Remote sensing of water clarity in Tampa Bay

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Abstract

We examined the spatial and temporal variability of the Secchi Disk Depth (SDD) within Tampa Bay, Florida, using the Sea-viewing Wide Field-of-View Sensor (SeaWiFS) satellite imagery collected from September 1997 to December 2005. SDD was computed using a two-step process, first estimating the diffuse light attenuation coefficient at 490 nm, $K_d(490)$, using a semi-analytical algorithm and then SDD using an empirical relationship with $K_d(490)$. The empirical SDD algorithm ($SDD = 1.04 \times K_d(490) - 0.82$, $0.9 < SDD < 8.0$ m, $r^2 = 0.67$, $n = 80$) is based on historical SDD observations collected by the Environmental Protection Commission of Hillsborough County (EPCHC) in Tampa Bay. SeaWiFS derived SDD showed distinctive seasonal variability, attributed primarily to chlorophyll concentrations and color in the rainy season and to turbidity in the dry season, which are in turn controlled by river runoff and winds or wind-induced sediment resuspension, respectively. The Bay also experienced strong interannual variability, mainly related to river runoff variability. As compared to in situ single measurements, the SeaWiFS data provide improved estimates of the “mean” water clarity conditions in this estuary because of the robust, frequent, and synoptic coverage. Therefore we recommend incorporation of this technique for routine monitoring of water quality in coastal and large estuarine waters like Tampa Bay.

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1. Introduction

Tampa Bay is the largest open-water estuary in Florida, U.S.A., with a surface area of $\sim 1000$ km$^2$. It is traditionally divided into four main sub-segments, namely Old Tampa Bay (OTB), Hillsborough Bay (HB), Middle Tampa Bay (MTB), and Lower Tampa Bay (LTM) (Fig. 1). 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), which contributes over $5$ billion annually to the economy of the state from trade, tourism, development, and fishing (FDCA, 1996). It is therefore critical that the development of the Bay area be conducted in an environmentally sound way to sustain a healthy system.

In the decades prior to the 1980’s, Tampa Bay was heavily polluted by nutrient loadings from sources like sewage and other wastewater. This led to sustained phytoplankton blooms that reduced the water clarity, which in turn is considered as the cause of the 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 coordinate and integrate efforts to restore and protect the Bay. In 1996, the 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 reducing nutrient (primary nitrogen) inputs into the Bay (Janicki & Wade, 1996). Water quality of the Bay has gradually improved, and some of the seagrass has recovered (Johansson, 2000; Tomasko et al., 2005). Thus water clarity in Tampa Bay has been monitored as a measure of the impact of nutrient load on phytoplankton concentrations, and is a key parameter used in riverine nutrient input management (Janicki et al., 2001).

Water clarity in Tampa Bay has been measured with a Secchi disk once per month at established stations (Janicki & Wade,
1996; Fig. 1), as done in many coastal environmental monitoring programs. A white disk (sometimes also painted in black/white quarters), usually \( \sim 20 \) 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, in units of meters). SDD provides a simple, inexpensive measurement of the rate at which light is attenuated with depth. Due to the size of Tampa Bay and logistical limitations, it usually takes three weeks to conduct bay-wide SDD observations at a series of pre-established historical stations (Fig. 1). Clearly this sampling program is not synoptic, so a natural question is whether this monitoring strategy is sufficient to help assess the mean and variability in water clarity in time over the extent of Tampa Bay, the extent and changes in eutrophication due to anthropogenic nutrient inputs, and the impact on areas where seagrass re-growth is desired.

Water clarity or specifically light attenuation coefficients have also been estimated for coastal and open ocean waters using satellite ocean color measurements drawing upon the repeated and synoptic sampling capability. However, previous applications frequently used site- and/or time-specific empirical algorithms (Austin & Petzold, 1981; Mueller, 2000; Prasad et al., 1998; Stumpf & Pennock, 1991). For example, the standard empirical algorithm used to estimate the diffuse light attenuation coefficient at 490 nm, \( K_d(490) \) (m\(^{-1})\), from the Sea-viewing Wide Field-of-View Sensor (SeaWiFS) data was developed based largely on open ocean observations where most \( K_d(490) < 0.15 \) m\(^{-1}\) (Mueller, 2000). Thus the previous empirical algorithms are prone to generate large errors when applied to coastal and estuarine waters where the optical properties are different from those waters for algorithm development (Lee et al., 2005b). More recently, improved light attenuation coefficient estimates for coastal waters have been possible by application of a semi-analytical algorithm to in situ collected data (Lee et al., 2005a,b). However, the accuracy of estimates based on space-based observations remains unknown, because satellite-derived reflectance contains uncertainties over coastal and estuarine zones due to non-zero remote sensing reflectance (\( R_{rs} \)) in the near-infrared in some turbid waters, and/or due to high concentrations of blue-absorbing aerosols in some near-shore atmosphere (Harding et al., 2005; Hu et al., 2000).

Here, we used a two-step transformation of SeaWiFS imagery to estimate water clarity in Tampa Bay between September 1997 and December 2005. We first we estimated \( K_d(490) \) based on the semi-analytical method of Lee et al. (2005a). The \( K_d(490) \) estimates were closely related to SDD observations collected by the Environmental Protection Commission of Hillsborough County (EPCHC). This allowed us to examine the temporal and spatial variability of SDD in Tampa Bay using the satellite data, by computing SDD based on the remotely-sensed \( K_d(490) \). Based on our results, we further provide recommendations for improving the water quality monitoring program of Tampa Bay and similar programs in other estuaries.

2. Methods and materials

2.1. Satellite data

SeaWiFS “merged local area coverage” (MLAC) Level-1A data (nominal spatial resolution of \( \sim 1 \) km) were downloaded from the NASA Goddard Space Flight Center (GSFC, http://
Fig. 3. Overall cross-year 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.
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 default SeaDAS empirical band-ratio algorithm (Mueller, 2000). This algorithm is based on the relationship between $K_d(490)$ and the blue-to-green ratio of normalized water leaving radiance, $L_{nw}(490)/L_{nw}(555)$. The second was the semi-analytical algorithm proposed by Lee et al. (2005a), which first derives absorption and backscattering coefficients from $R_{rs}$ and then uses these coefficients to estimate $K_d$. During SeaWiFS image processing, pixels were masked for conditions of atmospheric correction failure, land, clouds, large sun glint, and large solar/sensor angles. Processing software 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 over Tampa Bay.

2.2. Field and ancillary data

We did not find published values for in situ $K_d(490)$ observations in Tampa Bay. Therefore, historical in situ SDD measurements from the EPCHC’s Tampa Bay water quality monitoring program (Boler et al., 1991) were used as a surrogate of $K_d(490)$. Indeed SDD has been empirically related to light attenuation coefficients in some previous studies (Giesen et al., 1990; Jean-Franc & Giuseppe, 2004; Kratzer et al., 2003). The EPCHC program also collects chlorophyll concentrations, turbidity (reported in nephelometric turbidity units or NTU), and color (Pt-units) measurements. These parameters were used in this study to examine the factors affecting water clarity in the Bay.

Daily averaged river flow rates (1997–2005) of the Alafia River and the Hillsborough River, the two largest tributaries discharging fresh water into Tampa Bay, were obtained from the United States Geological Survey National Water Information System (USGS NWIS). We derived calendar monthly means of river flow, as well as overall cross-year monthly flow averages (i.e. averages of the same month across all years). Wind data (1997–2005) were obtained from one of the National Oceanic Atmospheric Administration (NOAA) Tampa Bay physical oceanographic real-time (PORT) stations located in Tampa Bay near Saint Petersburg (27°45.6′N, 82°37.6′W). Wind speed measurements were binned into daily means, and the number of days when daily wind speed was >4.0 m s$^{-1}$ was calculated to identify conditions for wind-induced sediment resuspension.

![Fig. 4. Overall cross-year monthly means of SeaWiFS (filled circles) and in situ (open circles) Secchi disk depth (SDD, m) at several stations across Tampa Bay (Fig. 1).](image-url)
Fig. 5. Overall cross-year monthly means of in situ (A) chlorophyll (mg m\(^{-3}\)), (B) color (Pt-units), and (C) turbidity (nephelometric turbidity units, NTU) measurements from the EPHC’s monitoring program at several stations in various bay-segments (see Fig. 1 for the station locations) collected between September 1997 and December 2005. The horizontal lines show the means of each measurement over the 8-year period at each station.
events. This wind speed threshold was based on visual inspections of time series of wind speed and sediment resuspension events in Tampa Bay (Chen et al., in press-b).

2.3. Satellite-in situ comparison

A narrow window of 2 h was used to find matching in situ and SeaWiFS satellite observations (Bailey & Werdell, 2006). A median value from a $3 \times 3$ pixel box centered at an in situ measurement site was used to filter 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 valid pixels identified with the satellite data processing flags was $>4$ and the coefficient of variation (CV) was $<0.4$. Since the average depth of Tampa Bay is $\sim 4.0$ m, all pixels shallower than 2.0 m were masked using a digital bathymetric database (Gesch & Wilson, 2001) and excluded from the match-up comparison to minimize possible interference due to bottom reflectance. The depth of 2.0 m was chosen by trial-and-error, seeking a depth threshold that provided the highest correlation coefficient between in situ SDD and satellite $K_d(490)$.

3. Results

3.1. Comparison between in situ SDD and satellite $K_d(490)$

A total of 80 matching pairs were found from 1997 to 2005 after applying the various data quality control criteria described above. The matching pairs were spatially distributed as follows: 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 also several small 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 the $K_d(490)$ derived semi-analytically (SA) were significantly different (Fig. 2). $K_d^{EA}(490)$ showed no significant relationship with in situ SDD ($r^2 = 0.14$, $n = 80$), while $K_d^{SA}(490)$ showed a strong correlation with in situ SDD (SDD $= 1.04 \times K_d^{SA}(490)^{-0.34}$, $0.9 <$ SDD $< 8.0$ m, $r^2 = 0.67$, $n = 80$). The median ratio (a measure of overall bias) between the predicted and in situ measured SDD from the 80 matching pairs was 1.00 (mean ratio was 1.02). The median absolute percentage difference (MPD, a measure of uncertainty, Bailey & Werdell, 2006) was 14% (mean absolute percentage difference was $\sim 16\%$). The $K_d^{SA}(490)$ root mean square error (RMSE) was 0.55 m over the observed SDD range from 0.9 to 8.0 m.

These comparisons suggested that $K_d^{SA}(490)$ can be used to estimate SDD over a large dynamic range (about one order of magnitude in both parameters) (Fig. 2), in most areas of Tampa Bay, and in all seasons across years. Therefore we applied the regression relationship to the SeaWiFS series of images (September 1997–December 2005) to obtain a time-series of SDD images for Tampa Bay. Calendar monthly means and

Fig. 5 (continued).
overall cross-year monthly means of SDD were derived from the nearly 8-year time-series of daily SDD imagery.

3.2. SDD image series

The overall cross-year monthly composites of SDD showed distinct spatial and temporal patterns across Tampa Bay (Fig. 3). A seasonal cycle was 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 along the deep channel in the central portion of the Bay. OTB and HB consistently showed smaller SDD values except in HB during July, August, and September, when SDD in these areas appeared to be overestimated (e.g., >4.0 m). This is likely the result of an erroneous atmospheric correction (see discussion below). Due to these artifacts and insufficient validation points for the relationship shown in Fig. 2 (only one station in HB), we omitted HB from subsequent analyses.

The spatial and seasonal variability can be further characterized by extracting time-series data at selected stations (Fig. 4). In general, chlorophyll was highest in the upper Bay and decreased toward the lower Bay, while turbidity was lowest in the intermediate reaches of the Bay and higher in 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. 4).

The seasonal patterns are consistent with the time series of chlorophyll, color, and turbidity measurements (Fig. 5). The largest SDD occurred in May or June, when the lowest chlorophyll concentration, color, and turbidity were measured. Then SDD gradually decreased with increasing chlorophyll and color, while turbidity remained relatively stable at low levels. This suggested that during summer season (corresponding to the rainy season from mid-June to mid-September; Fig. 6) SDD was primarily controlled by phytoplankton concentration and factors that affect “color” measurements. Chlorophyll and color reached maxima between July and October depending on the locations, after which they decreased through the fall and winter and reached minima in the late spring or until the start of a new rainy season. However SDD showed a different variation pattern from phytoplankton and color. SDD did not show a would-be increase as a response of reduced phytoplankton and color after the summer. In contrast it continued decreasing through the fall and winter. So SDD was generally lower in the dry season than in the rainy season, particularly in Middle and Lower Tampa Bay (Fig. 3). This lower SDD is coincident with increased turbidity observed in those areas and these times. SDD remained at the lower levels until in early spring (e.g., April) when it began to increase with continuously decreasing phytoplankton and color, and slightly reduced turbidity. SDD rapidly reached maxima in May or June when turbidity significantly decreased from April to May and all three factors were nearly the lowest levels over a year (Figs. 4 and 5).

After that, a new seasonal cycle of SDD started. These patterns indicate that in the dry season SDD is controlled mainly by turbidity rather than by phytoplankton or color. Indeed, in the upper bay (e.g., station 40), SDD slightly increased in the dry season when turbidity decreased, while phytoplankton and color varied little (Figs. 4 and 5).

The seasonality in water clarity can be explained by seasonal variations of river runoff and wind forcing or wind-driven sediment resuspension (Fig. 6). Larger river runoff in mid-June through mid-September (Fig. 6A) delivers higher nutrient and dissolved organic matter fluxes into the Bay, contributing phytoplankton growth and increased color in the Bay. In comparison, stronger winds lead to sediment resuspension in the dry season, especially in March–April (Fig. 6B). The sediment resuspension events lead to higher turbidity in the dry season than in the rainy season.

The SDD images show that the Bay experienced significant interannual variation in water clarity. Fig. 7 shows the time series of calendar monthly mean SDD at several stations in various bay segments. To study interannual variations, we extracted SDD anomalies (Fig. 8) by computing the difference between the calendar monthly means and the overall cross-year monthly means. Lower SDD occurred in winter–spring of 1998 and summer–fall of 2001, 2003, and 2004 at all four stations. SDD was higher in the middle to lower bay (stations 23 and 92) between late 2002 and early 2003, and in late 2005. In particular, at station 92, higher SDD was observed after 2002. A Student’s $t$-test indicated that the mean SDD (2.80 m) from July 2002 to December 2005 was significantly larger than that seen between January 1999 and June 2002 (2.42 m; $p<0.05$, $n=42$).
data before 1999 were not used due to strong El Niño effects on water quality in 1998). Whether or not this is an indication of a trend toward improved water quality needs to be further investigated by extending the SDD series beyond 2005.

The observed interannual SDD variations are generally in agreement with the variability in river discharge patterns (Fig. 9). Lower SDD coincided with higher river flow, and vice-versa. For example, the lowest SDD observed in early 1998 is associated with abnormally higher river flow in winter of 1997–1998, triggered by the 1997–1998 El Niño event (Schmidt & Luther, 2002). The high river flow in August and September 2004, a result of anomalous rainfall caused by several hurricanes (Hu et al., 2006), led to lower SDD particularly in the middle and lower Bay (also partly caused by higher winds). There were, however, some exceptions. Lower SDD values were found during the lower river flow of 2000. Higher SDD between 2002 and early 2003 occurred during a period of increased river flow, while wind speed during 2002 was slightly below the long-term cross-year wind speed mean of that month (Fig. 10). Clearly, river flow and wind are the two major factors that affect SDD, but other factors such as tides and estuarine circulation patterns (Weisberg & Zheng, 2006) may also contribute to modulate water clarity in the Bay.

Overall, SeaWiFS SDD estimates are consistent with in situ SDD within one standard deviation (Figs. 4 and 7). However, SeaWiFS SDD showed more pronounced seasonal and interannual variability that is not captured by the in situ SDD sampled once per month. 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 per month) showed lower SDD values (<3.0 m), comparable to those of other years. Although the higher in situ SDD values might capture actual events, they clearly suffer from the aliasing effect to represent monthly means of the SDD. Those differences of >1 or 2 m between the two data sets are likely due to the mismatch in sampling frequencies between the in situ program and the satellite collections, because the uncertainties of the SeaWiFS SDD (RMS error of 0.55 m in Fig. 2) are smaller than the differences observed. SeaWiFS typically has >4 quality-controlled observations per month (about once per week), and sometimes >10 observations per month between January and May (Fig. 7). This helps reduce aliasing of temporal variations and construct more realistic monthly means than simply using a single in situ measurement per month, at different times of the month for different areas of the bay.

4. Discussion

4.1. Algorithm issues

The $K_d(490)$ derived from satellite images using a semi-analytical algorithm provides an excellent estimate of in situ SDD values, particularly relative to the empirical band-ratio $K_d (490)$. The improvement can be attributed to two unique

Fig. 7. Monthly means of SeaWiFS and in situ SDD at selected stations (Fig. 1) from September 1997 to December 2005. The number of SeaWiFS observation days in each month is shown on the right-hand side. When this number is >1, standard deviation is shown. Note that there is only one in situ observation in each month. J, M, and S stand for January, May, and September.
features of the semi-analytical algorithm. First, the semi-analytical algorithm explicitly estimates absorption and backscattering coefficients (two major factors that determine $K_d$) based on radiative transfer theory. Various semi-analytical algorithms have demonstrated that the absorption and backscattering coefficients can be retrieved from ocean color remote sensing within the accuracy of $<15\%$ in various water types (Lee et al., 2005a, and references therein). Consequently, a semi-analytical algorithm can be accurately applied to a variety of regions even without concurrent in situ measurements with satellites. This general applicability contributes to extend ocean

Fig. 8. SeaWiFS SDD anomaly between September 1997 and December 2005 at several stations in Tampa Bay (Fig. 1). The anomaly is defined as the difference of SDD between the current month and the overall cross-year monthly mean (red lines). Some gaps at Sta. 14 and Sta. 40 are due to missing data in those months. The boxes indicate the four negative anomalies that occurred in winter–spring of 1998, and summer–fall of 2001, 2003, and 2004, respectively. The filled arrows in Sta. 92 show positive anomalies in late 2002–early 2003 and in late 2005.

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

Fig. 10. The number of days when the daily averaged wind speed was $>4.0$ m s$^{-1}$ in each month from September 1997 to December 2005 at the PORT station near Saint Petersburg (27 °45.6′N, 82 °37.6′W). The red line shows the long-term cross-year means of number of the days when the daily averaged wind speed was $>4.0$ m s$^{-1}$ of 12 months.
color remote sensing from the open ocean to coastal waters. Second, semi-analytical algorithms use more than two bands to estimate the light attenuation coefficient (Lee et al., 2005b). Therefore even though atmospheric correction over coastal and estuarine waters contains uncertainties over coastal waters (e.g., Hu et al., 2000), some water quality parameters may still be estimated with some accuracy and applicable for coastal water monitoring programs.

The present study focused on SeaWiFS data, but the same approach can be used with the Moderate Resolution Imaging Spectroradiometer (MODIS) data. The MODIS has similar spectral bands and spatial resolution as the SeaWiFS, and the atmospheric correction strategy and algorithms are comparable or identical. Since MODIS and SeaWiFS have different satellite overpass times, combining data from these sensors actually improves spatial and temporal coverage (e.g., Hu & Muller-Karger, 2003). However, a careful comparison of remote sensing reflectance data between the two sensors would be required beforehand.

SeaWiFS-derived SDD or $K_d$ estimates may suffer from some uncertainties in certain regions and times. The underestimates of light attenuation in Hillsborough Bay (HB) during the summer or rainy season are artifacts likely due to the performance of the atmospheric correction algorithm. During summer in this region, remote sensing reflectance ($R_{rs}$) in the blue and green wavelengths is very low (the maximum $R_{rs}$ at visible domain is <0.002 sr$^{-1}$, unpublished data) due to the high input of terrigenous colored dissolved organic matter (CDOM) (Chen et al., in press-a). A slight error in the atmospheric correction may cause large relative errors in $R_{rs}$ (Harding et al., 2005; Hu et al., 2001) and therefore lead to large errors in the estimates of light attenuation. For example, overestimation of $R_{rs}$ will result in underestimation of attenuation (thus overestimation of SDD), as $R_{rs}$ is inversely proportional to the attenuation coefficient. Indeed, a detailed examination of the satellite derived $R_{rs}$ reveals that satellite derived $R_{rs}$ at invalid pixels was often larger than $R_{rs}$ at (443), which is highly unlikely for this type of water. The exact reason for this discrepancy was not clear. However, these effects appear to be limited to HB and are negligible for other bay segments and for overall agreement between satellite and in situ observations (Figs. 2 and 4).

### 4.2. Implications for Tampa Bay water quality monitoring and ecosystem restoration

SeaWiFS SDD imagery clearly shows that the seasonal cycle of SDD is influenced by river runoff because river waters contain high nutrients and dissolved organic matter, thus increase phytoplankton and color concentrations (e.g., Chen et al., in press-a). The result is consistent with previous observations that Tampa Bay water quality is closely related to precipitation or river runoff (Lipp et al., 2001; Schmidt & Luther, 2002) and that SDD variation in Tampa Bay is largely the result of changes in chlorophyll concentrations (Janicki & Wade, 1996). These previous findings led to an implementation of Nitrogen Management Strategy by the Tampa Bay National Estuary Program (TBNEP), which seeks to increase water clarity for seagrass restoration through reducing phytoplankton concentration by controlling riverine nitrogen loadings into the bay (Janicki et al., 2001). However, our results also clearly show that SDD is controlled by turbidity as well, which is in turn related to winds or wind-induced sediment resuspension, particularly in the dry season. The effects of turbidity on water clarity have been observed in previous studies in Tampa Bay (McPherson & Miller, 1994) and in other estuaries (e.g., Christian & Sheng, 2003). Thus, to fully understand water clarity variations, both sediment load from runoff and wind-driven resuspension events need to be considered for an optimal management plan in Tampa Bay.

Because of the ability to provide much more frequent and synoptic coverage, satellite sensors such as the SeaWiFS can help improve estimates of the monthly “mean” patterns of SDD and monitoring long-term trends. It is difficult to determine short and long-term trends from the in situ data from the EPCHC monitoring program because they are collected only once per month and therefore are easily biased by “extreme” events. However, complementing these in situ data with satellite observations is ideal because together they help detect both events and trends, such as the water clarity improvement in the lower bay after 2002. We recommend that future monitoring plans include satellite ocean color remote sensing to help interpret the spatial-temporal patterns of some important water quality indices.

### 5. Conclusions

A major issue in the application of satellite data to study and monitor estuarine water quality has been the lack of accuracy and uncertainties introduced by both the atmospheric correction and bio-optical inversion algorithms. Using a semi-analytical algorithm and a rigorous data quality control step, we have shown that a critical parameter measured routinely in estuarine water quality monitoring programs, the Secchi Disk Depth (SDD), can be effectively derived from satellite data. We derived a time series (1997–2005) of SDD from SeaWiFS imagery for most of Tampa Bay (standard error of 0.55 m for SDD ranging from 0.9 to 8.0 m). Although artifacts remain due to imperfect atmospheric correction and interference of bottom reflectance (e.g., depth <2.0 m), the frequent and synoptic coverage achieved with the satellite provides a better characterization of the spatial–temporal patterns as well as long-term trends of SDD. Because of the synoptic, robust, and the repeated global coverage, satellite sensors such as the SeaWiFS and MODIS provide important complements to traditional in situ sampling methods. Thus, we strongly recommend incorporating satellite observations of light attenuation or water clarity to various coastal monitoring programs to help better manage estuarine and coastal resources.

These satellite data provide new insights that can greatly benefit long-term monitoring efforts of estuarine waters, most or all of which are based solely on field surveys. The distinct 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 or wind-induced sediment resuspension (turbidity) in the dry season by controlling the light attenuation (SDD) across Tampa Bay, particularly in the middle and lower portions of the Bay.

The results support the concept of ecosystem-based management, in the sense that optimal estuarine water quality management plans should focus on control of several critical parameters, i.e. not simply on nutrient input control but also on understanding and mitigating the inputs of colored dissolved organic matter and total sediment load from various sources such as storm water, river runoff, dredging, and transportation activities.

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