Middle States Geographer, 2006, 39:43-51

MONITORING COASTAL ESTUARY WATER CLARITY USING LANDSAT MULTISPECTRAL DATA

Shihyan Lee and Wenge Ni-Meister
Geography Department at Hunter College
Earth and Environmental Science at The Graduate Center, City University of New York
New York, NY 10021

ABSTRACT: *Following an approach used for monitoring inland water clarity, this study presented a feasible procedure of using Landsat satellite data to monitor coastal estuary water clarity. Based on six Landsat Thematic Mapper (TM) images and Secchi disc transparency (SDT) observations which are routinely sampled by New York Harbor Water Quality Survey Program, we developed a semi-empirical model to predict water clarity in coastal estuary New York Harbor from multispectral Landsat data. New York Harbor is a tidal dominant region with complex hydrography. We found that model-fit correlation coefficient (r^2) increased when the observation data moved closer to the satellite passing time. Overall, a ±4 days window yield reasonable results ($r^2 = 0.62$-0.84) and higher correlation coefficients were obtained for regions with similar hydrographic characteristics. The water characteristics reflect its optical properties, which determine the relationship between water clarity and satellite images. Distinct hydrographic settings in Jamaica Bay from other water bodies result in better correlation coefficients when it was removed in the analysis. Tide and precipitation have impacts on how ground observations can be used in deriving model coefficients; therefore, should be included in the future studies.*

Keywords: *Water clarity, Remote sensing, Landsat, Coastal water*

INTRODUCTION

Water clarity is an important water quality indicator because it is the result of combined effects from total suspended solids, dissolved organic and inorganic matters, and chlorophyll-a concentration (Doxaran et al., 2002). Water clarity reflects the amount of light that can penetrate water, which is vital to the survival of submerged aquatic vegetation (SAV) (Dennison et al., 1993). SAV provides habitat for fish and shellfish and is an important feeding ground for numerous waterfowl. Not only do SAV trap suspended sediments to decrease water turbidity, it provides favorable environments for shellfish. Shellfish are filter feeders, which can be more effective in removing suspended particles and deposit nutrients in sediments. To sustain this natural cleaning process, minimum water clarity is required to ensure the survival of SAV. Healthy SAV populations provide vital fish and shellfish habitat, which is crucial for near shore commercial fishery, since 80% of its catch depends on this environment to thrive. Additional value comes from recreational usage, which clear water is highly desirable. The benefits of having clear water in our estuaries are enormous, both ecological and economical.

The optical multispectral sensors onboard many of the remote sensing satellites possess high potential for enhancing regional water clarity assessment. Several previous studies have demonstrated the use of multispectral satellite sensors for assisting water clarity assessment in large estuaries (Stumpf and Pennock, 1989; Woodruff et al., 1999; Hu et al., 2004), lakes (Pozdnyakov et al., 2005), and other inland waters (Kloiber et al., 2002a; 2002b). Although these waters and coastal estuary waters are both classified as case II (Morel and Prieur, 1977), which their optical properties are affected by site-specific factors, such as suspended sediment types, the geographic and hydrologic settings are less complex. Application of using satellite remote sensing in regional, hydrological complex coastal estuarine waters has not been well studied due to the increased difficulties caused by the hydro-dynamics and water characteristics in these waters.

Past satellite remote sensing on case II water clarity assessment relied on the corresponding ground observations to determine the relationship between satellite sensor readings and water clarity. This is because universal relationships cannot be obtained due to the natural characteristic of case II waters, which its optical properties vary through time and space (Jensen, 1983). The need for the corresponding real-time ground observations to empirically determine the contemporary relationship between satellite data and water clarity is the main reason for the slow integration of using satellite data in water quality monitoring program in case II waters. It is also often prohibitively expensive to obtain enough ground observations at the same time when a satellite collects its image.

As most of the previous studies relied on contemporaneous ground data to determine satellite image-ground observation relationships, Kloiber et al. (2002a) demonstrated a ground observation window that could be used to achieve similar results on regional lakes. This is based on the assumption that water clarity in lakes do not change significantly within a short period of time especially when the lake water is stratified during the late summer time. This approach has proven to be practical with little change needed to be made on current ground sampling programs to take advantage of satellite remote sensing data to drastically improve the spatial knowledge of water clarity. However, unlike New York Harbor which has strong tidal influence and river inflows forming complex circulation patterns, the dynamics of these inland lakes are significantly lower with much less river discharges and weaker currents limited by short fetch distance.

Although the signal responses from satellite sensors with regard to the change of water clarity has been documented in case II waters, complex geological and hydrological characteristics make the same application over coastal estuaries nearly non-existent. Coastal estuaries are fast-changing environments fueled by oscillating tidal currents and often strong river discharges, and so minimized the applicable ground observation window. Previous remote sensing studies of estuaries have relied on expensive customized water sampling. A more forgiving observation window will significantly increase the potential of integrating satellite data into coastal estuary water clarity monitoring program.

Secchi disc transparency (SDT), the deepest viewable depth of Secchi disc, is used as water clarity indicator in this study. Water clarity can be translated to the amount of light available in the shallow water through Beer's Law.

$$I_z = I_0 * e^{-k\,z}$$

Where I_z is the light intensity at depth z, I_0 is the light intensity at the water surface, and k is the light attenuation coefficient. K can either be directly measured or calculated from Secchi depth (Giesen et al., 1990). SDT is not only widely sampled in New York Harbor but also measured in most of the other water monitoring programs (Heiskary et al., 1994) as it is a simple/low cost method. SDT, together with chlorophyll-a and total phosphorus, are used to calculate biomass-related trophic state index, an indicator of biological response to forcing factors such as nutrient additions (Carlson, 1977). SDT is the most commonly used parameter of the three because of the human perception about water quality (Heiskary and Walker, 1988). In additional, SDT has been successfully estimated from satellite remote sensing in large estuaries where circulation patterns are simple and easier to predict (Stumpf and Pennock, 1989; Hu et al., 2004).

A remote sensing water quality study in New York Harbor has recently been conducted by Hellweger et al. (2004). Although the conclusion on the applicability of using remote sensing on water quality in New York Harbor was positive, consistent relationships were not achieved on site specific measurements from different dates. For the water clarity, the relationship between SDT and Landsat was achieved by using the multi-day average SDT value and Landsat reflectance at all stations on the Hudson River. The averaging approach will undermine the spatial and temporal variation of water clarity in New York Harbor and make the single image water clarity retrieval impossible because multi-day images will be needed to calculate the SDT-satellite regression relationship.

The objective of this study was to develop a feasible strategy for monitoring water clarity in regional coastal estuarine waters with complex hydrography. Using New York Harbor as the study area, this paper investigates: (1) how to account for the tidal influence in terms of matching non-simultaneous ground observation with satellite data; (2) the general circulation patterns and water bodies' characteristics in New York Harbor; and (3) how these influence the retrieval of water clarity by satellite remote sensing.

DATA

New York Harbor was used as the site of this study. New York Harbor is a geological and hydrological complex coastal estuary with waters separated into several distinct hydrography regions (Figure 1). Hudson River carries substantial amount of sediment to Lower New York Bay and its estuary area; Harlem River, East River, and Kills Van Kull connect two different regions of water bodies with current mostly driven by tidal change. Jamaica Bay has almost no natural inflow but receives wastewater from four of New York City's wastewater treatment plants. As complex as the waters in New York Harbor are, this kind of complexity represents most of the world's urban coastal estuarine waters characteristics.

SDT was collected at selected locations (Figure 1) by New York City Department of

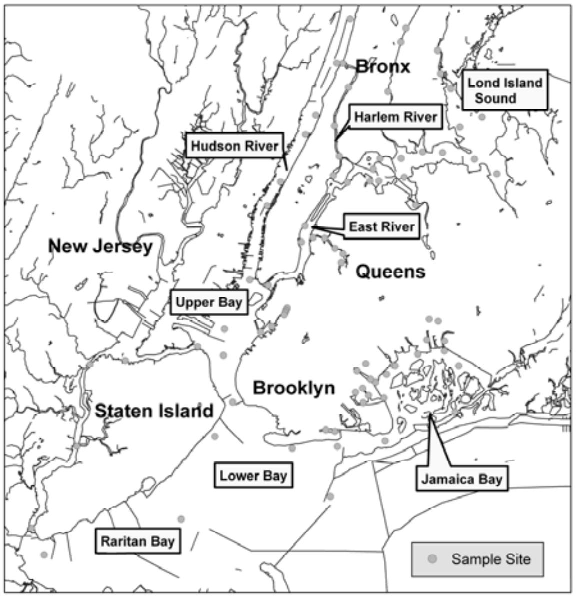

Figure 1. New York harbor water bodies and NYCDEP water sampling locations.

Environmental Protection (NYCDEP) as part of New York Harbor Water Quality Survey Program. Starting in 1985, SDT has been routinely sampled by the program as a water clarity indicator with 300-600 observations per year. Water sampling occurred every 2-3 weeks and the locations used in this program are identified with a verbal description and a GPS reading whenever possible.

Landsat was used in this study for its spatial and spectral resolution capabilities. Two Landsat 5 and four Landsat 7 images were obtained between 1989 and 2000 for this study. All images have <10% cloud cover with no cloud shadow over the Harbor. Shadows pose a challenge for determining water pixels accurately due to the difficulty to distinguish it from water since water and cloud shadow both having extremely low reflectance. All images are geometric and radiometric corrected Landsat L1B products. Sensor digital number (DN) readings were converted to top-of-atmosphere radiance then further converted into surface reflectance base on the standard procedure and parameters published in the Landsat hand book (http://landsathandbook.gsfc.nasa.gov/handbook.html). Simple image to image registration was performed to eliminate imperfect image geo-referencing. The goal of image registration was not to get the best geographical precision but the best fit between images and sampling locations. Image registration was performed by first identifying the best fit image by visually inspected the overlaid sampling site GPS locations with their verbal descriptions. Then, a simple pixel shift was used to register other images with this image within 2 pixel difference. As not all sampling locations had GPS locations, an area of interest (AOI) pixel-average approach was used to obtain sample site image value. The choice of simple pixel shift method was intended to avoid any undesired change of pixel value during image registration. Other commonly used image registration methods involve spatial averaging which will compromise near shore water pixels. The desire to preserve all the pure-water pixels in the image is because more than half of the samples were taken near shore or in narrow channels where pure-water pixels were scarce around sampling sites. The sacrificed accuracy in geographical locations will be offset by the implementation of a search algorithm discussed later.

Satellite Data Selection

A hybrid search approach was employed to retrieve corresponding satellite sensor readings for each individual ground-sampling site. First, a corresponding satellite image pixel was identified by the GPS reading of a ground sampling location. Then, a 3x3 pixel matrix (Area of Interest - AOI) with the center pixel containing the sampling location was used to calculate the average if the number of water pixels in the matrix was more than the minimum requirement (7). When the minimum was not met, (this normally happened for near shore and narrow channel observations), a larger matrix (5x5) then was used as AOI. This process was repeated until condition was satisfied or stopped if the maximum AOI (13x13) was reached. The reason for the minimum water-pixels requirement was to get enough pixels to calculate a representative average satellite reading. Satellite data was marked unavailable when the number of water pixels in the search radius was less than seven after reaching the maximum AOI. Figure 2 is the pictorial explanation of how the search algorithm was performed.

The purpose of applying such an algorithm is to compensate for the small shifting for the same sampling location from time to time, image registration uncertainty, and to find the best possible representative satellite sensor reading especially for sample sites located in narrow channels and near shore. The maximum AOI was set at 13x13, or 390m by 390m, to avoid water body cross-contamination. Following the work by Braga et al. (1993), Landsat near-infrared (NIR) band (TM4) was used to distinguish land features from waters with thresholds (pixel reflectance > threshold classified as land, otherwise as water). This method utilizes the water's high absorption property in NIR, which is a contrast

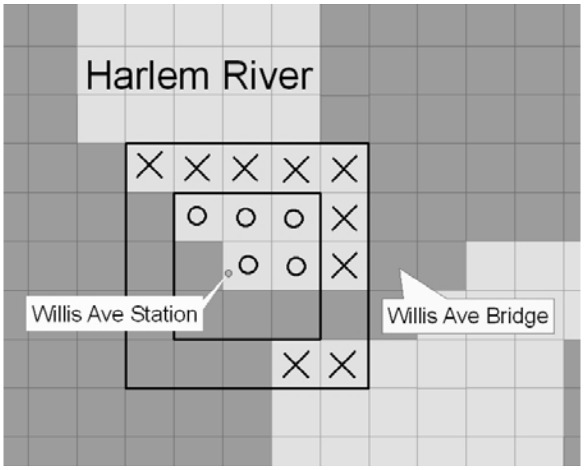

Figure 2. An example of how the satellite data for a particular water sampling site was derived. The image date is 99/7/30. Sample site is the Willis Ave Station as indicated in the figure. Willis Ave Bridge is ~13m wide and the bridge span is ~160m long on Harlem River. Light colored pixels are identified as water pixels and dark colored pixels are non-water pixels. The inner box shows the initial 3x3 pixel matrix used for searching corresponding satellite image pixels. Since only 5 pure-water pixels (need 9 pure-water pixels) were in this 3x3 matrix, a larger 5x5 matrix (outer box) then was used, which 14 pure-water pixels were identified. The average reflectance of these 14 pixels will then be used for this sample site on 99/7/30.

of most land surface features. Normally, deep clear water is assumed to have zero reflectance in NIR. However, in NYC's turbid waters, some reflectance might occur in NIR due to backscattering from suspended particles. In order to use TM4 to identify water pixels, different thresholds (range from 0.03 to 0.08) were set for individual image to account for backscatter effect from suspended particles as well as each image's calibration uncertainties and background radiance, such as path radiance from the atmosphere and adjacent effect from nearby land surface. This method was more effective than commonly used image classification methods, such as maximum likelihood, to exclude mixed water/land pixels in the near-shore areas. The advantage of using a threshold was to discard all mixed pixels or water pixels highly influenced by the adjacent landmass and only identify pixels with reflectance solely from water. It is important to only include pure-water pixel in this study since more than half of the sampling locations are near shore or in narrow channels.

Ground Data Selection

Ground observations conducted by the NYCDEP Harbor Survey Program usually take place between 10 AM and 3 PM. Due to the slim chance of concurrent space observation during satellite passes; it is not practical to use only ground data that taken during satellite passes. More importantly, the survey was not conducted daily and only about 10-15 samples were collected on each observation date. To successfully define the temporal relationship between satellite image and water clarity, an applicable ground data collection range is needed. Previous study had suggested good correlation for water clarity in lakes can be obtained between satellite data and ground observation within a 7-day observation window (Kloiber et al., 2002a). The water dynamics in New York Harbor are far more complex than inland lakes; therefore, this study will analyze the predictability from using ground observations date range from 0 up to 7 days to see if there exists an observation window for New York Harbor.

Matching ground observation with corresponding satellite image pixels will be used in this study despite the sometimes-rapid moving currents in parts of New York Harbor. A moving sampling location according to prevailing tidal movement to compensate for the tidal effect had been used in Delaware Bay (Stumpf and Pennock, 1989). This method performed reasonably well in coarse resolution satellite (AVHRR) with approximated prevailing currents; however, it is not practical for high-resolution satellite sensor used in this study with complex tidal and geographical systems like New York Harbor, where water movements cannot be easily predicted. Justification of the effectiveness of using matching satellite pixels will be discussed later.

New York Harbor is dominated by the M2 tide, which is the principal lunar semidiurnal constituent represents the rotation of the Earth with respect to the Moon. It has a 12.42 hr interval causing typical maximum tidal current velocity between 0.5 to 1 m/s (Blumberg et al., 1999). The tidal phase difference in New York Harbor is up to 3hr partly caused by the tidal phase difference between New York Bight (Atlantic Ocean) and Long Island Sound.

The justification of satellite data from the same spatial location as the ground sampling sites was based on the following observations. The actual water exchange between different water bodies is small despite rapid water movement driven by tidal force in New York Harbor (NYCDEP 2003 New York Harbor Water Quality Report). Therefore, water quality could remain relatively consistent at the similar tidal stage between tides. This assumption was consistent with the observed Total Suspended Sediments (TSS) concentration over the course of tidal cycle on Hudson River in May 1991 (Hellweger et al., 2004), when the changes of TSS remain almost constant at the same tidal stage between one tidal cycle despite the large change within the same tidal cycle among different tidal stages. Despite the rapid change in New York Harbor's waters, there could be a "relative stratified" phenomenon caused by the returning waters and condition when the tidal stage restored. In the other words, waters are simply moving back and fourth by tidal force with limited mixing and exchanging.

SECCHI DISC TRANSPARENCY MODEL

The correlation between water clarity and satellite sensor bands had been documented in previous studies (Decker et al., 1992; Cox et al., 1998). Kloiber et al. (2002b) did a comprehensive analysis on the correlation between Landsat bands and water clarity. To predict SDT, the following model derived from Kloiber et al. (2002b) was used after exhausting statistical analysis among different combination of Landsat bands and observed SDT values.

$$\ln(SDT) = a*TM1 + b*(TM3/TM1) + c$$

where, TM1 is Landsat band 1 (blue, 450-520 nm), TM3 is Landsat band 3 (red, 630-690 nm), and a, b, c, are coefficients derived from regression between ground data and Landsat image. Different Landsat scene will have a different set of coefficients to account for environmental conditions such as seasonality, atmospheric turbidity, and tides.

RESULTS

Ground Observation Window

The results from running the SDT model for various ground data intervals showed an observation window exists. The correlation coefficients of the SDT regression model for all six Landsat images showed increasing trend with decreasing gap between ground observation date and satellite passing time (Figure 3a). For ground-satellite data gap less or equal than 3 days, correlation coefficient greater than 0.7 are achieved for four out of the six images. The poor predictability for 2000/08/25 Landsat 5 image could be caused by the less reliable sensor quality and calibration due to Landsat 5 had already exceeded its design life period when the image was taken during late summer 2000 (Chander and Markham, 2003). The sensitivity of the sensor might have degraded and therefore may not be suitable for water clarity studies. The low, but consistent increasing predictability for 2000/7/5 Landsat 7 image, was because of competing dominant water characteristics, which will be explain in detail in the following section.

Root Mean Squared Error (RMSE) for the SDT model for the four better predicted images were about 1 foot (Figure 3c) when satellite and ground data gap is less or equal to 3 days. The average 1 foot of predicting error on SDT was very good considering the ground measuring accuracy was only half a foot. In order to avoid none-representative correlation coefficient and RMSE, regressions made with fewer than eight samples were discarded from the results. However, when small observation window caused SDT samples drop bellow certain number, regression calculations could still be affected. This can be seen in Figure 3, when data window moved from 1 to 0 day, correlation coefficients were up while RMSE got worse for L5_890928 image (N=8 at 0-day window). The same happened for L7_001020 image when data window moved from 3 to 2 days.

The general steadily increase of correlation coefficients and decrease of RMSE when data gap decreases echoed the two assumptions ("relative stratified" water condition and low mixing among water bodies between tides) made in the study. This trend on top of the high correlation coefficient and low RMSE when data gap was within certain range implied that water clarity can be predicted from satellite image and water characteristics does maintain for a short period of time in hydrological complex coastal estuaries, such as New York Harbor.

Water Bodies Characteristics

Coastal estuarine areas usually have complex geographic features separating water bodies into many different geologic and hydrologic regions. The different geologic and hydrologic effect causes the fundamental change in water characteristics, which then defines its optical properties and the relationship between satellite image and ground observations. This posed a challenge of using empirical relationship to study water clarity in complex coastal estuarine waters from satellite image when ground observations are obtained from different parts of waters.

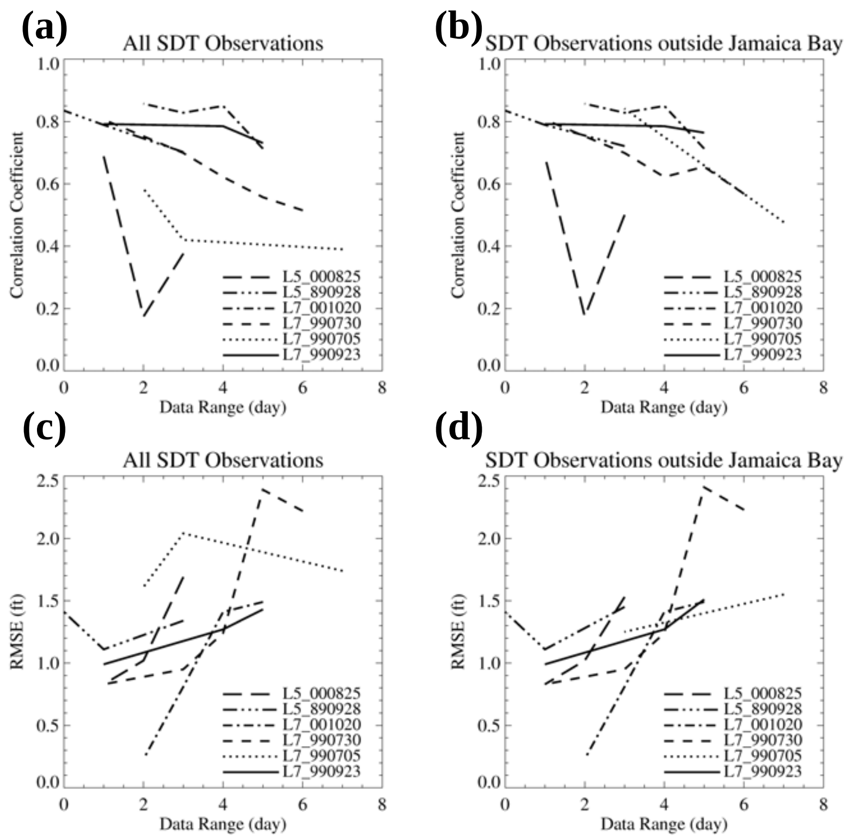

Figure 3. Correlation coefficients and Root Mean Squared Error (RMSE) between ground observations and SDT model predicts with observation data range from 0 to 7 days. The plots on top show the correlation coefficients and the plots at the bottom show the RMSE for the corresponding regression analysis. Plots on the left are the regressions using all available ground observations. Plots on the right are the regressions using observations taken outside of Jamaica Bay.

The types of suspended particles determine the water's spectral responses to changing water clarity. Therefore, restricting analysis in the hydrologic and geologic similar regions should reduce the discrepancy on water reflectance caused by the change of water clarity thus improve the SDT predictability. Overall, the SDT predictability from the model increased when observations from each water body were considered separately (Figure 4). Model correlations coefficients were mostly above 0.6 with about half of those between 0.7 and 0.95, except for Jamaica Bay and East River observations made around L5_000825 image. RMSE was about 1 foot except Jamaica Bay. Correlation coefficient and RMSE also decreased when observation data was closer to the satellite image date, which is consistent with the overall analysis, and confirm with the assumption made in this study.

From the regression analysis, Jamaica Bay appeared to be the worse predicted water body. Several factors may have contributed to the poor predictions. First of all, the observed SDT in Jamaica Bay have very small fluctuations within the same date. This not only made it hard to find correlation mathematically but also amplified the effect of image noise caused by sensor uncertainties and the atmosphere. Secondly, the sediment types in Jamaica Bay are different than the rest of the Harbor due to its distinct geology and hydrology. Most of the sediments in the Harbor are provided by Hudson River and subsequently dispersed by estuary circulation. Jamaica Bay, however, connected to the Lower Bay only through narrow Rockaway Inlet, receives most of its sediments from wastewater treatment plants. The change in dominant sediments types can result in different spectral responses at the same water clarity.

There is also high probability of bathymetry effect on satellite image over Jamaica Bay's water. The average depth of Jamaica Bay is about 13 ft with the average tidal range around 10 ft. Therefore, the average depth will be well bellow 8 ft on a low tide event near Spring tide cycle. Normally bottom reflectance will affect water-leaving radiance when

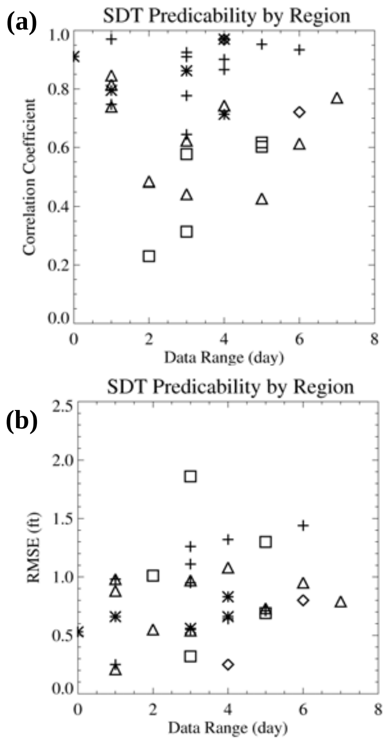

Figure 4. Correlation coefficients and root mean squared error (RMSE) for the SDT regression model broken down the observations to each of the NYC harbor regions. (a) SDT modeled correlation coefficient. (b) SDT modeled root mean squared error (RMSE). Legend: squared = Jamaica Bay, triangle=East River and western Long Island Sound, diamond=Harlem River, star=Kills Van Kull, and cross=Hudson River, upper and lower Bay. (Note: Most of the regressions have sample size 7-15 except Harlem River (N=4)).

SDT is at least half the depth of the water column (Baban, 1993). Therefore, bottom effects should be considered when SDT observations in Jamaica Bay are 4ft or greater. Historical observations and SDT values used for the six Landsat image in Jamaica Bay showed about half of the SDT were near or above 4ft. The effect from bathymetry reflectance will be even more significant for observations taken near shore in Jamaica Bay, which constitute more than half of the sample sites, where water is generally shallower than average.

When only observations taken outside of Jamaica Bay were used for the analysis, the predictability of SDT model increased with the improved correlation coefficient and decrease in RMSE (compare Figure 3a,c and 3b,d). SDT model predictability also significantly increased on both of the previously poorly performed images (Landsat 7 at 99/7/5 and Landsat 5 at 00/8/25) especially on the 99/7/5 image which does not have the potential sensor degrading issues.

The predictability improvement provided evidence supporting the previous argument that similarity in spectral response with regard to water clarity is crucial. This improvement in SDT predictability also added more confidence onto the applicability of estimating water clarity by satellite remote sensing in hydrologic and geologic complex regions.

Mapping Water Clarity in New York Harbor

The Landsat derived water clarity maps (Figure 5) showed the regional differences, which is the results of combined effects from tide, river flows, and algae growth. The water clarity in New York Harbor is affected by chlorophyll concentration especially during the peak summer season (New York Harbor Water Quality Report, 2003). The distribution of algae is usually patchy which post problem for point sampling, but this pattern can be readily resolved from the water clarity map. Overall, upper East River, Long Island Sound, and Upper/Lower Bay have higher clarity, this is because the exchange with clearer oceanic waters. On Hudson River, the estuary turbidity maximum (ETM) can be seen around the mouth of Harlem River, which was pushed upstream from the normal ETM (around George Washington Bridge) by the flood tide current (Blumberg et al., 1999).

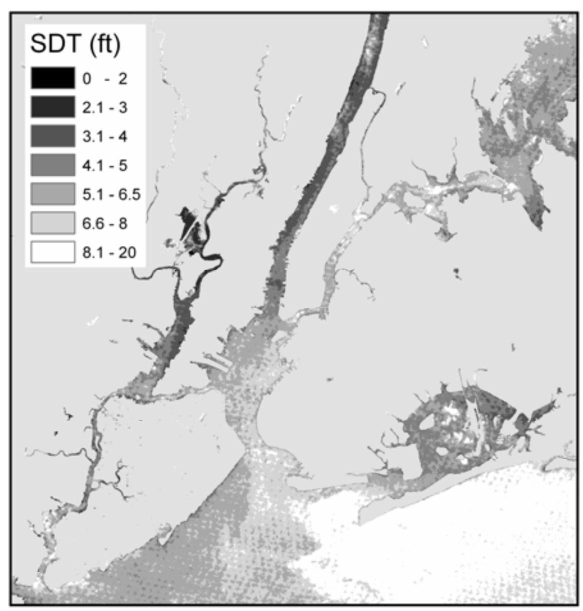

Figure 5. Secchi Disc Transparency (SDT) in New York Harbor. This map was created by using the SDT model on July 5, 1999.

CONCLUSIONS AND DISCUSSION

A feasible approach of using satellite remote sensing in estimating water clarity in complex coastal estuarine water was presented by using New York Harbor as the study area. A model to estimate SDT from Landsat TM1 and TM1/TM3 ratio data developed for inland lakes were used in the study and proved useful for the Harbor's waters. We implemented an efficient and practical method to extract satellite data for individual ground observation sites to reduce the uncertainties caused by lack of accurate geolocation information of the ground sampling points, imperfect image registration and mixed pixels around near-shore or narrow channel samplings.

In general, SDT predictability increased when the ground observation data used in the SDT regression model were closer to the satellite passing time. This showed water clarity in New York Harbor exhibits "relative stratified" phenomena where water clarity remained more or less constant over a short period of time. The "relative stratified" condition results in the 4-day observation window for in New York Harbor. The actual tidal effect on water clarity was not known in New York Harbor due to a lack of individual sampling times. It is recommended that tidal phase should be added if the actual sampling time becomes available. Results with larger gaps between ground observations and satellite image date could be improved with the addition of tidal phase information.

The optical properties of water bodies were another important factor on water clarity predictability. Water clarity was best predicted when excluding observation made in Jamaica Bay where its geologic and hydrologic setting results in different sediment types than the rest of the Harbor. The low bathymetry in Jamaica Bay undermined the empirical SDT-satellite image relationship. Incorporating bathymetry reflectance involved the dynamic understanding of bathymetry reflectance, which is impractical. One solution is only taking observation during high tide. An additional solution could be using only longer wavelength (e.g. TM3) data for estimating water clarity. Lower water penetration at longer wavelength should minimize the disturbance from bathymetry reflectance.

The increased turbidity caused by precipitation could disrupt the "relative stratified" condition thus affecting the use of an observation window. In this study, precipitation effects were not investigated which might have been the cause of the lower predictions in some images. Future work should incorporate the effect of precipitation on the SDT model.

The use of remote sensing technology can drastically increase the spatial knowledge in coastal estuarine water clarity. This can be a powerful information for water management authorities for water quality assessment, and the design of monitoring program to target the most dynamic and problematic area. Water clarity can also be used to infer total suspended sediments, which are critical for modeling sediment transport. Although with some uncertainty, the advantage in spatial coverage should be vastly superior than using only a few point measurements, especially in geographic complex estuaries where spatial interpolation is near impossible (Woodruff et al., 2001; Blumberg et al., 1999).

REFERENCES

Baban, S.M.J. 1993. Detecting Water Quality Parameters in Norfolk Broads, UK, Using Landsat Imagery. *International Journal of Remote Sensing* 14(7):1247-1267.

Blumberg, A.F., Khan, L.A., and St. John, J.P. 1999. Three-Dimensional Hydrodynamic Model of New York Harbor Region. *Journal of Hydraulic Engineering* 125(8):799-816.

Braga, C.Z.F., Setzer, A.W., and deLacerda, L.D. 1993. Water Quality Assessment with Simultaneous Landsat-5 TM Data at Guanabara Bay, Rio de Janeiro, Brazil. *Remote Sensing of the Environment* 45(1):95-106.

Carlson, R.E. 1977. A Trophic State Index for Lakes. *Limnology and Oceanography* 22:361-369.

Chander G. and Markham, B. 2003. Revised Landsat-5 TM Radiometric Calibration Procedures and Postcalibration Dynamic Ranges. *IEEE Transactions on GeoScience and Remote Sensing* 41(11): 2674-2677.

Cox, R.M., Forsythe, R.D., Vaughan, G.E., and Olmsted, L.L. 1998. Assessing Water Quality in the Catawba River Reservoirs Using Landsat Thematic Mapper Satellite Data. *Lake and Reservoir Management* 14(4):405-416.

Decker, A.G., Malthus, T.J., Wijnen, M.M., and Seyhan, E. 1992. The Effect of Spectral Bandwidth and Positioning on the Spectral Signature Analysis of Inland Waters. *Remote Sensing of Environment* 41(2-3):211–225.

Dennison, W.C., Orth, R.J., Moore, K.A., Stevenson, J.C., Carter, V., Kollar, S., Bergstrom P.W., and Batiuk, R.A. 1993. Assessing Water Quality with Submersed Aquatic Vegetation. Habitat Requirements as Barometers of Chesapeake Bay Health. *Bioscience* 43(2):86-94.

Doxaran, D., Froidefond, J.M., Lavender, S., and Castaining, P. 2002. Spectral Signature of Highly Turbid Waters: Application with SPOT Data to Quantify Suspended Particulate Matter Concentrations. *Remote Sensing of Environment* 81(1):149-161.

Giesen, W.B.J.T., van Katwijk, M.M., and den Hartog, C. 1990. Eelgrass Condition and Turbidity in the Dutch Wadden Sea. *Aquatic Botany* 37(1):71-85.

Heiskary, S.A. and Walker Jr., W.W. 1988. Developing Phosphorus Criteria for Minnesota Lakes. *Lake and Reservoir Management* 4(1):1-9.

Heiskary, S.A., Lindbloom, J., and Wilson, C.B. 1994. Detecting Water Quality Trends with Citizen Volunteer Data. *Lake and Reservoir Management* 9(1):4-9.

Hellweger, F.L., Schlosser, P., Lall, U., and Weissel J.K. 2004. Use of Satellite Imagery for Water Quality Studies in New York Harbor. *Estuarine, Coastal and Shelf Science* 61(3):437-448.

Hu, C., Chen, Z., Clayton, T.D., Swarzenski, P., Brock, J.C., and Muller-Karger F.E. 2004. Assessment of Estuarine Water-Quality Indicators Using MODIS Medium-Resolution Bands: Initial Results from Tampa Bay, FL. *Remote Sensing of Environment* 93(3):423-441.

Jensen, J.R. 1983. Biophysical Remote Sensing. *Annals of the Association of American Geographers* 73(1):111-132.

Kloiber, S.M., Brezonik, P.L., and Bauer, M.E. 2002a. Application of Landsat Imagery to Regional-Scale Assessment of Lake Clarity. *Water Research* 36(17):4330-4340.

Kloiber, S.M., Brezonik, P.L., Olmanson, L.G., and Bauer, M.E. 2002b. A Procedure for Regional Lake Water Clarity Assessment Using Landsat Multispectral Data. *Remote Sensing of Environment* 82(1):38-47.

Morel, A. and Prieur, L. 1977. Analysis of Variations in Ocean Color. *Limnology and Oceanography* 22(4):709–722.

New York City Department of Environmental Protection. 2003. 2003 New York Harbor Water Quality Survey. New York City Department of Environmental Protection, New York, New York.

Pozdnyakov, D., Shuchman, R., Korosov, A., and Hatt, C. 2005. Operational Algorithm for the Retrieval of Water Quality in the Great Lakes. *Remote Sensing of Environment* 97(3):352-370.

Stumpf, R.P. and Pennock, J.R. 1989. Calibration of a General Optical Equation for Remote Sensing of Suspended Sediments in a Moderately Turbid Estuary. *Journal of Geophysical Research* 94(C10):14363-14371.

Woodruff, D.L., Stumpf, R.P., Scope, J.A., and Paerl, H.W. 1999. Remote Estimation of Water Clarity in Optically Complex Estuarine Waters. *Remote Sensing of Environment* 68(1):41-52.

Woodruff, J.D., Geyer, W.R., Sommerfield, C.K., and Driscoll, N.W. 2001. Seasonal Variation of Sediment Deposition in the Hudson River Estuary. *Marine Geology* 179(1-2):105-119.