Long-term distribution patterns of remotely sensed water quality parameters in Chesapeake Bay

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ABSTRACT

Chesapeake Bay is the largest and one of the most productive estuaries in the U.S., where long-term monitoring and assessment of its water quality are necessary to understand trends and events in order to support management decisions. Significant progress has been made during the past decade in developing remote sensing algorithms for estimating two key water quality parameters, chlorophyll-a concentration (Chla, mg m⁻³) and diffuse light attenuation coefficient at 490 nm (Kd(490), m⁻¹), from satellite ocean color measurements in oceanic, coastal, and estuarine waters. Yet deriving a robust Chlo data product for Chesapeake Bay still remains a challenge because of its complex optical properties. Here, a recently developed algorithm approach (Red–Green Chlorophyll Index or RGCI, based on red–green remote-sensing reflectance (Rrs(λ)) ratios) was tested, validated, and applied to Sea-viewing Wide Field-of-view Sensor (SeaWiFS) and Moderate Resolution Imaging Spectroradiometer (MODIS) data to establish a 14-year (September 1997 to December 2011) Chla Environmental Data Record (EDR). The new approach showed significant improvement over the traditional blue–green Rrs(λ) band-ratio algorithms (e.g., OC4, OC3M), with consistent performance for MODIS (mean relative error = 40.9%, mean ratio = 1.09) and SeaWiFS (MRE = 45.8%, mean ratio = 1.09) for Chla ranging between 1 and 50 mg m⁻³. Anomaly and EOF analyses revealed strong spatial gradients, seasonality, and climate-driven inter-annual changes in the satellite-based Chla EDR. These changes were highly correlated with satellite-based Kd(490) EDR, leading to the development of a Water Quality Decision Matrix (WQDM) and providing support to on-going nutrient reduction management programs for this estuary.

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1. Introduction

Effective monitoring and management of estuarine and coastal water quality is an important task for local and state government management agencies for protecting and restoring marine resources (e.g., seagrass beds and fisheries) that are vital for local ecology and economy. One important water quality parameter is the water-column chlorophyll-a concentration (Chlo in mg m⁻³), which is often used as a measure of phytoplankton biomass (base of the food web) and serves as an indicator of an estuary’s eutrophic state. Another important water quality parameter is water clarity, which is often measured as secchi disk depth (SDD), but can more accurately be determined using the diffuse light attenuation coefficient at 490 nm (Kd(490), m⁻¹).

Traditionally, shipboard data has been used for estuarine water quality assessment. For example, monthly shipboard surveys between 1984 and the present have served as the main data source for water quality assessment in Chesapeake Bay (Chesapeake Bay Program, 1993), the largest estuary in the U.S. Because estuarine and coastal ecosystems are typically highly variable in both space and time in terms of phytoplankton biomass (indicated as Chlo) and primary productivity (Cloern, 2001; Harding Jr. et al., 2005a), shipboard measurements are often inadequate at capturing high-frequency changes. Satellite ocean color measurements may complement shipboard surveys through more synoptic and frequent observations (Udy et al., 2005).

However, deriving robust water quality data products and in particular chlorophyll-a concentration (Chlo) for optically complex estuarine waters from satellite measurements remain challenges despite recent advancements. This is because that 1) the major optically significant constituents (OSCs) in estuaries, namely phytoplankton pigments (e.g., Chlo), detrital (non-algal) particles, and colored dissolved organic matters (CDOM) often do not covary and the latter two OSCs can dominate light absorption at blue wavelengths (Babin et al., 2003; Harding Jr. et al., 2005a; Chang...
This makes it difficult to estimate Chl accurately using blue–green band-ratio algorithms that are tuned for waters in which non-living OSCs co-vary with Chl (O’Reilly et al., 2000); 2) satellite-derived reflectance in the blue bands (e.g., 412 nm) often contains large uncertainties due to imperfect atmospheric correction (Ahmad et al., 2007; Tzortziou et al., 2007; Werdell et al., 2009), making semi-analytical algorithms (e.g., Lee et al., 2002; Maritorena et al., 2002) also subject to large errors because these algorithms rely on the blue bands to estimate Chl.

Recently, a new Chl algorithm has been developed for the turbid Tampa Bay estuary (Le et al., 2013c). The red–green empirical band-ratio algorithm has been validated for both Sea-viewing Wide Field-of-view Sensor (SeaWiFS) and Moderate Resolution Imaging Spectroradiometer (MODIS) and was used to establish a 14-year Chl Environmental Data Record (EDR) as well as a water quality decision matrix (WQDM) for management decision support. However, as with any empirical algorithm, the applicability of this new algorithm to Chesapeake Bay has not been tested as yet. Here, using in situ data from two independent sources, we evaluate the performance of this new algorithm for the Chesapeake Bay with the following objectives: (1) test the algorithm applicability and fine-tune algorithm coefficients for SeaWiFS and MODIS; (2) establish long-term Chl and \( K_{\text{d}} \) (490) EDRs for the Chesapeake Bay; and (3) interpret spatial and temporal patterns from the Chl and \( K_{\text{d}} \) (490) EDRs in relation to climate variability and seagrass changes between 1998 and 2011.

2. Study area

The Chesapeake Bay is the largest estuary in the US with a surface area of \( ~1,160 \text{ km}^2 \) and average water depth of 7 m (Chesapeake Bay Program, 1993). The mean tidal range at the mouth is 0.78 m. The estuary can be divided into the following three segments (Magnuson et al., 2004): Upper Chesapeake Bay (UCB), Middle Chesapeake Bay (MCB) and Lower Chesapeake Bay (LCB) (Fig. 1). An extensive watershed contributes an annual average of \( 2.3 \times 10^9 \text{ m}^3 \text{ s}^{-1} \) freshwater flow, together with dissolved and particulate matter including nutrients and sediments, to the estuary. Chesapeake Bay suffers from excessive nutrient loading by freshwater flow (Malone, 1992; Malone et al., 1996; Fisher et al., 2006) and, consequently, has exhibited increasing eutrophication in recent years (Hagy et al., 2004; Kemp et al., 2005).

The Chesapeake Bay Program (CBP) initiated a Water Quality Monitoring Program, where 19 water quality parameters at 49 fixed stations were measured every month since 1984 (red in Fig. 1). Several targeted studies have also documented the spatial and temporal variability of bio-optical properties of the Chesapeake Bay based on shipborne measurements (Johnson et al., 2001; Harding Jr. and Magnuson, 2002; Magnuson et al., 2004; Harding Jr. et al., 2005a; Tzortziou et al., 2006, 2007). Tzortziou et al. (2007) reported that, on average, absorption by CDOM and non-algal particulates contributed 59% to the total non-water absorption coefficient at 488 nm. Harding Jr. et al. (2005a) showed that absorption coefficients of phytoplankton pigments, CDOM, and non-algal particles at 440 nm were comparable to each other. The complex optical properties make it a challenging task to develop reliable remote sensing Chl algorithms for this estuary.

3. Data and method

3.1. In situ data

Two independent in situ datasets \( (N = 64) \) were used in this study. The first set contained data collected in July 2011 at 64 stations in the Middle Chesapeake Bay and Upper Chesapeake Bay (blue in Fig. 1). These data were collected by the University of South Florida (USF) as part of a comprehensive field campaign in support of NASA’s Geostationary Coastal and Air Pollution Events (GEOCAPE, Fishman et al., 2012) planning mission. Data measured during this study included Chl and spectral absorption coefficients due to phytoplankton pigments \( \alpha_{\text{ph}} (\lambda) \), non-algal detrital particles \( \alpha_{d} (\lambda) \), and CDOM \( \alpha_{c} (\lambda) \) measured at the surface, as well as above-water spectral remote sensing reflectance \( R'_{s} (\lambda) \). This dataset was used to analyze the bio-optical properties of the water column and to determine the applicable forms of Chl retrieval algorithms. The data were collected and analyzed following community-accepted protocols that are detailed in Le et al. (2013a). Although no replicate samples were taken, analysis from the past and from unpublished data collected in the early 2000s (replicates analyzed by independent labs) showed that these data had uncertainties <10%. Further, \( \alpha_{c} (490) \) measured with a 10-cm cuvette in the 200–800 nm range and referenced against Mill-Q water was not normalized to 700 nm when \( \alpha_{c} (400) \) was >2 m\(^{-1}\). This is because that \( \alpha_{d} (700) \) is no longer negligible.

The second in situ dataset \( (N = 5452) \) included field-measured Chl provided by the Chesapeake Bay Program (http://www.chesapeakebay.net/data) collected every month covering the SeaWiFS and MODIS-Aqua data collection periods since September 1997 from the 49 fixed stations shown in Fig. 1. Only near-surface data (sample depth <1 m) were used in this study in order to compare with satellite data. This dataset was used to tune the Chl retrieval algorithm coefficients for SeaWiFS and MODIS.

3.2. Satellite data

SeaWiFS (September 1997–December 2010) and MODIS (July 2002–December 2011) Level-0 data were obtained from the NASA
SeaWiFS and OC3 for MODIS), and the Level-2 quality control pixels (i.e., after discarding pixels associated with the Level-2 quality control flags) within this 3 × 3 box exceeded 4 and the coefficient of variation (CV) of valid pixels was < 0.4 (Harding Jr. et al., 2005b) was a match-up pair found. To remove potential errors caused by the satellite sensor itself and atmospheric correction algorithm noise, the median value from valid pixels within the 3 × 3 box was used (Hu et al., 2001). These quality control criteria resulted in 34 MODIS and 47 SeaWiFS scenes from which satellite data were extracted and compared with the Chesapeake Bay Program field data.  

3.3. Environmental data

Monthly mean flow rates of rivers discharging into the three bay segments were obtained from the U. S. Geological Survey National Water Information System (USGS NWIS) for the period of January 1997–December 2011. Annual means and multi-year monthly climatology were derived from the monthly means. Underwater seagrass coverage data for the bay was obtained from the Chesapeake Bay Program (Chesapeake Bay Program, 1993; www.chesapeakebay.net).

4. Results

4.1. Chla and bio-optical properties

Table 1 summarizes the variability observed in in situ Chla and the spectral absorption coefficients at 443 nm and 490 nm for major OSCs determined during the GEO-CAPE field campaign (July 2011). Chla varied seven-fold, ranging from 7.4 to 54.3 mg m⁻³ with a mean value of 18.4 ± 8.9 mg m⁻³. Absorption coefficients for all three major OSCs (phytoplankton, detritus, and CDOM) showed ~5–10 fold variability at both wavelengths. These absorption coefficients and Chla showed similar spatial gradients, with decreasing values from the UCB to MCB and from waters near the shoreline to relatively offshore. On average, the mean absorption at 443 nm for detrital particles (0.57 m⁻¹) and CDOM (0.38 m⁻¹) together exceeded the mean absorption for phytoplankton

Table 1
Summary of Chla and spectral absorption coefficients (443 nm and 490 nm) determined from surface water samples collected from 64 stations during a GEO-CAPE field campaign (ship: NOAA Vessel SRV R8501) during July 2011. The field measurements were conducted in the middle Chesapeake Bay (MCB) and upper Chesapeake Bay (UCB) (Fig. 1).

<table>
<thead>
<tr>
<th>Chla (mg m⁻³)</th>
<th>Mean</th>
<th>SD</th>
<th>Min</th>
<th>Max</th>
<th>Medium</th>
</tr>
</thead>
<tbody>
<tr>
<td>443 nm</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(a_d(443)) (m⁻¹)</td>
<td>1.60</td>
<td>0.41</td>
<td>0.41</td>
<td>3.03</td>
<td>1.57</td>
</tr>
<tr>
<td>(a_g(443)) (m⁻¹)</td>
<td>0.57</td>
<td>0.20</td>
<td>0.19</td>
<td>1.02</td>
<td>0.53</td>
</tr>
<tr>
<td>(a_d(443)) (m⁻¹)</td>
<td>0.65</td>
<td>0.27</td>
<td>0.22</td>
<td>1.89</td>
<td>0.58</td>
</tr>
<tr>
<td>(a_g(443)) (m⁻¹)</td>
<td>0.38</td>
<td>0.06</td>
<td>0.06</td>
<td>0.52</td>
<td>0.37</td>
</tr>
<tr>
<td>(a_d/a_g)</td>
<td>0.35</td>
<td>0.08</td>
<td>0.08</td>
<td>0.55</td>
<td>0.35</td>
</tr>
<tr>
<td>(a_d/a_w)</td>
<td>0.40</td>
<td>0.09</td>
<td>0.09</td>
<td>0.62</td>
<td>0.41</td>
</tr>
<tr>
<td>(a_g/a_w)</td>
<td>0.25</td>
<td>0.04</td>
<td>0.04</td>
<td>0.35</td>
<td>0.24</td>
</tr>
<tr>
<td>490 nm</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(a_d(490)) (m⁻¹)</td>
<td>0.92</td>
<td>0.26</td>
<td>0.26</td>
<td>1.94</td>
<td>0.91</td>
</tr>
<tr>
<td>(a_g(490)) (m⁻¹)</td>
<td>0.32</td>
<td>0.13</td>
<td>0.10</td>
<td>0.61</td>
<td>0.29</td>
</tr>
<tr>
<td>(a_d(490)) (m⁻¹)</td>
<td>0.43</td>
<td>0.20</td>
<td>0.14</td>
<td>1.34</td>
<td>0.38</td>
</tr>
<tr>
<td>(a_g(490)) (m⁻¹)</td>
<td>0.18</td>
<td>0.03</td>
<td>0.03</td>
<td>0.24</td>
<td>0.18</td>
</tr>
<tr>
<td>(a_d/a_g)</td>
<td>0.34</td>
<td>0.09</td>
<td>0.09</td>
<td>0.59</td>
<td>0.33</td>
</tr>
<tr>
<td>(a_d/a_w)</td>
<td>0.46</td>
<td>0.10</td>
<td>0.10</td>
<td>0.69</td>
<td>0.47</td>
</tr>
<tr>
<td>(a_g/a_w)</td>
<td>0.20</td>
<td>0.04</td>
<td>0.04</td>
<td>0.31</td>
<td>0.20</td>
</tr>
</tbody>
</table>
pigments (0.65 m⁻¹). No significant correlation was found between Chl a and ad(443) or ag(443) (p > 0.3) (Fig. 2a). A similar pattern was also observed at 490 nm (data not shown). The lack of covariation between Chl a and absorption coefficients due to non-living OSCs, in addition to the dominant blue-light absorption by the non-living OSCs (Fig. 2b), suggests that empirical Chl algorithms that utilize blue wavelengths and are tuned to perform optimally in phytoplankton-dominated waters will perform poorly

<table>
<thead>
<tr>
<th>Data source</th>
<th>Independent variable(s)</th>
<th>Regression relationships</th>
<th>R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>USF measured Rrs</td>
<td>Log10 (Rrs(488)/Rrs(547))</td>
<td>Chla = 10⁻².15x+0.59</td>
<td>0.16</td>
</tr>
<tr>
<td>(λ) and Chl a (N = 32)</td>
<td>Log10 (Rrs(667)/Rrs(531))</td>
<td>Chla = 10³.25x+2.09</td>
<td>0.77</td>
</tr>
<tr>
<td>(Chla: 7.4–54.3 mg m⁻³)</td>
<td>Log10 (Rrs(667)/Rrs(547))</td>
<td>Chla = 10⁻3.57x+2.41</td>
<td>0.70</td>
</tr>
<tr>
<td></td>
<td>Log10 (Rrs(510)/Rrs(555))</td>
<td>Chla = 10⁻3.21x+0.61</td>
<td>0.14</td>
</tr>
<tr>
<td></td>
<td>Log10 (Rrs(670)/Rrs(490))</td>
<td>Chla = 10⁻2.45x+1.2</td>
<td>0.67</td>
</tr>
<tr>
<td></td>
<td>Log10 (Rrs(670)/Rrs(510))</td>
<td>Chla = 10⁻2.96x+1.59</td>
<td>0.71</td>
</tr>
<tr>
<td></td>
<td>Log10 (Rrs(670)/Rrs(555))</td>
<td>Chla = 10⁻4.38x+2.83</td>
<td>0.69</td>
</tr>
<tr>
<td></td>
<td>Log10 (Rrs(667)/Rrs(531))</td>
<td>Chla = 10⁻1.76x+1.61</td>
<td>0.43</td>
</tr>
<tr>
<td></td>
<td>Log10 (Rrs(670)/Rrs(510))</td>
<td>Chla = 10⁻1.76x+1.43</td>
<td>0.43</td>
</tr>
<tr>
<td>CBP measured Chla:</td>
<td>MODIS Rrs (λ) (N = 1079)</td>
<td>Rrs (667)/Rrs (531)</td>
<td>0.71</td>
</tr>
<tr>
<td>(1–50 mg m⁻³)</td>
<td>SeaWiFS Rrs (λ) (N = 1132)</td>
<td>Chla = 10⁻1.76x+1.43</td>
<td>0.43</td>
</tr>
</tbody>
</table>

Fig. 3. (a) and (b) Comparison of the OC3 and RGCI algorithm performance for MODIS (N = 1079); (c) and (d) Comparison of the OC4 and RGCI algorithm performance for SeaWiFS (N = 1132). RGCI refers to the specific red–green band ratio algorithms for MODIS and SeaWiFS. Note that satellite Chl > 100 mg m⁻³ was artificially set to 100 mg m⁻³ in order to present in the same figure. rRMS = (10⁻RMSE¹⁻¹) × 100, RMS = \sqrt{1 / N (\log_{10}(Chl_{sat}) - \log_{10}(Chl_{obs}))²}, (Chl_{sat} is satellite derived Chl, Chl_{obs} is in situ Chl, N is the number of the samples). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)
in the Chesapeake Bay (Gower et al., 1984; Daill’Olmo et al., 2005; Tzortziou et al., 2007).

4.2. Algorithm tuning and evaluation

Evidence in support of this hypothesis was provided by the poor correlation ($R^2 < 0.16$) observed between field-measured blue–
green Rrs band-ratios and Chla (Table 2). Neither Rrs (488)/Rrs 
(547) (used by MODIS) nor Rrs (510)/Rrs (555) (used by SeaWiFS) 
showed a meaningful relationship with Chla.

Because Tzortziou et al. (2007) and Le et al. (2013b) demonstrated 
the potential for using red–green Rrs band-ratio algorithms for estimating Chla in the Chesapeake Bay, the match-up in situ Rrs 
($\lambda$) and Chla data collected during the GEO-CAPE field campaign 
were used to fine-tune the algorithm coefficients for various combinations of red–green Rrs band ratios (Table 2). Compared to 
the blue–green band-ratio algorithms, significant improvement 
was observed for the red–green band-ratio algorithms. For MODIS 
wavebands, Rrs (667)/Rrs (531) showed the best performance 
($R^2 = 0.77$) (note that Rrs (678)/Rrs (531) also showed near-
identical performance). For SeaWiFS wavebands, Rrs (670)/Rrs 
(510) showed the best performance ($R^2 = 0.71$). Thus, these two 
algorithm forms showed the highest potential for application to the 
satellite data.

Next, the algorithm coefficients for these two red–green band-ratio algorithms (Rrs (667)/Rrs (531) for MODIS and Rrs (670) 
/Rrs (510) for SeaWiFS) were fine tuned using the more extensive CBP 
Chla data with near-concurrent satellite Rrs ($\lambda$) data. 1079 matching 
pairs were obtained for MODIS, and 1132 matching pairs were 
obtained for SeaWiFS. Despite the difference in the measurement 
size (1 km$^2$ from satellite versus point measurements in the 
field) and time (up to 24 h), significant correlation ($R^2 = 0.43$, $p < 0.01$) 
was still found between the satellite red–green band ratio and in 
situ Chla (Table 2). The algorithm coefficients determined for the satellite data differ from those determined from in situ Rrs data 
possibly due to the imperfect atmospheric correction (Son and 
Wang, 2012), causing inconsistency between in situ and satellite-
based Rrs. Also, while the field-measured Rrs were collected in the 
UCB and MCB during a single field sampling campaign only, the 
satellite data were collected in all three bay segments over a 14-
year period. The time-window ($\pm 24$ h) and sub-pixel variability 
could be other reasons causing the differences in the algorithm 
coefficients. Nevertheless, the algorithm coefficients were deter-
mined from the best statistical fit between in situ Chla and MODIS 
Rrs, thus minimizing the impact of all these potential artifacts.

Fig. 3 shows the performance of the newly developed so-called 
Red–Green-Chla-Index (RGCI) algorithms compared to the default 
algorithms. Note that in order to fit all data in the same graph, Chla 
values greater than 100 mg m$^{-2}$ were artificially set to 100 mg m$^{-2}$. 
Clearly, the RGCI algorithms showed significant improvement over 
the default OCx-type algorithms, as illustrated by the algorithm 
performance statistics such as mean relative error (MRE), relative 
root mean square uncertainty (rRMS), and mean ratio (annotated in 
Fig. 2b and d). Note that if the CBP match-up dataset were randomly 
split in two, with one set used for algorithm tuning and the other 
used for validation, near-identical statistics were obtained.

In order to combine long-term Chla EDRs for the Chesapeake 
Bay developed for both SeaWiFS and MODIS data, cross-sensor 
consistency must be verified as each sensor uses different wave-
bands for the RGCI algorithm. Monthly mean RGCI Chla data 
derived from SeaWiFS and MODIS measurements at three stations 
(CB4.1, CB5.2, and CB7.3) located in UCB, MCB, and LCB, respectively, 
showed good agreement between the two sensors (Fig. 4), with a 
mean ratio of 1.02, and relative root mean square (RMS) difference 
of 30.1%. These results indicate that a multi-sensor RGCI Chla time-
series can be constructed using both SeaWiFS and MODIS mea-
surements between September 1997 and December 2011.

4.3. Long-term trends in Chla

Fig. 5 shows the climatological annual mean RGCI-derived sat-
ellite Chla for the entire satellite data collection period (September 
1997–December 2011) and departure from the climatology during 
each individual year. Significant spatial and temporal variability 
was observed. In general, Chla decreased from the UCB to the MCB 
and LCB (Fig. 5a). UCB exhibited the highest Chla likely due to high 
freshwater input from the Susquehanna River at the head of the 
UCB, which accounts for nearly half of the total freshwater input 
to the whole estuary (Schubel and Pritchard, 1986). LCB showed 
the lowest Chla as it was under direct influence of the much clearer 
waters from the Atlantic. In general, years with large positive 
anomalies included 1998 and 2003–2006, while years with large 

An EOF analysis was performed to examine the dominant spatial 
and temporal modes, following the approach of Yoder et al. (2002). 
The first three eigenvalue modes contained >70% of the variability 
of the spatial patterns, with the first mode explaining 54% of the 
variability (Fig. 6). The Mode 1 spatial function (Fig. 6a) shows that 
the spatial variation is not significant, while significant variation is 
present in the temporal amplitude coefficients (Fig. 6b). These two 
figures indicate that the dominant interannual variation is nearly 
uniform for all bay segments. Mode 2, explaining 12% of the Chla 
variability, showed significant interannual variations with the 
corresponding spatial pattern showing opposite signs from the UCB 
to the MCB and LCB (Fig. 6c & d). This mode suggests that when 
overlaid on the dominant mode (mode 1) there is modulation 
where the UCB is out of phase from MCB and LCB on an interannual 
basis. Interestingly, outside the bay (lower right corner of Fig. 6c), 
the Mode 2 function is in phase with the UCB.

The spatial and temporal patterns in satellite-derived Chla vari-
ability were further analyzed and quantified by extracting the 
annual mean Chla of the three bay segments (Fig. 7a). Chla in UCB 
was consistently higher than in MCB and LCB, with mean of 
25.7 ± 1.77 mg m$^{-3}$ for the 14-year period, versus 11.5 ± 1.64 mg m$^{-3}$ 
and 7.7 ± 1.37 mg m$^{-3}$ in MCB and LCB, respectively. All three bay
segments exhibited similar temporal patterns, consistent with Mode 1 of the EOF analysis. Compared to the large variability exhibited between individual bay segments, interannual variability among each segment was relatively low. Using the long-term variance (based on 14 annual means) as a gauge, interannual variability for the three bay segments (UCB, MCB, and LCB) was $1.77/25.7 = 6.9\%$, $1.64/11.5 = 14.3\%$, and $1.37/7.7 = 17.8\%$, respectively. Thus, interannual variability showed an increasing pattern from the UCB to LCB. Over the 14-year time-series, satellite Chl $a$ for each bay segment decreased gradually from 1998 to 2002, exhibited a sharp increase in 2003, and then decreased gradually, once again, until 2008 after which variable trends were observed.

The interannual Chl $a$ variability showed significant correlations with river discharge patterns (Fig. 7b) for all three bay segments ($p < 0.01, N = 14$), with Pearson’s correlation coefficients of 0.71, 0.70, and 0.83 for the UCB, MCB, and LCB, respectively. Highest mean annual discharge and mean annual Chl $a$ in all three bay segments was observed in 1998 and 2003. Conversely, the lowest mean annual discharges corresponded to the lowest mean annual Chl $a$ in 2001 and 2002 for all three bay segments.

The strong relationship between river discharge and satellite Chl $a$ also existed at monthly scale between September 1997 and December 2011, where clear seasonality was observed during each year in all three bay segments. Winter-spring blooms were
observed during most years, following river discharge maxima. The Pearson correlation coefficients between monthly Chl and river discharge are 0.48 ($p < 0.01, N = 161$), 0.38 ($p < 0.01, N = 165$), and 0.30 ($p < 0.01, N = 165$) for UCB, MCB and LCB, respectively (data not shown).

4.4. Chla and light availability

We analyzed the relationship between Chl and $K_d (490)$ to understand how Chl might affect light availability in Chesapeake Bay. $K_d (490)$ was derived using the Lee et al. (2005, 2007) semi-analytical algorithm from MODIS- and SeaWiFS-derived Rrs data. $K_d (490)$ exhibited similar spatial and temporal distribution patterns as with Chl, especially in MCB and UCB. Indeed, there was a significant correlation between mean annual Chla and $K_d (490)$ when data from all three bay segments were considered together ($\ln (K_d (490)) = 1.1022 \times \ln (\text{Chla}) - 1.204; p < 0.01, R^2 = 0.94, N = 42$) (Fig. 8a). When monthly data were used, there was also a strong correlation between $K_d (490)$ and Chl ($\ln (K_d (490)) = 0.9846 \times \ln (\text{Chla}) - 0.949; p < 0.01, R^2 = 0.62, N = 491$) (Fig. 8b). When the three bay segments were considered individually, though, the correlations between Chl and $K_d (490)$ were lower due to smaller dynamic ranges. However, these relationships were still statistically significant, with the lowest coefficient of determination observed in UCB (0.24 for annual means and 0.21 for monthly means). This was likely due to the increased influence of suspended sediments and CDOM in the UCB as compared to the other two bay segments. These results indicate that most of the variability in light availability can be explained by changes in phytoplankton, especially in MCB and LCB. More than 90% of

Fig. 6. Spatial eigen-functions and time-varying amplitudes of the first two EOF modes derived from the annual mean Chla time series (1998–2011).
the annual variability and more than 60% of the monthly variability of light availability can be explained by phytoplankton variations when all three bay segments are considered together.

The strong correlation between phytoplankton and light availability was further supported by the negative correlation between Chl $a$ and seagrass coverage in Chesapeake Bay (Fig. 9). Both Chl $a$ and $K_d (490)$ showed significant, negative long-term correlations with baywide seagrass coverage. The Pearson correlation coefficient between seagrass coverage and Chl $a$ was $-0.54$ ($p < 0.01, N = 14$), and between seagrass coverage and $K_d (490)$ it was $-0.52$ ($p < 0.01, N = 14$). High seagrass coverage was observed in 2001–2002 and 2008–2009 when Chl $a$ and $K_d (490)$ were relatively low. Conversely, low coverage was observed in 2003 and 2006 when Chl $a$ and $K_d (490)$ were relatively high. These results support the nutrient loading management policy established for this estuary aimed at supporting seagrass recovery efforts and restoration of a healthy estuarine ecosystem (Chesapeake Bay Program, 1993).

5. Discussions

5.1. Chla algorithm performance

Developing robust Chla remote sensing algorithms for optically complex coastal and estuarine waters is challenging (IOCCG, 2000). CDOM and non-algal particles in estuaries such as Chesapeake Bay often contribute significantly to total light absorption at blue wavelengths, making it difficult to discriminate between Chl $a$ and non-algal material. This, in addition to the difficulty in obtaining accurate satellite-based Rrs data at blue wavelengths due to atmospheric correction uncertainties (Werdell et al., 2009; Son and Wang, 2012), makes it difficult to estimate Chl $a$ accurately using traditional blue–green empirical band-ratio algorithms (O’Reilly et al., 2000). Previous studies have shown that the SOA semi-analytical algorithm (Kuchinke et al., 2009) showed comparable performance with that of the OC3 and OC4 algorithms for the Chesapeake Bay, and while the GSM semi-analytical algorithm...
relationship between monthly mean Chl input into the estuary (Fisher et al., 1988). The weak discharge of the Susquehanna River, which contributes more than half of the total freshwater and inorganic nutrients inputs into the estuary (Fisher et al., 1988).

The work presented here is a natural extension of the previous Tampa Bay study, but for a much larger estuary that is also optical complex. Although the green Rrs wavelength used here is slightly different from that used in Tampa Bay (Le et al., 2013c) due to the optical differences between these two large water bodies, the principle remains the same and algorithm performance is acceptable. Indeed, the Chl retrieval uncertainty of >80% (corresponding to 0.255 in log-transformed data) for the global open ocean (Depth > 200 m) (Gregg and Casey, 2004), the much reduced uncertainties (58–69%) for this turbid estuary using the newly developed RGCI algorithms allows for the generation of consistent and accurate long-term Chl EDRs for assessing long-term variability in water quality to meet management needs.

It is noted that the optimal green bands were tuned for Chesapeake Bay (531 for MODIS and 510 for SeaWiFS) and therefore different from those used for Tampa Bay (547 for MODIS and 555 for SeaWiFS). In Tampa Bay, CDOM absorption overwhelms other OSCs in the blue wavelengths, while in Chesapeake Bay CDOM is relative low and absorption is dominated by particles (phytoplankton and non-living particles) (Fig. 2b). Thus, the wavelengths of the green bands for Tampa Bay are slightly longer than those for Chesapeake Bay to avoid the CDOM effect. For the same reason, for Chesapeake Bay the simply ratio of Rrs (667)/Rrs (531) yielded similar performance as the 4-band ratio of (Rrs (667)−Rrs (678))/ (Rrs (547)−Rrs (531)) as proposed by Le et al. (2013b). Clearly, as with any empirical approaches, the RGCI approach requires tuning and testing for any specific estuaries.

5.2. Chla variations due to climate variability

The 14-year combined SeaWiFS and MODIS Chla EDR established using the new RGCI algorithms showed the dominant role that river discharge plays in modulating the annual and monthly Chla patterns for all bay segments. UCB showed the highest Chla because it receives discharge from the Susquehanna River, which contributes more than half of the total freshwater and inorganic nutrients inputs into the estuary (Fisher et al., 1988). The weak relationship between monthly mean Chla and river discharge may be attributed to the lag between nutrient loading and phytoplankton growth, or to relatively long water residence times in the bay. For example, Shen and Wang (2007) found that it takes 120–300 days to observe a marked change in pollutants near the bay mouth in response to pollutants discharged from the Susquehanna River into UCB.

River discharge is controlled primarily by precipitation, which is strongly modulated by climate variability such as El Niño–Southern Oscillation (ENSO) events. In this region, El Niño (La Niña) years are typically wetter (drier) than normal due to increased (decreased) precipitation, thus leading to higher (lower) river discharge. The 14-year Chla EDR presented here encompassed four wet years (1998, 2003, 2004, and 2011) and four dry years (1999, 2001, 2002 and 2008) (Fig. 7b) (U.S. Geological Survey, 2012). Whereas two of the wet years (1998 and 2003) coincided with El Niño events, severe tropical storm activity was responsible for the increased discharge during 2004 and 2011. Similarly, dryer than normal conditions coincided with La Niña events (1999–2001, 2008).

5.3. Implications for environmental management

Phytoplankton affect the water clarity and light availability in estuaries (Morrison et al., 2006), and are a primary factor regulating submerged aquatic vegetation (SAV) abundance and spatial distribution in the Chesapeake Bay (Kemp et al., 2004, 2005). Yet the effect needs to be quantified. In this study, phytoplankton was found to be a major factor in explaining light availability in most bay waters (>30% annual variability, and >60% monthly variability can be explained by phytoplankton variations when all bay segments are considered together), exhibiting significant negative correlations with seagrass areal coverage. This result supports the nutrient loading management policy (Chesapeake Bay Program, 1993) to improve water clarity and to recover seagrass coverage.

It is also noted that the relatively low correlation between Chla and Kd (490) in UCB suggests that water constituents other than phytoplankton (e.g., suspended sediments, CDOM from river discharge) may play dominant roles in affecting Kd (490) at times in various portions of the bay (Son and Wang, 2012).

Previous efforts have shown the effectiveness of using a Water Quality Decision Matrix (WQDM) for long-term water quality monitoring and management (Janicki et al., 2000). Using SeaWiFS and MODIS derived Chla and Kd (490), a WQDM for the Tampa Bay estuary has been established (Le et al., 2013c). Using the same approach and threshold values determined from each bay segment (Table 3), a WQDM was developed for the three bay segments of Chesapeake Bay (Table 4). In the WQDM, green is derived when

<table>
<thead>
<tr>
<th>Bay segments</th>
<th>Chla threshold values (mg m⁻²)</th>
<th>Light attenuation threshold values (m⁻¹)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Small magnitude</td>
<td>Large magnitude</td>
</tr>
<tr>
<td>UCB</td>
<td>25.8</td>
<td>25.8–27.5</td>
</tr>
<tr>
<td>MCB</td>
<td>12.3</td>
<td>12.3–14.2</td>
</tr>
<tr>
<td>LCB</td>
<td>8.0</td>
<td>8.0–9.4</td>
</tr>
</tbody>
</table>
both water quality indexes (Chl and \(K_a\) (490)) are lower than the target values in Table 3. Yellow is derived when one of the water quality parameters is lower than the large-magnitude deviation, but higher than the small-magnitude deviation. Red is derived when both of the water quality parameters are higher than the large-magnitude deviation, signifying poor water quality conditions. Red for two consecutive years indicates the need for management actions.

The WQDM shows that water quality in Chesapeake Bay has been normal for most years between 1998 and 2011, with 2003 being exceptional for MCB and LCB, possibly driven by excessive nutrient loadings and improving water clarity.

6. Conclusion

A recently developed new Chla retrieval approach was tuned and evaluated using both SeaWiFS and MODIS data for Chesapeake Bay, with optimal bands selected. The results revealed that the red-green band ratio algorithms significantly outperformed the traditional blue–green band-ratio algorithms, leading to satisfactory results as measured by validation statistics. Using the regionally tuned RCCh algorithms, a long-term Chla EDR was established by combining SeaWiFS and MODIS data between late 1997 and 2011. To our best knowledge, it is the first time a 14-year long-term Chla EDR with minimal uncertainties was established for Chesapeake Bay. The Chla EDR showed specific spatial and temporal variations, some of which were previously unknown. In general, Chla during the 14-year period was mainly driven by river discharge. Based on strong correlations between Chla and \(K_a\) (490), Chla was found to play an important role in controlling light availability, in turn explaining observed variability in local seagrass coverage. These results support current management efforts aimed at reducing nutrient loadings and improving water clarity.

Based on results presented here as well as those published earlier for another turbid estuary (Le et al., 2013b, 2013c), the red-green band ratio algorithm approach for estimating Chla from satellite Rrs (\(\lambda\)) may be applicable to other estuaries in which non-living dissolved and particulate material play a significant role in affecting water column optical properties (absorption and backscattering) at green and red wavelengths. The algorithm coefficients as well as the exact band positions, however, may need to be fine-tuned for any given estuary. Likewise, long-term Chla and \(K_a\) (490) EDRs as well as WQDMs for other estuaries may be derived from satellite measurements using similar approaches outlined here in order to quantify estuarine responses to climate changes and human impacts, and to help manage in a timely manner.

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**References**


Harding Jr., L.W., Magnuson, A., Mallonee, M.E., 2005b. SeaWiFS retrievals of chlorophyll in Chesapeake Bay and the mid-Atlantic Bight. Estuarine, Coastal and Shelf Science 62, 75–94.


Tzortziou, M., Subramanian, A., Herman, J.R., Gallegos, C.L., Neale, P.J., Harding, L.W., 2007. Remote sensing reflectance and inherent optical properties in the mid Chesapeake Bay. Estuarine, Coastal and Shelf Science 72, 16–32.


