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REMOTE SENSING STUDIES FOR THE ASSESSMENT OF GEOHAZARDS: TOXIC ALGAL BLOOMS IN THE LOWER GREAT LAKES, AND THE LAND SUBSIDENCE IN THE NILE DELTA

by

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Richard H. Becker
Remote sensing techniques provide valuable tools for assessing a wide variety of environmental phenomena. They have been used for monitoring and assessment of various types of geologic and environmental hazards occurring on land, in the air, or in oceans. I present results from two studies, the first of which examines the spatial and temporal distribution of algal blooms in the Great Lakes; the second measures subsidence in the Nile Delta.

In the first study, methodologies to investigate the extent and distribution (temporally and spatially) of algal blooms in Lake Erie and Lake Ontario are studied. Millions of people in the U.S and Canada rely on the Great Lakes for drinking water, food, work, and recreation. Toxic algal blooms present a hazard to the substantial number of communities that draw water from the Great Lakes. Visible and infra red MODIS satellite data are used to map the extent of algal blooms in these lakes. Existing algorithms to retrieve chlorophyll concentrations are successfully tested against in situ measurements from sampling cruises. Algorithms
are developed to identify the potentially toxic cyanobacterial blooms.

The second study examines subsidence in the Nile Delta. The modern Nile Delta is the major agricultural production area for Egypt and was formed from sediments supplied by at least 10 distinct distributary channels throughout the Holocene. With an average elevation around a meter above sea level and with a predicted rise in sea level of 1.8-5.9 mm/year the subsidence of the northern 30 km of the delta is a topic of major concern to the Egyptian population and government. Ongoing subsidence rates in the northeastern Nile Delta were estimated using persistent scatterer radar interferometry techniques. The highest rates (~8 mm/yr; twice average Holocene rates) correlate with the distribution of the youngest deposition, with older depositional centers subsiding at slower rates of 2-6 mm/yr. Results are interpreted to indicate that: (1) modern subsidence in the Delta is heavily influenced by the compaction of the most recent sediments, and (2) the highly threatened areas are at the terminus of the Damietta, where the most recent deposition has occurred.
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CHAPTER 1

INTRODUCTION

1.1 Remote Sensing of Geologic Hazards

Remote sensing techniques provide valuable tools for assessing a wide variety of environmental phenomena. They have been used for monitoring and assessment of various types of geologic and environmental hazards. Examples of such applications on land include the use of interferometric synthetic aperture radar (INSAR) studies to investigate motion associated with earthquakes (e.g., Sandwell et al., 2002), subsidence related to mining (e.g., Carnec and Delacourt, 2000) and to groundwater extraction (e.g., Hoffmann et al., 2001; Watson et al., 2002), and surface rise due to aquifer recharge (Lu and Danskin, 2001). Landslides and slope stability have been investigated using INSAR and visible techniques and data sets (e.g., Berardino et al., 2003; Hilley et al., 2004; Mason and Rosenbaum, 2002; Ostir et al., 2003). Visible satellite data and satellite derived digital elevation models have been used for assessment of mudflows from volcanic eruptions (Kerle et al., 2003). Morphologic analyses of these data sets were used to assess potential hazards from volcanic eruptions (Aydar et al., 2003).

Remote sensing applications have been quite useful in monitoring
geohazards in the atmosphere as well. The most obvious would be weather-predictions and related hazards (Lynch, 2008) and monitoring spatial and temporal variations of the ozone layer in the middle stratosphere (Stolarski et al., 2006). Recent advances in remote extraction of precipitation data are now enabling early warning applications in flood prediction (Pultz and Scofield, 2002) and landslide risk assessment (Yang et al., 2006).

Remote sensing datasets and techniques have been used to address geohazards in oceans and inland lakes. Remote sensing data sets have been used to monitor the ongoing changes in the ocean circulation, including El Niño events (Fu and Smith, 1996). They have also been used to identify the overall abundances of phytoplankton blooms in the oceans and to estimate primary productivity (Campbell et al., 2002). Additional applications include examining the role phytoplankton plays in carbon cycling and its potential impacts on the global climate (Schneider et al., 2008).

Remote sensing techniques have also been used to examine geohazards at the interface of the land, atmosphere, and ocean systems. For example, remote sensing data sets were used to examine the impacts of land use and land cover change on water quality in the adjoining lakes and ocean systems (Ucuncuoglu et al., 2006). They have also been used to assess the impacts of tsunami on coastlines and vegetation. Examples include studies investigating the impacts of the 2004 Indian Ocean tsunami (Belward et al., 2007; Curran et al., 2007; Yang et al., 2007).
International institutions have recognized the importance of the potential of remote sensing techniques in assessing geohazards. UNESCO developed a Geohazards theme as a part of their Integrated Global Observation Strategy (IGOS). One of the key components of this theme is the strengthening of their existing Geosciences Application in Remote Sensing (GARS) Programme (IGOS, 2003).

A significant advantage of using remote sensing data techniques is that they can provide simultaneous measurements of observational parameters over large areas, and can make repeat measurements on regular schedules. With the deployment of more satellites and airborne instruments over the past two decades, the availability of these data sets is becoming far more widespread. Missions such as the National Aeronautic and Space Administration's (NASA) Earth Observation System (EOS) provide global coverage using multiple sensors on 30 different operational or planned platforms (e.g., visible, infra red optical sensors, passive microwave sensors, gravity, radar scatterometer) (NASA, 2006). Platforms such as NASA's ASTER and the commercial SPOT satellite series provide higher resolution (3-15 m) multispectral images and panchromatic stereo images. The European Space Agency and the Canadian MDA corporation have several operational radar satellites (ERS-2, ENVISAT, RADARSAT-2), as well as archived data from previous missions starting in the 1990s (ERS-1, RADARSAT-1). These and other platforms provide an extensive library of ongoing acquisitions as well as archival data which could be used to investigate a wide range of geohazards on land, in ocean water and in the atmosphere.
I have chosen to examine how remote sensing techniques can be used to examine two specific geohazards which have the potential to affect millions of people. The first geohazard examines the spatial and temporal distribution of algal blooms in the Great Lakes and the second examines subsidence in the Nile Delta. Both exercises are applications that heavily rely on the use of remote sensing datasets and techniques. The studies provide ways to better understand and monitor ongoing processes (algal bloom development and subsidence in the Delta) and have the potential for providing predictive tools to be used by community leaders and policy makers to address the investigated hazards.

In the first study, methodologies to temporally and spatially investigate the extent and distribution of algal blooms in Lake Erie and Lake Ontario were evaluated. Millions of people in the U.S. and Canada rely on the Great Lakes for drinking water, food, work, and recreation. Toxic algal blooms present a hazard to the substantial number of communities which draw water from the Great Lakes, or use them for recreation (Dyble et al., 2008). Visible and near infra red MODIS and SeaWiFS satellite data were used to map the distribution of algal blooms in these lakes. Existing algorithms were used to extract chlorophyll concentrations from MODIS scenes (Carder et al., 1999; O'Reilly et al., 1998) and results were compared to *in situ* measurements collected during sampling cruises conducted during the periods of acquisition of satellite measurements. The successful algorithms were defined as that best reproduced the *in situ* measurements. Algorithms were developed to identify the potentially toxic cyanobacterial blooms. Again, cyanobacterial concentrations that were derived using my
algorithms were successfully tested against in situ measurements.

The second study examines subsidence in the Nile Delta. The modern Nile Delta is the major agricultural production area for Egypt. It is formed from sediments supplied throughout the Holocene by at least 10 distinct distributary channels (Stanley and Warne, 1993b). With an average elevation of a meter or so above sea level and a predicted rise in sea level of 1.8-5.9 mm/year (IPCC, 2007) the subsidence of the northern 30 km of the delta is a topic of major concern to the Egyptian population and government.

Ongoing subsidence rates in the northeastern Nile Delta were measured using persistent scatterer radar interferometry techniques (Hooper et al., 2007; Hooper et al., 2004). Fourteen ERS-1 and ERS-2 satellite radar images covering the period of 1992-1999 were used. It was found that the highest rates (~8 mm/yr; twice average Holocene rates) correlate with the distribution of the youngest deposits, whereas the older depositional centers were found to subside at slower rates of 2-6 mm/yr. Results were interpreted to indicate that: (1) modern subsidence in the Delta is heavily influenced by the compaction of the most recent sediments, and (2) the highly threatened areas are at the terminus of the Damietta branch, where the most recent deposition has occurred.

These two problems are both good candidates for the use of remote sensing datasets and techniques. Both cover large areas, hundreds of square kilometers with observational parameters acquired over long periods (years). Predictions made from the remote sensing data over the study areas have the potential for providing guidelines to the policy makers when it comes to measures to address the geohazards of concern. For example, in the case of
the algal bloom study, the success in monitoring the propagation of blooms spatially and temporally could potentially affect decisions on the operations at water intake facilities, recreational usage of inland lakes and even government regulation regarding development plans. Similarly, results on the Nile subsidence could potentially be used to orchestrate plans for protecting the threatened areas in the Delta and in developing educated plans for urban development of these areas.

1.2 Dissertation Overview

Chapters two through four of the dissertation cover topics related to aquatic remote sensing, and summarize the results of the investigations that were conducted in Lake Erie and Lake Ontario. Chapter two of this dissertation provides a general overview of aquatic remote sensing principles, techniques, and applications. Chapter three is modified from two articles which have already been published and chapter four has been submitted for consideration for publication.

The content of chapter three is modified from two studies. The first is a study that was published in the proceedings of the 8th International Conference on Remote Sensing for Marine and Coastal Environments (Becker et al., 2005), and the second a study that was published in the Great Lakes Research Reviews (Becker et al., 2006). The study utilizes existing chlorophyll extraction algorithms to extract chlorophyll concentrations in the
optically complex waters of Lake Erie and Ontario. Comparisons between algorithms were conducted; the ability to integrate data series from MODIS and SeaWiFS was examined through comparisons of observations extracted from contemporaneous MODIS and SeaWiFS acquisitions. The study evaluates the effects of varying atmospheric conditions and new methodologies for extracting phycocyanin concentrations from reflectance data were developed and applied to Lakes Erie and Ontario to assess the distribution of blue-green algae blooms.

Chapter four addresses the same problem of extracting blue-green algae concentrations from satellite imagery, but uses absorption spectra instead, and has been submitted for consideration to the Journal of Great Lakes Research.

Chapter five provides a general overview of radar interferometry techniques. Chapter six covers the application of persistent scatterer radar interferometry techniques for measuring subsidence in the Nile Delta. The contents of chapter seven have been submitted to the journal Holocene for consideration for publication.

Chapter seven provides a summary of the work, and suggestion for future work in these two areas.
CHAPTER 2

AQUATIC REMOTE SENSING

2.1 Overview

Monitoring water quality in large water bodies (e.g., lake, sea, and ocean) spatially and temporally using traditional in situ based methods of sampling at discreet stations is costly due to the high costs for ship time and for analysis of collected samples. Moreover, in situ methods do not provide detailed analyses on regional scales given the large extent and the spatial and temporal variability of such dynamic systems. Remote sensing techniques have long held great promise for making synoptic measurements of the near surface properties for such extensive systems. By virtue of their capabilities for repeatedly conducting simultaneous measurements with the same observational parameters, remote sensing sensors could potentially provide consistent measurements of selected chemical and physical properties for surface water systems on regional scales. Examples of remotely sensed properties that could be readily measured include temperatures, concentrations for chlorophyll, suspended sediments, and total dissolved solids (Kirk, 1994).
For the majority of the published literature on this topic (remote sensing-based water composition), a distinction is being made between case I and case II waters (Morel and Prieur, 1977) as shown in figure 2.1.

Case I waters, the oceanic waters, are those in which phytoplankton is the dominant optically active component (Fig. 2.1). For case I waters, the
optical properties are dominated by the pigment concentration. Most of the existing algorithms for extracting water quality parameters were originally derived for these optically simpler case I waters (Muller-Karger et al., 2005). For case II or coastal and inland waters, the concentrations of these optically active components do not co-vary. The optically active components of phytoplankton, suspended organic and inorganic particulates (SPM), and colored dissolved organic matter (CDOM or gelbstoff) vary independently. The rivers discharging in lakes and coastal systems play an important role delivering these components in the form of sediments and nutrients.

2.2 Light at the Sensor

In using space-borne observation, the property that is being measured is the amount of light received by the sensor in discrete wavelength regions (bands). The intensity of light measured at the satellite is a function of the wavelength dependant solar irradiance, and interactions with the atmosphere, the surface of the water, and with the components dissolved and suspended in the water (Fig. 2.2).
Figure 2.2 Schematic showing components contributing to radiance measured at the sensor.

The upwelling radiance received at the sensor at the top of the atmosphere (TOA), $L_T(\lambda)$, can be broken down into multiple components (Hooker and McClain, 2000):

$$L_T(\lambda) = L_{Rr}(\lambda) + L_A(\lambda) + t(\lambda)L_{wc}(\lambda) + t(\lambda)L_g(\lambda) + t(\lambda)L_w(\lambda) \quad (2.1)$$

The first two components are atmospheric Rayleigh scattering from air and scattering from aerosols, including aerosol-Rayleigh interactions. The terms $L_{wc}$ and $L_g$ are radiances due to whitecaps and sun glint respectively. $L_w$ is the upwelling radiance directly above the water surface and $t(\lambda)$ is the diffuse transmittance of the atmospheric column.
To remove the variations in radiances that are related to varying illumination angles and viewing geometries, $L_w$ is converted to normalized water-leaving radiance ($nL_w$) (Gordon and Clark, 1981), which is the water leaving radiance corrected for the varying illumination angles, viewing angles and sun-earth distance.

2.3 Atmospheric Modeling

Atmospheric contributions dominate (up to 90%) the signal received at the satellite in aquatic remote sensing applications (Martin, 2004). All the data that are included in this dissertation were corrected for atmospheric contributions using algorithms included in the SeaDAS (SeaWiFS Data Analysis System) software package (Patt et al., 2003). To enable the implementation of these atmospheric corrections, SeaDAS uses ancillary meteorological data (e.g., magnitude and direction of surface winds, water vapor, and humidity) generated by the National Center for Environmental Prediction (NCEP), and ozone concentrations from the Earth Probe Total Ozone Mapping Spectrometer (EPTOMS). Wind speed and direction data are used as input for algorithms determining whitecap radiance. Other parameters from the meteorological data such as humidity are used as inputs to determine the appropriate atmospheric model (Gordon and Wang, 1994).
The ozone data are used to calculate diffuse transmittance through the ozone layer (Gordon, 1997).

The atmospheric contributions to the signal received by the satellite are affected by Rayleigh scattering, whitecaps, interactions between Rayleigh scattering and aerosols, and water in the atmosphere. For the MODIS (Moderate Resolution Imaging Spectrometer) data that are being used in this work, atmospheric corrections are processed using iterative near infra red correction techniques (Gordon and Wang, 1994; Stumpf et al., 2003). This technique first estimates and removes Rayleigh and whitecap atmospheric contributions, leaving only the remaining atmospheric contributions from aerosols and water (Gordon and Wang, 1994). Rayleigh and whitecap components are solved for in SeaDAS iteratively using the near infra red (NIR) bands (748 and 869 nm) and using over 25000 radiative transfer simulations that are based on multiple MODTRAN (Moderate resolution atmospheric Transmission) atmosphere models (Patt et al., 2003). Because water heavily absorbs in the NIR wavelength region, $L_w$ is assumed to be close to zero and $L_\tau(\lambda)$ will consist only of $L_R(\lambda) + L_A(\lambda)$ in this wavelength region. Since $L_R(\lambda)$ has already been modeled and removed, what is left consists only of contributions from aerosols and Rayleigh-aerosol interactions. The aerosol contribution to the NIR bands is iteratively fit to an aerosol model, and $L_A(\lambda)$ is calculated for all bands (Stumpf et al., 2003).
2.4 Optical Components of Water

A large number of previous studies have been carried out to characterize the optical properties of optically active components in water bodies in order to determine the relative abundance of these components in the water (such as Bukata et al., 1981; Clarke et al., 1970; Kahru and Mitchell, 1998; Morel and Prieur, 1977 among many). These components include the water, suspended sediments (suspended particulate matter, SPM and suspended particulate inorganic matter, SPIM), colored dissolved organic material (CDOM or gelbstoff), particulate organics (POM), and pigmented materials (i.e., chlorophyll-a, phycocyanin) (Davies-Colley et al., 2003).

Two basic approaches have been used to address this issue. The first involves extracting concentrations of the examined components from the apparent optical properties (AOPs) such as the radiance or reflectance at the sensor (e.g. O'Reilly et al., 1998; 2000; Vincent et al., 2004). Knowing the reflectances of various components, the atmospherically corrected water-leaving reflectance can be used to provide correlations with the concentrations of the various components in the examined waters. Most of the common chlorophyll algorithms used in case I waters are of this type (e.g. O'Reilly et al., 1998). The drawback of this type of method in optically complex (case II) waters is that the individual components concentrations are
non-linearly related to the measured apparent optical properties, requiring significantly more data to successfully model.

The second approach relies on extracting these concentrations from the inherent optical properties (IOPs) (e.g. Bukata et al., 1998; Pegau et al., 1999). IOPs refer to properties characterizing how a light field is modified by physical processes of absorption and scattering independent of the geometric properties of light field. Examples of the IOP include the total backscatter and absorption (Bukata et al., 1998; Carder et al., 1999; Lee et al., 2002). Several methods have been applied to retrieve inherent optical properties from the apparent optical properties. Examples of these methods are those of Maritorena (Maritorena et al., 2002), Carder (Carder et al., 1999) and Lee (Lee et al., 2002). The application of these methods that allows the extraction of total backscatter and absorption from the apparent optical properties is enabled in the SeaDAS domain. Knowing the absorption and backscatter characteristics of the individual components, total backscatter or absorption can then be deconvolved to calculate the concentrations of individual components contributing to the total absorption and backscatter.
CHAPTER 3

SPATIAL AND TEMPORAL VARIATIONS OF ALGAL BLOOMS IN THE LOWER GREAT LAKES

3.1 Abstract

As part of the MERHAB (Monitoring and Event Response for Harmful Algal Blooms) Lower Great Lakes project, we are exploring the utility of chlorophyll identification algorithms, and their use in mapping the spatial and temporal distribution of algal blooms in Lake Erie and Lake Ontario. We have processed SeaWiFS and MODIS data acquired in the summers of 2003, 2004, and 2005 over the investigated lakes. The remotely-sensed data were used to derive chlorophyll-a concentrations. The chlorophyll data were compared with in situ measurements acquired largely from mooring stations, buoys, and from cruise measurements. Comparisons were made between case I and case II water satellite-based estimates of chlorophyll-a concentrations and in situ cruise measurements for the 2003-2005 field seasons (July-August 2003, 2004, May-Sept 2005). We used algorithms which were developed for case I waters (where chlorophyll content and other dissolved and suspended materials are assumed to co-vary), and applied these algorithms to the more optically complex waters of Lake Erie and Lake Ontario (Bukata et al., 1981; O'Reilly et al., 2000). This approach has been successfully applied to Lake
Michigan waters (Lesht et al., 2002). We demonstrate similar applications and successes in Lakes Erie and Ontario, where comparisons of satellite-based chlorophyll-a concentrations with \textit{in situ} chlorophyll-a measurements indicate that these algorithms provide reasonably good estimates of chlorophyll-a. We also demonstrate an even better correlation with chlorophyll-a concentrations derived from the case II water algorithm. Using a series of SeaWiFS and MODIS scenes with minimal cloud cover, we mapped annual re-occurrence (same location and time) of chlorophyll distribution patterns as well as unique algal bloom events in Lakes Erie and Ontario in the summers of 2003-2005. Our results indicate: (1) a significant correlation between chlorophyll concentrations extracted from SeaWiFS and from MODIS scenes acquired on the same day, especially for days with minimal atmospheric contributions, (2) a general correspondence between SeaWiFS-based chlorophyll-a concentrations and \textit{in situ} chlorophyll measurements, and (3) annual recurrence (same location and time) of chlorophyll distribution patterns as well as unique algal bloom events in Lakes Erie and Ontario.

We used the unique spectral characteristics of the phycocyanin pigment to discriminate between phycocyanin containing blooms and other blooms. These results have been validated has using phycocyanin fluorescence data showing relative phycocyanin abundance.
3.2 Introduction

We evaluated the utility of SeaWiFS (Sea-viewing Wide Field-of-view Sensor) and MODIS (Moderate Resolution Imaging Spectrometer) platforms for mapping algal blooms as a first step towards the spectral identification of the toxic blooms in the lower Great Lakes. Comparisons were made between satellite-based estimates of chlorophyll-a concentrations and \textit{in situ} measurements for the 2003-2004 field seasons (July and August 2003, 2004). We used algorithms which were developed for case I waters where chlorophyll content and other dissolved and suspended materials are assumed to co-vary, and applied these algorithms to the more optically complex waters of Lake Erie and Lake Ontario (Bukata et al., 1981; O'Reilly et al., 2000). This approach has been successfully applied to Lake Michigan waters (Lesht et al., 2002). We demonstrate similar applications and successes in Lakes Erie and Ontario, where comparisons of satellite-based chlorophyll-a concentrations with \textit{in situ} chlorophyll-a measurements indicate that these algorithms provide reasonably good estimates of chlorophyll-a in these lakes. Current and future work is focusing on evaluating the case I chlorophyll algorithms over a wider array of concentrations and time spans of the year to further examine the reliability and accuracy of these methodologies. A case II model (Carder, 2003) is also tested, and the results are significantly better than the case I models.
Monitoring the distribution of algal blooms in the Great Lakes area using satellite data is often hindered by the cloud cover. The acquisition of a continuous series of images with minimal cloud cover over an algal bloom of interest is needed for proper mapping of the temporal and spatial distribution of the bloom. The acquisition of a series of SeaWiFS or a series of MODIS images of such quality over the study area has proven to be difficult. To begin addressing this problem, we will explore the possibility of integrating the information (derived chlorophyll-a) contained in SeaWiFS and MODIS images. Chlorophyll-a concentrations extracted from MODIS and SeaWiFS are compatible but are not identical, given the variations in number of, and the wavelength region covered by, the bands used in extracting the respective chlorophyll-a values. Nevertheless, we show that using a series of SeaWiFS and MODIS scenes that are acquired at approximately the same time and which show minimal cloud cover, the spatial extent of algal blooms of interest could be readily measured through time. Finally, we use this methodology to map the temporal and spatial patterns of algal blooms in Lakes Erie and Ontario in the summers of 2003 and 2004, and to identify the individual and annually occurring algal bloom events.
3.3 Image Acquisition and Processing

We examined SeaWiFS and MODIS (raw and chlorophyll-a concentrations) data for the summers of 2003 and 2004 over Lakes Erie and Ontario. Approximately 120 SeaWiFS scenes (2003, 2004) and 20 MODIS scenes (2004) were processed using SeaDAS software and applying the OC4V4 (SeaWiFS), and the OC3 (MODIS) algorithms (O'Reilly et al., 2000) for the calculation of water leaving radiance and chlorophyll-a concentrations. The OC3 and OC4V4 are techniques which extract empirical relationships between ratios of reflectances from three (OC3) or four (OC4v4) wavelength regions in the visible portion of the spectra and observed chlorophyll-a concentrations (O'Reilly et al., 2000).

Chlorophyll-a concentrations were also derived using Carder case II semi-analytic algorithm in SeaDAS (Carder et al., 1999) and results were compared to those extracted using the OC3 and OC4V4 techniques. The default iterative Near IR atmospheric models were utilized. Images were brought to a common projection using commercial image processing software (ENVI) to allow comparisons to be made between scenes and between remote sensing and in situ observations.
3.4 Field Measurements

3.4.1 In Situ Sampling and Measurements

Samples were collected and processed for station cruises on the RV Guardian and RV Limnos during the summers of 2003, 2004 and 2005 by Dr. Boyer’s research group at the State University at New York School of Environmental Science and Forestry (SUNY ESF). Fluorescence data were acquired by Dr. Boyer’s group at SUNY ESF during 2004 and 2005 and by Dr. Michael Twiss at the University of Binghamton in 2005.

Discrete water samples (1L) were collected at 1 m depth and filter onto 47-mm Whatman 934-AH glass fiber filters for phycocyanin and chlorophyll determinations. The concentration of chlorophyll-a was determined by fluorescence using a Turner Designs TD-700 fluorometer equipped with a chlorophyll excitation (436 nm) and emission (680 nm) filter set and a mercury blue light source (Welshmeyer, 1994). The concentration of chlorophyll-a was also computed using spectrophotogrammetry by analysis of chlorophyll pigments by the trichromatic technique described by Parsons (Parsons, 1963).

Phycocyanin concentrations were estimated fluorometrically using a modification of the method of Abalde et al (1998) and Siegelman and Kycia
(1983) as detailed in Konopko (2007). Phycocyanin was extracted from these filters by freezing the samples at -21 deg C and thawing at 4 deg C three times in 10 mM phosphate buffer (pH 6.8) under dim light. The extract was clarified by centrifugation at 22,000 x g for 15 min, and the phycocyanin concentrations in the supernatant determined by fluorescence using a Turner Designs 10-AU fluorometer equipped with a 577 nm band pass excitation filter and a 660 nm cutoff emission filter with a cool while light source.

3.4.2 Fluorometer Measurements

Sampling surveys were conducted in Lake Erie and Lake Ontario in 2004 and 2005. Horizontal fluorometer profiles were obtained throughout the surveys and water samples were occasionally collected for analysis and calibration of the fluorometer data.

A 45 kg steel “fish” was towed by the R/V Lake Guardian at a speed of 8-11 knots at a depth of 1 m. Water was pumped through a Teflon™-lined polyethylene tubing into a 15 L polyvinylchloride “ferry box” that provided an integrated water sample at a horizontal transect resolution of 0.5 km.

During the Sept 2005 cruise a FluoroProbe (bbe Moldeanke, GmbH), was submersed inside the ferry box and measured temperature and phytoplankton concentrations. The FluoroProbe uses five different excitation
wavelength ranges (450, 525, 570, 590 and 610 nm) sequentially to illuminate a sample. It detects fluorescence at 680 nm. Based on the different fluorescence responses to light at the individual excitation wavelengths, the concentration of different algal groups is calculated based on a gaussian fit. The FluoroProbe distinguishes phytoplankton into four groups: 1) Chlorophyta and Euglenophyta, 2) phycocyanin (PC)-rich Cyanobacteria, 3) Heterokontophyta and Dinophyta, and 4) Cryptophyta and phycoerythrin (PE)-rich Cyanobacteria based on fluorescence peaks specific to the phytoplankton types (Beutler et al., 2003; 2002). All data were time stamped and archived on a field computer (Panasonic, model CF-29). Time-stamped geographic coordinates were obtained simultaneously from the ship navigational system.

During the remaining 5 cruises, water was drawn by gravity from the ferry box to two Turner Designs 10-AU fluorometers, equipped with flow cells and either a chlorophyll or phycocyanin filter sets (340 to 500 nm excitation, >665 nm emission) and phycocyanin (excitation 577 nm, emission 660 nm). Water flow rate was controlled by the head pressure generated by a 5.5 cm x 1.3 m plastic tube. Air bubbles introduced during rough waters were also removed by this tube. Readings from the fluorometers were collected at one-minute intervals and linked to the ship's GPS system. This corresponded to approximately 300 m intervals when the ship was in motion at its normal cruising speed of 10 knots.
3.5 SeaWiFS vs. MODIS Measurements of Chlorophyll-a

SeaWiFS and MODIS images are routinely acquired approximately an hour apart over the study area (SeaWiFS around 12:00 pm and MODIS Aqua at 13:00 local time). A comparison between chlorophyll-a concentration extracted from SeaWiFS and MODIS Aqua was conducted for 20 pairs of scenes with each pair acquired approximately one hour apart in the summer of 2004. We found a correlation between chlorophyll-a concentrations derived from SeaWiFS and MODIS data (Fig. 3.1). The figure displays the range of observed variations in the degree of correspondence between the SeaWiFS and MODIS data sets. The highest correlation between SeaWiFS and MODIS data was observed for the pair of scenes acquired on 8/2/04 (correlation coefficient of 0.65) and the lowest correlation was for the pair of images acquired on the previous day (on 8/1/04) (correlation coefficient of 0.48). In addition, a least squares linear fit between the OC3 and OC4 satellite derived data for 8/2/04 had a slope of 0.78 (perfect fit slope=1), where the least squares linear fit for the data from 8/1/04 had a slope of 0.28, much further from the ideal 1:1 relationship. The correlation coefficient for the 6/23/04 data was .55, with a slope of 0.33, so again there is a correlation, but one where a bias is introduced, and the OC4 is underestimated relative to the OC3. The 9/23/04 had a correlation coefficient of .55, and a slope of the linear fit of 0.74, much closer to an ideal fit. Because such differences occurred in a relatively
short time period (1 day), we suspect that these variations largely reflect temporal variations in atmospheric contributions and are less likely to be related to variations in water characteristics. The variations cause a general decorrelation between the images, and also a bias towards higher OC3 values relative to OC4v4 derived values.

Figure 3.1 Density scatter plot comparing chlorophyll-a concentration derived from MODIS and SeaWiFS data. Areas in shades of red and blue represent the largest and the smallest densities of picture elements, respectively.
Atmospheric contributions will cause reflectance values for clear water to exceed zero in the wavelength regions: 745-785 nm and 845-885 nm. These spectral regions are covered by MODIS bands 15 and 16 and SeaWiFS bands 7 and 8 (Land and Haigh, 1996; Sturm and Zibordi, 2002). Reflectance over clear water ranged from 0.010 to 0.014 on 08/02/04 and varied from 0.010 to 0.030 on 08/01/04. Figure 3.2 shows MODIS band 16 images acquired over Lake Erie on 06/23/04, 08/01/04, 08/02/04, and 09/23/04. The brightest image, the one displaying the highest reflectance, and the least correspondence between the derived SeaWiFS and MODIS chlorophyll-a concentration is the image acquired on 8/01/04. The scene that was acquired on 8/02/04 is among the darkest images (lowest reflectance), and shows the highest
correspondence between the derived chlorophyll-a concentrations (Fig. 3.1). Thus application of improved atmospheric models (Ruddick et al., 2000) over inland waters such as Lakes Erie and Ontario should enhance the observed correlations.

Our results indicate that chlorophyll-a concentration extracted from MODIS and SeaWiFS scene pairs acquired around the same time and under favorable atmospheric conditions can be integrated together to aid analyses.

3.6 Satellite vs. In Situ Measurements of Chlorophyll-a

*In situ* chlorophyll-a measurements using multiple measurement techniques were compared with chlorophyll-a concentrations extracted from SeaWiFS data (Fig. 3.3); the remote sensing and *in situ* measurements were acquired around the same approximate date (within 48 hours). Inspection of figure 3.3 suggests that chlorophyll concentrations from SeaWiFS correlate well with *in situ* measurements (pink: Welchmeyer; blue: Parson) and shows that the SeaWiFS concentrations are more or less similar to the *in situ* measurements in magnitude. *In situ* chlorophyll-a measurements were also compared with chlorophyll-a concentrations extracted from case I and case II algorithms from SeaWiFS (Figs. 3.4 and 3.5); the remote sensing and *in situ* measurements were acquired around the same approximate date (within 48 hours). Figure 3.4 shows that the Carder case II algorithm does provide a
better fit to the *in situ* data (R² of 0.78 for Carder method vs R² of 0.551 for the OC4v4 method, and slope of the relationship closer to 1). Figure 3.5 shows the data (spectral and *in situ*) that were used to calibrate and derive the case I water algorithms for open oceans; the inner diagonal solid lines mark ± 35% agreement relative to the 1:1 central solid line and the dashed lines are the 1:5 and 5:1 lines encompassing the data set (http://seabass.gsfc.nasa.gov/matchup_results.html). For comparison, we plotted our *in situ* chlorophyll-a data and the chlorophyll-a data derived from SeaWiFS for the same locations and using case I and case II algorithms. Inspection of figure 3.5 suggests that all of our case I samples plot within the envelope defined by the 1:5 and 5:1 lines and for case II samples, the majority of them plot within the envelope defined by the ± 35% lines. These results suggest that the application of case I water algorithms provide reasonable approximations for the chlorophyll-a content in Lakes Erie and Ontario and that case II algorithms provide more precise estimates.
Figure 3.3 Satellite-derived chlorophyll-a concentrations plotted against in situ-measured chlorophyll-a concentrations. Blue diamonds represent measurements made using Parsons technique (Parsons, 1963), whereas those measured using Welschmeyer technique (Welschmeyer, 1994) are represented by pink squares. Linear fits for both relationships are displayed, showing a better correlation with measurements made using the Welschmeyer technique.
Differences between the SeaWiFS-based and in situ chlorophyll-a concentrations extracted using case II algorithms could be attributed to: (1)

Figure 3.4 Comparison between satellite-derived chlorophyll-a concentration using case I (OC4v4, blue diamonds) and case II (Carder, pink squares) algorithms and in situ measured chlorophyll-a concentrations. Linear fits for both relationships are displayed showing a better correlation with the Carder-derived chlorophyll-a concentrations.
differences in “sample size” (1 km$^2$ for satellite vs. point samples for ground measurements), (2) variations in chlorophyll concentrations with depth that are reflected in the depth-integrated satellite measurements, but not in the \textit{in situ} measurements, and (3) differences in the time of acquisition. Satellite measurements are not always acquired at the same time during which the ground sampling campaign is being conducted.

In figure 3.6, the chlorophyll-a concentrations obtained for seven water samples from Lake Erie, acquired on July 13, 2004 (location: Lat: 41.816 N; Lon: 82.983 E), at depths ranging from 0 to 7 m, and analyzed using the Parsons (blue symbol) and Welchmeyer (pink symbol) protocols are compared to concentrations extracted from SeaWiFS data (yellow line). The figure shows the large variations of \textit{in situ} measurements with depth and demonstrates how the SeaWiFS chlorophyll-a concentration could represent a depth integrated measurement of the \textit{in situ} chlorophyll-a concentrations.
Figure 3.5 SeaWiFS case I (OC4v4, blue diamonds) and case II (Carder, pink squares) derived concentrations vs. in situ results overlain over SeaWiFS validation results (gray squares) from http://seabass.gsfc.nasa.gov/matchup_results.html. Data from both case I and case II algorithms fall within validation data set ranges.
Figure 3.6 *In situ* chlorophyll-a concentration (Parsons, blue diamonds, Welchmeyer, pink squares) versus depth. Figure also shows the SeaWiFS-derived chlorophyll-a (yellow line).
3.7 Identification and Mapping of Algal Blooms

Examination of chlorophyll-a concentration images (extracted from SeaWiFS and MODIS) acquired in summers of 2003 and 2004 over Lakes Erie and Ontario revealed several algal blooms. Blooms were noted as early as early June in Lake Ontario, and through mid-October in Lake Erie. As described earlier, we integrated inferences from SeaWiFS and MODIS data to provide the most complete cloud free coverage. For example, mapping of a bloom which was noted in the Oswego Harbor at the beginning of August 2004 was enabled using a time series of chlorophyll-a images extracted from a combined set of SeaWiFS and MODIS data sets. The assembled time series provided a temporal coverage with minimal cloud cover (Fig. 3.7).

Figure 3.7 Progression of an algal bloom in the Oswego Harbor using a time series generated from SeaWiFS and MODIS images acquired in August of 2004.
Generally the blooms in Lake Erie originate in the western basin and propagate into the central portion of the Lake (Fig. 3.8). Although these blooms usually cover much of the central and western basins of Lake Erie, they do not propagate into the eastern basin (Fig. 3.8). An algal bloom in the western basin of Lake Erie coincided with a reported cyanobacterial bloom in the same area (Rinta-Kanto et al., 2005). The only bloom that was observed in the eastern basin of Lake Erie throughout the investigated period is a bloom that occurred in the same approximate location in years 2003 and 2004, around the end of June (Fig. 3.9).

Figure 3.8 Chlorophyll-a concentrations extracted from SeaWiFS images acquired in September of 2004. These are indicative of the propagation of an algal bloom in the Western and Central Basins of Lake Erie; the inferred bloom (from satellite data) coincided with a reported cyanobacterial bloom.
3.8 Locating Phycocyanin Containing Blooms

One of the primary goals of the MERHAB project is to be able to discriminate between potentially harmful and non-harmful algal blooms in the lower Great Lakes. *Microcystis* species and other toxin-producing cyanobacteria have been observed in Lake Erie (Brittain et al., 2000; Rinta-Kanto et al., 2005). As *Microcystis* is a cyanobacteria containing the phycocyanin pigment it should be possible to rule out the possible toxicity of many blooms by the absence of phycocyanin. We developed an algorithm to allow the identification of the location of potentially toxic cyanobacterial blooms from SeaWiFS satellite data, based on spectral characteristics of phycocyanin pigment.

To accomplish this goal, SeaWiFS images were processed to remote sensing reflectance using SeaDAS 4.8. A mixing model was adopted based on the following end member components: chlorophyll-a, phycocyanin and water.
(Vincent et al., 2004), chlorophyll and water (extracted from SeaWiFS images in areas of >8 µg/L chlorophyll-a and low phycocyanin as determined from fluorescence data), and water with chlorophyll-a levels below 1 µg/L.

![Figure 3.10 Relative abundance of phycocyanin from in situ fluorescence measurements (July 13-16, 2004) overlain on top of relative abundance of phycocyanin derived from SeaWiFS imagery (July 13 and 15, 2004).](image)

This phycocyanin abundance extracted from SeaWiFS was compared with relative abundances of phycocyanin based on fluorescence data acquired during July 2004 (Fig. 3.10). Our success in spectrally distinguishing phycocyanin is consistent with the earlier findings in the western Lake Erie using remote sensing techniques (Vincent et al., 2004). Despite the broad wavelength regions covered by the TM Landsat bands, and the absence of TM band(s) in the wavelength region affected by the phycocyanin (PC) (refer to
section 4.2 for further details), Vincent et al. (2004) successfully developed algorithms to detect PC from Landsat TM data for mapping cyanobacterial blooms in Lake Erie using ratios of reflectance data. We are currently refining our mixing model to include better end members for high turbidity and high CDOM areas in an attempt to remove some false positive identification and increase the areas where the model resolves.
CHAPTER 4

MAPPING CYANOBACTERIAL BLOOMS IN THE GREAT LAKES USING MODIS

4.1 Abstract

*Microcystis* and other toxin-producing cyanobacteria have been documented in Lake Erie and Ontario in the last several years. We developed algorithms to discriminate potentially toxic cyanobacterial blooms from other harmless blooms and to extract relative phycocyanin abundances from Moderate Resolution Imaging Spectrometer (MODIS) satellite data. Lee’s Quasi-Analytical Algorithm is used to calculate total absorption and backscatter from the 250 m, 500 m and 1 km bands of MODIS scenes. A nonnegative least square algorithm was then utilized to unmix relative concentrations of green algae, blue-green algae, and CDOM and sediments combined in lake waters using published absorption spectra for these components. MODIS-derived cyanobacterial concentrations and/or bloom distributions from 10 scenes acquired in the summers of 2004 and 2005 were successfully verified against contemporaneous calibrated measurements of pigments that were acquired from along track fluorometer measurements from six cruises, and three additional cyanobacterial blooms reported in the scientific literature between 2002 and 2006. The developed methodologies
could potentially be used to develop cost-effective practical screening methods for rapid detection of, and warning against, cyanobacterial blooms in the lower Great Lakes.

4.2 Problem Description

Lake Erie (surface area: >25,000 km²; average depth: 20 m) and Lake Ontario (surface area: 19,000 km²; average depth: 86 m) are two of the largest 20 lakes in the world (Fig. 4.1). The Niagara River carries the outflow from Lake Erie into Lake Ontario and accounts for over 85% of the total inflow to Lake Ontario (Shear et al., 1995). The outflow of Lake Ontario is carried by the St. Lawrence River which flows into the Atlantic Ocean. Millions of citizens of the U.S and Canada rely on Lakes Erie and Ontario and the remaining Laurentian lakes for drinking and recreation purposes. Increasing reports over the past years of occurrences of harmful algae in the Great Lakes demonstrated the vulnerability of these resources and the need for developing methodologies for expedited detection of the spatial distribution and propagation of these blooms on regional scales (Anderson et al., 2002; Hallegraeff, 1993).
Figure 4.1 Landsat Thematic Mapper false color composite showing the location of Lake Erie, Lake Ontario and surrounding metropolitan areas.

Conditions favoring the formation of the Harmful Algal Blooms (HABs) are not completely understood. It is believed that a number of factors (e.g., sunlight, nutrients, grazing pressure, water temperature, water depth, water flow, filter feeders) could collectively promote their development (Downing et al., 2001; Havens, 2008; Paerl, 2008). Cyanobacterial blooms occur in warm stable water masses where the species can maximize light capture and nutrient uptake through the formation of gas vacuoles to regulate buoyancy (Reynolds et al., 1987). Filter feeders (e.g., invasive zebra mussels; *Dreissena polymorpha*) discriminate against toxic cyanobacteria in feeding, giving them a competitive advantage (Vanderploeg et al., 2001).

In the Lower Great lakes, the toxin producing cyanobacterial species which have been observed include *Microcystis*, *Anabaena* and *Planktothrix*.
species (Boyer, 2006; Rinta-Kanto et al., 2005). Cyanobacterial blooms have been reported in the western basin of Lake Erie in late summer to fall of 2000 through 2007. The most significant levels of microcystin toxicity (14.3 to 20.0 µg L\(^{-1}\)) were associated with high chlorophyll-a (4 to 40 µg L\(^{-1}\)) blooms and was detected at the mouth of Maumee River in the summers of 2003 and 2004 (Rinta-Kanto et al., 2005) at stations in the western basin and at the mouth of the Sandusky River. In Lake Ontario a toxic bloom of *Microcystis* approached the World Health Organization (WHO) guideline value of 1 µg microcystin-LR L\(^{-1}\) in 2003 (Boyer et al., 2004; Makarewicz et al., 2006).

Given the potential health risks associated with the blooms and the large areal extent of these occurrences throughout Lakes Erie and Ontario, regional and cost effective monitoring solutions should be developed to provide adequate warning for the impacted populations. In this manuscript we describe one such approach that takes advantage of the spectral properties of these blooms as observed in the readily available, frequently acquired remote sensing Moderate Resolution Imaging Spectrometer (MODIS) data sets.

The toxic cyanobacteria in the Great Lakes not only possess the chlorophyll-a pigments like all other phytoplankton, but also have the accessory pigment phycocyanin (Fay, 1983) that strongly absorbs in the 620 to 630 µm wavelength region (Bryant, 1981; Sathyendranath et al., 1987), giving the blue-green algae in Lakes Erie and Ontario their characteristic
color. Because all of the toxin-producing species in the Great Lakes are cyanobacterial, the accessory pigments associated with these blooms can potentially be used to identify toxic blooms. Earlier attempts to use satellite data to remotely map the distribution of toxic algae in the Great Lakes and elsewhere taking advantage of the spectral signature introduced by the phycocyanin pigment (PC) are limited. One of these methods utilized band ratios of reflectance values extracted from Landsat TM images (Vincent et al., 2004). A second method, a semi-analytical algorithm, was applied to Medium Resolution Imaging Spectrometer (MERIS) reflectance images.
Vincent’s approach takes advantage of the high spatial resolution provided by the Landsat TM imagery, but is disadvantaged by the infrequent visits (at best every 7 days) of the Landsat system over the study area and by the absence of bands of sufficient spectral resolution over the critical wavelength regions to distinguish the phycocyanin absorption feature from the chlorophyll-a absorption feature. Specifically, there are no Landsat bands that are positioned over the maximum phycocyanin absorptions in the 620-630 nm wavelength region (Fig. 4.2). The figure shows that this is not the case with the MERIS data; the phycocyanin absorption features are covered by MERIS band 6. However, MERIS’s temporal availability (three day repeat, but only acquired when ordered) and the relatively high commercial cost of the data makes it a less practical system for routine screening and monitoring purposes.

Monitoring systems that are based on airborne or space-borne (e.g., Hyperion) hyperspectral reflectance algorithms (Dekker et al., 1991; Gons et al., 1992; Jupp et al., 1994) are costly and provide limited spatial coverage (USGS, 2008). Previous attempts using the 1 km MODIS bands were discounted as viable methods for discriminating cyanobacterial blooms (Kutser et al., 2006a), as these bands do not adequately sample the phycocyanin absorption feature.

In this study, we report the first MODIS-based algorithms which use absorption spectra to identify potentially toxic cyanobacteria by
distinguishing the phycoerythrin absorption feature from the chlorophyll absorption features. Unlike previous attempts, that solely used the 1 km or 250 m bands (Kutser et al., 2006a; Kutser et al., 2006b), our approach integrates the spectrally wider 250 m MODIS band 1 with the 1 km and 500 m bands enabling the discrimination between the green and cyanobacterial blooms (Fig. 4.2). A MODIS-based algorithm is advantageous for the following reasons: (1) the data are free and rapidly available, making the developed methodologies more appealing to users; (2) reliable atmospheric models are in place enabling comparisons to be made between MODIS-derived water compositions extracted from scenes acquired under varying atmospheric conditions; (3) the revisit time is short (daily coverage from Aqua) allowing monitoring of spatial and temporal propagation of blooms with confidence; (4) archival MODIS data are available since July of 2002 facilitating the identification of recurrent seasonal development and propagation of blooms; and (5) the MODIS bands are placed over critical wavelength regions enabling the discrimination between the phycoerythrin and chlorophyll absorption (Fig. 4.2).

4.3 Methodology

In this study we developed an algorithm that is based on a non-negative linear least squares algorithm to unmix the prevailing component
concentrations in the waters of Lakes Erie and Ontario both spatially and temporally. The investigated components include: Colored Dissolved Organic Matter (CDOM), suspended sediments, green algae, and blue-green algae. The adopted unmixing procedure was based on the individual components of the examined waters and on inherent optical property (IOP) of the system. The IOP-based algorithm provides linear relationships between components concentrations and the observed properties (Bukata et al., 1998). The developed algorithm was applied to selected MODIS data sets that were acquired over the study areas in July and August, 2004, and July, August, and September, 2005. The selected scenes were acquired around the time periods during which our field campaigns were conducted (within one week of the cruise) to enable comparisons to be made between relative cyanobacterial and other phytoplankton concentrations extracted from space-borne and field observations. The fluorescence data derived from along track horizontal profiles acquired during cruises were calibrated against individual on-station measurements. We further tested our algorithms by comparing space-borne observations from additional MODIS scenes (late August 2005) to field observations acquired in the study area (e.g. Dyble et al., 2008) for the western basin of Lake Erie.
4.4 Field Measurements

Sampling surveys were conducted in Lake Erie and Lake Ontario in 2004-2005 (Table 4.1). Four offshore Lake Erie surveys and two Lake Ontario surveys are reported here and compared with observations made from MODIS data. Horizontal fluorometer profiles were obtained throughout the surveys and water samples were occasionally collected for analysis and calibration of the fluorometer data.

<table>
<thead>
<tr>
<th>Cruise Name</th>
<th>Lake</th>
<th>Departure Port and Date</th>
<th>Return Port and Date</th>
<th>Instruments used to measure PC</th>
</tr>
</thead>
<tbody>
<tr>
<td>MELEE-VIII</td>
<td>Erie</td>
<td>Colborne, ON 7/12/2004</td>
<td>Colborne, ON 7/16/2004</td>
<td>10-AU</td>
</tr>
<tr>
<td>MELEE-IX</td>
<td>Erie</td>
<td>Colborne, ON 7/11/2005</td>
<td>Colborne, ON 7/15/2005</td>
<td>10-AU</td>
</tr>
<tr>
<td>MELEE-X</td>
<td>Erie</td>
<td>Amherstburg, ON 8/22/2005</td>
<td>Burlington, ON 8/26/2005</td>
<td>10-AU &amp; Hydrolab</td>
</tr>
<tr>
<td>IFYLE</td>
<td>Erie</td>
<td>Cleveland, OH 9/7/2005</td>
<td>Cleveland, OH 9/11/2005</td>
<td>Fluoroprobe</td>
</tr>
</tbody>
</table>

Table 4.1 Cruise dates and locations on which fluorometer horizontal profiles were acquired.

A 45 kg steel “fish” was towed by the R/V Lake Guardian at a speed of 8-11 knots at a depth of 1 m. Water was pumped through a Teflon™-lined polyethylene tubing into a 15 L polyvinylchloride “ferry box” that provided an
integrated water sample at a horizontal transect resolution of 0.5 km. During the September 2005 cruise a FluoroProbe (bbe Moldeanke, GmbH), was submersed inside the ferry box and measured temperature and phytoplankton concentrations. The FluoroProbe distinguishes phytoplankton into four groups: 1) Chlorophyta and Euglenophyta, 2) phycocyanin (PC)-rich Cyanobacteria, 3) Heterokontophyta and Dinophyta, and 4) Cryptophyta and phycoerythrin (PE)-rich Cyanobacteria (Beutler et al., 2003; 2002). All data were time stamped and archived on a field computer (Panasonic, model CF-29). Time-stamped geographic coordinates were obtained simultaneously from the ship navigational system. During the remaining 5 cruises, water was drawn by gravity from the ferry box to a fluorometer (Turner Designs, model 10-AU) which measured chlorophyll and phycocyanin abundance (Konopko, 2007).

Discrete water samples (1 L) were collected at 1 m depth and filtered onto 47-mm Whatman 934-AH glass fiber filters for phycocyanin and chlorophyll determinations and calibration of the fluorometer data. Chlorophyll-a was determined fluorometrically using the method of Welschmeyer (1994). Phycocyanin concentrations were estimated fluorometrically using a modification of the method of Abalde et al. (1998) and Siegelman and Kycia (1978). Phycocyanin was extracted from these filters and the phycocyanin concentrations determined by fluorescence as described in Konopko (2007).
4.5 Algorithm Development and Processing of MODIS Data

MODIS images were selected to provide the best spatial coverage of the lakes and with minimum cloud coverage. Preference was given to scenes where the lakes were viewed closer to nadir (in the center of the MODIS swath) to maximize spatial resolution and minimize atmospheric contributions. MODIS data scenes were processed in SeaDAS 5.2 software package. Atmospheric corrections were conducted using the Iterative Near Infra Red Atmosphere model (Patt et al., 2003). Atmospherically corrected scenes were then processed using the developed algorithms to extract compositional information (e.g., cyanobacterial and other phytoplankton abundances).

The quasi analytical methods of Lee et al. (2002) (Lee QAA method) was selected to solve for the total absorption ($a_T$) and total back scatter at each location from the reflectance data (Gordon et al., 1975) (equation 4.1):

$$R(0^-, \lambda) \sim f \frac{b_b}{a_T + b_b}$$  \hspace{1cm} (4.1)

Where $R(0^-, \lambda)$ is the below surface reflectance, $b_b$ is the total backscatter, $a_T$ is the total absorption, and $f$ is a constant that depends on the nature of the incident light field and volume scattering function.

The Lee QAA method was selected because it makes no a priori assumptions of phytoplankton or CDOM absorption either in shape or magnitude, has limited empirical relationships, has been successfully tested
with non case I datasets, and works with multi-spectral data. When the water leaving radiance in any bands fell below a threshold value of 0.01 \( \text{mW} \cdot \text{cm}^{-2} \cdot \mu \text{m}^{-1} \cdot \text{sr}^{-1} \), the absorption calculations from the QAA algorithm proved unreliable, producing artificially high very noisy absorption values. These locations were masked in the results as unusable.

The absorption component is directly related to the concentration of the individual colored components, through the following relationship (Bukata et al., 1998):

\[
a_{T}(\lambda) = \sum_{i=1}^{n} a_{i}(\lambda)c_{i} + a_{w}
\]

(4.2)

Where \( a_{T} \) is the total absorption, \( a_{i} \) and \( c_{i} \) are the absorption and concentration of each component, and \( a_{w} \) is the absorption of pure water. Knowing the absorption spectra of these components, this system of linear equations was then solved for component concentrations using a non-negative least squares technique (Lawson and Hanson, 1974).

The individual absorption spectra for the components in Lake Erie and Ontario were extracted from published data: (1) green algae from Kirk (1994), (2) blue-green Microcystis from Kuster (2006b), (3) water from Pope and Fry (1997), and (4) CDOM and sediment are represented by an average spectra generated from the spectra of these two endmembers (reported in Binding et al., 2008) because the spectra of CDOM and sediment are quite similar.
Binding (2008) found that $a_{\text{CDOM}}$ and $a_{\text{sediment}}$ in the western basin of Lake Erie are best represented by fitting an exponential function:

$$a = e^{(-S(\lambda-440))} \quad (4.3)$$

where $S$ is best represented by a value of 0.011 nm$^{-1}$ for suspended sediments, and by 0.0161 nm$^{-1}$ for CDOM.

The endmember spectra for CDOM/sediment, blue-green algae, green algae, and water were resampled to MODIS bands using the MODIS relative spectral response functions (Fig. 4.3). The figure shows that the blue-green algae possess absorption spectra that can be distinguished from those of the

![Figure 4.3 Relative absorption curves for CDOM, water, green and blue green algae. Absorption curves resampled to MODIS bands](image)

Figure 4.3 Relative absorption curves for CDOM, water, green and blue green algae. Absorption curves resampled to MODIS bands
green algae using the MODIS bands, largely due to absorption differences observed in MODIS bands centered at 645 and 555 nm.

Knowing the total absorption for each image pixel and the individual absorption spectra for the four selected endmembers, we then solved for the concentrations of these endmembers using all MODIS bands centered between 468 and 678 nm and applying a non-negative linear least squares technique implemented in MATLAB. This method was adopted to avoid physically meaningless negative solutions (i.e., negative concentrations). Solutions for each pixel were evaluated by calculating the root mean squared error (RMSE) between the modeled total absorption values to the satellite-derived total absorption values. Those with an RMSE value greater than 0.08m$^{-1}$ (approximately 20% of the $a_T$ at 645 nm in the western basin) were considered invalid and rejected. The solution for each endmember is a relative concentration of that endmember.

4.6 Results

Results (relative cyanobacterial concentrations) were re-projected to UTM zone 17, and compared to along-track fluorometer results from six cruises (four in Lake Erie and two in Lake Ontario) conducted in 2004-2005 (Table 4.1). We first demonstrate the correspondence between the patterns of blue-green algae abundances extracted from the September 7-11 2005 cruises
and the relative MODIS-derived cyanobacterial concentrations. We then extract a linear relationship between the FlouroProbe derived cyanobacterial abundances and the MODIS derived cyanobacterial abundances and use it to represent the relative MODIS cyanobacterial concentrations as concentrations. The calibrated algae abundance data from the FluroProbe used for this relationship is only available in the September 7-11 2005 cruise.

The horizontal profile extracted from the FluoroProbe fluorimeter measurements from the September 2005 cruise was compared with the satellite-based relative cyanobacteria concentrations extracted from the temporally closest satellite image with good coverage of the lake (Fig. 4.4). The scene was acquired on September 12, 2005, one day following the end of the five day cruise. The figure displays data as a function of time (first 48 hours of the cruise) and covers the western basin and the first section of the central basin. The selected sections of the cruise encompass the full range of measured variations in FluoroProbe phycocyanin concentrations.
Figure 4.4 Cyanobacterial abundance from FluoroProbe profile (open blue circles) plotted vs. time since cruise start. Corresponding MODIS derived cyanobacterial concentrations extracted for each the FluoroProbe location from the September 12, 2005 image are shown with red squares.

Inspection of figure 4.4 shows the agreement between the MODIS-derived relative cyanobacteria concentrations and the fluorometer concentrations for the September 2005 bloom events. This correlation is also observed on a plot of cyanobacterial abundance from FluoroProbe vs. MODIS derived relative cyanobacterial concentrations (Fig 4.5). A correlation coefficient of $R^2: 0.658$ was observed despite the differences in acquisition time between the two sets (up to 5 days). Variations are to be expected between the field and satellite-based algal distributions given that blooms will have moved...
between the time the satellite and the FluoroProbe measurements were made. The linear relationship was used to represent the relative MODIS cyanobacterial concentrations in units of \( \mu g/L \). The results are displayed in figure 4.6.

In this figure the MODIS-derived cyanobacterial concentrations for the entire lake are expressed in the same units as the fluorometer derived value, in units of \( \mu g/L \) as chlorophyll-a. Inspection of figure 4.6 shows the agreement between the MODIS derived relative cyanobacteria concentrations and the fluorometer concentrations for the September 2005 bloom events. Figure 4.4 demonstrates this correlation for a limited number of cruise line sections in...
the western and central Basins, whereas Figure 4.6 shows that the correlation applies to the remaining sections for the September 2005 cruise as well.

Figure 4.6 Abundances of cyanobacterial blooms in Lake Erie during Sept 2005 derived from MODIS data. Overlain on satellite images are along track fluorescence data from temporally overlapping cruises.

MODIS derived relative cyanobacterial abundances were also compared with phycocyanin fluorescence values from the remaining cruises in the summer of 2004 and 2005 (Table 4.1). Because the fluorometer data for these cruises were uncalibrated and reported in raw fluorescence, we chose to present our unmixing results as relative cyanobacterial abundances. Another approach that we could have adopted is to apply the linear relationship extracted from the September cruise data and report results in units of µg/L as chlorophyll-a. However, such an approach could be inaccurate given the reported variations in phycocyanin abundance (relative to algae
concentration) over the course of a season (Simis et al., 2007). Figure 4.7 shows along track relative phycocyanin fluorescence data overlain on relative cyanobacterial abundance derived from MODIS data. Again, the agreement in bloom distribution between the two data sets is evident. Although not shown, this is also true for the July 2004 sampling event, where the patterns seen in the fluorometer data are evident in the satellite data. In one case, the July 2005 cruise, the MODIS-derived concentrations showed a possible low level bloom throughout the entire western basin of Lake Erie, whereas the fluorescence data showed more variations in concentrations: higher towards the mouth of the Maumee River, lower towards the north-central portion of the western basin. Simis (2007) showed that the absorption spectra of cyanobacteria can change over the course of a season as the amount of

Figure 4.7 Relative abundances of cyanobacterial blooms in Lake Erie during August 2005 derived from MODIS data. Overlain on satellite images are along track fluorescence data from temporally overlapping cruises.
phycocyanin changes. This may provide one explanation for why the technique worked well in August and September of 2004 and 2005, but not as well in July of 2004.

Applications of our algorithms did not produce false positives when compared with fluorometer data. No cyanobacterial phycocyanin-bearing blooms were noted from the MODIS data acquired during two cruises over Lake Ontario, consistent with the fluorometer measurements. The latter showed negligible phycocyanin concentrations across the entire lake with one exception, the bay of Quinte, a long and narrow bay (length: >100 km; width: 1-3 km on average) that cannot be resolved from the coarse MODIS data.

The developed algorithms were also successful in identifying phycocyanin blooms in the western basin of Lake Erie that were reported by other researchers. The MODIS-derived relative phycocyanin patterns matched the field-based contoured cell count patterns reported by Dyble (2008) (Fig. 4.8). Although not shown, the MODIS-derived phycocyanin concentration patterns also matched those reported by Vincent (2004) for the September 2002 bloom in the western basin, the blooms in August of 2003 (Rinta-Kanto et al., 2005), and others in 2006 (Bridgeman, personal communication).
Despite the reported success identifying toxic algal blooms, one has to be aware of the potential uncertainties that could be introduced given the complexities of the investigated systems, the encountered technical difficulties, and the adopted assumptions and approximations. These factors could introduce uncertainties in the bloom patterns and concentrations as attempts are made to extend the developed methodologies spatially (beyond Lake Erie and Ontario) and temporally (2002 through 2006). Next, we provide examples of such complexities, uncertainties, and approximations.

There are difficulties in correlating and calibrating MODIS data to field data. Simultaneous acquisition of *in situ* and satellite data is not always possible. Fluorometer measurements are acquired over a period of 4-6 days, whereas the satellite data represent a single point in time. The sample size for MODIS (pixel size at nadir: 250 m to 1 km) exceeds that of the samples acquired in the field. The sample depth differs as well, MODIS integrates measurements across a water column of varying depth depending on the
concentration of the different absorbers and scatterers and the wavelength of the light (Bukata et al., 1998) whereas field samples are generally acquired at a particular depth (in this case 1.5 m below the surface for fluorometer data). These difficulties are compounded by the fact that wind pattern can significantly affect the movement of cyanobacterial blooms laterally (Kanoshina et al., 2003) and the ability of cyanobacteria to regulate their vertical position in the water column (Reynolds et al., 1987).

Compositionally distinct endmembers can display similar absorption spectra as is the case with CDOM and sediments. In such cases, it is best to represent the spectrally similar endmembers as a single endmember, making it difficult to estimate the proportions of these two components. One or more of the endmembers could experience natural variations, such as the variations observed amongst individual cyanobacterial species making the representation of such similar, yet spectrally variable population, by a single spectrum, an oversimplification. There are conceivable potential spatial and temporal variations in endmember compositions and associated spectral signatures. One such potential variation was described above, the seasonal variation in phycocyanin composition. Similarly, the CDOM and sediment spectra can vary with the value of S varying from .007 to .018 nm$^{-1}$ (refer to equation 3), variations which can lead to significant spectral differences in the shorter (412 nm and 443 nm) wavelengths. Locally, one or more
endmembers can go undetected resulting in fictitious solutions given the unsatisfactory selection of endmembers for a particular location.

Unmixing of spectral components works best when extensive field data are available for correlating and calibrating the sensor-derived component concentrations, when all of the endmembers are well characterized spatially and temporally and are spectrally orthogonal (distinct). The developed methodologies could potentially be used to develop cost-effective practical screening method for rapid detection of, and warning against, cyanobacterial blooms in the lower Great Lakes.
CHAPTER 5

RADAR INTERFEROMETRY

5.1 Overview

Radar interferometry is a technique that uses multiple radar images to infer topography, and to detect subtle temporal changes in topographic relief. It has been demonstrated that changes on the order of several cm/yr and as small as 0.1 mm/yr (under optimum conditions) could be readily measured using this technique (Massonnet and Feigl, 1998). This technique has been used to map deformation and fault slip from earthquakes (Sandwell et al., 2002), mine subsidence (Carnec and Delacourt, 2000), aquifer compaction from pumping (Burbey, 2003), and landslides (Amelung and Day, 2002), as well as seasonal changes in surface topography due to groundwater extraction and recharge (Hoffmann et al., 2001). The ideal setting for applying these techniques is in arid areas, where interferences from vegetation and atmospheric effects are minimal. Over the past decade, advances in radar interferometry applications and techniques have led to successful applications in temperate regions and over a wider range of climatic conditions and landscapes.
The Synthetic Aperture Radar (SAR) Interferometry technique exploits the information contained in the phase of two or more acquired over the same location. The technique makes use of the difference in phase (interferometric phase) between two radar scenes to determine the exact differences in range from the satellite, and subsequently determines the precise $x$, $y$, and $z$ location of the reflector, enabling the extraction of topography or subtle changes in topography.

Figure 5.1 shows the basic configuration of a pair of images used in repeat pass interferometry. $\rho$ is the range to a target from the satellite reference position, and $\rho + \delta \rho$ is the range to the same target acquired in the second pass. $B$ is the baseline, or physical distance between the location of the satellite in the first and second pass. $\theta$ is the look angle, and $\alpha$ is the angle between the baseline vector and the tangent plane. It is then possible to define $\delta \rho$ as a function of $B$, $\theta$, $\alpha$, $\rho$, and $\lambda$, the wavelength of the radar beam. $\delta \rho$ is proportional to the phase difference component of the radar return $\phi$, measured during the two radar acquisitions:

$$\phi = \frac{4\pi\lambda}{\lambda} \cdot \delta \rho \quad (5.1)$$

The common terminology for the reference scene is the master scene, and the repeat scene is the slave scene.
The factors which contribute to phase differences between two radar scenes include topography, deformation, and atmospheric effects.

\[ \phi = \phi_{\text{topo}} + \phi_{\text{def}} + \phi_{\text{atm}} + \phi_{\text{noise}}. \]  

The phase \( \phi \) is recorded cyclically from \(-\pi < \phi < \pi\), so there is by default an ambiguity in determining \( \rho \) from \( \phi \).
This process is described extensively by Gabriel and Massonnet elsewhere (Gabriel et al., 1989; Massonnet and Feigl, 1998).

There are three basic families of radar interferometry techniques currently in use and under development. These are the basic 2-4 pass differential INSAR (DINSAR) techniques, as well as two classes of multi-temporal techniques which use numbers of scenes ranging from tens to hundreds. The multi-temporal techniques are expansions and refinements of the basic 2-4 pass techniques. They repeat many of the same steps, and then extract usable information from results which are ambiguous in the 2-4 pass techniques.

The basis for all of these techniques is the generation of an interferogram. To generate an interferogram, the two scenes need to be co-registered in radar-space. This means that the slave scene (or a subset thereof) has to be co-registered to the master scene (or a subset of the master scene). This processing is done in the Delft object-oriented radar interferometric software (DORIS), a public domain radar interferometry software application (Kampes et al., 2003). With DORIS, the orbits are used to provide an initial estimate of the registration, and then the images are iteratively correlated using the cross correlation amplitude of the radar signal in individual subsets of the radar images. The radar images can be filtered (optional) to improve the registration. The slave image is then re-
sampled to the master image. The interferogram is then calculated from the co-registered images as the dot-product of the complex images (Fig. 6.2). This step is repeated for every interferogram that is generated. Any interferogram generated like this will have a phase component related to the curvature of the earth's surface. The curvature is then calculated and removed before any further processing is done.

Figure 5.2 Sample interferogram generated from a pair of radar images acquired on 9-2-92 and 10-31-92.

The second necessary component of these techniques is phase unwrapping. In the above interferogram (Fig. 5.2), a repeating ripple pattern is evident; the ripples trend from the lower left to the upper right. This is caused by the phase ranging from \(-\pi < \phi < \pi\), cyclically. In order for this to be turned into a measure of range, the cycles have to be added together, so that
the phase numbers then extend from 0 to $\sim 20\pi$, instead of the original cyclical distribution ($-\pi < \phi < \pi$). This is called unwrapping, and is a major challenge in interferometry. The method we use (snaphu) is described in full in Chane and Zebker (2002). If correlation between scenes is low or if coherence in the interferogram is low due to changes in the scene through time or increased perpendicular baseline, then this step becomes almost impossible.

5.2 Two-Pass Method

In the two-pass INSAR technique an interferogram is generated from two scenes which span a deformation event (the master is acquired before, the slave after). $\phi_{atm}$ and $\phi_{noise}$ are assumed to be negligible. $\phi_{\text{Topo}}$ is calculated from a digital elevation model (DEM) which has been registered with the master scene and subtracted from $\phi$ to yield $\phi_{\text{def}}$. This method is fairly simple, but it relies heavily on the availability of a high quality DEM and excellent registration between the DEM and the master. Any error in the DEM or in registration will cause ambiguities in detecting and mapping deformation.

5.3 Three-Pass Method

In three-pass interferometry, instead of a DEM being used, an unwrapped interferogram is used to remove the $\phi_{\text{Topo}}$ component. Noise and
atmospheric contributions are again considered to be negligible. An interferogram from a co-registered master and slave with a very small temporal and spatial baseline (i.e., 1 day) is generated. An additional slave image on the other side of the deformation (also with a small spatial baseline) is co-registered to the same master, and an interferogram is generated. The interferogram from the first pair is unwrapped, scaled to match the second baseline, and re-wrapped. The second interferogram is subtracted from the first, removing the topographic phase, leaving $\phi_{\text{def}}$.

5.4 Four-Pass Method

In the four-pass interferometry, a master-slave pair with very small temporal and spatial baselines is acquired before and after the deformation event. Each slave is co-registered to the appropriate master. An interferogram is generated for each pair. One interferogram is unwrapped and re-sampled to match the radar coordinates of the other pair. It is then scaled and re-wrapped. The second interferogram is subtracted from the first, yielding $\phi_{\text{def}}$. This method has several distinct advantages over the three-pass method. The $\phi_{\text{noise}}$ due to de-correlation is significantly reduced. All four scenes do not need to share the same small baseline range, but pairs can be selected to minimize spatial and temporal baselines. This significantly increases the detection of the resultant deformation.
5.5 Multi Temporal Methods

The multi-temporal methods generate a far higher number of interferogram pairs, throughout a deformation event. By making a large number of interferograms, and with educated assumptions about the nature of the deformation (i.e. linear deformation) and of the atmospheric contributions, the errors associated with the solution can be minimized. In the Small Baseline Subset (SBAS) approach, patches of coherent data are processed. In the Persistent/Permanent scatterer techniques, individual objects (single rooftops, etc.) which are exceptionally good scatterers that stay coherent over long times and spatial baselines are used instead.

The selection of the family of techniques to be used depends on data quality, environment, deformation type, availability of scenes, and processing time. The technique which we have focused on in the Nile Delta exercise is the Persistent Scatterer techniques as outlined by Hooper (Hooper et al., 2007; Hooper et al., 2004) and Kampes (Kampes, 2006). The following summarizes the main characteristics of each of these techniques, as well as the advantages and disadvantages of each method.

5.6 Summary

- Basic 2, 3 or 4 Pass DINSAR
  - 2 to 4 scenes required
o Good coherence between scenes mandatory
o Atmospheric effects assumed negligible
o Two-pass
  • Needs supplemental DEM information
  • Subject to inaccuracies in DEM
  • Pair needs to bracket deformation event
  • DEM needs to be accurately radar coded
o Three-pass
  • Subject to atmospheric effects
  • One pair needs to be very close together in time (1 day) on one side of the deformation event, the third scene has to be on the other side of the event
  • Difficult to maintain correlation over long times (years)
  • Scenes registered to common master
o Four-pass
  • 4 scenes, pairs of scenes from before and after the deformation event
  • Each pair needs small baseline, good correlation
  • Allows for longer time for deformation to occur
  • Scenes co-registered as pairs, pairs co-registered to each other.

• Multi-temporal techniques:
  o Small Baseline Techniques (SBAS)
    • 10-20 scenes and more are used
    • Assumes areas of good coherence in interferogram
    • Entire scenes need not be coherent
    • Scenes spatially resampled to one common scene, directly or through cascading sequence (Refice et al., 2003)
    • Only useful for gradual deformations (i.e., subsidence)
• Examples can be found in (Lanari et al., 2004a; Lanari et al., 2004b)

• High number of interferograms generated

• Processing time intensive

  o Permanent Scatterer Techniques

    • >6 (Persistent Scatterer) to >40 (Permanent Scatterer) scenes

    • Good coherence at individual points (Permanent/Persistent Scatterers)

    • Deformation can be gradual (subsidence) or sharp (faulting)

    • Non-linear estimate of deformation

    • Scenes spatially resampled to one common scene, directly or through cascading sequence

    • Very high number of interferograms generated

    • Processing time intensive

    • Examples include: (Ferretti et al., 2000, 2001; Hooper et al., 2007; Hooper et al., 2004)
CHAPTER 6

LAND SUBSIDENCE IN THE NILE DELTA: INFERENCES FROM RADAR INTERFEROMETRY

6.1 Abstract

The Nile Delta has formed by progression of a complex system of deltaic fans throughout the Pleistocene, with the modern delta being formed from sediments supplied by at least 10 distinct distributary channels throughout the Holocene. With an average elevation of a meter or so above sea level and a predicted rise in sea level of 1.8-5.9 mm/yr (IPCC, 2007) the subsidence of the northern delta is becoming a topic of major concern both to the Egyptian population and the government. The Nile Delta is home to more than 50 million people and the major agricultural production area for Egypt. We evaluated the modern rates of subsidence of sections of the northeastern Nile Delta (a total length of 110 km, up to 50 km from the coastline) using persistent scatterer radar interferometry techniques applied to 14 ERS-1 and ERS-2 scenes. The area covered includes the present active depocenter of the Damietta promontories, and the nearby Mendesian depocenter that was active up to recent times (up to 2500 years ago). The highest subsidence rates (~8 mm/yr; twice the average Holocene rates) do not correlate with the distribution of the thickest Holocene sediments, but rather with the
distribution of the youngest depositional centers (major deposition occurred between ~3500 years bp and present) at the terminus of the Damietta branch. The adjacent slightly older (8000 – 2500 years bp) Mendesian branch depositional center is subsiding at slower rates of 2-6 mm/yr. Results are interpreted to indicate that: (1) modern subsidence in the Delta is heavily influenced by the compaction of the most recent sediments, and (2) the highly threatened areas are at the terminus of the Damietta and possibly the Rosetta branches, where active deposition is occurring.

6.2 Introduction

Deltas worldwide witness phases of progradation and destruction, phases that are largely related to the interplay between fluvial processes, sea level changes and coastal erosion at the mouth of the river. Deltas prograde when fluvial processes dominate and retreat when coastal erosion intensifies. Many of the world's large deltas are subsiding, in large part due to compaction and isostatic response to loading by thick depositional sequences (Stanley et al., 1996). Over the past 7000 years (Holocene) many deltas all over the world have been witnessing an overall constructional phase. Recently (over the past tens of years), there have been indications that this trend is being reversed in a number of these deltas world-wide.
Modification of free-flowing rivers for energy generation or irrigation projects can accelerate changes in delta plains and coasts including delta subsidence due to the deprivation of the coastal systems of the silt and clay which accumulate in deltas. Increased coastal erosion, and accelerated net subsidence of deltas under the weight of the thick delta deposits combined with rising sea level also exacerbates deltaic changes (Kay, 1993).

The Nile Delta (Fig. 6.1), the area of this study is witnessing a

Figure 6.1 False color Landsat TM mosaic showing the Nile Delta, the Damietta and Rosetta branches, and urbanized centers (cities and villages) that appear in shades of purple. The thickest Holocene deposits are located north of the black dashed line (Stanley and Warne, 1993a). The red box outlines the area covered in Figure 6.2. Inset (lower left corner) shows the location of Nile Delta, Nile River, and the Aswan High Dam.
destructional phase largely related to anthropogenic activities (damming, water diversion, etc.) by the nations of the Nile Basin throughout the last several centuries, with the most drastic changes occurring in the last 100 years. Egypt increased its water storage capacity by constructing dams (e.g., Aswan Dam, Aswan High Dam) and impounding water behind dams in extensive artificial reservoirs (e.g., Lake Nasser: total capacity: $1.6 \times 10^{11} \text{ m}^3$) (Said, 1993). Egypt is embarking on diversion projects (e.g., Toshka project, El Salam Canal) to channel large volumes of Nile River water to reclaim lands in the Western Desert and Sinai. As a result, water discharged at the Rosetta and Damietta channels (Fig. 6.1) has been dramatically reduced (1950s: $40 \times 10^9 \text{ m}^3/\text{yr}$; 2000s: $< 5 \times 10^9 \text{ m}^3/\text{yr}$) (Frihy and Lawrence, 2004) altering the balance that existed between sediment influx, sea level rise, coastal erosion, and subsidence. For example, since 1972 the retreat of the Damietta promontory has increased to alarming rates of up to 52 m/yr (Frihy and Lawrence, 2004).

The pioneering work by Stanley, Warne, and co-workers (Krom et al., 2002; Stanley and Warne, 1993b, 1998; Stanley, 2001; Stanley et al., 2004; Warne and Stanley, 1993) on the subsidence of the Nile Delta throughout the Holocene, and the accelerated subsidence of the area following the erection of the Aswan High Dam and subsequent cut off of sediment supply, has received a great deal of attention from the scientific community as well as extensive media coverage. Eighty-seven radiocarbon-dated cores across the northern
delta were used to interpret the interactions between sea-level changes, climatic oscillations, subsidence, and sediment transport. Average subsidence rates (0.5 to 5 mm/yr for the past 7500 years) were calculated from radiocarbon dated sediments from wells in the northern delta plain.

There are several uncertainties associated with using the average Holocene subsidence rates to infer precise estimates of modern subsidence: (1) subsidence rates for deltas change with time (Meckel et al., 2007) and thus, average Holocene values do not necessarily represent shorter temporal scales (modern) rates, (2) spatial heterogeneities in subsidence rates might not be adequately captured using a limited number of samples collected from widely spaced wells drilled in the northern delta, (3) uncertainties associated with the $^{14}$C ages may be large as the position of dated samples in the stratigraphic sequence may have been altered in many cases resulting in underestimating the subsidence rates calculated from these samples (Said, 1993; Stanley and Hait, 2000; Stanley, 2001). Persistent scatterer radar interferometry techniques were applied over large sections of the northeastern sections of the Delta to overcome these problems.

6.3 Geology of the Nile Delta

The modern Nile Delta sits on the Nile Cone, a depositional feature resulting from more than 5 million years of discharge and deposition of 3500
m of sediment by the Nile and Paleonile drainage systems (Sestini, 1989). The Pleistocene section consists of up to 800 m of deltaic sands with minor clay layers (RIGW, 1992). During the late Pleistocene, from roughly 35 to 18 ka, the region of the modern Nile Delta was a seasonally active alluvial plain with braided stream channels. This was followed between 15 and 8 ka by a period of rapid sea level rise, which reworked much of these sediments. Some 8000 years ago, a slowing down in sea level rise prompted the development of the modern Nile Delta (Said, 1990; 1993). The Delta prograded up to 10 m/yr into the Mediterranean through accretion of silts and clays (1-7mm/yr) giving rise to thicknesses of up to 60 m of Holocene deltaic fluvial/marine deposits (Stanley and Warne, 1993a).

Throughout the Holocene the centers of deposition continued to shift from one spot to another along the delta coastline depending on which channel(s) were active at any particular time (Stanley et al., 2004). For example, from 8000 years ago, the eastern sections of the Nile delta were building out along the Tanitic and Mendesian branches (Fig. 6.2a). The Tanitic branch deposited material underneath what is now the Manzala Lagoon, and prograded across to present day Port Said (Fig. 6.2). The Mendesian branch formed a depositional center under the western portion of the Manzala Lagoon and prograded to the northeast to merge with the depositional center of the Tanitic branch. The supply of sediments by these two branches gave rise to up to 40 m thick sections of Holocene deposits,
currently underlying the Manzala Lagoon. Around 1500 to 2500 years ago these two branches silted up allowing the Damietta branch to become the largest contributor of Nile sediment flux (Stanley and Warne, 1993a).

In addition to natural phenomena, and as early as 5000 bp, human intervention has played an increasing role in modifying the natural flow system and flood patterns. By the middle of the 19th century, earlier smaller individual projects (e.g., raised levees) quickly gave way to larger irrigation canal systems to irrigate large sectors of the Nile Delta (Sestini, 1989). Up to that time, the annual floods still delivered considerable silt to the delta, a situation that rapidly changed beginning in the late 19th century and continued throughout the 20th century. Major engineering projects were implemented including dams and barrages culminating in the construction of the Aswan High Dam in 1964. Prior to the construction of the latter, approximately $9.5 \times 10^6$ metric tons of sediment were deposited onto the Nile Delta floodplain each year, an amount equivalent to a ~1 mm layer of silt across the Delta. This added thickness partially balanced continued subsidence of the Delta. Following the construction of the Aswan High Dam, the sediment load no longer reaches the delta, instead it settles in Lake Nasser behind the dam (Said, 1993).
6.4 Radar Interferometry

Radar interferometry has been successfully used to map small (as small as 0.1 mm/yr) (Massonnet and Feigl, 1998) deformation and fault slip from earthquakes (Sandwell et al., 2002), mine subsidence (Carnec and Delacourt, 2000), aquifer compaction from pumping (Burbey, 2003), and landslides (Amelung and Day, 2002), as well as seasonal changes due to groundwater extraction and recharge (Hoffmann et al., 2001).

Interferometric synthetic aperture radar (InSAR) processing makes use of the difference in phase between two radar scenes to determine precise differences in range to a target and to subsequently determine the exact surface location, and subtle changes in topography. In conventional three-pass InSAR interferometry, the deformation is calculated from the difference between the unwrapped phase of a reference interferogram (no deformation between scene acquisitions) and a pair spanning the deformation (Massonnet, 1996). Successful implementation of this method relies on maintaining a high correlation for pairs of scenes over the time period of the deformation. If changes in scatterers occur between passes, such as those introduced by growing vegetation, phase will vary randomly and the process of extracting phase differences indicative of subsidence will be jeopardized. Because the Nile Delta is highly vegetated, and the variations we are examining are long term variations compared to those introduced by growing vegetation, the
conventional three-pass interferometry technique was inadequate for the study area (Aly et al., 2005).

We took advantage of recent refinements in persistent scatterer radar interferometry techniques (Hooper et al., 2007; Hooper et al., 2004) that are now enabling successful applications over a wider range of physiographic and atmospheric conditions. To date, applications of the related permanent scatterer techniques in the Nile Delta have been restricted to two major cities, Mahala and Mansura, in central Nile Delta (Fig. 6.1) (Aly et al., 2005). We applied the persistent scatterer technique (Hooper et al., 2007; Hooper et al., 2004) to investigate the spatial variations in subsidence rates across large sections (area: ~2400 km²) of the heavily vegetated northeastern delta (Fig. 6.2). The adopted persistent scatterer method generates multiple three-pass interferograms, but restricts the phase unwrapping and analysis to pixels containing individual scatterers which dominate individual pixels, and remain stable over the time period of interest. Because the signal from these scatterers is much larger than the random noise from a large number of small scatterers, the variance in phase in these pixels reflects the underlying deformation (Ferretti et al., 2000; Hooper et al., 2004). In the northern delta, these scatterers include buildings, individual outcrops, rocks, or utility poles. In applying this technique, we took advantage of the extensive distribution of small buildings and scattered dwellings, present largely in villages and cities (areas appearing in shades of violet in Fig. 6.1) across the delta. The Stanford
Method for Persistent Scatterers (StAMPS) algorithm was adopted; this method uses the spatial correlation of the interferogram phase to identify such pixels (Hooper et al., 2007). For the majority of the investigated area, the density of the permanent scatters ranged from 4 to 30 permanent scatterers/km² enabling the estimation of atmospheric contributions (Colesanti et al., 2003).

Synthetic aperture radar (SAR) scenes covering the period 1992-1999 were acquired from the European Remote Sensing satellites (ERS-1 and ERS-2; Table 6.1). In the selection of scenes, attempts were made to pick scenes with minimal differences in their spatial baselines (perpendicular baseline <500m) and which are temporally as evenly distributed as possible throughout the investigated period. Fourteen scenes in track 436 were processed, and mean line of sight velocities were first calculated and then converted to equivalent vertical motions.

ERS precise orbit information was obtained from Delft Institute for Earth-Oriented Space Research (Scharroo and Visser, 1998). All of the interferometric processing was conducted using: (1) the Delft Object-oriented Radar Interferometric Software (DORIS) (Kampes et al., 2003), (2) the Repeat Orbit Interferometry Package (ROI_PAC) from JPL, and (3) StAMPS (Hooper et al., 2004).
Table 6.1 ERS-1 and ERS-2 scenes used in permanent scatterers study. Temporal and perpendicular baselines are shown relative to the scene acquired on 8/24/1995.

<table>
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6.5 Discussion and Results

Results of permanent scatterer analysis applied to the 13 ascending scenes are shown in figure 6.2a. A large number (>10,000) of persistent scatterers were identified and used to constrain modern subsidence rates in the study area. Subsidence rates represented on this figure are relative to the average motion of the permanent scatterers in the southwestern portion of...
Figure 6.2 (a) Mean velocities extracted from 14 ascending ERS-1 and ERS-2 scenes acquired over the period 1992-1999 and expressed as vertical motion of permanent scatterers (negative velocities indicate downward motion). Areas of highest modern subsidence include areas at the terminus of the Damietta branch that are underlain by significant (>5 m) amounts of young (<3500 years) sediments (areas shaded in white). Also shown in white solid lines are the current Damietta branch, the paleo Mendesian and Tanitic branches, and shown in black dashed lines, the paleo-coastlines positions at 4000, 3500, 2000 and 1500 years bp (Coutellier and Stanley, 1987; Stanley and Warne, 1993a). (b) Average Holocene subsidence (Stanley and Warne, 1993a), and Holocene thicknesses from individual borings (colored squares) (Stanley et al., 1996). High modern subsidence rates correlate with the distribution of younger (<3500 yr) Holocene sediments rather than thick Holocene sediments. Radar data provided by the European Space Agency.
the study area, an area that experienced minimal subsidence (<0.5mm/yr) (Stanley and Warne, 1993a) throughout the Holocene. Previous estimates of average Holocene subsidence rates were based on data from 87 wells across the northern delta, 22 of which were drilled in the study area (Fig. 6.2b). The subsidence rates that we report and their spatial distribution differ considerably from those previously reported for the Holocene (Emery et al., 1988; Stanley and Warne, 1993a). Modern rates are generally high (up to 8 mm/yr) compared to previously calculated average Holocene rates (0.5 to 4.5 mm/yr). The highest modern rates are observed over the youngest (<3500 year old) sediments under the terminus of the Damietta branch (Fig. 6.2a). Moderate rates (4-6 mm/yr) are calculated around the Manzala Lagoon (Fig. 6.2), a depocenter that was active more than 3500 years ago.

The highest subsidence rates were calculated at the terminus of the Damietta branch suggesting a causal relationship between rapid subsidence and the distribution of young sediments that were probably deposited during the recent progradation of the Damietta branch and have been undergoing compaction and isostatic subsidence since then. This hypothesis is supported by the general spatial correspondence between rapidly subsiding areas and those underlain by thick, young (<3500 years old) sediments. Figure 6.2 shows a correspondence between the area subtended by a contour defining domains of 5 or more meter thick young deposits and the areas undergoing rapid subsidence (clusters of orange, red, and yellow dots on Fig. 6.2a). The
contour was defined using data extracted from radiocarbon dated cores and sediment thicknesses from 22 drilled wells in the study area (Stanley et al., 1996). Only cores where the $^{14}$C age sequence increases sequentially with depth were used. The locations of these cores are represented as squares color coded to total Holocene depth in figure 6.2b.

The proposed hypothesis is consistent with the documented evolution of the depositional environments over the past 3500 years in the northeast delta. The Damietta branch has prograded some 40 km to the northeast over the past 3500 years as the coastline has migrated to the north (Fig. 6.2a). The highest modern subsidence rates (6-8 mm/yr) correspond to areas of this most recent deposition along the Damietta branch between the paloeshoreline of 3500 years bp (Coutellier and Stanley, 1987) and the modern shoreline (Fig. 6.2a).

The proposed hypothesis is also consistent with the documented evolution of the depositional environments for the time period preceding the past 3500 years. If modern subsidence is largely controlled by compaction of younger sediments, one should expect to observe moderate subsidence rates in areas of slightly older (>3500 years old) sediments that were transported by the earlier Mendesian and Tanitic branches and deposited in the area occupied by Manzala Lagoon. In these areas, only a thin cover of younger sediments (1-4 meters) were deposited by the earlier Mendesian and Tanitic branches
(Stanley et al., 1996). Our results indicate that this is indeed the case; moderate (2-6 mm/yr) subsidence rates are observed in the area occupied by the Mendesian depocenter (area outlined by dashed white line: Fig. 6.2a). Unfortunately the examined radar scene does not cover the Tanitic depocenter. We suggest that these large thicknesses of the Holocene sediments in the Manzala Lagoon must have witnessed early periods of rapid compaction and subsidence followed by a progressive decline in subsidence rates with time as sediments became less prone to compaction. Such an interpretation could explain why the highest average Holocene rates are reported for areas with the thickest Holocene sediment in the Manzala Lagoon (Stanley and Warne, 1993a), whereas the modern subsidence rates we report for these areas are moderate.

It is unlikely that the observed modern subsidence was caused by tectonic movements, as there have not been any reported earthquakes (ISC, 2001) along the previously identified faults (Frihy, 2003; Stanley, 1988) in the area or in any other location within the study area throughout the investigated period (1992-1999). Our findings do not preclude seismic activities occurring on larger timescales. The lack of any recent (1992-1996) seismic activities also argues against the observed displacements being related to horizontal motion along faults. The observed modern displacements are interpreted here to be vertical in nature and are largely attributed to compaction and isostatic adjustment.
Our findings in the Nile Delta are consistent with those reported from deltas elsewhere. Modern subsidence rates in the Mississippi are interpreted to indicate that compaction of sediments constitutes a substantial source of subsidence in deltaic systems, especially during the earlier periods following deposition, and that average Holocene subsidence rates do not necessarily predict current subsidence rates. Compaction rates in the Mississippi Delta system within the first tens of years to centuries can range from 5 mm/yr to values as high as 10 mm/yr in organic rich peat systems, considerably higher than the estimated average Holocene subsidence rates of <3 mm/yr (Törnqvist et al., 2008). Mekel et al. (2007) modeled the compaction of Holocene sediments in the Mississippi Delta; his simulations predicted rapid compaction of deposits shortly after deposition, with progressive decline in compaction with increasing age of sediments.

In the northern delta, it has been assumed that the areas underlain by the highest sediment thickness are currently subsiding the fastest, and would be impacted most severely by projected sea level rises. This study shows that the sediment age rather than the thickness might be the dominant factor controlling subsidence in the Nile Delta. Results indicate that areas around the city and harbor of Damietta may be the most vulnerable to inundation. The conditions described for the Nile Delta are typical of many of the world’s deltas.
CHAPTER 7

CONCLUSIONS

In this manuscript, I demonstrated methodologies and applications addressing two specific problems pertaining to mapping the abundance of algal blooms in the Great Lakes, and land subsidence in the Nile Delta. Specifically, I investigated methodologies to temporally and spatially investigate the extent and distribution of algal blooms in Lake Erie and Lake Ontario, and proposed a method for discriminating between potentially toxic and non-toxic blooms. Visible and near infra red MODIS and SeaWiFS satellite data were used to map the distribution of algal blooms in these lakes. Existing algorithms for mapping blooms were applied and results were compared. Moreover, new methodologies were developed to distinguish between the non-toxic blooms and the potentially toxic cyanobacterial blooms. Cyanobacterial concentrations that were derived using my algorithms were successfully tested against in situ measurements.

These results show great promise for establishing cost-effective, remotely-based monitoring systems which could be used by various municipalities to secure water intake systems and the recreational areas in Lakes Erie and Ontario. To achieve this goal, we now have in place an automated system which produces chlorophyll images (using case II Carder algorithms applied to MODIS data) and posts the results on the web (http://www.esrs.wmich.edu/MERHAB-LGL) for all interested parties.

Future steps will include automation of the cyanobacterial
identification method to provide rapid access to results and to make these available to scientists and city managers. Better refinement of the spectral properties of the endmembers is also planned. Currently, Microcystis is the only cyanobacteria included in the model. Plans are underway to better represent the known variations in toxic species in the lakes, including Planktothrix, and Anabaena. The model should be also tested and refined in other locations in the Great Lakes (e.g., Saginaw Bay) and in other settings where cyanobacterial blooms were reported (e.g., Baltic Sea).

In the second study I examined subsidence in the northeastern portion of the Nile Delta. Because of its low average elevation, and a predicted rise in sea level of 1.8-5.9 mm/year (IPCC, 2007) the potential for inundation of this region of the delta is high. This provides a significant concern to the Egyptian population and government. I calculated modern subsidence rates in the northeastern Nile Delta using persistent scatterer radar interferometry techniques, and found that the modern subsidence rates are as high as 8 mm/year. The highest rates are twice the average Holocene rates, and correlate with the distribution of the youngest deposits. Slower rates of 2-6 mm/yr. were found under the older depositional centers. These results were interpreted to indicate that the modern subsidence in the Delta is heavily influenced by the compaction of the most recent sediments, and that the highly threatened areas are at the terminus of the Damietta branch, where the most recent deposition has occurred.

This information about the ongoing modern distribution of subsidence rates is useful for Egyptian officials in the Damietta region. Prior to my work it had been assumed that the maximum subsidence rates were about 5
mm/yr, approximately half of the maximum rate we report in this study. Moreover, the previous studies predicted that the highest subsidence rates were underneath the Manzala Lagoon, whereas our study shows that it is around the Damietta region. Naturally, the high subsidence rates under Damietta city and its surroundings raises the concern of inundation in this area.

Future work in this area should include verification of these calculations. Geodetic stations could be established in or near Damietta city and the harbor. The radar interferometry study should be extended both spatially to cover larger portions of the northern Nile Delta region, and temporally, to include data later than 1999. Future studies could take advantage of the L-band radar instrumentation on the ALOS satellite. The later provides better penetration of vegetation canopy, and could potentially provide more coherent applications compared to those based on the C band of ERS-1 and ERS-2. As longer acquisition periods of radar data are achieved better precision in results will be accomplished.
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APPENDIX
SELECTED INTERMEDIATE INSAR PRODUCTS
Figure A.1 Three Pass interferogram generated from scenes acquired 8-24-1995 and 8-23-1995 prior to persistent scatterer selection. Good coherence is seen due to small spatial and temporal baselines.
Figure A.2 Three Pass interferogram generated from scenes acquired 8-24-1995 and 1-11-1996. Coherence is maintained in areas around cities and buildings. These areas are good candidates for persistent scatterers.
Figure A.3 Sample subsidence rate calculation for location in Damietta City before atmospheric corrections are applied. Error bars show 1 standard deviation from average of all nearby points within 1 km$^2$. Y axis shows vertical position real relative to entire scene average using the 5-15-1997 scene as the reference.