Salinity Assessment in Northeast Florida Bay Using Landsat TM Data

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Human activities in the past century have caused a variety of environmental problems in the Greater Everglades of South Florida. In 2000, Congress authorized the Comprehensive Everglades Restoration Plan (CERP), a $10.5-billion mission to restore the South Florida ecosystem. Many environmental projects in CERP need effective salinity monitoring in Florida Bay to provide a measure of the progress and effects of restoration on the ecosystem of the Everglades. Salinity modeling is also important given contemporary impacts and future projections of sea level rise. This study examined the potential for the Landsat Thematic Mapper (TM) sensor to serve as a regular salinity monitoring tool for Florida Bay. Spatially and temporally matched field data and TM imagery collected during Water Years 2004–2006 were employed to establish algorithms that quantitatively and qualitatively assess salinity in the northeastern area of the bay. The U.S. Geological Survey (USGS) defines Water Year *as the 12-month period from October 1 of one year to September 30 of the following year, and designates it by the calendar year in which it ends. The empirical algorithms for quantitative assessment of salinity generated a reasonable level of accuracy and a neural network based technique for qualitative assessment presented a promising result. We conclude that Landsat TM can be used as a monitoring tool to assess salinity with desirable spatial and temporal resolution and accuracy. Extendibility of algorithms for the entire Florida Bay will be tested in the future.*

Las actividades humanas en el siglo pasado han causado una gran variedad de problemas ambientales en los Everglades del sur de la Florida. En el 2002, el Congreso autorizó el Plan Comprensivo de Restauración de los Everglades (CERP, por sus siglas en inglés), una misión de $10.5 millones de dólares para restaurar el ecosistema del sur de Florida. Muchos proyectos ambientales en los CERP requieren un seguimiento eficaz de la salinidad en la Bahía de Florida para proporcionar una medición del progreso y efectos de la restauración en el ecosistema de los Everglades.

SOUTHEASTERN GEOGRAPHER, 52(3) 2012: pp. 267–281

Modelos de salinidad son también importantes teniendo en consideración los impactos actuales y proyecciones futuras sobre el incremento del nivel del mar. Este estudio examinó el potencial del sensor Landsat Thematic Mapper (TM) para servir como un una herramienta de monitoreo regular de salinidad para la Bahía de Florida. Una combinación de datos de campo espaciales y temporales, e imágenes TM recolectadas durante "Water Years" 2004–2006 fueron empleados para establecer algoritmos que evaluaran cuantitativa y cualitativamente la salinidad en la zona noreste de la bahía. El Servicio Geológico de los EE.UU. (USGS) define "Water Year" como el periodo de 12 meses desde el 1 de octubre de un año hasta el 30 de septiembre del siguiente año, y se designa por el calendario anual en el que termina. Los algoritmos empíricos para la evaluación cuantitativa de salinidad generaron un nivel razonable de precisión, y una técnica neutral de redes bases para la evaluación cualitativa presentó resultados prometedores. Concluimos que la TM Landsar puede ser utilizada como herramienta de monitoreo para evaluar salinidad con resolución y precisión espacial y temporal deseable. La extensión de los algoritmos para toda la Bahía de Florida será probada en el futuro.

KEY WORDS: Salinity monitoring, Landsat TM, Florida Bay.

PALABRAS CLAVE: control de salinidad, Landsat TM, Bahía de Florida.

INTRODUCTION

The Greater Everglades of South Florida (Figure 1), a vast subtropical wetland, has been designated as an International Biosphere Reserve, a World Heritage Site, and a Wetland of International Importance as a result of its unique combination of hydrology and water-based ecology that supports many threatened and endangered species (Davis and Ogden 1994). Historically, water in the Greater Everglades flowed freely from Kissimmee River (central Florida) to Lake Okeechobee and southward over low-lying lands to the estuaries of Biscayne Bay, Ten Thousand Islands, and Florida Bay. This finely balanced ecosystem existed for thousands of years, but due to anthropogenic disturbances in the past century, it has been severely altered. This has resulted in a variety of environmental issues in South Florida, such as degradation of water quality, declines of wildlife abundance, widespread invasion of exotic plant species, and the death of seagrass in Florida Bay (McPherson and Halley 1996). In fact, there has been an overall loss of about half of the original wetland area (Davis et al. 1994). To protect this valuable resource, Congress authorized a project in 2000 to restore South Florida's natural ecosystem, while maintaining urban and agricultural water supply and flood control. The restoration project, known as the Comprehensive Everglades Restoration Plan (CERP), is a $10.5 billion mission that is expected to take 30 or more years to complete. It contains a variety of pilot environmental engineering projects, many of which require salinity monitoring in Florida Bay, because the restoration of Everglades may cause dramatic modification of the bay environment (CROGEE 2002). Florida Bay is a key feature of the Everglades with a unique environment supporting at least 22 commercially and/or recreationally important aquatic species. Observing changes of salinity in the bay can provide a measure of the progress and effects of restoration on environmental health and water quality. In addition, mean sea level has risen by about

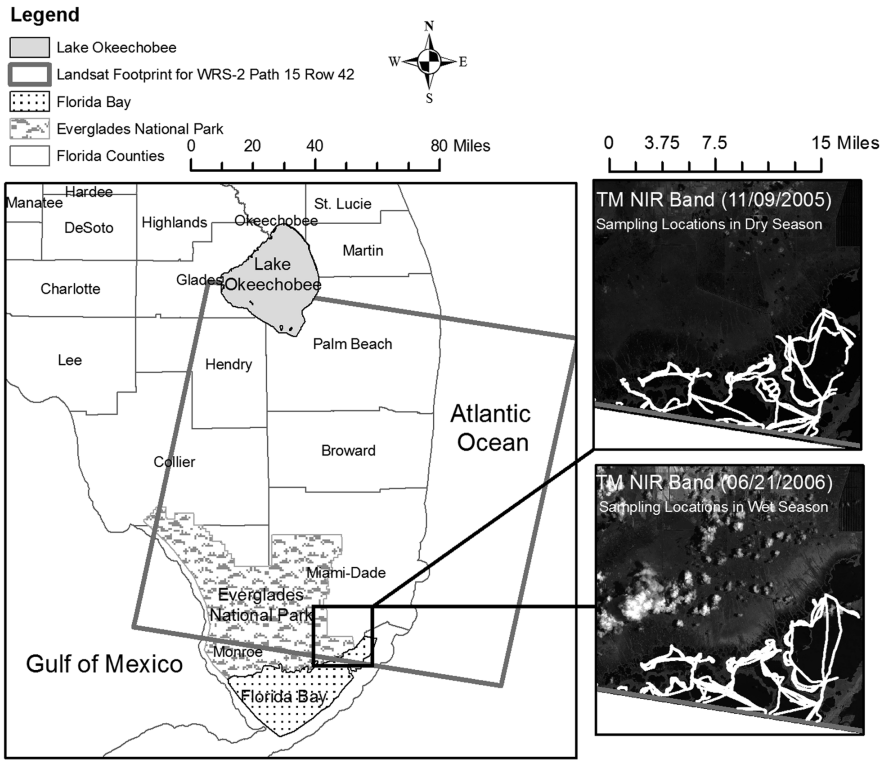

Figure 1. Map of Greater Everglades, Florida Bay, and Study Area Showing Salinity Sampling Locations in Dry Season and Wet Season during Water Years 2004–2006.

6 inches (15.2 cm) since many of the canal structures were created and the models that project sea level rise all indicate increases in salinity.

Salinity is a fundamental characteristic of the physical conditions of the Everglades. Salinity affects water quality, plant associations, and the spatial distribution of vegetative communities. Effective salinity monitoring is critical for the achievement of CERP, especially with sea level change. Current observation of salinity in Florida Bay includes regular collection of station-based point data managed by the Everglades National Park and the South Florida Water Management District, and boat-based surveyed data managed by the United State Geological Survey (USGS). To assist in the salinity monitoring, the USGS developed a boat-mounted measuring system conducting bimonthly salinity surveys in Florida Bay. Surveys typically take 3–5 days to collect data along several predesigned transects. Little or no salinity data can be collected for regions where research boats cannot access. Field surveys are time-consuming, labor-intensive, and expensive. The surveyed datasets, although supplemented with station collected salinity, is still inadequate for ef-

fective salinity monitoring because of spatial and temporal heterogeneity of the bay. Thus, salinity simulation and forecast models were constructed in order to generate a dataset with a finer temporal and spatial resolution covering larger portions of Florida Bay. These models can be grouped into two types: statistical models and mechanistic models (Marshall and Nuttle 2008). Statistical models developed thus far for Florida Bay depend on accurately describing observed salinity variations and correlative relationships with other parameters (Marshall et al. 2009). Mechanistic models can be further grouped into mass-balance models (Nuttle et al. 2000) and hydrological models (Hamrick and Moustafa 2003), which rely on accurately accounting for the physical processes that drive changes in salinity. The accuracy of these models is limited by the data available to describe patterns of salinity and their driving processes and their applications are still in preliminary stages (Marshall and Nuttle 2008).

The literature has demonstrated that remote sensing has the capability to assess water salinity. The lower microwave frequency (i.e. 1.4 GHz) is the ideal spectral channel to directly sense water salinity because of its high sensitivity to surface emissivity, which is closed related to salinity (Lagerloef et al. 1995). Several research experiments with the NOAA's scanning low-frequency microwave radiometer (SLFMR) demonstrated the proof-of-concept and operational capability of airborne salinity data acquisition. A reasonable salinity pattern was obtained in Florida Bay with the use of the SLFMR in a pilot effort (D'Sa et al. 2002a). The adoption of airborne SLFMR for salinity monitoring in support of CERP, however, is unpractical due to the high cost in data collection. In 2011, a space-borne microwave instrument, Aquarius, was launched as the first satellite platform whose primary goal was to measure sea surface salinity. This instrument was designed to provide global salinity maps on a monthly basis with a spatial resolution of 150 km. The coarse spatial resolution limits its application in coastal regions. Studies have demonstrated that water salinity can be also indirectly assessed from concentrations of detritus and colored dissolved organic material (CDOM) in water. In coastal regions, a large concentration of CDOM is terrestrial in origin and thus associated with fresh water (Opsahl and Benner 1997). An inverse relationship is expected between salinity and CDOM. The CDOM is commonly estimated by two satellite remote sensors: Sea-viewing Wide Field-of-view Sensors (SeaWiFS) and Moderate Resolution Imaging Spectroradiometer (MODIS). SeaWiFS and MODIS have a suitable temporal resolution of 1 day in data acquisition, which makes them attractive for salinity monitoring. However, at a spatial resolution of 1.13 km for regional-scale applications, SeaWiFS data are of little use in shallow and small water bodies (Liu et al. 2003). As far as MODIS is concerned, Bands 8 to 16 were specifically designed to estimate ocean color, phytoplankton, and biogeochemistry at a spatial resolution of 1 km. Again, this coarse spatial resolution reduces its usefulness for applications at the regional-scale. Researchers also made efforts to estimate water quality using the Advanced Very High Resolution Radiometer (AVHRR). Among the five AVHRR channels, Channel 1 (0.58 μm–0.68 μm) is directly applicable to monitoring water quality. A small number of cases involving shallow waters suggest

that AVHRR imagery is appropriate for monitoring water quality parameters at the mesoscale due to its coarse spatial resolution of 1.09 km (Liu et al. 2003). To the best of our knowledge, no documents reported the application of AVHRR to estimate water salinity. It is difficult, if not impossible, to delineate salinity patterns in Florida Bay with these coarse spatial resolution sensors because of the high degree of spatial heterogeneity of the bay. Florida Bay is divided into numerous discrete basins by a series of interconnected carbonate mudbanks, which function as barriers to water circulation, thus leading to marked spatial differences in water salinity (Hall et al. 2007).

A number of studies have illustrated that Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper Plus (ETM^+) have spectral and spatial characteristics that are suitable to monitor shallow water quality (e.g., Khorram 1981, 1982, and 1985; Carpenter and Carpenter 1983; Lathrop and Lillesand 1986; Khorram et al. 1991; Braga et al. 1993; Forster et al. 1993; Lavery et al. 1993; Vuille and Baumgartner 1993; Kabbara et al. 2008; Song et al. 2011). The TM system has 7 spectral bands covering visible (Band 1: 0.45–0.52 μm; Band 2: 0.52–0.60 μm; and Band 3: 0.63–0.69 μm), near-infrared (Band 4: 0.76–0.90 μm), mid-infrared (Band 5:1.55–1.75 μm and Band 7: 2.08–2.35 μm), and thermal wavelengths (10.4–12.5 μm) with a pixel resolution of 30 meters (except the thermal band) and a repetitive coverage of 16 days. Compared to other remote sensing missions, such as MODIS and SeaWiFS, the major benefits of Landsat TM for water quality monitoring include its mission continuity, affordable data products, and absolute calibration. Landsat is a remote sensing spacecraft with a 40-year long history, dating to the launch of Landsat 1 in 1972. The new mission, Landsat Data Continuity Mission (LDCM), is on schedule for a launch date of December 2012. Landsat data products are available from the USGS at no cost to the public. Landsat calibrates data by its own onboard radiometric calibration devices and the collected data serve as an on-orbit standard for cross-calibration of other Earth remote sensing missions, such as EOS-AM1 and EO-1. These features, combined with its finer spectral, spatial, and temporal resolutions, make Landsat TM data attractive for salinity monitoring. Several empirical models have been created to estimate salinity from Landsat data (e.g., Khorram 1982, 1985; Lavery et al. 1993; Vuille and Baumgartner 1993), but literature on applications of TM data to salinity and water quality estimation in Florida Bay is thin. In this paper, we examine the potential of Landsat sensor as a tool for assessing salinity in the bay using northeast Florida Bay as the study site.

STUDY AREA AND DATA

Study Area

The study area is located in northeast Florida Bay, a marine lagoon at the southern end of Florida (Figure 1). The average depth of the bay is less than 1.5 meters (Hall et al. 2007). It is bounded on the east and south by the Florida Keys and on the west by the Gulf of Mexico. Its northern boundary corresponds to the primary interface between the bay and the upstream ecosystems of the Everglades. Fresh water from the southern Everglades enters the bay and mixes with the saltwater from the Gulf of Mexico, resulting in a salinity gra-

dient pattern in the bay. The variation of salinity is highly dependent on local rainfall and evaporation. Cells of hypersaline water are common during the dry season.

In the past century, upstream water management activities have drastically altered the quantity, quality, timing, and distribution of fresh water flowing into the bay, which have dramatically modified its original healthy ecosystem for supporting a diversity of wildlife. Many environmental projects in CERP will affect the salinity level in the bay. The northeastern bay area is the discharge location of the wide C-111 canal and Taylor Slough carrying a large volume of fresh water into the bay, which makes its water mass different from its surroundings. Studies cited in the literature conclude that models for water quality parameter estimations are always site-specific (Liu et al. 2003), indicating that particular algorithms need to be developed for this geographic area.

Data

Data used in this study include the field surveyed salinity data and Landsat TM imagery collected in northeast Florida Bay between Water Years 2004–2006. The U.S. Geological Survey (USGS) defines *Water Year* as the 12-month period from October 1 of one year to September 30 of the following year, and designates it by the calendar year in which it ends. Field data were collected by USGS with a project titled "Coastal Gradients Salinity Surveys". In this project, salinity and temperature were measured along the southern coastline of Everglades National Park from Barnes Sound to Everglades City using four separate boats. Salinity was collected every five seconds via a boat-mounted flow-through cell to a continuous water quality meter. All salinity and temperature meters were checked in known conductivity standards prior to and following all surveys. Position is determined using a GPS unit which interfaces with the water quality meter. The surveyed data are posted on the website of South Florida Information Access (SOFIA http://sofia.usgs.gov/). Currently, the collected salinity data are available for Water Years 2004 to 2006 during which a total of 12 boat-based surveys were conducted. In this study, we employed the surveyed data in northeast Florida Bay to develop the salinity assessment algorithms for this selected area.

Landsat-5 (WRS-2 Path 15, Row 42/43) collects TM images over the study area every 16 days. The footprint of the TM scene covering the study region is shown in Figure 1. Geometrically corrected and geographically projected TM data are available at no cost on the USGS's Earth-Explorer website (http://edcsns17.cr.usgs.gov/EarthExplorer/). Unfortunately, salinity surveys during Water Years 2004–2006 were not conducted concurrently at the time of Landsat satellite overpass. The surveyed data can only be matched to the closest 7-day temporary window during which TM images are available. If the TM data were contaminated by cloud, then the matched datasets were dropped. This resulted in 6 matched datasets that could be used for this study. Table 1 lists the salinity survey date, TM acquisition date, and the number of observed surface salinity for each matched dataset. The non-synchronization between the field survey data and TM data is not a problem for salinity modeling at the seasonal scale because of the uniqueness of Florida Bay. Rather than the large, open system it appears to be on maps, Florida Bay is made up of many

Table 1. Matched field surveyed salinity data and TM images used in this study.

Water Year	Field Data (surveyed date, mm/dd/yyyy)	Matched TM Images (acquisition date, mm/dd/yyyy)	Number of Salinity Samples
2004	12/11/2003*	12/06/2003*	8358*
	06/02/2004**	05/30/2004**	3391**
2005	10/14/2004**	10/21/2004**	3353**
	03/10/2005*	03/14/2005*	3779*
2006	11/10/2005*	11/09/2005*	2129*
	06/28/2006**	06/21/2006**	2410**

*: denotes data collected in dry season; **: denotes data collected in wet season

shallow basins that are separated by an intricate network of mudbanks. These mudbanks extend throughout the bay and function as barriers that severely restrict water circulation. The mudbanks along the western margin are especially broad, several miles wide, and can effectively prevent free mixing of bay water with the Gulf of Mexico, even though these two water bodies share an open water boundary tens of miles long (Florida Bay Watch 2004). As a consequence, water is held in Florida Bay for a long period of time. Some of the inner basins, such as the northeastern area, take as long as a year for water to be completely flushed by tides or wind. This effectively dampens tidal effects on water salinity estimation (D'Sa et al. 2002a).

There are other factors that also reduce tidal effects on water salinity estimates. Salinity in northeast Florida Bay is mainly-controlled by rainfall, evaporation, and runoff from C-111 canal and Taylor Slough. These factors are highly dependent on seasonal variations in the Everglades. A seasonal mapping of salinity is thus possible even though the data was not concurrently collected. The Everglades has two seasons: dry and wet season. The dry season is from about November through April and the wet season from May until October. The matched datasets were divided into two groups representing the dry season (12/11/2003, 03/10/2005, and 11/20/2005) and the wet season (06/02/2004, 10/14/2004, and 06/28/2006) in an attempt to establish TM monitoring models delineating seasonal variations in salinity. The surveyed salinity sample locations in latitude/longitude coordinates were transformed into the Universal Transverse Mercator, Zone 17N to be consistent with the coordinate system of the TM images. Figure 1 shows these sample locations in white dots projected on two TM near-infrared images collected on two given dates in Water Year 2006. An atmospheric correction of the TM data was conducted, using the Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes (FLAASH) module in the ENVI software package. The TM reflectance values for each sample locations were then extracted to generate spatially matched data with the surveyed salinity records. To remove the potential noise in the TM data and errors in the sample point locations, the matched dataset were spatially resampled into a resolution of 90 meters by using a moving window (3x3 pixels) which output the average reflection of the 3x3

Table 2. Data correlation matrix for the dry/wet seasons.

	TM Band					
	1	2	3	4	5	7
Salinity	0.548/0.448	0.355/0.304	0.178/0.183	0.498/0.427	0.524/0.432	0.484/0.419
Band 1		0.957/0.970	0.880/0.919	0.716/0.568	0.596/0.544	0.553/0.543
Band 2			0.937/0.953	0.602/0.474	0.460/0.449	0.426/0.454
Band 3				0.673/0.556	0.493/0.510	0.457/0.509
Band 4					0.868/0.867	0.787/0.817
Band 5						0.910/0.939

window in the central kernel of the window. This resulted in a total of 2059 and 3177 samples for dry season and wet season respectively, which will be used for model establishment. The thermal band was not used in this study. Datasets for Water Years 2004 and 2005 were used to build the models, and the dataset for Water Year 2006 was employed to validate the models.

RESULTS AND DISCUSSION

To effectively assess salinity from Landsat TM data, exploration of the original data is important. Scatter plots revealed the nonlinear character of the relationship between salinity and each TM band, which suggests that a nonlinear transformation of the datasets is necessary. The simple logit transformation for the TM records was found to best typify the data in this case. The correlation matrix of the data (shown in Table 2) illustrate that three visible bands were highly correlated (Bands 1, 2, and 3). Similarly, two mid-infrared bands (Bands 5 and 7) were also highly correlated. The near-infrared band (Band 4) was more correlated to the mid-infrared bands than the visible bands. Among the three visible bands, Band 1 generated the highest correlation to the salinity. Band 4 also presented a higher correlation with salinity. As far as the two mid-infrared bands are concerned, Band 5 presented a relative higher correlation to the salinity. Results of the correlation matrix for the dry season and wet season were consistent, although differences were observed for the derived coefficients between two seasons.

Univariate regression and multivariate regression analyses were performed with the observed salinity as the dependent variable and one TM band or a combination of TM bands as independent variables in order to determine the optimal bands for establishing the empirical models. The results are presented in Table 3. Univariate regression results illustrated that all the bands were significantly predictive of salinity for both dry season and wet season. Bands 1 and 5 explained the highest variance among them. However, adoption of a single band is inadequate for salinity estimation because no single band explained more than 30 percent of the variation in salinity. Using all bands as independent variables in a multivariate regression model greatly increased its accuracy. We obtained an explained variance of 83.01 percent for the dry season and 70.5 percent for the wet

Table 3. Results of univariate and multivariate regression analyses for dry/wet season.

	TM Band					
Variable	1	2	3	4	5	7
Salinity R^2	0.30/0.23	0.12/0.09	0.04/0.02	0.23/0.22	0.30/0.23	0.24/0.20
	1, 2, 3, 4, 5, and 7					
Salinity R^2	0.8301/0.7050					
	1, 2, 3, 4, and 5					
Salinity R^2	0.8301/0.7048					
	1, 3, and 4					
Salinity R^2	0.8239/0.7013					

season. The estimated coefficient for Band 7, however, was statistically insignificant because of the multicollinearity among these independent variables. After dropping this band, all estimated coefficients were statistically significant with a p-value less than 0.05. The R^2 was not changed for the dry season and was decreased only 0.02 percent for the wet season (Table 3).

To further refine the model, a stepwise regression analysis was conducted. The result suggested that Bands 1, 3, and 4 are the most effective variables in salinity prediction. To validate this selection, a partial F-test was carried out. The partial F-test examines whether the difference is statistically significant between a full model (i.e. including Bands 1, 2, 3, 4, and 5) and a reduced model (i.e. including Bands 1, 3, and 4). The results were consistent with the stepwise regression outcomes. This selection is different from those adopted by other authors. For example, Lavery et al. (1993) used a single Band 4 over Peel Inlet and Band 7 over Harvey Estuary for the salinity estimation over the Peel-Harvey Estuarine System in Western Australia; Khorram (1985) used the combination of Bands 5 and 6 over San Francisco Bay; and Vuille and Baumgartner (1993) selected TM Bands 1, 4, and 7 for the North Chilean Altiplano. This confirms the conclusion in the literature that empirical models are site-specific and the appropriate TM band varies from region to region. An established algorithm for one site that generates good results may fail in another site. The preferred empirical algorithms for quantitative assessment of salinity in northeast Florida Bay are:

Dry season (N=2059):

$$salinity = -173.3 + 78.5\,ln(Band\,1) - 52.1\,ln(Band\,3) + 11.7\,ln(Band\,4) \quad (1)$$

Wet season (N=3177):

$$salinity = -156.4 + 76.5\,ln(Band\,1) - 54.2\,ln(Band\,3) + 13.0\,ln(Band\,4) \quad (2)$$

where, N is the total number of samples adopted in model establishment. The estimated intercepts, coefficients, and "F" values for the empirical models were statistically significant with a p-value less than 0.05. The significant "F" values of the models indicate that variations in TM spectral response account for a significant portion of the variations in salinity. Combination of Bands 1, 3, and 4 in the regression models explained 82.39 percent and 70.13 percent of variation in salinity for dry season and wet season respectively.

Studies have illustrated that the CDOM has a strong absorption in the ultraviolet and blue portion (i.e. Band 1 in TM data) of the visible spectrum (e.g., D'Sa et al. 1999). The blue channel has been frequently used as the tracer of CDOM concentration in coastal water bodies (D'Sa et al. 2002b; Ahn et al. 2008). An inclusion of Band 1 in the model and a positive relationship between this variable and salinity is expected. Band 3 (red) and Band 4 (near-infrared) are found to be good indicators of bathymetric information for unclear water (Jensen 2006). Water depth is an index of light intensity that is closely related to densities, species composition, and spatial distribution of seagrass. Seagrass communities cover 95 percent of the bottom of Florida Bay and are tightly connected with the spatial pattern of salinity (Hall et al. 2007). It is worthwhile to mention that Band 3 is very useful in characterizing vegetation. It is therefore a good indicator of seagrass characteristics and responsible to salinity in this unique seagrass-controlled coastal area. The non-synchronization of data collection date between the *in situ* salinity survey and recording of TM data accounts for partial of unexplained variance. The R^2 was observed to be higher for the dry season (0.8239) than for the wet season (0.7013). This may attribute to the fact that the physical, chemical, biological, and hydrological properties of water in the wet season are more complex than those in the dry season. Heavier rainfall and a larger volume of runoff from Taylor Slough and C-111 canal are the major factors in the complexity of the water body during the wet season, which makes the salinity assessment more difficult.

The derived empirical models were validated using the field surveyed salinity data collected in Water Year 2006. The root mean squared error (RMSE) can be used to evaluate the accuracy of estimations. Salinity values were estimated for the sample locations using TM data extracted from two TM scenes collected on 11/09/2005 (dry season) and 06/21/2006 (wet season). The estimations were compared with the field surveyed data obtained on 11/10/2005 (dry season) and 06/28/2006 (wet season) respectively. A RMSE of 5.8 parts per thousand (PPT) was generated for the dry season, and a lower RMSE of 4.8 PPT was produced for the wet season. The scatter plots of the TM estimations and surveyed data revealed dozens of outliers in both dry and wet seasons. A geographical projection of the locations of these outliers on the map presented a clustered pattern, suggesting systematic errors may be occurring during the surveys. Omission of these outliers resulted in the RMSE decreasing from 5.8 PPT to 3.9 PPT for the dry season, and decreasing from 4.8 PPT to 3.5 PPT for the wet season.

A map of salinity for northeast Florida Bay can be generated from a TM scene using the empirical models. The water body over the study area needs to be identified first. This was achieved using the near-infrared band because of the strong absorption of water over this spectral region. Salinity values were then calculated for the cloud-free water pixels using equation 1 or 2 based on the acquisition date of the TM data. The generated salinity maps for the selected TM scenes during Water Years 2004–2006 are shown in Figure 2 in grayscale. For comparison purposes, the salinity maps derived from the surveyed data are also presented in Figure 2. The distribution of salinity over this region showed a gradient pattern, with lower sa-

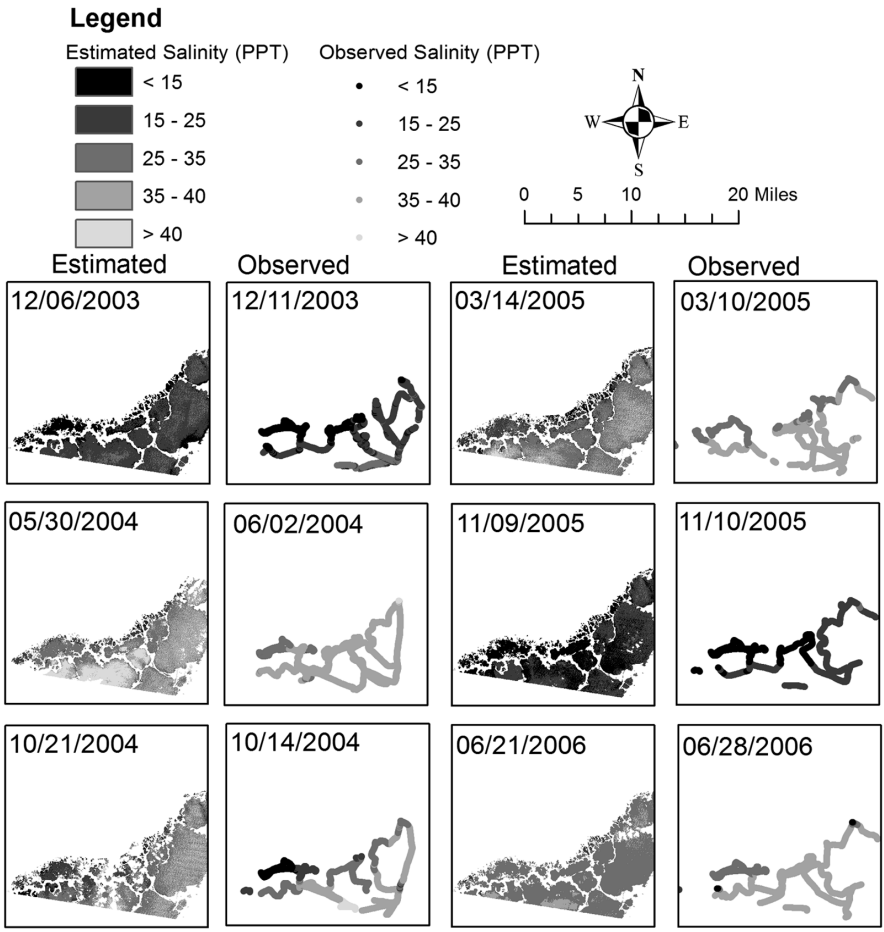

Figure 2. Maps of Salinity Estimated from the TM Empirical Algorithms and Observed from the Surveyed Data During Water Years 2004–2006.

linity (in dark) being observed along the coastline of Everglades National Park, from where the salinity increased southward to the Florida Keys. The lower salinity values along the coast are expected due to the freshwater inflow from the Taylor Slough and C-111 canal. The TM estimated salinity pattern was in general agreement with the salinity maps derived from the field surveyed data in this area. A large number of cells of hypersaline water with salinity more than 40 PPT (in light gray) were observed on 05/30/2004. Lower salinity values for the entire northeastern bay were observed on 12/11/2003 and 11/09/2005.

We also explored the techniques for qualitative assessment of salinity using the minimum distance classification method and a neural network approach. The field

samples were grouped into several classes representing low, medium, high, and hyper salinity water categories. The sample data for each class were then randomly divided into two parts. One part was used as training data, and the other part as testing data for accuracy assessment. The commonly used minimum distance method was examined first using all TM bands. The conventional error matrix approach was employed to evaluate the classification results (Jensen 2005). The total accuracy was calculated from the number of correctly discriminated salinity classes against the total number of validation samples. The Kappa statistics is believed to be a better representation of the general quality of classification because it removes effects caused by differences in sample size and also accounts for the off-diagonal elements in the error matrix (Congalton et al. 1983). Thus, the Kappa value was also calculated to quantify the classification accuracy. An average of the total accuracy of 58.9 percent and Kappa coefficient of 0.43 was obtained for the dry season after running the algorithm 50 times with different training data and testing data selected. Correspondingly, an average total accuracy of 46.3 percent and Kappa coefficient of 0.23 were generated for the wet season. The minimum distance approach assumes that each class has one spectral signature that is the spectral mean vector of the training data for this class. Poor outcomes will be generated if multiple spectral signatures exist for each class. A supervised neural network developed by Qiu and Jensen (2004) was tested in an attempt to obtain better accuracy for the qualitative assessment of salinity. One of the advantages of this neural network is its capability to model the multiple spectral signatures within a class and catch the spectral difference between classes. Similarly, after running the neural network algorithm 50 times, an average of 61.5 percent for the total accuracy and an average of 0.47 for the Kappa coefficient were obtained for the dry season. Poor results were generated for the wet season with an average of total accuracy of 56.6 percent and an average of Kappa coefficient of 0.37. This confirms the findings in the empirical algorithms that it is more difficult to assess the salinity in the wet season. Analysis of the error matrix revealed that it is easier to identify water pixels with low salinity or hyper salinity than water bodies with medium or high salinity. The neural network approach, although generating better results than the minimum distance method, was inferior to the empirical algorithms in this case.

SUMMARY AND CONCLUSIONS

In this study, we explored the potential of the Landsat TM sensor to serve as a regular salinity monitoring tool in Florida Bay to support the CERP and monitor changes in salinity with projected future sea level rise. Both quantitative and qualitative techniques were examined based on the spatially and temporally matched field surveyed salinity data and TM collected images in the northeastern bay area. The following conclusions are indicated in terms of the applicability of Landsat TM data to salinity monitoring:

- Landsat TM data appear to be effective for salinity assessment in northeast Florida Bay. A highly significant relationship between the TM data and salinity are identified for both dry and

wet seasons. Expected salinity patterns are presented on the TM estimated salinity maps. Time-series salinity maps can provide variability of salinity in the bay, which can be used to measure the effects of restoration projects in CERP.

- The empirical approaches for quantitative salinity estimation generate more acceptable results than the classification methods for qualitative salinity assessment. The empirical algorithms are statistically significant and are preferable for operational purposes in this area.
- Bands 1, 3, and 4 were suitable for salinity estimation when used together. A combination of these three bands in the established models explained more than 70 percent of the variation in salinity. They afford a reliable surface salinity prediction capability.
- Salinity in the dry season is more predictable than in the wet season. Heavy rainfall and runoff in the wet season make the bay environment more complex. This causes the salinity assessment in the wet season more difficult.
- Extrapolating our empirical models to the entire Florida Bay must be done with caution. This study confirms the conclusion in the literature that models are site-specific. To obtain a general model applicable to the entire bay, more samples need to be collected to represent the range of possible salinity values in the entire bay. Further study will focus on the extendibility of these models for the entire bay using more field surveyed data.
- Cloud cover and time delays in data acquisition may reduce the potential of the TM sensor to serve as an independent salinity monitoring tool in spite of its predictive capability. However, it may provide a supplementary tool to reduce the cost of overall salinity monitoring programs in CERP.

Acknowledgements

We wish to thank the U.S. Geological Survey (USGS) for financial support to this research. Caiyun Zhang and Ge Chen also acknowledge the support from the Global Change Research Program of China under Project 2012CB955603 and the Natural Science Foundation of China under Project 41076115.

References

Ahn, Y.H., Shanmugam, P., Moon, J.E., and Ryu, J.H. 2008. Satellite remote sensing of a low-salinity water plume in the East China Sea. *Annales Geophysicae* 26:2019–2035.

Braga, C.Z.F., Setzer, A.W., and De Lacerda, L.D. 1993. Water quality assessment with simultaneous Landsat 5 TM data at Guanabara Bay, Rio de Janeiro, Brazil. *Remote Sensing of Environment* 45:95–106.

Carpenter, D.J., and Carpenter, S.M. 1983. Modelling inland water quality using Landsat data. *Remote Sensing of Environment* 13:345–352.

Committee on Restoration of the Greater Everglades Ecosystem (CROGEE). 2002. Florida Bay research programs and their relationship to the comprehensive everglades restoration plan. The National Academies Press, p 5. Accessed 15 May 2012 at http://www.nap.edu/openbook.php?record_id=10479&page=R5.

Congalton, R.G., Oldwald, R.G., and Mead, R.A. 1983. Assessing Landsat classification accuracy using discrete multivariate statistical technique. *Photogrammetric Engineering & Remote Sensing* 49:1671–1678.

Davis, S.M., Gunderson, L.H., Park, W.A., Richardson, J.R., and Mattson, J.E. 1994. Landscape dimension, composition, and function in a changing everglades ecosystem. In *Everglades: the ecosystem and its restoration*, eds. Davis, S.M., and Ogden, J.C., 419–444. Delray Beach, Florida: St. Lucie Press.

D'Sa, E.J., Zaitzeff, J.B., Yentsch, C.S., Miller, J.L., and Ives, R. 2002a. Rapid remote assessments of salinity and ocean color in Florida Bay. In *The Everglades, Florida Bay, and coral reefs of the Florida Keys: An ecosystem sourcebook*, eds. Porter, J.W., and Porter, K.G. Boca Raton, Florida: CRC Press.

D'Sa, E.J., Hu, C., Muller-Karger, F.E., and Carder, K.L. 2002b. Estimation of coloured dissolved organic matter and salinity fields in case 2 waters using SeaWiFS: Examples from Florida Bay and Florida Shelf. *Journal of Earth System Science* 111(3):197–207.

D'Sa, J.D., Steward, R.G., Vodacek, A., Blough, N.V., and Phinney, D. 1999. Determining optical absorption of coloured dissolved organic matter in seawater with a liquid capillary waveguide. *Limnology and Oceanography* 44:1142–1148.

Florida Bay Watch. 2004. "Acquiring a taste for Florida Bay." Accessed 2 February 2012 at http://nsgl.gso.uri.edu/.

Forster, B.C., Sha, X., and Xu, B. 1993. Remote sensing of sea water quality parameters using Landsat-TM. *International Journal of Remote Sensing* 14:2759–2771.

Hall, M.O., Madley, K., Durako, M.J., Zieman, J.C., and Robblee, M.B. 2007. Florida Bay. In *Seagrass status and trends in the northern Gulf of Mexico: 1940–2002*, eds. Handley, L., Altsman, D., and DeMay, R., 243–254. Reston, Virginia: US Geological Survey Scientific Investigations Report 2006–5287.

Hamrick, J.H., and Moustafa, M.Z. 2003. "Florida Bay hydrodynamic and salinity model analysis." Conference abstract from Joint Conference on the Science and Restoration of the Greater Everglades and Florida Bay Ecosystem. Palm Harbor, FL, April 13–18.

Jensen, J.R. 2005. *Introductory digital image processing*, 3rd edition. Upper Saddle River, NJ: Prentice Hall.

——. 2006. *Remote sensing of environment: An Earth resource perspective,* 2nd edition. Upper Saddle River, NJ: Prentice Hall.

Khorram, S. 1981. Water quality mapping from Landsat digital data. *International Journal of Remote Sensing* 2:145–153.

——. 1982. Remote sensing of salinity in the San Francisco Bay Delta. *Remote Sensing of Environment* 12:15–22.

——. 1985. Development of water quality models applicable throughout the entire San Francisco Bay and delta. *Photogrammetric Engineering and Remote Sensing* 51:53–62.

Khorram, S., Cheshire, H., Geraci, A., and Rosa, G.L. 1991. Water quality mapping of Augusta Bay, Italy from Landsat TM data. *International Journal of Remote Sensing* 12:803–808.

Kabbara, N., Benkhelil, J., Awad, M., and Barale, V. 2008. Monitoring water quality in the coastal area of Tripoli (Lebanon) using high-resolution satellite data. *ISPRF Journal of Photogrammetry and Remote Sensing* 63:488–495.

Lagerloef, G.S.E., Swift, C., Le Vine, D. 1995. Sea surface salinity: the next remote sensing challenge. *Oceanography* 8:44–50.

Lathrop, R.G., and Lillesand, T.M. 1986. Use of Thematic Mapper data to assess water quality in Green Bay and central Lake Michigan. *Photogrammetric Engineering and Remote Sensing* 52:671–680.

Lavery, P., Pattiaratchi, C., Wyllie, A., and Hick, P. 1993. Water quality monitoring in

estuarine waters using the Landsat Thematic Mapper. *Remote Sensing of Environment* 46:268–280.

Liu, Y., Islam, M.A., and Gao, J. 2003. Quantification of shallow water quality parameters by means of remote sensing. *Progress in Physical Geographer* 27:24–43.

Marshall, F.E., and Nuttle, W.K. 2008. "Task 7: Simulating and forecasting salinity in Florida Bay: a review of models." Critical Ecosystems Studies Initiative Project Task Report for Everglades National Park. New Smyrna Beach, Florida: Cetacean Logic Foundation. Accessed 2 February 2012 at http://sofia.usgs.gov/publications/reports/salinity_flbay/index.html.

Marshall, F.E., Wingard, G.L., and Pitts, P. 2009. A simulation of historic hydrology and salinity in Everglades National Park: Coupling paleoecologic assemblage data with regression models. *Estuaries and Coasts* 32:37–53.

McPherson, B.F., and Halley, R. 1996. The south Florida environment—A region under stress: U.S. Geological Survey Circular 1134. Denver, CO: USGS.

Nuttle, W.K., Fourqurean, J.W., Cosby, B.J., Zieman, J.C., and Robblee, M.B. 2000. The influence of net freshwater supply on salinity in Florida Bay. *Water Resources Research* 36:1805–1822.

Opsahl, S., and Benner, R. 1997. Distribution and cycling of terrigenous dissolved organic matter in the ocean. *Nature* 386:480–482.

Qiu, F., and Jensen, J.R. 2004. Opening the black box of neural networks for remote sensing image classification. *International Journal of Remote Sensing,* 25:1749–1768.

Song, K., Wang, Z., Blackwell, J., Zhang, B., Li, F., Zhang, Y., and Jiang, G. 2011. Water quality monitoring using Landsat Themate Mapper data with empirical algorithms in Chagan Lake, China. *Journal of Applied Remote Sensing* 5, 053506 (Mar 14, 2011); doi:10.1117/1.3559497.

Vuille, M., and Baumgartner, M.F. 1993. Hydrological investigation in the North Chilean Altiplano using Landsat -MSS and -TM data. *Geocarto International* 3:35–45.

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