This is to certify that the

dissertation entitled

The Use of Remote Sensing in Freshwater Wetland and Lake Studies

presented by

Stacy A. C. Nelson

has been accepted towards fulfillment
of the requirements for

Ph.D. degree in Fish. & Wildl.

Major professor

Date 9/17/02

MSU is an Affirmative Action/Equal Opportunity Institution

O-12771

THE USE OF REMOTE SENSING IN FRESHWATER WETLAND AND LAKE STUDIES

By

Stacy Arnold Charles Nelson

A DISSERTATION

Submitted to
Michigan State University
in partial fulfillment of the requirements
for the degree of

DOCTOR OF PHILOSOPHY

Department of Fisheries and Wildlife

2002

ABSTRACT

THE USE OF REMOTE SENSING IN FRESHWATER WETLAND AND LAKE STUDIES

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Wetlands and freshwater lakes are currently under threat from anthropogenic pressures that are occurring across large spatial scales. We need approaches to study these changes that can accommodate these large spatial scales. For example, the Barataria Basin, Louisiana, is an extensive wetland and coastal estuary system of great economic and intrinsic value that has experienced high rates of coastal land loss. However, little information exists on whether freshwater wetlands in the upper basin have changed. My objectives in chapter 1 were to: 1) quantify land cover change in the upper basin over twenty years from 1972-1992; and to 2) determine land cover transition rates among land cover types. Using 80-m resolution Landsat MSS data, I found significant changes in land cover occurred within the upper Barataria Basin over the study period with a 21% increase in total wetland area. If present trends in total wetland area continue, bottomland hardwood forests may be eliminated by the year 2025. In Chapter 2, I examined whether Landsat-7 ETM+ could be used to measure water clarity across a large range of lakes. My objectives were to: 1) develop a model to estimate lake water clarity from Landsat data calibrated on 93 lakes in Michigan, and to 2) examine how the distribution of water clarity across the 93 lakes influences the model. My regression model resulted in a much lower r^2 value than previously published studies. So, to examine the role of the distribution of calibration lake water clarity data to the model, I simulated a calibration

dataset with a different water clarity distribution by sub-sampling the original dataset. The subsampled dataset had a much higher percentage of lakes with shallow water clarity. The regression model for the subsampled dataset resulted in a much higher r^2 value. My results show that the use of Landsat to measure water clarity is sensitive to the distribution of water clarity used in the calibrated dataset. In Chapter 3, I examine the use of Landsat-5 to monitor macrophytes in inland lakes. My objectives were to: 1) determine if different aquatic plant cover types could be detected using Landsat-5; and to 2) determine if I could improve predictions of macrophytes in lakes by including lake characteristics in the models. Using logistic regression models, I found statistically significant relationships between most macrophyte measures in 12 calibration lakes and Landsat-5 spectral values. However, using another lake to validate the model resulted in poor model validation. Thus, it is still unclear exactly how useful Landsat data is for monitoring aquatic plants. Remote sensing provides an effecting monitoring tool for large area studies in historical wetland change. I demonstrate one application of this in chapter 1. In aquatic studies, remote sensing can play a vital role in reducing the cost, labor, and time required to monitor regional inland lake water clarity and assess the distribution of macrophytes. However, caution should be used in assessing water quality based solely on remotely sensed data until our methods have been refined or better sensors are developed for aquatic applications.

This body of work is dedicated to my parents, and God from whom all blessing flow.

ACKNOWLEDGEMENTS

I would like to acknowledge the many people whose assistance has allowed me to reach this level: Patricia Soranno, David Lusch, David Skole, Jack Liu, Jiaguo Qi, Walter Chowmentowski, Chris Barber, Danielle Gwinn, Jay Samek, Sam Batzli, Jonathan Chipman, Ralph Bednarz, Kevin Hoffman, John Whitlock, Tamara Brunger-Lipsey, Kristy Rogers, Sarah Wills, Narumon Wiangwang, Marc Linderman, Russel Minnerick, Stephen Aichele, Orlando "Ace" Sarnelle, Ken Frank, Jim Bence, Emily Szali, Daniel Hayes, William Taylor, Ken Poff, James Jay, Jane Thompson, Jim Brown, Sarah Cline, Carla Dombroski, Julie Traver, Terie Snyder, Jill Cruth, Deana Haner, Lesley Knoll, Andrew "Drew" Kramer, Sherry L. Martin, Konrad Kulacki, Michael Belligan, Sarah Walsh, Alan Wilson, and Kendra Spence Cheruvelil. If I've forgotten anyone, please know that you help was truly a blessing. Thank you all so very much.

PREFACE

This dissertation examines applications of remote sensing to freshwater studies, especially focusing on regional applications across large geographic areas. I examine aspects of both the land surrounding freshwater ecosystems as well as features of the water itself. In particular, I have used remote sensing to assess regional changes in wetland area, regional lake water clarity, and to measure freshwater macrophyte distributions across multiple lakes. The dissertation is divided into three separate, but related chapters, preceded by an introduction that provides the overall background for this research. Each of these chapters stands alone as a separate manuscript that has been or will be submitted for peer-reviewed publication. Chapter 1 has been published already in the journal, Environmental Management (see citation below). Chapter 2 has been submitted for publication to the journal, Remote Sensing of the Environment. Chapter 3 is in preparation for submission to the journal, Aquatic Botany. Below are the citations for each of the chapters including the co-authors who have contributed to each chapter.

Chapter 1:

Nelson, S.A.C., P.A. Soranno, and J. Qi. May 2002. Land cover change in the upper Barataria Basin Estuary, Louisiana from 1972-1992: Increases in wetland area. Environmental Management 29(5): 716-727.

Chapter 2:

Nelson, S.A.C., P.A. Soranno, K.S. Cheruvelil, S.A. Batzli, and D.L. Skole. Assessing regional lake water clarity using Landsat and the role of inter-lake variability. Submitted to Remote Sensing of Environment September 2002.

Chapter 3:

Nelson. S.A.C., K.S. Cheruvelil, and P.A. Soranno. Remote sensing of freshwater macrophytes and the influence of lake characteristics. To be submitted to Aquatic Botany, October 2002.

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INTRODUCTION

Environmental Applications of Remote Sensing

Historical investigations of our natural ecosystems predominantly have focused on local or small scale studies because researchers in the past were limited by phenomena they could either physically examine in the field, or the area which could be sampled and returned to the laboratory during the study period (Hardisky et al. 1986). Today, increased understanding of ecosystem interactions and functions have led to much broader scale research approaches as the need to investigate the ecosystem as a whole becomes more apparent (Sullivan 1994; Brouha 1994). In particular, as the local, regional, and global land surface is continually transformed as a direct result of earth's growing human population and competition for resources, there is a continual threat to the sustainability of sensitive natural areas (Brouha 1994).

In fact, human's ability to alter the natural environment has been noted one of the greatest concerns for global environmental change (Brown et al. 1992, Southwick 1996; Wilke and Finn, 1996). Today, the global population is over 6 billion and the human population continues to grow at a rate of 90 million/year; this type of population growth can have severe consequences on the natural environment (Brown et al. 1992). For example, it is now estimated that we have transformed approximately 1/3 to 1/2 of earth's ice-free surface, thus making human-caused land use/land cover change one of the most important components of global change (Wilke and Finn, 1996). In the U.S., one of the most prominent areas of land cover change involves the extent of coastal and inland wetlands loss that has occurred since European settlement. According to the U.S. Fish and Wildlife Service and the National Wildlife Federation, out of the > 81 million ha of wetlands that were present in the continental United States in the early 1700's, only 35 - 40 million ha remained as of the mid 1980's (Dahl et al. 1991).

Human's effects on the natural environment have also led to an additional need for understanding the effects of cumulative small scale land use transformations that occur across large regions. Western and Pearl (1989) note that the speed and scale with which we are modifying the Earth limits our ability to use traditional field methods over large areas. Green et al. (1994) suggested that remote sensing provides a mechanism versatile enough to keep up with the rapid and extensive changes made to the Earth's surface as the world's population grows. Because remote sensing offers a tremendous potential as a rapid, large-area, synoptic source for data acquisition, it has become an important part of many ecological studies (Lillesand and Kiefer 1994).

Since the 1970's, technological advances and better sensor configurations have further refined the use of remote sensing to include monitoring and research of agriculture, forestry and range resources, land use mapping and planning, geology and environmental applications, and coastal and water investigations. In particular, remote sensing has been identified as an effective means of detecting and monitoring land use and land cover change in the terrestrial environment (Green et al. 1994). However, satellite remote sensing of inland lakes has been less studied as a result of the difficulties inherent in interpreting reflectance values of water (Verbyla 1995). Clear water provides little spectral reflectance because longer wavelengths are absorbed and the reflected shorter wavelengths, which sensors rely on for surface feature detection, are subject to atmospheric scattering. Although sensors such as the Landsat Multispectral Scanner

(MSS) and Thematic Mapper (TM; and now ETM+) were primarily designed for land studies, and may not be completely applicable to aquatic studies, recent improvements now provide better spatial and spectral resolutions than previously available, which may improve their usefulness to aquatic studies, such as for small inland lakes (Kloiber et al. 2000).

Despite these limitations, remote sensing still has the potential to provide a valuable tool for monitoring freshwater systems. Several studies have successfully used remote sensing to measure lake characteristics such as chlorophyll and Secchi disk transparency, suspended sediments and dissolved organic matter (Lathrop and Lillesand 1986, Jensen et al. 1993, Narumalani et. al. 1997, Lillesand et al. 1983, Khorram and Cheshire 1985, Dekker and Peters 1993, Kliober et al. 2000). Other studies have used remote sensing to map aquatic plant abundance in large areas of homogenous cover or for species detection in smaller areas they have used high resolution hand or aircraft sensors (Ackleson and Klemas 1987, Armstrong 1993, Penuelas et. al. 1993, Lehmann et al. 1997). While remote sensing has been used in large-scale land change studies for many years, few studies have used Landsat data to measure water quality parameters of multiple lakes, over large regions, or covering multiple images. Additionally, current research on detecting aquatic macrophytes on a regional scale is still lacking.

One additional challenge to regional remote sensing is combining images from multiple dates or regions of varying atmospheric influences (i.e. haze, cloud cover, etc.). Song et al. (2001) found that atmosphere corrections are necessary when using two or more satellite images collected on different dates, such as imagery used in land use/cover change studies. Multi-temporal image to image differences are a result of atmospheric absorption and light scatter, which can be highly variable from one period of time to the next (Moore 1980). This difference can have a pronounced effect on the interpretation of imagery for trend analyses when using multiple images that are collected on different days, months, or years. For example, for aquatic studies, Brivio et al. (2001) found that without the appropriate corrections for atmospheric scattering and transmittance effects, successful remote sensing of lake water quality parameters could not be accurately achieved from four Landsat TM images. Brivio et al. (2001) were able to develop two image-based rectification models which were used to correct lake atmospheric effects in multi-seasoned Landsat images of Lake Lseo and Lake Garda, Italy. However, accurate and simple procedures to correct for these effects are still an area of future research (Rahman et al. 2001, Song et al. 2001).

These atmospheric limitations may be reduced with many recent technological advances. A few of the newest sensors include IKONOS, the EOS (Earth Observing System) Terra sensors, and the Landsat ETM+. These sensors will ultimately employ more advanced data calibrations than possible with some of the older sensors. However, the advantage of the older Landsat platforms is that they provide consistent historical data not yet available from new sensors and the temporal and spatial resolutions provided by Landsat MSS and TM are still more effective in monitoring landscape changes. For example, since the early 1980's, remote sensing techniques have become commonly used to detect wetland change (Ricketts 1992). However, few studies have taken advantage of the wealth of historical data available from the satellite platforms that have been operating across several decades, and that are becoming widely available and inexpensive

(Munyati 2000). Images obtained using the Landsat Multispectral Scanner (MSS) sensor presently represent our longest, continuous satellite remotely sensed historic record.

The availability of newer data will, however, allow for the integration of cross-platform data in developing band and image sharpening algorithms which will serve to fill in the gaps present in the older system data acquisitions (clouds, haze, etc.) and enhance the ability to develop multi-image calibrations for cross referencing. Furthermore, three of the main Terra sensors (MODIS - Moderate Resolution Imaging Spectrometer, ASTER - Advanced Spaceborne Thermal Emission and Reflectance Radiometer, and MISR - Multi-angle Imaging Spectroradiometer) have been identified as being particularly useful in the remote sensing of large area land cover and land use changes and vegetation dynamics studies (NASA 1998, Jensen 2000). However, aquatic remote sensors have yet to see the production of sensors specifically designed to monitor freshwater environments.

The primary focus of my research involves the application of remote sensing to studies of freshwater ecosystems. This body of research is important because there is an increasing need to assess large-scale changes in aquatic ecosystems as a result of anthropogenic impacts, just as has been done for terrestrial ecosystems. I have examined a wide range of applications in this research, focusing on two important ecosystems (lakes and wetlands) from two different states (Louisiana and Michigan, USA).

Large area wetlands and inland lakes within a large region represent two areas where the use of large-scale monitoring techniques would prove very beneficial, as research and management agencies are limited in their resources to develop rapid, regional assessments from ground based inventories.

My first chapter investigates changes in a large area wetland system (628,600 ha) in southeastern Louisiana, the Barataria Basin. This area has experienced well documented wetland loss along the coastal margin for many years. However, less is known about wetland changes occurring in freshwater portion of the upper basin. In this study, I investigate historical changes within this area using Landsat MSS over three time periods; 1972, 1985, and 1992.

My second chapter investigates the application of data from the Landsat-7 ETM+ sensor to effectively predict Secchi Disk Transparency across a large region (94, 350 km^2) within the lower peninsula of Michigan, USA. In this study, I use linear regression models to explore the statistical relationship between Landsat data and the wide distribution of Secchi values (collected *in situ*) found throughout a large area, such as the lower peninsula of Michigan.

My third chapter investigates the application of data from the Landsat TM sensor to detect aquatic macrophyte distributions in inland lakes across a large region (70,000 km^2) within the lower peninsula of Michigan, USA. Like the second chapter, this study also uses statistical models to determine the relationship between Landsat data and a wide range of *in situ* data across a large area. In this study, macrophytes from randomly chosen lakes are used to develop logistic regression models which indicate the probability of correctly classifying the various levels of plant cover based on the Landsat data and the depth at each individual sample point of plant cover.

Theses research efforts represent three areas of research where an assessment tool such as the one provided by remote sensing is valuable, both from and ecological and an operational point of view. Furthermore, this collective research presents important information which may ultimately provide the impetus for further detailed research in my study sites and in the area of regional remote sensing for wetland and inland lakes. We clearly need more research on the application of current and future sensors to wetland and freshwater studies, and I hope my dissertation significantly contributes to this important area.

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Chapter 1: Land Cover Change in the Upper Barataria Basin Estuary, Louisiana, from 1972-1992: Increases in Wetland Area

Introduction

The extent of coastal and inland wetlands in the United States has declined markedly since European settlement. According to the U.S. Fish and Wildlife Service and the National Wildlife Federation, more than 81 million ha of wetlands were present in the continental United States in the early 1700's, but only 35 - 40 million ha remained as of the mid 1980's (Dahl and others 1991). Wetland losses have been attributed to a number of factors such as agricultural land conversions, urbanization, and erosive natural processes. The draining and filling of wetlands for agriculture accounted for as much as 54% of total wetland losses between the mid-1950's and the 1970's, while urban land conversions accounted for only 5% (Dahl and others 1991). Because of recent legislation protecting wetlands and changes in how wetlands are valued, it is unclear whether these land use transitions have continued from the 1970's to today.

Natural changes in coastal wetlands result from wind and wave pressures, episodic storm events, land subsidence, variations in hydrological cycles leading to flooding or drying out, and eustatic sea level rise along coastal margins (Mitsch and Gosselink 1986). Currently, coastal Louisiana, which contains approximately 27% of the coastal wetlands found within the continental United States, is experiencing estimated loss rates ranging from 6,000 to 12,450 ha/yr (Visser and others 1999). These estimates are the highest rates of wetland loss in the United States and have been attributed to high land subsidence rates and sea level rise compounded by the artificial levying of the

Mississippi River Deltaic Plain and other factors (e.g. canal dredging and erosion) (Scaife and others 1983, Conner and others 1987, Visser and others 1999). Although coastal estuaries, which are experiencing such high loss rates, have been well studied, there has been less documentation of the changes occurring in the freshwater portions of the estuary systems, which are subject to additional pressure from agriculture and urban development.

In particular, within the Barataria Basin, Louisiana, a large coastal estuary, much attention has focussed on the high coastal wetland loss and increases in open water in the lower coastal basin that are a result of anthropogenic modifications and natural processes (Turner 1997, Sklar and Browder 1998, Martin and others 2000). However, little information exists on how other components of the estuary have changed, especially the freshwater wetlands in the upper basin. Some have suggested that increased urbanization, industrialization and agricultural practices will lead to increasingly eutrophic conditions within the Basin's upper freshwater zones (Stow and others 1985). Because the upper basin is tightly linked hydrologically to the lower basin, large changes in the upper basin may strongly impact the lower basin.

Understanding changes in the Barataria is especially important because an estimated 97% of all commercially valuable Louisiana Gulf of Mexico fisheries species require some or part of their life cycle on the productivity of the Barataria and adjacent coastal estuarine basins. This estimate makes up approximately 20% of the U.S. commercial seafood harvest, approximately one half billion pounds of fish and shellfish per year. However, this region has only recently been officially designated as a nationally valuable resource, being included in the U. S. Environmental Protection

Agency's (EPA) National Estuary Program in 1990 as part of the Barataria-Terrebonne estuarine system.

Since the early 1980's, remote sensing techniques have become commonly used to detect wetland change. Remotely sensed images and geographic information systems (GIS) are being used to address critical coastal resource management problems, providing researchers with the ability to make rapid decisions at large spatial scales using recent data (Ricketts 1992). However, fewer studies have taken advantage of the wealth of historical data available from the few satellite platforms that have been operating across several decades, and that are becoming widely available and inexpensive (Munyati 2000). For example, the images obtained using the Landsat Multispectral Scanner (MSS) sensor presently represents my longest, continuous, satellite remotely sensed historic record. This sensor spans a time period where known large changes have occurred in land cover (1972-present). Although, few studies have used the MSS sensor's 20-plus year, archival data source for historic wetland change determination, several researchers have used Landsat MSS data to identify wetland change across smaller time periods with a fairly high degree of accuracy (Jensen and others 1986, Haack 1996, Munyati 2000). The coarse resolution of MSS (80m) provides an additional advantage in that it allows coverage of a large spatial area.

My objectives were to quantify land cover change in the upper Barataria basin from 1972-1992, to determine land cover transition rates among land cover types, and to evaluate the accuracy of MSS to detect wetland and other land cover change. I obtained Landsat MSS data from the North American Landscape Characterization (NALC) data archive and classified land cover in each scene using a supervised image classification approach. I use the term land cover to refer to both human (agricultural and urban) and natural (wetland and forest) land covers. I found large changes in both human and natural land covers across the study period that are different from known changes in the lower, coastal regions of the Barataria basin.

Study Area

The Barataria Basin (Figure 1.1) makes up the eastern-most region of the Barataria-Terrebonne estuary system. This 628,600 ha area is located in southern Louisiana south of New Orleans and extends into the Gulf of Mexico at its widest portion. Natural and artificial levees, completed in the 1940's, hydrologically isolate the Barataria from sources of riverine sediment input (Conner and others 1987, Miller and others 1995). The Barataria can be divided into three zones based on a salinity gradient. The upper freshwater portion, or upper Barataria Basin, consists of swamp forest/freshwater marshes (0-2 ppt), the middle low salinity portion (2-10 ppt) is made up of brackish marsh, and the lower portion (6-22 ppt) is the saltwater coastal marsh zone (Conner and others 1987, Miller and others 1995). For this study, I focus on the upper swamp forest/freshwater marsh zone only, which makes up 27% (170,370 ha) of the total basin area. There are two open water bodies within the upper basin: Lac des Allemands and Lake Boeuf, which did not change across the study period so were removed from the land cover change analysis.

Agriculture and urban land covers are found in higher elevation areas along the levee system of the upper Barataria, whereas the freshwater marsh, and swamp forest are in the lowest elevation areas (Figure 1.1). Bottomland hardwood forest exists in less frequently flooded lower elevation areas and along the lower perimeter of the levee system. The bottomland hardwood forest land cover is comprised largely of American elm (*Ulmus americana*), sweetgum (*Liquidambar styraciflua*), sugarberry (*Celtis laevigata*) and swamp red maple (*Acer rubrum* var. *drummondii*). Swamp forest is comprised of baldcypress (*Taxodium distichum*) and water tupelo (*Nyssa aquatica*). Freshwater marsh is comprised largely of a floating marsh known locally as "flotant". Flotant consists of vegetative mats of detritus, algae, and plant roots that support maidencane (*Panicum hemitomon*), spikerush (*Eleocharis sp.*) and bulltongue (*Sagittaria falcata*).

The majority of freshwater input into the upper Barataria is from rainfall (Conner and others 1987). Average annual rainfall measured at the New Orleans, Louisiana Weather Data Center from 1972 to 1992 was 171 cm/year (+/- 36 cm/yr S.D.). Annual rainfall for each of the three time periods used in this study was 163, 170 and 208 cm/yr for 1972, 1985 and 1992 respectively. During my study period, annual rainfall showed no significant trends through time (R^2=0.009, P=0.68).

Materials and Methods

Satellite Image Data

I acquired four, 80m resolution, Landsat MSS scenes covering the upper Barataria Basin from the North American Landscape Characterization (NALC) data archive (Earth Resources Observation Systems Data Center Distributed Active Archive Center Sioux Falls, SD) for three time periods: 1 October 1972, 10 October 1972, 31 August 1985, and 5 October 1992. Because the 1972 data were sensed from the older Landsat (1, 2, and 3)

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platforms with a larger swath width, these scenes were slightly out of phase with the 1985 and 1992 scenes and required two scenes to cover the extent of the upper Barataria Basin. All scenes were geometrically rectified to a digitally scanned, 1:100,000 scale USGS quadrangle topographic map covering the upper Barataria Basin. Each scene was coregistered with a corresponding digital elevation model (DEM) and transformed to Universal Transverse Mercator (UTM). A nearest neighbor algorithm was used to perform the resampling procedure and the image-to-map registrations which yielded a root-mean-square error of 0.95 pixels for all data. The two 1972 scenes were mosaicked to create a single 1972 image.

Supervised Image Classification

To ensure consistency among classifications of the three time steps, I performed two pre-processing procedures on each scene. First, each scene was normalized to the 1992 scene using contrast stretching and histogram matching procedures to reduce atmospheric differences across all three scenes. Second, I developed a ratio of bands 1 and 2 to correct distortions inherent in each scene. The band ratioing procedure reduced the scene distortion by dividing brightness values of pixels in one band by the brightness values of the corresponding pixels in another band.

I then used a supervised classification procedure to classify the 1992 scene using spectral training samples, seed pixels, and a maximum likelihood algorithm. I identified six major land cover types as described by Conner and others (1987): agriculture, urban, bottomland hardwood forest, swamp forest, freshwater marsh, and open water. Histograms of all bands were developed for each land cover class to determine average spectral signatures. Spectral signature separability was computed to determine the statistical distance between signatures. The final spectral signatures for the 1992 classification, resulting from a band combination of 4, 2, and my band ratio, were then used to classify the 1972, 1985, and 1992 scenes. I then applied a 3 x 3 focal majority filter model to all three classifications, which is a post classification smoothing operation to reduce the number of misclassified pixels. Finally, I manually recoded < 10% of the pixels in all three classified images that were obviously misclassified when compared to the raw scenes. For example, some obviously urban and agricultural pixels were misclassified as freshwater marsh land cover. Freshwater marsh should not occur in the higher elevation areas. This obvious misclassification represented the majority of my manual pixel reclassifications.

Accuracy Assessment

To estimate the classification accuracy, I developed two error contingency matrices from the 1992 classification using two different reference scenes, and calculated the probability of misclassifications through estimates of omission and commission errors. For the first assessment, I used a 28 September 1995 Landsat Thematic Mapper (TM) scene (30m resolution) that covered 100% of the study area, and yielded an overall classification accuracy of 91% using 256 randomly generated points (Table 1.1). For the second assessment, I used high resolution (3m) photographs from a 3-band digital aircraft camera from 20 October 1995 that covered approximately 43% of the study site. The MSS data was subset to match the spatial extent of the aircraft photographs. One hundred ten points were randomly generated to represent 43% of the total area. The overall classification accuracy of this assessment was 87%. Because both assessments yielded similar results, I present data for only the Landsat TM scene since it covered the entire study area. No reference imagery was available for the 1970's and 1980's classifications. However, given the high accuracy of the 1990's classification, I assumed that the identical techniques used in the development of all three classifications would have produced comparable accuracy. Field validation would have provided optimal assessment of my classification accuracy. However, due to the large size of my study area and the fact that my study used historical data, ground-truthing was not possible (Jensen and others 1995).

Land Change Analysis and Transition Matrices

Land cover area and percentages for the entire upper basin were calculated for each time step for individual cover types, and for two broader categories: developed land (urban and agriculture) and natural land cover (bottomland hardwood forest, swamp forest, and freshwater marsh). I developed transition matrices to identify shifts between individual land cover types in successive time steps and overall changes occurring throughout the entire study period. To develop these matrices I calculated: (1) the area of land in ha converted from each land cover into each of the remaining categories, (2) the proportional area of land (%) converted from each land cover into other categories, and (3) the total proportion (%) of each individual land category converted into other categories.

Results

In all time steps, agriculture and urban land cover dominated the upland areas around the perimeter of the basin and natural land classes dominated the lower elevation areas (Figure 1.2). However, distinct changes in land cover occurred across the time steps (Figure 1.3). Agricultural land, bottomland hardwood forest and freshwater marsh all decreased through time; whereas urban land and swamp forest increased. Because open water remained unchanged throughout the study period, I removed this category from all further analysis.

Across the broader categories, there were small changes in total human dominated land cover and in total natural land cover (Figure 1.4). However, there were large changes within each category. In 1972, agriculture land cover made up 75% of the human developed land, but only approximately 50% by 1992. Urban land cover made up 25% of the human developed land in 1972 and increased to approximately 50% by 1992. For the natural land cover category, bottomland hardwood forest and freshwater marsh decreased whereas swamp forest increased throughout the entire study period. I further combined two wetland categories (freshwater marsh and swamp forest) to examine total wetland area changes in the upper basin (Figure 1.5). In 1972, the total wetland area was 64,718 ha (38% of the upper basin). By 1992 this area had increased to 78,488 ha (46%), gaining 13,770 ha over the entire study period.

Table 1.2 shows the rate of land cover change between each time step. The largest overall rates of change across the whole study period was an increase of 937 ha/yr of swamp forest from 1972-1992, and an increase of 993 ha/yr for urban land cover from 1972-1992. However, the rate of change of urban land significantly decreased over the next time step to 288 ha/yr (1985-1992). Freshwater marsh showed a net loss at a rate of 363 ha/yr (4,720 ha) between 1972 and 1985, but only 36 ha/yr (249 ha) between 1985 and 1992.

To examine in more detail how land classes changed, I calculated land cover transition matrices (Tables 1.3-1.5). Two land cover conversions were most prominent: the conversion of land in the upland perimeter of the basin from agriculture to urban land, and the conversion in the lower elevations from bottomland hardwood forest to swamp forest land cover. All land cover categories changed as might be expected: agriculture land cover primarily changed to urban; freshwater marsh to swamp forest; and bottomland hardwood forest to swamp forest. However, although most urban land cover was converted from agricultural land there were also unlikely transitions from urban land to freshwater marsh, swamp forest, and bottomland hardwood forest. In most cases these transitions occurred at a rate of 1 percent or less, which is within the error of the data. Another unlikely transition was from urban land cover to agriculture land cover (3 - 6% of the total urban area of the upper basin landscape) (Table 1.5). This transition is also likely to be a misclassification, and it also falls within the error of the data.

Discussion and Conclusions

Studies of wetland change in the Barataria basin as well as other coastal estuaries have focussed on wetland loss primarily in lower coastal zones (Turner 1997, Martin and others 2000, Day and others 2000). However, because the upper freshwater zones of coastal estuaries are subject to different human influences and physical drivers than the lower coastal zones, different trends in land cover changes are likely to occur. I found that important changes have occurred in the upper freshwater parts of the basin, which are quite different from trends observed for lower coastal zones. In particular, I found two major land cover trends in the upper Barataria Basin. The first is a change within human developed land cover (agriculture and urban land cover) in the upland regions of b

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the upper basin, and the second is a change within the natural land cover (swamp forest, bottomland forest and freshwater marsh) in the low elevation regions of the upper basin. I explore both trends in detail below.

For the upper Barataria Basin, Hopkinson and Day (1980) predicted a 321% increase in urban land from 1975-1995 based on projections from the Louisiana State Planning Office. I found only a 108% increase in urban land from 1972-1992, which is lower than predicted, but still large. Based on data from 1985 to 1992, it appears that urban lands are increasing at a rate of 288 ha/yr at the expense of agricultural lands. The conversion from agricultural lands in 1972 to urban lands in the upper basin in the 1990's and beyond may have significant impacts on nutrient loading to the adjacent swamp forest, the open water areas, and the lower coastal zones, which warrants further research. Any changes that are observed in natural land cover in the lower elevations must be considered in light of these changing patterns in upland areas.

In the low elevation regions of the upper basin, I found that swamp forest increased at the expense of bottomland forest and freshwater marsh, although the transition from bottomland forest was the dominant change. My results suggest an encroachment of the wetter swamp forest areas into higher elevation edge areas that are dominated by bottomland hardwood forest. I found that 46% of bottomland hardwood forest was converted to swamp forest over this period. It is very likely that land subsidence is the cause of these changes in natural land cover (Kress and others 1996). However, I must also consider other human drivers of change. Although I found only moderate transitions from bottomland forest to urban land cover (115 ha/yr), this rate may increase if urbanization continues, and as agricultural lands are diminishing, creating a further threat to bottomland hardwood forests. Based on my results, if present trends in the reduction of bottomland forest land cover were to continue, the upper Barataria Basin may have no bottomland hardwood forests left by the year 2025, as it is subjected to multiple stressors both in the higher elevations (from urbanization) and lower elevations (most likely from land subsidence). Protections should be put in place now to prevent further loss of this important habitat type of the upper basin.

Previous studies suggest that high rates of land subsidence within the Louisiana-Mississippi River deltaic plain are one of the primary causes of wetland loss within coastal regions of Louisiana (Scaife and others 1983, Conner and Day 1988, Visser and others 1999). Land subsidence within the deltaic plain results primarily from the compaction of sediments within the basin over time. The complete levying of the basin has largely eliminated overflow of the Mississippi River, which was the primary source of marsh-building sediments (Visser and others 1999). Land subsidence may also be related to increases in water level, which has been measured at approximately 8.5 mm/yr within the upper Barataria Basin (Conner and Day 1988). Conner and Day (1988) suggested that water levels should increase over time and, along with decreasing sedimentation rates (vertical accretion), lead to a reduction in forested wetlands as a result of prolonged, deep flooding. I did not find a reduction in swamp forest wetlands in the Barataria upper basin; rather I found that swamp forest area increased 37%. One possible explanation for the increased swamp forest in my study is the existence of numerous oil, gas and drainage canals throughout the basin. These canals may allow swamp forest areas to periodically drain during drier seasons, providing the necessary dry seed recruitment periods for the baldcypress and water tupelo species that dominate this land cover class (Conner and others 1986, Souther and Shaffer 2000). However, it is quite possible that the presence of these canals have only slowed changes predicted by Conner and Day (1988). A second possible explanation for the increased swamp forest would be if rainfall had changed in any way over time. However, annual rainfall data measured at the New Orleans, Louisiana Weather Data Center shows no trend through time.

Current management plans, such as the Coastal 2050 management plan (Bourne 2000), call attention to the alarming rate of shoreline erosion in coastal zones, and to a lesser degree, the impacts of inland wetland and marsh change higher in the watershed. Management strategies include reintroducing Mississippi River sediments over portions of the Barataria coastal areas through freshwater diversion projects and filling some canals that have led to saltwater intrusion and tidal action in the middle and lower basins. However, these strategies may do little to affect land cover changes in the upper basin. Freshwater diversions, which target rebuilding coastal margins of the basin that are subject to erosion and sea level rise, may be instituted at points too low in the watershed to aid in rebuilding land that could eventually be reclaimed by bottomland forest areas in the upper basin. The levee system, which completely isolates both the upper and lower Barataria Basin from Mississippi River sediments, will continue to inhibit vertical accretion, allowing subsidence to continue to increase the lower wetland area in the upper basin at the cost of reductions in bottomland hardwood forests.

Although bottomland hardwood forests provide important habitat for wildlife, migratory bird species, and sport and commercial resources, the expanding wetlands in the upper region may provide benefits as well. My results suggest that urbanization within this region of the Barataria Basin may continue which increases the threat of nonpoint source pollution. Expanding wetland areas in the upper basin may provide an increased capacity to buffer excess upland nutrient loading to the inland lakes within this region of the basin, and reduce sediment and nutrient export into the Gulf of Mexico. Furthermore, with the alarming rates of coastal wetland loss in this region, upper basin wetlands may prove to be critical in maintaining the rich ecological habitats of southern Louisiana. However, further research needs to be conducted to assess the impacts of losing bottomland forest in this important ecosystem.

Quantifying historical land cover change provides a reference for investigating current landscape change. However, large-scale studies can be limited by the ability to acquire timely, cost effective, and accurate data. Remote sensing using sensors that span decades allows us to quantify historic land cover patterns for large areas such as the upper Barataria Basin. My classification of Landsat MSS data produced an overall estimated accuracy of 89% among the six land use categories, which is an error rate that is lower than the changes that I detected. Failure to understand the type of changes that are taking place within a watershed, and the degree to which these changes occur can lead to serious errors in assessing ecological risks. Remote sensing provides both temporal and spatial information on the structure of the landscape. Further study is needed to examine the effects of these observed land cover changes on water quality within both the upper and lower Barataria basins.

Acknowledgements

This research was supported by funds from the Earth System Science Office at the NASA Stennis Space Center, MS, provided to S.A.C.N. from the NASA Graduate Student Research Fellowship Program and the Michigan State University Minority Competitive Doctoral Fellowship. I thank Richard Miller, Armond Joyce, Marco Giardino, Greg Booth, Patrick Jones and Ramona Pelletier-Travis for technical assistance, laboratory space and computing resources at Stennis Space Center. Partial funds were provided by a NASA rangeland project at MSU/USDA. I are grateful to Jianguo Liu, David Lusch, David Skole and Walter Chomentowski for their contributions to this research. I would also like to thank Kendra Spence Cheruvelil and Marc Linderman for providing comments on earlier drafts that greatly improved the manuscript. Finally, I would like William Taylor and James Jay for their invaluable support and assistance.

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Chapter 2: Assessing regional lake water clarity using Landsat and the role of inter-lake variability

Introduction

Monitoring the status of inland lakes is critical because they provide an important recreational, commercial and aesthetic resource to the public. The water quality monitoring of lakes often includes the monitoring of water clarity using a Secchi disk. Although more sophisticated measurement techniques exist, Secchi disk transparency (SDT) appears to be a relatively good coarse measure of water clarity, partly because it is inexpensive and easy to use. The use of SDT has been widely adopted in many lake monitoring programs worldwide (Bukata et al., 1995). Several studies have found SDT to correlate well with a number of other water quality variables, such as trophic status, phosphorus loads, planktonic chlorophyll concentrations, hypolimnetic oxygen concentrations, suspended sediment concentrations, and fish yields (Oglesby, 1977; Lorenza, 1980; Lee et al., 1995). Despite the ease of obtaining Secchi data, collecting SDT on large numbers of lakes can be costly and challenging for monitoring agencies, especially in states with thousands of lakes. However, in the past several decades, citizen-volunteer lake monitoring programs using SDT measurements have allowed data collection over larger regions than capable through local and state agencies alone. Many studies have shown that the accuracy of volunteer collected is comparable to data collected by professional monitoring personnel with no statistical difference in summer averages of SDT between volunteer and professional measurements (Heiskary et al., 1994; Kerr et al., 1994; Obrecht et al., 1998; Canfield et al., 2002). However, extending

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volunteer collection programs to thousands of lakes, on a statewide level, is still costly and logistically prohibitive. Thus, other approaches are needed to collect SDT on large numbers of lakes.

Satellite remote sensing using Landsat Thematic Mapper (TM) has been explored in several studies as a method of reducing the cost and labor of sampling water clarity in the field (Khorram and Cheshire, 1985; Lathrop, 1992; Kloiber et al., 2000; Dewider and Khedr, 2001). An advantage of using remote sensing is that data for multiple lakes within a single image can be collected quickly and relatively inexpensively. Remote sensing technology has been used for several years in oceanography to measure chlorophyll, water color, and suspended sediments over large areas, but has only recently been explored in lake studies (Packard and Emery, 1982; Kloiber et al., 2000). Although sensors such as Landsat TM were primarily designed for detecting land features, recent improvements now provide better spatial and spectral resolutions for aquatic studies (Zilioli, 2001). Recently, remotely sensed data has been shown to correlate well with lake SDT values (Khorram and Cheshire, 1985; Lathrop, 1992; Kloiber et al., 2000; Dewider and Khedr, 2001). However, to effectively implement remote sensing into a state monitoring program for inland lakes, there still remain some unanswered questions.

For inland lakes, the relationship between remotely sensed images and SDT has been examined through simple linear regression analysis of *in-situ* measurements of SDT and spectral brightness values from the sensor (Lillesand et al., 1983; Lathrop and Lillesand, 1986; Kloiber et al., 2002). Regression models developed for single water bodies using a single image have resulted in high r^2 values (0.80 – 0.90, $p < 0.05$) (Lathrop and Lillesand, 1986; Lavery et al., 1993; Giardino et al., 2001). These strong

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relationships suggest that remote sensing may be useful for measuring SDT in a large number of lakes across larger spatial scales.

There have been fewer studies that have used Landsat data to measure SDT of multiple lakes, over a large region, or covering multiple images (Table 2.1). The few studies that have been conducted using multiple lakes from a single image have resulted in relatively high r^2 values (Table 2.1). However, to apply these approaches to the statewide scale, such as for the lakes of Michigan, I must test this approach in cases where I have data from multiple images and a wider diversity of lakes than is often present in a single image. My objectives in this study were to determine if I could use Landsat-7 data to measure lake water clarity across a large region of lakes from three images in a single path (94,350 km^2), and to determine how the regional distribution of SDT affects models of regional lake water clarity.

Materials and Methods

Study area

The state of Michigan has approximately 3,500 inland lakes > 10 ha in surface area and many thousands of smaller lakes (unpublished data from the Michigan Department of Environmental Quality). My study lakes included 93 lakes in the lower peninsula of Michigan (Figure 2.1). The lakes were distributed throughout an area of 94,350 km^2, which made up approximately 80% of the lower peninsula of the state. My lakes ranged in surface area from 12 – 4,125 ha with a mean Secchi depth of 3.1 m (Table 2.2).

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Field Observations

Field observations of SDT data were obtained for the 93 lakes from three sampling programs: (1) the Michigan Citizens Lake Monitoring Program (CLMP), (2) the Michigan Department of Environmental Quality's (MDEQ) Lake Water Quality Assessment (LWQA) Monitoring Program, (3) Michigan State University (MSU; Table 2.2). I selected lakes that: (1) were sampled from late July through August to ensure samples were taken during the summer stratified period; (2) had a surface area of $\geq$ 10 ha within the lower peninsula of Michigan; and (3) were sampled within $\pm$ 7 days of the satellite imagery.

Satellite Image Data

I used three Landsat-7 Enhanced Thematic Mapper Plus (ETM+) scenes from August 28, 2001 from ground track Path 21 (Worldwide Reference System-2) that covered the lower peninsula of Michigan (Figure 2.1). Spectral digital number (DN) values were extracted within the pelagic region of each lake, which was identified by creating an area of interest (AOI) using ERDAS Imagine version 8.4 image processing software. The pelagic region of each lake was defined within an area > 4.5 m in depth. I used bathymetric maps to identify the 4.5 m depth contour within the 80 sample lakes for which I had maps. For the 13 lakes without bathymetric maps, I created an AOI for each lake from groups of pixels within the center of each lake, avoiding any shoreline or shallow areas to ensure that each AOI would be free of reflections from the lake bottom or submerged macrophytes. From each lake AOI, I extracted the mean DN for each spectral band to use in all subsequent analyses. My AOI values ranged from 8 to 1,012 pixels ($\pm$ 183 pixels).

Statistical Analysis

All statistical analyses were done using SYSTAT (SPSS Software, Inc., 2001). Probability distribution plots of SDT indicated that a natural log-transformation was necessary for SDT. I developed a linear regression model using the band ratio of ETM1/ETM3 as the independent variable and the natural log of SDT as the dependent variable. Previous studies found these regression variables to be the best predictor of SDT (Lathrop, 1992; Pattiaratchi et al., 1994; Kloiber et al., 2000). Outliers and lakes having large leverages within the SDT and Landsat datasets were removed from the final regression analysis, reducing the number of lakes for the final analysis from 96 to 93.

To examine the role of lake SDT distribution in My regression model, I developed an additional regression model with a different SDT distribution based on a subsample of My complete dataset. I used a manual selection technique to create the subsampled dataset with a similar SDT distribution to match a previous study that found a strong relationship between multiple lake SDT values and Landsat spectral values (Kloiber et al., 2000). To compare the regressions of the complete and subsampled datasets, I used a slope heterogeneity test and analysis of covariance (ANCOVA). I also performed an F-test on the residual values to determine if there was a significant difference between the variances of the residuals of each dataset.

SDT Distributions

I extracted values of SDT in Figure 2.5 of Kloiber et al. (2000) to compare their SDT distribution to my complete and subsampled dataset. I also compiled a distribution of statewide Michigan summer lake SDT data available from the US EPA Storage and

Retrieval (STORET) database. These data included 675 lakes (>20 ha) sampled during the 1970's and 1980's. Data from some lakes were averaged across sample years if multiple years were sampled. Otherwise the data represented average summer SDT values from biweekly samples in June, July, and August.

Results

My regression of SDT and ETM1/ETM3 produced an r^2 value of 0.43 ($p < 0.001$; Figure 2.2). To examine why my models explained so much less variation than previous studies, I compared the SDT distribution of the 47 lakes included in the Kloiber et al. (2000) study to the distribution of my 93 lakes. I found that approximately 62% of the lakes used in the Kloiber et al. (2000) study had a SDT of 1.5 m or less (Figure 2.3). For the 93 lakes used in my study, only 9% had a SDT of 1.5 m or less (Figure 2.3). Thus, the majority of lakes included in Kloiber et al. (2000) are predominantly eutrophic (Forsberg and Ryding, 1980). The lakes included in my study would be considered largely mesotrophic to oligotrophic (Figure 2.3). To examine the effect these different distributions may have on SDT prediction, I manually adjusted my SDT sample distribution to have a mean Secchi depth of 1.8 meters and a distribution with 47% of the lakes having a SDT of $\leq$ 1.5m. This subsample included 17 lakes and resembled the sample distribution found in the Kloiber et al. (2000) study (Figure 2.4). The regression for this subsampled dataset had an r^2 value of 0.82 ($p < 0.001$; Figure 2.5).

I compared the trend lines from the regressions of my two models, the complete dataset model (n = 93) and the subsampled dataset model (n = 17), and found that the difference in the slopes of the two models was not statistically significant (ANCOVA p =

0.247; Figure 2.6). I also examined the residuals against their predicted Landsat ETM values (Figure 2.7). This analysis suggests that there is less variability in the residuals about the mean for the subsampled dataset than the complete dataset, thus leading to the lower r^2 value of the complete dataset model. I used an F-test to determine if the variance of the residuals of the two datasets were significantly different. This test indicated that there was a significant probability that the residual variances in the two datasets are statistically different ($F = 2.86$, $p = 0.0099$).

Finally, I further explored the models by plotting the residuals against the observed Secchi values (log transformed) to determine if the residual errors differed at different SDT values (Figure 2.8). This analysis suggests that the complete dataset model may provide better SDT predictions, as its confidence intervals for the predicted mean are narrower for both shallower and deeper Secchi depths than for the subsampled dataset.

Discussion and Conclusions

My results show that I can develop a standard regression model for many lakes within a large geographic region, encompassing multiple Landsat scenes, to predict SDT. These results are in agreement with authors such as Lathrop and Lillesand (1986) who recommended the establishment of common statistical models (e.g. standardized regressions) to use remote sensing for monitoring water quality and enhance the development of future sensors tailored to freshwater lake systems. Several previous studies have developed successful statistical relationships between a single Landsat image and water quality of a single lake or water body. However, to my knowledge only Kloiber et al. (2000) has examined this relationship on a larger scale, using 47 lakes within a 7,700 km^2 area. The results from Kloiber et al. (2000) show promise in developing larger scale satellite-based water clarity monitoring protocols using my current sensors. My study expands on this work by examining almost twice the number of lakes within an area of approximately twelve times the areal extent of the Kloiber et al. (2000) study. However, I had much more inter-lake variation in my study leading to substantially lower r^2 values than those in the Kloiber et al. (2000) study. Previous single-lake studies using similar Landsat bands also have higher regression results than I did (Lathrop, 1992; Pattiaratchi et al., 1994; Cox et al., 1998). This discrepancy was likely a result of the SDT distribution of my study lakes. My complete dataset consisted of a broad range of SDT values, including deeper SDT lakes. Lakes with deeper SDT values return less signal reflectance from algal turbidity in the water column to a remote sensor and, thus, may not be well detected using current sensors. In contrast, the Kloiber et al. (2000) study was based on a cluster of lakes within the metropolitan area of Minneapolis and St. Paul, Minnesota, USA, in which over 60% of the lakes included were eutrophic (Forsberg and Ryding, 1980). My subsampled dataset incorporated a larger percentage of eutrophic lakes and yielded a comparable r^2 result to the Kloiber et al. (2000) study. My results suggest that inter-lake variably plays an important role in influencing the strength and reliability of regression models of Landsat and lake SDT.

Two questions remain: (1) what are the best ranges of SDT that can be predicted from Landsat; and (2) what are the best regression models for regions containing lakes with a wide range of SDT values? To address the first question, I explored the residual plots of each dataset against the observed SDT (Figure 2.8). This analysis is useful to determine how the residual errors differed in closeness of fit about the mean for both models. The confidence intervals of the subsampled dataset were wider for both shallow and deep SDT values than for the complete dataset. Although a wider interval in the subsampled dataset may be related to the much smaller sample size of the subsampled dataset, the wider interval may also indicate a higher overall degree of uncertainty, or possibly inconstant variance throughout the residual terms (Van Belle, 2002). Both the complete and subsampled dataset plots show a distinct cluster of residual values within the 2 – 3 m Secchi range and a narrowing of the confidence intervals within this range. This result may suggest that my models are better suited for predicting Secchi depths within these ranges than they are at predicting Secchi depth at the shallow or deep end of the distribution. Overall, my residual analyses showed wider confidence intervals in the subsampled dataset compared to the complete dataset. This suggests the results of the complete dataset model provides a better estimate of the range of the true distribution, but that less of the variation in the dataset is explained.

To address the second question of which regression model is better for predicting SDT in regions with a wide range of SDT values, we first need to consider the goal of the study in question. For shallow SDT lake studies within a smaller region, models such as my subsampled dataset and the Kloiber et al (2000) study should provide desirable results. This type of investigation could be particularly useful for studies of eutrophic lakes in urbanized watersheds. However, if the goal is to examine SDT at a statewide level, a broader range of inter-lake variability must be considered. For example, my complete model, with a lower r^2 value, incorporated a wide range of SDT. A wider range of SDT should be expected when modeling many lakes throughout a large geographic region, such as the state of Michigan. In fact, the range of the SDT data included in my complete dataset model is comparable to the range of SDT collected from 675 lakes in Michigan (US EPA STORET; Figure 2.9). The data for Secchi in the state of Michigan ranges from 0.5 – 8.0 m, with a mean of 3.0 m. My complete dataset captures this range, from 0.9 – 7.6 m with a mean 3.1 m (Figure 2.9).

To use remote sensing for statewide assessments of water clarity, there still must be an investment in some degree of statewide sampling efforts that coincide with satellite overflights. Although I included ground observations from a number of reliable sources, I was still somewhat limited in the number of lakes to include in the model. For example, during this study, I experienced a large number of days with high cloud cover that resulted in few cloud free scenes. This made it difficult to match field SDT data from more than 93 lakes across the state within $\pm$ 7 days of the satellite over flight. In addition, I experienced difficulties in creating a single regression relationship that included images from multiple paths. Further research is necessary to explore the effect of path to path atmospheric variations. Within the three contiguous Landsat scenes used in this study, atmospheric corrections were not necessary for sampling SDT because the images were free from atmospheric haze and all of the images were taken on a single date.

In conclusion, although a standard equation relating Landsat data and water clarity over a large area can be used to predict SDT, the sensitivity of the regression model to the distribution of lake calibration data must be taken into consideration. Further research is required to determine the optimal ranges in which Secchi depth can be predicted from Landsat data, the reliability of predictive models in shallow as well as deep SDT lakes, and the best regression estimates for states with a wide range of Secchi depth values. Remote sensing can play a vital role in reducing the cost, labor, and time required to monitor inland lake water clarity. It has the potential to be used as a tool to develop statewide assessments that are currently impossible using traditional field operations. However, caution should be used in assessing water quality based solely on remotely sensed data. Current methods and sensors may be able to effectively measure shallow SDT lakes, but may not do as well for lakes with deeper SDT. Until our method can be improved or possibly better sensors are developed for aquatic applications, inland lake remote sensing will be most useful as a supplement to existing volunteer and agency monitoring programs, rather than a replacement of these programs.

Acknowledgements

This research was funded in part by a Michigan State University Minority Competitive Doctoral Fellowship to SACN. Landsat-7 ETM+ imagery was provided by the Basic Science and Remote Sensing Initiative (BSRSI, now known as the Center for Global Change and Earth Observation) and through the NASA-funded Upper Midwest RESAC project (Regional Earth Science Applications Center). Additional funding was provided through a USGS/DEQ grant to BSRSI. The CLMP field observation data were provided by Ralph Bednarz, MDEQ. I thank Kevin Hoffman, John Whitlock, Tamara Brunger-Lipsey, Kristy Rogers, Sarah Wills, and Konrad Kulacki for field data collection and processing. I am also grateful to Jiaguo Qi, Jianguo Liu, David Lusch, and Walter Chowmentowski for their contributions to this research. Additionally, I would like to thank Jonathan Chipman, Michael Belligan, Narumon Wiangwang, Marc Linderman, and Chris Barber for technical support and database assistance. Finally, I thank Daniel Hayes

and Orlando "Ace" Sarnelle for statistical advice.

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Chapter 3: Remote sensing of freshwater macrophytes and the influence of lake characteristics

Introduction

Macrophytes play several important roles in lake ecosystems, such as stabilizing shorelines, reducing erosion, and improving water clarity. Macrophytes also provide many benefits for aquatic organisms, such as providing refuge and nursery habitat for young and small species, increasing dissolved oxygen in water, and providing surface area for the growth of invertebrates and algae, which provide food for larger organisms (Carpenter and Lodge, 1986). For example, of particular interest to many lake managers is the role that macrophytes play in fish growth. Based on a qualitative review of the literature, Schneider (2000) reported that 25-36% macrophyte cover is optimal for largemouth bass (*Micropterus salmoides*) and bluegill (*Lepomis macrochirus*) growth rates. Thus, knowing information about the macrophyte community, such as the amount of macrophyte cover in a lake can provide valuable information.

Information on the species composition of plants can also be important, especially the presence or absence of exotic plants. Nuisance exotic macrophyte species, such as Eurasian watermilfoil (*Myriophyllum spicatum*, EWM), are now widespread throughout much of North America (Couch and Nelson, 1985). EWM forms dense surface canopies that suppress native plant growth, which can lead to homogeneous macrophyte beds (Aiken et al., 1979; Madsen et al., 1988, Madsen et al., 1991). High percent cover of these dense canopies and loss of macrophytes diversity can influence littoral zone food webs in many important ways (Lyons 1989; Trebitz et al., 1996; Cheruvelil et al., 2002).

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These concerns have prompted much research into EWM ecology and management (Chilton, 1990, Smith and Barko, 1990, Trebitz et al., 1993). However, management agencies in many affected areas do not have good data on the extent of the EWM problem in their state. This lack of information is largely due to the expense and challenges associated with sampling macrophytes.

Assessing macrophyte distribution and abundance in an individual lake takes a significant amount of time, expense and labor. Assessments are further complicated in regions containing thousands of lakes. For example, the state of Michigan has approximately 3,500 inland lakes > 10 ha in surface area and many thousands of smaller lakes (unpublished data, Michigan Department of Natural Resources). Currently, it is not possible to inventory this many lakes using traditional field sampling techniques such as sampling along transects, within quadrants, or subsampling randomly-stratified lake points. Although these techniques can give good estimates of local macrophyte biomass and species composition, and results from these approaches are sometimes extrapolated to the whole lake, these methods cannot capture the patchy distribution of aquatic plants in an entire lake (Zhang, 1998). Remote sensing has the potential to help improve estimates of plant cover because of its ability to provide a synoptic view of pant distribution within an entire lake and for multiple lakes within a single image. Using remote sensing to measure plant cover in general and especially EWM, would be an invaluable tool for lake managers to monitor the cover of macrophytes and the presence and distribution of nuisance species.

Although satellite sensors such as Landsat Thematic Mapper (TM) were primarily designed for detecting land features, recent improvements now provide better spatial and spectral resolutions that may be applicable for aquatic studies (Zilioli, 2001). However, remotely sensed images have been used to measure macrophyte cover by mapping the areal distributions of macrophytes along coastal margins from visual interpretations of aerial photographs (Orth and Moore, 1983; Marshall and Lee, 1994). Although this technique provides a quick and cost effective method of qualitatively and quantitatively assessing aquatic vegetation, studies have reported that these techniques correctly record submersed coastal macrophytes only 56-70% of the time (Scholoesser et al., 1987; Marshall and Lee, 1994). Additionally, this technique can be fairly labor intensive. Some of the advantages of using remote sensing for lake studies include acquiring instantaneous sampling of multiple lakes within a single image that can be collected relatively inexpensively. However, satellite remote sensing of aquatic plants, especially submersed plants, has been less studied as a result of the difficulties inherent in interpreting reflectance values of water (Penuelas et al. 1993, Lehmann et al., 1997). Clear water provides little atmospheric reflectance and either absorbs or transmits the majority of incoming radiation (Lillesand and Kiefer 1994, Verbyla 1995). For mapping purposes, unless a sharp contrast exists between the water body and adjacent shore, soils, or vegetation, even boundary delineations can be challenging using remote sensing (Verbyla 1995). As a result, researchers have relied on using remotely sensed data to detect primarily emergent vegetation or homogenous clusters of submersed vegetation (Ackleson and Klemas, 1987; Armstrong, 1993). Other studies have reported successful detection of submersed aquatic plants using high-resolution aircraft or hand sensors (Penuelas et al. 1993, Lehmann et al., 1997, Ullah et al., 2000). However, these studies are mostly limited to few or individual macrophytes species and are often restricted to a

single water body. Despite the potential limitations of using current sensors such as Landsat to detect submersed aquatic plants, more research clearly needs to be done to determine whether Landsat can be used to map macrophytes in large numbers of lakes across a state such as Michigan.

Several studies have shown that remotely sensed images can measure lake characteristics such as chlorophyll, Secchi disk transparency, and suspended sediments (Lathrop and Lillesand 1986, Jensen et al., 1993; Narumalani et al., 1997; Lillesand et al., 1983; Khorram and Cheshire, 1985; Dekker and Peters, 1993; Kliober et al., 2000). However, lakes within a region may vary widely in several of the above characteristics, as well as others that may strongly influence how submersed plants are remotely sensed such as watercolor and lake water depth. It is likely that it will be necessary to incorporate such factors into models predicting aquatic macrophytes. For example, water depth has also been incorporated into models to detect submersed plants using sensors such as Landsat in individual water bodies (Raitala and Lampinen, 1985; Ackleson and Klemas, 1987; Armstrong, 1993; Narumalani, 1997). However, to my knowledge, no studies have linked the influence of these physical and chemical lake features to the ability to detect submersed plants on a regional scale, across multiple lakes.

My objectives in this study were: 1) to determine if different aquatic plant cover types and growth forms (overall littoral plant cover, emergent plants, floating leaf plants, submersed vegetation, and submersed EWM) could be detected using the Landsat-5 TM sensor and 2) to determine if I could improve predictions of macrophyte distributions in lakes by including lake characteristics (Secchi disk transparency, chlorophyll *a*, phytoplankton biovolume, water color, and sediment color) in the models. I hypothesize that including these additional lake characteristics will improve the strength of relationships between macrophyte cover and Landsat-5 TM spectral values.

Materials and Methods

Study Area

The 13 study lakes, located in the lower peninsula of Michigan, U.S.A., were selected using a random-stratified procedure (Figure 3.1). These lakes are distributed throughout an area of approximately 70,000 km^2. The lakes were stratified by surface area (20 - 140 ha), mean depth (2 - 10 m), and Secchi disk transparency depth (0.6 – 8.2 m). A total of 36 lakes were selected and sampled. However, due to cloudy weather during late summer 2001, the final analyses were conducted on only 13 lakes for which cloud-free imagery could be obtained. One lake was selected randomly and withheld from the model development for use as a validation dataset (Table 3.1a).

Macrophyte Sampling

The lakes were sampled during the summer-stratified season during peak plant biomass (July 17 - September 12, 2001). Plants were sampled using a modification of the point intercept method (Madsen, 1999; Figure 3.2). Each lake was mapped using a geographic information system (GIS) and then overlain with a grid of points which represented the macrophyte survey points in the field. Plant cover was assessed at each point for an area of 40 x 40 m or 50 x 50 m depending on lake area. This technique resulted in 138-467 points per lake. The sample points were located in the field with a global positioning system (GPS). At each point, I measured water depth, assessed plant cover of the site, and recorded plant presence in each of four categories: emergent, fl

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floating leaf, total submersed, and submersed EWM. Plant cover at each site was assessed by qualitatively assigning a 'plant cover level', which was done by visual inspection in shallow/clear water, or by throwing a two-sided rake in deeper water. Plant cover levels were: 0 (0 - 20% plant cover), 1 (21 - 40% plant cover), 2 (41 - 80% plant cover), and 3 (81 - 100% plant cover). An additional category of total littoral zone plant cover was developed by combining each of the 4 levels recorded at each point for each plant category, which represents plant presence or absence at each point as 0 (0 - 20% plant cover) or 1 (21 - 100% plant cover).

I also calculated littoral and total lake percent plant cover for each lake as the number of points sampled with any plant category greater than level 0 (i.e., > 20% cover at an individual site), divided by the total number of points in the littoral zone or lake, respectively. The littoral zone was defined $\leq$ 4.5 m water depth. Depths > 4.5 m were regarded as pelagic in which volume reflectance of the water column would dominate the reflectance spectra necessary for submersed plant detection by Landsat (Lillesand et al., 1983; Kloiber et al., 2000).

Examples of the plant species included in the emergent category were *Typha latifolia*, *Pontederia cordata*, and *Scirpus spp*. Representative species of the floating leaf category included *Nuphar advena*, *Nymphaea odorata*, and *Brasenia schreberi*. Examples of plants in the total submersed category included *Chara spp.*, *Potamogeton spp.*, as well as *Myriophyllum spicatum*. The submersed EWM category consisted of only the exotic, *Myriophyllum spicatum*.

Lake Characteristics

In the pelagic zone, water samples were taken from the deepest area of each lake for nutrients, chlorophyll *a*, total alkalinity, and total phytoplankton biovolume. For each lake, the depth of the epilimnion was calculated from a temperature profile and an integrated tube sampler was used to take an integrated epilimnetic sample. Total alkalinity (mg/L $CaCO_3$) was determined on site with a titration test kit (LaMotte). For chlorophyll analysis, water was filtered on site through a glass fiber filter (Whatman GF-C) and stored in dark containers until being returned to the lab and frozen. Chlorophyll *a* concentrations were determined fluorometrically with phaeopigment correction following 24 hour extraction in methanol (Nusch, 1980). Total nitrogen was determined using a persulfate digestion followed by second derivative spectroscopy (Crumpton et al., 1992). Total phosphorus was determined using a persulfate digestion (Menzel and Corwin, 1965) followed by standard colorimetry (Murphy and Riley 1962). Secchi disk depth was measured for each lake off of the shady side of the boat. Phytoplankton were preserved with 1% Lugol's solution and stored in the dark until samples were counted and identified using an inverted microscope. For each lake, a 50 ml phytoplankton sample was settled for 5 days except for 3 lakes (Nevins, Little Whitefish, and Round (Jackson)), which were only settled for 48 hours. The counts from these 3 lakes were then extrapolated to 5-day counts based on comparisons of the 2 settling lengths for 6 lakes that were counted after being settled for both 48 hours and 5 days. For each lake, more than 400 individuals were counted using multiple magnifications (40, 100, 400, and 1000X), and phytoplankton densities (μm^3/ml) were then calculated.

I developed sediment type estimates in the littoral zone of each lake by visually assessing an average of 6-10 sites per lake. I categorized the estimates of sediment type into one of 4 categories; sand, gravel/rock/cobble, marl, or silt/much/peat.

Satellite Imagery

I used three Landsat-5 TM scenes: one from August 4, 2001 and two from September 5, 2001. All three scenes were from the Landsat ground track Path 21 (Worldwide Reference System-2; WRS) (Figure 3.1). Image rectification and geoprocessing was conducted using ERDAS Imagine 8.4 image processing software. Spectral digital number (DN) values for all single pixels located at the same position of each lake sample point were extracted from the imagery using the field-recorded GPS coordinates within each lake. This extraction was performed using the ArcInfo GRID module of ArcGIS 8.1 (ESRI). Spectral DN values for the pelagic region of each lake (sample points with depth measurements > 4.5 m) were also extracted to analyze the relationship between pelagic zone lake characteristics and spectral values (see below). Because the pelagic zone is more homogeneous than the littoral zone, I averaged the spectral DN values for all pixels within the pelagic zone to come up with one spectral value.

Statistical Analysis

I regressed the satellite imagery DN values against macrophyte data using binomial and multinomial logistic regression (logit models) in SAS/STAT software (SAS Institute, Inc. 2001). Spectral DN values for TM bands 2 and 4 were selected as the best bands to include in the models as the independent variables based on numerous attempts to fit several individual and combined bands to the data (Nelson, unpublished data). In all of the models, I also included lake depth at each sampling point as an interaction term with each main effect variable (band 2 and band 4).

For all analyses, I included sample points from multiple lakes in the logit models (unless noted otherwise). However, because I had images from two different sample dates, I developed three separate models to assess whether including results from different sample dates (and potentially different atmospheric levels, i.e. haze) would change model predictions. Thus, I grouped the 12 sample lakes into three datasets to coincide with the image dates: August, September, and a combined dataset (both August and September lakes).

Each of the five plant categories served as individual response variables for each of the three models. The logit model uses the explanatory and interaction covariates to predict the probability that the response variable will take on a given value (SAS Institute Inc., 1995). For binomial logistic regression, the logit model indicates how increases or decreases in the explanatory variable (TM values) affect the probability of the event being observed versus not being observed. For the multinomial logistic regression, probable outcomes of observations are calculated by analyzing a series of binomial submodels that represent the overall model's ability to map changes in the explanatory variable, which are related to the plant cover response variable. For all logit model analyses, I used the descending option to select the highest plant category level as the response variable reference (level 3 for emergent, floating leaf, total submersed, and submersed EWM and level 1 for littoral plant cover). This selection ensured that the results were based on the probabilities of modeling an event (plants present), rather than a nonevent (plants not present).

I assessed the models by examining the percent concordant values and the Wald test statistic. The percent concordant values provide an indication of overall model quality through the association of predicted probabilities and observed responses. These values are based on the maximum likelihood estimation of the percent of paired observations of which values differ from the response variable (Kleinbaum, 1994; SAS Institute, Inc. 2001). The higher the predicted event probability of the larger response variable (based on the highest plant category level), the greater the percent concordant value will be. The chi-square level of significance of the Wald test statistic tests the hypothesis that the coefficients of the independent variables are significantly different from zero by fitting the model using the intercept terms (Kleinbaum, 1994; Pampel, 2000). I used the Wald test because it is regarded as being more accurate than other test statistics when large sample sizes are used (Kleinbaum, 1994).

To examine whether there were significant differences between data from the two image dates, and whether it was valid to include lakes in a combined model, I developed separate logit models for individual lakes. I then compared the model output and model coefficients from lakes in the August image to lakes in September image. First, I used a two sample t-test to test the difference between the means of the model coefficients (log transformed) of the September lakes to the August lakes. The p-values reflected the p-values of the pooled variance, and significance was determined at the 0.1 level. Insignificant results from these tests suggest that the variance of the means of the 12 individual lakes are not statistically different, thus atmospheric effects may not significantly affect the datasets and it may be valid to include lakes in a combined model across image dates. Second, I compared the means of the percent concordant values from the individual models for the September lakes and the August lakes. In this analysis, the absence of large differences between the September and August percent concordant values may also suggest that it may be valid to include lakes in a combined model across image dates.

Using the logit model for individual lakes, I also examined whether various lake characteristics can help improve predictions of plant cover using Landsat imagery. Using ordinary least squares regression, I regressed each of the four model coefficients (TM2, TM4 and the interaction terms with lake depth for both) from the individual lake logit models against each of the measured lake characteristics individually: Secchi disk transparency, water color, chlorophyll *a*, total phytoplankton biovolume, and sediment type.

Logit Model Validation

I validated the results of the logit models by using field- collected data for Winfield Lake, a lake not included in model development. Because the date of data collection for Winfield Lake fell within the range of dates for the lakes sampled in the September model, I validated only the September and the combined logit models. The validation was done by calculating the logit values for each sample point in Winfield Lake from the logistic (for plant cover) and bionomial (for all other plant variables) regression equations for both the September and combined models. The logit values represented the cumulative probability of each sample point being in each plant cover level (0, 1, 2, and 3). The cumulative probability value of the logit was then used to calculate the actual probability of each sample point being in each plant cover level. The actual probabilities were then averaged to determine the overall probability of sample points belonging in plant cover level for each plant category.

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Results

The 13 study lakes (including the validation lake) had some sites with each of the four plant categories, although there was a fair amount of variation across all lakes as well as among categories (Figure 3.3). In particular, few lakes had very dense amounts of emergent and floating leaf vegetation compared to submersed macrophytes. In addition, although EWM was present in relatively low amounts compared to total submerged plants, it was present in all lakes. The overall percent cover of plants in the study lakes ranged from 5% to 42%, and the percent cover of plants in the littoral zone was fairly high in most lakes (Figure 3.4). Four lakes had $\leq$ 50% plant cover in the littoral zone; so in these lakes, the littoral zone was dominated by exposed lake sediments rather than plants. Although the presence of plants was quite high in all lakes, the 'density' (or cover) of plants at each sample point was quite low (Figure 3.5). The majority of sample points had only 0-20% plant cover (level 0) at a site, which led to skewed distributions of plant levels across the four categories. The total submersed plant category was the most evenly distributed category.

The highest concordance values for predicting the plant cover measures from Landsat DN values using the logit models were for the floating leaf and emergent (74-89%) plant categories (Table 3.2). Lower concordance values were found for the two submersed categories, total submersed (62-71%) and submersed EWM (39-62%). These results suggest it may be easier to predict plant categories that are above the water surface than below the water surface. Interestingly, when all plant categories were aggregated into a single category (littoral plant cover), the logit models had relatively high percent concordance (65-72%). The *p*-values for the Wald test were highly significant ($p<0.001$)

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for all categories except for submersed EWM (p=0.067) in the September model. This result may be due to the slightly lower amount of plant level 3 in for the lakes in the September model, compared to the other models (Figure 3.5).

To compare the validity of combining lakes into a combined August-September model, I developed individual logit models for each. I found no significant differences in the model coefficients between the August and September lakes, suggesting that the relationships between the means of the spectral DN values and plant cover estimates are similar across different images, despite any atmospheric differences between the two images (Table 3.3). Additionally, the comparisons of the percent concordant values from the individual lake logit models suggest that the August and September models produced similar model fits to the data (Figure 3.6). Given the above results, I assumed that there are no statistically significant differences between the two images and therefore, it is valid to combine all lakes into a single 'combined' model, even though data for the spectral DN values come from two different images from two different dates.

The ordinary least squares regressions of the logit model coefficients estimated for the 12 individual lake datasets versus lake characteristics produced very low r^2 values and insignificant p-values for the majority of the variables (Table 3.4). Total phytoplankton biovolume produced the highest r^2 values and four of the plant categories were significant at the 0.10 level (littoral plant cover, emergent, total submersed, submersed EWM; Table 3.4). This result suggests that knowing phytoplankton biovolume may be helpful to improve predictions of plant cover in a lake using Landsat. However, although some relationships were significant, this result was not consistent for all independent variables tested and the significant relationships were not strong (r^2 =

0.25 – 0.42). Because I found it surprising that these lake characteristics did not appear to improve model predictions, I examined how well I could predict these lake characteristics from Landsat DN values from the pelagic zone. I examined the pelagic zone because variables such as chlorophyll a, Secchi disk transparency, phytoplankton biovolume, and water color are better assessed in the pelagic zone than in the littoral zone. I found significant correlations between all variables and spectral DN values of the pelagic zone except for water color (Table 3.5). Thus, I was able to detect differences in these variables across the 12 lakes sampled. However the r^2 values were only moderately high for the significant variables ($r^2 = 0.56 – 0.65$) and perhaps there was too much variation in these relationships to help predict plant abundance.

I validated the September and the combined models using field-collected data from Winfield Lake. The overall plant characteristics (Figures 3.3-3.4) and the distribution of plant cover levels in Winfield Lake (Figure 3.7) were similar to the distributions found in the 12 lakes used to develop the models. Skewed distributions of plant levels across the four categories also occurred in Winfield Lakes because the majority of sample points had only 0-20% plant cover at most site sampled. The total submersed plant category was the most evenly distributed category.

The validation of the September and the combined models showed little difference (Table 3.6). I found relatively low, yet similar probabilities of correctly classifying each multilevel plant cover category (emergent, floating leaf, total submersed, and submersed EWM) and a somewhat higher result for the aggregated category of plant cover presence or absence (littoral plant cover), although this result is skewed by the fact that I correctly classified level 0 at a very high probability level, but I did not correctly

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classify level 1 at all. However, within each of the multilevel categories, I obtained the best probability of correct classification from the higher levels of plant cover (level 2 and 3). High classification levels were also seen in the submersed EWM category for level 2, which was the highest level for this category since a level 3 was not observed for this category in Winfield Lake. The most evenly distributed range of probabilities occurred in the total submersed category with probabilities of classification ranging from 0.17 – 0.31 for the September model, and 0.18 – 0.35 for the combined model.

Discussion and Conclusions

I found relatively strong relationships between the five plant categories and Landsat spectral TM values using logistic regression models. For each plant cover type, I obtained significant model fits and reasonably high percent concordant values. All models showed the highest percent concordant values for the plant categories with plants above water: floating leaf and emergent plants. Lower percent concordant values were seen for the submersed categories (total submersed and submersed milfoil). This result is not surprising, considering the difficulties inherent in remotely sensing the aquatic environment (Lillesand and Kiefer 1994, Verbyla 1995). However, the fact that the models resulted in percent concordant values for the two submersed categories ranging from 39 - 71%, suggests that remote sensing may prove to be a valuable tool for measuring plant distributions in lakes and that further research is necessary to improve the fit of the models. Interestingly, I did not find an effect of lake characteristics on the ability to detect aquatic plants in lakes. I found this result surprising given the wide range of water clarity that was present in the study lakes. However, it is possible that with only 12 lakes for the combined model (and 6 lakes for the single-date models), the sample size was too low to detect the effects of lake characteristics. Additionally, although studies by Lathrop (1992), Cox et al. (1998), and Kloiber et al. (2000) have found Landsat to be significantly correlated to a variety of water clarity and water quality parameters, there may be enough variation around these relationships that it is not possible to quantify the effect that they have on model predictions of aquatic plants, which themselves have a significant amount of variation as well. Although the regressions of three of the four lake characteristics against Landsat spectral values were significant, the regressions had relatively low r^2 values (0.56-0.65; Table 3.5).

The model validation analysis adds additional insights into the use of remote sensing to detect aquatic vegetation. The validation resulted in low probabilities (0.23-0.49) of correctly classifying plants in all plant categories. This result was surprising because the models produced high overall percent concordant values and significant Wald test statistics, suggesting a good model fit of the data. I can only speculate as to why the validation and the model statistics resulted in different interpretations. For example, because the validation analysis was based on only one lake, some feature of the validation lake that was not present in the model lakes may have influenced the validation results. However, using the categories and levels of plant cover, the validation lake seemed very similar to the model lakes. In addition, the models themselves, although significant, may be sensitive to the distributions of plants in each category. Therefore, if the plant-cover level distributions of both the model datasets and the validation datasets had been more equally balanced between levels, I may have found higher probabilities in the validation results. In fact, low validation probabilities seemed to be related to low numbers of actual observed sites in those categories (Table 3.7). For this study, I sampled a total of 36 randomly selected lakes. The 13 lakes I was able to incorporate into the models were not necessarily representative of the overall 36 lakes. For example, 9 out of the 36 lakes had total plant cover > 42%. However, no clear images were available for these higher plant cover lakes. Therefore, additional clear images, would have increased the number of lakes included in the models, and may have allowed the distributions to be more evenly distributed. Finally, it is possible that I did not experience adequate positional accuracy with the GPS unit on the days I sampled either any of the model lakes or of the validation lake. Although greater GPS accuracy is currently possible now that selective availability has been turned off, horizontal accuracy of hand-held GPS units is still from 7- 15m depending on environmental and satellite signal reception conditions. Perhaps sampling at an even finer grid resolution in the field (< 40 m) would solve the potential problem of sample point/pixel misalignment.

It is commonly accepted that values sampled from images collected on different dates should not be combined because they are affected by different atmospheric effects (such as haze) specific to the date of image acquisition (Song, 2001). However, I did not find this to be the case. In fact, any atmospheric differences produced no statistically significant differences between the datasets. This conclusion is also evident in the validation analysis. The application of the validation data to models developed based on the coefficients of the both the September and combined models produced very similar results for all plant cover categories and category levels. This result is important because it allowed us to increase the sample size by including all lakes in a combined model; which also allowed us to examine the effect of lake characteristics on the models.

Although I sampled 36 lakes for this study, I was only able to find clear images for 12 lakes, thus being able to use images from multiple dates will increase the likelihood in future studies that clear images and field data can be matched.

The use of remote sensing in freshwater lake studies can play a vital role in reducing the cost, labor, and time required to monitor these systems over a large geographic area. Remote sensing also has the potential to be used as a tool for statewide assessments that are currently impossible using traditional field operations. Here, I have provided a general method for detecting littoral zone plant cover in inland freshwater lakes using satellite imagery. However, the attempts to predict plant categories in unsampled lakes (i.e. validation analysis) produced varying results, despite the relatively good fit of the models.

I conclude that more research is necessary to conclusively assess the utility of using Landsat TM data to predict macrophyte cover in lakes. I offer the following suggestions. First, one option would be to include more sample lakes into the model calibration to provide representative distributions of regional plant cover within the lakes modeled. A second possibility is to use a finer spatial resolution of the field-collected data to match more exactly the spatial resolution of Landsat data. Third, perhaps a different method of assigning plant levels could be developed. The method of sampling macrophytes and assigning category levels was relatively coarse, which may have influenced to the ability to detect plants using Landsat data. However, more detailed plant sampling methods, such as linear shoreline transects, are often very limited in spatial scale, which would also be difficult to relate to remotely sensed data. Fourth, current sensors such as Landsat, may be limited in providing the appropriate spectral resolution necessary to more effectively measure macrophyte distributions and the water quality parameters that affect these distributions. We need to determine the best spectral band configurations of sensors to more accurately measure aquatic plants. Until our methods can be improved or possibly better sensors are developed for aquatic applications, inland lake remote sensing may be most useful as a supplement to existing volunteer and agency monitoring programs, rather than a replacement of these programs.

Acknowledgements

This research was funded in part by a Michigan State University Minority Competitive Doctoral Fellowship to SACN and an EPA STAR Fellowship to KSC. Landsat-5 ETM+ imagery was provided by the Basic Science and Remote Sensing Initiative (BSRSI, now known as the Center for Global Change and Earth Observation) and through the NASA-funded Upper Midwest RESAC project (Regional Earth Science Applications Center). I thank Kevin Hoffman, John Whitlock, Tamara Brunger-Lipsey, Kristy Rogers, Sarah Wills, and Konrad Kulacki for field data collection and processing. I are also grateful to David Skole, Jiaguo Qi, Jianguo Liu, David Lusch, and Walter Chowmentowski for their contributions to this research. Additionally, I would like to thank Michael Belligan, Marc Linderman, and Chris Barber for technical support and database assistance. Finally, I thank Daniel Hayes, Orlando "Ace" Sarnelle, Ken Frank, Jim Bence, and Emily Szali for statistical advice.

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CONCLUSIONS

The strength of remote sensing techniques for large-scale ecosystem studies lie in its ability to provide spatial measurements of features across large areas that are typically not possible with *in situ* sampling procedures. In addition, sensors such as Landsat provide an excellent tool to examine changes over time, since this imagery has been collected over large areas of the earth's surface for several decades. To date, Landsat and other such sensors have been used extensively for land-based studies to measure such things as land use change, leaf area, forest inventories, etc. (Wilkie and Finn 1996). However, sensors such as these have been less well applied to wetland and inland lake studies. Because Landsat sensors were primarily designed for the detection of terrestrial features, the detection of aquatic features has been more problematic for some applications. For example, the band placement within the Landsat sensor is such that the band wavelength with the maximum capability of penetrating water (blue, 0.45-0.52 um) is also the band which is most scattered by the atmosphere, making it extremely sensitive to atmospheric conditions during image capture. In contrast, the longer wavelength bands are more absorbed by clear water, thus limiting the amount of spectral energy returned to the sensor for feature detection. Despite these potential limitations, Landsat has been used successfully in aquatic studies for the remote sensing of Secchi disk transparency (SDT), Chl *a*, and suspended sediments (Khorram and Cheshire 1985, Lathrop 1992, Lathrop and Lillesand 1986).

However, I believe despite these limitations, remote sensing in general, and Landsat in particular, can still provide valuable information on aquatic ecosystems such

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as wetlands and lakes. In my dissertation, I explore how far we can take the Landsat sensor in detecting features of aquatic ecosystems that span the range from above water-measures such as wetland and emergent plant cover, the littoral zone features of lakes that includes submerged plants, and finally the pelagic zones of lakes that includes water clarity. I have been interested in exploring what we can and cannot detect using the Landsat sensor. In this section, I will discuss: (1) some of my significant overall findings and applications of this research to monitoring and management, (2) some of the logistical problems that I encountered during this research, and (3) what I believe is needed for future development of wetland and inland lake remote sensing capabilities.

Major conclusions and applications of this research

In chapter 1, I examined historical changes within the Barataria Basin, LA. This study was unique for two reasons. First, this study used historical imagery from the Landsat MSS sensor across a 20-year period. Landsat MSS has been in orbit since 1972 and currently provides our longest available historical record of earth surface remote sensing, however this historical record has only rarely been examined (Jensen et al. 1995, Haack 1996, Munyati 2000). The spatial resolution of MSS data is approximately 80 meters. For smaller-scale studies, this coarse resolution may be a limiting factor. However, in my investigation of the upper Barataria Basin (200,000 ha), an area of this magnitude necessitated larger resolution imagery. Additionally, in comparison to smaller-scaled field studies or aerial surveys, this large-scale analysis using MSS, allowed me to identify changes in the upper basin that simply may not have been obvious at a local scale or ground level investigation. Secondly, Landsat MSS allowed me to

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assess land cover changes through time within the upper basin. I related observed increases in urban and swamp forest to known drivers of change affecting the basin as a whole (i.e. land subsidence and water level rise). The bottomland forest land cover occupied the mid-elevation land cover within the basin. As the swamp forest in the lower elevations increase, and the human land use in the higher elevations increase, the bottomland forest is subjected to multiple stressors. As a result, this land cover has shown a remarkable decline and has the potential to be lost to the system within the next 25 years. The main management implication in this study is that there are major changes occurring in the more inland regions of this coastal estuary, namely, the loss of bottomland forest and gains in total wetland area; and these changes have been previously overlooked because of the focus on the coastal wetland losses, which are some of the highest losses in the world. Changes in the upper freshwater portion of this important estuary may have important additional implications for the lower brackish regions and is an important area for future study.

In my second chapter, I investigated the use of Landsat-7 to detect lake water clarity using SDT which incorporates the range of lake SDT values found within a region comparable to 80% of the lower peninsula of Michigan, USA. To my knowledge, an assessment of water clarity of this scale has never been attempted using remotely sensed data. In this study, I identified an important consideration necessary for modeling water clarity on a large scale: models developed for large regions such as this, must incorporate the full range of lake SDT values found throughout the region in the model calibration. Models that incorporate this complete range of SDT values, such as the one developed in my study, may not produce r^2 results as high as models that are developed for groups of lakes that don't incorporate the full regional range of SDT values (Lathrop and Lillesand 1986, Dekker and Peters 1993, Kliober et al. 2000). In addition, my results suggest that Landsat is better at predicting shallow SDT values than deep SDT values. Although the model that I developed has a lower r^2 than some previously published studies, I believe that it can still be used my state management agencies for selected purposes. For example, it could provide managers with a method to inventory shallow SDT lakes (eutrophic) across the entire state where *in situ* data is difficult to obtain. In particular, using the current model produced in my study, state agencies (i.e Michigan Department of Environmental Quality, MDEQ) would be able to monitor private lakes without spending resources on these lakes and without requiring the permission of the property owner. Additionally, using my model to detect eutrophic lakes may also be useful in the historical analysis of watershed changes that may have caused lake eutrophication to occur over time. This application is a very attractive use of remote sensing since we can always obtain historical imagery for lakes we know that have become eutrophic over time.

In my third chapter, I investigated the use of Landsat-5 to monitor aquatic plants in inland lakes within the lower peninsula of Michigan. The remote sensing of aquatic plants in lakes has been less well studied than SDT. Previous studies have focused on detecting emergent vegetation or homogenous clusters of submersed vegetation (Ackleson and Klemas, 1987; Armstrong, 1993). Also, many of these studies have been limited to few or individual macrophytes species and restricted to a single water body (Penuelas et al. 1993, Lehmann et al., 1997, Ullah et al., 2000). My study demonstrates that multiple types of plant cover, both emergent and submersed, can be detected using g

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remote sensing. I developed a model to detect five different types of macrophyte cover that was calibrated using twelve different lakes across a large region of the state of Michigan. The models developed in my study fit the calibration data very well and resulted in statistically significant model fits. However, when I tried to validate the model using a single lake, the outcomes were disappointing. This suggested further research might be necessary to validate these models, since perhaps there was something unique about our single validation lake. In the immediate future, I will explore other options to validate this model. For example, I will attempt to validate the complete model, which has a larger number of total lakes (N=13). I will randomly choose nine lakes to calibrate the model and four lakes to validate the model. This would reduce the total number of lakes in the complete model dataset. However, because the validation analysis would be based on more than one lake, it would reduce the influence of features of the lakes used for validation that may not possibly be present in the model lakes, and vice versa. In general, the significant value of this research is that it lays the foundation for more research to improve on our ability to detect submerged plants in lakes. Further development of these models will benefit lake managers interested in assessing several lakes within a large region for the monitoring and assessment of aquatic plants and nuisance species.

Logistical issues involved in this research

There are several logistical issues in using remote sensing for aquatic studies that I found throughout my research. For example, in chapter 1, I found the storage and retrieval of the large Landsat MSS image files to be one of the most limiting factors.

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Each Landsat MSS image required approximately 340 megabytes of hard drive storage space. This not only made file storage a problem, but also combined with limited CPU processing power, file manipulation and processing in ERDAS Imagine was very slow. Another problem I found involved the use of high-resolution digital aerial photographs for classification accuracy assessment. Approximately 115 individual air photos had to be mosaicked and georectified to the 1992 MSS scene. This was a time consuming procedure because detailed ground maps that matched the spatial resolution of the air photos (3 meters) were not available. Thus, the each photo required manual "stitching" in ERDAS until a larger mosaicked scene was created for overlay and georectifying with the MSS imagery. A final problem area in this study occurred in the preprocessing of the imagery itself. Linear spectral "bandings" were very visible in the 1972 image data. Further observation revealed the same spectral distortions were also present in the 1985 and 1992 imagery, however not as prominent as in the 1972 image. After performing a series of supervised classifications without correcting these distortions, I found that the accurate separation between the bottomland forest and the swamp forest land cover was impossible to achieve, even with numerous training samples selected from the corresponding land cover. By using a band ratio, developed by dividing MSS band 1 by MSS band 2, the scene distortion was reduced and allowed for accurate classification of each land cover type. Some of the above issues will be reduced as newer hardware technology and software advances become available. For instance, personal computers have more than tripled in processing power and storage capabilities, almost daily, since I began this study. Additionally, software improvements have also produced easier management of larger files in the ERDAS Imagine program. However, historical data obtained from these sensors in the earlier 1970's to mid-1980's still remain archived on magnetic tape throughout many datacenters in the U.S. This media has a tendency to begin oxidizing after 20 years or so, resulting in partial or total loss of the stored data. This could severely limit our ability in developing historical land cover change studies.

In Chapter 2, one of the greatest challenges to this research was locating cloud-free Landsat TM-7 images for a large number of lakes throughout the lower peninsula of Michigan. I was only able to obtain a total of six images which had no or limited cloud cover over lake within the lower peninsula of Michigan, for the sample period of mid-July to mid-September. The three path 21 images, used in chapter 2, proved to have the least amount of could cover allowing for cloud-free extraction of the pelagic spectral values of the 93 lakes used in this study. Additionally, during the summer of 2001, our sampling program sampled 36 randomly stratified lakes, however only one lake had available cloud-free imagery and was within +/- 7 days of the satellite overflight. Interestingly, I found that SDT data from the Michigan Citizens Lake Monitoring Program (CLMP) provided the most usable data source because the volunteers sampled most lakes weekly or biweekly. I received a dataset of 195 lakes from CLMP and was able to incorporate 79 lakes within +/- 7 days of the satellite overflight. However, one limitation of using CLMP data was that no geographic coordinate information is provided with this data, other than county, or sometimes township names, in which the lake was located. Of the total CLMP 195 lakes, 42 lakes had to be discarded because accurate identification of the lake could not be made as a result of incorrect county or township names, or multiple lakes within the county or township bearing the same name. The above limitations maybe overcome by continued used of the CLMP data, as volunteers are collectively able to sample a large number of lakes throughout the state and throughout the summer season. This frequency will allow for lake samples to be obtained without the need of synchronizing sampling operations will cloud-free satellite acquisition periods. The collective volunteer data will inevitably contain dates that meet the 7 day criteria necessary for detecting SDT. Additionally, I would recommend that the volunteers be provided with handheld GPS units, which would allow researchers to accurately identify the sampled lake. These units have become relatively inexpensive over the last few years and, in states with thousands of lakes, it may actually be more economical for the agencies to supply GPS units and training to volunteers than to conduct an agency statewide inventory of lakes themselves.

In chapter 2, I also explored a combined regression model of all available SDT lake data (+/- 56 days of the satellite overflight) from lakes within the three adjacent ground track paths in the lower peninsula of Michigan (paths 20, 21, and 22). This regression model yielded an r^2=0.05 (p<0.01, n=142). I then explored a combined regression model based on all available SDT lake data, +/- 27 days of the satellite overflight, from lakes within path 21. This regression model yielded an r^2=0.27 (p<0.01, n=104). Reducing this model to 93 lakes, within path 21, and within +/- 7 days of the satellite overflight produced my highest r^2 result (r^2=0.43, p<0.01) using the largest number of lakes possible. I did not atmospherically correct the lake images because the spectral values extracted for each lake were so low that the likelihood of finding a lower dark object (in which to base a dark body subtraction procedure) within each image was highly unlikely.

One possible source of error in the model developed in chapter 2 is the use of 'averaged' spectral DN values to represent the pelagic zone. I do not believe that this is a large source of error however. First, it is similar to the protocol that has been developed and used in other state programs (Minnesota RESAC project; Kloiber et al. 2000). I tested the validity of this approach by examining the variation in pelagic spectral DN values in the pelagic zone and the variation was found to be very low. Additionally, using the averaged value would have removed the chance that individual pixels may have been spuriously elevated from a spurious bottom reflection or dense plant reflectance from a shoal area occurring within the lake's pelagic region.

In my final chapter (chapter 3), again the greatest logistical challenge was finding cloud- free satellite images. During the late summer of 2001, 36 lakes were sampled for macrophyte abundance. However, I was only able to obtain cloud free imagery for 13 of these lakes using Landsat-5 TM. The days between lake sampling and image acquisition were 5-18(+/-). Using Landsat-7 ETM+ I would have been limited to one sample lake within 7 days of overflight and 2 lakes within 27 days of overflight. An additional concern was that the TM band 2 values in the August dataset were slightly higher than the TM2 values in the September dataset, which led me to believe that this dataset was affected by atmospheric haze. Several models have been developed for the correction of atmospheric effects for improved image interpretations (Chavez 1988, Campbell and Ran 1993). However, there still exists a large discrepancy in the literature concerning a universal model, or how one (or several) correction models should be used (Brivio et al. 2001, Rahman et al. 2001, Song et al. 2001). To correct for haze, I attempted an image-based method of atmospherically correcting for haze by regressing the visible bands

(TM1, TM2, TM3) each against the TM4 band. In the absences haze scattering, the regression Y-intercepts should pass through the X-Y origin (Wilkie and Finn 1996). The visible bands in both the August and September datasets were adjusted by the value at which the regression line crossed the Y-axis and the origin (0). The adjusted TM values were then tested in the Secchi model developed in chapter 2 using pelagic TM values (TM1:TM3). I felt this was a sufficient test since the SDT model had been established within the literature. The Y-intercept model was then compared to an uncorrected Secchi model using the lakes from both the August and September datasets. I found that the Y-intercept adjusted models failed to improve the regression results when compared to the uncorrected models. This may indicate that other effects that are not influenced by atmospheric conditions elevate the TM values in these lakes. My further statistical analyses (two sampled t-test) support this conclusion, which showed no statistically significant difference between the mean TM coefficient values produced from the 12 individual lakes.

One additional problem in chapter 3 occurred in determining the "best" bands or band combinations to use in developing my logistic regression models. I explored several series of binomial and logistic stepwise regression models for 42 individual and ratioed band combinations for all datasets. These analyses produced varying results. Actually, several bands appeared to be very similar. Box plots for each band revealed few differences across the different band combinations. However, several bands were still identified as significant variables. Additionally, box plot failed to reveal any large degree of separation between bands. Thus, we selected bands TM2 and TM4, which appeared to be the most consistent significant bands when tested against all plant cover types and levels of plant abundance. Additionally, my decision to select 2 bands versus several, allowed for the development of a simpler model with fewer parameters to fit.

Future use of remote sensing for freshwater studies

Currently, Landsat provides one of our richest data sources for the remote sensing of historical changes in large areas of wetlands, water quality and aquatic plants. This is evident by the high revisit cycle, spatial resolutions, and 30 years of operation provided by these sensors. Based on my research, and the research of others, it appears that the spectral resolution of these sensors (4 in MSS and 6 in TM) currently allow us to identify broad vegetation land cover types in wetland areas, SDT estimates (at least for shallow SDT lakes), emergent and floating aquatic plants, and past and present rates of change of each. However, there are features that Landsat has problems in detecting. For example, individual plant species within highly mixed vegetation patches or within patches which have an areal extent below the spatial resolution of the sensor. To improve these problems, sensors with finer spectral and spatial band resolutions may be necessary to fine-tune these models for improved feature detection within the aquatic environment. However, Landsat-7 data now has the capability of being ordered with adjusted high or low gain settings. The low gain setting is what has traditionally been used by the Landsat sensor series and is optimized for highly reflective features, such terrestrial vegetation. However, the new option of obtaining the high gain settings may have the potential for improving aquatic feature detection. I may also explore this capability of Landsat-7 in the near future.

Finally, I will conclude by posing my thoughts on the future prospects of remote sensing in wetland and inland lake studies. Given some of the limitations I have detailed above I think that new sensors for aquatic studies should include the following specifications. First, it would be helpful to have self calibrating sensors with lowered or compensated calibrations for water absorption in IR bands and lowered or compensated atmospheric scattering in the visible bands because these are the most problematic regions for aquatic remote sensing. Additionally, hand-held or boom-held, multi-band, hyperspectral sensor systems have become popular for ecological studies within the last 10 years. However, only a few studies have applied these systems to the aquatic environment (Penuelas et al 1993, Ullah et al. 2000). Also, because these sensors have such fine spatial resolutions, which depends solely on the height on the sensor above the feature of interest, they cannot be used across large regions as I have used Landsat in my research. Additionally, the imagery cost is still prohibitive for most large scale research applications. For these hyperspectral sensors to become widely usable for regional wetland and inland lake studies, I suggest a configuration similar to the Landsat orbit, revisit period, and spatial resolution. More specifically, I would like to see a sensor system with incremental narrow band placements in the near-IR where water absorption lessens and vegetative reflection begins to slightly increase, as well a several incremental narrow bands within the green and red portions of the visible spectrum, as these regions are known to strongly match vegetation and chlorophyll reflectance peaks. Finally, it would helpful to have a multi-satellite constellation systems, real-time acquisition systems, and user-definable/employable micro-satellites which would be directly geared towards improving the capability of remote sensing for monitoring small and large areas, wetland systems, inland waters, as well as global landscape change.

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Jense

Khorra

Kloibe

Lathro

Lathro

Lehma

Munya

Penue

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Rah

Song

Ulla

Will

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APPENDICES

APPENDIX 1

Chapter 1 Tables and Figures

Table 1.1A. Error matrix for comparison between the 1992 classification to the higher resolution Landsat TM (30m) reference scene

Table 1.1A. Error matrix for comparison between the 1992 classification to the higher resolution Landsat TM (30m) reference scene from 20 October 1995. The number of correctly classified pixels for each land cover are on the diagonal in bold.

	Urban	**Agriculture**	**Forest** [1]	**Swamp**[2]	**Marsh** [3]	**Water**	**Total**
Urban	**41**	1	1	0	0	0	*43*
Agriculture	9	**42**	0	0	0	0	*51*
Bottomland forest	1	0	**22**	0	0	1	*24*
Swamp forest	1	0	4	**107**	0	0	*112*
Freshwater marsh	2	0	0	1	**11**	0	*14*
Water	0	0	0	1	0	**11**	*12*
Total	54	43	27	109	11	12	*256*

[1] Bottomland forest [2] Swamp forest [3] Freshwater marsh

Table 1.1B. Classification accuracy for comparisons between the 1992 classification to the higher resolution Landsat TM (30m

Table 1.1B. Classification accuracy for comparisons between the 1992 classification to the higher resolution Landsat TM (30m resolution) reference scene. The reference scene totals column refers to the number of pixels in each land cover identified within the Landsat TM reference scene. The classified totals are the number of pixels in each land cover from our 1992 classification scene. The number correct is the number of pixels in our classification that match the Landsat TM scene. Accuracy (%) is the percent correctly classified for each land cover. The overall classification accuracy produced from this assessment was 91% with an overall Kappa statistic of 0.88.

	Reference Scene Totals	**Classified Totals**	**Number Correct**	**Accuracy (%)**
Urban	54	43	41	76 %
Agriculture	43	51	42	98 %
Bottomland forest	27	24	22	82 %
Swamp forest	109	112	107	98 %
Freshwater marsh	11	14	11	100 %
Water	12	12	11	92 %
Total	**256**	**256**	**234**	**91 %**

Table 1.2. The total area of land cover change between each time step (ha) and the rate of land cover change (ha/yr) between each time step for each land cover category. Positive numbers are gains in land cover area and negative numbers are losses in land cover.

	1972-1985		1985-1992		Total: 1972-1992	
	Area (ha)	Rate of Change (ha/yr)	Area (ha)	Rate of Change (ha/yr)	Area (ha)	Rate of Change (ha/yr)
Urban	12,906	993	2,013	288	14,919	746
Agriculture	-8,534	-656	-4,075	-582	-12,609	-630
Bottomland forest	-10,228	-787	-5,305	-758	-15,533	-777
Swamp forest	10,582	814	8,157	1,165	18,739	937
Freshwater marsh	-4,720	-363	-249	-36	-4,969	-248

Table 1.3A. The total area (ha) of land converted from one land cover to the next between 1972 and 1985. The areas of no change are in parentheses. The total column represents the land use areas in the earlier time step.

		1985					
		Urban	**Agriculture**	**Forest[1]**	**Swamp[2]**	**Marsh[3]**	**1972 Total**
1972	**Urban**	(8,670)	4,379	102	104	8	**13,264**
	Agriculture	14,706	(25,335)	1,059	498	21	**41,618**
	Forest[1]	1,968	2,784	(23,593)	11,825	356	**40,526**
	Swamp[2]	362	132	4,772	(44,798)	571	**50,635**
	Marsh[3]	57	26	1,004	4,236	(7,729)	**13,053**

[1] Bottomland forest [2] Swamp forest [3] Freshwater marsh

Table 1.3B. The total area (ha) of land converted from one land cover to the next between 1972 and 1992, and between 1985 and 1992. The areas of no change are in parentheses. The total column represents the land use areas in the earlier time step.

		1992					
		Urban	**Agriculture**	**Forest[1]**	**Swamp[2]**	**Marsh[3]**	**1972 Total**
1972	**Urban**	(8,609)	4,370	329	84	46	**1,3437**
	Agriculture	16,674	(22,663)	2,207	203	94	**41,841**
	Forest[1]	2,296	1,698	(17,642)	18,682	355	**40,674**
	Swamp[2]	317	32	2,749	(47,108)	550	**50,756**
	Marsh[3]	24	47	2,166	3,373	(7,582)	**13,192**
							1985 Total
1985	**Urban**	(15,681)	9,107	871	348	158	**26,164**
	Agriculture	11,256	(19,389)	2,286	193	65	**33,188**
	Forest[1]	640	423	(15,205)	14,048	240	**30,556**
	Swamp[2]	474	229	5,678	(52,846)	2,148	**61,375**
	Marsh[3]	5	6	961	1,655	(6,023)	**8,650**

[1] Bottomland forest [2] Swamp forest [3] Freshwater marsh

Table 1.4A. The area (percent) of land converted from one land cover to the next between 1972 and 1985. For example, the percent of agricultural land present in 1972 that was converted to urban land in 1985 is 35%. Areas of no change are in parentheses. The total column represents the land use areas in the earlier time step.

		1985					
		Urban	**Agriculture**	**Forest[1]**	**Swamp[2]**	**Marsh[3]**	**1972 Total**
1972	**Urban**	(65)	33	1	1	<1	**100**
	Agriculture	35	(61)	3	1	<1	**100**
	Forest[1]	5	7	(58)	29	1	**100**
	Swamp[2]	1	<1	9	(88)	1	**100**
	Marsh[3]	<1	<1	8	32	(59)	**100**

[1] Bottomland forest [2] Swamp forest [3] Freshwater marsh

Table 1.4B. The area (percent) of land converted from one land cover to the next between 1972 and 1992, and between 1985 and 1992. 1972 and 1985 to 1992. For example, the percent of agricultural land present in 1972 that was converted to urban land in 1992 is 40%. The areas of no change are within parentheses. The total column represents the land use areas in the earlier time step.

		1992					
		Urban	**Agriculture**	**Forest**[1]	**Swamp**[2]	**Marsh**[3]	**1972 Total**
1972	**Urban**	(64)	33	2	1	<1	**100**
	Agriculture	40	(54)	5	<1	<1	**100**
	Forest[1]	6	4	(43)	46	1	**100**
	Swamp[2]	1	<1	5	(93)	1	**100**
	Marsh[3]	<1	<1	16	26	(57)	**100**
							1985 Total
1985	**Urban**	(60)	35	3	1	1	**100**
	Agriculture	34	(58)	7	1	<1	**100**
	Forest[1]	2	1	(50)	46	1	**100**
	Swamp[2]	1	<1	9	(86)	3	**100**

***Marsh*[3]**	*<1*	<1	11	19	(70)	**100**

[1] Bottomland forest [2] Swamp forest [3] Freshwater marsh

Table 1.5A. The area (percent) of land converted from one land cover to the next between 1972 and 1985. Changes here show the total percentage of each land cover in the basin as a whole that changed into other categories. For example, 9% of the total basin area was converted from agriculture to urban land from 1972 to 1985. The total column represents the land cover areas in the earlier time step. The areas of no change are in parentheses.

		1985					
		Urban	**Agriculture**	**Forest[1]**	**Swamp[2]**	**Marsh[3]**	**1972 Total**
1972	**Urban**	(5)	3	0	0	0	**8**
	Agriculture	9	(16)	1	0	0	**26**
	Forest[3]	1	2	(15)	7	0	**25**
	Swamp[2]	0	0	3	(28)	0	**31**
	Marsh[1]	0	0	1	3	(5)	**8**

[1] Bottomland forest [2] Swamp forest [3] Freshwater marsh

Table 1.5B. The area (percent) of land converted from one land cover to the next between 1972 and 1985, and between 1985 and 1992. Changes here show the total percentage of each land cover in the basin as a whole that changed into other categories. For example, 10% of the total basin area was converted from agriculture to urban land from 1972 to 1992. The total column represents the land cover areas in the earlier time step. The areas of no change are in parentheses.

		1992					
		Urban	**Agriculture**	**Forest[1]**	**Swamp[2]**	**Marsh[3]**	**1972 Total**
1972	**Urban**	(5)	3	0	0	0	**8**
	Agriculture	10	(14)	1	0	0	**26**
	Forest[3]	1	1	(11)	12	0	**25**
	Swamp[2]	0	0	2	(29)	0	**31**
	Marsh[1]	0	0	1	2	(5)	**8**
							1985 Total
1985	**Urban**	(10)	6	1	0	0	**16**
	Agriculture	7	(12)	1	0	0	**21**
	Forest[3]	0	0	(9)	9	0	**19**

Swamp[2]	*0*	0	4	(33)	1	**38**
Marsh[1]	0	0	1	1	(4)	**5**

[1] Bottomland forest [2] Swamp forest [3] Freshwater marsh

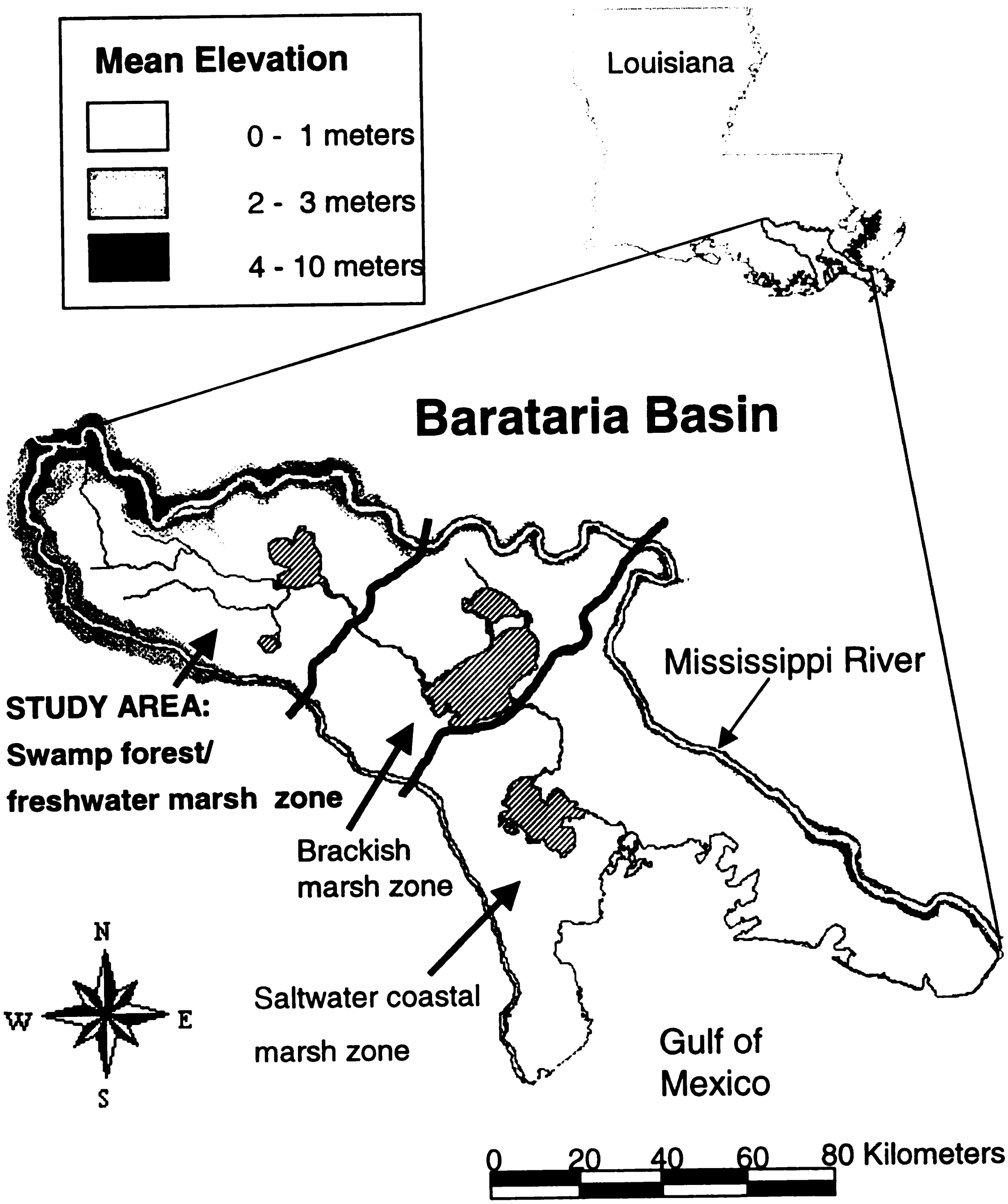

Mean Elevation
0 - 1 meters
2 - 3 meters
4 - 10 meters
Louisiana
Barataria Basin
Mississippi River
STUDY AREA:
Swamp forest/
freshwater marsh zone
Brackish
marsh zone
Saltwater coastal
marsh zone
N
W
E
S
Gulf of
Mexico
0 20 40 60 80 Kilometers

Figure 1.1.

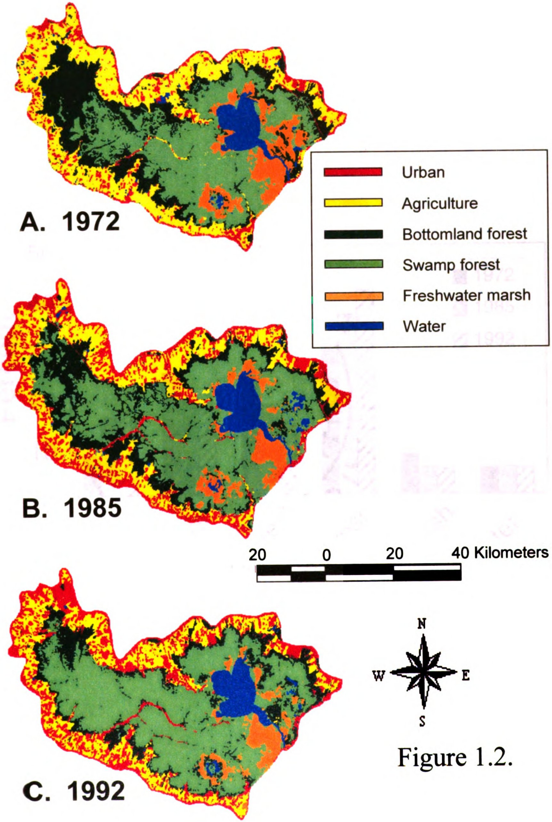
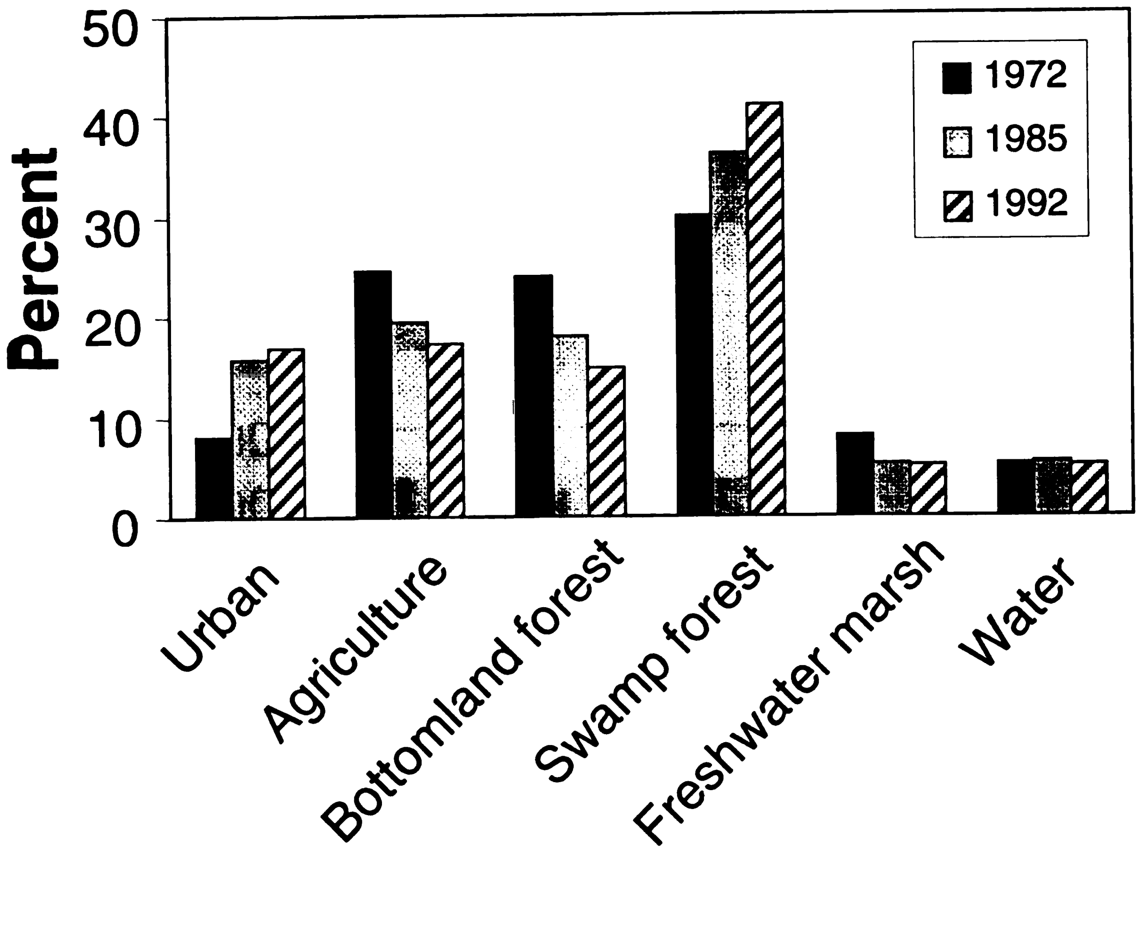

A. 1972
B. 1985
C. 1992
Urban
Agriculture
Bottomland forest
Swamp forest
Freshwater marsh
Water
20
0
20
40 Kilometers
N
W
E
S

Figure 1.2.



Percent
50
40
30
20
10
0
1972
1985
1992
Urban
Agriculture
Bottomland forest
Swamp forest
Freshwater marsh
Water

Figure 1.3.

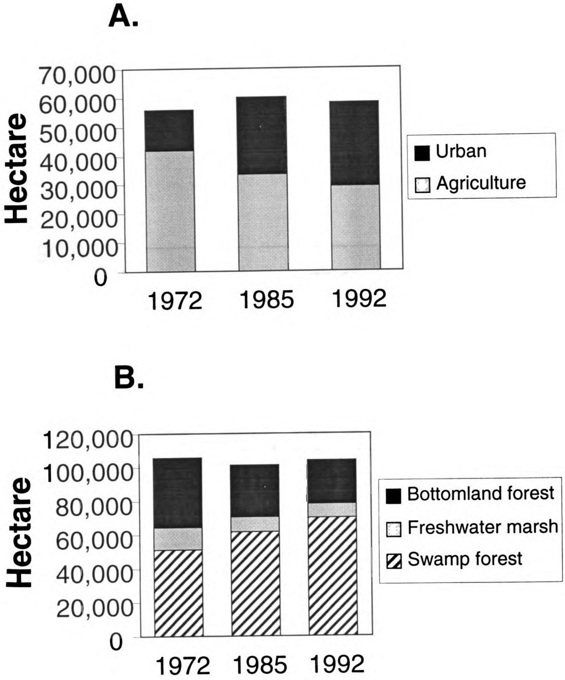

A.
Hectare
70,000
60,000
50,000
40,000
30,000
20,000
10,000
0
1972
1985
1992
Urban
Agriculture
B.
Hectare
120,000
100,000
80,000
60,000
40,000
20,000
0
1972
1985
1992
Bottomland forest
Freshwater marsh
Swamp forest

Figure 1.4.

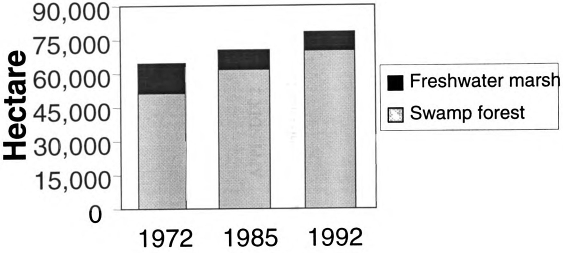

90,000
75,000
60,000
45,000
30,000
15,000
0
Hectare
1972
1985
1992
Freshwater marsh
Swamp forest

Figure 1.5.

APPENDIX 2

Chapter 2 Tables and Figures

Table 2.1. Landsat remote sensing studies of Secchi depth using multiple inland lakes.

Citation	Study Site	Sample Dates	Number of lakes	Secchi range (m)	r^2
Kliober et al. 2000	Twin Cities Metropolitan Area, MN	Sept. 1991	47	0.5 - 3.5	0.83
Dekker and Peters 1993	Loosdrecht lakes, Amsterdam	June 1986, July 1987	15	0.26 - 3.1	0.66 - 0.81
Lillesand et al. 1983	Otertrail Lakes Region and Twin Cities Metropolitan Area, MN	July 1980, August 1980	63	---	0.91 - 0.98

Table 2.2. Information for the 93 study lakes used to collect field observations.

Sampling Organization	Number of Lakes	Surface Area (ha) Mean	Surface Area (ha) Range	Secchi (m) Mean	Secchi (m) Range
CLMP[1]	79	208	12 – 4125	3.2	0.9 – 7.6
MDEQ[2]	13	545	60 – 3750	2.4	1.1 – 3.7
MSU[3]	1	58	---	3.1	---
Total	**93**	**270**	**12 – 4125**	**3.1**	**0.9 – 7.6**

[1]Citizens Lake Monitoring Program

[2]Michigan Department of Environmental Quality

[3]Michigan State University

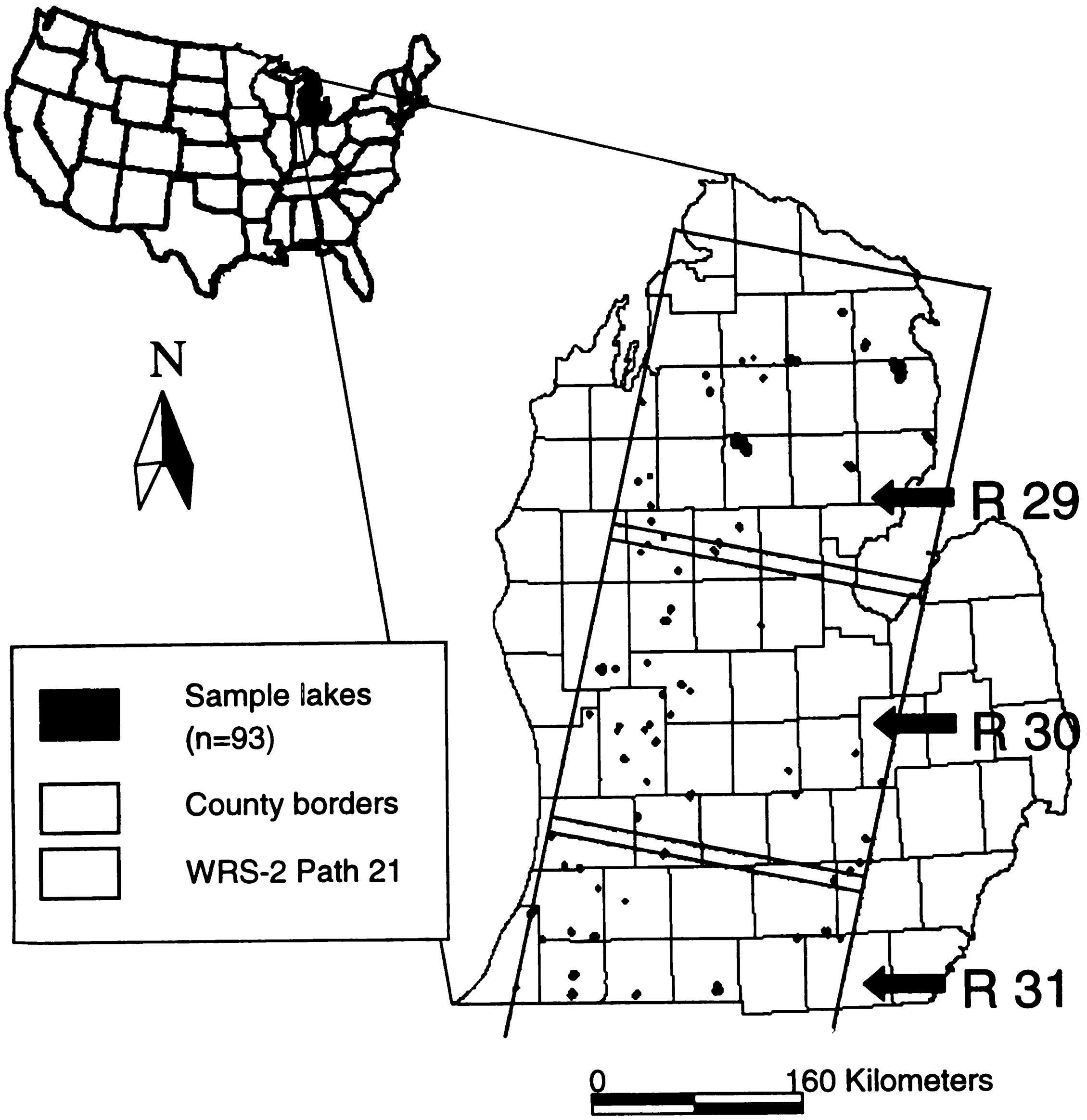

N
Sample lakes
(n=93)
County borders
WRS-2 Path 21
R 29
R 30
R 31
0
160 Kilometers

Figure 2.1.

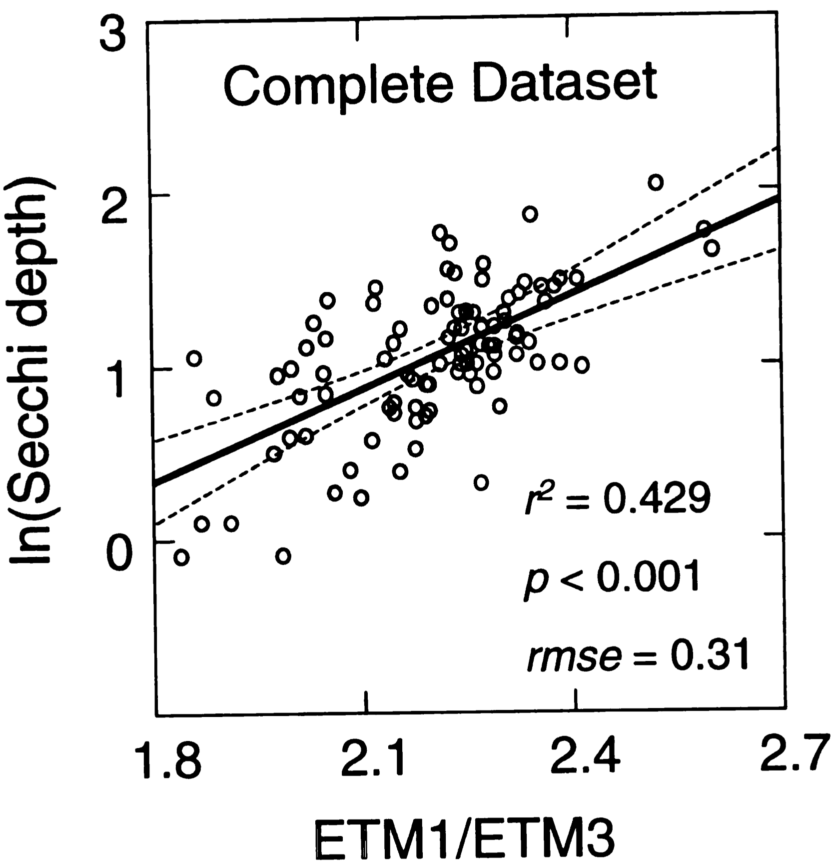

Complete Dataset
$r^2 = 0.429$
$p < 0.001$
$rmse = 0.31$
ln(Secchi depth)
ETM1/ETM3
3
2
1
0
1.8
2.1
2.4
2.7

Figure 2.2.

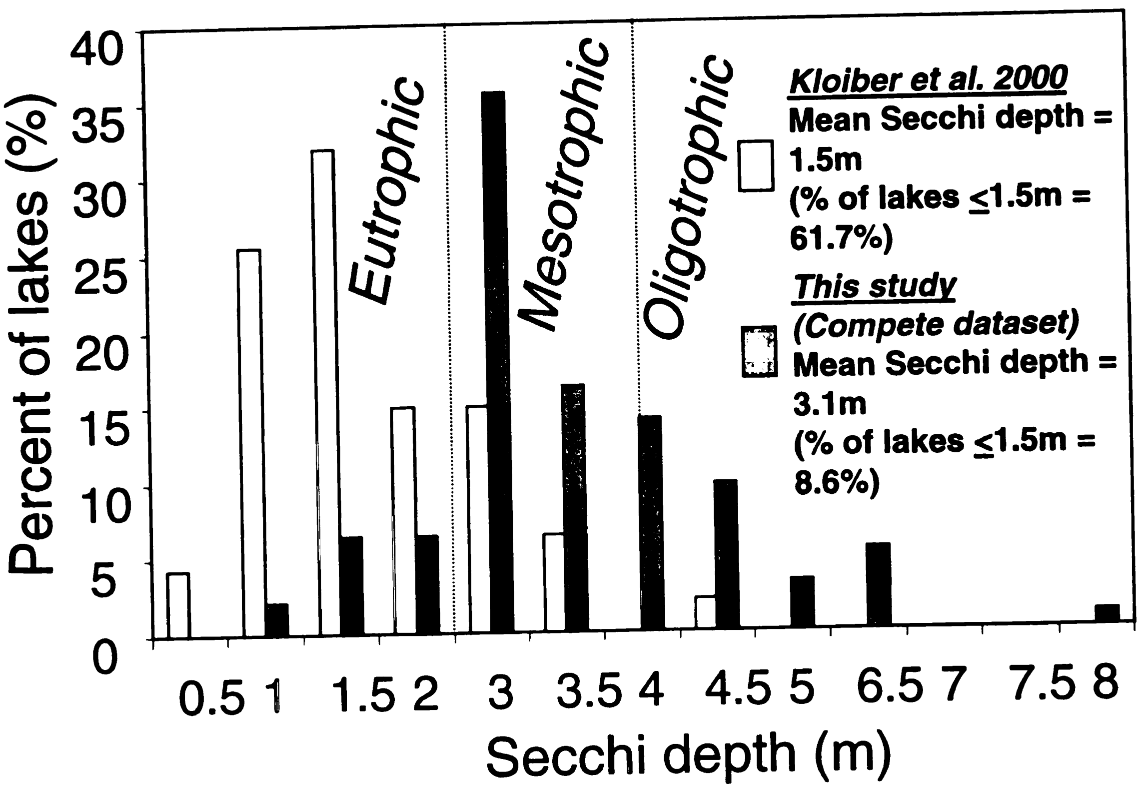

Percent of lakes (%)
40
35
30
25
20
15
10
5
0
Eutrophic
Mesotrophic
Oligotrophic
Kloiber et al. 2000
Mean Secchi depth =
1.5m
(% of lakes ≤1.5m =
61.7%)
This study
(Compete dataset)
Mean Secchi depth =
3.1m
(% of lakes ≤1.5m =
8.6%)
0.5 1 1.5 2 3 3.5 4 4.5 5 6.5 7 7.5 8
Secchi depth (m)

Figure 2.3.

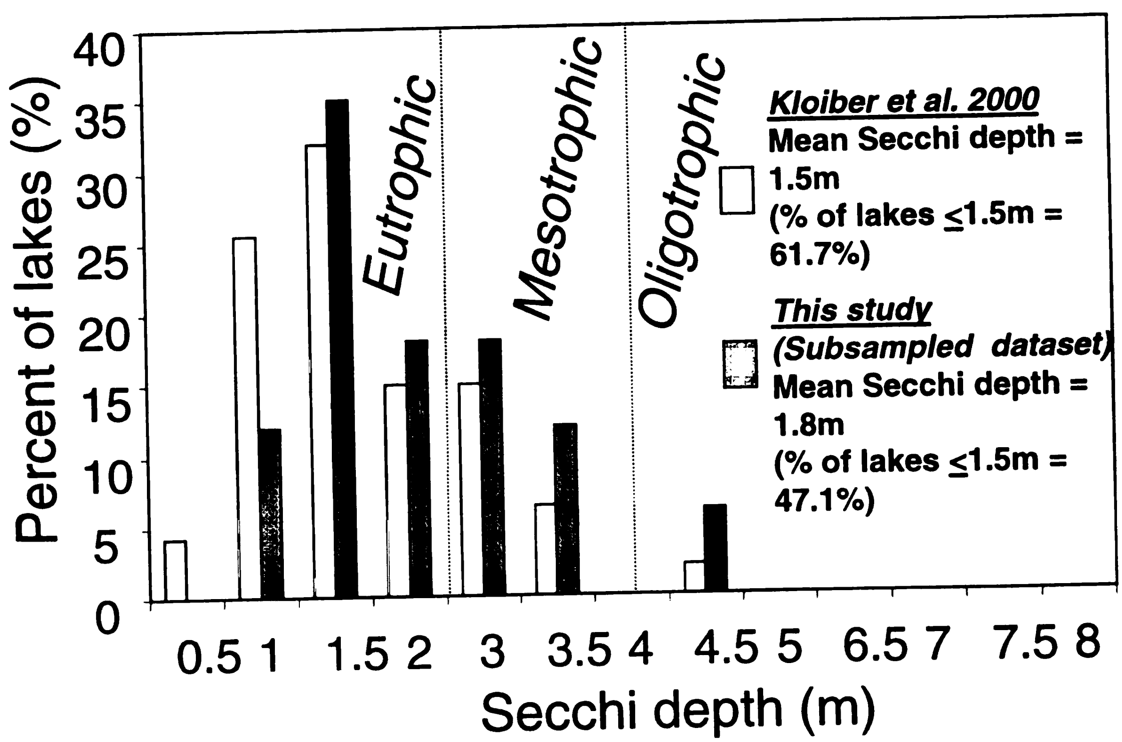
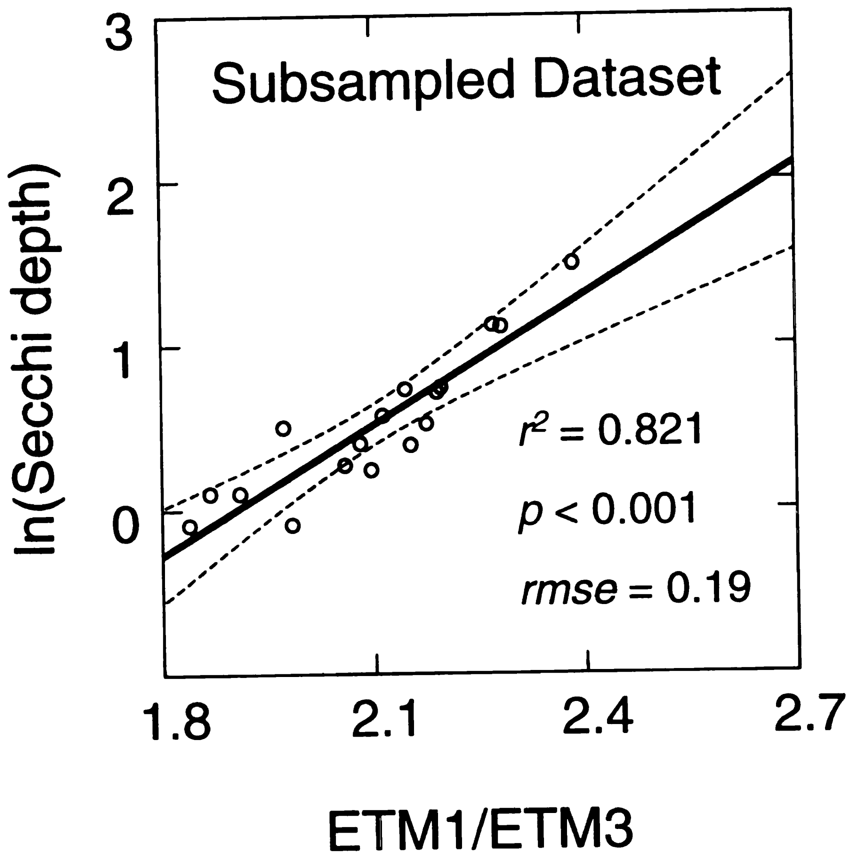
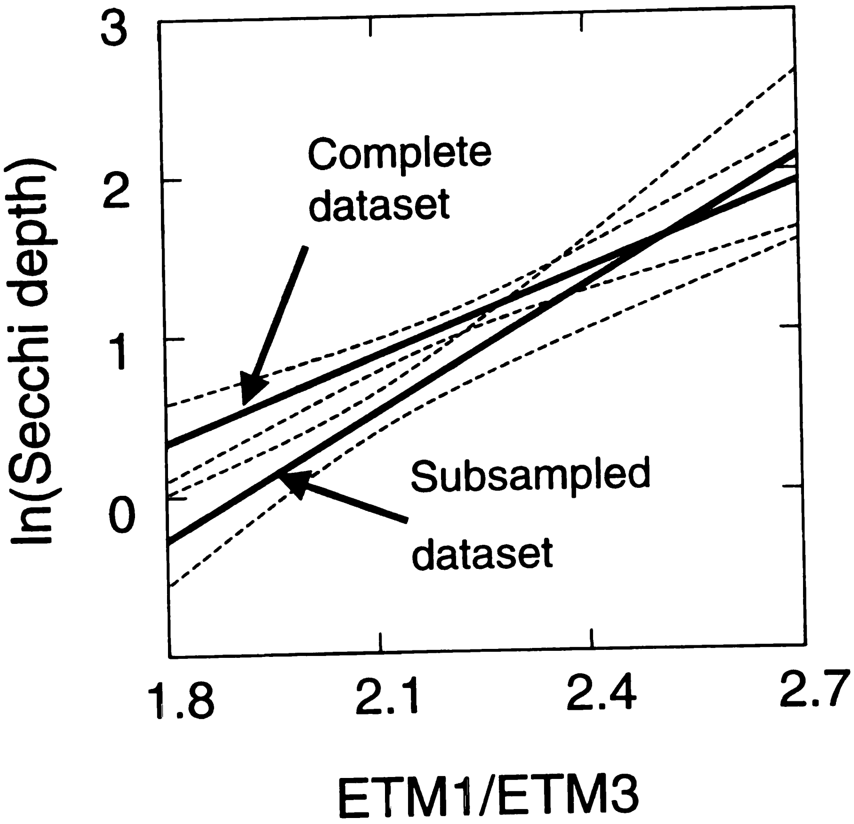

Percent of lakes (%)
0
5
10
15
20
25
30
35
40
Eutrophic
Mesotrophic
Oligotrophic
Kloiber et al. 2000
Mean Secchi depth = 1.5m
(% of lakes ≤1.5m = 61.7%)
This study
(Subsampled dataset)
Mean Secchi depth = 1.8m
(% of lakes ≤1.5m = 47.1%)
0.5 1 1.5 2 3 3.5 4 4.5 5 6.5 7 7.5 8
Secchi depth (m)

Figure 2.4.



Subsampled Dataset
ln(Secchi depth)
ETM1/ETM3
$r^2 = 0.821$
$p < 0.001$
$rmse = 0.19$
3
2
1
0
1.8
2.1
2.4
2.7

Figure 2.5.



3
2
1
0
ln(Secchi depth)
Complete
dataset
Subsampled
dataset
1.8
2.1
2.4
2.7
ETM1/ETM3

Figure 2.6.

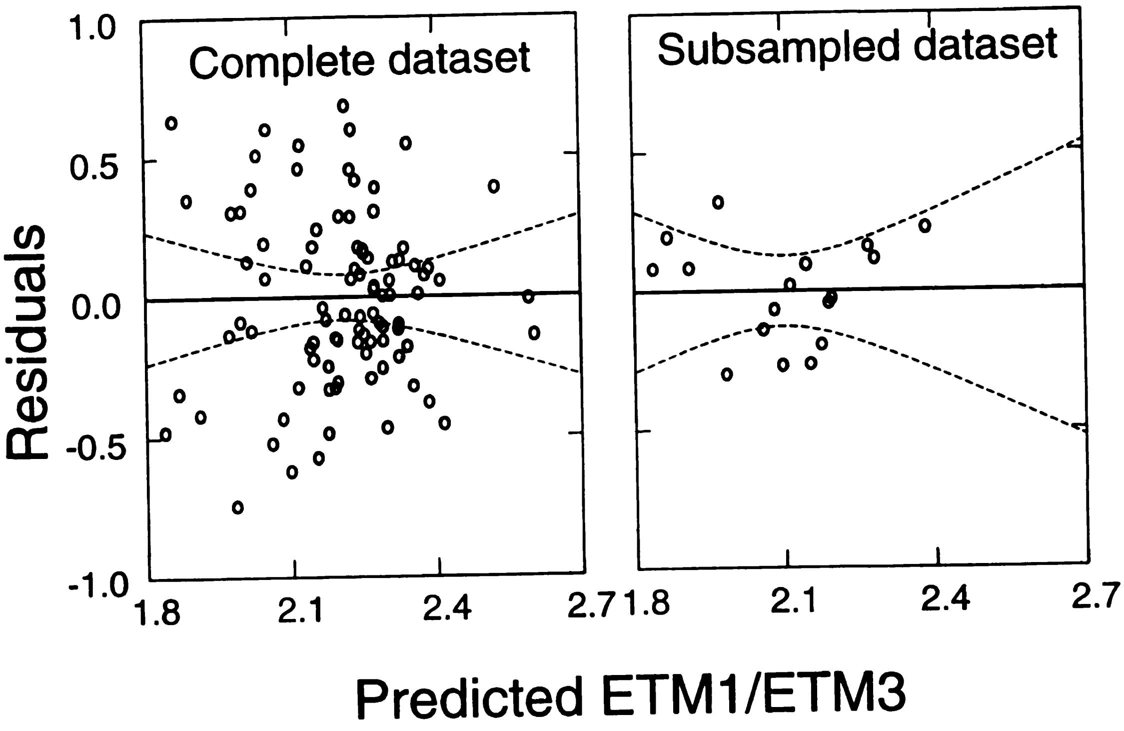

Complete dataset
Subsampled dataset
Residuals
1.0
0.5
0.0
-0.5
-1.0
1.8
2.1
2.4
2.7
Predicted ETM1/ETM3

Figure 2.7.

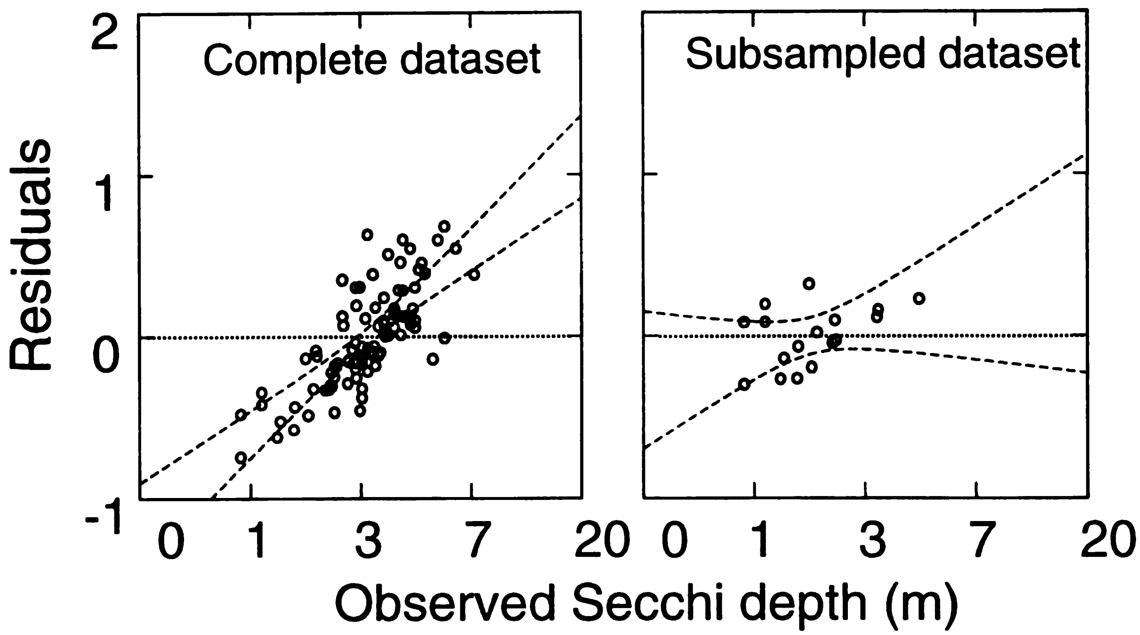

Complete dataset
Subsampled dataset
Residuals
2
1
0
-1
0
1
3
7
20
0
1
3
7
20
Observed Secchi depth (m)

Figure 2.8.

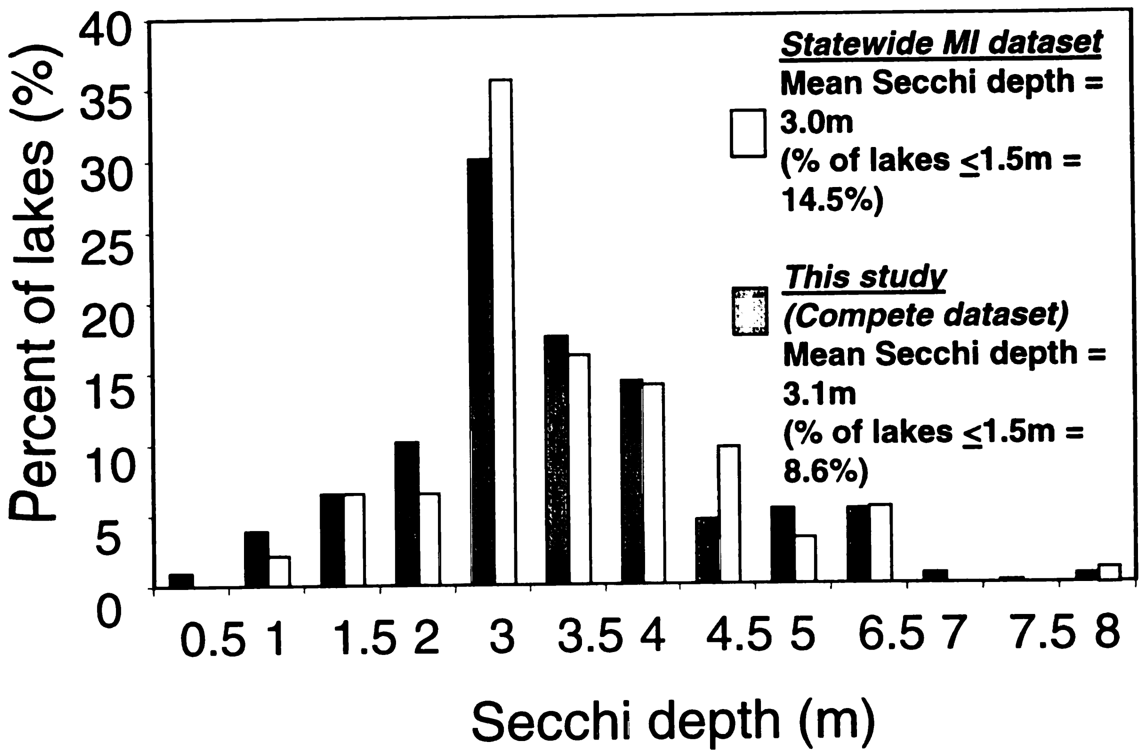

Percent of lakes (%)
40
35
30
25
20
15
10
5
0
0.5 1 1.5 2 3 3.5 4 4.5 5 6.5 7 7.5 8
Secchi depth (m)
Statewide MI dataset
Mean Secchi depth = 3.0m
(% of lakes ≤1.5m = 14.5%)
This study
(Compete dataset)
Mean Secchi depth = 3.1m
(% of lakes ≤1.5m = 8.6%)

Figure 2.9.

APPENDIX 3

Chapter 3 Tables and Figures

Table 3.1a. Physical characteristics and image information for study lakes.

Lake	County	Image date	Days between lake sampling and image acquisition	Surface area (ha)	Mean depth (m)	Sediment color[a]
Deep	Lenawee	August 4, 2001	-10	26.1	7.3	marl
Eagle	Kalamazoo	August 4, 2001	-5	29.1	5.2	sand
Round	Lenawee	August 4, 2001	-9	25.8	5.3	marl
Round	Jackson	August 4, 2001	-18	62.4	2.4	marl
Swains	Jackson	August 4, 2001	-12	30.8	4.3	marl
Vandercook	Jackson	August 4, 2001	-11	57.9	6.8	rocks / cobble / gravel
Baptist	Newaygo	September 5, 2001	-7	34.9	6.9	sand
Dickerson	Montcalm	September 5, 2001	-9	60.2	7.4	rocks / cobble / gravel
Horseshoe	Montcalm	September 5, 2001	-11	37.9	5.1	sand

Little Whitefish	Montcalm	September 5, 2001	-16	72.5	5.5	marl
Nevins	Montcalm	September 5, 2001	-9	21.0	7.2	marl
Sunrise	Osceola	September 5, 2001	+7	82.4	8.4	rocks / cobble / gravel
Winfield[b]	Montcalm	September 5, 2001	-11	47.3	4.5	sand

[a] Littoral zone sediment color estimates were based on an average of six to ten sample sites per lake which were qualitatively assigned a category: sand, rocks/cobble/gravel, marl, or silt/muck/peat.

[b] Winfield Lake was used for model validation, thus was not used for model development.

Table 3.1b. Limnological characteristics of study lakes.

Lake	Image date	Secchi disc transparency (m)	Water color[a] (Co-Pt)	Chl[b] a (*u*g/L)	Total phosphorus (*u*g/L)	Total nitrogen (*u*g/L)	Alkalinity (mg/L $CaCO_3$)	Phytoplankton biovolume (um^3/mL)
Deep	8/4/2001	2.6	14	1.8	8	297	200	1,467,500
Eagle	8/4/2001	2.0	5	3.5	25	182	192	1,415,600
Round (Lenawee)	8/4/2001	3.3	9	2.2	16	486	144	5,110,100
Round (Jackson)	8/4/2001	2.0	7	1.6	15	462	184	498,300
Swains	8/4/2001	1.6	10	3.0	20	448	200	7,318,100
Vandercook	8/4/2001	2.5	29	3.2	13	329	280	5,838,000
Baptist	9/5/2001	4.5	5	3.3	23	275	86	10,591,300
Dickerson	9/5/2001	2.7	20	2.5	19	385	196	4,695,700
Horseshoe	9/5/2001	1.0	11	13.7	27	429	200	11,642,100

Little Whitefish	9/5/2001	4.1	7	4.1	14	238	192	3,731,000
Nevins	9/5/2001	2.8	3	2.0	6	277	140	3,189,400
Sunrise	9/5/2001	3.1	10	5.0	8	248	44	7,094,000
Winfield[c]	9/5/2001	1.9	30	7.7	18	485	144	3,226,700

[a] Water color values collected by MI-DEQ 1974-1981, STORET. Measured on the cobalt-platinum scale (Co-Pt units), which ranges from 0 in very clear lakes to 300 Co-Pt in heavily stained bog waters, which have high concentrations of humic substances.

[b] Chlorophyll

[c] Winfield Lake was used for model validation, thus was not used for model development.

Table 3.2. Results from the logit regressions for the three models.

Plant category	Statistical test	August model	September model	Combined model
Littoral plant cover	*Percent concordance* [a]	65 %	72 %	71 %
	Wald test [b]	<0.001	<0.001	<0.001
	N^c	6	6	12
Emergent	*Percent concordance* [a]	89 %	78 %	74 %
	Wald test [b]	<0.001	<0.001	<0.001
	N^c	5	6	11
Floating	*Percent concordance* [a]	89 %	83 %	86 %
	Wald test [b]	<0.001	<0.001	<0.001
	N^c	5	6	11
Total submersed	*Percent concordance* [a]	71 %	62 %	66 %
	Wald test [b]	<0.001	<0.001	<0.001
	N^c	6	6	12

Submersed EWM	*Percent concordance*[a]	62 %	39 %	59 %
	Wald test[b]	<0.001	0.067	<0.001
	N[c]	6	6	12

[a] Percent concordance assesses the overall model quality based on the maximum likelihood estimation of all pairs of observations with different values of the response variable (plant category). For example, because the models predict the probability of detecting a plant category, if the larger response value (> 0 for a level of plant cover) has a higher predicted event probability than the smaller response value (0, nonevent or < 20% plant cover), then the observation pair is concordant. Pairs are calculated from the number of observations within each category level submodel, which makes up the overall logit regression for each plant category.

[b] The Wald test is the chi-square statistic for overall model fit. It tests the hypothesis that the coefficient of an independent variable is significantly different from zero.

[c] N refers to the total number of lakes in the model.

Table 3.3. T-test p values from testing the difference between the means of the beta coefficients (log transformed) for the 12 individual lakes used in the August and September logit models.

Plant Category	**TM2**	**TM4**	**TM2*Depth**	**TM4*Depth**
Littoral plant cover	0.30	0.24	0.40	0.19
Emergent	0.23	0.24	0.18	0.40
Floating	0.30	0.49	0.30	0.30
Total submersed	0.23	0.38	0.82	0.68
Submersed EWM	0.20	0.33	0.90	0.28

Table 3.4. Regression results of the model coefficients estimated on individual lake datasets versus selected lake variables. Values in bold are significant at the 0.10 level. See table 1a. for lake characteristic units.

		Secchi disk transparency		Water Color		Chlorophyll a		Phyto.* biovolume		Sediment color	
Plant Category	**Coefficient Values**	r^2	p	r^2	P	r^2	P	r^2	p	r^2	p
Littoral plant	TM2	0.05	*0.50*	0.09	*0.39*	0.13	*0.28*	0.08	*0.40*	0.06	*0.49*
cover	TM4	0.03	*0.62*	0.05	*0.53*	0.00	*0.96*	0.10	*0.35*	0.23	*0.14*
	TM2*Depth	0.09	*0.36*	0.00	*0.87*	0.07	*0.44*	0.00	*0.88*	0.00	*0.99*
	TM4*Depth	0.01	*0.80*	0.07	*0.44*	0.04	*0.57*	**0.27**	***0.10***	0.00	*0.90*
Emergent	TM2	0.02	*0.70*	0.00	*0.89*	0.11	*0.31*	**0.28**	***0.10***	0.11	*0.32*
	TM4	0.24	*0.13*	0.20	*0.16*	0.00	*0.91*	0.07	*0.43*	0.13	*0.28*
	TM2*Depth	0.02	*0.67*	0.13	*0.28*	0.02	*0.66*	0.02	*0.70*	0.10	*0.36*
	TM4*Depth	0.03	*0.59*	0.08	*0.39*	0.05	*0.53*	0.18	*0.19*	0.04	*0.55*

Floating	TM2	0.00	*0.87*	0.03	*0.64*	0.02	*0.66*	0.11	*0.32*	0.03	*0.61*
	TM4	0.00	*0.86*	0.02	*0.67*	0.03	*0.61*	0.14	*0.25*	0.06	*0.47*
	TM2*Depth	0.01	*0.80*	0.02	*0.66*	0.01	*0.76*	0.11	*0.32*	0.04	*0.56*
	TM4*Depth	0.00	*0.85*	0.02	*0.71*	0.02	*0.66*	0.14	*0.26*	0.06	*0.47*
Total submersed	TM2	0.01	*0.74*	0.09	*0.35*	0.14	*0.23*	**0.42**	***0.02***	0.13	*0.25*
	TM4	0.06	*0.46*	0.06	*0.47*	0.00	*0.98*	0.11	*0.30*	0.22	*0.12*
	TM2*Depth	0.00	*0.85*	0.02	*0.64*	0.02	*0.67*	0.05	*0.48*	0.00	*0.98*
	TM4*Depth	0.04	*0.54*	0.21	*0.14*	0.00	*0.92*	0.14	*0.23*	0.04	*0.51*
Submersed EWM	TM2	0.01	*0.84*	0.11	*0.29*	0.03	*0.62*	0.13	*0.25*	0.12	*0.27*
	TM4	0.06	*0.46*	0.08	*0.37*	0.01	*0.79*	0.16	*0.20*	0.16	*0.20*
	TM2*Depth	0.05	*0.51*	0.10	*0.32*	0.05	*0.51*	0.17	*0.18*	0.00	*0.89*
	TM4*Depth	0.09	*0.33*	0.05	*0.50*	0.03	*0.57*	**0.25**	***0.10***	0.04	*0.53*
	Average r^2	0.04		0.07		0.04		0.15		0.08	

* Phytoplankton.

Table 3.5. Regression results of Landsat TM2 and TM4 versus selected pelagic lake characteristics using the combined dataset of all lakes (N = 12). See table 1a for lake characteristic units.

Lake Characteristics	r^2	p
Secchi disk transparency	0.62	0.01
Water color	0.03	0.87
Chlorophyll *a*	0.65	0.01
Phytoplankton biovolume	0.56	0.03

Table 3.6. Results of the model validation using Winfield Lake. The total number of littoral zone sites in Winfield Lake is 137.

Plant Category	Cover Level	September model Average probability of correctly classifying each level	Combined model Average probability of correctly classifying each level	# of observed sites
Littoral Plant Cover	0	0.97	0.96	14
	1	0.00	0.00	123
	Average	**0.49**	**0.48**	
Emergent	0	0.02	0.00	128
	1	0.09	0.03	3
	2	0.78	0.11	5
	3	---	0.89	1
	Average	**0.29**	**0.26**	
Floating Leaf	0	0.02	0.04	123
	1	0.06	0.09	6

	2	0.22	0.12	5
	3	0.69	0.66	3
	Average	**0.25**	**0.23**	
Total Submersed	0	0.30	0.26	17
	1	0.22	0.18	15
	2	0.17	0.20	24
	3	0.31	0.35	81
	Average	**0.25**	**0.25**	
Submersed EWM	0	0.00	0.02	99
	1	0.05	0.05	32
	2	0.94	0.92	6
	3	---	---	0
	Average	**0.33**	**0.33**	

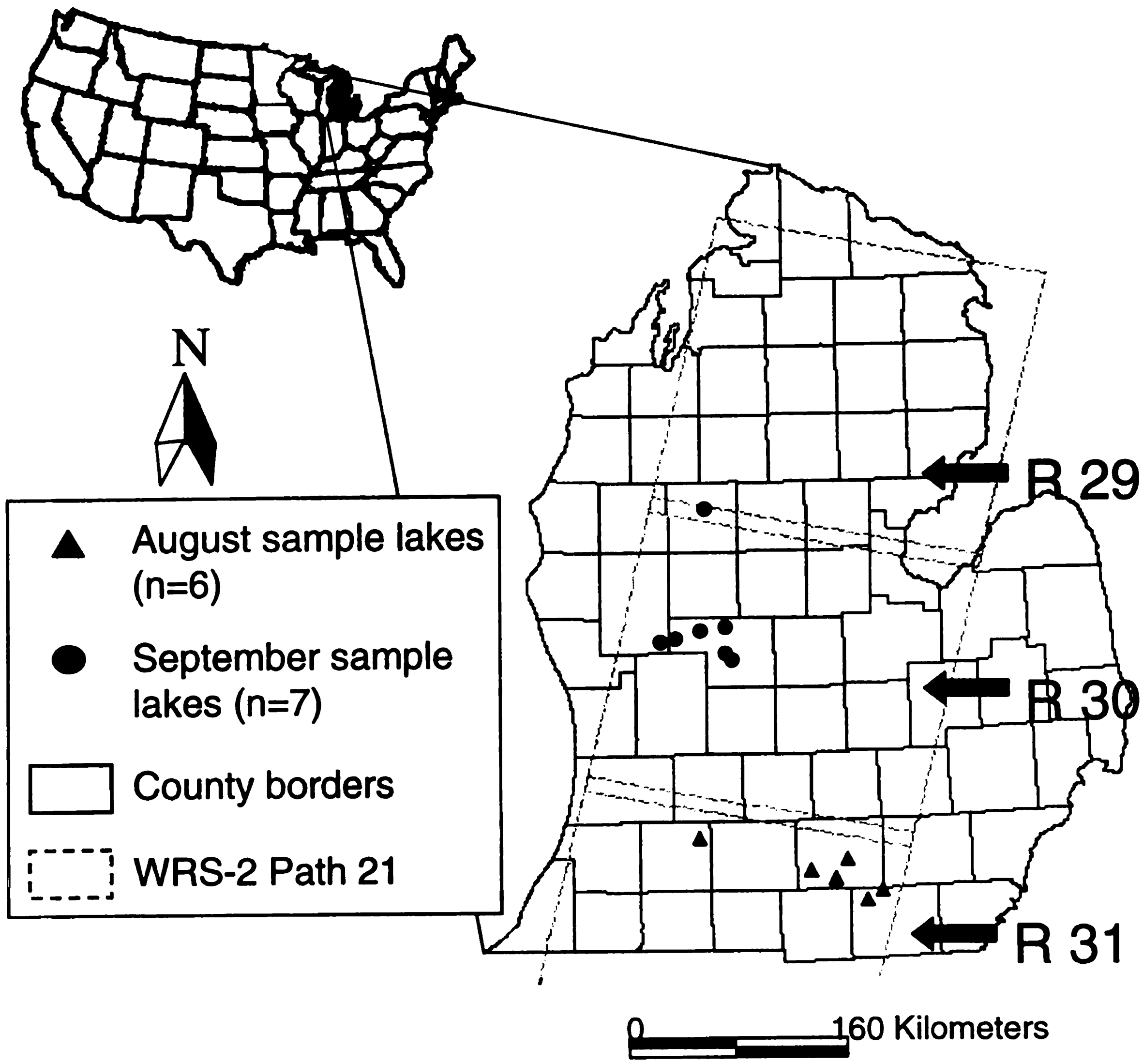

N
August sample lakes (n=6)
September sample lakes (n=7)
County borders
WRS-2 Path 21
R 29
R 30
R 31
0
160 Kilometers

Figure 3.1.

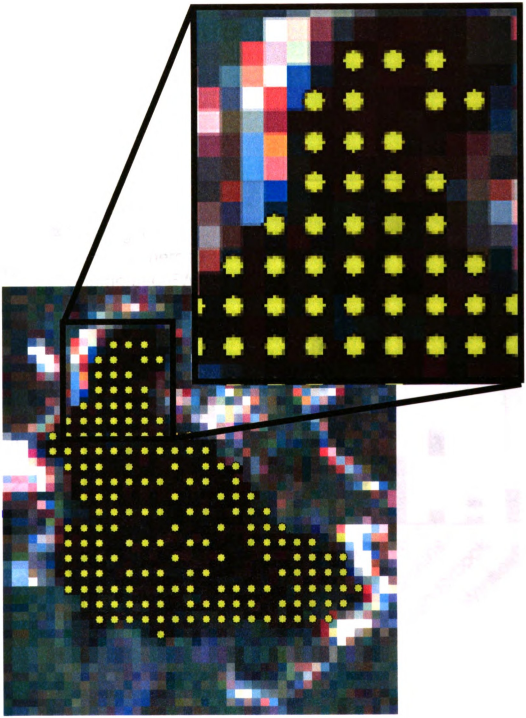
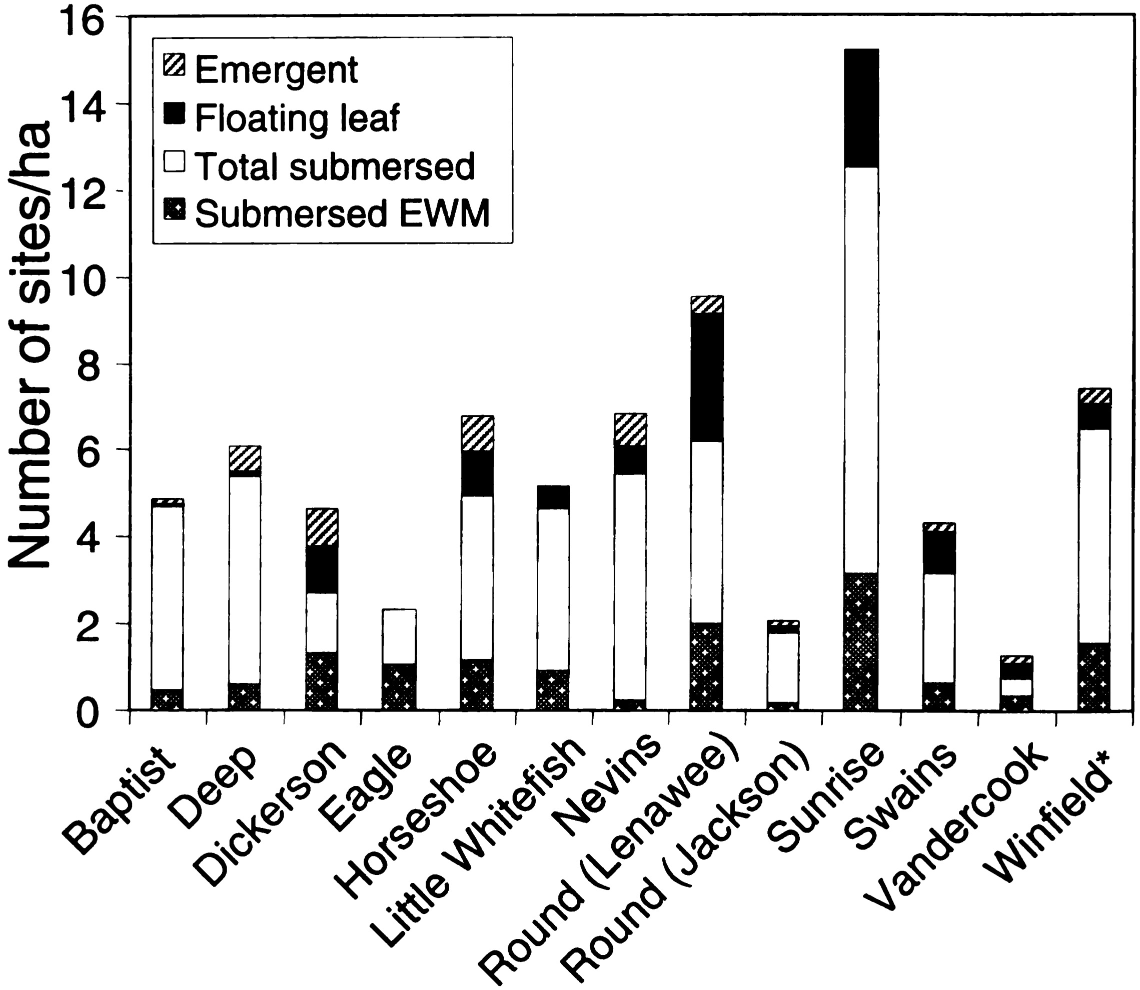


Figure 3.2.



16
14
12
10
8
6
4
2
0
Number of sites/ha
Emergent
Floating leaf
Total submersed
Submersed EWM
Baptist
Deep
Dickerson
Eagle
Horseshoe
Little Whitefish
Nevins
Round (Lenawee)
Round (Jackson)
Sunrise
Swains
Vandercook
Winfield*

Figure 3.3.

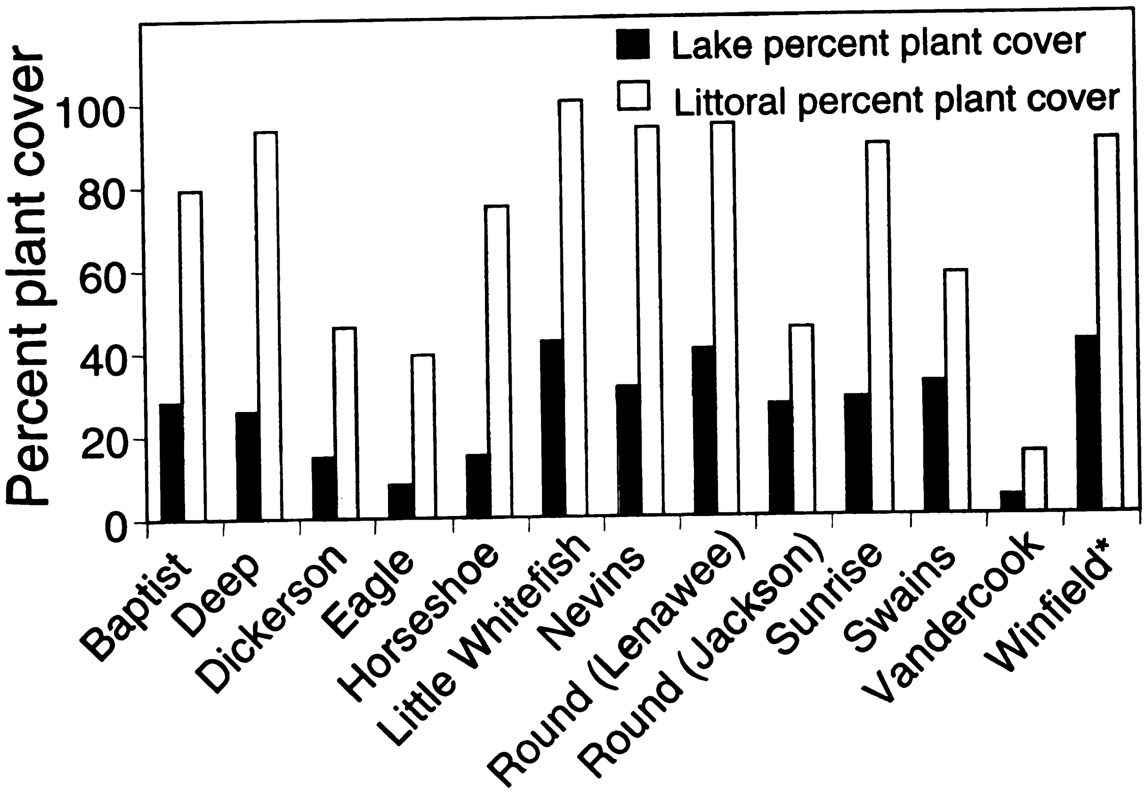

Lake percent plant cover
Littoral percent plant cover
Percent plant cover
0
20
40
60
80
100
Baptist
Deep
Dickerson
Eagle
Horseshoe
Little Whitefish
Nevins
Round (Lenawee)
Round (Jackson)
Sunrise
Swains
Vandercook
Winfield*

Figure 3.4.

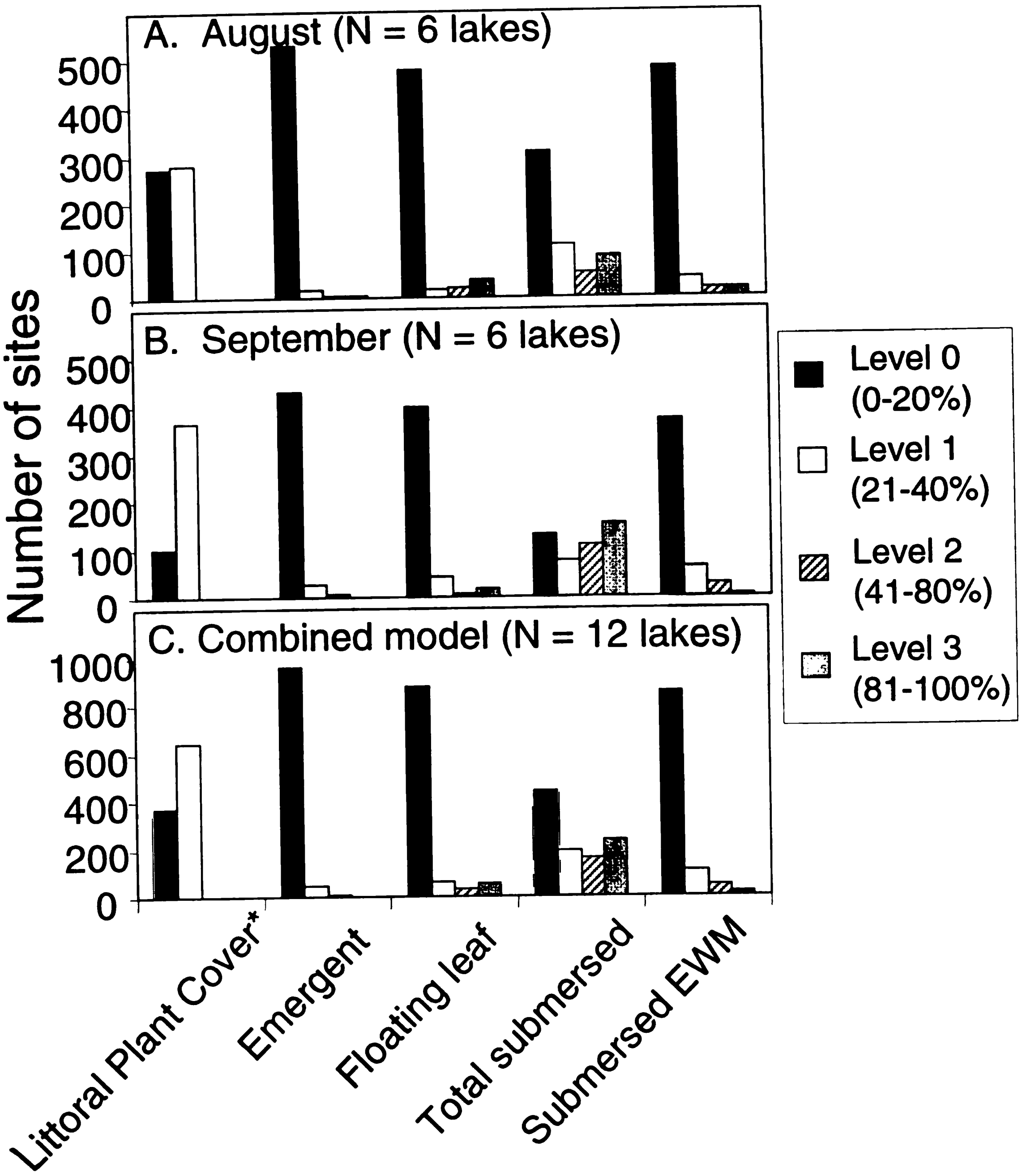

A. August (N = 6 lakes)
B. September (N = 6 lakes)
C. Combined model (N = 12 lakes)
Number of sites
0
100
200
300
400
500
600
800
1000
Level 0
(0-20%)
Level 1
(21-40%)
Level 2
(41-80%)
Level 3
(81-100%)
Littoral Plant Cover*
Emergent
Floating leaf
Total submersed
Submersed EWM

Figure 3.5.

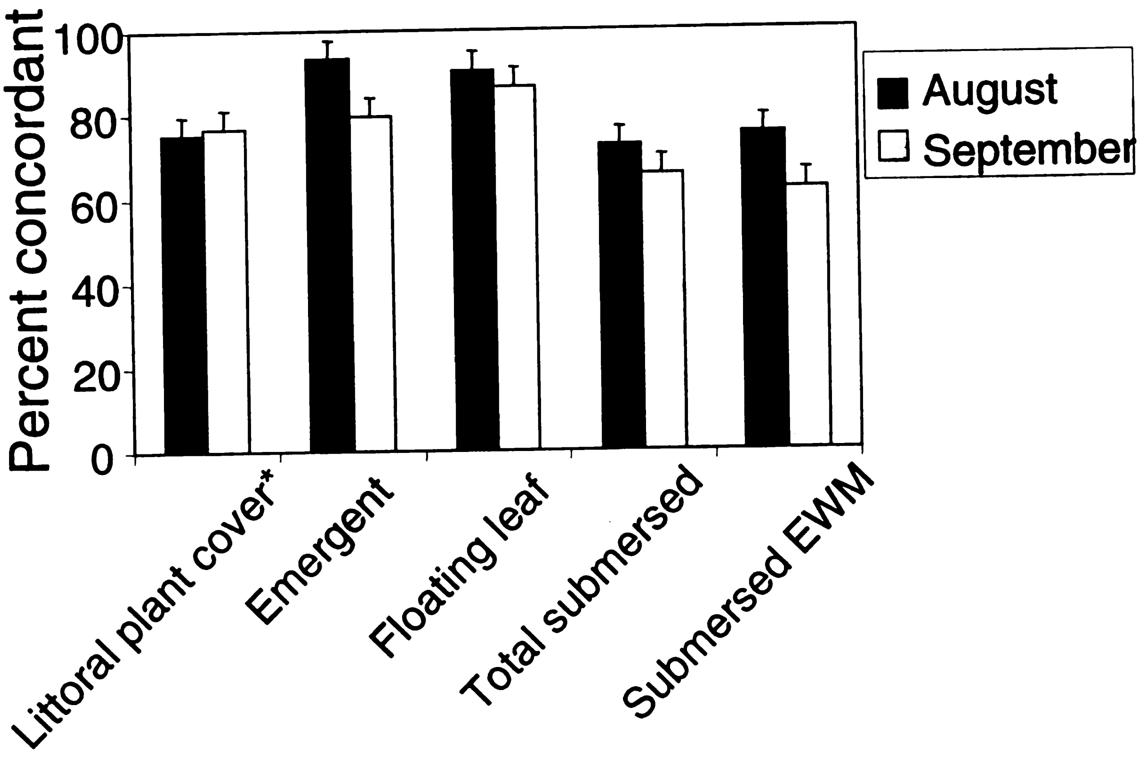
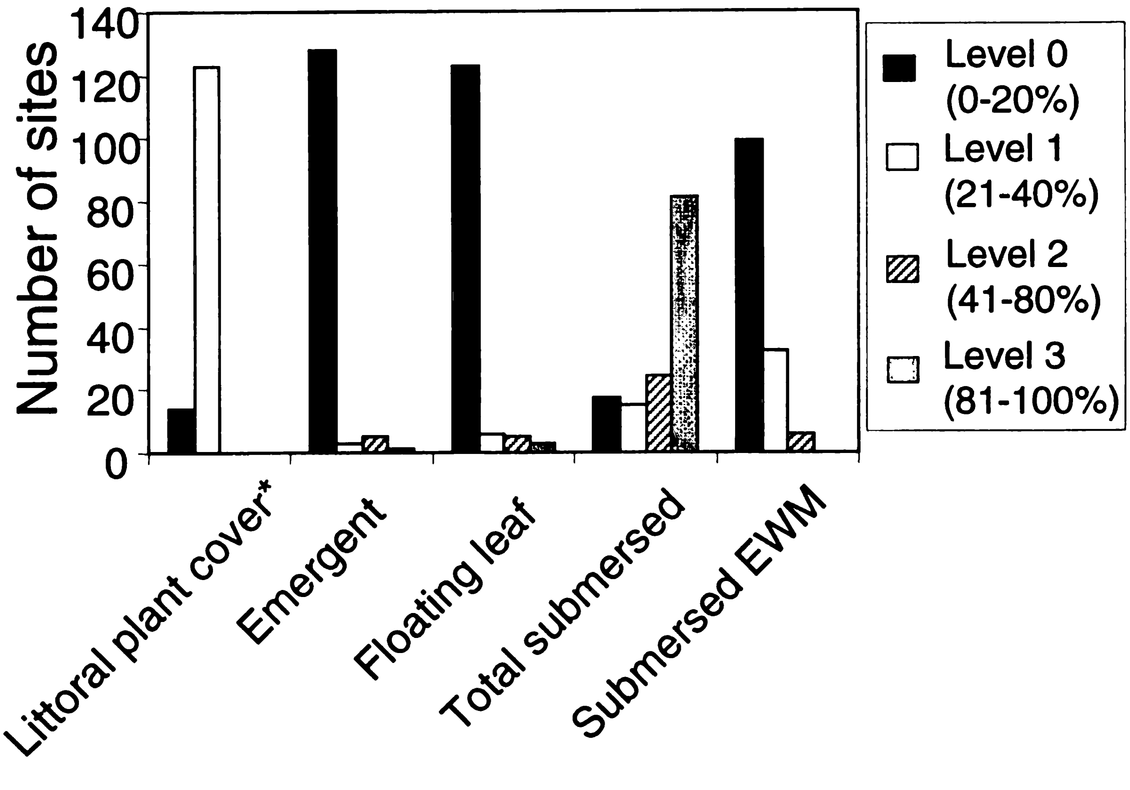

Percent concordant
100
80
60
40
20
0
August
September
Littoral plant cover*
Emergent
Floating leaf
Total submersed
Submersed EWM

Figure 3.6.



Number of sites
0
20
40
60
80
100
120
140
Littoral plant cover*
Emergent
Floating leaf
Total submersed
Submersed EWM
Level 0 (0-20%)
Level 1 (21-40%)
Level 2 (41-80%)
Level 3 (81-100%)

Figure 3.7.