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# Climate-driven chlorophyll-a changes in a turbid estuary: Observations from satellites and implications for management

Chengfeng Le [a,*], Chuanmin Hu [a], David English [a], Jennifer Cannizzaro [a], Charles Kovach [b]

[a] College of Marine Science, University of South Florida, St. Petersburg, FL, USA
[b] Florida Department of Environmental Protection, Temple Terrace, FL, USA

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## ABSTRACT

Significant advances have been made in ocean color remote sensing of turbidity and water clarity for estuarine waters, yet accurate estimations of chlorophyll-a concentrations (Chla in mg $m^{-3}$) has been problematic, posing a challenge to the research community and an obstacle to managers for long-term water quality assessment. Here, a novel empirical Chla algorithm based on a Red-Green-Chorophyll-Index (RGCI) was developed and validated for MODIS and SeaWiFS observations between 1998 and 2011. The algorithm showed robust performance with two independent datasets, with relative mean uncertainties of ~30% and ~50% and RMS uncertainties of ~40% and ~65%, respectively, for Chla ranging between 1.0 and >30.0 mg $m^{-3}$. These uncertainties are comparable or even lower than those reported for the global open oceans when traditional blue-green band ratio algorithms are used.

A long-term Chla time series generated from SeaWiFS and MODIS observations showed excellent agreement between sensors and with *in situ* measurements. Substantial variability in both space and time was observed in the four bay segments, with higher Chla in the upper bay segments and lower Chla in the lower bay segments, and higher Chla in the wet season and lower Chla in the dry season. On average, river discharge could explain ~60% of the seasonal changes and ~90% of the inter-annual changes, with the latter mainly driven by climate variability (*e.g.* El Niño and La Niña years) and anomaly events (*e.g.* tropical cyclones). Significant positive correlation was found between monthly mean Chla anomalies and monthly Multivariate ENSO Index (MEI) (Pearson correlation coefficient = 0.43, $p<0.01$, $N=147$), with high Chla associated with El Niño and lower Chla associated with La Niña. Further, a Water Quality Decision Matrix (WQDM) was established from satellite observations, providing complementary and more reliable information to the existing WQDM based on less synoptic and less frequent field measurements. The satellite-derived WQDM and long-term time-series data support the decision making efforts of the management agencies that regulate nutrient discharge to the bay. Similar approaches may be established for other estuaries where field data are much more limited than for Tampa Bay.

## 1. Introduction

Coastal ocean eutrophication has been reported globally in recent decades (Bonsdorff et al., 1997; Davis & Koop, 2006; Le et al., 2010), and regionally in many estuaries in the United States (Bricker et al., 2008; Fisher et al., 2006; Wang et al., 1999). Algal blooms, mostly a typical result of eutrophication, are indicators of degraded water quality conditions that can adversely affect the use of estuarine resources, including commercial and recreational fishing, boating, swimming, and tourism. Toxic algal blooms may also cause risks to human health, including serious illness and death that result from the consumption of shellfish contaminated with algal toxins, or from direct exposure to waterborne or airborne toxins (Bricker et al., 2008; Lipton & Hicks, 1999, 2003). In response to eutrophication, various government agencies and environmental groups have taken management actions. For example, in order to support habitat protection and seagrass restoration in Tampa Bay estuary (the largest estuary in the state of Florida, with a surface area of ~1000 $km^2$), the Tampa Bay National Estuary Program (TBNEP) in coordination with other local and federal agencies and partners has developed and implemented a nutrient reduction plan since 1996, where nutrient numeric criteria and Total Maximum Daily Load (TMDL) target were developed from water quality data collected routinely from the bay waters. Threshold values for annual mean water quality indicators (*e.g.* chlorophyll-a, water clarity, and color) were also established and used to assess whether water quality met the target values to support seagrass recovery, and to determine whether further actions were required (Janicki & Wade, 1996; Janicki et al., 2000a, 2011).

The U.S. Environmental Protection Agency (EPA) has implemented the National Estuary Program to protect estuarine resources for several estuaries. However, only a few estuaries have water quality monitoring

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[*] Corresponding author. Tel.: +1 727 331 3948.
*E-mail address:* chengfeng@marine.usf.edu (C. Le).

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programs similar to the TBNEP. Most of the local estuary programs suffer from lack of technical and financial resources to implement a strategy for long-term and routine water quality assessment. Even for well-established programs such as the Tampa Bay Estuary Program (1996) and the Chesapeake Bay Program (1993), only a limited number of stations can be visited each month (*e.g.* 56 stations in Tampa Bay and 49 stations in Chesapeake Bay). Such inherent limitations in any field program would result in temporally and spatially discontinuous data due to unfavorable sampling conditions (*e.g.*, poor weather). Further, given the fast-changing nature of water quality parameters (*e.g.*, turbidity and Chla) in estuarine waters (Chen et al., 2010; Harding et al., 2005), potential aliasing in long-term climatologies and trend analyses may occur. Clearly, a better approach needs to be developed to minimize the aliasing problem for estuaries with existing water quality assessment program and, more importantly, to help other estuary programs that do not have sufficient technical and financial resources to support sustainable field activities.

The use of satellite data has proven beneficial for deriving water quality parameters when direct field measurements are unattainable (Sathyendranath et al., 2004), and the synoptic and frequent coverage may also reduce potential spatial and temporal aliasing (Harding et al., 2005). However, it is not trivial to derive the water quality parameters from satellite measurements for optically complex estuarine waters. This is particularly true for the water column Chla, which is an index of phytoplankton biomass. This is because optical properties in estuaries are often dominated by water constituents other than phytoplankton, such as colored dissolved organic matter (CDOM), detrital particles (both organic and inorganic), and the shallow bottom. Consequently, the traditional OC3 (for MODIS) and OC4 (for SeaWiFS) empirical blue/green band ratio algorithms resulted in large uncertainties when estimating Chla from satellite measurements (Gitelson et al., 2007; Le et al., 2012; Werdell et al., 2009). While other algorithms tried to avoid this problem by using the red and near-infrared (NIR) wavelengths (Dall'Olmo et al., 2005; Le et al., 2009; Thiemann & Kaufman, 2000), most of these alternative approaches cannot be applied to MODIS or SeaWiFS because the sensors do not have the proposed spectral bands (Le et al., 2012). Currently, EPA is attempting to use satellite-derived Chla to help establish numerical nutrient criteria for coastal waters (Schaeffer et al., 2012), yet the large uncertainties in the satellite-based Chla data make it difficult to extend the approach to estuaries. Because SeaWiFS (1997–2010) and MODIS (2000–present) represent the longest satellite ocean color measurements, developing a feasible Chla algorithm applicable to these two sensors for estuarine waters becomes an urgent task for the research community.

Aside from the technical difficulty in obtaining more frequent and synoptic assessment of water quality parameters than those from field programs, understanding the long-term trend and short-term variability also requires in-depth investigation. Climate variability and weather events, which are not manageable, can greatly influence water quality conditions and bloom occurrence in estuaries (Abler et al., 2002; Cloern et al., 2005; Morrison et al., 2006; Paerl & Paul, 2012; Struyf et al., 2004; Whitehead et al., 2009), affecting interpretation of trends in long-term water quality data.

Thus, given the potential spatial and temporal aliasing problem in the existing water quality assessment program, the lack of reliable algorithms to derive Chla from satellite measurements, and the lack of understanding of the potential linkage of the long-term water quality trend in Tampa Bay to climate variability, the objectives of this study are to:

1) Develop a reliable Chla algorithm applicable to both MODIS and SeaWiFS as well as to future ocean color sensors, and establish a long-term Chla environmental data record (EDR) based on these synoptic and frequent satellite observations;
2) Understand the long-term trend and short-term variability of the Chla EDR, especially in the context of climate variability and nutrient reduction management;
3) Make recommendations for management decision support for Tampa Bay and other estuaries.

We will begin by briefly introducing the Tampa Bay estuary and the current water quality assessment and management plan. Then, *in situ* and satellite data collection and processing methods are described. The Chla algorithm based on a new approach is developed and validated using field and satellite measurements, and then used to construct the Chla EDR from SeaWiFS and MODIS. Spatial and temporal distributions of the Chla EDR are analyzed with environmental data to show their potential linkage with climate variability. Finally, a water quality decision matrix (WQDM) is derived from the Chla EDR, and its implications for management decision support are discussed.

## 2. Study area

Tampa Bay is the largest estuary in the state of Florida, USA. It is conventionally subdivided into four geographical segments, namely Old Tampa Bay (OTB), Hillsborough Bay (HB), Middle Tampa Bay (MTB), and Lower Tampa Bay (LTB) (Fig. 1a). With a surface area of ~1000 km$^2$ and average water depth of ~4 m, the estuary provides vital habitats for crustaceans, fish, shellfish, and a variety of marine mammals (Harwell et al., 1995). Trade, tourism, development, and fishing industries are all located here, contributing more than $5 billion annually to the economy of this region (Florida Department of Community Affairs, 1996). Four major rivers discharge nutrients, sediments, and CDOM into different Tampa Bay segments (Chen et al., 2007; Pillsbury & Byrne, 2007). These are the Hillsborough River (HR), Alafia River (AR), Little Manatee River (LMR), and Manatee River (MR) (Fig. 1a) (Lewis & Estevez, 1988). These four rivers drain approximately 75% of the bay's watershed and account for up to 82% of the total stream flow into the bay (Schmidt & Luther, 2002).

By the late 1970s, this estuary was deeply impacted by eutrophication, exhibiting frequent phytoplankton and macroalgal blooms and significant seagrass loss (Greening & Janicki, 2006). Since then, the Environmental Protection Commission of Hillsborough County (EPCHC) implemented a long-term water quality monitoring plan, from which a suite of water quality parameters, including water-column Chla and water clarity (Secchi Disk Depth), were collected every month from 56 pre-defined stations (white in Fig. 1b). In the 1990s, the TBNEP was established to coordinate efforts to sustain a healthy bay-wide ecosystem through managing nutrient loadings and habitat restoration. For example, Chla and water clarity targets and threshold values for warnings were established for each bay segment based on the statistics of *in situ* measured data from 1984 to 1998 (Table 1) (Janicki et al., 2000b). An approach has been developed to use a WQDM based on these target and threshold values (Janicki et al., 2000a). The WQDM was used to track annual mean water quality conditions (as measured by Chla and light attenuation) in order to help make management decisions (Table 2). In the WQDM, a “Green” state is derived when both water quality indexes (Chla and light attenuation) are better than target values in Table 1. Here “better” means that the quality is better, *i.e.*, with Chla and light attenuation lower than the target values. “Green” means ‘stay on course’ and no management action is required. The color of “Yellow” is derived when one of the water quality parameters becomes worse (*i.e.*, higher than the small-magnitude deviation (1 standard deviation) but lower than the large-magnitude deviation (2 standard deviations)). In terms of management, “Yellow” means caution and stay alert. The color of “Red” is derived when both water quality parameters become much worse (*i.e.*, higher than the large-magnitude deviation), signifying poor water quality conditions. “Red” for two consecutive years indicates the need for management action. However, because of the inherent limit in spatial coverage and sampling frequency in any field program, it is necessary to examine whether the results suffer from spatial or temporal aliasing, and whether the alarming water quality state resulted from increased nutrient releases or climate variability. This