Ocean Color Remote Sensing Applications in the Chesapeake Bay Region

A. Goodgrad
(this would have been even better if the figure had been in-line!)

GEOS 555 Advanced Environmental Remote Sensing, Fall 2009
Earth and Environmental Studies, Montclair State University, Montclair, NJ 07043

Submitted December 23, 2009

Introduction

Ongoing research in remote sensing techniques shows that data from different types of satellite and aircraft-based sensors can be manipulated in a variety of ways to provide information about both specific environmental events and daily environmental changes. Useful information is extracted from the information collected by sensors through modeling techniques and statistical comparison with in situ data collection. An area where these types of analyses are particularly useful is in estuarine environments.

The Chesapeake Bay is an area of interest for studying chlorophyll-a concentration because of its large size and high level of productivity (Werdell et al, 2009). Heavy anthropogenic impacts on the Bay have raised environmental concerns for the present and future state of this extensive natural resource. Nutrient loading is a major culprit in the degrading of ecosystem dynamics in the Bay. The result of excess nutrient
input can lead to problems such as excess algal biomass and primary productivity that can lead to anoxic conditions (Werdell et al, 2009). Techniques in optical remote sensing have been developed to quantitatively assess the extent of primary productivity.

The use of ocean color data to determine changing physical and chemical parameters is accomplished through the use of remote sensing systems such as SeaWiFS, which is the Sea-viewing Wide Field of view Sensor launched on August 1, 1997 aboard the Sea Star satellite (SeaWiFS Project). The information gained from quantification of ocean color using data from the SeaWiFS sensor can be used to determine the concentration of chlorophyll-a (chl-a). This paper investigates some of the methodology employed in extracting useful information from remotely sensed images of ocean color.

**The SeaWiFS Mission**

The goal of the SeaWiFS mission is to collect ocean color data that can be used primarily to determine the type and abundance of marine phytoplankton in the world’s oceans. An increase in the concentration of phytoplankton means that the pigment chlorophyll, which is used by the phytoplankton in converting sunlight to energy, will increase in abundance. The pigment gives these organisms a green color that can be detected through optical remote sensing in the visible wavelengths. A high concentration of phytoplankton in an area of the ocean, which is likely to occur in the shallow marine coastal and estuarine environments, will yield a green color that distinguishes it from areas of lower primary productivity. The color can also be quantified through
atmospherically corrected algorithms developed specifically for SeaWiFS data.
Understanding primary production dynamics has major implications in assessing
biogeochemical cycling and atmospheric sinks. For example, data on oceanographic
primary production can be used to determine the rate at which carbon is removed from
the atmosphere by marine phytoplankton relative to the rate at which carbon is removed
from the atmosphere by terrestrial plants during photosynthesis (SeaWiFS Project). Thus,
a more global-based understanding of nutrient and gas exchange can be obtained with a
more detailed understanding of global ocean color.

The SeaWiFS sensor has eight spectral bands that collectively sense
electromagnetic radiation in the visible through part of the near-infrared (NIR)
wavelength region from 402 nm to 885 nm. The first six of these bands have 20 nm
wavelengths, while the last two have 40 nm wavelengths. The sensor has a higher spatial
resolution of 1.1 km for local area coverage (LAC) and a lower spatial resolution of 4.5
km for global area coverage (GAC) (SeaWiFS Project). The swath width for GAC is
1502 km, and the revisit time at nadir is one day (SeaWiFS Project). A folded telescope
assembly collects electromagnetic radiation from the viewing area and reflects it onto a
rotating half-angle mirror. This information is then passed through a beam-splitting and
filtering system that separates the received radiation into the 8 SeaWiFS spectral bands.
The entire scanner can be tilted to ensure that calibration and scanning characteristics do
not change depending on the attitude of the sensor during data collection. A final data
product from raw sensor data is corrected using specified algorithms for atmospheric
conditions such as ozone concentrations.
The SeaWiFS sensor operates on a sun-synchronous orbit (SeaWiFS Project), which means that it views a given point on the Earth’s surface always at the same local mean solar time. This is important in obtaining accurate ocean color information because different illumination conditions could result in changes in data collected that are caused by the sun’s illumination coming from a different angle, not changes in concentrations of marine phytoplankton. Having consistent illumination conditions means that a correction does not have to be applied to obtain accurate data.

**The MODIS Mission**

The goal of the MODIS mission is to collect spectral data with high radiometric resolution in 36 spectral bands (MODIS Web). These bands cover the electromagnetic spectrum from 0.4 m to 14.4 m, which covers wavelengths from the visible through thermal infrared (TIR) part of the spectrum. The sensor collects data at a moderate spatial resolution of 250-1000 m with a large along-track swath that reaches 10 km at nadir. The optical system directs energy to a system that refracts the light for each of the four available spectral regions used to collect data (MODIS Web). Its capabilities are used for a variety of applications for land, atmospheric, and ocean imaging, making it a versatile sensor that has been used for mapping forest fires, cloud thickness, and ocean color data used to determine chl-a. Like SeaWiFS, it has a sun-synchronous orbit that allows for consistent illumination when making multiple passes over a given area (MODIS Web). Two satellites with sun-synchronous orbits carry MODIS sensors. The Terra satellite
orbits from north to south at its local sun time pass, while the Aqua satellite orbits south to north at its local sun time pass. Four calibration systems are present on board.

**Sensor Applications**

SeaWiFS is an excellent tool for quantifying variations in ocean color. However, in a natural environment other factors are usually present that make collecting accurate measurements difficult. In the case of the Chesapeake Bay, determining the concentration of chlorophyll-a (chl-a) is difficult due to its coexistence with dissolved organic matter and other phytoplanktonic pigments (Gitelson et al, 2007). This presents a problem when determining which spectral band is optimal for assessing chl-a concentration. Figure 1 displays a plot of total suspended solids (TSS) versus chl-a concentration. The linear regression implies that the two parameters are independently variable. Therefore, spectral data that provides information about both parameters cannot provide specific information about a single parameter. The blue and green spectral regions were used in the past to monitor chl-a concentrations. However, this is only really viable for open ocean waters that have less surface productivity. The problem with using the blue and green spectral regions for turbid, productive waters is that the “dissolved organic matter, tripton, and phytoplankton pigments in the blue spectral region overlap.” (2007) The high concentration of these other materials prevents the use of the blue spectral region for accurate assessment of chl-a concentrations.
Gitelson et al (2007) proposed that a way of getting rid of the effects of the other materials in assessing chl a is to use one spectral band that is very sensitive to chl a and another spectral band that is least sensitive to chl a. The band that is least sensitive to chla but is sensitive to other materials could be subtracted from the band that is very sensitive to chla. Also, a third band that is not very sensitive to ANY of the materials (including chla) could be used to correct for backscattering. To do this, algorithms based on the reflectance peak at 700 nm were developed to assess the chl a concentration in turbid and productive waters. In addition to SeaWiFS, the Medium Resolution Imaging Spectrometer (MERIS) and the Moderate Resolution Imaging Spectroradiometer (MODIS) were considered in terms of their spectral capabilities in the red and NIR spectral region. Gitelson et al (2007) propose three-band and two-band modes that use the slightly different wavelengths each of these sensors uses to collect data in the red and NIR spectral regions. The correlation between chl-a concentration and the two and three band models are shown in Figure 2. The relatively good fit of the measured chl-a data with the values plotted for the models suggest that these models can potentially be used to extract specific information on chl-a concentration even in turbid and productive waters where other constituents would normally interfere with accurate measurements. The models were tuned to the optimal wavelengths that would allow for the lowest root mean square error (RMSE) in model calculations. Further work in assessing the performance of this model includes expanding the in situ sampling to other seasons of the year, since the chl-a concentration and other parameters will vary seasonally.
Another study by Werdell et al (2009) sought to employ regionally-tuned algorithms that would provide accurate measurement of chl-a concentrations in different parts of the Chesapeake Bay. Instead of focusing on developing algorithms for different parts of the spectral region such as in the work of Gitelson et al (2007), Werdell et al (2009) propose to work with two existing algorithms used in processing SeaWiFS and MODIS data. The first is the Ocean Chlorophyll (OC) algorithm described in O’Reilly et al (1998). The OC4 version of this method is used for SeaWiFS data and employs spectral data from the 443, 490, 510, and 555 nm wavelengths. The OC3 version is used for MODIS data and employs spectral data from the 443, 488, and 551 nm wavelengths. These algorithms do not assess regional variability or small scale variation in chl-a. Rather, they are used to infer mean trends over a chl-a range (Werdell et al, 2009). Figure 3 displays a plot of chl-a concentration versus unitless output values for the OC3 and OC4 models. The data from the Chesapeake Bay appear to fit the model curve, suggesting that the models are sensitive to chl-a concentration.

The second algorithm investigated in this study is the Garver – Siegel – Maritorena (GSM) model from Maritorena et al (2002) that was tuned by Magnuson et al (2004) for the Chesapeake Bay. The model considers parameters that would affect measurement of chl-a concentration, such as non-algal particles (NAP) and chromophoric dissolved organic matter (CDOM) (Werdell et al, 2009). Correction is also included for marine absorption and backscattering issues. The 443 nm wavelength is used in determining the concentration of chl-a in the Bay from this model.
To assess the models’ performances in determining chl-a concentration, *in situ* data from the Chesapeake Bay were collected from the near-surface water since the Bay has generally “has shallow optical depths” (Werdell et al, 2009). This means that constituents that influence turbidity and water color exist primarily near the surface in the Bay. The *in situ* data was then statistically compared to SeaWiFS and MODIS-Aqua data retrievals using several methods. The first method involved analysis by the NASA Ocean Biology Processing Group’s (OBPG) satellite data product validation system (2009). Factors such as estuarine circulation and tidal changes probably need to be considered to obtain accurate results using this method. The next method involved producing histograms and time-series for the data. Histograms were based upon relative percent differences (RPD) between the satellite and *in situ* measurements. Time series were produced using monthly geometric means for the chl-a data.

The results of the model to *in situ* comparison are displayed in Figure 4 and show increasing output values for the OC model with increasing chl-a concentration. However, the GSM model does not appear to distinguish differences in chl-a concentration very well. However, the environmental conditions under which the data were collected need to be considered. The information extracted from the models needs to be considered along with the information from the histograms and the time-series plots, not as an isolated source of information (Werdell et al, 2009). The complex optical properties of the Bay
require that multiple sources of information need to be integrated to determine the optimal sampling techniques for extracting an accurate assessment of chl-a.

Data distributions show that chl-a retrievals vary according to location in the Bay and the method used to determine chl-a concentration (Figure 5). MODIS chl-a retrievals are displayed by the thin dashed line and show that in the Upper Bay, for example, MODIS chl-a retrievals exceed those determined by the algorithms for SeaWiFS. This analysis includes data from all four seasons and, therefore, provides more information on sensitivity to changes that occur such as seasonal anoxic conditions (Werdell et al, 2009). Understanding the seasonal changes that can be observed in satellite remote sensing is essential in assessing the overall health of the Bay’s productive ecosystem.

The differences in the each sensor’s radiometric characteristics and the models used to determine their chl-a retrieval affect how well the derived data compare to the in situ chl-a measurements. Werdell et al (2009) argue that the chl-a concentrations derived from both models using SeaWiFS data were more accurate based on comparison with in situ measurements. Model inputs are adjusted for sensor specific wavelengths that may be in a similar spectral region but differ by a small factor. For example, a calculation in the model is based upon the 555 nm wavelength for SeaWiFS and the 551 nm wavelength for MODIS (2009). Another issue concerning model calculations is how the atmospheric correction is implemented. Extra challenges are presented in obtaining a good atmospheric correction due to the optical complexity and the regional variability in
the Bay. The proximity of parts of the Bay environment to the coast results in some light reflected from land interfering with light received by the sensor from the water. This requires an additional correction to remove “stray” light (Werdell et al, 2009). Ground validated data become especially important when dealing with complex coastal systems. However, insufficient in situ data were available for assessing aerosol composition over the Bay. Werdell et al (2009) propose that future work in collecting in situ atmospheric data over the Bay can be used to fine tune atmospheric correction in the chl-a models.

Another study by Zawada et al (2007) compared in situ measurements of total suspended solids (TSS) in the Chesapeake Bay to the particle backscattering coefficient at 400 nm ($b_{bp}(400)$) obtained from SeaWiFS data. The study looked at data from a six-year time frame that included two major hurricane events. Seasonal variation in TSS was observed in this study, which is useful in determining how the SeaWiFS and in situ data compare temporally under changing environmental conditions that affect turbidity. Zawada et al (2007) cite similar problems (i.e., land reflectance) with obtaining accurate remotely sensed data in this large estuarine environment, adding that reflectance from the sea floor is an issue in shallow water. In the deep ocean environment, light is not reflected through the water column from the seafloor to a satellite-based sensor. In fact, sunlight will not even penetrate to the sea floor in the deep ocean realm. Factors that can affect remotely sensed data such as salinity due to mixing with open ocean water and freshwater input from river sources vary regionally and temporally in the Bay.
SeaWiFS data for the study were collected at a spatial resolution of 1 km/pixel when the sensor was collecting data at nadir. Data quality was maintained by excluding image pixels that appeared to be adversely affected by cloud cover, atmospheric correction failure, and other factors such as stray light contamination (Zawada et al., 2007). The *in situ* TSS data were obtained from the Chesapeake Bay Program (CBP) Water Quality Database, which contained information about Secchi disk depth measurements (2007). In several parts of the Bay, the Secchi disk was lowered to the seafloor and was still visible, meaning that the water column in that area was optically shallow and may contribute to the reflectance received at the sensor. However, Zawada et al. (2007) found that the Bay was mostly optically deep based on Secchi disk depth measurements, meaning that bottom reflectance is not a major factor in $b_{bp}(400)$ data.

The distributions represented on the histograms in Figure 6 are similar for the *in situ* TSS data and the SeaWiFS $b_{bp}(400)$ data. The high values with low frequency counts were recorded during a two day period when TSS values spiked in the Lower Bay (Zawada et al., 2007). Both the *in situ* measurements and the SeaWiFS $b_{bp}(400)$ data reflect the two-day spike in their data distributions, suggesting that the two methods have similar sensitivity to the concentration of TSS. A positive relationship that shows increasing TSS levels with increasing $b_{bp}(400)$ values is shown in Figure 7. The linear regression has a coefficient of determination ($r^2$) value of 0.40 (2007), which suggests that the relationship between the *in situ* and sensor data sets is not truly linear. One of the major factors affecting differences in sampling results from satellite sensor derived data versus *in situ* water sampling is the discrepancy in scale. While the SeaWiFS sensor
collects data at a spatial resolution of 1 km, an *in situ* water sample is collected in a 500 mL bottle at a much smaller point near the top of the water column (2007). The small-scale variations that could be determined by doing numerous *in situ* point samples will not be as easily discerned using remotely sensed data. In other words, the SeaWiFS and *in situ* data sets are more likely to match if there is less spatial variability in TSS over a remotely sensed area that would yield different results depending on sample locations.

Another issue to bear in mind when comparing SeaWiFS data to *in situ* data is the reproducibility of two disparate analytical techniques. The SeaWiFS $b_{op}(400)$ results are sensitive to changes in particulate size and shape (Zawada et al, 2007), not just the abundance of TSS suspended in the water column. Therefore, variations in sediment entrainment from the seafloor and the general way in which the sediments flow and reflect light can have a significant impact on the calculated $b_{op}(400)$ values. Corrections need to be considered that can be implemented to make more accurate calculations of TSS quantity, and a better understanding of optical properties of TSS is needed to do this.

A study by Dzwonkowski and Yan (2005) used SeaWiFS and MODIS data to track the evolution of an estuarine outflow plume from the Chesapeake Bay. Figure 8 displays an example of the MODIS imagery used to assess the beginning stages of the outflow plume based on chl-a variation. The higher chl-a values are associated with the plume area. This study did not have available *in situ* data to compare to the remotely sensed data. However, the behavior of the proposed plume on the imagery was analogous
to the behavior expected for an outflow plume. Gradients in parameters such as salinity and temperature have been correlated in other studies such as Johnson et al (2001), who argue that inherent optical properties of dissolved organic matter (IOP-DOM) strongly correlate with salinity measurements in the Bay. The potential exists to extract significant information from sensor ocean color data about the behavior of outflow plumes. To obtain more detailed information, however, similar problems encountered in other studies such as the spectral similarity of chl-a and other organic matter need to be corrected.

A major issue with the study by Dzwonkowski and Yan (2005) is the need to compare the SeaWiFS and MODIS data. Each sensor sampled the study region at slightly different spatial resolutions, making resampling of the MODIS data to 1.1 km grid size necessary to match the SeaWiFS data. This was accomplished using bilinear interpolation (2005). The data from the two sensors were projected onto a basemap of the coast for analysis. The data were analyzed for a five day time period that displayed a plume event. The successive images observed in this study suggest that the changes seen were representative of a plume originating in the Bay and migrating toward the ocean.

Conclusion

Developing research in remote sensing of estuarine and oceanic properties shows that assessment of certain parameters that are evaluated by in situ field sampling is attainable by using ocean color sensors such as SeaWiFS and MODIS. By combining current in situ sampling programs with modeling techniques for extracting remotely sensed data that can be compared to in situ field data, a more comprehensive view of
these dynamic Earth systems can be obtained. The first step in tuning these modeling
techniques is to collect relevant field data that can be compared to the raw sensor data.
Confidence in remotely sensed data will only be acknowledged if it can consistently
correlate with field-validated data. However, issues concerning the scale at which field
data are collected versus the scale at which remotely sensed data are collected may hinder
the progress in using remotely sensed data. Regional specific algorithms need to be
developed that account for small scale variations in parameters such as chl-a that are not
currently easily detected through data from ocean color sensors. Future work is promising
for obtaining a synoptic view of complex processes that impact important ecosystems.
Figure 1. Plot of TSS vs. chl-a from Gitelson et al (2007)

Figure 2. Plot of chl-a vs. proposed models from Gitelson et al (2007)
Figure 3. Plot of chl-a concentration vs. OC model values from Werdell et al (2009).

Figure 4. Plot of model values vs. chl-a concentrations from Werdell et al (2009)
Figure 5. Data distributions comparing in situ data from the Lower, Middle, and Upper parts of the Bay to corresponding SeaWiFS and MODIS chl-a model retrievals from Werdell et al (2009).

Figure 6. Histograms for in situ TSS and $b_{bp}(400)$ from Zawada et al (2007).
Figure 7. Relationship between SeaWiFS $b_{bp}(400)$ and TSS with a coefficient of determination ($r^2$) value of 0.40. From Zawada et al (2007)

Figure 8. MODIS image from Dzwonkowski and Yan (2005)
References


