.000
678	1.039	1.002	0.999	0.914	0.959	0.994

Table 2. Statistical results for absorption coefficients of phytoplankton ( $a_{ph}$ ), non-pigmented particles ( $a_d$ ), and CDOM plus non-pigmented particles ( $a_{dg}$ ) at selected wavelengths from log\_linear\_model:  $\log[a_x(\lambda)] = C_0(\lambda) + C_1(\lambda)R$ , where  $R = \log[R_{rs}(\lambda_1)/R_{rs}(\lambda_2)]$ . The size of the dataset is N=25.

Parameter	$R_{rs}(490)/R_{rs}(555)$			$R_{rs}(490)/R_{rs}(551)$		
	$C_1$	$C_0$	$r^2$	$C_1$	$C_0$	$r^2$
$a_{ph}(670)$	-2.602	-1.467	0.921	-2.769	-1.487	0.923
$a_d(380)$	-2.797	-1.319	0.933	-2.976	-1.340	0.932
$a_d(400)$	-2.812	-1.387	0.933	-2.992	-1.408	0.931
$a_d(412)$	-2.849	-1.427	0.933	-3.031	-1.449	0.931
$a_d(443)$	-3.048	-1.633	0.925	-3.243	-1.656	0.924
$a_d(490)$	-3.260	-1.950	0.902	-3.468	-1.975	0.902
$a_d(510)$	-3.584	-2.105	0.864	-3.813	-2.132	0.864
$a_d(531)$	-3.676	-2.223	0.848	-3.911	-2.251	0.848
$a_d(555)$	-3.315	-2.297	0.891	-3.526	-2.322	0.891
$a_{dg}(380)$	-1.394	-0.434	0.919	-1.487	-0.445	0.919
$a_{dg}(400)$	-1.489	-0.576	0.921	-1.588	-0.587	0.920
$a_{dg}(412)$	-1.535	-0.651	0.922	-1.637	-0.663	0.922
$a_{dg}(443)$	-1.593	-0.879	0.923	-1.698	-0.891	0.923
$a_{dg}(490)$	-1.649	-1.190	0.910	-1.758	-1.203	0.910
$a_{dg}(510)$	-1.725	-1.308	0.899	-1.840	-1.322	0.899
$a_{dg}(531)$	-1.633	-1.406	0.885	-1.743	-1.419	0.886
$a_{dg}(555)$	-1.983	-1.564	0.822	-2.117	-1.580	0.823

Table 3. Statistical results for CDOM absorption coefficient ( $a_g$ ) at selected wavelengths

from the reverse\_exponential\_model:  $\frac{R_{rs}(\lambda_1)}{R_{rs}(\lambda_2)} = H_0(\lambda) + H_1(\lambda) \exp[-H_2(\lambda)a_g(\lambda)]$ . The

size of the dataset is N=34.

Parameter	$R_{rs}(490)/R_{rs}(555)$				$R_{rs}(490)/R_{rs}(551)$			
	$H_0$	$H_1$	$H_2$	$r^2$	$H_0$	$H_1$	$H_2$	$r^2$
$a_g(355)$	0.538	3.149	3.978	0.882	0.546	2.805	3.844	0.879
$a_g(380)$	0.534	3.015	6.110	0.902	0.542	2.692	5.909	0.900
$a_g(400)$	0.540	2.940	8.656	0.915	0.547	2.625	8.366	0.912
$a_g(412)$	0.523	2.849	9.914	0.916	0.531	2.551	9.592	0.914
$a_g(443)$	0.531	2.857	17.700	0.908	0.539	2.557	17.130	0.906
$a_g(490)$	0.547	3.138	39.960	0.891	0.555	2.798	38.690	0.890
$a_g(510)$	0.493	2.352	39.870	0.857	0.503	2.126	38.640	0.858
$a_g(531)$	0.494	2.271	50.240	0.829	0.504	2.056	48.700	0.831
$a_g(555)$	0.335	1.798	40.690	0.795	0.346	1.657	39.120	0.799



Table 4. The mean absolute percent difference (MAPD) and root mean square error (RMSE) from validation match-ups for  $a_{ph}$ ,  $a_d$ ,  $a_g$ , and  $a_{dg}$  at selected wavelengths. The derived exponential decay slope ( $S$ ) for  $a_d$  ( $S_d$ ),  $a_g$  ( $S_g$ ), and  $a_{dg}$  ( $S_{dg}$ ) from non-linear regression and chlorophyll  $a$  concentration ([Chl\_a]) are also compared. Data used for algorithm development are not included in this analysis. The size of the datasets are N=22, 36, 8, and 19 for  $a_{ph}$ ,  $a_d$ , or  $a_{dg}$ , and N=29, 45, 14, and 25 for [Chl\_a], and N=31, 47, 14, and 25 for  $a_g$  for SeaWiFS  $\pm 8$  and  $\pm 32$  hours and MODIS  $\pm 8$  and  $\pm 32$  hours overpass windows, respectively.

Parameter	SeaWiFS ( $\pm 8h$ )		SeaWiFS ( $\pm 32h$ )		MODIS ( $\pm 8h$ )		MODIS ( $\pm 32h$ )	
	MAPD	RMSE	MAPD	RMSE	MAPD	RMSE	MAPD	RMSE
$a_{ph}(443)$	23.5	0.0501	23.4	0.0470	23.4	0.0137	23.1	0.0206
$a_{ph}(670)$	25.7	0.0371	30.1	0.0329	21.2	0.0051	27.8	0.0106
[Chl_a]	32.3	3.6808	32.5	3.0339	28.8	3.2805	29.3	2.5474
$a_d(380)$	35.3	0.1447	38.2	0.1350	41.9	0.1684	39.3	0.1275
$a_d(443)$	41.8	0.0787	42.1	0.0726	50.5	0.0876	44.6	0.0664
$S_d$	13.4	0.0018	11.7	0.0016	11.5	0.0014	12.1	0.0015
$a_g(380)$	25.2	0.1636	20.7	0.1359	20.1	0.2096	23.4	0.1607
$a_g(443)$	22.8	0.0516	20.1	0.0432	20.1	0.0662	21.5	0.0509
$S_g$	5.8	0.0011	5.5	0.0011	5.2	0.0011	6.7	0.0012
$a_{dg}(380)$	26.5	0.2104	25.2	0.1965	18.4	0.1761	25.6	0.1478
$a_{dg}(443)$	24.4	0.0923	24.4	0.0870	22.1	0.0896	23.1	0.0711
$S_{dg}$	11.9	0.0020	12.7	0.0021	15.5	0.0024	15.1	0.0023

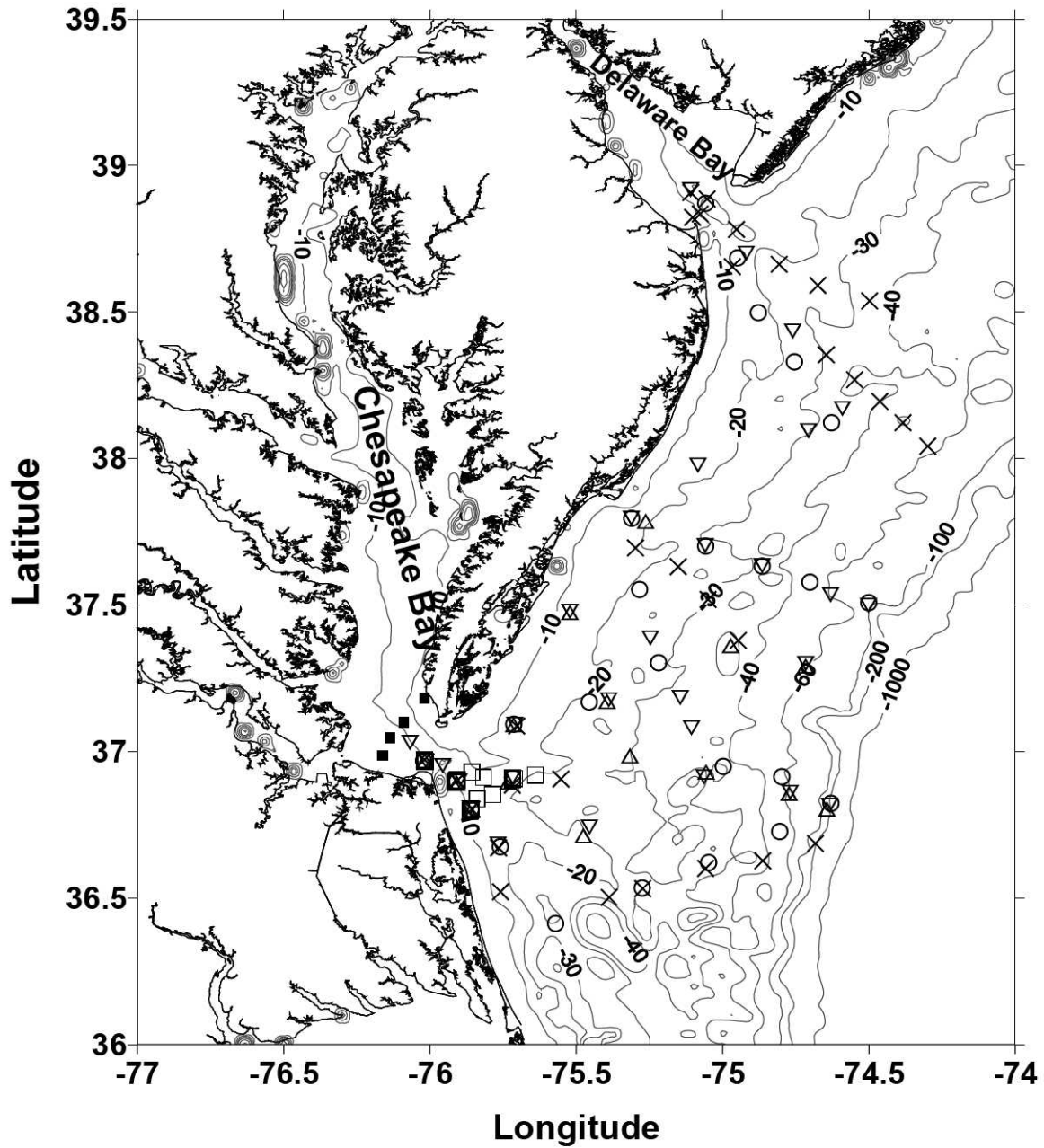


Figure 1. Map of the study area within the southern Middle Atlantic Bight (SMAB). Symbols representing the sampling stations from the following cruises are:  $\triangle$  – BIOME1 (30 March to 1 April 2005),  $\nabla$  – BIOME2 (26 to 30 July 2005),  $\circ$  – BIOME3 (5 to 9 May 2006),  $\times$  – BIOME4 (2 to 6 July 2006),  $\square$  – CBP (four daily cruises), and  $\blacksquare$  – CBH (ten daily cruises).

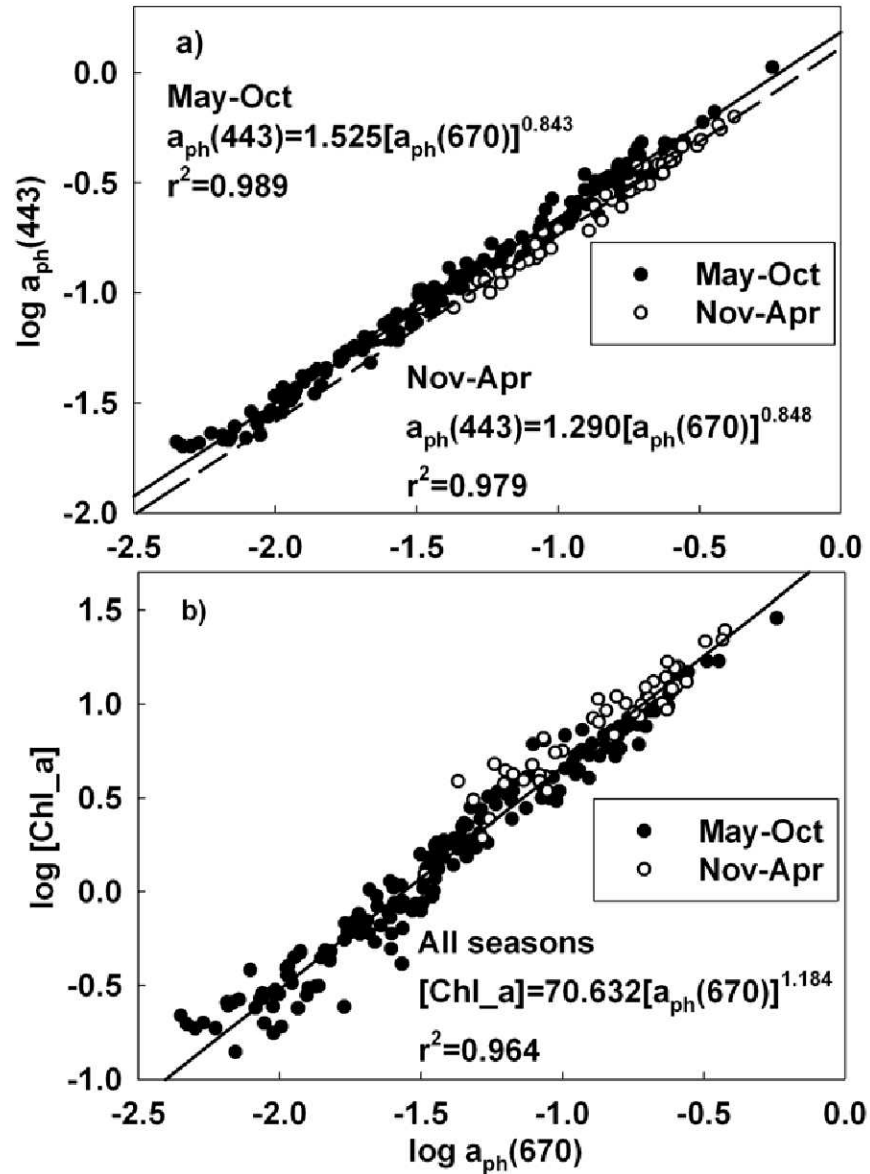


Figure 2. Log-transformed linear regression of phytoplankton absorption coefficient at 670 nm [ $a_{ph}(670)$ ] to a)  $a_{ph}(443)$ , and b) chlorophyll *a* concentration [Chl *a*]. The solid and dashed lines in the upper figure represent the regression for summer-fall season (May to October) and winter-spring season (November to April), respectively.

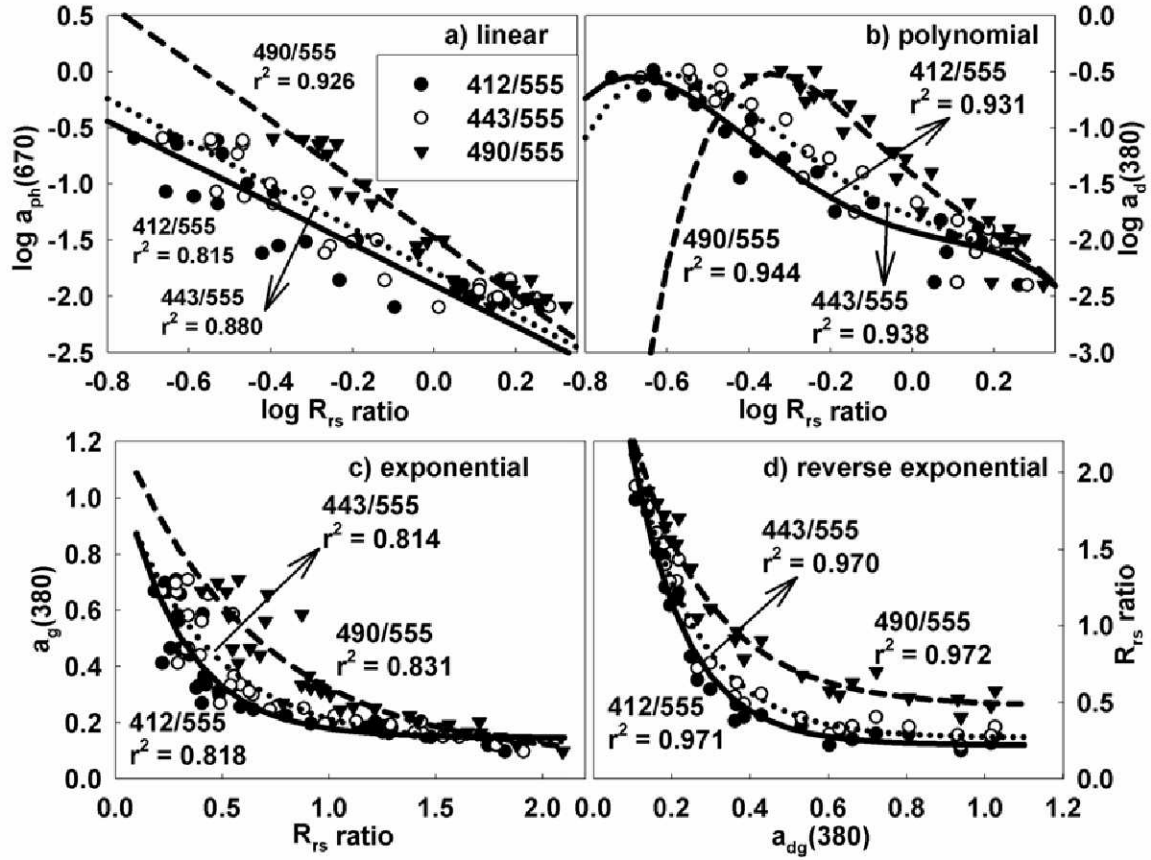


Figure 3. Absorption algorithms derived from field observations of remote sensing reflectance ( $R_{rs}$ ) from a) log\_linear\_model for  $a_{ph}(670)$ :  $\log[a_{ph}(\lambda)] = C_0(\lambda) + C_1(\lambda)R$ , where  $R = \log[R_{rs}(\lambda_1)/R_{rs}(\lambda_2)]$ ; and b) log\_polynomial\_model for non-pigmented particulate absorption coefficient at 380 nm [ $a_d(380)$ ]:

$$\log[a_d(\lambda)] = D_0(\lambda) + D_1(\lambda)R + D_2(\lambda)R^2 + D_3(\lambda)R^3 + D_4(\lambda)R^4; \text{ and c)}$$

exponential\_model for CDOM absorption coefficient at 380 nm [ $a_g(380)$ ]:

$$a_g(\lambda) = G_0(\lambda) + G_1(\lambda) \exp[-G_2(\lambda) \frac{R_{rs}(\lambda_1)}{R_{rs}(\lambda_2)}]; \text{ and d) reverse_exponential_model for}$$

absorption coefficient by non-pigmented particles plus CDOM at 380 nm [ $a_{dg}(380)$ ]

$$\frac{R_{rs}(\lambda_1)}{R_{rs}(\lambda_2)} = H_0(\lambda) + H_1(\lambda) \exp[-H_2(\lambda)a_{dg}(\lambda)]. \text{ Regression lines from } R_{rs} \text{ band ratios of}$$

412/555, 443/555, and 490/555 are represented as solid, dotted, and dashed lines, respectively.

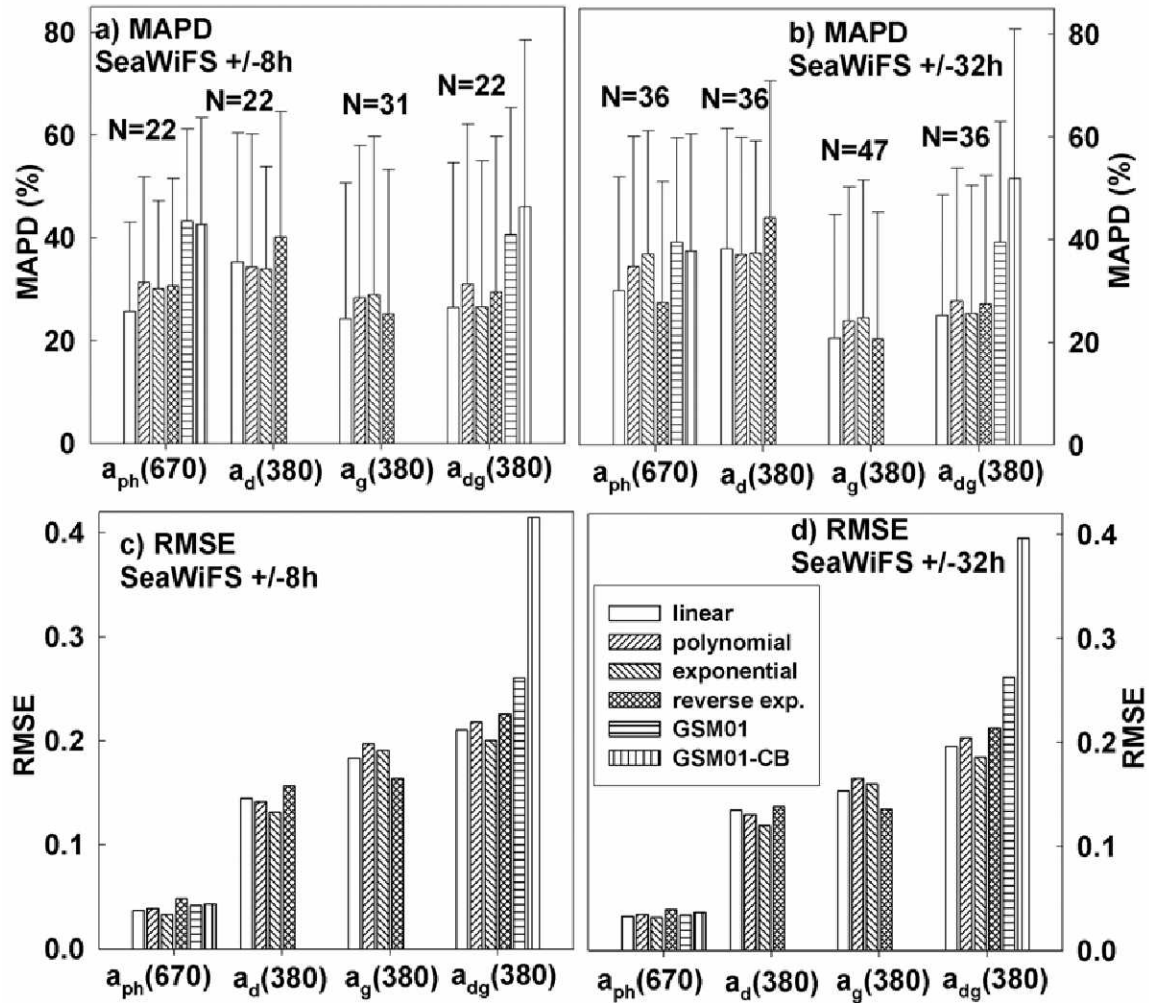


Figure 4. Validation results comparing SeaWiFS observations with field measurements of  $a_{ph}(670)$ ,  $a_d(380)$ ,  $a_g(380)$ , and  $a_{dg}(380)$  from multiple models (log\_linear\_model, log\_polynomial\_model, exponential\_model, reverse\_exponential\_model). Figures a) and b) show the mean absolute percent difference (MAPD), while c) and d) show the root mean square error (RMSE) of the validation results within 8 hours and 32 hours of the satellite overpass, respectively. The data from stations applied to develop the algorithms were not included in this analysis. The satellite derived  $a_{ph}(670)$  and  $a_{dg}(380)$  from GSM01 model [Maritorena et al., 2002] and GSM01-CB model [Magnuson et al., 2004] are also shown for comparison.

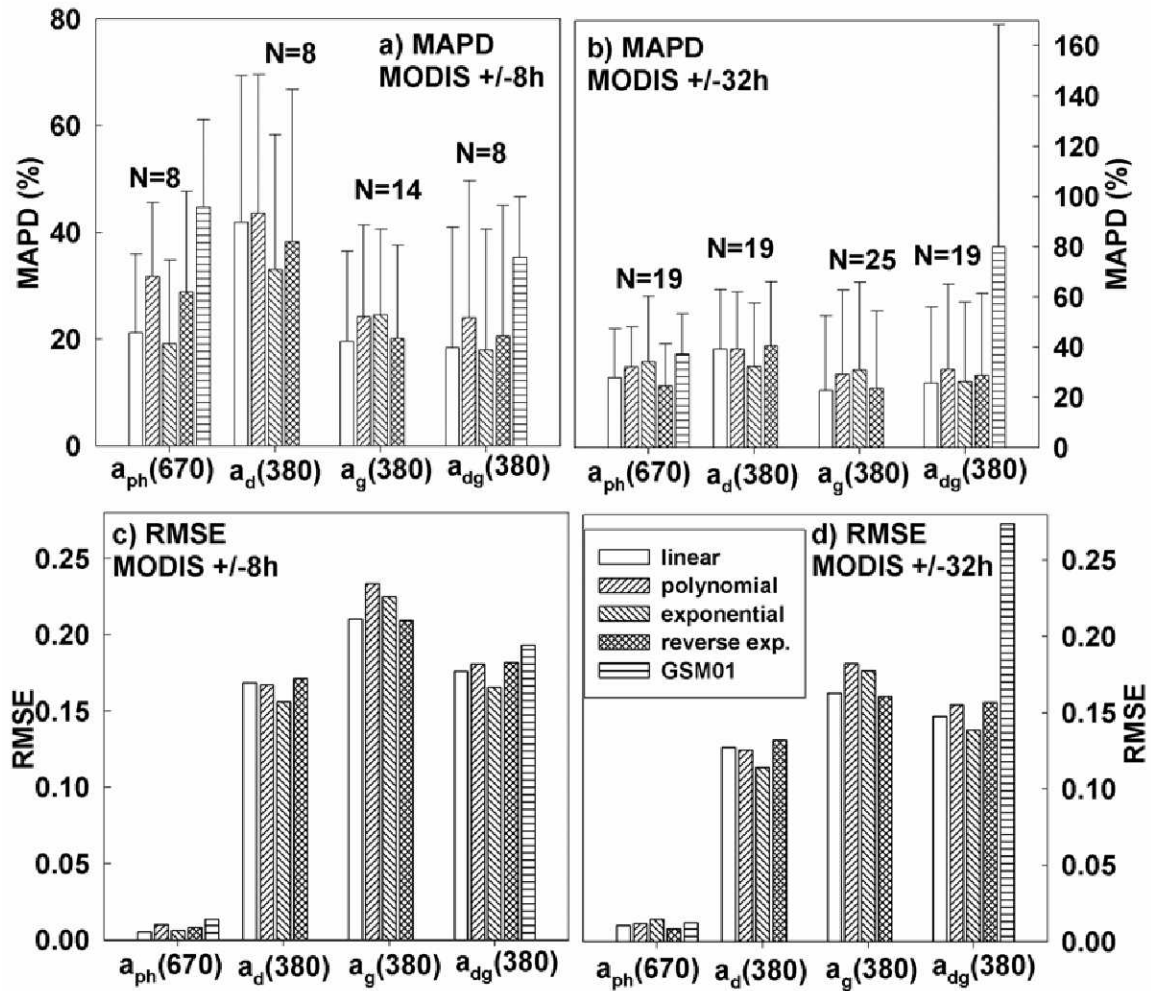


Figure 5. Validation results comparing MODIS-Aqua observations with field measurements of  $a_{ph}(670)$ ,  $a_d(380)$ ,  $a_g(380)$ , and  $a_{dg}(380)$  from multiple models. See Figure 4 for details.

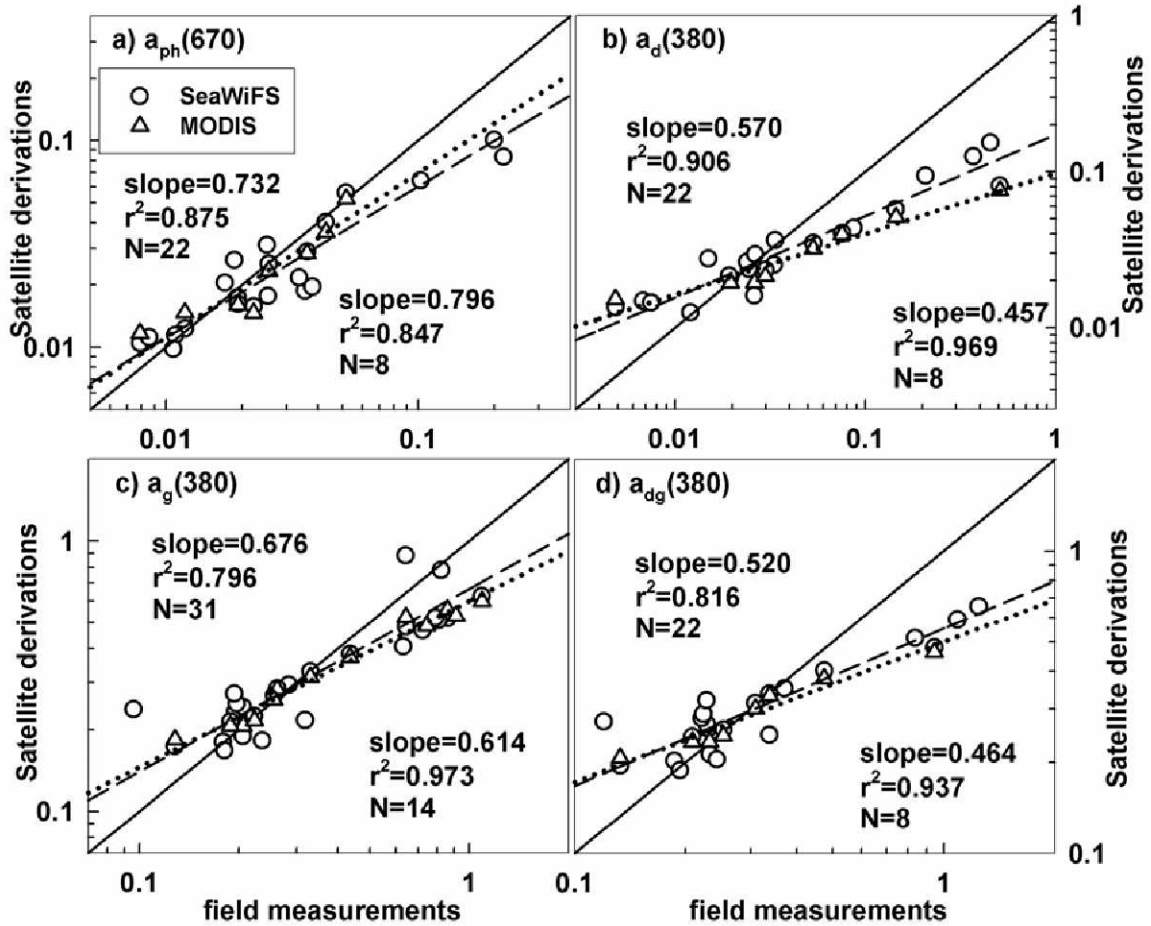


Figure 6. Comparisons of SeaWiFS and MODIS-Aqua and field observations of the absorption coefficients of a)  $a_{ph}(670)$ , b)  $a_d(380)$ , c)  $a_g(380)$ , and d)  $a_{dg}(380)$ . The values are plotted on log scale. The satellite derivations of  $a_{ph}(670)$ ,  $a_d(380)$ , and  $a_{dg}(380)$  were from the `log_linear_model`, while  $a_g(380)$  from the `reverse_exponential_model`. The match-ups procedure is limited to within  $\pm 8$  hours, and the data from stations used to develop algorithms are excluded for validation analyses. The statistical results are based on log-transformation of the data and shown on upper left for SeaWiFS and lower right for MODIS-Aqua. The solid lines represent the 1:1 lines, while dashed lines and dotted lines represent the regression for SeaWiFS and MODIS-Aqua respectively.



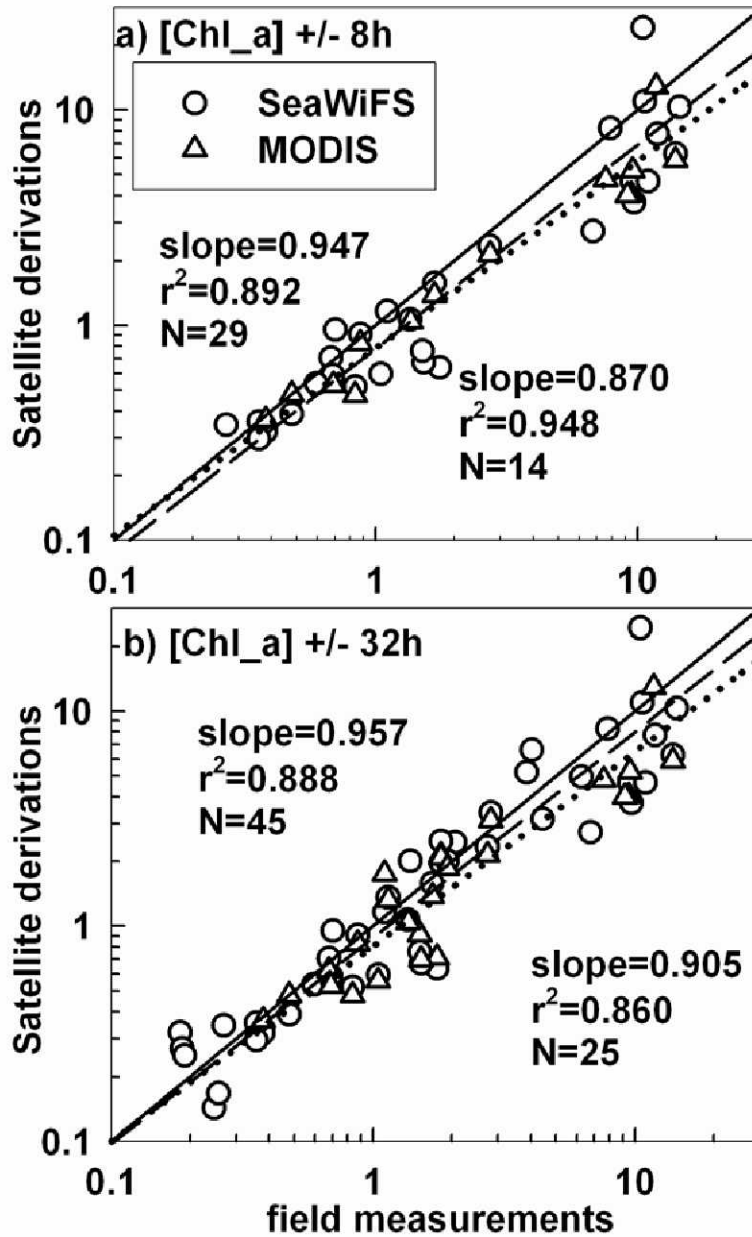


Figure 7. Comparisons of SeaWiFS and MODIS-Aqua and field observations of [Chl\_a] for satellite overpass window of a)  $\pm 8$  hours and b)  $\pm 32$  hours. The data from stations used to develop algorithms of  $a_{ph}$  are excluded for this analysis. The solid lines represent the 1:1 lines, while dashed lines and dotted lines represent the regression for SeaWiFS and MODIS-Aqua respectively. See Figure 6 for detail.

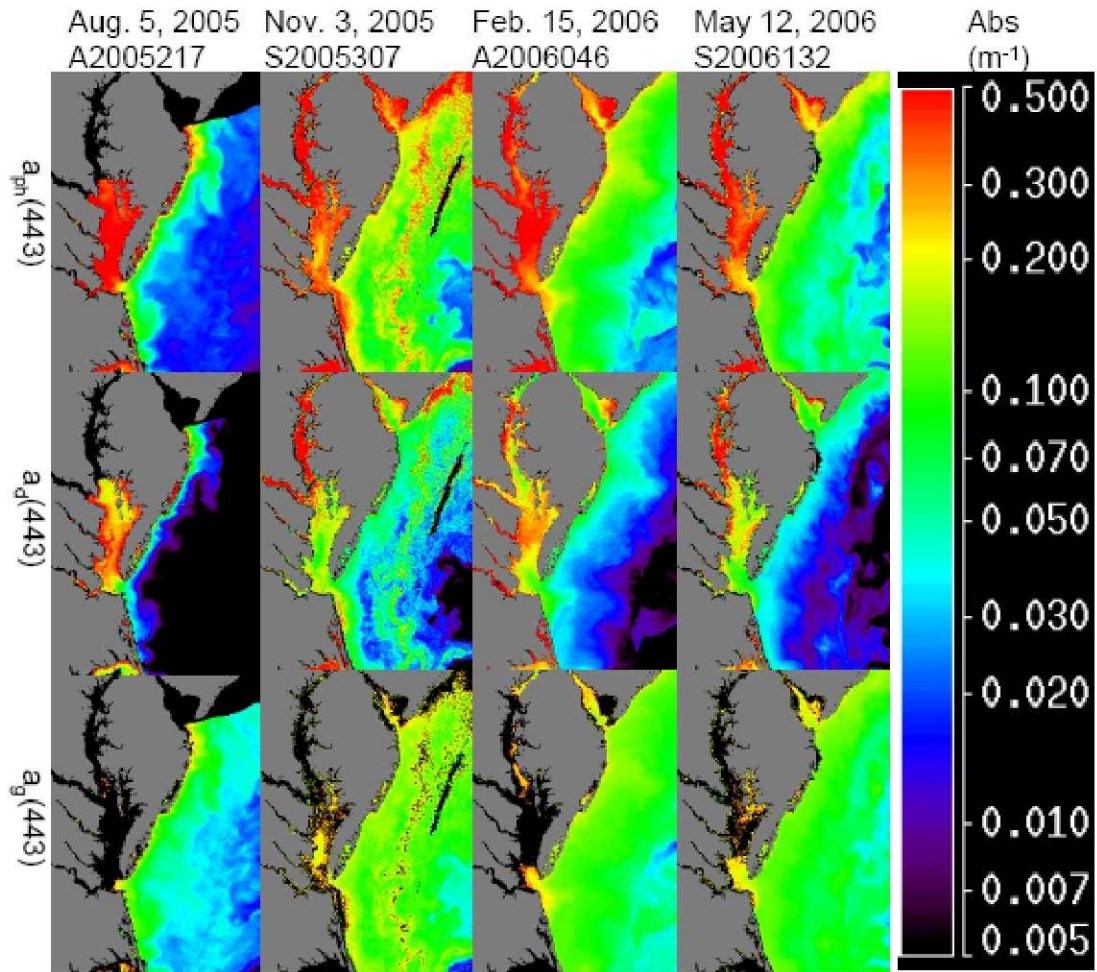


Figure 8. The distribution of  $a_{ph}$ ,  $a_d$ , and  $a_g$  at 443 nm within the SMAB for 5 August and 3 November 2005, and 15 February and 12 May 2006 representing four seasons. The derived images for 5 August 2005 and 15 February 2006 were from MODIS-Aqua, while the other two were from SeaWiFS.

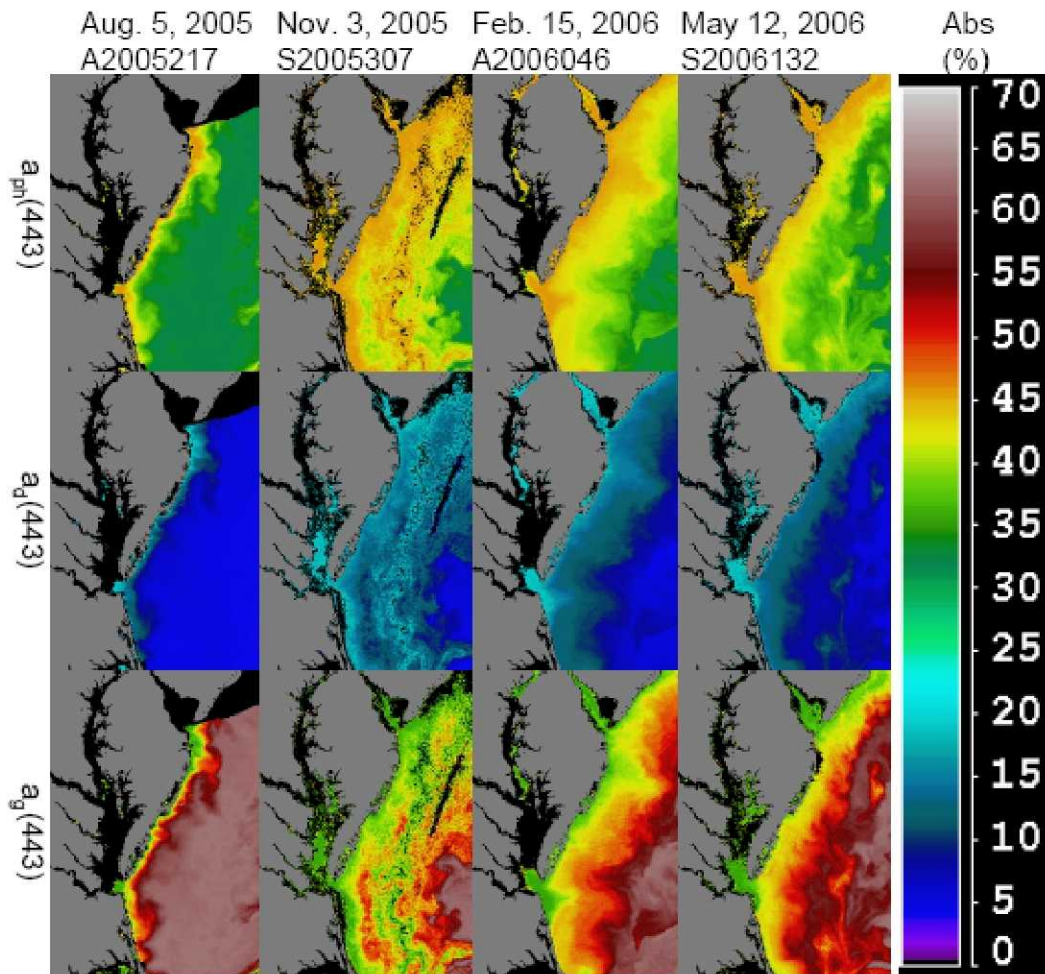


Figure 9. The distribution of the relative percentage of  $a_{ph}$ ,  $a_d$ , and  $a_g$  to their sum at 443 nm within the SMAB. See Figure 8 for detail.

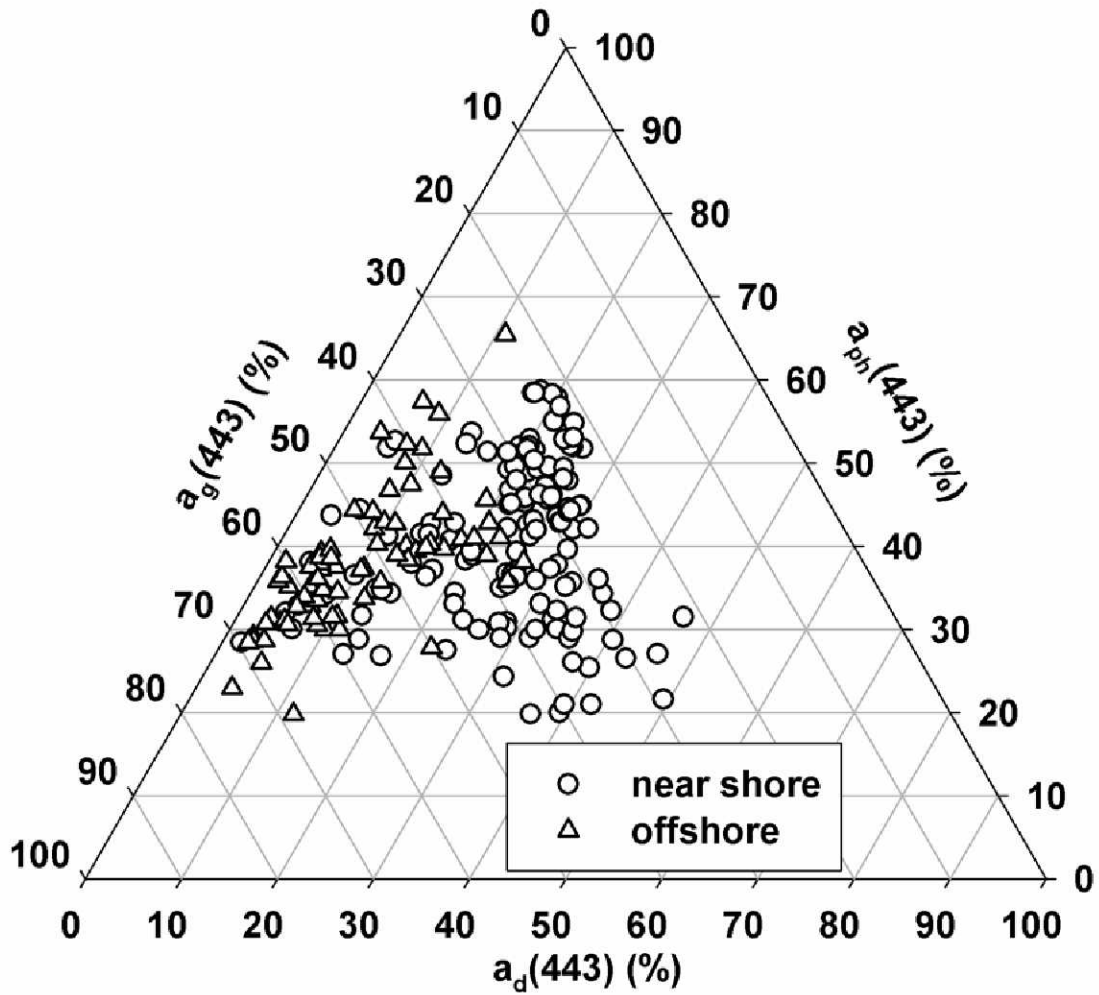


Figure 10. The relative percentage of  $a_{ph}$ ,  $a_d$ , and  $a_g$  to their sum at 443 nm from field measurements grouped into two regions (near shore region with bottom depth <20 m, and offshore region with bottom depth  $\geq 20$  m) within the SMAB.

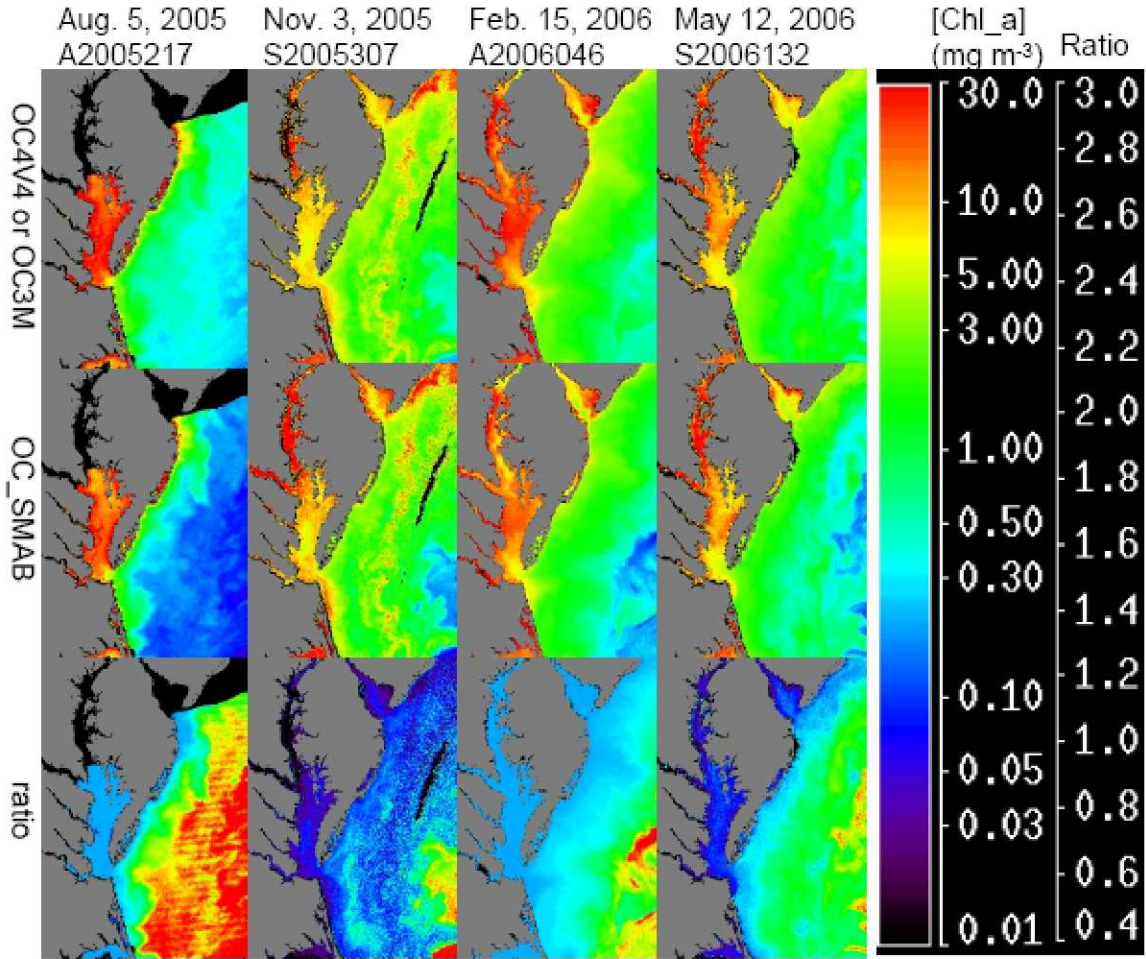


Figure 11. The distribution of [Chl\_a] calculated from operational ocean color algorithms (OC4V4 for SeaWiFS and OC3M for MODIS-Aqua) and from the empirical method described in this paper (OC\_SMAB;  $[Chl\_a] = 70.632 \times [a_{ph}(670)]^{1.184}$ ), and their ratio  $[(OC4V4 \text{ or } OC3M)/OC\_SMAB]$  within the SMAB. See Figure 8 for detail. The responding scales of the color bar are in log units for [Chl\_a] and in linear units for the ratio.

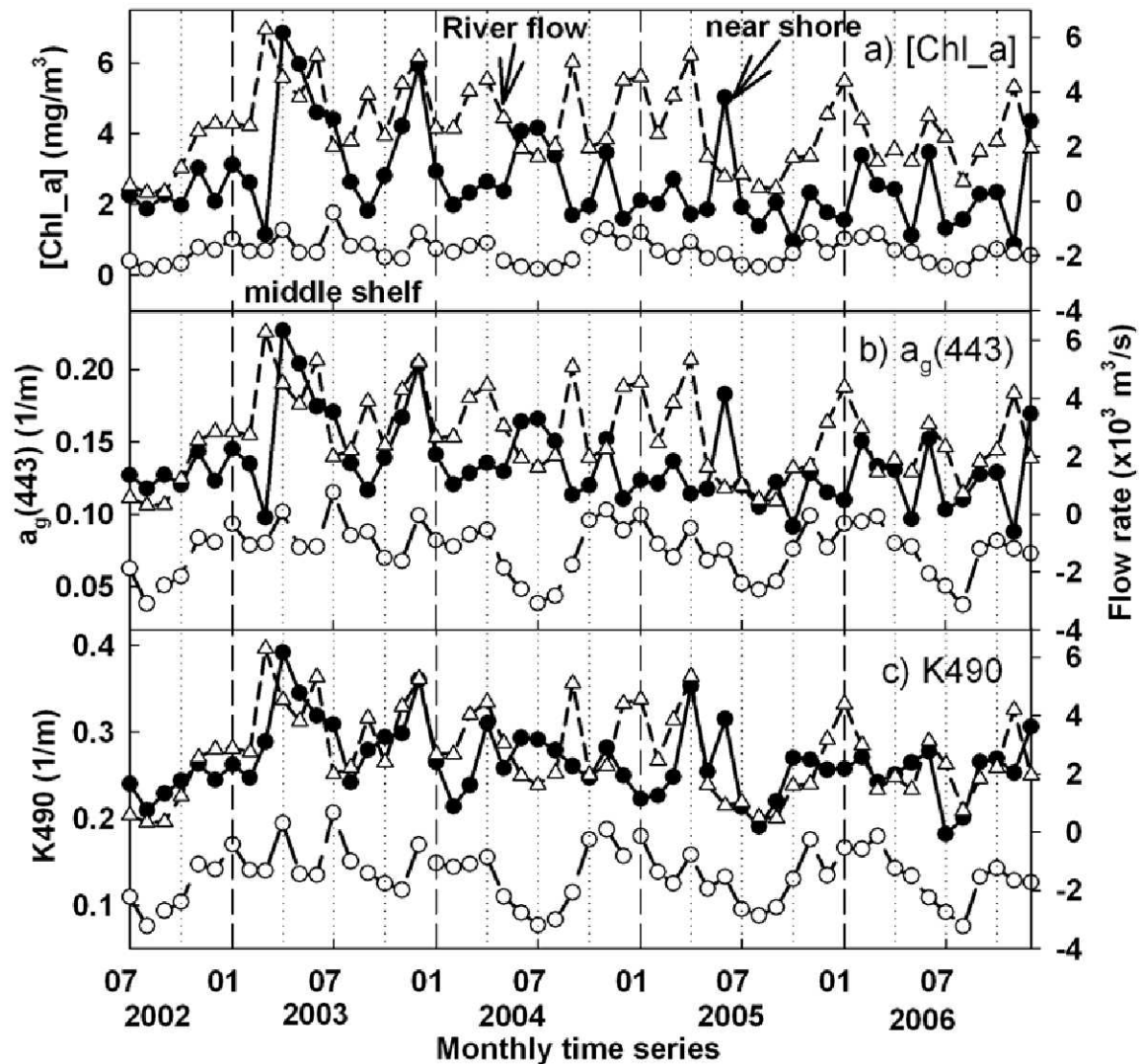


Figure 12. Monthly time series of a) [Chl\_a], b)  $a_g(443)$ , and c) diffuse attenuation coefficient at 490 nm (K490) from MODIS-Aqua Level-3 images (4x4 km resolution) for a near shore location (75.90W, 36.93N; solid circle) and a middle shelf location (75.30W, 36.93N; open circle). [Chl\_a] and  $a_g(443)$  are calculated from algorithms developed in this paper, while K490 is a direct product from the Level-3 images. Monthly river discharge rates at the mouth of Chesapeake Bay (open triangle; Data sources: <http://waterdata.usgs.gov/nwis/>; written communication from Gary Fisher, U.S. Geological Survey, 17 July 2007) are also shown for comparison.