Monitoring Water Quality in Tampa Bay: Coupling *in Situ* and Remote Sensing

by

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of the requirements for the degree of
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To my parents
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Table of Contents

List of Tables iii
List of Figures iv
Abstract viii

Chapter 1. Introduction 1
  1.1. The quality of the water of Tampa Bay 1
  1.2. Remote sensing of water quality in estuarine waters 4
  1.3. Objectives and outline 6

  2.1. Abstract 7
  2.2. Introduction 8
  2.3. Methods and Materials 9
    2.3.1. Deployment of sensors 9
    2.3.2. Ancillary data 11
    2.3.3. Data analysis 12
  2.4. Results and Discussion 13
    2.4.1. Physical variations 13
    2.4.2. Bio-optical variations 14
    2.4.3. Sediment resuspension versus phytoplankton blooms 20
    2.4.4. Implications for water quality monitoring 21
  2.5. Conclusions 24

Chapter 3. Colored Dissolved Organic Matter in Tampa Bay 26
  3.1. Abstract 26
  3.2. Introduction 27
  3.3. Methods 28
    3.3.1. Temperature, salinity, chlorophyll and total suspended solids 28
    3.3.2. Dissolved Organic carbon 31
    3.3.3. CDOM absorption coefficients and fluorescence 31
    3.3.4. Phytoplankton pigment absorption coefficients 32
    3.3.4. Statistic test 32
  3.4. Results 33
    3.4.1. Distribution of TSS and Chl 33
    3.4.2. Light absorption by CDOM 33
    3.4.3. DOC 42
    3.4.4. CDOM fluorescence efficiency 44
  3.5. Discussion 45
List of Tables

Table 3-1  Correlation coefficients (r) between surface salinity and TSS and between surface salinity and Chl in Tampa Bay and the AR in the dry and wet seasons 35

Table 3-2  Results of regression analysis between aCDOM(400) and surface salinity in Tampa Bay and the AR in the dry and wet seasons. 39

Table 3-3  Correlation coefficients (r) between aCDOM(400) and TSS and between aCDOM(400) and Chl in Tampa Bay and the AR in the dry and wet seasons 40

Table 3-4  The averages and standard deviations (in parentheses) of CDOM absorption (aCDOM(443)) and phytoplankton pigment absorption (aph(443)) in different bay segments and seasons 41

Table 3-5  Results of regression analysis between CDOM fluorescence and aCDOM(400) Tampa Bay and the AR during the dry season. 45

Table 4-1  Symbols, definitions and Units 58

Table 4-2  Comparison between the measured at-sensor radiances (mW cm
\(^{-2}\) \(\mu m^{-1} sr^{-1}\)) at the MODIS 250 m bands and those predicted from the 1 km ocean color bands 62

Table 4-3  Comparison between in situ versus MODIS remote sensing reflectance at 645 nm \((R_a(645), sr^{-1})\), with the latter derived using 1) single scattering approximation and the original at-sensor radiance (i.e., pre-launch calibration) and 2) multi-scattering method and the cross-calibrated at-sensor radiance, respectively 62
List of Figures

Figure 1-1. MODIS/Aqua 250 m resolution image of Tampa Bay showing the four sub-basins of the Bay and four major tributaries 2

Figure 1-2. NOAA/USGS merged bathymetric/topographic digital elevation model (DEM) of the Tampa Bay estuary at 30 m spatial resolution (Gesch & Wilson, 2001) 3

Figure 2-1. (Left): Schematic of in situ monitoring station 10

Figure 2-2. Hourly averaged time-series of (A) winds, (B) water levels, (C) currents, (D) salinity, and (E) temperature 15

Figure 2-3. Hourly averaged time-series of (A) significant wave period, (B) significant wave height, (C) near bottom wave orbital velocity, and (D) near-bottom wave shear stress 16

Figure 2-4. (A) Hourly averaged time series of backscattering coefficient (bbp(532)) in the surface (thin solid line) and bottom layers (thin dashed line) 19

Figure 2-5. Spectral density of time series of (A) water levels, (B) bbp(532), and (C) Chl 20

Figure 2-6. Variations of bbp(532) and Chl with relation to salinity, water levels, and currents from 11-19 December 2004 22

Figure 2-7. The relative errors ($\frac{mi - mm}{mm} \times 100\%$) of Chl (thin blue) and bbp(532) (thick red) incurred by representing a monthly mean by a single snapshot measurements (mi) 22

Figure 2-8. The monthly time series of (A) Chl (mg m$^{-3}$) and (B) turbidity (NTU) at one of the EPCHC stations (See Fig. 1 for station location) from 1997 to 2003 24

Figure 3-1. Map of Tampa Bay with sampling locations overlaid 29
Figure 3-2. (A) Percentage of average (1973-2003) monthly mean flow rates of Hillsborough River (HR), Alafia River (AR), Little Manatee River (LMR), Manatee River (MR) relative to the total monthly mean flow rate from these four major rivers of each month.

Figure 3-3. Surface salinity versus (A) total suspended solids concentration (TSS) and (B) chlorophyll concentration (Chl).

Figure 3-4. Surface salinity versus CDOM $a_{\text{CDOM}(400)}$ for Tampa Bay and the AR in the dry and wet seasons (see also Table 3).

Figure 3-5. $a_{\text{CDOM}(400)}$ versus (A) TSS and (B) Chl and (C) $a_{\text{CDOM}(443)}$ versus aph(443) for Tampa Bay and the AR in the dry and wet seasons (also see Table3-3)

Figure 3-6. CDOM absorption spectral slope ($S$) versus surface salinity for Tampa Bay and the AR in the dry and wet seasons.

Figure 3-7. Surface salinity versus DOC concentration for Tampa Bay and the AR in the dry season in June, 2004

Figure 3-8. $a_{\text{CDOM}(400)}$ versus DOC concentration for Tampa Bay and the AR in the dry season in June, 2004

Figure 3-9. CDOM fluorescence (QSE) versus $a_{\text{CDOM}(400)}$ (m$^{-1}$) for Tampa Bay and the AR during the dry season in June, 2004

Figure 4-1. MODIS 250 m image of Tampa Bay showing the four segments of the bay and major tributaries

Figure 4-2. (a) MODIS at-sensor radiance at 667 nm (1 km) on 13 December 2004, 18:43 GMT over the study area

Figure 4-3. Scatter plots of the at-sensor radiance (mW cm$^{-2}$ μm$^{-1}$ sr$^{-1}$) in the two 250 m bands (645 nm in (a) and 859 nm in (b)) as measured by the sensor and predicted by the calibrated 1 km ocean color bands
Figure 4-4. Remote sensing reflectance in Tampa Bay at band 1 ($R_{rs}(645), \text{sr}^{-1}$) from *in situ* measurements and MODIS estimates derived using 1) multiple-scattering atmospheric correction of the cross-calibrated at-sensor radiance (filled circles); and 2) single-scattering atmospheric correction of the original (i.e., pre-launch calibration) at-sensor radiance (open circles)

Figure 4-5. The relationship between *in situ* turbidity (NTU) and MODIS remote sensing reflectance at band 1 ($R_{rs}(645), \text{sr}^{-1}$) in a log-log scale

Figure 4-6. The relationship between *in situ* turbidity from the 2004 measurements and that estimated from concurrent MODIS data using the relationship derived from the 2005 data

Figure 4-7. Climatological (May 2003 to April 2006) monthly means of turbidity derived from MODIS 250 m data

Figure 4-8. The climatological monthly means of turbidity derived from MODIS between May 2003 and April 2006 at several stations in Tampa Bay (see Fig. 1 for station locations)

Figure 4-9. Monthly turbidity images from MODIS 250 m data (top panels) and from *in situ* measurements (lower panels) for April of 2004, 2005, and 2006 (no *in situ* measurement was available for April 2006)

Figure 4-10. Daily averaged wind speed measured at Port of Manatee (27.64, -82.56) in April 2004, 2005, and 2006 (data courtesy of NOAA)

Figure 4-11 Time-series of monthly turbidity estimates derived from *in situ* and MODIS measurements at selected stations shown in Fig. 1

Figure 5-1. A SeaWiFS quasi-true-color RGB image of Tampa Bay showing the four sub-segments, namely, Old Tampa Bay (OTB), Hillsborough Bay (HB), Middle Tampa Bay (MTB), and Lower Tampa Bay (LTB)

Figure 5-2. *In situ* secchi disk depth (SDD, m) versus light attenuation coefficient at 490 nm ($K_d(490), \text{m}^{-1}$) derived from SeaWiFS using (1) an empirical band-ratio algorithm (EA) (triangles, updated Mueller’s (2000) algorithm) and (2) a semi-analytical algorithm (SA) (circles, Lee et al., 2005a)
Figure 5-3. Climatological monthly composites (September 1997 – December 2005) of SeaWiFS SDD (m) 84

Figure 5-4. Climatological monthly means of SeaWiFS (filled circles) and in situ (open circles) secchi disk depth (SDD, m) at several stations within Tampa Bay (Fig. 1) 87

Figure 5-5. Climatological monthly means of (A) in situ chlorophyll (mg m$^3$), (B) color (Pt-unit), and (C) turbidity (nephelometric turbidity units, NTU) measurements from the EPCHC monitoring program at several stations from the various bay-segments (see Fig. 1 for the station locations) collected between September 1997 and December 2005 88

Figure 5-6. (a) Climatological monthly means of river flow from the Hillsborough River (open circles) and the Alafia River (filled circles) from 1997 to 2005 92

Figure 5-7. Monthly means of SeaWiFS and in situ SDD at selected stations (Fig. 1) from September 1997 to December 2005 93

Figure 5-8. SeaWiFS SDD anomaly between September 1997 and December 2005 at several stations in Tampa Bay (Fig. 1) 94

Figure 5-9. Monthly means of river flow from the Hillsborough River (open circles) and the Alafia River (filled circles) from September 1997 to December 2005 95

Figure 5-10. The number of days when the daily averaged wind speed was > 4.0 m s$^{-1}$ of each month from September 1997 to December 2005 at the PORT station near Saint Petersburg (27°45.6'N, 82°37.6'W) 95
Monitoring Water quality in Tampa Bay: Coupling in Situ and Remote Sensing

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ABSTRACT

Water quality in Tampa Bay was examined using concurrent in situ and satellite remote sensing observations. Chlorophyll and suspended sediment concentrations showed large short-term variability, primarily driven by tide and wind forcing. Superimposed on these high frequency variations were recurrent phytoplankton blooms stimulated by decreases in turbidity 1-2 days after wind-induced bottom sediment resuspension events; the blooms were particularly strong if neap tides occurred after the wind events. The in situ data show that observations once per month are inadequate to sample short-term variability and that therefore the current monthly water quality surveys may have uncertainties of -50 to 200% if they are used to represent the monthly mean concentrations of chlorophyll or suspended sediment. Such uncertainties make it difficult to identify trends and interannual variability based on the in situ monitoring program.

Colored dissolved organic matter (CDOM) generally showed good relationship with salinity and primarily delivered by riverine inputs but showed conservative and non-conservative mixing behaviors for the dry and wet seasons, respectively. CDOM in Old Tampa Bay (OTB), however, showed properties that were different from those in other Bay segments, and the non-conservative CDOM mixing behavior may be simply due to a three-end-member mixing scenario in which Hillsborough Bay and Middle Tampa Bay also receive water from Old Tampa Bay. A turbidity algorithm was successfully developed for application of MODIS/Aqua 250 m imagery. The MODIS turbidity images showed distinct spatial and temporal patterns related to river runoff in the upper bay and...
wind-induced sediment resuspension events in the middle and lower portions of the Bay. Similarly, light attenuation from SeaWiFS estimated using a new semi-analytical algorithm confirmed that water clarity was related to river runoff and to wind-induced sediment resuspension events. Wind is shown repeatedly to be another important factor controlling water quality in the Bay. The study shows that remote sensing products have the potential to be an important tool to help resource managers assess conditions in a large estuary like Tampa Bay synoptically, frequently and repeatedly.
Chapter 1. Introduction

1.1. The quality of the water of Tampa Bay

Tampa Bay, with a surface area of \( \sim 1000 \text{ km}^2 \), is Florida’s largest open-water estuary. For practical purposes, it is typically divided into four sub-basins, namely: Old Tampa Bay (OTB), Hillsborough Bay (HB), Middle Tampa Bay (MTB), and Lower Tampa Bay (LTM) (Fig. 1-1). The estuary has an average depth of \( \sim 4.0 \text{ m} \), but it has an extensive navigation system with a \( >10.0 \text{ m} \) deep shipping channel running along its axis from the mouth to HB (Fig. 1-2). This channel plays an important role in determining estuarine circulation (Weisberg & Zheng, 2005) and water quality characteristics (Bendis, 1999).

Tampa Bay is a diverse and productive natural system that provides a vital habitat for crustaceans, fish, shellfish and a variety of marine mammals, reptiles and birds (Harwell et al., 1995), and contributes over $5 billion annually to the local economy from trade, tourism, development, and fishing (FDCA, 1996). It is therefore critical that the development of the Bay be conducted in an environmentally sound way to sustain a clean and healthy system.

Tampa Bay has undergone substantial anthropogenic alterations. In the decades prior to the 1980s, Tampa Bay was heavily polluted by nutrient loadings from sources such as sewage and wastewater, causing severe eutrophication and phytoplankton blooms (Johansson, 2000). The decline in water quality due to pollution led to substantial losses of seagrass coverage (Lewis et al., 1998; Tomasko et al., 2005). Since then, significant ecosystem restoration efforts have been under way. In 1990, the Tampa Bay National Estuary Program (TBNEP) was established to integrate efforts to restore and protect the Bay. In 1996, TBNEP developed a Comprehensive Conservation and Management Plan (CCMP), which focused on restoration of seagrass to levels similar to those observed in the 1950s by improving water quality through construction of better sewage treatment
facilities in the neighboring cities and controlling the amount of nitrogen reaching the bay (Janicki & Wade, 1996). These efforts gradually improved the water quality of the Bay, and some of the seagrass has recovered (Johansson, 2000; Tomasko et al., 2005).

Figure 1-1. MODIS/Aqua 250 m resolution image of Tampa Bay showing the four sub-basins of the Bay and four major tributaries. The sub-basins are Old Tampa Bay (OTB), Hillsborough Bay (HB), Middle Tampa Bay (MTB), and Lower Tampa Bay (LTB). The rivers are the Hillsborough River (HB), the Alafia River (AR), the Little Manatee River (LMR), and the Manatee River (MR). The Environmental Protection Commission of Hillsborough County’s (EPCHC) water quality monitoring stations are overlaid with various symbols to indicate different monthly sampling times: diamond (OTB) generally sampled the first week, triangles (HB) the second week, and squares (MTB and LTB) the last week. The inset shows the location of Tampa Bay in the State of Florida.
Figure 1-2. NOAA/USGS merged bathymetric/topographic digital elevation model (DEM) of the Tampa Bay estuary at 30 m spatial resolution (Gesch & Wilson, 2001). The resolution of the gridded dataset is 250 m. Grey and white represent land and missing data, respectively.

Previous studies have suggested that the primary factors regulating water quality seem local precipitation or river runoff and associated nutrients and sediments (Janicki et al., 2001). For example, HB receives the discharge of the two largest rivers emptying into Tampa Bay (the Hillsborough River and the Alafia River, Fig. 1-1). HB also generally has higher chlorophyll concentrations, turbidity and light attenuation coefficients than MTB and LTB (Janicki et al., 2001). The seasonal and inter-annual variability of water quality is closely related to hydrologic conditions (e.g., precipitation and river flow) (Lipp et al., 2001; Schmidt and Luther, 2002). Deteriorating water quality and the discontinuous recovery of seagrass in 1998 was widely attributed to increased rain fall associated with the stronger 1997-1998 El Nino event (Tomasko et al., 2005).

Our current understanding of the causes of variability in water quality is based on in situ field surveys. As for most coastal environmental monitoring programs, at present water quality in Tampa Bay is measured on a monthly basis at established stations. Fig. 1-1 shows the location of sampling stations used in the Tampa Bay water quality
monitoring program conducted by the Environmental Protection Commission of Hillsborough County (EPCHC). Due to the size of Tampa Bay and logistical support, the EPCHC usually takes 3 weeks to sample the Bay, with approximately one segment sampled per week sequentially (Fig. 1-1, and Boler et al., 1991). These observations are used to represent the monthly conditions of the Bay, and to infer seasonal and inter-annual trends (Janicki et al., 2001; Johansson, 2000). Clearly, the sampling is intensive, yet not synoptic. It would be ideal to sample the Bay synoptically and more frequently, as routinely done in open ocean waters using satellite remote sensing technologies, to provide resource managers and decision-makers with a more realistic view of the variability of water quality Tampa Bay.

1.2. Remote sensing of water quality in estuarine waters

Satellite remote sensing is a powerful tool to observe physical and biological processes in the open ocean (e.g., Behrenfeld et al., 2001). However, its routine application in estuarine and coastal waters has been limited (IOCCG, 2000). Retrieved products such as chlorophyll lack of sufficient accuracy in coastal waters due to problems with atmospheric correction and bio-optical inversion algorithms. The operational atmospheric correction algorithms were designed primarily for the open oceans (Gordon & Wang, 1994; Gordon 1997). In coastal waters, these algorithms often result in erroneous masks of coastal waters and underestimates of water-leaving radiance, including negative values in the blue 412 nm band (Hu et al., 2000; Harding et al., 2005). The assumption that near infrared (NIR) wavelengths provide a “black pixel” breaks down due to high suspended sediment loads in coastal waters (Wang & Shi, 2005). In addition, absorbing aerosols over coastal waters can further degrade the performance of the general atmospheric correction, especially for the blue bands. Various modifications have been proposed (Stumpf et al., 2000), but no fully satisfactory solution has been achieved yet. The generalized bio-optical inversion algorithms also contain large uncertainties when applied to coastal waters (Lee et al., 2005b). Therefore, a regional bio-optical algorithm has often been developed for specific coastal water (Dzwonkowski and Yan, 2005).
The optical properties of estuarine and coastal waters are highly variable and complex, posing a great challenge to de-convolution of the mixed contributions of different optical components. For example, colored dissolved organic matter (CDOM) and detritus or sediments often exhibit larger absorption than phytoplankton (Babin et al., 2003; Maguson et al., 2004). Therefore, small errors in sediment concentration or CDOM light absorption estimates cause substantial errors in chlorophyll estimates (Wozniak & Stramski, 2004). Indeed, to develop better bio-optical inversion algorithms, a detailed characterization of optical properties for specific coastal waters is a necessary first step.

Another problem is that current satellite ocean color sensors have limited spatial and spectral resolution applications in estuarine and coastal waters. The standard Sea-viewing Wide Field-of-View Sensor (SeaWiFS) and the Moderate Resolution Imaging Spectroradiometer (MODIS) ocean color data have 1 km resolution at nadir, while estuarine and coastal waters are highly patchy, with variables having spatial scales ranging from 100 to 1000 m (Sanderson and Taylor, 2003). This precludes wide application of ocean color observations in quantitative studies of coastal waters.

Recent advances in both algorithm developments and sensor technology promises to overcome some of the difficulties. First, an improved atmospheric correction algorithm has been developed using short-wave infrared wavelengths (SWIR) to account for the non-zero water-leaving radiance at NIR (Wang & Shi, 2005). This may improve the performance of atmospheric corrections in coastal waters with high sediment loads. Second, various semi-analytical bio-optical algorithms have been proposed to estimate water constituents (Carder et al., 1999; Lee et al., 1999; Lee et al., 2002 Lee et al., 2005a; Maritorena et al., 2002). These algorithms can be further improved using locally-derived parameterizations (Cota et al., 2004; Maguson et al., 2004).

MODIS sensors are equipped with 250m and 500m “sharpening bands”, originally designed for land and aerosol mapping. These medium resolution bands also have the serve to potential to map water quality indices due to their finer spatial resolution and adequate sensitivity (Hu et al., 2004; Miller & Mckee, 2004). MODIS also has spectral bands designed to retrieve solar-induced chlorophyll fluorescence. Preliminary studies show that satellite-retrieved sun-induced chlorophyll fluorescence is related to phytoplankton concentrations in coastal waters (Hoge et al., 2003; Hu et al.
These advances provide unprecedented opportunities of using satellite remote sensing to monitor water quality in estuaries like Tampa Bay.

1.3. Objectives and outline

The overall objective of this thesis is to characterize temporal and spatial variability of water quality in Tampa Bay and understand the governing processes and mechanisms. For this purpose, data collected from discrete samples, continuous underway measurements, high frequency bio-optical sensors, and synoptic remote sensing imagery were examined. The combination of in situ and satellite remote sensing observations provides better temporal and spatial coverage of water quality and is expected to reveal more realistic and complete variation patterns and trends of water quality. Among a wide variety of indices, several key water quality indices were selected (Boler et al., 1991), namely: colored dissolved organic matter (CDOM), turbidity or total suspended substance (TSS), and secchi disk depth (SDD, a surrogate of water clarity).

This thesis is structured as follows. Chapter 2 focuses on the short-term (tidal and subtidal) variability in chlorophyll and suspended sediment indices in Tampa Bay. Chapter 3 examines CDOM distribution in Tampa Bay in the dry and wet seasons. Chapter 4 investigates turbidity variability in the Bay using MODIS 250 m imagery, which required cross-calibration with the 1 km resolution ocean color bands, and development of simple atmospheric correction and bio-optical algorithms. Chapter 5 studies water clarity using SeaWiFS imagery. Chapter 6 summarizes the findings and provides suggestions to improve monitoring of water quality in Tampa Bay.
Chapter 2. Physical forcing of short-term bio-optical variability in Tampa Bay: Observations from a coastal tower

2.1. Abstract

Short-term phytoplankton and sediment dynamics of Tampa Bay were examined with data collected from bio-optical, physical, and meteorological sensors mounted on a coastal tower from 8 December 2004 to 17 January 2005. Both chlorophyll concentration (Chl, 2.0 to 12.0 mg m$^{-3}$) and the backscattering coefficient at 532 nm (bbp(532), an indicator of sediment concentration, 0.03 to 0.20 m$^{-1}$) showed large fluctuations. These variations were dominated by the semidiurnal and diurnal frequencies of tides. In addition, three major sediment resuspension events were observed, and these were followed by increases in Chl. The sediment resuspension events were caused primarily by wind-induced mixing (e.g., hourly averaged wind speed >8.0 m s$^{-1}$). Minimum critical bottom shear stress for sediment resuspension was ~0.2 N m$^{-2}$ at the study site. Sediments remained in the water column for 2-3 days after the wind event. Moderate increases in Chl were often observed about 1-2 days after sediments settled, possibly due to the combined effects of increased nutrients and light regime. One such event developed into an intensive (Chl >10 mg m$^{-3}$), transient (2 days) phytoplankton bloom, which was uniquely coincident with a neap tide. This suggested that phytoplankton blooming was related not only to the magnitudes of winds and tides but also to their relative timing. The results suggest that single monthly observations are not good estimators of monthly mean conditions, as they have uncertainties ranging from -50% to 200% relative to actual monthly mean conditions.
2.2. Introduction

Estuaries are highly dynamic environments where rivers, winds, and tides interact to determine hydrological, biological, and geological variability. These forcings lead to a wide range of temporal scales of variation in phytoplankton and suspended sediment concentrations in estuaries. Riverine inputs can determine the magnitude and extent of phytoplankton blooms by delivering nutrients and influencing stratification of the water column over seasonal and interannual scales (Cloern, 1991; Harding, 1994). Semidiurnal or diurnal tides lead to variations in phytoplankton biomass and sediment concentrations through tidal advection and tidal mixing (Cloern et al., 1989; Li & Smayda, 2001; Roegner et al., 2002). Superimposed on these “periodic” variations are wind events. Pulsed winds modify estuarine circulation and water level, and generate waves that can suspend sediments (e.g., Schoellhamer, 1995) and mix nutrients and benthic algae into overlying waters (Lawrence et al., 2004; Yeager et al., 2005).

Many studies have addressed high frequency variations of phytoplankton in estuarine ecosystems (Cloern et al., 1989; Cloern, 1991; Desmit et al., 2005; Li & Smayda, 2001; Roegner et al., 2002). However, one of the main obstacles has been the lack of reliable means for high frequency sampling of phytoplankton in larger estuaries over synoptic scales (e.g., Roegner et al., 2002). High frequency variability of sediments has been well documented using optical and/or acoustic sensors (Li & Amos, 2001; references therein). This variability results primarily from sediment resuspension, driven by highly variable winds, waves, tides, and interactions among them (Jing & Ridd, 1996; Li & Amos, 2001; Schoellhamer, 1995). Few studies have been able to address the relationship between sediment and phytoplankton dynamics, even though turbidity is a crucial factor affecting phytoplankton blooms (Desmit et al. 2005; May et al., 2003).

The Tampa Bay water quality monitoring program has been conducted since 1974 by the Environmental Protection Commission of Hillsborough County (EPCHC). This program assesses water quality, but there has been little information available on short-term scales (such as tidal and subtidal) of phytoplankton and sediment concentrations. The EPCHC conducts monthly field surveys which typically span 3 weeks, with approximately one in one week (Figure 2-1). The single monthly in situ measurements
conducted at each station are often used to characterize variation and trends of Chl and sediments in the bay over seasonal and interannual scales (Janick et al., 2001; Johansson, 2000). But as observed in other estuaries (e.g., Johnson et al., 2000), the monthly observations inherently suffer from aliasing. The extent to which the high frequency variability may influence a long term trend analysis has not been evaluated.

In this chapter, we studied the short-term variability of phytoplankton and suspended sediments in Tampa Bay using data collected from bio-optical, physical, and meteorological sensors mounted on a coastal tower station. Our objectives were to (1) characterize high frequency variations in phytoplankton and suspended sediments in Tampa Bay (variability); (2) understand governing processes responsible for the observed variability (forcing); and (3) discuss implications of these findings on long-term trend analyses of water quality in the Bay.

2.3. Methods and Materials

2.3.1. Deployment of sensors

Bio-optical sensors were deployed on a coastal tower located in Manatee Channel (27.661°N, 82.5834°W, Fig.2-1) on 14-27 July 2004 and from 8 December 2004 to 17 January 2005, respectively. The station is located near the middle of the Bay at a bottom depth of ~4.6 m (http://comps.marine.usf.edu/BRACE/).

Two types of bio-optical sensors were deployed, a WETLabs™ ECO-BBSB sensor measuring backscattering coefficient at 532 nm (bbp(532)) and a WETLabs™ ECO-FLNTUSB sensor measuring LED stimulated chlorophyll fluorescence near 685 nm. Both sensors had an internal battery and memory for data logging. To determine if there were differences in chlorophyll and sediment between the surface and bottom, one set of scattering and chlorophyll sensors was installed at 1m depth below the surface with sensors facing down, and another set at 1.5 m above the bottom with sensors facing up (Fig. 2-1). Sample frequency was set to once per hour. The recorded raw data (voltages) were processed with the WETLabs™ ECOView software and converted to Chl (mg m⁻³) and bbp(532) (m⁻¹) using calibration coefficients provided by the manufacturer. Chl
Figure 2-1. (LEFT): Schematic of in situ monitoring station. (Right): Moderate Resolution Imaging Spectroradiometer (MODIS/Aqua, 250m) image of Tampa Bay on 20 December 2004 showing four bay segments, namely: Old Tampa Bay (OLB), Hillsborough Bay (HB), Middle Tampa Bay (MTB), and Lower Tampa Bay (LTB), and various sampling stations: Manatee Channel station (+) where chlorophyll fluorometers, backscattering meters and Sea-Bird SeaGauge were mounted; Port of Manatee (◊) where wind data were collected; Sunshine Skyway Bridge station (Δ) where Acoustic Doppler Current Profile (ADCP) current data near surface were obtained; One station (□) from the EPCHC Tampa Bay water quality monitoring program where 7-year monthly time series of Chl (mg m$^{-3}$) and turbidity (NTU) from 1997 to 2003 were obtained. Schematic diagram also shows how the sensors were mounted onto the Manatee Channel station. MSL in the schematic stands for Mean Sea Level.
values were further calibrated using concurrent discrete water samples collected at the station location and analyzed using the fluorometric method (Strickland and Parsons, 1972). A Sea Bird Electronics SeaGauge wave and tide recorder was also deployed on the station about 2.2 m below the sea surface (Fig. 2-1), measuring salinity, temperature, pressure, significant wave height and wave period (ftp://comps.marine.usf.edu/pub/BRACE/seagauge_data).

The WETLab™ sensors were equipped with an anti-biofouling mechanism: before each measurement, a copper wiper cleaned the optical window. Unfortunately, during the two week summer deployment, barnacles grew and covered the sensors after only about one week, preventing further data collection. In contrast, the sensors deployed during the winter successfully collected data for 40 days. Therefore, only winter data were used in this study.

2.3.2. Ancillary data

Wind (both speed and direction) and currents from the Tampa Bay Physical Oceanographic Real Time System (PORTS) located at the Port of Manatee (27.637°N, 82.5633°W, ~3.3 km to the tower) and at the Sunshine Skyway Bridge (27.620°N, 82.6558°W, ~8.5 km to the tower), respectively, were obtained to represent general wind and current conditions. All data were binned into hourly data for this study. Pressure (pounds per square inch, PSI) collected from the seagauge was converted to water level (m) using the following equation:

\[
\text{Water Level} = (\text{pressure} - 14.7) \times 0.689476 - 2.05
\]

where 14.7 is the standard atmospheric pressure (PSI), 0.689476 is the conversion factor for pressure (PSI) to depth (m), and 2.05 is the offset of the sea gauge relative to the mean lower low water (MLLW) (Fig. 2-1). The absolute accuracy of water level is not critical for this study and only relative oscillations are relevant in this study.

Monthly time series of Chl (mg m⁻³) and turbidity (Nephelometric Turbidity Unit, NTU, a practical indicator of sediment concentration) between 1997 and 2003 were obtained from a nearby EPCHC water quality station (station 23, 27.666°N and 82.5992°W, ~1.7 km from our tower) (Fig. 2-1).
2.3.3. Data analysis

All time series data collected by the sensors were passed through a low-pass filter with cutoff time of 36 hours to separate tidal and subtidal variability. A spectral power analysis was also applied to extract dominant frequencies associated with the data.

In principle, bottom shear stress ($\tau_b$, N m$^{-2}$) includes shear stress from waves, currents, and interactions between waves and currents near the bottom boundary layer (Li & Amos, 2001). Due to the lack of current data at the tower station, only wave induced bottom shear stress ($\tau_w$) was estimated.

Maximum wave bottom shear stress was estimated using the model proposed by Li and Amos (2001). Briefly, linear wave theory was used to calculate wave properties and estimate wave bottom shear stress as follows:

\[
L = \frac{g \times T^2}{2 \times \pi} \tanh(k \times h) \tag{2}
\]

\[
ub = \frac{\pi \times H}{(T \times \sinh(k \times h))} \tag{3}
\]

\[
Ab = \frac{ub \times 2 \times \pi}{T} \tag{4}
\]

\[
\tau_w = 0.5 \times \rho \times fw \times ub^2 \tag{5}
\]

\[
fw = \exp(5.213 \times \left(\frac{kb}{Ab}\right)^{0.194} - 5.997), \quad \frac{Ab}{Kb} > 1.7 \tag{6a}
\]

\[
fw = 0.28, \quad \frac{Ab}{Kb} \leq 1.7 \tag{6b}
\]

where \(L\), \(T\), \(H\), \(h\), \(k\) are wave length (m), wave period (s), wave height (~0.707 times of wave significant height, m), water depth (m), and wave number \((2 \times \pi/L, \text{m}^{-1})\), respectively; \(U_b\), \(A_b\), \(f_w\), \(\rho\) are wave orbital velocity (m s$^{-1}$), near-bed wave orbital amplitude (m), wave friction factor (dimensionless), and seawater density (kg m$^{-3}$), respectively. The bottom roughness height (Kb) was taken as 0.003 m as obtained in Old Tampa Bay by Schoellhamer (1995) based on the assumption that within a limited geographic region this parameter is uniform (Peter Howd/USGS, personal communication).
2.4. Results and Discussion

2.4.1. Physical variations

Five distinct wind events were documented during the 40 day winter deployment period. These events occurred around 11, 14, 19, 26 December 2004 and 14 January 2005, respectively (arrows in Figs. 2-2A and 2-3B). Wind speeds associated with these events were typically > 8.0 m s\(^{-1}\) for ~1-2 days (>18.0 m s\(^{-1}\) on 26 December 2004). Dominant directions of these wind events mostly alternated from southerly/southeasterly (from south or southeast toward north or northwest) wind to northeasterly/northwesterly (from northeast or northwest toward southwest or southeast) wind. This transition pattern is typical of Southern Florida during passages of cold fronts from the north or northwest (Wang, 1998).

Water levels exhibited distinctive oscillations in mixed semidiurnal and diurnal forms with the highest water level of about 1.0 meter (Fig. 2-2B). Superimposed were fluctuations of water levels resulting from spring (e.g., around 10 January 2005) and neap (e.g., around 18 December 2004) tides. Low-pass filtered water levels revealed that local winds also played an important role in water levels. Northerly (from the north toward the south) winds led to decreased water levels (e.g., on 14 December 2004), while southerly (from the south toward the north) winds increased water levels (e.g., 25 December 2004). Current speeds ranged from 0.1 to 1.2 m s\(^{-1}\) with similar fluctuations as water levels, indicating that currents were driven primarily by tides. For example, despite similar wind conditions (< 3.0 m s\(^{-1}\)), daily average of current speed on 10 January 2005 (under a spring tide) was approximately 0.60 m s\(^{-1}\), about two-fold of that on 18 December 2004 (.about 0.30 m s\(^{-1}\), during neap tide). The directions of currents mostly reversed from about 62° to 242° true within one tidal cycle, primarily along the orientation of the deep channel at the Sunshine Skyway Bridge station (Fig. 2-2C).

Salinity showed similar fluctuations as water levels, ranging from 26 to 31 with higher salinity during flood tides and lower salinity during ebb tides (Fig. 2-2D), suggesting that water masses are horizontally transported by tidal advection. Water temperature ranged from 14 to 22 °C, and it mirrored passages of cold fronts depressing
temperature, otherwise water would gradually warm up under calm conditions (Fig. 2-2E).

Wave periods varied from 1 to 9 s with most waves having a period <2 s, showing that short waves prevailed in Tampa Bay in winter (Fig. 2-3A) due to the limited wind fetch inside Tampa Bay. Higher periods (e.g., >4 s) appeared independent of wind speed. For example there were higher periods on 4-10 January 2005, but wind speed was consistently lower. These longer waves (or swells) were likely transmitted from the West Florida Shelf (WFS). Significant wave height generally ranged from 25 to 200 cm with 5 peaks >100 cm (Fig. 2-3B), coincident with each of the five strong wind events. Wave bottom orbital velocities and bottom shear stresses exhibited similar patterns as wave height and wind speed except for some moderate peaks occurring on January 4-10 2005. The relatively higher wave periods during that period may explain the increased bottom shear stresses (Figs. 2-3C and 2-3D), indicating that bottom shear stress can be influenced by both local wind-induced waves and remotely transported swells.

2.4.2. Bio-optical variations

The backscattering coefficient, bbp(532), exhibited similar changes in the bottom and surface layers with the bottom values (mean and standard deviation were 0.092 and 0.044, m$^{-1}$, respectively) slightly higher than the surface values (mean and standard deviation were 0.072 and 0.040 m$^{-1}$, respectively) (Fig. 2-4A). The bottom chlorophyll fluorometer malfunctioned after about 9 days, but prior to that, similar Chl patterns were observed between the surface and bottom layers (Fig. 2-4B). These results indicate
Figure 2-2. Hourly averaged time-series of (A) winds, (B) water levels, (C) currents, (D) salinity, and (E) temperature. To show the subtidal variations, winds, water levels, salinity, and temperature data were filtered using a low-pass filter with cutoff time of 36 hours and shown in wind stickplot (A) and with red solid lines in B, D, E panels. Current data (C) were not filtered because there were too many missing data points.
Figure 2-3. Hourly averaged time-series of (A) significant wave period, (B) significant wave height, (C) near bottom wave orbital velocity, and (D) near-bottom wave shear stress. As in Figure 2-2, significant wave height and wave period were also filtered using the low-pass filter and shown with red solid lines in A, B panels. To show details of bottom shear stress, y-axis of panel D is presented with a logarithm scale and the black thick line stands for the minimum critical shear stress of 0.2 N m$^{-2}$, which was identified by visual inspection of time series of sediment resuspension. The points of zero values are not shown in this panel due to the logarithm scale.
that the water column of Tampa Bay is well-mixed in winter. To simplify the comparison, we focused on examining the surface Chl and bbp (532) data in this study.

The green backscattering coefficient, bbp(532), showed large variations ranging from 0.03-0.20 m$^{-1}$ (Fig. 2-4A). A spectral analysis revealed that the highest energy of bbp(532) variation is associated with semidiurnal and diurnal frequencies, similar to the water level spectrum (Fig. 2-5). This coherence suggests that sediment variability was primarily driven by tidal mixing. A closer look into the time series of bbp(532), salinity, water level and currents revealed that higher bbp(532) typically occurred in low salinity waters during ebb or early flood tides, sometimes displaying a double-peak feature (Fig. 2-6A). Similar features were also found in other studies, and can be attributed to the tidal effects on deposition and resuspension of sediments (e.g., Jing & Ridd, 1996). The low-pass filtered bbp(532) showed a baseline bbp(532) appeared to be about 0.06 m$^{-1}$ (the maximum value under calm conditions at wind speed <3.5 m s$^{-1}$). Compared to the baseline value, three sediment resuspension events can be identified, specifically on 8-16 and 25-30 December 2004 and 8-17 January 2005 (Fig. 2-4A). Apparently, the first two events were caused by winds or wind-induced waves. Sediments were typically suspended when hourly averaged wind speeds were > 8.0 m s$^{-1}$ (or daily averaged wind speeds >5.0 m s$^{-1}$, not shown) and bottom shear stress > 0.2 N m$^{-2}$ (Fig. 2-3D). These suspended sediments remained in the water column for ~ 2-3 days after a wind event. The above calculation of bottom shear stress (~0.2 N m$^{-2}$) is, however, conservative given that the current contributions to bottom shear stress were not included in our wave model, and therefore represents a minimum estimate of critical bottom shear stress for a pronounced sediment resuspension event.

However, winds alone do not account for all sediment resuspension. For example, the wind event on 19 December 2004 with speed > 8.0 m s$^{-1}$ did not result in a clear resuspension event. Likewise, the early stage of the third moderate sediment resuspension event could not be attributed to winds but was coincident with higher wave period at that period (Fig. 2-3A), suggesting the remotely transported wave may also contribute to sediment resuspension. Another possible reason for this resuspension is stronger currents observed at the same time (coincident with a spring tide). Unfortunately, we could not quantify the relative importance of currents versus waves for bottom shear stress in this
study, but previous studies suggested that currents played a minor role in sediment resuspension at some sites in Tampa Bay (Schoellhamer, 1995; 1996). The observed currents in this study are occasionally $> 1.0 \text{ m s}^{-1}$, significantly higher than $0.2 \text{ m s}^{-1}$ reported by Schoellhamer (1995, 1996) for Old Tampa Bay and Hillsborough Bay. Thus further studies are necessary to evaluate the importance of stronger currents in sediment resuspension in the Lower Tampa Bay.

Chl showed high frequency variations, with concentrations ranging from $\sim 2.0$ to $12 \text{ mg m}^{-3}$ (Fig. 2-4B). A spectral analysis suggested that Chl variation was coherent with water level variations and, therefore, driven by tides (Fig.2-5). These results are consistent with observations in other estuaries (Cloern et al., 1989; Li & Smayda, 2001; Roegner et al., 2002). Within a tidal cycle, higher Chl values frequently occurred in lower salinity waters and/or during early flood tides, indicating that tidal advection transports water masses with different chlorophyll concentrations and salinity back and forth along the Bay, in agreement with overall bay-wide chlorophyll and salinity distributions with higher chlorophyll and lower salinity in the upper bay and vice versa (Bendis, 1999; Weisberg & Zheng, 2005).

The low-pass filtered Chl time series showed that the Chl baseline is $\sim 3.5 \text{ mg m}^{-3}$ (the mode value of Chl data, representing the most common Chl values during the deployment period). Compared to this baseline concentration, three Chl increases were also identified. These increases in Chl did not exactly coincide with sediment resuspensions but occurred later, with a lag time of 1-2 days (Figs.2-4 and 2-6). One such an increase developed into an intensive phytoplankton bloom (Chl $> 12.0 \text{ mg m}^{-3}$) on 17-18 December 2004, $\sim 1$ day after suspended sediments returned to the normal condition.
Figure 2-4. (A) Hourly averaged time series of backscattering coefficient (bbp(532)) in the surface (thin solid line) and bottom layers (thin dashed line). The horizontal black thick solid line represents bbp(532) of 0.06 m$^{-1}$ as a baseline value, which is the maximum bbp(532) under calm conditions (wind speed < 3.5 m s$^{-1}$); (B) Hourly averaged time series of Chl data in the surface (thin solid line) and bottom layers (thin dashed line). The horizontal black thick solid line represents Chl of 3.5 mg m$^{-3}$ as a baseline concentration, which is the mode of surface Chl time series. The thick red lines are the low-pass filtered data with cutoff time of 36 hours to show subtidal variability of surface bbp(532) and Chl.
2.4.3. Sediment resuspension versus phytoplankton blooms

Given that there was no simultaneous Chl increase with sediment resuspension events, we conclude that there were minimal concentrations of benthic algae in the bottom sediment near the tower station. Therefore, increases in Chl after sediment settlement must have resulted mainly from phytoplankton growth in the water column adjacent to the station due to enhanced nutrient levels and optimal light availability. Indeed, both direct and indirect experiments suggested that phytoplankton growth in Tampa Bay is limited by nutrient availability, specifically by nitrogen concentration (Johansson, 2000; Vargo et al., 1991). Sediment resuspension has been widely suggested to increase nutrients in the water column and therefore is closely coupled to
phytoplankton dynamics (Lawrence et al., 2004; Stephen et al., 2004). Increased nutrients, however, can't be used until sediment concentrations decline and sufficient light become available for phytoplankton growth.

Sediment resuspension alone can't account for the intensive phytoplankton bloom observed December 17-18, 2004. In addition to winds, tides appeared to play critically important role in stimulate phytoplankton blooms. The sediment resuspension event of December 8-16, 2004 was triggered by high bottom shear stress (2.0 N m$^{-2}$, Fig. 2-3D), and was followed by a neap tide. Observations in other estuaries have shown that rapid increase in phytoplankton growth often occurs during periods of low tidal energy (such as during a neap tide) (Cloern, 1991; Huisman et al., 1999; Monbet, 1992; May et al., 2003). Our data for October 31 to December 13, 2005 (not shown) showed a similar phytoplankton bloom, which also occurred after a sediment resuspension event and during a neap tide.

2.4.4. Implications for water quality monitoring

The EPCHC water quality monitoring program performs monthly surveys over the entire Tampa Bay with each survey spanning ~ 3 weeks. Each week samples one segment of Tampa Bay (Boler et al., 1991). Because of the extensive sampling across the Bay, the program is not able to characterize the high frequency variations shown above. The question is whether this program can provide adequate information on variability over seasonal or interannual scales. Average conditions for a specific month in a time series are ideally represented by a monthly mean value ($mm$) derived by averaging all data collected over the month. If a single observation ($mi$) is used to represent monthly conditions, such as with the EPCHC water quality monitoring program, the relative error can be estimated as follows:

$$\text{Relative Error (RE)} = \frac{|mi - mm|}{mm} \times 100\% \quad (7)$$
Figure 2-6. Variations of bbp(532) and Chl with relation to salinity, water levels, and currents from 11-19 December 2004. A double-peak feature of bbp(532) and higher Chl associated with tides are highlighted with red circles.

Figure 2-7. The relative errors \(\times 100\%) \) of Chl (thin blue) and bbp(532) (thick red) incurred by representing a monthly mean by a single snapshot measurements (mi).
The error analysis is based on a comparison of a monthly means (mm) computed with data collected continuously from 8 December 2004 to 7 January 2005. The potential error ranges from -50% to 200% for both Chl and bbp(532) if a single snapshot is used to represent the monthly mean value.

The *in situ* time series data collected with automated sensors between 8 December 2004 and 7 January 2005 suggest that the potential errors introduced by using a single observation as the monthly mean range from -50% to 200% for both chlorophyll and sediment concentrations (Fig.2-7). These errors are larger than, or at least comparable to, the seasonal and interannual variations in Chl and turbidity observed in the longer EPCHC records (Fig.2-8). Therefore for a particular site, single monthly observations are inadequate to infer either seasonal or interannual variability. Only after the multi-year data are averaged to reduce aliasing effects does the seasonal cycle become apparent (Fig.2-8). Similarly, when data from multiple locations during one survey are averaged, the aliasing errors are also reduced. Hence, a trend analysis from the EPCHC monthly data can only be conducted either over a large region for any particular month or over multi-year averages for a particular station. In addition, the 3-week difference in sample time for different bay segments makes it more difficult to assess spatial biases or differences because different sites may have experienced different wind and/or tidal effects during the stratified sampling periods. This difference may introduce further errors in characterizing spatial and temporal variability in phytoplankton and sediment. Thus, it is highly desirable to combine the monthly surveys with other data, such as buoy or mooring observations as well as remote sensing imagery, to obtain a more reliable assessment of water quality variations in estuaries like Tampa Bay. The ongoing implementation of the integrated ocean observation system (IOOS) would provide an unprecedented opportunity to advance our understanding of variability of water quality and their driving mechanisms.
Figure 2-8. The monthly time series of (A) Chl (mg m$^{-3}$) and (B) turbidity (NTU) at one of the EPCHC stations (See Fig.2-1 for station location) from 1997 to 2003. The thicker lines represent the 7-year averages.

2.5. Conclusions

Bio-optical, physical, and meteorological observations showed that short-term variability of phytoplankton and suspended sediment concentrations in Tampa Bay was driven primarily by winds and tides. Sediment resuspension events were caused by wind-induced waves, swell, and currents, including tidal currents. The minimum critical shear stress for sediment resuspension at the study site was $\sim 0.2$ N m$^{-2}$. Once suspended, sediments remained in the water column for $\sim 2$-3 days after winds decreased. No increase in Chl was observed in the water column during resuspension events, implying that benthic algae contribute little to the phytoplankton biomass in the water column. Instead, phytoplankton increased 1-2 days after sediments settled. This may be due to enhanced nutrient concentrations released during sediment resuspension events and optimal light availability subsequent to sediment deposition. Intensive phytoplankton
blooms (Chl >10 mg m$^{-3}$ from a background level of about 3.5 mg m$^{-3}$) occurred when a sediment resuspension event was followed by low winds and a neap tide. This suggests that minimal mixing following strong mixing and resuspension events leads to the largest blooms, since these conditions allow turbidity to decrease and phytoplankton to utilize new nutrients delivered either by sediment resuspension or riverine inputs.

The tidal and subtidal variability highlights some limitations in the current water quality monitoring program. These surveys are useful to characterize seasonal trends for any particular site if multi-year data are averaged, or characterize inter-annual trends if Tampa Bay is treated as several bay segments or as a whole. For smaller regions or specific sites, -50% to 200% errors could be introduced if those snapshot measurements are used to represent monthly mean conditions, making it impossible to derive inter-annual trends for those specific sites.

Although the results presented here were obtained only from 40-day continuous measurements (one sample per hour) at one station, the observed variability and responsible processes should be representative for variability across the bay in winter. In shallow regions, benthic algae may play a more important role in influencing phytoplankton biomass in the water column. Further studies at multiple stations and in different seasons are necessary to fully characterize the short-term spatial and temporal variability of phytoplankton and sediments across the bay.
3.1. Abstract

Absorption and fluorescence of colored dissolved organic matter (CDOM) and concentrations of dissolved organic carbon (DOC), chlorophyll and total suspended solids in Tampa Bay and its adjacent rivers were examined in June and October of 2004. Except in Old Tampa Bay (OTB), in June, 2004, CDOM properties showed a conservative relationship with salinity \( a_{\text{CDOM}}(400) = -0.19 \times \text{salinity} + 6.78, \quad R^2 = 0.98, \quad n=17, \quad \text{salinity range} = 1.1 - 32.5 \) with little variation in absorption spectral slope and fluorescence efficiency. CDOM distribution was therefore controlled by mixing between various end members, including rivers entering Tampa Bay and marine waters of the Gulf of Mexico. In October, 2004, the average CDOM absorption coefficients measured around the Bay \( a_{\text{CDOM}}(400), \sim 7.76 \text{ m}^{-1} \) were about seven times larger than values observed in June \( \sim 1.11 \text{ m}^{-1} \) and appeared to behave non-conservatively. The non-conservative behavior may have been caused by mixing between various end-members, specifically rivers, marine waters, and mixing of waters from Hillsborough Bay, Middle Tampa Bay and Old Tampa Bay. Alternatively, removal of CDOM may have occurred at intermediate salinities (e.g., \( a_{\text{CDOM}}(400) \text{ removal} >15\% \text{ at salinity} \sim 13.0 \)) due to photobleaching due under stratified conditions. The spatial and seasonal distributions of CDOM showed that the two largest rivers, the Alafia River (AR) and Hillsborough River (HR) were dominant CDOM sources. In OTB, CDOM showed lower absorption coefficients, higher absorption spectral slopes, lower ratios of CDOM absorption to DOC, and higher fluorescence efficiency. These differences may be due to (1) changes in CDOM composition by photobleaching due to the longer residence time in OTB; (2) other sources of CDOM such as local creeks, streams, groundwater, bottom re-suspension or primary production from either phytoplankton or seagrass. Compared to phytoplankton pigment absorption, \( a_{\text{ph}}(443) \), average \( a_{\text{CDOM}}(443) \) was about five times higher in June
and about ten times higher in October, showing that blue light attenuation was dominated by CDOM rather than by phytoplankton absorption throughout the year.

3.2. Introduction

Colored Dissolved Organic Matter (CDOM) is one of the most important constituents affecting water quality in estuaries. It has strong effects on light attenuation (Branco & Kremer, 2005; Clementson et al., 2004; Magnuson et al., 2004), affecting the light available to phytoplankton and submerged aquatic vegetation (Anastasiou et al., 2005). Further, CDOM may also serve as a tracer of dissolved organic carbon (DOC), if the ratio between the colored and uncolored fractions of DOC is known. Since DOC affects the transport and bio-availability of trace metals and organic pollutants (Santschi et al., 1997; Guo et al., 2001), it is of interest in the assessment of CDOM of estuarine and coastal waters.

CDOM distribution and variation patterns, however, have not been well studied in Tampa Bay. The current water quality monitoring program conducts only visual comparison of water samples with color standards. Thus these observations lack detailed information about the optical properties to track sources, sinks, and changes in the composition and relative abundance of constituents. Furthermore, these color measurements are not reliable when used to estimate CDOM concentrations, primarily due to subjective assessment of colors by each user (Gallegos, 2005).

In this study, absorption and fluorescence of CDOM were examined using observations collected during two cruise surveys, specifically in June and October, 2004. I examined how CDOM optical properties varied relative to salinity, Chlorophyll concentration (Chl), total suspended solids concentration (TSS), and DOC. The objectives of the study were to (1) characterize the distribution and variability of CDOM in Tampa Bay; (2) understand processes that control its origins, dispersal and sinks; and (3) help understand the ecological significance of high light attenuation due to CDOM in Tampa Bay.
3.3. Methods

Fig. 3-1 shows sample locations for the two surveys, conducted on June 1−3 and October 12−14, 2004, respectively. Seventeen stations were collected from three of the four sub-basins of the Bay during each survey. Six samples were also collected from the Alafia River (AR) in June, 2004. The AR was not sampled in October, 2004, because the river’s effect was readily observable in the bay due to high discharge at that time.

River flow rates (1973 to 2003) were obtained from US Geological Survey National Water Information System (USGS NWIS). While four major rivers discharge fresh water to the Bay, the Alafia River (AR) and the Hillsborough River (HR) contribute, on average, >80% of the total freshwater delivered to the Bay (Robinson, 2004; and Fig. 3-2a). Fig. 3-2 also shows the general trend of river flow rates (the wet season from June to October and the dry season for the rest months of a year) and interannual variability of this typical seasonality for year of 2004. It can be clearly seen that the sampling dates of June 1-3 and October 12-14, 2004 are in the dry and wet seasons, respectively. Therefore the data from June and October are used to represent general CDOM concentrations in the dry and wet seasons, respectively although interannual variation in river flow rates may impact CDOM seasonal contrasts.

3.3.1. Temperature, salinity, chlorophyll, and total suspended solids

Surface water samples for temperature, salinity, chlorophyll, and total suspended solids (TSS) were collected using a bucket from a small boat. Temperature and salinity were measured immediately using a WTW™ Multi 340i Meter (Aquatic eco-system, FL, USA). Samples were stored in brown plastic bottles in a cooler with ice. They were filtered the same day after returning to the lab through GF/F Whatman filters (pump pressure < 120 mmHg) to determine chlorophyll concentration (Chl) using a Turner-Designs fluorometer (Mueller et al., 2003). Whatman™ Nylon membrane filters (0.2µm pore size) were used to obtain CDOM filtrates. TSS estimates were based on 500–800 ml water samples filtered through pre-weighed 47mm Millipore GN filters (0.45 µm pore size). Filters were dried in a desiccator and weighed again. The difference of filter
weights between with- and without particulates, together with the volume of filtered seawater, was used to calculate TSS (Mueller et al., 2003).

Figure 3-1. Map of Tampa Bay with sampling locations overlaid. The Bay is divided into four segments: Old Tampa Bay (OTB), Hillsborough Bay (HB), Middle Tampa Bay (MTB), Lower Tampa Bay (LTB). Major rivers are the Alafia River (AR), Hillsborough River (HR), Little Manatee River (LMR), and Manatee River (MR). AR station numbers increase toward the mouth of the river (numbers discussed in the text but not shown here). The inset shows the location of Tampa Bay in Florida.
Figure 3-2. (A) Percentage of average (1973-2003) monthly mean flow rates of Hillsborough River (HR), Alafia River (AR), Little Manatee River (LMR), Manatee River (MR) relative to the total monthly mean flow rate from these four major rivers of each month. (B) The long-term average (open circle) and 2004 daily flows (filled circle) of the AR and (C) of the HR. Highlighted areas indicate the sampling dates in this study: day 153-155 (1–3 June, 2004, dry season) and day 286-288 (12–14 October 2004, wet season).
3.3.2. Dissolved organic carbon

Dissolved organic carbon samples (DOC) were collected directly from surface waters of the Bay using 500 ml brown glass bottles previously rinsed three times with Milli-Q water. Samples were filtered through pre-combusted (500°C overnight) 47-mm Whatman® GF/F filters. The initial 250 ml of filtrate was discarded, and 50 ml of subsequent filtrate was preserved by poisoning with 30 µL of 1.1 M high purity hydrochloric acid, then stored at –17°C. A Shimadzu TOC-5000A total DOC analyzer (using high temperature catalytic oxidation) equipped with the ASI-5000A accessory was used to analyze DOC samples. Milli-Q water was used as a reference blank and to prepare a standard solution of potassium hydrogen phthalate (KHP). The accuracy and precision of the measurements were better than 5%. DOC was not measured in the wet season.

3.3.3. CDOM absorption coefficient and fluorescence

CDOM abundance based on its light absorption and fluorescence properties. A Hitachi U3310 double-beam spectrophotometer (300-850 nm, 2 nm resolution) was used to measure CDOM spectral absorbance \( A(\lambda) \), dimensionless) in 10 cm quartz cells with Milli-Q water as the blank reference. \( A(\lambda) \) was measured three times and the mean was used to calculate the CDOM absorption coefficient, \( a_{\text{CDOM}}(\lambda) \) (m\(^{-1}\)) as follows (Hu et al., 2002):

\[
a_{\text{CDOM}}(\lambda) = \ln 10 \times \frac{A(\lambda)}{L},
\]

where \( L \) is the cuvette pathlength (0.1 meter).

A nonlinear least square regression was used to derive spectral slope \( S \) (nm\(^{-1}\)) over the wavelength range 350-550 nm:

\[
a_{\text{CDOM}}(\lambda) = a_{\text{CDOM}}(400) \exp[-S(\lambda - 400)] + K,
\]

where \( a_{\text{CDOM}}(400) \) is the CDOM absorption coefficient at a reference wavelength of 400 nm, and \( K \) is an offset to account for residual scattering and/or noise.

CDOM fluorescence spectroscopy was performed according to the method of Coble (1996) using a SPEX Industries Fluoromax-2 spectrofluorometer. Samples with \( A(300) > 0.02 \) were diluted to avoid self-shading (Green, 1992). The fluorescence signal,
after corrections for Raman scattering and instrument configuration, was normalized to units of quinine sulfate equivalents (QSE) in ppb using the fluorescence of a diluted series of quinine sulfate dihydrate in 0.05 M sulfuric acid at excitation/emission (Ex/Em) of 350/450 nm. CDOM fluorescence intensity was reported as fluorescence at Ex/Em of 300/420 nm, located in Humic Peak C region (Coble, 1996).

3.3.4. Phytoplankton pigment absorption coefficient

In the wet season, the spectral absorption coefficient due to particulate matter, \( a_p(\lambda) \), was determined using the technique of Yentsch (1962). I used a custom-made, 512-channel spectroradiometer (~350-850nm) to measure absorption. Pathlength amplification was corrected using the \( \beta \) factor of Carder et al. (1999). Detrital absorption spectra, \( a_d(\lambda) \), were obtained after chemical extraction of phytoplankton pigments from the sample using hot methanol (Kishino et al., 1985). Phytoplankton pigment absorption spectra, \( a_{ph}(\lambda) \), were then calculated by difference:

\[
a_{ph}(\lambda) = a_p(\lambda) - a_d(\lambda).
\] (3)

Because the maximum absorption of phytoplankton occurs near 443 nm, \( a_{ph}(443) \) was chosen to compare with \( a_{CDOM}(443) \). In the dry season, when no particulate absorption was measured, \( a_{ph}(443) \) was modeled using following equation (Bricaud et al., 1995; Babin et al., 2003):

\[
a_{ph}(443) = 0.04 \times \text{Chl}^{0.668}.
\] (4)

3.3.5. Statistical tests

Pearson’s product moment correlation and linear and non-linear regression analyses were used to evaluate the statistical relationships between variables. Statistical significance was reported as either not significant (NS) (\( p > 0.05 \)), weak (*, 0.01 < \( p < 0.05 \)), moderate (**, \( p < 0.01 \)), or high or strong (***, \( p < 0.001 \)).
3.4. Results

Appendix 3-1 lists the results for all stations by segments and seasonal surveys. These results are discussed below.

3.4.1. Distribution of TSS and Chl

TSS concentrations ranged from 1.6 mg/l in Middle Tampa Bay (MTB) to 18.2 mg/l in the Alafia River (AR). In general, there was no apparent relationship between TSS and salinity (Fig. 3-3A, Table 3-1) within individual sampling locations except in Hillsborough Bay (HB), where TSS was higher in the wet season than in the dry season (Fig. 3-3A, Appendix 3-1), indicative of higher riverine sediment inputs directly into this area in the wet season. MTB generally showed the lowest TSS of the three bay segments in both seasons. This suggests that TSS in Tampa Bay was not directly controlled by riverine inputs.

Chl showed significant seasonal variations. The wet season Chl exceeded those of the dry season by factors ranging from 2 to 10 (Appendix 3-1). The highest Chl were observed in the wet season in HB (79.0 mg/m$^3$) and MTB (>40.0 mg/m$^3$). In the AR, highest Chl (18.0 mg/m$^3$) in June was observed in the intermediate salinity range 10.0–20.0, and Chl decreased with increasing salinity (Fig. 3-3B), consistent with earlier observations (Vargo et al., 1991).

Looking at individual stations, there was a moderate inverse correlation between Chl and salinity in the wet season (Fig. 3-3B, Table 3-1). This correlation was attributed to nitrogen supply through rivers in the wet season, as Tampa Bay phytoplankton are generally nitrogen limited (Vargo et al., 1991).

3.4.2. Light absorption by CDOM

CDOM absorption coefficients generally decreased with increasing salinity. The lowest CDOM absorption values occurred in MTB in the dry season (Fig.3-4, Appendix 3-1). The relationships between $a_{\text{CDOM}}(400)$ and salinity, however, varied with bay segments and seasons.

In the dry season, except in Old Tampa Bay (OTB), $a_{\text{CDOM}}(400)$ was strongly inversely correlated to salinity, indicating that riverine CDOM was dominant. CDOM
from the AR was conservatively mixed into the MTB. In the wet season, however, $a_{\text{CDOM}}(400)$ in HB and MTB showed an exponential decrease with increasing salinity (Fig.3-4, Table 3-2). This may indicate that CDOM was not conservatively mixed or that there were multiple end-members mixing different proportions of CDOM and salinity in the central regions of the Bay. If the behavior is non-conservative, then >15% of $a_{\text{CDOM}}(400)$ was removed around salinities of about 13.0, which was the median salinity in October, 2004. Alternatively, CDOM absorption in OTB was significantly lower than in HB and MTB in both seasons,, indicative of possible differences in CDOM sources in OTB (Fig. 3-4). Mixing of OTB water with water from HB and MTB would also lead to an exponential decrease in the salinity-CDOM curve, which would give the appearance of non-conservative behavior. It is difficult to determine which effect caused the observed patterns without additional detailed experiments and observations.

Figure 3-3. Surface salinity versus (A) total suspended solids concentration (TSS) and (B) chlorophyll concentration (Chl). Open symbols show dry season observations and filled symbols show wet season observations.
Table 3-1 Correlation coefficients (r) between surface salinity and TSS and between surface salinity and Chl in Tampa Bay and the AR in the dry and wet seasons

<table>
<thead>
<tr>
<th>Season</th>
<th>Parameter</th>
<th>Parameter</th>
<th>AR</th>
<th>HB+MTB</th>
<th>HB+MTB+O TB</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dry Season</td>
<td>TSS vs salinity</td>
<td>0.58 NS</td>
<td>0.43 NS</td>
<td>0.46 NS</td>
<td></td>
</tr>
<tr>
<td>(June, 2004)</td>
<td>Chl vs salinity</td>
<td>0.77 NS</td>
<td>0.41 NS</td>
<td>0.58* (n=17)</td>
<td></td>
</tr>
<tr>
<td>Wet Season</td>
<td>TSS vs salinity</td>
<td>N.D.</td>
<td>0.82* (n=9)</td>
<td>0.43 NS</td>
<td></td>
</tr>
<tr>
<td>(October, 2004)</td>
<td>Chl vs salinity</td>
<td>N.D.</td>
<td>0.79* (n=9)</td>
<td>0.73** (n=14)</td>
<td></td>
</tr>
</tbody>
</table>

Note:
(1) Statistical significance is reported as either NS (p>0.5), * (0.01<p<0.05), ** (p<0.01), *** (p<0.001)
(2) The numbers in parentheses are numbers of sample used for correlation analysis.
(3). N.D. = “not determined”
CDOM absorption exhibited significant seasonal variations. Average $a_{CDOM}(400)$ in the wet season was about four, seven and ten times higher than in the dry season for OTB, MTB and HB, respectively (Appendix 3-1). For example, at TB17, $a_{CDOM}(400)$ in the dry season was 1.50 m$^{-1}$ (salinity=27.3), but increased to 16.80 m$^{-1}$ in the wet season (salinity=8.8). The average $a_{CDOM}(400)$ over the entire bay increased from $\sim1.11$ m$^{-1}$ in the dry season (salinity =27.9) to $\sim7.76$ m$^{-1}$ in the wet season (salinity =14.3), or about sevenfold. Furthermore, extrapolations from regression analysis between $a_{CDOM}(400)$ and surface salinity in the dry season and from the hypothesized conservative mixing line in the wet season indicate that $a_{CDOM}(400)$ of the river end member in the wet season (> 26.5 m$^{-1}$ at salinity =0.0) was significantly higher than that in the dry season (about 6.78 m$^{-1}$). The difference suggests a seasonal difference in the amount of land-based CDOM delivered to the Bay.

CDOM absorption showed no significant correlation (p>0.05) with TSS or Chl in the dry season (Figs. 3-5A and 3-5B, Table 3-3). In the wet season, however, CDOM was
moderately correlated with Chl over most of Tampa Bay (Fig. 3-5B, Table 3-3), likely as a result of the coincidence that both high loads of nutrients and CDOM were delivered into the bay via increased riverine discharge in the wet season.

As a result of the high CDOM concentrations, CDOM absorption of blue light was significantly higher than that due to phytoplankton pigment absorption. Average $a_{\text{CDOM}}(443)$ was about 5 and 10 times higher than $a_{\text{ph}}(443)$ in the dry and wet seasons, respectively (Fig. 3-5C). The ratios of $a_{\text{CDOM}}(443)$ and $a_{\text{ph}}(443)$ ranged 3-11 for the different bay segments and seasons, with maxima in HB in the dry season and in MTB in the wet season. The minima were observed in OTB in both seasons (Table 3-4).

CDOM absorption spectral slope ($S$) within the AR, HB, and MTB stations were similar in both seasons ($p<0.05$). Higher spectral slopes were, however, found in OTB in both seasons, with much higher slopes in the dry season (Fig. 3-6). Chemical composition of the CDOM seems to be different in OTB, possibly due to photobleaching or due to different CDOM sources in OTB, as discussed below.
Figure 3-5.  $a_{\text{CDOM}}(400)$ versus (A) TSS and (B) Chl and (C) $a_{\text{CDOM}}(443)$ versus $a_{\text{ph}}(443)$ for Tampa Bay and the AR in the dry and wet seasons (also see Table 3-3).
Table 3-2 Results of regression analysis between $a_{\text{CDOM}(400)}$ and surface salinity in Tampa Bay and the AR in the dry and wet seasons.

<table>
<thead>
<tr>
<th>Region</th>
<th>Regression equation</th>
<th>$R^2$</th>
<th>Number of samples</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Dry Season (June, 2004)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AR</td>
<td>$a_{\text{CDOM}(400)} = -0.19 \times \text{salinity} + 6.77$</td>
<td>0.90**</td>
<td>6</td>
</tr>
<tr>
<td>HB and MTB</td>
<td>$a_{\text{CDOM}(400)} = -0.19 \times \text{salinity} + 6.72$</td>
<td>0.90**</td>
<td>11</td>
</tr>
<tr>
<td>AR, HB + MTB</td>
<td>$a_{\text{CDOM}(400)} = -0.19 \times \text{salinity} + 6.78$</td>
<td>0.98***</td>
<td>17</td>
</tr>
<tr>
<td>HB+MTB+OTB</td>
<td>$a_{\text{CDOM}(400)} = -0.077 \times \text{salinity} + 3.27$</td>
<td>0.29 NS</td>
<td>16</td>
</tr>
<tr>
<td><strong>Wet Season (October, 2004)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HB and MTB (without OTB)</td>
<td>$a_{\text{CDOM}(400)} = 43.70 \times \exp(-0.11 \times \text{Salinity})$</td>
<td>0.98***</td>
<td>9</td>
</tr>
</tbody>
</table>

Note:

(1) Statistical significance is reported as either NS ($p>0.5$), * ($0.01<p<0.05$), ** ($p<0.01$), *** ($p<0.001$).
Table 3-3 Correlation coefficients (r) between $a_{CDOM}(400)$ and TSS and between $a_{CDOM}(400)$ and Chl in Tampa Bay and the AR in the dry and wet seasons.

<table>
<thead>
<tr>
<th>Season</th>
<th>Parameter</th>
<th>AR</th>
<th>HB+MTB</th>
<th>HB+MTB</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>AR</td>
<td>HB+MTB</td>
<td>HB+MTB</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>+OTB</td>
</tr>
<tr>
<td>Dry Season</td>
<td>TSS vs $a_{CDOM}(400)$</td>
<td>0.43 NS (n=6)</td>
<td>0.60 NS (n=11)</td>
<td>0.36 NS (n=17)</td>
</tr>
<tr>
<td>(June, 2004</td>
<td>Chl vs $a_{CDOM}(400)$</td>
<td>0.74 NS (n=6)</td>
<td>0.55 NS (n=11)</td>
<td>0.24 NS (n=17)</td>
</tr>
<tr>
<td>Wet Season</td>
<td>TSS vs $a_{CDOM}(400)$</td>
<td>N.D.</td>
<td>0.79 * (n=9)</td>
<td>0.22 NS (n=14)</td>
</tr>
<tr>
<td>(October, 2004)</td>
<td>Chl vs $a_{CDOM}(400)$</td>
<td>N.D.</td>
<td>0.77 * (n=9)</td>
<td>0.73 ** (n=14)</td>
</tr>
</tbody>
</table>

Note:

(1) Statistical significance is reported as either NS (p>0.5), * (0.01<p<0.05), ** (p<0.01), *** (p<0.001)
(2) The numbers in parentheses are numbers of sample used for correlation analysis.
(3) N.D. = “not determined”
Table 3-4 The averages and standard deviations (in parentheses) of CDOM absorption ($a_{\text{CDOM}}(443)$) and phytoplankton pigment absorption ($a_{\text{ph}}(443)$) in different bay segments and seasons.

<table>
<thead>
<tr>
<th>Season</th>
<th>Parameter</th>
<th>Hillsborough Bay</th>
<th>Middle Tampa Bay</th>
<th>Old Tampa Bay</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dry Season</td>
<td>$a_{\text{CDOM}}(443)$</td>
<td>0.71 (0.04)</td>
<td>0.50 (0.22)</td>
<td>0.42 (0.09)</td>
</tr>
<tr>
<td>(June, 2004)</td>
<td>$a_{\text{ph}}(443)$</td>
<td>0.11 (0.05)</td>
<td>0.09 (0.03)</td>
<td>0.13 (0.01)</td>
</tr>
<tr>
<td>Wet Season</td>
<td>$a_{\text{CDOM}}(443)$</td>
<td>7.75 (1.87)</td>
<td>5.09 (1.79)</td>
<td>1.80 (0.34)</td>
</tr>
<tr>
<td>(October, 2004)</td>
<td>$a_{\text{ph}}(443)$</td>
<td>1.14 (0.42)</td>
<td>0.46 (0.32)</td>
<td>0.30 (0.12)</td>
</tr>
</tbody>
</table>

Figure 3-6. CDOM absorption spectral slope (S) versus surface salinity for Tampa Bay and the AR in the dry and wet seasons. The dashed and solid lines represent the average spectral slope without OTB samples in the dry and wet seasons, respectively. Student’s t-test showed that these average values were significantly smaller than those from OTB in both seasons (p<0.01).
3.4.3. DOC

During the dry season, DOC varied from 200 to 500 µM, with higher concentrations in the AR and OTB and lower in the HB and MTB. Unlike CDOM (Fig. 3-4), however, DOC in the AR did not decrease with increasing salinity but remained almost constant along the AR salinity gradient (Fig. 3-7). When comparing CDOM absorption with DOC, OTB showed consistently lower ratios of CDOM absorption to DOC (Fig. 3-8), suggesting that DOC in OTB may have originated from different sources or that the rate of bleaching of CDOM was higher than in other parts of the bay.

![Figure 3-7. Surface salinity versus DOC concentration for Tampa Bay and the AR in the dry season in June, 2004.](image-url)
3.4.4. CDOM fluorescence efficiency

The ratio of CDOM fluorescence to absorption, or "equivalent fluorescence efficiency", was relatively constant throughout the bay and the AR during the dry season (Fig.3-9). This is consistent with the inference that most CDOM was derived from river inputs, and that CDOM was conservatively mixed in most of Tampa Bay. In contrast, the OTB CDOM showed slightly higher fluorescence efficiency than those in other areas (Fig.3-9, Table 3-5), along with other differences in the other CDOM optical properties in the OTB: lower CDOM absorption, higher spectral slopes, and lower ratios of CDOM absorption to DOC.
Figure 3-9. CDOM fluorescence (QSE) versus $a_{\text{CDOM}(400)}$ (m$^{-1}$) for Tampa Bay and the AR during the dry season in June, 2004.
Table 3-5 Results of regression analysis between CDOM fluorescence and $a_{CDOM(400)}$

<table>
<thead>
<tr>
<th>Region</th>
<th>Regression equation</th>
<th>($R^2$)</th>
<th>Number of samples</th>
</tr>
</thead>
<tbody>
<tr>
<td>AR</td>
<td>Fluorescence=12.02× $a_{CDOM(400)}$ +5.95</td>
<td>0.91**</td>
<td>6</td>
</tr>
<tr>
<td>HB and MTB (Without OTB)</td>
<td>Fluorescence=13.23× $a_{CDOM(400)}$ +4.23</td>
<td>0.89***</td>
<td>11</td>
</tr>
<tr>
<td>HB+MTB+OTB</td>
<td>Fluorescence=1095× $a_{CDOM(400)}$ +10.10</td>
<td>0.34NS</td>
<td>16</td>
</tr>
<tr>
<td>HB and MTB+AR</td>
<td>Fluorescence=12.12× $a_{CDOM(400)}$ +5.53</td>
<td>0.99***</td>
<td>17</td>
</tr>
<tr>
<td>All data</td>
<td>Fluorescence=12.12× $a_{CDOM(400)}$ +9.53</td>
<td>0.95***</td>
<td>22</td>
</tr>
</tbody>
</table>

Note: Statistical significance is reported as either NS (p>0.5), *(0.01<p<0.05), ** (p<0.01), *** (p<0.001).

3.5. Discussion

3.5.1. CDOM sources and sinks

Previous studies have shown that much, if not most CDOM in estuarine and coastal waters is of terrestrial origin (Blough and Del Vecchio 2002; and references therein). In Tampa Bay, we found a high correlation between CDOM and salinity along a salinity gradient from the Alafia River (AR) to Middle Tampa Bay (MTB) in both seasons (June and October 2004, respectively), showing that riverine inputs were dominant CDOM sources.

The largest of the four major rivers discharging into Tampa bay (Fig.3-1) are the Hillsborough River (HR) and AR (Robinson, 2004). Statistically similar salinity vs. CDOM absorption slopes and intercepts from the AR, HB and MTB (Fig. 3-4) indicate...
that CDOM properties from the HR and AR might be optically similar so that a single conservative mixing behavior (or effectively the same riverine end-member) was observed. Indeed, Hastings et al. (2004) suggested that CDOM from the HR was not optically distinct from that derived from the AR. These rivers have similar watersheds (Chen et al., 2004), while rivers with different watersheds show different CDOM loads (Chen and Gardner, 2004). Similarly, in Tampa Bay, CDOM from the Little Manatee River (LMR) and Manatee River (MR) showed higher CDOM fluorescence/absorption ratios than those from the HR and AR. The AR and HR are associated with similar urban watersheds (Estevez et al., 1991), but the LMR and MR are related to more rural, agriculture-intensive watersheds (Hastings et al., 2004).

Conservative mixing of CDOM is common in estuarine systems because high CDOM concentrations mask small variations caused by other processes, such as photochemical and biological processes (Nieke et al., 1997; Blough and Del Vecchio, 2002; Rochelle-Newall and Fisher, 2002; Kowalczyk et al., 2003; Chen et al., 2004). CDOM absorption in Tampa Bay is indeed relatively high compared to those reported for other estuaries. For instance, at salinity of 25.0, $a_{\text{CDOM}}$ (400) in Tampa Bay in the dry season was about 1.50 m$^{-1}$, while it was about 0.50 m$^{-1}$ in the Chesapeake Bay (Rochelle-Newall and Fisher, 2002) and about 0.70 m$^{-1}$ in the Mississippi River plume (Hu et al., 2003).

In various ecological settings, phytoplankton (Carder et al., 1989) or submerged aquatic vegetation such as seagrasses (Otis et al., 2004) may release CDOM into the water. The poor correlation between $a_{\text{CDOM}}$ (400) and Chl in the dry season, and particularly the lack of corresponding CDOM increase in Chl peaks in the AR, however, indicate that phytoplankton played only a minor role in regulating CDOM abundance in the dry season in Tampa Bay. While $a_{\text{CDOM}}$ (400) showed a moderate correlation with Chl in the wet season, this correlation likely resulted from a coincidence between high concentrations of nutrients (therefore Chl) and CDOM, rather than an inherent cause-and-effect relationship between Chl and CDOM. Little contribution of CDOM from phytoplankton has also observed in other estuaries, such as in the Chesapeake Bay (Rochelle-Newall et al., 1999; Rochelle-Newall and Fisher, 2002). Similarly, the poor correlation between $a_{\text{CDOM}}$ (400) and TSS suggests that CDOM contribution from
sediment resuspension was also negligible. However, further study is required to provide more direct evidence for the relationship between CDOM variation and sediment resuspension events in Tampa Bay, since previous studies in other coastal and estuarine waters have suggested that CDOM could be derived from bottom sediments (e.g., Boss et al., 2001; Burdige et al., 2004).

Several processes have been reported to be responsible for CDOM removal, such as flocculation and precipitation of sediments in estuaries (Uher et al., 2001), microbial transformation and photobleaching (Blough and Del Vecchio, 2002; and references therein). We found no significant correlation between CDOM and TSS in either season, which suggested that TSS in Tampa Bay (1.6 ~ 18.2 mg/l) may not be actively involved in CDOM removal by sediment adsorption (Uher et al., 2001).

CDOM removal by photobleaching in Tampa Bay might also be negligible in the dry season. Previous studies have found that photobleaching usually takes weeks to months to effect a noticeable removal of CDOM, depending on insolation and water column stability (e.g., Vodacek et al., 1997). Numerical modeling of Tampa Bay, however, suggest that the e-folding time (the time required for the number of particles in a grid cell to decrease by 65%) in Lower Tampa Bay (LTB) and in the adjacent deep channel is about 10 days or less (Burwell et al., 2000). Furthermore, the water column was generally well mixed in the dry season, which would further limit photobleaching. This hypothesis is consistent with the small variation observed in the spectral slope (Fig. 3-6) and fluorescence efficiency (Fig.3-9) along the salinity gradient from the AR to MTB.

In the wet season, we observed an apparent non-conservative behavior along the salinity gradient going from HB to MTB, suggesting the presence of a sink. If a sink was present, at least 15% of $a_{\text{CDOM}}(400)$ might have been removed at salinity ~13.0, assuming no CDOM was added from other processes (Fig.3-4). Indeed, if we hypothesize that conservative mixing yields $a_{\text{CDOM}}(400) = 0.00 \text{ m}^{-1}$ at salinity=36.0, then CDOM removal at salinity ~13.0 would be >50%. If CDOM removal occurred in the wet season, it may have been due to photobleaching under increased stratification conditions in the wet season Tampa Bay due to buoyancy input from freshwater and heat (Burwell et al.,
2000). Also, CDOM delivered via rivers in the wet season may be younger and therefore susceptible to degradation (Zanardi-Lamardo et al., 2004).

An alternate hypothesis is that the ‘apparent’ non-conservative mixing was due to mixing of water from more than two endmembers. About 20% of the freshwater delivered to the Bay is derived from the LMR and MR (Fig. 3-2) (see also Hu et al., 2004). Yet, the contribution of OTB water can cause lower CDOM concentrations than those from mixing between HB and MTB because CDOM in OTB is about half of that observed in HB at similar salinities.

As mentioned above, CDOM in OTB showed distinctive properties relative to other bay segments. The higher spectral slopes might be an indicator of photobleaching due to loss of the CDOM fraction with higher molecular weight (Twardowski and Donaghay, 2002), in agreement with the longer water residence time in OTB (> 140 days) (Burwell et al., 2000) allowing for sufficient photobleaching (Vodacek et al., 1997). The longer water residence time also implies that the CDOM exchange through water circulation is weaker in OTB compared with in the HB and MTB, making local processes (phytoplankton and benthic production/degradation, CDOM released by sediment resuspension, photobleaching) more effective in determining its optical properties. The differences in CDOM properties in OTB may also simply arise from different sources of CDOM, including local creeks, streams, rivers, groundwater, or from autochthonous production from phytoplankton (Carder et al., 1989) or submerged aquatic vegetation (Otis et al., 2004).

3.5.2. Seasonal variation in CDOM absorption

Average $a_{CDOM}(400)$ in Tampa Bay during the wet season was ~7.76 m$^{-1}$, or about 7-fold higher than in the dry season (~1.11 m$^{-1}$). These values are near the upper limit of published ranges of CDOM absorption coefficients in coastal and estuarine waters (Kowalczuk et al., 2003). Indeed, $a_{CDOM}(400)$ extrapolated to a riverine endmember (salinity = 0.0) are ~7.0 m$^{-1}$ and 26.5 m$^{-1}$ in the dry and wet seasons, respectively. Thus, about 4-fold higher CDOM was present in rivers in the wet season than in the dry season. These changes are linked to seasonal variation in river flow (Fig.3-2). Hurricanes or tropical storms may transport additional CDOM from watersheds into rivers and estuaries.
Implications for water clarity monitoring and remote sensing

The absorption of blue light was dominated by CDOM rather than by phytoplankton pigments (Fig. 3-5C). Our results show that CDOM and phytoplankton pigments covary in the wet season, which is likely the primary reason why earlier studies concluded that chlorophyll could account for some of the variation in light attenuation (e.g., Janicki et al., 2001). However, this correlation is seasonal and is uncommon in the dry season. A better index of water clarity is CDOM absorption or fluorescence, since this serves as a proxy for CDOM concentration and light absorption. This is a simple measurement that would benefit water quality monitoring programs. The high ratio of CDOM to pigment absorption in Tampa Bay makes it difficult to estimate Chl reliably using the sea spectral reflectance band-ratio algorithms that are applied in Case I waters (O’Reilly et al., 2000). Instead, in complex CDOM-rich coastal environments, chlorophyll fluorescence line height (FLH) observations are better suited to assess synoptic patterns of Chl distribution (Hu et al., 2005). Both MODIS (Moderate Resolution Imaging Spectroradiometer Sensors) and the European MERIS (Medium Resolution Imaging Spectrometer) collect remotely-sensed fluorescence data, and these images should be evaluated for application in Tampa Bay.

Conclusions

Two surveys, one each in June and October of 2004, were conducted in Tampa Bay to study the applicability of optical observations to assess water quality indices. The results show that colored dissolved organic matter (CDOM) dominates the absorption of blue light relative to phytoplankton pigments. Average $a_{\text{CDOM}}(443)$ was five and ten times higher than phytoplankton pigment absorption, $a_{\text{ph}}(443)$, in the dry and wet seasons, respectively. The Alafia River and the Hillsborough River were the main CDOM
sources to Tampa Bay. These rivers showed $a_{\text{CDOM}}(400)$ of about 7.00 m$^{-1}$ and 26.50 m$^{-1}$ at zero salinity in the dry and wet seasons, respectively.

CDOM absorption coefficient within Tampa Bay showed significant seasonal variations with average $a_{\text{CDOM}}(400)$ of ~1.11 m$^{-1}$ and ~7.76 m$^{-1}$ in the dry and wet seasons, respectively. In the dry season, except for Old Tampa Bay, CDOM distribution was primarily controlled by conservative mixing between riverine inputs (Alafia and Hillsborough Rivers) and marine coastal waters ($a_{\text{CDOM}}(400)= -0.19 \times \text{salinity} + 6.78, R^2=0.98, N=17, \text{salinity}=1.1 \sim 32.5$). Other processes such as phytoplankton production, sediment resuspension, and photobleaching seemed to have little impact on CDOM abundance. In the wet season, $a_{\text{CDOM}}(400)$ showed an exponential decrease with increasing salinity along a gradient from Hillsborough Bay to Middle Tampa Bay. Two possibilities are proposed to explain this. One is that CDOM was removed during mixing. The other is that there is a significant contribution of CDOM from Old Tampa Bay with lower CDOM concentrations. Old Tampa Bay showed relatively lower $a_{\text{CDOM}}(400)$, higher CDOM spectral slope, lower ratios of CDOM absorption to DOC and higher fluorescence efficiency than other parts of Tampa Bay. These differences might suggest more intensive photobleaching in shallower waters, or different CDOM sources, such as local rivers, streams, ground water, bottom resuspension or even phytoplankton or submerged aquatic vegetation. Further studies may help clarify these differences.

The predominance of CDOM absorption over phytoplankton pigment absorption precludes reliable estimates of Chl using conventional empirical or semi-analytical bio-optical algorithms. Chlorophyll fluorescence line height from MODIS or MERIS may be a good alternative to these absorption-based chlorophyll algorithms.

The study provided first results of seasonal variations of CDOM distribution as well as general inferences of CDOM sources, distribution and sinks in Tampa Bay. However, these were based on two quasi-synoptic surveys in two short time periods of two typical seasons. For a better understanding of the interactions between CDOM and rivers, sediment and phytoplankton, more intensive sampling is required.
Chapter 4. Monitoring turbidity in Tampa Bay using MODIS/Aqua 250 m imagery

4.1. Abstract

An approach to map turbidity in Tampa Bay is developed for application with the 250 m imagery collected with the Moderate Resolution Imaging Spectroradiometer Sensor (MODIS). The approach includes cross-calibration of MODIS 250 m data with well-calibrated MODIS 1 km data, a simple atmospheric correction, and development of a bio-optical inversion algorithm based on in situ reflectance and turbidity measurements. Results show that the MODIS pre-launch radiometric calibration of the 250 m bands was adequate for this application. A simple atmospheric correction provided reliable retrievals of remote sensing reflectance at 645 nm (0.002 < $R_{rs}(645) < 0.015$ sr$^{-1}$, median bias = -7%, slope = 0.95, intercept = 0.00, $r^2$=0.97, n=15). A more rigorous approach, using a multiple-scattering atmospheric correction of the cross-calibrated at-sensor radiance, retrieved similar $R_{rs}(645)$. $R_{rs}(645)$ estimates, after rigorous quality control, showed a close correlation with in situ turbidity (turbidity = $1203.9 \times R_{rs}(645)^{1.087}$, 0.9 < turbidity < 8.0 NTU, $r^2$=0.73, n=43). The MODIS turbidity maps derived using this algorithm showed distinct spatial and temporal patterns related to river runoff in Upper Tampa Bay, and to wind-induced sediment resuspension events in the middle and lower portions of the bay. The monthly mean turbidity patterns estimated from MODIS were different from those determined from single monthly in situ observations, which I attribute to aliasing in a fast-changing estuary. Synoptic and frequent sampling facilitated by satellite remote sensing helps improve estimates of the “mean” patterns of turbidity in estuaries like Tampa Bay and are a valuable tool that should be used in monitoring of water quality of estuarine and coastal waters.
4.2. Introduction

The "turbidity" of water is a common index used to assess coastal and estuarine water quality. It is used to help understand factors that control light attenuation and therefore the productivity of planktonic and benthic algae (Cloern, 1987; Cole & Cloern, 1987; Fisher et al., 1999; Pennock & Sharp, 1994), seagrass, and coral reefs (Anthony et al., 2004; Moore et al., 1997). In coastal and estuarine waters, turbidity is frequently directly associated to concentrations of total suspended solids or sediments (TSS) in the water column. Knowledge of the distribution of suspended or resuspended particles is important to understand processes like coastal erosion and mobilization of chemicals or pollutants (Heyes et al., 2004). Therefore, understanding how turbidity varies is of critical interest to coastal resource managers and researchers.

Turbidity in coastal and estuarine waters shows a wide range in spatial and temporal variability. Rivers deliver terrestrial materials to estuaries following seasonal patterns, but also in events that may trigger marked interannual variability (Pribble et al., 2001). Currents and waves lead to suspension of bottom sediments, changing turbidity in response to storms and other wind events at tidal and subtidal frequencies (Cloern et al., 1989; Schoellhamer, 1995). In addition to these natural forcings, human activities such as transportation and dredging also influence the magnitude and distribution of turbidity (Schoellhamer, 1996). As a result of these processes, turbidity in estuaries is highly variable. Conventional sampling methods often fail to characterize turbidity patterns because of their limitations in temporal and spatial sampling (Chen et al., submitted).

Satellite remote sensing has been used successfully to map sediment concentrations and turbidity in coastal and estuarine waters (Doxaran, et al., 2002; Miller et al., 2005; Ruddick et al., 2003; Stumpf & Pennock, 1989). However, due to the inherent problems associated with sensors (e.g., spatial resolutions, revisit times and accessibility of images), routine application of satellite remote sensing to monitor turbidity and sediments in coastal waters has been limited. For example, although Landsat ETM+ provides high-resolution (30-m) imagery, the revisit time is ~ 16 days. This long revisit time, cloud cover, and high cost make it inadequate to resolve turbidity dynamics in coastal and estuarine waters. Sensors with nearly daily overpasses and designed to observe marine waters (e.g., the Advanced Very High Resolution Radiometer
(AVHRR), the Sea-viewing Wide Field-of-View Sensor (SeaWiFS), and the ocean bands of the Moderate Resolution Imaging Spectroradiometer Sensor (MODIS) typically have coarse spatial resolution, such as ~1 km per pixel, and are of limited value to examine processes in most estuarine waters.

The MODIS flown aboard the Aqua spacecraft, launched in July 2002, provides near-daily coverage of the subtropical ocean and has two bands that observe the Earth at 250 m resolution (band 1: 645 nm, from 620-670 nm; band 2: 859 nm, from 841-876 nm). These bands have sufficient sensitivity to detect a wide range of changes in the color of estuarine waters (Hu et al., 2004). Several studies have demonstrated the potential of these bands to monitor water quality in coastal and estuarine waters (Hu et al., 2004; Miller & Mckee, 2004).

Two key issues, however, must be resolved before MODIS 250 m data can be routinely applied in coastal studies (Hu et al., 2004). First, the reliability of at-sensor (i.e., the top of atmosphere, TOA) radiance observations has to be assessed, and a method has to be available to estimate remote sensing reflectance ($R_{rs}$) of aquatic environments. The MODIS 250 m bands were originally designed to serve as "sharpening bands" to detect land, aerosol, and cloud features. Therefore, there has been no effort to apply an oceanic vicarious calibration such as done for the MODIS ocean 1 km bands. Remote sensing of aquatic environments demands rigor and accuracy in sensor calibration because a 5% error in at-sensor radiance may result in a 50% $R_{rs}$ error or worse. Also, bio-optical algorithm (an algorithm to convert $R_{rs}$ to water-quality parameters such as turbidity or TSS) typically derived from limited in situ data frequently is inadequate for application elsewhere or at other times (Hu et al., 2004; Miller & Mckee, 2004).

Hu et al. (2004) discussed desired improvements to the MODIS 250 m products, including vicarious calibration and coupling with in situ measurements. Here I present results of a vicarious calibration effected by cross-calibration of MODIS 250 m bands with the MODIS 1 km ocean color bands which have been calibrated using the Marine Optical Buoy (MOBY) located near Hawaii. I then develop and validate an empirical algorithm to convert the atmospherically corrected data ($R_{rs}$) to turbidity. Finally, I derive monthly mean patterns of turbidity using a time series of MODIS/Aqua 250 m images collected between May 2003 and April 2006, and compare them with in situ observations.
from the Tampa Bay water quality monitoring program conducted by the Environmental Protection Commission of Hillsborough County's (EPCHC).

4.3. Methods and Materials

4.3.1. Field data

Turbidity data (reported in nephelometric turbidity units or NTU) were obtained from the Environmental Protection Commission of Hillsborough County's (EPCHC) Tampa Bay water quality monitoring program (Bolder et al., 1991). The EPCHC conducts monthly surveys which span 3 weeks. Each week covers approximately one segment of the bay (Fig. 4-1). Water samples were collected approximately about mid-depth between the surface and the bottom if the depth was greater than 3 m, otherwise only surface samples were collected. The EPCHC estimates turbidity of water samples in the lab with a Hach® Model 2100N Turbidimeter. This device measures light intensity (peak spectral response is ~ 570 nm) at 3 different angles (90° scattered, forward scattered, and transmitted light). The normalized scattered light at 90° relative to the total scattered light at 3 angles was calibrated with four standard solutions ranging from 2 to 2000 NTU. This ratio mode was constantly run to remove the possible effects of colors on turbidity measurement (Hach® Model 2100N Turbidimeter manual, 1999). Thus turbidity values generally represent the bulk scattering caused by particles in water samples, primarily by suspended sediments. Therefore, turbidity is frequently used as a good indicator of sediment concentration, although the relationship between turbidity and sediment concentration can be highly variable, and depends on sediment properties (e.g., size, shape, composition, and refractive index) and measurement uncertainties. For example, when TSS concentration is low, relative uncertainty in the TSS concentration determined by the dry weight method can be larger (Christian & Sheng, 2003).
Figure 4-1. MODIS 250 m image of Tampa Bay showing the four segments of the bay and major tributaries. The segments are Old Tampa Bay (OTB), Hillsborough Bay (HB), Middle Tampa Bay (MTB), and Lower Tampa Bay (LTB). The rivers are the Hillsborough River (HB), the Alafia River (AR), the Little Manatee River (LMR), and the Manatee River (MR). The Environmental Protection Commission of Hillsborough County’s (EPCHC) water quality monitoring stations are overlaid with various symbols to indicate different sampling times in each month: diamond (OTB) generally in the first week, triangle (HB) in the second week, and square (MTB and LTB) in the last week. Five stations marked with white crosses and labeled with numbers are also overlaid (stations 92, 23, 14, 40, 55 from the EPCHC program).
Remote sensing reflectance ($R_{rs}$, sr$^{-1}$) data were collected in situ during several field surveys on 21-22 October 2003, 1-3 June 2004, 12-14 October 2004, 13 December 2005, and 27 February 2006, respectively, with an handheld PR650 (Photo Research Inc.) or Analytical Spectral Device (ASD Inc.) spectroradiometer, following the method described in Hu et al. (2004). Briefly, upwelling radiance from the water surface and from a standard reflectance plaque (as a reference), and the sky radiance were measured. $R_{rs}$ was derived by dividing the water spectra, corrected for sky radiance reflected off the surface, by downwelling irradiance estimated from the plaque spectra. These in situ hyperspectral $R_{rs}$ data were then integrated over the relative spectral response (RSR) function of MODIS band 1 to obtain $R_{rs}(645)$ for MODIS validations.

4.3.2. Cross-calibration of the MODIS 250 m with 1 km bands

Vicarious calibration of the satellite at-sensor radiance is the procedure used to adjust the measured radiance to a predicted radiance, based on well calibrated measurements and a radiative transfer model. It is critical for ocean color sensors to conduct periodic vicarious calibrations, because the pre-launch laboratory calibration typically has uncertainties of 2-5%, which can translate to 20-50% relative errors or worse in the retrieved $R_{rs}$ after atmospheric correction. The vicarious calibration and the subsequent atmospheric correction using consistent radiative transfer codes can be considered to be as a “self-tuning” process.

Vicarious calibration of ocean color sensors is typically performed at a well-defined site (i.e., spatially homogeneous water away from land) with a well-calibrated instrument (e.g., the Marine Optical Buoy or MOBY at Hawaii). When such an option is not available, an alternative is to calibrate one sensor against another well-calibrated sensor, for example calibrating MOS using SeaWiFS (Wang & Franz, 2000) or calibrating Landsat/ETM+ using SeaWiFS (Hu et al., 2001b). Calibration against another calibrated satellite sensor is hereafter referred to as cross-calibration in this paper. Here I take the approach described in Hu et al. (2001b) to calibrate the 250 m bands using MODIS/Aqua 1 km ocean bands. Because all MODIS bands have identical solar/viewing geometry, the procedure is simpler than when cross-calibrating two sensors are on
separate satellites as in Hu et al. (2001b). In short, the 250 m data are adjusted according to the at-sensor radiances predicted by the 1 km data. For clarity I briefly describe this cross-calibration procedure below.

After removal of the ozone effect (Hu et al., 2004), at-sensor radiances, $L_t$, can be predicted as (for brevity the wavelength dependency is suppressed here):

$$L_t = L_r + L_a + t_v \times L_w$$  \hspace{1cm} (1)

where definitions of these terms are given in Table 4-1. Here the effects of sunglint and whitecaps are omitted because during the quality control step, data affected by these artifacts can be discarded. The effects of water vapor, oxygen absorption, or light polarization are also negligible for the 250 m bands (e.g., Meister et al., 2005). The terms on the right-hand side of Eq. (1) were estimated from the MODIS 1 km ocean bands in the following way:

1. Eleven cloud-free MODIS images from May 2003 to April 2006 were randomly chosen. From each image, a clear-water ocean area adjacent to Tampa Bay was chosen as the calibration site (Fig. 4-2).
2. MODIS 1 km Level 1 data were processed using SeaDAS 4.8 to estimate $L_r$, $L_a$, $t_v$, and $L_w$ for each of the 1 km wavelengths ($\lambda=412$, 443, 488, 531, 551, 667, 674, 748, 859 nm), and further adjusted to the nominal center wavelengths of MODIS/Aqua similar to the procedure for SeaWiFS described by Hu et al.(2001b).
3. The above multispectral data were used to construct an artificial hyperspectral dataset covering from 400 to 900 nm by interpolation. $L_w(859)$ for the clear-water site was assumed 0, and $L_w(645)$ was approximated as $1.30 \times L_w(667)$ according to the extensive in situ hyper-spectral data collected from the West Florida shelf (Cannizzaro et al., accepted). Sensitivity analyses indicated that the results were not sensitive to using a constant (i.e. 1.30) if a substituted value is in the range of 1.0 - 1.4 (results not shown here).
4. The simulated hyperspectral data (except the $L_w$ term) were integrated over the bandpass of the 250 m bands, while modulated by the relative spectral response (RSR) function, to provide the corresponding radiance for the 250 m bands:
\[ L_x (\text{band}) = \frac{\int L_x(\lambda) \times S(\lambda) \times d\lambda}{\int S(\lambda) \times d\lambda}, \quad (2) \]

where \( S(\lambda) \) is the RSR of the 250 m bands, \( x \) can be \( r \) or \( a \), and “band” is 645 or 859 nm (see Table 4-1 for nomenclature).

Table 4-1 Symbols, definitions and Units

<table>
<thead>
<tr>
<th>Symbols</th>
<th>Definitions</th>
<th>Units</th>
</tr>
</thead>
<tbody>
<tr>
<td>( t_0 )</td>
<td>Diffuse transmittance from the sun to the ground due to Rayleigh and aerosol scattering</td>
<td>Dimensionless</td>
</tr>
<tr>
<td>( t_v )</td>
<td>Diffuse transmittance from the ground to a sensor due to Rayleigh and aerosol scattering</td>
<td>Dimensionless</td>
</tr>
<tr>
<td>( t_{ox} )</td>
<td>Diffuse transmittance from the sun to the ground and from the ground to a sensor due to absorption by ozone</td>
<td>Dimensionless</td>
</tr>
<tr>
<td>( L_a )</td>
<td>Radiance from aerosol scattering and aerosol-Rayleigh interaction</td>
<td>( \text{mW cm}^{-2} \mu\text{m}^{-1} \text{sr}^{-1} )</td>
</tr>
<tr>
<td>( L_r )</td>
<td>Radiance from Rayleigh scattering in the absence of aerosols</td>
<td>( \text{mW cm}^{-2} \mu\text{m}^{-1} \text{sr}^{-1} )</td>
</tr>
<tr>
<td>( L_t )</td>
<td>Total radiance at the top of atmosphere (TOA)</td>
<td>( \text{mW cm}^{-2} \mu\text{m}^{-1} \text{sr}^{-1} )</td>
</tr>
<tr>
<td>( L_w )</td>
<td>Water-leaving radiance at the sea surface</td>
<td>( \text{mW cm}^{-2} \mu\text{m}^{-1} \text{sr}^{-1} )</td>
</tr>
<tr>
<td>( L_{gn} )</td>
<td>Normalized sun glint radiance if there were no atmosphere and solar irradiance ( F_0=1 )</td>
<td>( \text{sr}^{-1} )</td>
</tr>
<tr>
<td>( \theta_0 )</td>
<td>Solar zenith angle</td>
<td>Degree</td>
</tr>
<tr>
<td>( \theta_v )</td>
<td>Sensor zenith angle</td>
<td>Degree</td>
</tr>
<tr>
<td>( F_0 )</td>
<td>Adjusted extraterrestrial solar irradiance</td>
<td>( \text{mW cm}^{-2} \mu\text{m}^{-1} )</td>
</tr>
</tbody>
</table>

For simplicity, the wavelength dependency of all terms (except solar and sensor angles) is suppressed.
Figure 4-2. (a) MODIS at-sensor radiance at 667 nm (1 km) on 13 December 2004, 18:43 GMT over the study area; (b) MODIS at-sensor radiance at 645 nm (250 m) from the same satellite pass. Data in the rectangular box were used for cross-calibration.

4.3.3. Satellite image processing

MODIS L1B direct broadcast data were captured in real-time by an X-band antenna located at the University of South Florida (USF) in Saint Petersburg, Florida. For regions without a local antenna, historical data can be obtained from the NASA Goddard Space Flight Center's Distributed Active Archive Center (DAAC).

Clouds were masked according to the TOA reflectance \((sr^{-1})\) at 859 nm,

\[
R_t = \frac{L_t}{F_0 \times \cos \theta_0},
\]

with a threshold of 0.018 \(sr^{-1}\). This step filters out most of the clouds and severe sun glint contaminations. Then, an atmospheric correction step was carried out using the methods outlined in Hu et al. (2004), and summarized as the following equation.
Both single scattering approximation and multi-scattering “exact” calculations (the latter used with the cross-calibrated at-sensor radiance) were used to estimate \( L_r \). The latter method was used to ensure consistency with the cross-calibrated data. The details of these two methods can be found in Hu et al. (2004).

4.3.4. Satellite - in situ comparison

Comparison between satellite and in situ observations is complicated in coastal and estuarine waters, where high spatial and temporal variations in both water and atmosphere properties make it difficult to have observations congruent in space and time. Bailey & Werdell (2006) made several key recommendations for such comparisons. Here we used the following criteria to select the satellite and in situ matching pairs:

First, the satellite data must be collected within 2 hours of the in situ measurements. For comparison of remote sensing reflectance, the time window was relaxed to 4 hours to increase the matching points. Second, to ensure relative homogeneity and to remove sensor noise (Hu et al., 2001a), a 3×3 pixel box centered at the in situ measurement site was used. Within this box, there must be at least 4 valid (see below) pixels, and the coefficient of variance (standard deviation divided by mean) of the valid pixels must be <0.4. Then, the median value of valid pixels in the 3×3 box is compared with the in situ data. By trial and error, any pixel that meets one of the following criteria is considered invalid: 1) water depth <2.8 m (bottom contamination); 2) satellite zenith angle >50° (scan edge); 3) \((R_t(859) – R_r(859)) > 0.019 \text{ sr}^{-1}\) (large aerosol); 4) normalized sun glint radiance \((L_{gn}) > 0.0001 \text{ sr}^{-1}\) (sun glint contamination, Wang & Bailey, 2001).
4.4. Results

4.4.1. Cross calibration and data validation

Fig. 4-3 shows the comparison between the ozone-corrected at-sensor radiances in the 250 m bands and those predicted from the 1 km bands, with statistics presented in Table 4-2. Both MODIS 250 m bands show excellent linear relationships with the estimates derived from the 1 km bands, with median ratios (indicating overall biases) of 0.96 and 1.01 for the 645 nm and 859 nm bands, respectively. The median absolute percentage differences (MPD, Bailey & Werdell, 2006, a measure of uncertainty) were 3.61% and 1.30%, respectively. These uncertainties correspond to ~2 counts for the 645 nm band ($L_t(645)$ is normally > 60 counts with TSS ranging between 2-15 mg L$^{-1}$ in Tampa Bay) and <1 count for the 859-nm band. From the slopes and intercepts of the linear regressions, the vicarious gains and offsets for the two 250 m bands are [1.0904, -0.067] and [1.0303, -0.0124], respectively.

The at-sensor radiances were adjusted by the above vicarious gains and offsets, and the rigorous atmospheric correction (multi-scattering) was applied to process the MODIS imagery for those dates when concurrent in situ $R_{\text{rs}}$ data were collected. Note that the 11 cloud-free scenes were randomly chosen between May 2003 and April 2006 and therefore these days with in situ $R_{\text{rs}}$ measurements were different than those used in the cross-calibration. The derived $R_{\text{rs}}(645)$ is shown in Fig.4-4 to compare with in situ $R_{\text{rs}}(645)$, with statistics listed in Table 4-3. To show how much improvement may be gained from this extra effort (cross-calibration and rigorous atmospheric correction), $R_{\text{rs}}(645)$ derived from the simple atmospheric correction and the original at-sensor radiance (i.e., without cross-calibration) is also shown in Fig.4-4 and Table 4-3. The improvement in terms of bias (5% versus -7%) or other measures is not significant (paired Student’s t-test, p<0.001). Therefore, the pre-launch calibration (i.e., original at-sensor radiance) and the single-scattering atmospheric correction were deemed sufficient to process the entire time-series of MODIS imagery between May 2003 and April 2006.
Table 4-2 Comparison between the measured at-sensor radiances (mW cm\(^{-2}\) \(\mu\)m\(^{-1}\) sr\(^{-1}\)) at the MODIS 250 m bands and those predicted from the 1 km ocean color bands.

<table>
<thead>
<tr>
<th>Band</th>
<th>Ratio(^a)</th>
<th>% Difference(^b)</th>
<th>Slope</th>
<th>Intercept</th>
<th>(r^2)</th>
<th>RMSE(^c)</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>(L_t(645))</td>
<td>0.96</td>
<td>3.61</td>
<td>0.91</td>
<td>0.07</td>
<td>0.997</td>
<td>0.04</td>
<td>11</td>
</tr>
<tr>
<td>(L_t(859))</td>
<td>1.01</td>
<td>1.30</td>
<td>0.97</td>
<td>0.01</td>
<td>0.995</td>
<td>0.02</td>
<td>11</td>
</tr>
</tbody>
</table>

\(a\) - Median ratio between the measured and predicted radiances, indicating overall biases.
\(b\) - Median absolute percentage difference (MPD) between the measured and predicted at-sensor radiances, indicating typical uncertainties (Bailey and Werdell, 2006).
\(c\) - RMSE represents root mean square errors of the linear regression fitting, in units of mW cm\(^{-2}\) \(\mu\)m\(^{-1}\) sr\(^{-1}\).

Table 4-3 Comparison between \textit{in situ} versus MODIS remote sensing reflectance at 645 nm (\(R_{rs}(645), \text{sr}^{-1}\)), with the latter derived using 1) single scattering approximation and the original at-sensor radiances (i.e., pre-launch calibration) and 2) multi-scattering method and the cross-calibrated at-sensor radiances, respectively.

<table>
<thead>
<tr>
<th>Calibration</th>
<th>Ratio</th>
<th>% Difference</th>
<th>Slope</th>
<th>Intercept</th>
<th>(r^2)</th>
<th>RMSE (\times 10^{-4})</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pre-launch</td>
<td>0.93</td>
<td>8</td>
<td>0.95</td>
<td>0.00</td>
<td>0.97</td>
<td>0.0007</td>
<td>15</td>
</tr>
<tr>
<td>Cross-calibration</td>
<td>1.05</td>
<td>10</td>
<td>1.04</td>
<td>0.00</td>
<td>0.98</td>
<td>0.0007</td>
<td>15</td>
</tr>
</tbody>
</table>

The ratio, % difference, and RMSE are defined in the same way as in Table 4-2.
Figure 4-3. Scatter plots of the at-sensor radiance (mW cm$^{-2}$ μm$^{-1}$ sr$^{-1}$) in the two 250 m bands (645 nm in (a) and 859 nm in (b)) as measured by the sensor and predicted by the calibrated 1 km ocean color bands. The dashed lines are 1:1 lines. (Results of the comparison are shown in Table 4-2).

4.4.2. Turbidity from satellite R$_{rs}$

After rigorous quality control of the satellite data (see Methods), a total of 43 matching pairs were found for concurrent satellite and in situ measurements. Fig. 4-5 shows that MODIS R$_{rs}$(645) is closely related to in situ turbidity for values ranging from 0.9 to 8.0 NTU and R$_{rs}$(645) from 0.001 to 0.008 sr$^{-1}$, respectively ($r^2 = 0.73$, n=43). Further, the relationship appeared to be stable over time, specifically for 2004 and 2005 (Fig. 4-5), indicating that a time-independent regression relationship could be obtained. Indeed, if the relationship derived from the 2005 data is used to predict the 2004 turbidity, the results agree well with the in situ turbidity values (median predicted versus in situ ratio of ~0.98 and median absolute percentage difference/MPD of 10%; Fig. 4-6). Hence, the regression relationship of Fig. 4-5 and the rigorous data quality control criteria were applied to the MODIS R$_{rs}$(645) imagery to obtain the turbidity time-series maps.
4.4.3. Image series of turbidity

The 3-year (May 2003 to April 2006) MODIS turbidity maps were used to generate monthly and climatological monthly means. The climatological monthly means showed distinctive spatial and temporal patterns in Tampa Bay (Figs. 4-7). Turbidity in Hillsborough Bay (HB) was consistently higher than in other sub-regions except in August and September; at this time, however, turbidity in HB may be underestimated due to high input of colored dissolved organic matter (CDOM) from “major” rivers (see below). Turbidity in the upper Middle Tampa Bay (MTB, around Station 14) was lower relative to that in HB and OTB throughout the year. In contrast, both Old Tampa Bay (OTB) and Lower Tampa Bay (LTB) showed clear seasonal variations. LTB, particularly near the bay mouth, showed high turbidity between November-March and lower turbidity between May-October, while opposite seasonality existed in OTB. Bay-wide high turbidity was found in April. Such seasonality can also be visualized by extracting time-series data from several selected stations from the various sub-regions (Fig. 4-8). For example, the upper bay (Sta. 55 in HB and Sta. 40 in OTB; see Fig. 4-1 for location) typically showed higher turbidity than MTB and LTB, particularly in the wet season (from May to October, turbidity > 3.0 NTU). MTB (Sta. 14) showed the lowest turbidity and seasonality (typically ~2.0 NTU). LTB showed moderate turbidity but the largest seasonal variations.

Turbidity also showed significant interannual variations. For example, Fig.4-9 shows the contrast between the turbidity patterns from April of 2004, 2005, and 2006. Such interannual variations can be attributed to different wind forcing, as shown in Fig.4-10. We may assume that 6.0 m s$^{-1}$ wind speed is a threshold above which sediment resuspension occurs. Then, there are 7, 8, and 2 days for April of 2004, 2005, and 2006, respectively, which can explain the observed spatial patterns variations.
Figure 4-4. Remote sensing reflectance in Tampa Bay at band 1 ($R_{rs}(645)$, sr$^{-1}$) from in situ measurements and MODIS estimates derived using 1) multiple-scattering atmospheric correction of the cross-calibrated at-sensor radiance (filled circles); and 2) single-scattering atmospheric correction of the original (i.e., pre-launch calibration) at-sensor radiance (open circles). The dashed and dotted line represents the 1:1 ratio (Comparison results listed in Table 4-3).

$$\text{Turbidity}=1203.9xR_{rs}(645)^{1.087}$$

$$R^2=0.73, n=43$$

Figure 4-5. Relationship between in situ turbidity (NTU) and MODIS remote sensing reflectance at band 1 ($R_{rs}(645)$, sr$^{-1}$) in a log-log scale. The 2004 and 2005 data are represented with open and filled circles, respectively. The fitted lines from 2004, 2005, and 2004+2005 data are represented with dashed line, thin solid line, and thick solid line, respectively.
Figure 4-6. Relationship between *in situ* turbidity from the 2004 measurements and that estimated from concurrent MODIS data using the relationship derived from the 2005 data. The dashed line is the 1:1 line.

Fig. 4-9 shows an example of the contrast between the “monthly” turbidity maps derived from satellite observations and from *in situ* data. While the monthly MODIS turbidity estimates were generally consistent with those determined from *in situ* observations (Fig. 4-9), there were some important differences. Some fine-scale features are different due to either the different temporal and spatial sampling frequencies or the artificial effects from the interpolation method for the *in situ* data. In addition, the single monthly *in situ* turbidity observations are frequently within 1 standard deviation of the multiple satellite estimates collected during the same month (Fig. 4-11). However, MODIS mean turbidity showed less short-term temporal variability, but much more pronounced seasonal and interannual variability than *in situ* observations. For example, abnormally high *in situ* turbidity values (> 10.0 NTU) were observed at Sta. 55 in October and December 2003, respectively, but the monthly MODIS means showed low turbidity, comparable to that seen in other months. The high turbidity events sampled *in situ* through single monthly collections unfortunately masked the relative increases in turbidity observed in the wet season, thus obscuring seasonal changes (Fig. 4-8). Similarly, the high *in situ* turbidity observed at Sta. 23 in late 2003 and at Sta. 92 in early 2004 obscured the higher overall turbidity inferred from MODIS data for late 2004 and early 2005 (Fig. 4-11).
These differences between these data sets are likely due, in great part, to the mismatch in sampling frequencies between the in situ program and the satellite collections. MODIS typically has >4 high-quality observations per month (about once per week), and even >10 observations were collected frequently between October and March (Fig. 4-11). This helps minimize the aliasing of temporal variations and helps construct more reliable monthly means than using the single in situ monthly measurements. I also find that the satellite observations provide higher detail of the spatial heterogeneity in turbidity patterns.

Because of these increased temporal and spatial sampling frequency, MODIS provides a useful synoptic product that helps improve assessments of the monthly “mean” turbidity. Clearly, MODIS observations require cloudless skies and minimal sun glint. These factors limit the number of MODIS observations in the wet season. For example, in the upper bay (e.g., Sta. 55) I had no valid observations during some months.

4.5. Discussion

4.5.1. Calibration and algorithm issues:

The results I obtained using the complex cross-calibration scheme and the exact atmospheric correction I used similar to those obtained with the simpler, single-scattering atmospheric correction of data calibrated with pre-launch coefficients. On the other hand, there may be some small calibration uncertainties in the 1 km MODIS ocean band data that can erroneously propagate to the 250 m bands through the cross-calibration. This may be the cause for the residual errors observed in the retrieved $R_{\text{s}}$ data obtained from this rigorous approach. Overall, I find that MODIS 250 m imagery can be used with the pre-launch calibration and simple atmospheric correction to assess long-term trends in water turbidity. Other error sources are discussed below.
Figure 4-7. Climatological (May 2003 to April 2006) monthly means of turbidity derived from MODIS 250 m data. White color inside Tampa Bay (not offshore) represents the mask of shallow water (bottom depth < 2.8 m) and grey color represents land.
Figure 4-7. (Continued)
Figure 4-8. The climatological monthly means of turbidity derived from MODIS between May 2003 and April 2006 at several stations in Tampa Bay (see Fig.4-1 for station locations). Sta. 55 was affected by high CDOM and cloud cover during later summer; consequently, turbidity was possibly underestimated and there was no valid data in August.
Figure 4-9. Monthly turbidity images from MODIS 250 m data (top panels) and from *in situ* measurements (lower panels) for April of 2004, 2005, and 2006 (no *in situ* measurement was available for April 2006). Crosses represent sample stations with bottom depths > 2.8 m, and the values shown are *in situ* turbidity measurements. The *in situ* “monthly” map is a graphical composite of single observations taken at different times in different parts of Tampa Bay and is not a “true” monthly mean. The satellite-derived mean is based on multiple MODIS observations during the month.
I use a “white aerosol” assumption, which considers aerosol reflectance at 645 nm equal to that at 859 nm. Yet this assumption is simplistic and it works because these bands are close spectrally, making extrapolation from 859 to 645 nm feasible even if the aerosol is not “white”. Indeed, for non white-aerosols the errors can be several counts (e.g., Hu et al., 2001b), and of the order of 5-10% in the retrieved $R_{rs}(645)$. However, the black-pixel assumption ($L_w(859)=0$) may not be accurate in very turbid waters (Hu et al., 2000; Siegel et al., 2000; Wang & Shi, 2005). In this case an alternative may be the nearest neighboring approach to apply nearby aerosol reflectance from clear waters to the “turbid” pixels (e.g., Hu et al., 2000; Miller & Mckee, 2004). In coastal areas where aerosol reflectance is often spatially heterogeneous (Hu et al., 2004), this technique is thus limiting. Using longer wavelengths may circumvent the non black-pixel problem (Wang & Shi, 2005), but the larger spectral distance between the wavelength of interest (645 nm) and the reference wavelength (1640 nm) may yield some errors in the aerosol reflectance extrapolation. Therefore, at present there is no perfect atmospheric correction method for MODIS 250 m bands in coastal waters. However, future sensors may add one
more band in the short wave infrared (SWIR) wavelength, in addition to the present 1640 nm MODIS band. This will help determine aerosol type as well as aerosol reflectance in

Figure 4-11. Time-series of monthly turbidity estimates derived from *in situ* and MODIS measurements at selected stations shown in Fig 4-1. The period covered is May 2003 to December 2005 (no *in situ* data available for 2006). The number of MODIS observations during each month is shown on the right-hand side. Where number of samples was >1, the standard deviation of the monthly mean is also shown on the MODIS data. There is only one *in situ* observation in each month. The circles highlight the relatively high turbidity observed from late 2004 to early 2005 in the Lower Tampa Bay, which are not observed with the *in situ* measurements. The y-axis scale for station 55 is different from that in the other panels.
the SWIR region, making extrapolation of the atmospheric correction of shorter wavelengths more accurate.

Hu et al. (2004) showed differences between MODIS/Terra and MODIS/Aqua data and inconsistency in the time-dependent $R_{rs}$ retrievals, especially for the 500 m bands (469 and 555 nm). The more extensive MODIS and in situ data set examined in the present turbidity study allowed for a rigorous data quality control. These data showed that using a single sensor, specifically MODIS/Aqua 250 m data and rigorous data quality control, helps improve accuracy and time-independent consistency. Indeed, when only the 2-hour time window and homogeneity check (see the Methods) were allowed for match-ups between MODIS and in situ data, 751 pairs were found. After several quality-control criteria (bathymetry, Rayleigh corrected $R_0(859)$, sensor viewing angles and normalized sun glint radiance) were applied, only 43 matching pairs were left and used to develop the $R_{rs}(645) \Rightarrow$ turbidity algorithm. The threshold values were found by trial-and-error, and therefore may need to be adjusted if the same approach is applied to other estuaries.

4.5.2. Effects of colored dissolved organic matter (CDOM)

The apparent low turbidity in the wet season (e.g, August and September) in HB is likely an artifact due to the interference by CDOM, whose absorption coefficient at 645 nm ($a_{cdom}(645)$) could be $\sim 0.40$ m$^{-1}$ in the wet season (Chen et al., in press). This is greater than the water absorption at this wavelength ($\sim 0.33$ m$^{-1}$, Pope & Fry, 1997). Because $R_{rs}(645)$ for most waters is not only a function of turbidity (a proxy for TSS) but also inversely proportional to total absorption coefficient, presence of high and variable CDOM will make $R_{rs}(645)$ smaller, leading to low, unrealistic turbidity retrievals. Similar effects have also been observed elsewhere (e.g., Woodruff et al., 1998). This effect, however, is limited to HB in the wet season only and generally negligible for the other bay segments and seasons when $a_{cdom}(645)$ is typically $< 0.03$ m$^{-1}$. Indeed, MODIS turbidity showed comparable variation patterns to those from in situ measurements in most time (Fig. 4-11).
4.6. Conclusions

Two issues towards operational application of MODIS 250 m data for monitoring of estuarine turbidity were addressed: calibration of the at-sensor radiance and methods to convert such radiance to turbidity. Cross-calibration of the MODIS 250 m bands with the 1 km ocean color bands, and use of a rigorous, multiple-scattering atmospheric correction led to no substantial improvements over using the pre-launch calibration and a simple, single-scattering atmospheric correction approach in terms of the retrieved surface remote sensing reflectance ($R_{rs}$) for a large dynamic range. Further, the retrieved MODIS $R_{rs}$, after rigorous quality control, showed a high correlation with concurrent in situ turbidity observations. Therefore, the simple approach presented here seems adequate to generate accurate and consistent time-series of turbidity maps over estuaries of moderate size, such as Tampa Bay.

Although similar features were observed both in the MODIS turbidity maps and those based on in situ observations, of particular importance are their differences. MODIS provides multiple cloud-free measurements at high spatial resolution, and these provide an improved record of the “mean” state of the Bay each month, as well as of seasonal and inter-annual variability. The distinctive spatial and temporal viability revealed from MODIS imagery can be explained well by wind-driven bottom-resuspension events during the winter and river inputs during the rainy season.

There still remain several issues to be addressed in the future, for example the interference of high CDOM and shallow (< 2.8 m) but bright bottom in the conversion from $R_{rs}$ to turbidity. However, because of the relative ease, robustness, low cost, and simple methods for data processing, as well as the repeated global coverage, MODIS has important advantages over traditional in situ sampling methods. Thus we strongly recommend implementing a similar scheme for all estuaries of moderate size and coastal regions to help better manage estuarine and coastal resources.
Chapter 5. Remote Sensing of water clarity in Tampa Bay

5.1. Abstract

Understanding the distribution and variability of water clarity in Tampa Bay is critical for ecosystem restoration and protection efforts focused on this major estuary. Traditionally, water clarity in Tampa Bay has been measured with a Secchi disk (Secchi Disk Depth or SDD) during monthly surveys at established stations. Here I estimate SDD and the light attenuation coefficient at 490 nm, $K_d(490)$ (m$^{-1}$), from Sea-viewing Wide Field-of-View Sensor (SeaWiFS) imagery using a new semi-analytical light attenuation algorithm ($SDD=1.04 \times K_d(490)^{-0.82}$). $K_d(490)$ derived with the traditional band-ratio algorithm showed no significant relationship with in situ SDD ($r^2=0.14$, n=80), but the new estimates were closely correlated with in situ SDD ($0.9<SDD<8.0$ m, $r^2=0.67$, n=80). Thus, SeaWiFS imagery was used to derive SDD fields for September 1997 through December 2005. SDD patterns followed expected river runoff temporal and spatial patterns in the rainy season and reflected wind-induced sediment resuspension events in the dry season. The SeaWiFS data show that the frequency of past in situ surveys is inadequate to capture the spatial and temporal variability in water clarity observed in Tampa Bay. The SeaWiFS SDD imagery provides improved estimates of the “mean” patterns of water clarity in estuaries like Tampa Bay, and should be used more extensively for routine monitoring of coastal and estuarine environments.
5.2. Introduction

Tampa Bay is the largest open-water estuary in Florida, featuring a surface area of \(~1,000 \text{ km}^2\)\). It has been traditionally divided into 4 sub-segments, namely: Old Tampa Bay (OTB), Hillsborough Bay (HB), Middle Tampa Bay (MTB), and Lower Tampa Bay (LTM) (Fig. 5-1). Contributing more than \$5 billion annually from trade, tourism, development, and fishing (FDCA, 1996), Tampa Bay is a diverse and productive natural system that provides a vital habitat for crustaceans, fish, shellfish and a variety of marine mammals, reptiles and birds (Harwell et al., 1995). It is therefore critical that the development of the Bay be conducted in an environmentally sound way to sustain a clean and healthy system.

Tampa Bay has undergone substantial anthropogenic alterations. In the decades prior to the 1980s, Tampa Bay was heavily polluted by nutrient loadings from sources like sewage and wastewater. The decline in water quality due to pollution led to severe eutrophication and increases in light attenuation, therefore causing substantial losses of seagrass coverage (Lewis et al., 1998; Tomasko et al., 2005). Since then, significant ecosystem restoration efforts have been under the way. In 1990, Tampa Bay National Estuary Program (TBNEP) was established to integrate efforts to restore and protect the Bay. In 1996, TBNEP developed a Comprehensive Conservation and Management Plan (CCMP), which focused on restoration of seagrass to levels similar to those observed in the 1950s (Janicki & Wade, 1996). These efforts gradually improved the water quality of the Bay, and some of the seagrass has recovered (Johansson, 2000; Tomasko et al., 2005). Water clarity is an index of water quality, taken to reflect the impact of nutrient load on phytoplankton concentration. It is also a critical factor controlling seagrass extent in coastal and estuarine waters (Gallegos, 2001; Kirk, 1994). It therefore has been selected as a key parameter that is routinely monitored in Tampa Bay, and ultimately serves to direct riverine nutrient input management plans (Janicki et al., 2001).

Water clarity in Tampa Bay is measured with a Secchi disk once a month at established stations (Janicki & Wade, 1996; Fig. 5-1), similar as in most coastal environmental monitoring programs. A white or white-black disk (usually \(~20 \text{ cm in diameter}) is lowered into the water, and the depth at which the disk is no longer visible is
recorded as the Secchi Disk Depth (SDD, m). SDD provides an inexpensive index of the rate at which light is attenuated with depth. Due to the size of Tampa Bay and logistic support, it usually takes three weeks to collect the field SDD observations across the estuary (see Fig. 5-1). While these observations were used to characterize the monthly conditions of the Bay, clearly the sampling program is not synoptic and also inadequate to reflect the mean status of water clarity in a fast changing estuarine system like Tampa Bay (Chen et al., submitted, and Chapter 2).

Satellite remote sensing has been used to derive light attenuation coefficients in coastal and open waters using site-specific (and frequently time-specific) empirical algorithms (Austin & Petzold, 1981; Muller, 2000; Prasad et al., 1998; Stumpf & Pennock, 1991). Further, the standard empirical algorithm used to estimate the diffuse light attenuation coefficient at 490 nm ($K_d(490)$, m$^{-1}$) from Sea-viewing Wide Field-of-View Sensor (SeaWiFS) satellite data was developed based largely on open ocean observations where most $K_d(490) < 0.15$ m$^{-1}$ (Muller, 2000). Therefore, these historical empirical methods are prone to generate large errors in coastal and estuarine waters (Lee et al., 2005b). More recently, improved light attenuation coefficient estimates for coastal waters have been possible by application of a semi-analytical algorithm (Lee et al., 2005a; Lee et al., 2005b). However, the previous algorithm development and evaluation relied entirely on in situ measurements of above-water remote sensing reflectance ($R_{rs}$), and it remains unknown that how well the semi-analytical model retrieves the light attenuation from satellite observations because satellite derived remote sensing reflectance often contains uncertainties in coastal and estuarine waters (Harding et al., 2005; Hu et al., 2000).

Here I evaluate the semi-analytical method of Lee et al. (2005a) to estimate $K_d(490)$ using in situ SDD measurements collected in Tampa Bay by the EPCHC. I then estimate SDD using SeaWiFS imagery between September 1997 and December 2005 and characterize the temporal and spatial variability of water clarity in Tampa Bay. These analyses are compared to patterns inferred from the in situ surveys. Finally, some recommendations are provided for improving the water quality monitoring program of Tampa Bay and similar programs.
Figure 5-1. A SeaWiFS quasi-true-color RGB image of Tampa Bay showing the four sub-segments, namely, Old Tampa Bay (OTB), Hillsborough Bay (HB), Middle Tampa Bay (MTB), and Lower Tampa Bay (LTB). Major rivers shown are Hillsborough River (HR), Alafia River (AR), Little Manatee River (LMR), and Manatee River (MR). Environmental Protection Commission of Hillsborough County’s (EPCHC) water quality monitoring stations are shown using different symbols to indicate monthly sampling times: diamond (OTB) is generally sampled in the first week of the month, triangle (HB) generally in the second week, and squares (MTB and LTB) in the third or fourth weeks. Four stations (92, 23, 14, and 40, crosses) where time-series data were extracted for this study are also shown. The inset represents the relative position of Tampa Bay estuary in the state of Florida.
5.3. Materials and methods

5.3.1. Satellite data

SeaWiFS merged local area coverage (MLAC) Level-1A data were downloaded from the NASA Goddard Space Flight Center (GSFC, http://oceancolor.gsfc.nasa.gov/) and processed using the SeaWiFS Data Analysis System software (SeaDAS, Version 4.9). Two methods were used to estimate $K_d(490)$. One was the empirical band-ratio algorithm (the default algorithm in SeaDAS; http://oceancolor.gsfc.nasa.gov/REPROCESSING/SeaWiFS/R5.1/k490_update.html, updated Mueller’s (2000) algorithm). The second used the semi-analytical algorithm of Lee et al. (2005a). The standard method is an empirical algorithm based on the relationship between $K_d(490)$ and the blue-to-green ratio of water leaving radiance, $L_w$ (Mueller, 2000). The second method is a semi-analytical approach, which first derives absorption and backscattering coefficients from remote sensing reflectance, $R_{rs}$, and then uses these coefficients to estimate $K_d$ (Lee et al., 2005a). Standard SeaWiFS processing assessments for atmospheric correction failure, land, clouds, sun glint, and large solar/sensor angle were used to mask invalid pixels. Flags for stray light, shallow water, negative water-leaving radiance, and turbid case 2 water were disabled to increase the data coverage in time and space.

5.3.2. Field and ancillary data

In situ $K_d(490)$ observations were not available, so in situ SDD was used instead as a surrogate of water clarity. Previous studies have shown that SDD is empirically related to $K_d$ at certain wavelengths (Giesen et al. 1990; Jean-Franc & Giuseppe, 2004; Kirk, 1994; Kratzer et al., 2003). SDD was obtained from the Environmental Protection Commission of Hillsborough County's (EPCHC) Tampa Bay water quality monitoring program (Boler et al., 1991). Chlorophyll concentrations, turbidity (reported in nephelometric turbidity units or NTU), and color (Pt-units) were also collected along with SDD observations.

Daily averaged river flow rates of the Alafia River and the Hillsborough River, the two largest tributaries discharging fresh water into Tampa Bay, were obtained from the United State Geological Survey National Water Information System (USGS NWIS)
between 1997 and 2005. Monthly and climatological monthly means of river flow were derived. Wind data were obtained from one of the National Oceanic Atmospheric Administration (NOAA) Tampa Bay physical oceanographic real-time (PORT) stations at Saint Petersburg (27°45.6'N, 82°37.6'W) from 1997 to 2005. Wind data were binned into daily means of wind speed and the number of days when daily wind speed was $> 4.0 \text{ m s}^{-1}$ was calculated with the intent of understanding wind-induced sediment resuspension events. The cutoff wind speed of $4.0 \text{ m s}^{-1}$ was chosen based on Chen et al.’s (submitted) observations relating wind speed and possible sediment resuspension events in Tampa Bay.

5.3.3. Satellite-\textit{in situ} comparison

A narrow window of 2 hours between \textit{in situ} SDD measurements and the SeaWiFS overpass was used to find matching \textit{in situ} and satellite observations. A median value from a $3 \times 3$ pixel box centered at the measurement site was used to filter out sensor and algorithm noise (Hu et al., 2001). To ensure spatial homogeneity in the satellite data, the median value was used only when the number of the valid pixels within the $3 \times 3$ box was $> 4$ and the coefficient of variation (CV) of the valid pixels was $< 0.4$. To remove pixels where the bottom contaminated satellite radiances, pixels with water depths $< 2 \text{ m}$ (Gesch & Wilson, 2001) were masked and excluded from the match-up comparisons.

5.4. Results

5.4.1. Comparison between \textit{in situ} SDD and satellite $K_d(490)$

A total of 80 matching pairs were found after applying the various data quality restrictions described above. Old Tampa Bay (OTB) had seven matching station pairs, Middle Tampa Bay (MTB) had eight, and Lower Tampa Bay (LTB) had five stations. Only one match-up station was found for Hillsborough Bay (HB) due to the small area of that segment of the Bay, where there are several islands. The matching pairs were
relatively evenly distributed in time across four seasons (24 in spring, 20 in summer, 9 in fall, and 27 in winter).

The statistical relationships between in situ SDD and $K_d(490)$ derived empirically (EA) and semi-analytically (SA) were significantly different (Fig. 5-2). $K_d^{EA}(490)$ showed no significant relationship with in situ SDD ($\text{SDD} = 0.99 \times K_d^{EA}(490)^{-0.68}$, $r^2 = 0.14$, $n=80$), while $K_d^{SA}(490)$ showed a high correlation with in situ SDD ($\text{SDD} = 1.04 \times K_d^{SA}(490)^{-0.84}$, $0.9 < \text{SDD} < 8.0$ m, $r^2 = 0.67$, $n=80$). The median ratio between the predicted and in situ measured SDD from the 80 matching pairs, a measure of the bias, was 1.00 (mean ratio is 1.02), while the median absolute percentage difference (MPD, a measure of uncertainties, Bailey and Werdell, 2006) was 14% (mean absolute percentage difference was ~16%). The root mean square error (RMSE) was about 0.55 m over the observed SDD range from 0.9 to 8.0 m, suggesting that $K_d^{SA}(490)$ can be used to reliably estimate SDD. More importantly, the matching data covered a large dynamic range (about one order of magnitude in both parameters), and scattered nearly evenly across the entire range and across the regression line, and were spread evenly in space (except HB) and time. Given that the regression relationship was robust, it was applied to the entire SeaWiFS series of images collected between September 1997 and December 2005 to obtain a time-series of SDD fields for Tampa Bay. The monthly mean series and climatological monthly means of SDD were derived from the 8-year time-series of daily SDD imagery.

5.4.2. SDD image series

The climatological monthly composites of SDD showed distinctive spatial and temporal patterns across Tampa Bay (Fig. 5-3). A seasonal cycle is apparent with smaller $K_d(490)$ (larger SDD) from May to August and larger $K_d(490)$ (smaller SDD) from November to March. Relatively larger SDD values were consistently found in LTB and MTB in all months (e.g., >4.0 m in May), primarily near the deep channel along the central portion of the Bay. In contrast, OTB and HB consistently showed smaller SDD values except in HB during July, August, and September. At this time, SDD appeared to be overestimated (e.g. >4.0 m), likely due to the effects of erroneous atmospheric correction in these
months (see below). Due to these artifacts and insufficient validating point (e.g., only one station available in HB) for the relationship shown in Fig 5-2, we omitted HB from subsequent analyses.

Figure 5-2. *In situ* secchi disk depth (SDD, m) versus light attenuation coefficient at 490 nm ($K_d(490)$, m$^{-1}$) derived from SeaWiFS using (1) an empirical band-ratio algorithm (EA) (triangles, updated Mueller’s (2000) algorithm) and (2) a semi-analytical algorithm (SA) (circles, Lee et al., 2005a).

The spatial and seasonal variations revealed in the images can be better visualized by extracting time-series data at selected stations (Fig.5-4). In general, chlorophyll was highest in the upper Bay and decreased systematically toward the Lower Bay, while turbidity was lowest in the intermediate reaches of the Bay and higher in both the upper and lower Bay. Yet, SDD was relatively uniform across the Bay in November-March, but increased from the upper (Sta. 40 and Sta. 14) to lower bay portions (Sta. 23 and Sta. 92) in late spring (May to June). These patterns are visible both in the satellite and *in situ* data (e.g., within 1 standard deviation; Fig. 5-4).
Figure 5-3. Climatological monthly composites (September 1997 – December 2005) of SeaWiFS SDD (m). Color legend also shows the corresponding $K_d(490)$ values (m$^{-1}$). White color within Tampa Bay represents shallow water (bottom depth < 2.0 m). Grey color represents land.
Figure 5-3. (Continued)
The seasonal patterns are consistent with the time series of chlorophyll, color, and turbidity measurements (Fig. 5-5). The largest SDD coincided with the lowest chlorophyll concentration, color, and turbidity in May or June. Then, SDD gradually decreased with increasing chlorophyll and color while turbidity was slightly lower, suggesting that during the summer (corresponding to the rainy season from mid-June to mid-September; Fig. 5-6) SDD was primarily controlled by phytoplankton concentration. Chlorophyll reached maxima between July and October depending on location, and SDD showed lower values during this time, corresponding to a winter turbidity maximum. In the Middle and Lower Bay, minimal chlorophyll concentrations occurred starting in January through late spring around May, but turbidity did not reach minima until May, suggesting that SDD in the spring is controlled by factors such as sediment resuspension events.

The seasonality in water clarity in different parts of the Bay can therefore be explained by variations of river runoff and wind-driven sediment resuspension events (Fig. 5-6). Larger river runoff in August-October (Fig. 5-6a) delivers a higher nutrient flux into the Bay, contributing to phytoplankton growth. In comparison, stronger winds in March-April (Fig. 5-6b) lead to higher turbidity due to sediment resuspension.

SDD showed significant interannual variation. Fig. 5-7 shows the time series of monthly mean SDD extracted at several stations from the various bay segments. This interannual variations are better observed in SDD anomalies (the difference between the monthly means and the climatological monthly means; Fig. 5-8). Relatively lower SDD occurred in winter-spring of 1998 and summer-fall of 2001, 2003, and 2004 than in other years for all four stations. For stations 23 and 92 (middle to lower bay), SDD appeared higher between late 2002 and early 2003 and in late 2005. In particular, at station 92 there appeared to be a trend toward higher SDD after 2002. A Student’s t-test indicated that mean SDD (2.80 m) from July 2002 to December 2005 is significantly larger than that (2.42 m) between January 1999 and June 2002 (p<0.05, n=42, data before 1999 were not used due to El Niño effects on water quality in 1998, see below). Whether or not this is an indication of sustained improved water quality needs to be further investigated by extending the series beyond 2005.
Figure 5-4. Climatological monthly means of SeaWiFS (filled circles) and *in situ* (open circles) secchi disk depth (SDD, m) at several stations within Tampa Bay (Fig. 5-1). The number of SeaWiFS observation days during each month is shown on the right-hand side, note that the y-axis scale for Sta. 92 is different from those for other stations and there are only 8 *in situ* observations in each month. The vertical error bars indicate the standard deviation of satellite or *in situ* observations. No station from HB is shown here due to the uncertainties and insufficient points for the relationship shown in Fig. 5-2.
Figure 5-5. Climatological monthly means of (A) in situ chlorophyll (mg m⁻³), (B) color (Pt-unit), and (C) turbidity (nephelometric turbidity units, NTU) measurements from the EPCHC monitoring program at several stations from the various bay-segments (see Fig. 5-1 for the station locations) collected between September 1997 and December 2005. The horizontal lines indicate the means of all measurements during 8 years at each station.
Figure 5-5. (Continued)
Figure 5-5. (Continued)
The observed interannual SDD variations are generally in agreement with the variability in river discharge patterns (Fig. 5-9). Low SDD coincided with high river flow and vice-versa. For example, abnormally higher river flow during winter of 1997-1998, linked to the 1997-1998 El Niño event (Schmidt & Luther, 2002), led to the lowest SDD in early 1998. The hurricane-induced high river flow in August and September 2004 (Hu et al., 2006) led to the lower SDD in the corresponding months, particularly in the middle and lower Bay. There are, however, occasional exceptions. No corresponding high SDD values were found for the low river flow during 2000. Relatively higher SDD between 2002 and early 2003 occurred during a period of larger river flow, although wind speed during 2002 was slightly below the climatological means (Fig. 5-10). Clearly, although river flow and wind are the two major factors that affect SDD, other factors such as tides and estuarine circulation patterns (Weisberg & Zheng, 2005) may also contribute to modulate water quality in different parts of the Bay.

Overall, SeaWiFS SDD estimates are consistent with in situ SDD (Figs. 5-4 and 5-7, e.g., within 1 standard deviation). However, SeaWiFS SDD showed more pronounced seasonal and interannual variability that is not captured by the in situ SDD. For example, abnormally high in situ SDD values (> 5.0 m) were observed at Sta. 92 in February and March 2003, but the monthly SeaWiFS means (> 4 observations in each month) showed lower SDD values, comparable to those seen in other years. Although the high in situ SDD values in those months may capture actual events, they mask the seasonal patterns revealed in satellite observations (Fig. 5-7). These large differences (e.g., > 1-2 m) between two data sets are likely due, in great part, to the mismatch in sampling frequencies between the in situ program and the satellite collections because the uncertainties in the SeaWiFS SDD estimates, as measured by the RMS error (0.55 m in Fig. 5-2), are much smaller than the observed differences. Indeed SeaWiFS typically has > 4 quality-controlled observations per month (about once per week), and sometimes >10 observations per month between January and May (Fig. 5-7). This helps reduce aliasing of temporal variations and helps construct more reliable monthly means than using the single in situ monthly measurements.
Figure 5-6. (a) Climatological monthly means of river flow from the Hillsborough River (open circles) and the Alafia River (filled circles) from 1997 to 2005. (b) The total number of days when the daily averaged wind speed was > 4.0 m s\(^{-1}\) from 1997 to 2005 at the PORT station near Saint Petersburg (27°45.6'N, 82°37.6'W).
Figure 5-7. Monthly means of SeaWiFS and *in situ* SDD at selected stations (Fig. 5-1) from September 1997 to December 2005. The number of SeaWiFS observation days during each month is shown on the right-hand side. When this number is >1, standard deviation is also shown. Note that there is only one *in situ* observation in each month. J, M, and S stand for the month of January, May, September, respectively, and are denoted in a same way in the subsequent figures.
Figure 5-8. SeaWiFS SDD anomaly between September 1997 and December 2005 at several stations in Tampa Bay (Fig. 5-1). The anomaly is defined as the difference of SDD between the current month (Fig. 5-8) and the climatological month (red lines). Some gaps in anomaly lines at Sta. 14 and Sta. 40 are due to no valid values in those months. The box areas indicate 4 negative anomalies occurred around winter-spring of 1998, summer-fall of 2001, 2003, and 2004, respectively, while filled arrows in Sta. 92 indicate the positive anomalies in late 2002-early 2003 and in late 2005, respectively.
Figure 5-9. Monthly means of river flow from the Hillsborough River (open circles) and the Alafia River (filled circles) from September 1997 to December 2005.

Figure 5-10. The number of days when the daily averaged wind speed was > 4.0 m s\(^{-1}\) of each month from September 1997 to December 2005 at the PORT station near Saint Petersburg (27°45.6'N, 82°37.6'W). The overlaid red line indicates climatological means of number of the days of 12 months.
5.5. Discussion

5.5.1. Algorithm issues

The semi-analytically derived $K_d(490)$ showed a much improved relationship with \textit{in situ} SDD relative to the empirical band-ratio $K_d(490)$. The agreement is remarkably good given a general algorithm without any fine tuning was applied. The improvement can be attributed to two unique features employed the semi-analytical algorithm. Firstly, the semi-analytical algorithm explicitly estimates absorption and backscattering coefficients (two major contributors to $K_d$) based on the vigorous radiative transfer theory, therefore it is less dependent of water types. More importantly, various semi-analytical algorithms have demonstrated that the absorption and backscattering coefficients can be well retrieved from ocean color remote sensing with ~15% in various waters (Lee et al., 2005a, and references therein). Secondly, semi-analytical algorithms use more than two bands in the algorithm to estimate the light attenuation coefficients; therefore retrievals contain more information than those from simple two-band ratio algorithms (Lee et al., 2005b). These results suggest that although there may be relatively large uncertainties in the atmospheric correction over coastal and estuarine waters (e.g., Hu et al. 2000), water quality parameters derived from an improved bio-optical algorithm may be sufficiently accurate for coastal water monitoring programs. Indeed, Magnuson et al. (2005) also showed better performance in retrievals of chlorophyll concentration using an improved, locally tuned bio-optical algorithm.

However, the apparent underestimates of light attenuation in Hillsborough Bay (HB) during the summer/rainy season are likely due to the artifacts in the atmospheric correction. At this time of the year and in this region, remote sensing reflectance ($R_{rs}$) in the blue-green wavelengths is very low (the maximum $R_{rs}$ at visible domain is < 0.002 sr$^{-1}$, unpublished data) due to the high terrestrial input of colored dissolved organic matter (CDOM) (Chen et al., in press). A slight error in the atmospheric correction may cause much larger relative errors in $R_{rs}$ (Harding et al., 2005; Hu et al., 2001) and therefore create erroneous estimates in light attenuation. A detailed look into the satellite derived $R_{rs}$ found that after atmospheric correction $R_{rs}(412)$ in those invalid pixels was often larger than $R_{rs}(443)$, an impossible feature for this type of water. The exact reason for this
discrepancy was not clear. However, these effects appear to be limited to HB only, and are negligible for other bay-segments as shown in the relationship between $K_d(490)$ and SDD (Fig., 5-2). Therefore, the results presented for other bay segments are still valid.

5.5.2. Implications for Tampa Bay ecosystem restoration and water quality monitoring

SeaWiFS SDD imagery clearly shows that the seasonal cycle is influenced by river flow through inputs of CDOM and nutrients. This observation is consistent with previous studies that found that Tampa Bay water quality is closely related to precipitation and river runoff (Chen et al., in press; Lipp et al., 2001; Schmidt & Mark, 2002). This is likely the primary reason that chlorophyll variation accounts for the majority of light attenuation variation in Tampa Bay (Janicki et al., 2001). Based on this finding, the Tampa Bay National Estuary Program (TBNEP) proposed a Nitrogen Management Strategy that seeks to increase water clarity for seagrass restoration through reducing phytoplankton concentration by controlling total nitrogen loadings into the bay (Janicki et al., 2001).

However, our results suggest that SDD is also controlled by other processes. Indeed, although increased phytoplankton and color lead to decreasing SDD in the summer/rainy season, the SDD values are still larger than those in the winter season when turbidity is at larger levels (Fig. 5-3). Particularly SDD reaches a maximum (i.e., highest water clarity) in May only when turbidity turns into lower values, while phytoplankton and color show little change during this variation. This suggests that turbidity due to an increase in sediment resuspension is an important factor impacting water clarity, as seen in previous studies in Tampa Bay (McPherson & Miller, 1994) and in other estuaries (e.g., Christian & Sheng, 2003). Therefore, an optimal management plan may also include controls of sediment load or at least greater understanding of factors leading to sediment resuspension in the Bay.

Because of more frequent and synoptic coverage, SeaWiFS provides improved estimates of the monthly “mean” patterns of SDD and monitoring long-term trends. For example, it is difficult to determine trends from the in situ data because they are collected
only once per month and are easily biased by “extreme” events. Complementing the in situ data with satellite observations helps detect, for example, trends such as the water clarity improvement in the lower bay after 2002. Clearly, future monitoring plans should include satellite remote sensing to help interpret the spatial-temporal patterns as well as the long-term trends.

5.6. Conclusions

One major issue in application of satellite data to monitor estuarine water quality has been the lack of sufficient accuracy due to uncertainties in the atmospheric correction and bio-optical inversion algorithms. Using a semi-analytical algorithm and rigorous data quality control, I showed that one of the critical water quality parameters, the Secchi Disk Depth (SDD, an index for water clarity), can be accurately derived from SeaWiFS data for most of Tampa Bay waters and for all seasons (standard error of 0.55 m for SDD ranging from 0.9 to 8.0 m). Although some artifacts exist due to erroneous atmospheric correction, the frequent and synoptic coverage of the satellite data provides better estimates of the spatial-temporal patterns as well as long-term trends of SDD. This can greatly benefit long-term monitoring efforts of estuarine waters, most or all of which are based only on field surveys. The distinctive spatial and temporal viability revealed in SeaWiFS SDD imagery highlights the importance of river runoff (phytoplankton and color) in the rainy season and of wind-induced sediment resuspension (turbidity) in the dry season in controlling the light attenuation and therefore SDD across Tampa Bay, particularly in the middle and lower portions of the Bay.

Therefore, optimal management plans should not only focus on total nitrogen control, but also on understanding and mitigating total sediment load from various sources such as storm water, river runoff, dredging and transportation activities. Because of the synoptic, robust, and the repeated global coverage, satellites like the SeaWiFS represent an important complement to traditional in situ sampling methods. Thus, I also strongly recommend incorporating satellite observations of light attenuation or water clarity to various coastal monitoring programs to help better manage estuarine and coastal resources.
6.1. Main conclusions

This study addressed monitoring of water quality in Tampa Bay using both *in situ* and remote sensing techniques. Four key water quality indices, specifically chlorophyll, dissolved colored organic matter, turbidity, and water clarity were examined. The results showed the following:

Hourly observations collected with bio-optical sensors attached to a moored buoy showed large short-term variability at tidal and sub-tidal scales in both chlorophyll and suspended sediment concentrations in the dry season. The variability was primarily driven by tides and winds. During the wet season, the data was not useful due to severe bio-fouling of the instruments.

Phytoplankton blooms occurred 1-2 days after high turbidity caused by wind-drive sediment suspension events subsided, with the largest blooms occurring if a neap tide coincided with the subsidence of turbidity.

The hourly *in situ* observations collected with the automated sensors showed that the sampling strategy presently used by the Environmental Protection Commission of Hillsborough County (EPCHC), which consists of single observations at a series of stations occupied over a period of three weeks every month, introduces biases (-50% to 200%) if they are used to represent the monthly mean conditions in the chlorophyll and suspended sediment concentration of Tampa Bay. A higher frequency of sampling is needed to characterize a fast changing estuary like Tampa Bay.

The *in situ* spatial sampling of optical properties revealed that CDOM is delivered to Tampa Bay primarily by riverine inputs, and that it exhibited conservative mixing during the dry season and apparent non-conservative mixing during the wet season. The non-conservative behavior of CDOM in the gradient between Hillsborough
Bay and Middle Tampa Bay could be explained by photobleaching, but it could also be due to CDOM delivered by Old Tampa Bay in a scenario of multiple endmembers. Old Tampa Bay CDOM showed distinctively different properties with higher spectral slopes and fluorescence efficiency and lower absorption coefficients relative to CDOM in the other basins. These differences may be related to the shallow bathymetry in OTB and some local processes like photobleaching, inputs from primary production in water column and/or seagrass.

Satellite remote sensing showed promising results as a tool to monitor Tampa Bay water quality frequently and synoptically. A turbidity algorithm for application of MODIS/Aqua 250 m imagery was developed by systematically evaluating the radiometric observations, atmospheric correction algorithm, and developing a relationship between turbidity and remote sensing reflectance at 645 nm. MODIS turbidity images showed distinct spatial and temporal patterns related to river runoff in the upper bay, and to wind-induced sediment resuspension events in the middle and lower portions of the bay. As compared to the single station measurements from the monthly water quality surveys, MODIS derived turbidity provided more 'realistic' and consistent estimates of the mean and varying conditions of “turbidity” in Tampa Bay. MODIS provided as many as 10 views of the Bay per month.

Light attenuation coefficients were derived using SeaWiFS images through application of a new semi-analytical algorithm designed to estimate secchi disk depth (SDD). The SeaWiFS SDD image series confirmed that water clarity is related to temporal and spatial patterns of river runoff and also to wind-induced sediment resuspension events.

6.2. Future work

(1) My study of short-term variability was limited to one station and one (dry) season. To fully understand the spatial and temporal variability in chlorophyll and sediment dynamics, bio-optical sensors should be deployed in different bay segments and in different seasons. However, current bio-optical sensors suffer
from bio-fouling in the summer season. Therefore a new deployment method has to be developed.

(2) More studies are needed to understand the cause for increased chlorophyll during neap tides after wind induced bottom sediment resuspension events.

(3) The effects of bottom contamination on satellite remotely sensed signals have not been fully addressed in my thesis. I simply masked suspected areas of shallow water. Because Tampa Bay is on average only 3-4 m deep, quantitative evaluation of this effect is necessary;

(4) More effort should be placed in developing a robust algorithm to estimate chlorophyll in the Bay. Similarly, near-IR band ratios are two promising methods that should be tested in the Bay.

(5) Work with resource managers to develop a prototype water-quality monitoring tool based on information collected automatically from sensors deployed on buoys and satellite imagery of turbidity and water clarity would significantly help efforts to monitor Tampa Bay. These tools and applications need to be developed.


104


Ruddick, K., Park, Y, & Nechad, B. (2003). MERIS imagery of Belgian coastal waters: mapping of suspended particulate matter and chlorophyll-a. MERIS user workshop, 10-13th November, (Frascati), ESA, SP-549


Appendices
Appendix 3-1. Surface salinity, CDOM absorption coefficient at 400 nm ($a_{\text{CDOM}(400)}$, m$^{-1}$) and spectral slope (S, nm$^{-1}$), total suspended solids concentration (TSS, mg/l), chlorophyll concentration (Chl, mg/m$^3$), dissolved organic carbon concentration (DOC, µM) and normalized CDOM fluorescence (Quinine Sulfate equivalent, QSE) in Tampa Bay and the Alafia River (AR) in the 2004 dry (June, first row per station) and wet (October, second row per station) seasons. Station locations can be found in Fig. 1.

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Appendix 3-1 (Continued)
### Old Tampa Bay

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|          | **Dry Season Average** | 25.5(1.2) | 1.03 (0.19) | 21.6 (2.1) | 6.8(1.7) | 6.5 (0.9) | 375 (51) | 28 (3.6) |
| Wet Season Average | 14.9(1.4) | 4.05 (0.72) | 17.8 (0.4) | 8.8 (4.3) | 17.7 (8.9) | N.D. | N.D. |

Appendix 3-1 (Continued)
### Tampa Bay Average

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### The Alafia River

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<td>18.2</td>
<td>398</td>
<td>45</td>
<td></td>
</tr>
</tbody>
</table>

| Dry Season Average |          |           | 7.4 (6.6) | 5.35 (1.34) | 16 (1) | 7.3 (5.4) | 11.0 (5.9) | 414 (56) | 70 (17) |

Appendix 3-1 (Continued)

Notes:

1. CDOM absorption spectral slope (S) was determined over the wavelength range 350 ~ 440 nm.
2. N.D. = “not determined”.
3. The numbers in parentheses in each average row represent standard deviations.
About the Author

Zhiqiang Chen was enrolled in the College of Marine Science (CMS) at the University of South Florida (USF) in August, 2001. Before coming to USF, he obtained his B.S. of marine chemistry at Xiamen University in Fujian, China and his M.S. of Chemical Oceanography at the Second Institute of Oceanography (SIO) in Hangzhou, China.

The study at Institute of Marine Remote Sensing (MaRS) at USF provides him opportunity of receiving extensive training in radiative transfer theory, *in situ* and lab experiments and other oceanographic topics. In 2003, he was awarded the U.S. Geological Study (USGS)-USF cooperative research assistantship. Since then he has focused on monitoring water quality in Tampa Bay using the lastest remote sensing techniques. During his study period, he published 5 papers.