5-2012

Remote Estimation of Regional Lake Clarity with Landsat TM and MODIS Satellite Imagery

Ian M. McCullough

REMOTE ESTIMATION OF REGIONAL LAKE CLARITY WITH

LANDSAT TM AND MODIS SATELLITE IMAGERY

By

Ian M. McCullough

B.A. Colby College, 2010

A THESIS

Submitted in Partial Fulfillment of the

Requirements for the Degree of

Master of Science

(in Ecology and Environmental Science)

The Graduate School

The University of Maine

May, 2012

Advisory Committee:

Cynthia S. Loftin, Unit Leader, U.S. Geological Survey Maine Cooperative Fish and Wildlife Research Unit, Associate Professor of Wildlife Ecology, Co-Advisor

Steven A. Sader, Professor of Forest Resources, Co-Advisor

Aram J. K. Calhoun, Professor of Wetlands Ecology

William A. Halteman, Professor of Mathematics

THESIS ACCEPTANCE STATEMENT

On behalf of the Graduate Committee for Ian McCullough, I affirm that this manuscript is the final and accepted thesis. Signatures of all committee members are on file with the Graduate School at the University of Maine, 42 Stodder Hall, Orono, Maine.

Cynthia S. Loftin, Unit Leader, USGS ME Coop. Research Unit	Date
Steven A. Sader, Professor of Forest Resources	Date

LIBRARY RIGHTS STATEMENT

REMOTE ESTIMATION OF REGIONAL LAKE CLARITY WITH LANDSAT TM AND MODIS SATELLITE IMAGERY

By

Ian M. McCullough

Thesis Co-Advisors: Dr. Cynthia S. Loftin and Dr. Steven A. Sader

An Abstract of the Thesis Presented
in Partial Fulfillment of the Requirements for the
Degree of Master of Science
(in Ecology and Environmental Science)
May, 2012

Water clarity is an ideal metric of regional water quality because clarity can be accurately and efficiently estimated remotely on a landscape scale. Remote sensing of water quality is useful in regions containing numerous lakes that are prohibitively expensive to monitor regularly using traditional field methods. Field-assessed lakes generally are easily accessible and may represent a spatially irregular, non-random sample. Remote sensing provides a more complete spatial perspective of regional water quality than existing, interest-based sampling; however, field sampling accomplished under existing monitoring programs can be used to calibrate accurate remote water clarity estimation models. We developed a remote monitoring procedure for clarity of Maine lakes using Landsat Thematic Mapper (TM) and Moderate-Resolution Imaging Spectroradiometer (MODIS) satellite imagery. Similar Landsat-based procedures have

been implemented for Minnesota and Wisconsin lakes, however, we modified existing methods by incorporating physical lake variables and landscape characteristics that affect water clarity on a landscape scale. No published studies exist using MODIS data for remote lake monitoring owing to the coarse spatial resolution (500 m) (Landsat=30 m), however, daily image capture is an important advantage over Landsat (16 days). We estimated secchi disk depth during 1990-2010 using Landsat imagery (1,511 lakes) and during 2001-2010 using MODIS imagery (83 lakes) using multivariate linear regression (Landsat: R^2=0.69-0.89; 9 models; MODIS: R^2=0.72-0.94; 14 models). Landsat is useful for long-term monitoring of lakes > 8 ha and MODIS is applicable to annual and within-year monitoring of large lakes (> 400 ha).

An important application of remote lake monitoring is the detection of spatial and temporal patterns in regional water quality and potential downward shifts in trophic status. We applied the Landsat-based methods to examine trends in Maine water clarity during 1995-2010. Remote change detection of water clarity should be based on August and early September (late summer) imagery only owing to seasonally poor clarity conditions and stratification dynamics, so our analysis was restricted to years in which late summer imagery were available. We focused on the overlap region between Landsat TM paths 11-12 to increase late summer image availability. We divided Maine intro three lake regions (northeastern, south-central and western) to examine spatial patterns in lake clarity. The overlap region contains 570 lakes > 8 ha and covers the entire north-south gradient of Maine. We found an overall decrease in average statewide lake water clarity of 4.94-4.38 m during 1995-2010. Water clarity ranged 4-6 m during 1995-2010, but consistently decreased during 2005-2010. Clarity in both the northeastern and western regions has experienced declines from 5.22 m in 1995 to 4.36 and 4.21 m respectively in 2010, whereas clarity in the south-central region remained unchanged since 1995 (4.50 m).

ACKNOWLEDGMENTS

Financial support for this project was provided by the U.S. Geological Survey Maine Cooperative Fish and Wildlife Research, the University of Maine Department of Wildlife Ecology and the Maine Department of Environmental Protection (MDEP).

I would like to thank my co-advisors, Cynthia Loftin and Steven Sader, and my committee members, Aram Calhoun and Bill Halteman for their assistance in developing the scope and structure of my research project. Each member of my advisory committee contributed bright ideas that were instrumental in making my thesis a success. I also thank Kasey Legaard for providing important advice for satellite image processing and atmospheric corrections.

I would like to extend a special thanks to the Maine Volunteer Lake Monitoring Program, which in conjunction with MDEP, has collected lake water clarity data throughout Maine since 1971. This dedicated organization of citizen-scientists has collectively made invaluable contributions to scholarly research and my academic career through the creation of a 40-year long-term water clarity dataset. Remote assessment of statewide water clarity in Maine would not be possible if not for the efforts of volunteers and MDEP.

I appreciate the help of Doug Suitor and Leslie Latt of MDEP for creating a GIS layer of lake watersheds in Maine. This is a significant contribution that helped make my first chapter publishable in an international remote sensing journal. Also deserving of thanks is Linda Bacon, a biologist at MDEP, who compiled all lake clarity field data and consistently raised important questions concerning successful implementation of the methods described in this study.

I finally owe thanks to those who have helped me get where I am today. The continued support of my family ultimately makes my scientific career possible. Russ Cole of Colby College gave me my first research job as a sophomore and remarkably still does not regret it. Manuel Gimond, also of Colby, has shared his quantitative expertise throughout my years working in Maine and tolerates me having his office phone number memorized. It was incredibly helpful to speak with him when I was initially designing the methods for this project.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1

COMBINING LAKE AND WATERSHED CHARACTERISTICS WITH LANDSAT TM DATA FOR REMOTE ESTIMATION OF REGIONAL LAKE CLARITY

1.1. INTRODUCTION

Water clarity (or transparency) is a common metric of lake water quality often measured as secchi disk depth (SDD). Lake clarity is closely linked to other water quality variables such as trophic status, chlorophyll-a and total phosphorus and is a generally strong indicator of lake health (Carlson 1977). Assessments are relatively cheap, simple and efficient and can be performed by lakeshore residents who may own and operate boats on the lakes they monitor and are direct stakeholders in lake water quality. Increased lake clarity increases lakefront property value in Maine (Michael et al. 1996, Boyle et al. 1999) and New Hampshire (Gibbs et al. 2002) and also enhances user-perception of Minnesota lake water quality (Heiskary and Walker 1988). Because clarity assessments are widely used and have strong ecological and economic implications, clarity is an ideal metric of regional lake water quality. Regional water quality assessments, however, are logistically challenging owing to costs, lake accessibility and the number of waterbodies requiring repeated sampling. These restrictions lead to field assessments concentrated in developed, easily accessible areas, which create spatially irregular, non-random samples. Many lakes are rarely or never monitored, so an accurate assessment of their status and change over time cannot be made.

Remote data collection in regional water quality monitoring reduces costs associated with inaccessibility of remote lakes and enables monitoring to occur simultaneously across an extensive area. Remote sensing, however, has a number of limitations. Clouds constrain usable imagery and affect reliability of monitoring on targeted dates. Haze in the atmosphere (Rayleigh scatter) interferes with spectral-radiometric responses and may cause inaccurate assessments. Cost potentially is a limiting factor; although some platforms are free (e.g., Landsat Thematic Mapper - TM), others are more costly in routine assessments, particularly high-resolution sensors such as those carried on WorldView and GeoEye satellites. Calibration of remotely collected data requires site-based sampling that is nearly concurrent with remote data capture, illustrating that remote sensing is not entirely independent of field-based monitoring.

Regional remote monitoring procedures have been developed for lakes in Wisconsin (Chipman et al. 2004) and Minnesota (Kloiber et al. 2002b, Olmanson et al. 2008) using Landsat TM imagery and volunteer-collected SDD data. These programs considerably increased knowledge of regional water quality, however, their procedures rely solely on spectral data and do not consider additional factors that potentially affect water clarity. In this study, we developed models to estimate water clarity of lakes in Maine, USA from Landsat data, and we improved model performance by including physical lake characteristics and landscape features to explain variability in lake clarity consistently across years.

1.2. DESCRIPTION OF STUDY AREA

Located in the northeastern United States, Maine contains over 5,500 lakes and ponds > 1 ha in surface area across a total area of approximately 90,000 km² (Fig. 1.1). Maine ranks first among states east of the Great Lakes in total area of inland surface waters (Davis et al. 1978). Maine is a cold-temperate climate with long, cold winters and short, warm summers. Western Maine is rural and mountainous, whereas southern coastal areas are more developed. Lakes are well-distributed throughout the state and average depth ranges 1-32 m. Lakes range in size from small ponds < 1 ha to Moosehead Lake (30,542 ha), the largest lake in Maine. The state's lake water clarity monitoring program began in 1970 and SDD has ranged 0.1-21.3 m since 1970. The average annual SDD consistently has remained 4-6 m, with a historical average of 5.27 m during 1970-2009, and was 5.14 m in 2009 (n=457) (Maine Department of Environmental Protection, MDEP; Bacon 2010, Maine Volunteer Lake Monitoring Program 2010). The number of lakes sampled changes annually and generally has increased from 18 lakes sampled in 1970 to consistently > 400 lakes since 1999.

1.3. METHODS

1.3.1. Landsat data selection

Most of Maine is covered by Landsat paths 11-12, rows 27-30 (Fig. 1.1). Paths of images captured during mid-late summer were selected every 3-7 years from 1990-2010 based on image quality and temporal adjacency of images from both paths. Mid-late summer (July 15-September 15) is the best time to estimate lake clarity remotely, because lake clarity is relatively stable during this time (Stadelmann et al. 2001). This also is the period with the greatest abundance of volunteer-collected calibration data. Owing to cloud cover, suitable images were available only during August 9-September 14 over the 20-year period, with most images from early September (Table 1.1). A 20-year window was chosen to assess model applicability over time. All images except 1 date were Landsat 5, owing to better image quality on targeted dates and the 2003 scan line corrector (SLC) failure in Landsat 7. SLC-off images can be used to estimate SDD (Olmanson et al. 2008), however, this requires careful pixel extraction and more processing time. No suitable images were available for path 11 to correspond with path 12 images from 1990

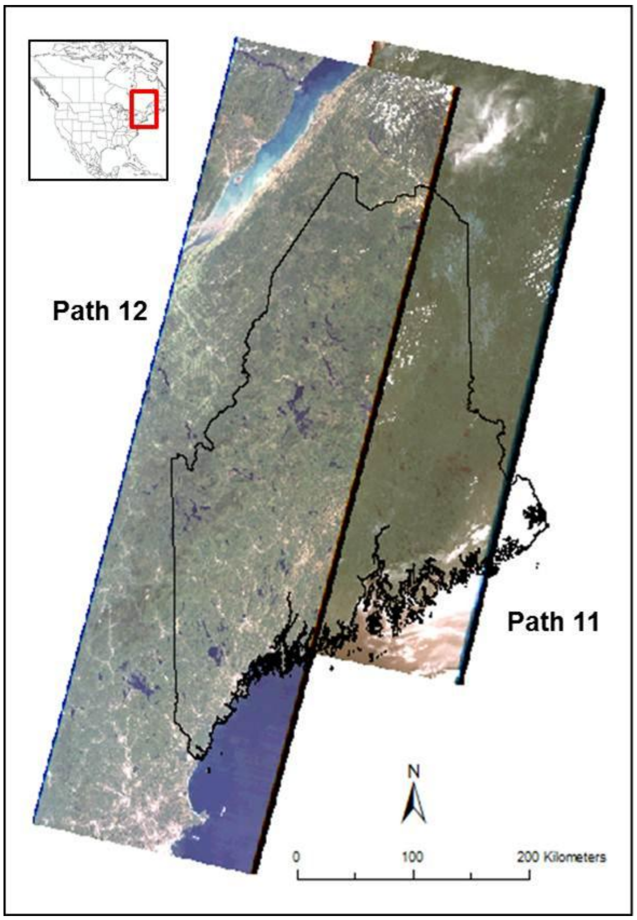

Fig. 1.1. Landsat TM paths 11 and 12 over Maine, USA.

Table 1.1. Landsat imagery used for remote estimation of lake clarity

Path[a]	Rows	Acquisition Date	% Clouds	Satellite/Sensor
12	27-30	8/30/2010	0	Landsat 5 TM
12	27-30	9/14/2004	0	Landsat 5 TM
12	27-30	9/1/1999	0	Landsat 5 TM
12	27-30	9/6/1995	0	Landsat 5 TM
12	27-30	9/8/1990	0	Landsat 5 TM
11	28-29	9/5/2009	6	Landsat 5 TM
11	27-29	8/9/2005	8	Landsat 5 TM
11	27-29	8/9/2002	0	Landsat 7 ETM+
11	27-29	8/14/1995	2	Landsat 5 TM

[a] Path 11, row 27 scene omitted due to cloud cover on 9/5/2009

1.3.2. Supplementary lake data

Although satellite imagery previously has been used to monitor lake water clarity (Kloiber et al. 2002a, Chipman et al. 2004, Olmanson et al. 2008), ancillary lake variables were not considered in these applications. We combined satellite imagery data with variables describing physical lake characteristics and watershed disturbance in our models. We obtained previously collected average and maximum depth data to characterize lake bathymetry (MDEP; Bacon 2011). We used a watershed perimeter layer (MDEP; Suitor 2011) combined with an enhanced National Wetlands Inventory (NWI) layer (Houston 2008) to calculate the proportion of wetland area in lake watersheds (ArcGIS ® version 10.0; Environmental Systems Research Inc., Redlands, CA, United States). We used wetland area as a proxy for watershed disturbance because wetlands help regulate lake clarity and inversely indicate land potentially available for development. The proportion of wetland area in lake watersheds is positively correlated with lake color, which is significantly associated with water clarity of Minnesota lakes (Detenbeck et al. 1993). Water color is regulated by dissolved organic carbon (DOC), which negatively affects water clarity (Gunn et al. 2001). DOC has a particularly strong influence on water clarity in oligotrophic lakes (Gunn et al. 2001), of which there are many in Maine. Lake area, perimeter and surface area/perimeter ratio were calculated from a lakes layer downloaded from the Maine Office of GIS (MEGIS 2010).

1.3.3. Image processing

We mosaicked paths of consecutive images from a single date in ERDAS Imagine ® (version 10.0; ERDAS Inc., Norcross, GA, United States). Unsupervised classification (ISODATA clustering) and the visible/thermal infrared band combination (RGB 1, 6, 6) were used to interpret extent of clouds and cloud shadows. Cloud pixels were reclassified as null values and removed in ArcGIS. Cloud shadows could not be removed by unsupervised classification without simultaneously removing unaffected lake pixels, so images were visually inspected to remove lakes affected by shadows. We reduced the negative effects of Rayleigh scattering by normalizing all images from each path to the clearest swath of images of the respective path with orthogonal regression. Orthogonal regression differs from ordinary least squares by assuming error in both horizontal and vertical directions and calculating the perpendicular distance from the regression line (Rencher 1995). We selected bright (e.g., large buildings, airport tarmacs) and dark (e.g., deep lake centers) ground targets distributed across the state that appeared spectrally invariant over the study period. We identified only 6 ground targets in path 12, owing to few developed features. We increased the number of ground targets for path 11 because clouds often obscured targets in this path. For path 12, the targets were digitized as points and buffered 10 m. An average of the encompassed pixel values (up to 4 adjacent pixels) was regressed against the average value of pixels of the same area in the reference image for path 12 collected 1 September 1999. For path 11, we minimized inter-annual cloud interference by normalizing to a single pixel in the target center instead of using pixels in a buffered target. The reference image used for path 11 was captured on 14 August 1995. We used principal components analysis (PCA) to complete our orthogonal regressions. PCA uses an orthogonal transformation and because our analyses each contained two components (reference and non-reference image paths), the second eigenvector of each PCA allowed easy calculation of the gain and offset to apply to each non-reference image path.

1.3.4. Secchi sampling site representation

We uniquely identified each secchi disk sampling station in a geographic information system (GIS) points layer. We estimated sampling site locations in the deepest region of lakes based on georeferenced bathymetric maps (Maine PEARL 2011). Bathymetric data were not available for 163 lakes; we placed those stations at lake centers to avoid spectral interference from the shoreline, lake bottoms or aquatic plants. We created circular buffers with 50, 75 and 100 m radii around each sampling station to define the area for satellite data extraction. We calculated the average pixel value for each zone with zonal statistics. A 75 m zone captured approximately 20 pixels and yielded the greatest R^2 values for SDD estimates from satellite data. We excluded lakes < 8 ha (Olmanson et al. 2001) as well as larger lakes that are narrow and could not contain a 75 m area in the imagery without overlapping shoreline. Water clarity of a total of 1,511 Maine lakes can be estimated remotely from Landsat paths 11 and 12.

1.3.5. Model development

Kloiber et al. (2002b) and (Olmanson et al. 2008) determined secchi data collected ± 7 days of the Landsat overpass are acceptable for use in lake clarity estimation regressions. Secchi data collected ± 10 days may be usable owing to late summer stability (Olmanson et al. 2008). Although a longer time window increases the sample size and geographic extent of the calibration dataset, less estimation error is introduced if calibration data are collected close to the time of the satellite overpass. We used windows of 1, 3 and 7 days determined by the amount of calibration data available, which generally was greater for later years in the study. Longer time windows help ensure a wide distribution of SDD values is captured in the calibration, which is critical for model accuracy (Nelson et al. 2003). We used historic SDD field data collected by MDEP and the Maine Volunteer Lake Monitoring Program in our regressions.

We estimated natural log-transformed SDD from the 75 m zonal means of spectral band data with linear ordinary least squares regression (R version 2.12.0; R Foundation for Statistical Computing, Vienna, Austria). We identified models that performed consistently over several images with forward stepwise regression. We included spectral and supplementary lake variables in the models. Spectral variables were zone means calculated from Landsat TM bands 1-4. Bands 1-3 are correlated with lake water clarity (Kloiber et al. 2002b). The wavelength of band 4 may be too long to penetrate beyond the water surface, however, we included these data because they are correlated with chlorophyll and suspended solids in eutrophic waters (Lathrop 1992). The TM1/TM3 band ratio has been used to estimate water clarity (Kloiber et al. 2002, Nelson et al. 2003, Chipman et al. 2004, Olmanson et al. 2008) and we included this ratio in regressions when TM1 and TM3 were significant in accordance with model hierarchy. We validated regression assumptions with standard tests and regression coefficients with subsampled datasets and jackknifing following Sahinler and Topuz (2007). We used jackknifing when $n < 50$ lake stations to minimize the influence of individual data points with small sample size. We compared predicted residual sum of squares (PRESS) statistics to SSE of regressions using subsampled datasets when $n \geq 50$ lake stations to compare the fitness of full and subsampled models.

1.4. RESULTS

Landsat TM bands 1 and 3 were consistent predictors of ln(SDD) for calibration datasets ranging 31-119 lake stations and ± 1-7 day field data capture windows (Table 1.2). The TM1/TM3 ratio was inconsistently significant and created redundancies in models. Average depth was positively correlated with ln(SDD) and wetland area was negatively correlated with ln(SDD) only in path 11 models. Lake area, perimeter and area/perimeter ratio were not strong predictors of lake water clarity. Path 11 model R^2 values were consistent, ranging 0.79-0.90 (RMSE=1.18-1.23 m); however, path 12 models were more variable with R^2 values ranging 0.69-0.89 (RMSE=1.15-1.30 m). Relationships between observed and estimated ln(SDD) consistently were strong throughout 1990-2010 (Figs. 2-3). Estimated SDD ranged < 0.10-18.10 m. Average absolute difference between observed and satellite-estimated SDD ranged 0.65-1.03 m (Table 1.4). Estimates consistently were more accurate for eutrophic (SDD ≤ 4m) and mesotrophic (SD =4-7 m) than oligotrophic lakes (SDD ≥ 7 m) (Table 1.4), based on established relationships between trophic status and SDD (Maine PEARL 2011). Estimates for eutrophic and mesotrophic lakes consistently were on average within 1 m of observed conditions, however, estimates for oligotrophic lakes on average deviated > 1 m from observed conditions in all but one model (Table 1.4).

We used the same methods to fit alternate models for 163 lakes for which bathymetric data were not available. These models consistently produced smaller R^2 values and larger average absolute differences between estimated and observed SDD (Tables 1.3, 1.5). Primary model R^2 averaged 0.85 for path 11 (Std. dev; SD=0.04) and 0.80 for path 12 (SD=0.08) and alternate model R^2 averaged 0.78 (SD=0.06; RMSE= 1.24-1.26 m) for path 11 and 0.76 (SD=0.08; RMSE=1.20-1.32 m) for path 12. Average absolute difference between estimated and observed SDD was 0.75 m for paths 11 (SD= 0.12) and 0.88 for path 12 (SD=0.12) over all primary models and 0.89 m for path 11 (SD =0.13) and 1.01 m (SD=0.08) for path 12 in all alternate models.

Table 1.2. Summary of primary regression models[a] for remote clarity estimation

Date	Path	Rows	Band Combination	R^2	Days	n
8/30/2010	12	27-30	(-0.244) TM3 + (8.39x10^{-3}) AvgDepth + 5.22	0.7305	1	65
9/14/2004	12	27-30	(0.134) TM1 - (0.392) TM3 + 2.484	0.8342	1	44
9/1/1999	12	27-30	(-0.427) TM3 + (4.48x10^{-3}) AvgDepth + 6.20	0.8939	1	31
9/6/1995	12	27-30	(6.28x10^{-2}) TM1 - (0.361) TM3 + (1.03x10^{-2}) AvgDepth + 7.96	0.8439	3	73
9/8/1990	12	27-30	(0.145) TM1 - (0.436) TM3 + (6.40x10^{-3}) AvgDepth + 2.93	0.6916	7	117
9/5/2009	11	28-29	(3.72x10^{-2}) TM1 - (0.320) TM3 + (7.77x10^{-3}) AvgDepth - (3.61x10^{-4}) Wetland + 5.51	0.8631	3	65
8/9/2005	11	27-29	(0.113) TM1 - (0.315) TM3 + (7.89 x10^{-3}) AvgDepth - (3.70 x10^{-4}) Wetland - 0.868	0.8244	3	55
8/9/2002	11	27-29	(-3.22x10^{-2}) TM3 + (1.29x10^{-2}) AvgDepth - (7.51x10^{-4}) Wetland + 4.25	0.9010	1	35
8/14/1995	11	27-29	(9.35x10^{-3}) TM1 - (5.87x10^{-2}) TM3 + (9.83x10^{-3}) AvgDepth - (3.06x10^{-4}) Wetland + 3.91	0.7919	7	119

[a] TM1 = Landsat band 1, TM3 = Landsat band 3, AvgDepth = average lake depth, Wetland = proportion of watershed covered by wetland

Table 1.3. Summary of alternate regression models[a] for remote clarity estimation without knowledge of depth

Date	Path	Rows	Band Combination	R^2	Days	n
8/30/2010	12	27-30	(-0.257) TM3 + 5.57	0.7018	1	65
9/14/2004	12	27-30	(0.134) TM1 - (0.392) TM3 + 2.48	0.8342	1	44
9/1/1999	12	27-30	(-0.479) TM3 + 6.90	0.8248	1	31
9/6/1995	12	27-30	(6.37x10^{-2}) TM1 - (0.366) TM3 + 8.25	0.8168	3	73
9/8/1990	12	27-30	(0.157) TM1 - (0.467) TM3 + 3.10	0.6313	7	117
9/5/2009	11	28-29	(4.30x10^{-2}) TM1 - (0.334) TM3 - (4.29x10^{-4}) Wetland + 5.56	0.8273	3	65
8/9/2005	11	27-29	(0.135) TM1 - (0.364) TM3 - (4.07x10^{-4}) Wetland - 1.40	0.7019	3	55
8/9/2002	11	27-29	(-3.10x10^{-2}) TM3 - (8.90x10^{-4}) Wetland + 4.54	0.8642	1	35
8/14/1995	11	27-29	(1.30x10^{-2}) TM1 - (6.75x10^{-2}) TM3 - (3.46x10^{-4}) Wetland + 3.95	0.7412	7	119

[a] TM1 = Landsat band 1, TM3 = Landsat band 3, Wetland = proportion of watershed covered by wetland

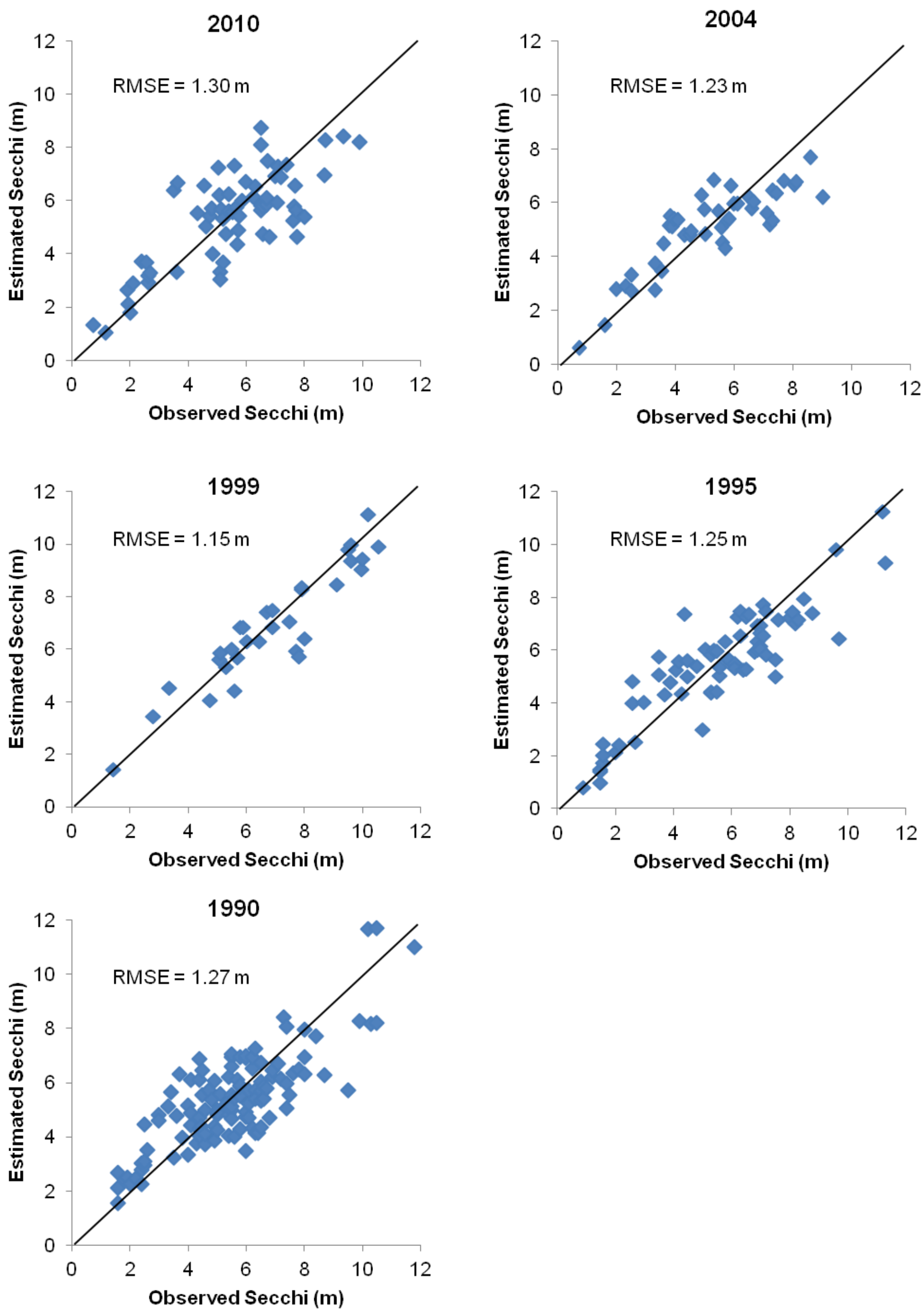

Fig. 1.2. Scatter plots of Landsat-estimated and observed secchi disk depth (m) for primary path 12 models with 1:1 fit line. Observed values are based on field data gathered by the Maine Volunteer Lake Monitoring Program (VLMP) ± 1-7 days of the Landsat satellite overpass. RMSE = root mean squared error.

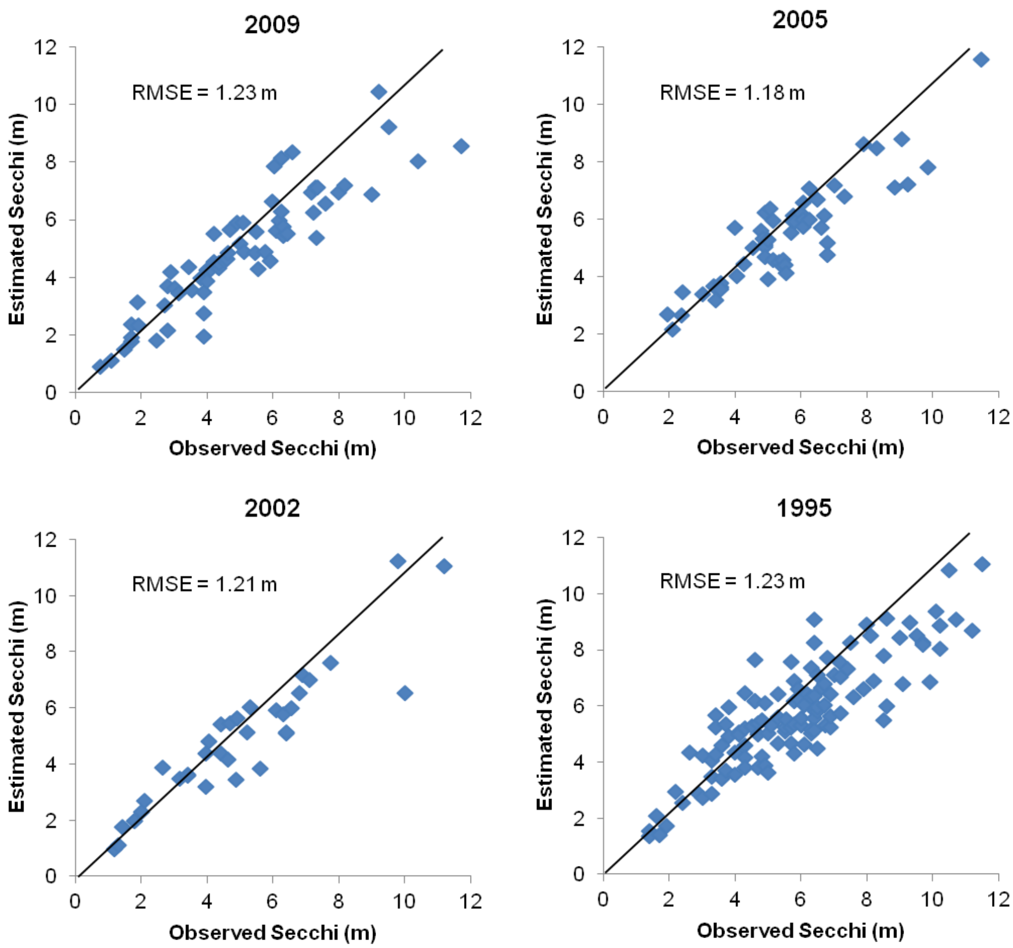

Fig. 1.3. Scatter plots of Landsat-estimated and observed secchi disk depth (m) for primary path 11 models with 1:1 fit line. Observed values are based on field data gathered by the Maine Volunteer Lake Monitoring Program (VLMP) ± 1-7 days of the Landsat satellite overpass. RMSE = root mean squared error.

Table 1.4. Average absolute difference (m) between observed and remotely estimated SDD among lake types[a] in primary models

Date	Path	Eutrophic	Mesotrophic	Oligotrophic	Overall
8/30/2010	12	0.90	0.97	1.33	1.03
9/14/2004	12	0.73	0.65	1.49	0.87
9/1/1999	12	0.60	0.54	0.81	0.66
9/6/1995	12	0.75	0.82	1.22	0.93
9/8/1990	12	0.91	0.89	1.47	0.91
9/5/2009	11	0.58	0.62	1.20	0.73
8/9/2005	11	0.33	0.67	1.08	0.68
8/9/2002	11	0.41	0.71	1.05	0.65
8/14/1995	11	0.78	0.85	1.31	0.95

[a] Eutrophic < 4m, Mesotrophic = 4-7 m, Oligotrophic ≥ 7 m

Table 1.5. Average absolute difference (m) between observed and remotely estimated SDD among lake types[a] in alternate models

Date	Path	Eutrophic	Mesotrophic	Oligotrophic	Overall
8/30/2010	12	0.87	0.95	1.61	1.08
9/14/2004	12	0.73	0.65	1.49	0.87
9/1/1999	12	0.75	0.85	1.27	1.03
9/6/1995	12	0.79	0.78	1.38	0.97
9/8/1990	12	1.00	0.89	1.89	1.09
9/5/2009	11	0.65	0.68	1.79	0.89
8/9/2005	11	0.45	0.73	1.85	0.88
8/9/2002	11	0.52	0.66	1.45	0.72
8/14/1995	11	0.84	0.82	1.81	1.08

[a] Eutrophic < 4m, Mesotrophic = 4-7 m, Oligotrophic ≥ 7 m

1.5. DISCUSSION

1.5.1. Trophic state affects model accuracy

Although the primary model R^2 values indicate good agreement between TM3, TM1 and ln(SDD), model-estimated SDDs consistently were more accurate for eutrophic and mesotrophic lakes. TM3 is correlated with chlorophyll reflectance and is an effective indicator of clarity of turbid waters. Chlorophyll and suspended solids, associated with increased turbidity and phytoplankton abundance, increase the amount of energy received by the satellite (Lathrop 1992), rendering TM3 a less accurate predictor of SDD in clear water. In shallower oligotrophic lakes, the longer wavelength of TM3 may bottom out before the deepest potential SDD is reached, which could potentially produce misleading results. SDD may be more of a function of lake depth in clear water where fewer particles reflecting transmitted light are present. From a management perspective, eutrophic and mesotrophic lakes are of greater interest owing to their susceptibility to development-related eutrophication. Although our model predictions applied to oligotrophic lakes are less accurate, the models may be useful indicators of deteriorating water clarity as predicted SDD decreases. Consideration of factors such as depth and lake water quality history may improve interpretation of lake clarity estimates for oligotrophic lakes.

1.5.2. Applying ancillary data in models for water clarity monitoring

TM1 and TM3 are strong predictors of Maine lake clarity, providing a tool to track potential changes from the current overall high clarity of Maine lakes. Olmanson et al. (2008) reported an average Minnesota statewide lake clarity of 2.25 m from 1985-2005, considerably more eutrophic than the average annual clarity of Maine lakes (4-6 m) since 1970. Lathrop's (1992) finding that TM3 is strongly correlated with turbid waters such as those found in lakes in the Upper Midwest supports the results of Olmanson et al. (2008) for an overall eutrophic dataset. Models predicting Minnesota lake clarity explained 71-96% of the variation in lake clarity with only spectral data (Olmanson et al. 2008), similar to our alternate models (R^2=0.63-0.86). Considering the trophic conditions in Maine, our reduced model fitness is not surprising, however, the inclusion of physical lake variables in our primary models helps explain additional variability in lake clarity in a relatively clearer set of lakes despite small differences in RMSE. Satellite data alone may be sufficient for monitoring of eutrophic inland waters, however, physical lake characteristics and landscape features improve models applied to remote monitoring of clearer waters, especially when eutrophic lakes are uncommon.

The family of models that best estimates lake water clarity across a range of biophysical regions emphasizes the relationship between lake water clarity and watershed characteristics. Maine is a relatively small and undeveloped state spanning several biophysical regions (e.g., western mountains to eastern lowlands and foothills; Krohn et al. 1999). Eastern Maine falls largely in the eastern lowlands and foothills biophysical region and contains more wetland area, likely explaining the lack of significance of wetland area in path 12 models. Differing trends in lake clarity across U.S. Environmental Protection Agency Ecoregions have been found in Wisconsin (Peckham and Lillesand 2006) and Minnesota (Olmanson et al. 2008), suggesting there is a recognition of regional lake clarity variation. It may not be practical to model lake clarity according to ecoregion owing to calibration data availability, however, ecoregions capture general landscape characteristics and are useful aids in interpreting and detecting potential patterns in lake clarity estimates.

1.5.3. Limitations

There are limitations to monitoring water clarity with Landsat imagery. Landsat returns every 16 days, limiting the number of available mid-late summer images each year. Cloud cover affects image availability, especially for coastal areas such as path 11 in Maine. Over our 20 year study period, clear imagery was available for path 12 (western Maine) in late August-early September every 4-5 years, however, clear imagery for coastal path 11 was less consistently available. The compromised utility of Landsat 7 and potential expiration of Landsat 5 are additional complications that may be alleviated by the expected 2013 deployment of the Landsat Data Continuity Mission. Other satellite remote sensors such as MODIS with greater temporal resolution (2 images per day) may be a useful alternative for large lakes (McCullough et al. in review). Minnesota, Michigan and Wisconsin contain 388, 108 and 90 lakes respectively that can be routinely sampled remotely for SDD using MODIS 500 m imagery (Chipman et al. 2009).

The need for alternate models demonstrates the problem with including ancillary variables such as depth and wetland area. Although these variables are acceptably consistent year-to-year at the landscape scale, depth requires field-collected data and wetland area requires spatial data in addition to the satellite data, which may not be practical for some areas. An intention of this study is to estimate water clarity without visiting lakes and ideally, added variables would be restricted to those that could be easily remotely sensed. In our study, remotely sensed variables such as lake size, perimeter and surface area/perimeter ratio were inconsistent predictors of lake water clarity, however, these variables may still be useful in other landscapes. Lake depth, however, should be considered regardless of its predictive capacity. It can be argued that lake clarity estimates without knowledge of depth are less useful because it is helpful to know the proportion of the water column exposed to visible light. For example, a 10 m deep lake with SD=2 m should be viewed differently from a 3 m deep lake with SDD=2

m. It is our opinion that when additional information is known about certain lakes, this information should be used when it considerably improves estimates. As this study demonstrates, alternate, less accurate models can be used when ancillary data are lacking.

We would ideally develop an operational model that would not have to be calibrated specifically for each future image. Under this scenario, we could apply this model to future Landsat images with minimal or no field calibration data. Unfortunately, developing an accurate operational model is unrealistic with Landsat imagery. At the landscape scale, there is already a fairly large amount of error included in SDD estimates when models are calibrated with concurrent satellite and field data; attempting to use models calibrated with non-concurrent field data introduces additional error associated with changing lake or atmospheric conditions and pushes the limit of error acceptability. Known field SDD values cannot be accurately predicted with a model calibrated for a different date. We recommend calibrating future models with concurrent satellite and field data. It would be a useful and efficient strategy to direct management and volunteer agencies to collect field data near satellite overpass dates to maximize calibration data availability.

1.6. CONCLUSION

Accurate long-term water quality monitoring programs are essential for effective lake management. Simultaneous monitoring of a large number of lakes is facilitated by data that can be gathered remotely. Landsat TM bands 1 and 3 are consistent predictors of water clarity of Maine lakes and those predictions are more accurate when average depth and watershed wetland area are included in models. Bands 1 and 3 previously were found to be strong indicators of water clarity in lakes considerably less clear than those in Maine, demonstrating the wide applicability of Landsat data for monitoring lake trophic condition. Estimates are more accurate for eutrophic and mesotrophic than oligotrophic lakes, owing to the lack of suspended particles in oligotrophic lakes that are detectable by satellite sensors and the longer TM3 wavelength that may bottom out before the deepest potential SDD is reached. Although the spatial and temporal resolution of Landsat TM are limited, Landsat is useful for monitoring lake clarity over long time periods because satellite-based monitoring alleviates the non-random lake sampling employed by agencies and volunteers and greatly increases knowledge of regional water quality. We are currently conducting a separate study examining spatial and temporal patterns of Maine lake clarity using the methods described in this manuscript. The continuation of field-based lake water clarity monitoring is essential for calibration and spot validation of future remote clarity estimation models and remote monitoring should not replace field-based programs. The long-term clarity estimates produced by this study are available electronically at the USGS Maine Cooperative Fish and Wildlife Research Unit website (http://www.coopunits.org/Maine/).

CHAPTER 1 REFERENCES

Boyle, K. J., Poor, P.J. and Taylor, L. O. (1999). Estimating the demand for protecting freshwater lakes from eutrophication. *American Journal of Agricultural Economics* 81 (5): 1118-1122.

Carlson, R. E. (1977). A trophic state index for lakes. *Limnology and Oceanography* 22(2): 361-369.

Chipman, J. W., Lillesand, T. M., Schmaltz, J. E., Leale, J. E. and Nordheim, M. J. (2004). Mapping lake clarity with Landsat images in Wisconsin, U.S.A. *Canadian Journal of Remote Sensing* 30(1): 1-7.

Chipman, J. W., Olmanson, L. G. and Gitelson, A. A. (2009). Remote sensing methods for lake management: a guide for resource managers and decision-makers. Developed by the North American Lake Management Society in collaboration with Dartmouth College, University of Minnesota, University of Nebraska and University of Wisconsin for the United States Environmental Protection Agency.

Davis, R. B., Bailey, J. H., Scott, M, Hunt, G. and Norton, S. A. (1978). Descriptive and comparative studies of Maine lakes. Life Sciences and Agricultural Experiment Station. Technical Bulletin 88.

Detenbeck, N. E., Johnston, C. A. and Niemi, G. J. (1993). Wetland effects on lake water quality in the Minneapolis/St. Paul metropolitan area. *Landscape Ecology* 8(1): 39-61.

Gibbs, J. P., Halstead, J. M., Boyle, K. J. and Huang, J. (2002). An hedonic analysis of the effects of lake water clarity on New Hampshire lakefront properties. *Agricultural and Resource Economics Review* 31(1): 39-46.

Gunn, J. M., Snucins, E., Yan, N. D. and Arts, M. T. (2001). Use of water clarity to monitor the effects of climate change and other stressors on oligotrophic lakes. *Environmental Monitoring and Assessment* 67: 69-88.

Heiskary, S. A. and Walker. W. W. (1988). Developing phosphorus criteria for Minnesota lakes. *Lake and Reservoir Management* 4(1): 1-9.

Houston, B. (2008). Coastal Maine updates. U.S. Fish and Wildlife Service. Gulf of Maine Coastal Program. Falmouth, ME 04105.

Kloiber, S. M., Brezonik, P. L. and Bauer, M. E. (2002a). Application of Landsat imagery to regional-scale assessments of lake clarity. *Water Research* 36: 4330-4340.

Kloiber, S. M., Brezonik, P. L., Olmanson, L. G. and Bauer, M. E. (2002b). A procedure for regional lake water clarity assessment using Landsat multispectral data. *Remote Sensing of Environment* 82: 38-47.

Krohn, W. B., Boone, R. B. and Painton, S. L. (1999). Quantitative delineation and characterization of hierarchical biophysical regions on Maine. *Northeastern Naturalist* 6: 139-164.

Lathrop, R. G. (1992). Landsat thematic mapper monitoring of turbid inland water quality. *Photogrammetric Engineering and Remote Sensing* 58(4): 465-470.

Maine PEARL. (2011). Lakes Guide. Senator George J. Mitchell Center for Environmental Research, University of Maine, Orono. http://www.pearl.maine.edu/windows/community/default.htm. Accessed 1/18/11.

Maine Volunteer Lake Monitoring Program. (2010). http://www.mainevolunteerlakemonitors.org/. Accessed 12/17/10.

McCullough, I. M., Loftin, C. S. and Sader, S. A. In review. High-frequency remote monitoring of large lakes with MODIS 500 m imagery. *Remote Sensing of Environment.*

MDEP; Bacon, L. (2010). Maine Department of Environmental Protection. Augusta, ME 04333.

MDEP; Bacon, L. (2011). Maine Department of Environmental Protection. Augusta, ME 04333.

MDEP; Suitor, D. (2011). Maine Department of Environmental Protection. Augusta, ME 04333.

MEGIS. (2010). Maine Office of GIS Data Catalog. http://www.maine.gov/megis/catalog/. Accessed 10/15/10.

Michael, H. J., Boyle, K. J. and Bouchard. R. (1996). Water quality affects property prices: a case study of selected Maine lakes. Maine Agricultural and Forest Experiment Station, University of Maine, Orono, ME.

Nelson, S. A. C., Soranno, P. A., Cheruvelil, K. S., Batzli, S. A. and Skole, D. L. (2003). Regional assessment of lake water clarity using satellite remote sensing. *Journal of Limnology* 62: 27-32.

Olmanson, L. G., Bauer, M. E. and Brezonik. P. L. (2008). A 20-year Landsat water clarity census of Minnesota’s 10,000 lakes. *Remote Sensing of Environment* 112: 4086-4097.

Olmanson, L. G., Kloiber, S. M., Bauer, M. E. and Brezonik, P. L. (2001). Image processing protocol for regional assessments of lake water quality. Water resources center and remote sensing laboratory, University of Minnesota, St. Paul, MN, 55108, October 2001.

Peckham, S. D. and Lillesand, T. M. (2006). Detection of spatial and temporal trends in Wisconsin lake water clarity using Landsat-derived estimates of secchi depth. *Lake and Reservoir Management* 22(4): 331-341.

Rencher, A. C. 1995. Methods of multivariate analysis. New York: John Wiley & Sons.

Sahinler, S. and Topuz, D. (2007). Bootstrap and jackknife resampling algorithms for estimation of regression parameters. *Journal of Applied Quantitative Methods* 2(2): 188-199.

Stadelmann, T. H., Brezonik, P. L. and Kloiber, S. M. (2001). Seasonal patterns of chlorophyll a and Secchi disk transparency in lakes of East-Central Minnesota: Implications for design of ground- and satellite-based monitoring programs. *Lake and Reservoir Management*, 17(4): 299-314.

CHAPTER 2

APPLICATION OF LANDSAT TM IMAGERY REVEALS DECLINING CLARITY OF MAINE'S LAKES DURING 1995-2010

2.1. INTRODUCTION

Water clarity is a measurement of visible light attenuation in the water column. Often quantified in terms of secchi disk depth (SDD), water clarity is strongly correlated with chlorophyll-a, total phosphorus and trophic status (Carlson 1977). Trophic status is an indicator of lake productivity and can be evaluated based on SDD (eutrophic < 4 m, mesotrophic = 4-7m and oligotrophic > 7 m) (Maine PEARL 2011). Unlike these variables, however, clarity can be accurately and efficiently estimated with spectral reflectance captured remotely on a landscape scale (Kloiber et al. 2002, Chipman et al. 2004, Olmanson et al. 2008, McCullough et al. in press), thus making clarity an ideal metric of regional water quality. SDD measurements are widely conducted and less costly than other water quality assessments requiring chemical analyses; however, large-scale field sampling programs often gather a spatially irregular, non-random representation of regional water quality owing to limited lake accessibility. Remote sensing can eliminate spatial biases associated with non-random sampling, particularly in regions with numerous lakes that cannot be monitored efficiently with traditional field methods. Much of existing field data are amassed by volunteer lakeshore residents who not only collectively make regional assessments more feasible by collecting necessary data for remote model calibration, but also are important stakeholders in lake water quality. Increased lake clarity positively affects lakefront property value in Maine

(Michael et al. 1996, Boyle et al. 1999) and New Hampshire (Gibbs et al. 2002) and also enhances human-perception of lake water quality in Minnesota (Heiskary and Walker 1988).

Remote sensing frequently is used in landscape change detection and can be similarly applied to monitor change in regional lake water quality. Peckham and Lillesand (2006) and Olmanson et al. (2008) used Landsat TM satellite imagery to evaluate long-term patterns in water quality of Wisconsin and Minnesota lakes, respectively. Identification of areas experiencing downward trends in water quality enables management agencies to direct limited resources more effectively and efficiently to remediate causes for water quality decline. Accuracy of long-term change detection is maximized with assessments on or near anniversary dates to minimize error associated with seasonal variation. Existing remote lake clarity monitoring procedures have focused on mid-late summer (July 15-September 15), a period of relative stability in lake algal communities and lake stratification ideal for remote estimation of water clarity. Assessments during this time period typically capture the seasonally poorest conditions in lake water clarity (Stadelmann et al. 2001, Kloiber et al. 2002, Chipman et al. 2004, Olmanson et al. 2008). We applied a procedure we previously developed for remote estimation of lake clarity to analyze spatial and temporal patterns in clarity of 570 Maine lakes during 1995-2010 with Landsat 5 and 7 satellite imagery and field-collected SDD data. Our analyses also allowed us to examine whether existing field sampling programs adequately characterize regional water quality in Maine.

The Landsat satellite program was first launched in 1972 and 2 satellites currently are in operation. Landsat 5, launched in 1984, was temporarily suspended in November

2011 after a mechanical failure; however, Landsat 5 is an important historical data source. Landsat 7 was launched in 1999; however, the 2003 failure of the scan-line corrector (SLC), an instrument that corrects for the forward motion of the satellite, has since compromised image quality. Post SLC failure (SLC-off) images contain lines with no data and require additional processing. The expected 2013 launch of the Landsat Data Continuity Mission (LDCM), if successful, will ensure future availability of Landsat data for remote lake monitoring. Both Landsat 5 and 7 contain three visible bands and four infrared bands at 30-m resolution, and Landsat 7 contains a 15-m panchromatic band. Images (scenes) of the same location are captured every 16 days and cover approximately 185 km^2. Scenes are indexed by path and row and are freely downloadable from the U.S. Geological Survey Global Visualization Viewer (http://glovis.usgs.gov/).

2.2. DESCRIPTION OF STUDY AREA

Maine is located in the northeastern United States and ranks first among states east of the Great Lakes in total area of inland surface waters (Davis et al. 1978). Maine contains over 5,500 lakes and ponds > 1 ha in surface area across an area of approximately 90,000 km^2, and wetlands cover 26% of the state (Tiner 1998). The climate is cold-temperate and moist with long, cold winters and short, warm summers. Maine is dominated by the Northeastern Highlands (#58) and the Acadian Plains and Hills (#82) Level III Ecoregions (Omernik 1987). The Northeastern Highlands are remote, mostly forested, mountainous, and contain numerous high-elevation, glacial lakes. The Acadian Plains and Hills are comparatively more populated and less rugged; however, the area is also heavily forested and contains dense concentrations of glacial lakes (U.S. EPA 2010). Lakes are well-distributed throughout the state and average depths ranges 1-32 m. Lakes range in size from small ponds < 1 ha to Moosehead Lake (30,542 ha), the largest lake in Maine. Statewide lake water clarity monitoring began in 1970. The average annual SDD consistently has remained 4-6 m, with a historical average of 5.27 m during 1970-2009, and was 5.14 m in 2009 (n=457; Maine Department of Environmental Protection; MDEP; Bacon, Maine Volunteer Lake Monitoring Program; VLMP 2010). The number of lakes sampled in the field by state biologists and volunteers changes annually and generally has increased from 18 lakes in 1970 to consistently > 400 lakes since 1999. We focused our study on the overlap region of Landsat TM paths 11 (rows 27-29) and 12 (rows 27-30), which captures a strong north-south gradient over an area of 3,000,000 ha, and includes 570 lakes > 8 ha (Fig. 2.1). Lakes < 8 ha cannot be reliably estimated with 30-m Landsat data (Olmanson et al. 2008). We partitioned Maine's lakes (> 8 ha) into three geographic regions (northeastern: 227 lakes; south-central: 256 lakes; western: 162 lakes) based on cluster analysis of morphometric and chemical lake variables including surface area, flushing rate, average and maximum depth, elevation, color, alkalinity and specific conductance (Bacon and Bouchard 1997) (Fig. 2.1).

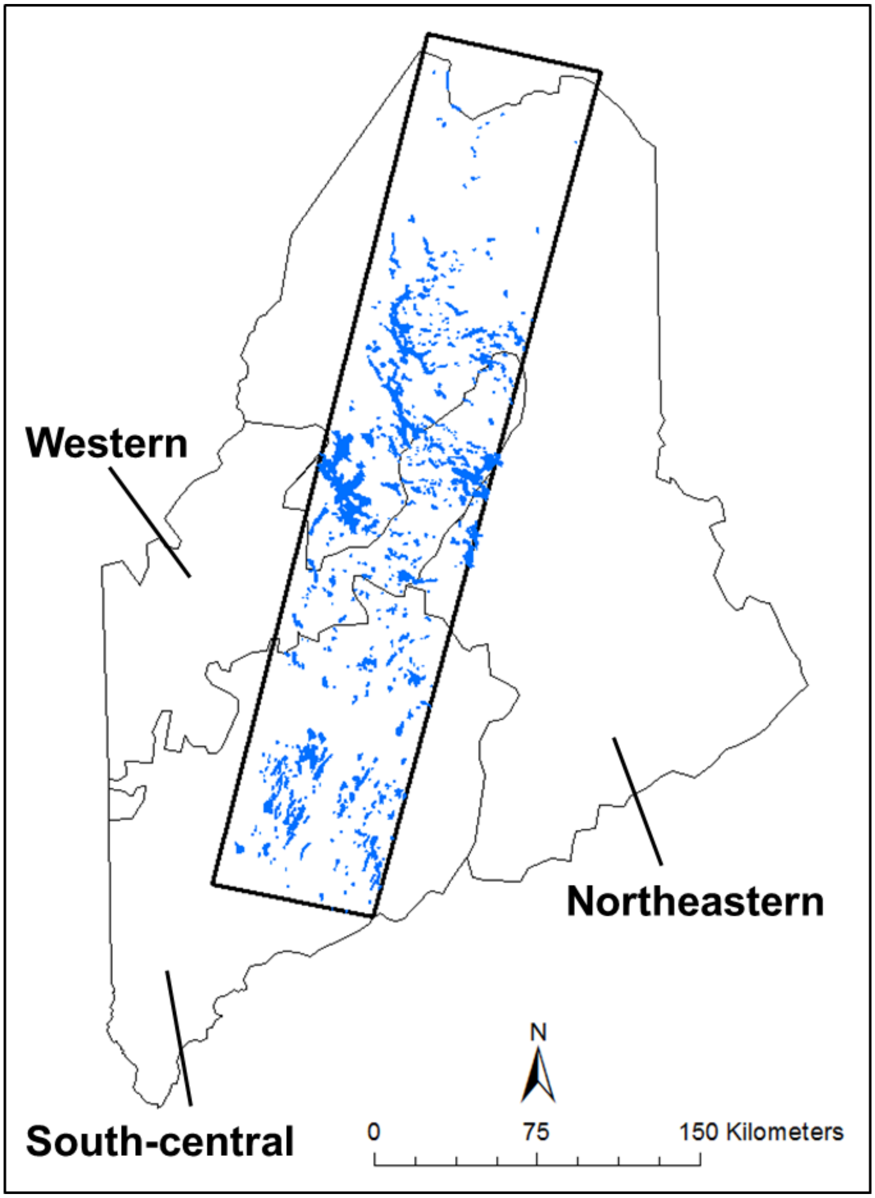

Fig. 2.1. Lake regions of Maine and the overlap area between Landsat TM paths 11 and 12, containing 570 lakes > 8 ha.

2.3. METHODS

2.3.1. Catalog of lake clarity estimates during 1995-2010

Our methods used to create the catalog of lake clarity estimates are detailed in McCullough et al. (in press) and are summarized here. We estimated regional lake clarity with field-collected SDD data ± 1-7 days of satellite image capture, Landsat TM brightness values from bands 1 (blue visible; 0.45-0.52 μm) and 3 (red visible; 0.63-0.69 μm), average lake depth (MDEP 2010) and the proportion of a lake watershed in wetlands (National Wetlands Inventory [NWI]) with linear regression. Landsat bands 1 and 3 are strongly correlated with SDD (Kloiber et al. 2002, Chipman et al. 2004, Olmanson et al. 2008, McCullough et al. in press) and lake depth and landscape characteristics that affect water clarity improve model accuracy (McCullough et al. in press). We extracted spectral data from areas delineated by a 75 m buffered GIS points layer in ArcGIS® (version 10.0) of digitized sample stations where SDD data are collected in the field. We extracted data from the deepest areas of lakes or lake centers in the absence of established sampling locations. Calibration of the relationship between lake conditions and Landsat brightness values that targets deep portions of lakes away from the shoreline avoids spectral interference from aquatic plants, lake bottoms and shoreline features (Kloiber et al. 2002, Olmanson et al. 2008). We analyzed radiometrically normalized, mostly cloud-free (< 10% cloud cover) Landsat 5 and 7 images captured in 1995, 1999, 2002, 2003, 2005 (two dates), 2008, 2009 and 2010. We restricted our image dates to late summer (1 August - 5 September) to capture the seasonally poor clarity conditions that occur in late summer before fall turnover. Although dimictic lakes can undergo turnover as early as late August in northern Maine

(Davis et al. 1978), we found SDD estimates generated from 5 September 2009 were consistent with late summer, pre-turnover clarity conditions (McCullough et al. in press).

SLC-off images have been used to calibrate remote SDD estimation models for Minnesota lakes with strong fitness (R^2=0.72-0.86) (Olmanson et al. 2008); however, we used only Landsat 5 and 7 SLC-on images (Table 2.1) owing to inconsistencies in our calibrations of models generated with SLC-off images (e.g., 17 August 2003, 8 August 2005, and 1 September 2008). We calibrated six primary models (R^2=0.73-0.90) during 1995-2010 (Table 2.1). We calibrated six similar, alternate models with slightly reduced fitness (R^2=0.70-0.86) corresponding to each primary model when ancillary lake data were unavailable (102 lakes). Calibration datasets included 31-119 field-collected SDD data points based on the number of lakes sampled within the ± 1-7 day calibration window.

Table 2.1. Regression models[a] for remote clarity estimation in Maine's lakes.

Date	Satellite	Path	Model	R^2
8/14/1995	Landsat 5	11	$(9.35\text{x}10^{-3})$ TM1 - $(5.87\text{x}10^{-2})$ TM3 + $(9.83\text{x}10^{-3})$ AvgDepth - $(3.06\text{x}10^{-4})$ Wetland + 3.91	0.7919
9/1/1999	Landsat 5	12	(-0.427) TM3 + $(4.48\text{x}10^{-3})$ AvgDepth + 6.20	0.8939
8/9/2002	Landsat 7	11	$(-3.22\text{x}10^{-2})$ TM3 + $(1.29\text{x}10^{-2})$ AvgDepth - $(7.51\text{x}10^{-4})$ Wetland + 4.25	0.9010
8/9/2005	Landsat 5	11	(0.113) TM1 - (0.315) TM3 + $(7.89\text{x}10^{-3})$ AvgDepth - $(3.697\text{x}10^{-4})$ Wetland - 0.868	0.8244
9/5/2009	Landsat 5	11	$(3.72\text{x}10^{-2})$ TM1 - (0.320) TM3 + $(7.77\text{x}10^{-3})$ AvgDepth - $(3.61\text{x}10^{-4})$ Wetland + 5.51	0.8631
8/30/2010	Landsat 5	12	(-0.244) TM3 + $(8.39\text{x}10^{-3})$ AvgDepth + 5.22	0.7305

[a] TM1 = Landsat band 1, TM3 = Landsat band 3, AvgDepth = average lake depth, Wetland = proportion of watershed covered by wetland

2.3.2. Statistical analyses

Our dataset consisted of nearly the entire population of lakes > 8 ha in the Landsat overlap region. We used SDD data from a minimum of 455 lake estimates in 2005 to a maximum of 645 lake estimates in 2010 (some lakes have > 1 sample station). We tested for differences in SDD according to lake region and year with a three by five analysis of variance (ANOVA) (with three and five levels of two factors) based on type III sum of squares and unequal sample sizes to avoid eliminating data points (R version 2.12.0/ R Foundation for Statistical Computing, Vienna, Austria). We considered using a repeated measures design, however, shifting positions of clouds (which prevent remote sampling) resulted in incomplete spectral data prohibiting sampling of the same lakes across all years. Furthermore, part of the intention of remote monitoring of water quality is to reduce the need for extrapolations based on incomplete data. Restricting our dataset to lakes sampled in each year of the study would reduce our dataset to 347 lake estimates, whereas maintaining a larger sample size during the 15-year time interval reduced the risk of committing type I and II errors. We compared average SDD between pairs of years and lake regions with pairwise t-tests (α=0.05). We did not pool standard deviation and we assumed equal variance within group pairs. We also used pairwise t-tests to compare average SDD data collected remotely on our six image dates to all field data collected in the overlap region during theoretical calibration windows (± 7 days of image capture constrained within 1 August -5 September; McCullough et al. in press). Basing our comparison on field data gathered during this time frame reduced error introduction associated with changing lake conditions, as field data collected within this window were eligible for model calibration. We considered comparing remotely sensed data to all field data collected in Maine during the ± 7 day window, however, including lakes outside the overlap region could introduce unnecessary error attributable to geographic variability. These analyses allowed us to evaluate the effectiveness of current field monitoring for assessing regional water quality in Maine. We were unable to analyze lake regions separately owing to insufficient field data in the northeastern and western regions.

2.4. RESULTS

2.4.1. Temporal analysis

Water clarity estimated by SDD during 1995-2010 was related to year (ANOVA, $F=16.472$, $df=5, 10$, $p<0.001$). Average SDD decreased from 4.94 to 4.38 m during 1995-2010 (Table 2.2, Fig. 2.2). SDD varied during this 15-year period, with a statewide peak at 5.64 m in 1999, followed by a consistently more shallow SDD (< 5.00 m) since 2002. The 0.56 m estimated decrease during 1995-2010 was a significant reduction ($t=4.725$, $df=1230$, $p<0.001$) representing an 11% overall reduction in lake clarity.

The proportion of eutrophic lakes in Maine increased from 35.3% to 42.6% during 1995-2010 (Fig. 2.3), based on all lakes remotely assessed. The proportion of mesotrophic lakes was unchanged since 1995, however, the proportion of oligotrophic lakes decreased from 14.8% in 1995 to 6.8% in 2010 (Fig. 2.3), suggesting that Maine lakes are generally becoming more eutrophic. Of the 547 lakes from which SDD data were retrieved during 1995-2010, 79 (14.4%) previously mesotrophic lakes became eutrophic and 66 (12.1%) previously oligotrophic lakes became mesotrophic, whereas 327 (59.8%) lakes were unchanged in trophic status, 72 (13.2%) lakes improved and three (0.55%) previously oligotrophic lakes became eutrophic (Fig. 2.4).

Table 2.2. Remotely estimated annual secchi disk depth (m) in Maine (1995-2010).

	1995	1999	2002	2005	2009	2010
Mean	4.94	5.64	4.64	4.81	4.65	4.38
Median	4.75	6.09	4.36	4.67	4.52	4.27
Min	0.43	0.02	0.30	0.86	0.34	0.02
Max	14.25	11.83	15.02	11.65	10.90	11.41
n[a]	587	644	630	455	517	645

[a] n varied among years due to cloud cover

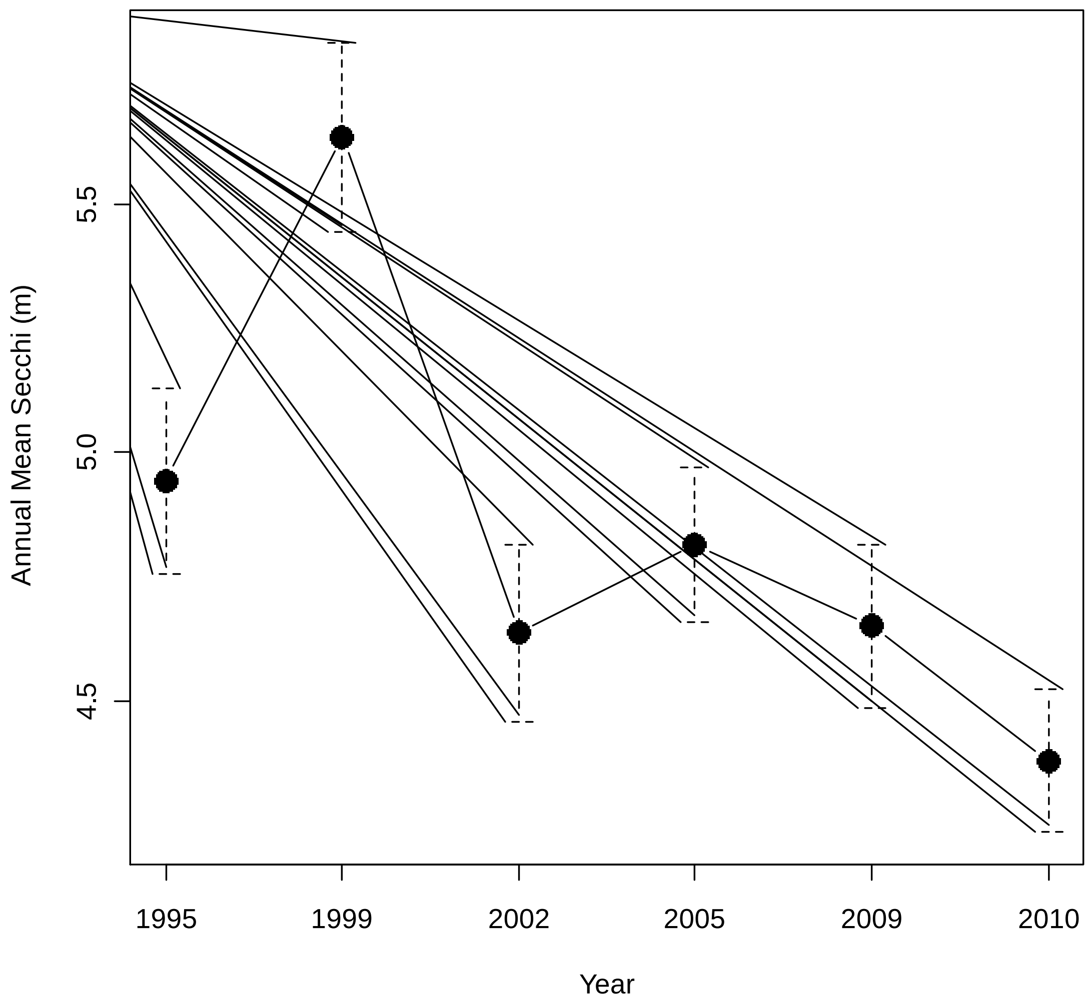

Fig 2.2. Remotely estimated average annual late summer secchi disk depth (m) (with 95% confidence intervals) of Maine lakes during 1995-2010 based on the overlap area between Landsat TM paths 11-12. N=455-645 lake samples (Table 2.2).

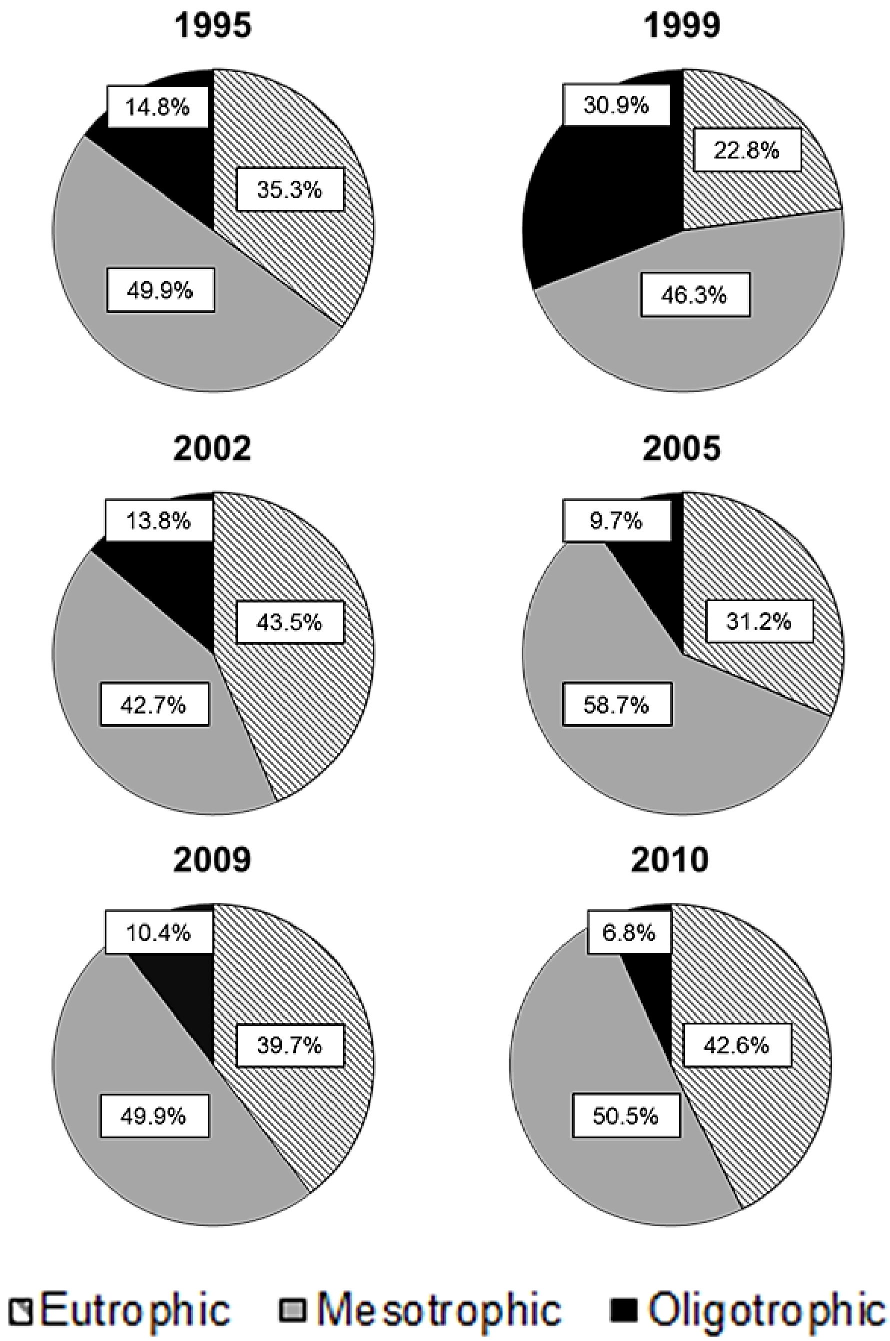

Fig. 2.3. Proportions of Maine lakes in trophic states during 1995-2010 based on remotely sensed data in the Landsat TM paths 11-12 overlap area. Eutrophic SDD < 4 m, mesotrophic SDD = 4-7 m, and oligotrophic SDD > 7 m.

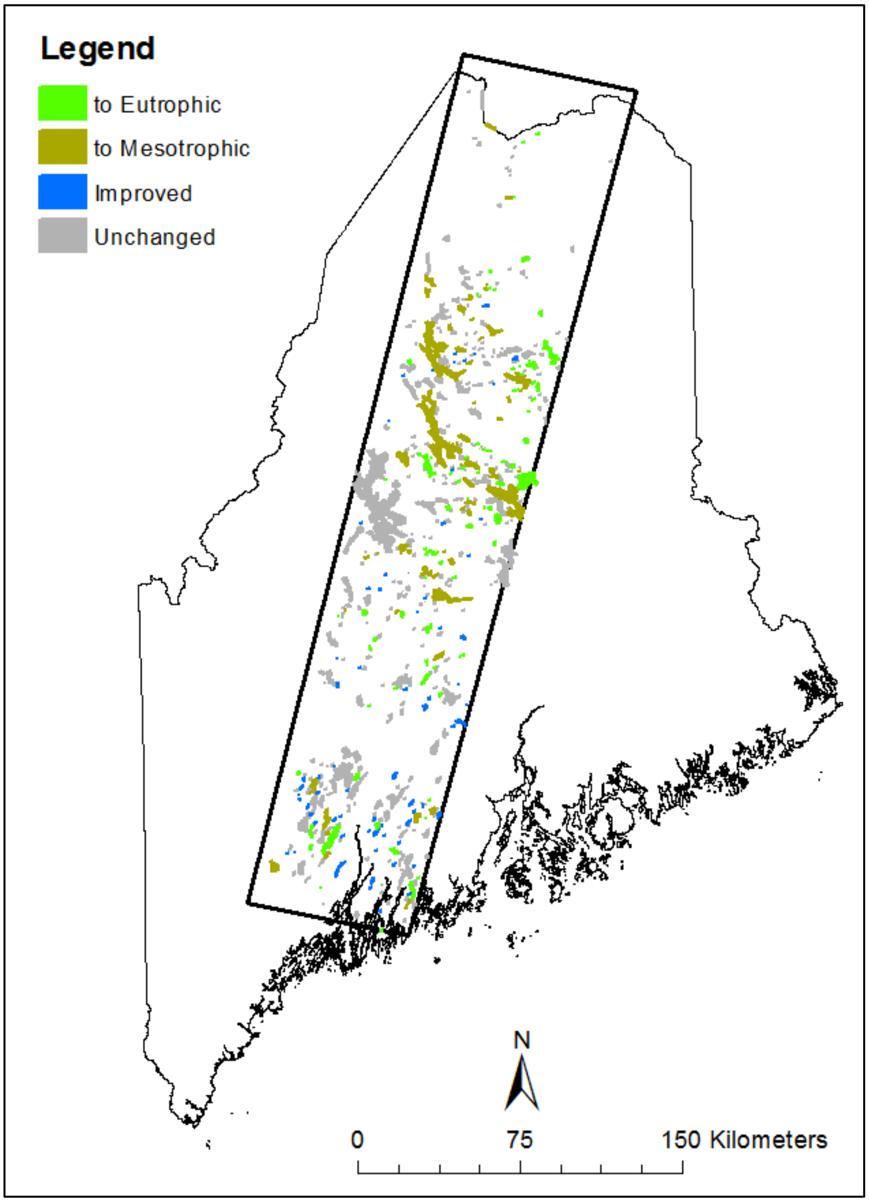

Fig. 2.4. Trophic state change in Maine lakes based on remotely estimated secchi disk depth (m) during 1995-2010 in the overlap region between Landsat TM paths 11-12. Eutrophic SDD < 4 m, mesotrophic = 4-7 m and oligotrophic > 7 m.

2.4.2. Regional analysis

Water clarity estimated by SDD during 1995-2010 was related to lake region (ANOVA, $F=8.015$, $df=2, 5$, $p<0.001$). Average SDD was slightly greater than 5 m in both the northeastern and western lake regions and approximately 0.5 m less than this in the south-central lake region, except in 2005, when SDD was fairly uniform throughout Maine, and in 2010, when SDD in the south-central region exceeded SDD in the other two regions (Table 2.3, Fig. 2.5). Pairwise t-tests revealed significant differences ($\alpha=0.05$, $p<0.001$ except where specified) between average SDD in the northeastern and south-central lake regions in 1995 ($t=3.320$, $df=436$), 1999 ($t=3.808$, $df=480$) and 2009 ($t=3.902$, $df=358$) and in the western and south-central lake regions in 1995 ($t=3.496$, $df=376$), 1999 ($t=2.026$, $df=415$, $p=0.043$), 2002 ($t=4.121$, $df=406$) and 2009 ($t=5.488$, $df=401$). In 1995, average SDD in both the northeastern and western regions was estimated at 5.22 m, however, it decreased to 4.36 and 4.21 m, respectively, in 2010. Conversely, average SDD in the south-central lake region fluctuated within a 1 m range and was nearly the same in 1995 as in 2010 (4.50 m) (Table 2.3, Fig. 2.5).

2.4.3. Analysis of existing sampling record

The existing water clarity field sampling program in Maine does not consistently provide a representative sample of regional water quality. We compared the average SDD of all remote estimates of lakes > 8 ha in the overlap region on each of our six dates (Table 2.1) to the average field-collected SDD during theoretical model calibration windows (± 7 days of image capture, constrained within 1 August – 5 September). Pairwise t-tests indicated that remotely sensed average SDD estimates differed significantly from field data in 3 of 6 years: 1995 (t=1.985, df=676, p=0.048), 2002 (t=2.165, df=709, p=0.031) and 2010 (t=3.837, df=714, p=0.001) (Table 2.3). The absolute differences between annual average SDD measured in the field and remotely ranged 0.13-0.97 m and remote estimates under-predicted field conditions in four of six years (Table 2.3).

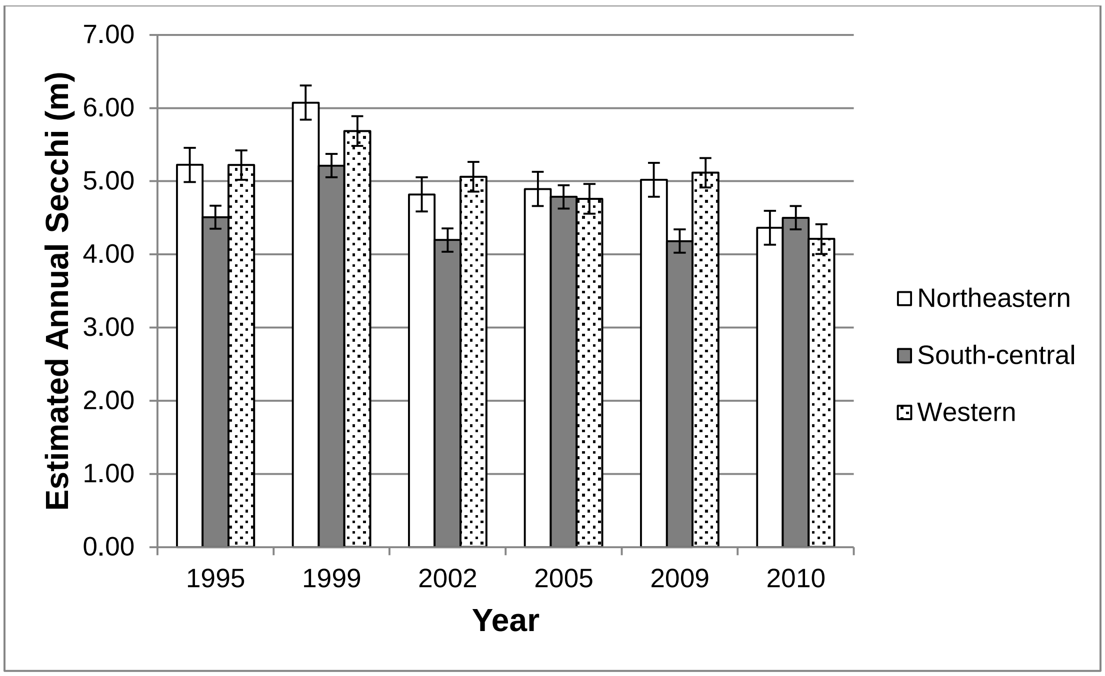

Fig. 2.5. Average annual late summer secchi disk depth (m) of Maine lakes by lake region during 1995-2010 based on remotely sensed data from the Landsat TM paths 11-12 overlap area. Bars represent standard error.

Table 2.3. Average annual late summer secchi disk depth (m) ± one standard error by lake region (remote assessment) and assessment type in the Landsat path 11-12 overlap area of Maine (1995-2010).

	1995	**1999**	**2002**	**2005**	**2009**	**2010**
Lake region						
Northeastern	5.22 (± 0.19)	6.07 (± 0.18)	4.82 (± 0.17)	4.89 (± 0.17)	5.02 (± 0.22)	4.36 (± 0.14)
	n[a]=209	n=227	n=222	n=152	n=114	n=227
South-central	4.51 (± 0.10)	5.21 (± 0.14)	4.20 (± 0.12)	4.79 (± 0.10)	4.18 (± 0.10)	4.50 (± 0.12)
	n=229	n=255	n=248	n=168	n=246	n=256
Western	5.22 (± 0.20)	5.69 (± 0.18)	5.06 (± 0.19)	4.76 (± 0.13)	5.11 (± 0.14)	4.21 (± 0.12)
	n=149	n=162	n=160	n=135	n=157	n=162
Assessment						
Field	5.46 (± 0.57)	5.51 (± 0.69)	5.22 (± 0.58)	4.96 (± 0.54)	4.43 (± 0.68)	5.31 (± 0.63)
	n=91	n=63	n=81	n=84	n=43	n=71
Remote	4.94 (± 0.20)	5.64 (± 0.22)	4.64 (± 0.18)	4.81 (± 0.23)	4.65 (± 0.20)	4.38 (± 0.17)
	n=587	n=644	n=630	n=455	n=517	n=645

[a] n varied in remote assessments due to cloud cover and in field assessments due to data availability

2.5. DISCUSSION

2.5.1. Spatial and temporal patterns in Maine lake clarity

Water clarity of Maine lakes appears to be declining statewide. Although average SDD in both the northeastern and western regions exceeded 5 m in 2009, depths similar to 1995 levels (Table 2.3), we may be witnessing a downwardly shifting baseline and general trend toward eutrophication in Maine lakes. The proportion of Maine lakes in mesotrophic status appears stable, however, 79 formerly mesotrophic lakes have become eutrophic and 66 previously oligotrophic lakes have become mesotrophic, which are further evidence of a general trend toward eutrophication (SDD<4 m). Based on our regional analysis, the disproportional shifts in the northeastern and western regions were not surprising (Fig. 2.4). Lakes with increased SDD during 1995-2010 generally occurred in the south-central region (52 of 72 lakes) and were comparatively smaller in size (average=49 ha), whereas lakes with reduced clarity occurred disproportionately in the rural northeastern and western lake regions (55 of 66 lakes) and were relatively larger (average=403 ha). Overall, clarity in the south-central lake region remained unchanged during this time.

Possible explanations for the disproportionate decline in lake clarity in the northeastern and western lake regions are climate change and forest harvest. Warmer temperatures and extended growing seasons associated with climate change may be creating conditions for increased lake productivity. The dominant land use (forest harvest) in northern Maine may also be affecting the region’s lake water clarity. Although we found no correlation between the proportion of lake watersheds harvested for timber during 1991-2007 based on Landsat-derived forest change detection data (Noone and

Sader in press) and the decline in SDD, the total area of forest harvest is insensitive to harvest intensity, which has varied considerably throughout the history of Maine's forests. Additional research is necessary to evaluate potential influences of harvest intensity on regional lake clarity in northern Maine.

2.5.2. Evaluation of existing sampling record

Maine's current water clarity sampling approach does not necessarily acquire a representative sample of regional water quality owing to spatially biased field sampling and omission of inaccessible, rural lakes. Remote lake monitoring schemes enable spatially balanced sampling because assessment is not limited by access. Although Landsat-based models produce accurate estimates of water clarity in Maine overall (McCullough et al. in press), there is greater prediction error in regions with few field-sampled lakes. Discrepancies between remote SDD estimates and field-collected SDD in Maine are attributable to spatially biased, non-random field sampling. Landsat-based models developed for assessing statewide water clarity can be calibrated with these non-random field data, however, a spatially imbalanced calibration dataset potentially decreases water clarity prediction accuracy. During the selected six study years, field data were available for 43-91 unique lakes, representing only 8-16% of the 570 lakes > 8 ha in the imagery overlap region. There were insufficient field-collected data (≤ 5 sampled lakes within ± 7 day calibration windows) in the northeastern and western lake regions to evaluate model predictions for lakes in those regions, underscoring the spatial biases in current field sampling programs. Seasonal dynamics in lake water clarity also potentially contribute to discrepancies between remotely-sensed and field-collected SDD data, however, restricting analysis to the ± 7 day calibration window constrained to August 1 – September 5 minimizes this error.

2.5.3. Application of Landsat imagery for change detection of regional water quality

Landsat TM data are an effective tool in regional water quality monitoring because the spatial extent of Landsat imagery eliminates the biases of non-random sampling typically employed in the field. Although near-concurrent (± 7 days of satellite overpass) field data must be collected for model calibration, remote water quality monitoring with Landsat TM data potentially reduces lake monitoring costs substantially, especially if field sampling efforts were planned to coincide with satellite overpasses. Despite these considerable advantages, this procedure has some notable limitations. Restricting usable imagery to late summer, when lakes are expected to be least clear, reduces image availability. Cloud-free late summer images may not be available owing to cloud cover and the 16 day revisit cycle. The reduced quality of Landsat 7 SLC-off images and the age of Landsat 5 exacerbate the issue of future image availability; however, a successful launch of the Landsat Data Continuity Mission in 2013 would help alleviate issues of future image availability. Using scene overlap areas between Landsat paths is a practical approach to increase image availability.

The poor image quality of Landsat 7 SLC-off imagery limits its use for remote water clarity monitoring. Calibration of SLC-off models required we eliminate as many as 100 lake stations per Landsat path owing to missing satellite data in deep areas of lakes. Lake sample stations shifted to within the working scan lines may not be representative of conditions at the actual sample station (i.e., the SDD estimate is calculated for a shallower area than where the SDD data were or would be collected in the field), potentially reducing model fit and accuracy of SDD predictions. Smaller lakes (~ 8 ha) with less surface area for remote data extraction are more likely to be affected or requiring of omission.

The R^2 values of models we produced using SLC-off imagery (R^2 =0.74-0.82) were comparable to those reported by Olmanson et al. (2008) (R^2 =0.72-0.86), however, we found that our SLC-off models could not accurately estimate SDD in areas lacking field calibration data. Approximately 90% of our calibration data consisted of lakes in the south-central lake region; consistently ≤ 5 lakes from the northeastern and western lake regions combined were available in calibrations. Average south-central SDD between the 8 August 2005 (SLC-off) and 9 August 2005 (Landsat 5) models differed 0.05 m, a negligible difference, whereas average northeastern and western SDD differed > 1 m between the two days. Satellite data loss in SLC-off images exacerbated the limited availability of calibration data in these remote areas. Management agencies intending to use SLC-off imagery for remote lake monitoring should consider increasing field data collection in remote areas to increase model accuracy for these areas. Although SLC-off imagery can be used to calibrate models with strong fitness, spatially unbalanced calibration datasets cause inaccurate SDD predictions in regions lacking calibration data.

CHAPTER 2 REFERENCES

Bacon, L. and Bouchard, R. (1997). Geographic analysis and categorization of Maine lakes: a trial of the draft bioassessment and biocriteria technical guidance. Maine Department of Environmental Protection, Augusta, ME 04333.

Boyle, K. J., Poor, P. J. and Taylor, L. O. (1999). Estimating the demand for protecting freshwater lakes from eutrophication. *American Journal of Agricultural Economics* 81 (5): 1118-1122.

Carlson, R. E. (1977). A trophic state index for lakes. *Limnology and Oceanography* 22(2): 361-369.

Chipman, J. W., Lillesand, T. M., Schmaltz, J. E., Leale, J. E. and Nordheim, M. J. (2004). Mapping lake clarity with Landsat images in Wisconsin, U.S.A. *Canadian Journal of Remote Sensing* 30(1): 1-7.

Davis, R. B., Bailey, J. H., Scott, M., Hunt, G. and Norton, S. A. (1978). Descriptive and comparative studies of Maine lakes. Life Sciences and Agricultural Experiment Station. Technical Bulletin 88.

Gibbs, J. P., Halstead, J. M., Boyle, K. J. and Huang, J. (2002). An hedonic analysis of the effects of lake water clarity on New Hampshire lakefront properties. *Agricultural and Resource Economics Review* 31(1): 39-46.

Heiskary, S. A. and Walker, W. W. (1988). Developing phosphorus criteria for Minnesota lakes. *Lake and Reservoir Management* 4(1): 1-9.

Kloiber, S. M., Brezonik, P. L., Olmanson, L. G. and Bauer, M. E. (2002). A procedure for regional lake water clarity assessment using Landsat multispectral data. *Remote Sensing of Environment* 82: 38-47.

Maine PEARL. (2011). Lakes Guide. Senator George J. Mitchell Center for Environmental Research, University of Maine, Orono. http://www.pearl.maine.edu/windows/community/default.htm. Accessed 1/18/11.

Maine Volunteer Lake Monitoring Program. (2010). Auburn, ME 04210.

McCullough, I. M., Loftin, C. S. and Sader, S. A. In press. Combining lake and watershed characteristics with Landsat TM data for remote estimation of regional lake clarity. *Remote Sensing of Environment*.

MDEP; Bacon, L. (2010). Maine Department of Environmental Protection. Augusta, ME 04333.

Michael, H. J., Boyle, K. J. and Bouchard, R. (1996). Water quality affects property prices: a case study of selected Maine lakes. Maine Agricultural and Forest Experiment Station, University of Maine, Orono, ME.

Nelson, S. A. C., Soranno, P. A., Cheruvelil, K.S., Batzli, S. A. and Skole, D. L. (2003). Regional assessment of lake water clarity using satellite remote sensing. *Journal of Limnology* 62: 27-32.

Noone, M. D. and Sader, S. A. In press. Are forest disturbances influenced by ownership change, conservation easement status, and land certification? *Forest Science*.

Olmanson, L. G., Bauer, M. E. and Brezonik, P. L. (2008). A 20-year Landsat water clarity census of Minnesota's 10,000 lakes. *Remote Sensing of Environment* 112: 4086-4097.

Omernik, J. M. (1987). Ecoregions of the conterminous United States. *Annals of the Association of American Geographers* 77(1): 118-125.

Peckham, S. D. and Lillesand, T. M. (2006). Detection of spatial and temporal trends in Wisconsin lake water clarity using Landsat-derived estimates of secchi depth. *Lake and Reservoir Management* 22(4): 331-341.

Stadelmann, T. H., Brezonik, P. L. and Kloiber, S. M. (2001). Seasonal patterns of chlorophyll a and Secchi disk transparency in lakes of East-Central Minnesota: Implications for design of ground- and satellite-based monitoring programs. *Lake and Reservoir Management* 17(4): 299-314.

Tiner, R. W. (1998). Wetland indicators: a guide to wetland identification, delineation, classification, and mapping. Boca Raton: CRC Press. 293 pp.

U.S. EPA. (2010). Primary distinguishing characteristics of Level III Ecoregions of the continental United States. United States Environmental Protection Agency. Washington, D.C. 20460. http://www.epa.gov/wed/pages/ecoregions/level_iii_iv.htm. Accessed 12/28/11.

CHAPTER 3

HIGH-FREQUENCY REMOTE MONITORING OF LARGE LAKES WITH MODIS 500 M IMAGERY

3.1. INTRODUCTION

Water clarity is a widely used metric of lake water quality often measured as secchi disk depth (SDD). Lake water clarity is closely associated with water quality indicators such as trophic status, chlorophyll-a, and total phosphorus and is a strong indicator of overall lake productivity (Carlson 1977). Increased lake clarity increases lakefront property value in Maine (Michael et al. 1996, Boyle et al. 1999) and New Hampshire (Gibbs et al. 2002) and enhances user-perception of lake health in Minnesota (Heiskary and Walker 1988). Because clarity assessments are easy to administer and have important ecological and economic implications, clarity is an ideal metric of regional lake water quality. Regional assessments, however, are logistically challenging and expensive to perform regularly. Consequently, field assessments tend to exclude rural and relatively inaccessible areas, thereby producing spatially irregular, non-random samples.

An approach to reducing costs and eliminating problems associated with lake accessibility is use of remote sensing. Recently, there has been an emergence of published procedures for remote monitoring of regional lake water clarity with satellite imagery (Kloiber et al. 2002a, Chipman et al. 2004, Olmanson et al. 2008, McCullough et al. in press). These procedures rely on continued access to Landsat Thematic Mapper (TM) data. The Landsat platform has a number of key advantages including nearly 30 years of archived imagery, a 185 km scene width suitable for regional analyses, free data access, and good resolution in the visible and infrared portions of the electromagnetic spectrum. The 30 m spatial resolution of Landsat permits simultaneous assessment of hundreds of lakes ≥ 8 ha and within-lake assessment of large lakes. Repeated application of Landsat underscores its usefulness in regional water quality monitoring, however, Landsat still has limitations. Of two Landsat satellites currently in operation, Landsat 7 ETM+ has compromised image quality owing to the 2003 scan-line corrector (SLC) failure. Landsat 5 TM, launched in 1984, has long exceeded its life expectancy and was suspended in November 2011 in an attempt to restore operation after an amplifier malfunction. Image availability limitations could be mitigated by the intended launch of the Landsat Data Continuity Mission (LDCM) in 2013. In addition, Landsat has a 16 day temporal resolution, which can be problematic when short time windows are of interest, particularly in the presence of cloud cover.

Moderate-Resolution Imaging Spectroradiometer (MODIS) sits aboard two NASA satellites: Terra, launched in 1999, and Aqua, launched in 2002. Each satellite captures daily images of the entire Earth surface, yielding two images per day. Many MODIS image products arrive pre-converted to surface reflectance, eliminating potential need for radiometric correction. MODIS contains 29 bands at 1,000 m, five bands spectrally similar to Landsat TM at 500 m, and two bands (red visible and near infrared) at 250 m resolution. Scenes are approximately 2,300 km wide. The large pixel size restricts application only to large area analyses; however, the greater temporal resolution and pre-conversion to surface reflectance are notable, potential advantages over Landsat.

There are relatively few previous applications of MODIS for lake water quality monitoring. Koponen et al. (2004) classified water quality of Finnish lakes into broad categories (i.e. excellent, good, satisfactory and fair) with 250 m MODIS data, and various MODIS band combinations were used to estimate seasonal chlorophyll-a of Taihu Lake, China (Zhu et al. 2005). Dall'Olmo et al. (2005) found simulated MODIS and SeaWiFS imagery could be used to estimate chlorophyll-a concentrations in turbid, productive waters including lakes. MODIS data were used to estimate chlorophyll-a, total phosphorus, total nitrogen and water clarity in Chaohu Lake, China, with R^2 values > 0.60 for clarity and chlorophyll-a (Wu et al. 2009). Chipman et al. (2009) showed that the visible blue (500 m resampled to 250 m)/visible red (250 m) MODIS band ratio was strongly correlated (R^2=0.79) with natural log-transformed chlorophyll-a in Minnesota and Ontario lakes and used various band combinations at 500 m to map water clarity in Lake Michigan. Olmanson et al. (2011) were the first to demonstrate that MODIS 250, 500 and 1,000 m imagery can be effectively used in regional estimation of clarity and chlorophyll-a in Minnesota lakes using concurrent August imagery, however, they note that the number of lakes monitored is limited by spatial resolution.

Despite these recent advances in the use of MODIS imagery for remote lake monitoring, previous research has not yet evaluated the application of the high temporal resolution of MODIS data for intra-annual lake monitoring, which is a potentially major advantage of MODIS over conventionally-used Landsat. Additionally, our past analyses of Maine lakes using Landsat imagery indicate that incorporation of physical lake features and watershed characteristics improve accuracy of remote SDD estimates (McCullough et al. in press), however, it is unclear if these findings are applicable at the scale of MODIS-based lake monitoring. The objectives of this study were to (1) investigate the effectiveness of MODIS 500 m data in regional lake clarity monitoring during May-September, (2) evaluate the contributions to MODIS model performance of physical lake features and watershed characteristics that drive regional water clarity at the scale and resolution of Landsat, and (3) compare the respective utilities of MODIS and Landsat data in regional lake clarity monitoring. We developed a reliable and efficient MODIS-based remote monitoring protocol for water clarity of large lakes that is applicable over time and incorporates knowledge of seasonal lake dynamics and landscape characteristics that contribute to regional water clarity. We propose that MODIS is a valuable complement to Landsat-based monitoring programs and hypothesize that whereas Landsat is useful for long-term, low-frequency lake assessment, especially of historical clarity owing to its long data archive, MODIS may be more effective for recent and future intra-annual monitoring of large lakes.

3.2. DESCRIPTION OF STUDY AREA

Maine, USA contains over 1,500 lakes ≥ 8 ha in surface area distributed across approximately 90,000 km^2. Maine ranks first among all states east of the Great Lakes in total area of inland surface waters (Davis et al. 1978) and 26% of the state is covered by wetlands (Tiner 1998). The climate is cold-temperate with long, cold winters and short, warm summers. Maine is dominated by the Northeastern Highlands (#58) and the Acadian Plains and Hills (#82) Level III Ecoregions (Omernik 1987). The Northeastern Highlands are remote, mostly forested, mountainous, and contain numerous high-elevation, glacial lakes. The Acadian Plains and Hills are comparatively more populated and less rugged; however, the area also is heavily forested and contains many glacial lakes (U.S. EPA 2010). Lakes range in size from small ponds < 1 ha to Moosehead Lake (30,542 ha), the largest lake in Maine. The average SDD of Maine lakes was 5.14 m in 2009 (n=457; Maine Department of Environmental Protection; MDEP; Bacon, Maine

Volunteer Lake Monitoring Program; VLMP 2010). Since statewide monitoring began in 1970, average annual SDD consistently has ranged 4-6 m, with a statewide average of 5.27 m during 1970-2009. The number of lakes sampled annually generally has increased since 1970 and consistently has exceeded 400 lakes since 1999 (MDEP, VLMP 2010).

3.3. METHODS

3.3.1. Selection of MODIS imagery

We retrieved archived, free Level 1B daily surface reflectance imagery (MOD 09) at 500 m resolution collected on Aqua and Terra satellites (http://glovis.usgs.gov/). We selected 500 m over 250 m resolution because the spectral sensitivity of MODIS 250 m imagery does not span both the blue and red visible portions of the electromagnetic spectrum correlated with lake water clarity (Kloiber et al. 2002a, Chipman et al. 2004, Olmanson et al. 2008, McCullough et al. in press). We conducted date-specific analyses of images in 2001, 2004 and 2010 during May-September to evaluate within-year lake clarity monitoring with MODIS data. We analyzed additional images captured 20 October 2004 and 5 October 2010 to evaluate model accuracy in mid-fall. We also analyzed images captured 9 August 2002, 5 September 2009 and 30 August 2010 to compare respective SDD predictions derived from concurrently captured Landsat TM imagery (McCullough et al. in press). We restricted our dataset to imagery with minimal cloud cover, although imagery chosen to coincide with Landsat imagery contained some clouds owing to comparative lack of flexibility in Landsat image selection. We attempted to analyze MODIS and Landsat imagery collected on 9 August 2005, however, clouds obscured too many of the large lakes necessary to calibrate MODIS models.

3.3.2. Ancillary lake data

Physical lake variables and landscape characteristics improve Landsat-based predictions of SDD of Maine lakes (McCullough et al. in press). We included average lake depth and the proportion of wetland coverage in lake watersheds (wetland area) in our calibrations of MODIS data because these variables were significant predictors of Maine lake clarity using Landsat imagery; however, different ancillary variables may be strongly correlated with lake clarity in other regions. We obtained bathymetric data (MDEP; Bacon 2011) and a watershed boundary geographic information system (GIS) layer (MDEP; Suitor 2011). We used the watershed layer to calculate wetland area (ArcGIS ® version 10.0; Environmental Systems Research Inc., Redlands, CA, United States). Our wetland dataset was an updated NWI (National Wetlands Inventory) GIS layer (Houston 2008). No lakes in our calibrations were missing ancillary data because we selected large, relatively well-mapped lakes for model development.

3.3.3. Lake size and shape limitations

Clarity of many small lakes cannot be estimated reliably with MODIS imagery owing to the 500 m spatial resolution. Lakes < 400 ha were omitted from a statewide study of Wisconsin (Lillesand 2002) and Minnesota (Olmanson et al. 2011) lakes conducted at 500 m resolution. Although lake size provides a threshold for unsuitable lakes, shape also affects lake eligibility. Pixels overlapping with lake boundaries introduce spectral interference from shoreline features (Chipman et al. 2009). Lakes with a large surface area owing to a long axis and convoluted shoreline will be represented with few water-only pixels. At 500 m resolution, 385 lakes can be monitored in

Minnesota (Olmanson et al. 2011) and 108 and 90 lakes can be monitored in Michigan and Wisconsin respectively (Chipman et al. 2009). We used the lake perimeter (m)/surface area (m^2) ratio to characterize lake shape and determine eligibility for remote monitoring with MODIS 500 m data. We generated this ratio with GIS-derived lake perimeter and area metrics and limited our dataset to lakes with a perimeter/surface area ratio < 0.019. The smaller this ratio, the greater the likelihood of avoiding mixed pixels. Based on size and shape requirements, 83 Maine lakes can be routinely monitored using MODIS 500 m imagery (Fig. 3.1).

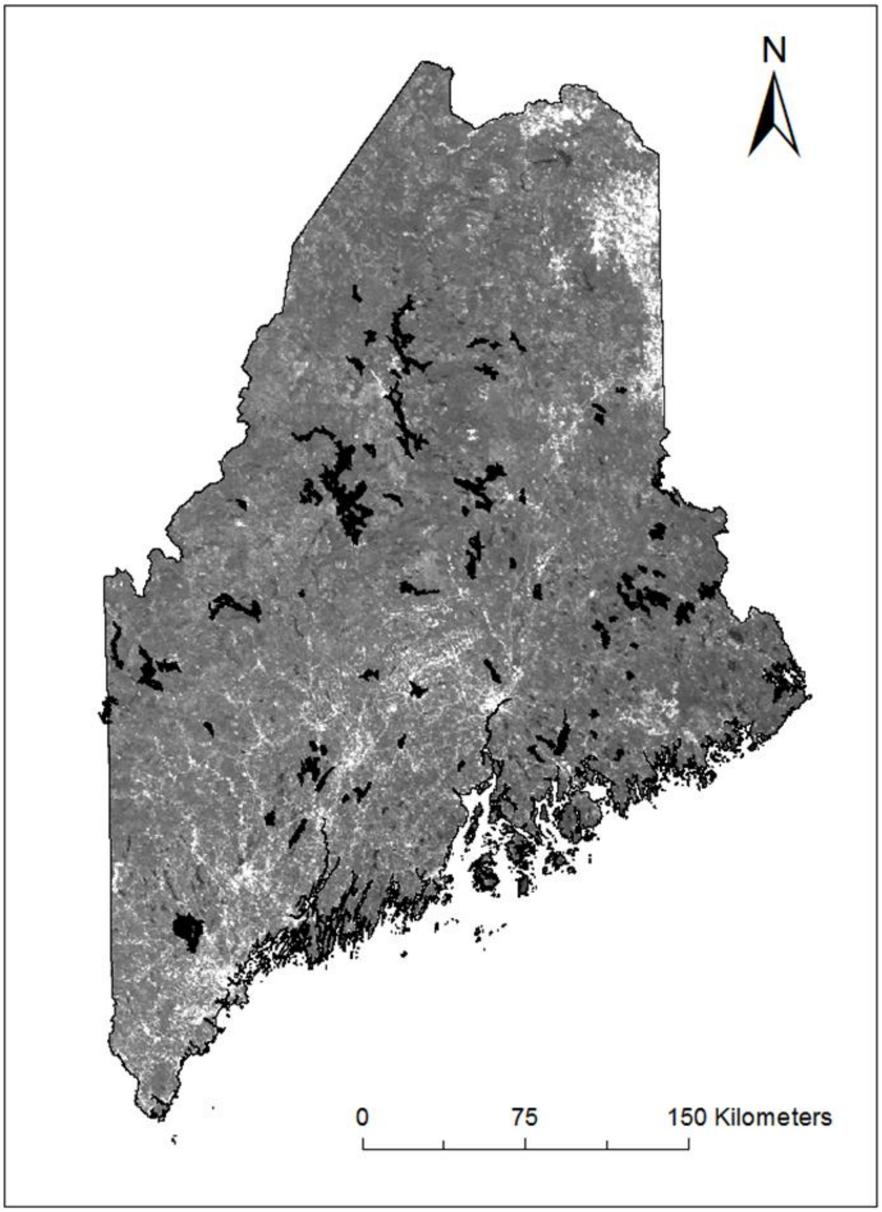

Fig. 3.1. Eighty-three Maine lakes can be monitored routinely with MODIS 500 m imagery. This imagery was captured by the Aqua satellite on 2 September 2004.

3.3.4. Image pre-processing

Level 1B images are pre-converted to surface reflectance, requiring only minimal additional pre-processing. We reprojected all images to WGS1984 UTM Zone 19 N with nearest neighbor resampling with the MODIS Reprojection Tool (https://lpdaac.usgs.gov/lpdaac/tools/modis_reprojection_tool). We mosaicked images (ERDAS Imagine ® version 10.0; ERDAS Inc., Norcross, GA, USA) and clipped them to the state boundary. We mostly used completely cloud-free imagery; however, if clouds were present, we used an unsupervised classification (ISODATA clustering) to identify cloud pixels, which we reclassified as null values and removed from further analysis. Cloud shadows could not be removed by unsupervised classification without simultaneously removing unaffected lake pixels, so images were visually inspected to remove lakes affected by shadows.

3.3.5. Data extraction and model development

We created a remote sampling GIS points layer of SDD sampling stations delineated on bathymetric maps (Maine PEARL 2011). SDD sampling stations generally are located in the deepest areas of lakes; however, we manually relocated these sites to lake centers when lake boundaries compromised water-only pixels. We assigned sampling stations to lake centers in the absence of established locations. We buffered the points by 500 m for pixel extraction. A buffer size of 500 m captures 4-9 pixels and provides a general characterization of lake surface reflectance. Larger samples may improve correlation with SDD; Kloiber et al. (2002b) found including up to 25 pixels improved model fitness with Landsat imagery. Use of > 4-9 pixels at 500 m resolution, however, restricts assessment to a small number of very large lakes. We also applied 300 and 400 m buffers as well as single pixels; however, a 500 m buffer yielded the greatest R^2 values. A disadvantage of this method is that the requirement of several water-only pixels inevitably limits the number of lakes sampled. We calculated the average pixel value for MOD 09 bands 1 (red visible; 620-670 nm) and 3 (blue visible; 459-479 nm) in each buffered area with zonal statistics. Bands 1 and 3 correspond to the visible portions of the electromagnetic spectrum most strongly correlated with clarity of Maine lakes using Landsat (McCullough et al. in press). Other Landsat-based studies determined the blue/red band ratio is a strong predictor of SDD (Kloiber et al. 2002a, Chipman et al. 2004, Olmanson et al. 2008), however, we found the individual red and blue TM bands were more consistently, strongly correlated with SDD in Maine than green or near infrared TM bands or various combinations and ratios of TM bands 1-4 (McCullough et al. in press).

SDD data collected ± 10 days of the satellite overpass in mid-late summer (July 15-September 15) are acceptable for use in remote clarity estimation models because water clarity is relatively stable at this time of year (Kloiber et al. 2002a); however, time windows of ± 10 days are not ideal and should be used only when insufficient data are available within shorter time frames. Lake clarity usually is at a seasonal low during late summer owing to peak development in algal communities, making late summer the optimal period for remote clarity estimation (Stadelmann et al. 2001). Outside late summer, however, field calibration data should be collected as closely as possible to satellite image capture dates to minimize variability associated with changing lake conditions, such as stratification and mixing, which may vary across a landscape. We used time windows of ± 3-7 days of the satellite overpass based on SDD data availability, using ± 7 day windows during August only when necessary.

We used spectral data (bands 1 and 3) average depth and wetland area to estimate natural log-transformed SDD with linear regression (R Version 2.12.0; R Foundation for Statistical Computing, Vienna, Austria). We included the MODIS band 1/3 ratio owing to its established, strong correlation with ln(SDD) (Kloiber et al. 2002a, Chipman et al. 2004, Olmanson et al. 2008). We validated all regression models with leave-one-out jackknifing (Sahinler and Topuz 2007) and verified standard regression assumptions. We identified and eliminated outliers with the Bonferroni outlier test and case-by-case inspection of residuals and input parameters. Non-outlying influential cases were not removed unless considerable model fitness was gained.

3.4. RESULTS

3.4.1. Regression results

We found strong correlations (R^2=0.72-0.94; RMSE=1.18-1.39 m) between ln(SDD), MODIS bands 1 and 3, average depth and wetland area (Table 3.1). Band 1 was negatively correlated and band 3 was positively correlated with ln(SDD). Band 3 was generally correlated with ln(SDD) during May-August, although during May only in 2010. The band 1/3 ratio created model redundancies and was less consistently correlated with ln(SDD) than individual bands 1 and 3. Average lake depth was positively correlated with ln(SDD) during the stratified period (mid-June-August) and wetland area was consistently negatively correlated with ln(SDD) in May. Our best-performing MODIS models were produced for July-September, however, models with $R^2 > 0.70$

were produced throughout the study (Table 3.1, Fig. 3.2). We failed to calibrate models for 9 May 2004 and October dates owing to lack of calibration data.

The average absolute difference between all observed and model-estimated SDD values was 1.04 m (± 0.88; one standard deviation), however, lake trophic status affected this difference (Table 3.2). Eutrophic lakes (SDD < 4 m) generally were estimated most accurately, differing 0.77 m (± 0.58) on average from observed conditions. Estimates for mesotrophic lakes (SDD=4-7 m) averaged 0.96 m (± 0.71) from observed SDD and estimates for oligotrophic lakes (SDD > 7 m) were the least accurate, differing 1.50 m (± 1.07) on average from observed conditions.

Table 3.1. Summary of clarity estimation models with MODIS 500 m imagery

Date	**Satellite**	**Model**	**R^2**	**± Days**	**n**
9/18/2010	Terra	$-1.31\text{x}10^{-2}$ (Band 1[a]) + 2.65	0.9237	3	20
8/29/2010	Terra	$-1.08\text{x}10^{-2}$ (Band 1) + $1.37\text{x}10^{-2}$ (AvgDepth[b]) + 2.58	0.7941	3	19
8/19/2010	Terra	$-9.65\text{x}10^{-3}$ (Band 1) + $9.29\text{x}10^{-3}$ (AvgDepth) + 2.41	0.8231	3	20
6/15/2010	Terra	$-9.04\text{x}10^{-3}$ (Band 1) + $2.16\text{x}10^{-2}$ (AvgDepth) + 2.25	0.8040	3	22
5/21/2010	Terra	$-1.02\text{x}10^{-2}$ (Band 1) + $7.25\text{x}10^{-3}$ (Band 3[c]) - $3.61\text{x}10^{-4}$ (Wetland[d]) + 2.20	0.7651	3	13
9/14/2004	Aqua	$-8.63\text{x}10^{-3}$ (Band 1) + 2.60	0.8797	3	20
9/2/2004	Aqua	$-3.58\text{x}10^{-2}$ (Band 1) + $3.54\text{x}10^{-2}$ (Band 3) + 1.99	0.9376	3	10
8/24/2004	Aqua	$-1.53\text{x}10^{-2}$ (Band 1) + $1.22\text{x}10^{-2}$ (Band 3) + $6.08\text{x}10^{-3}$ (AvgDepth) + 1.83	0.8173	7	37
7/7/2004	Aqua	$-1.29\text{x}10^{-2}$ (Band 1) + $1.48\text{x}10^{-2}$ (Band 3) + $7.27\text{x}10^{-3}$ (AvgDepth) + 1.46	0.8856	3	15
6/5/2004	Aqua	$-1.24\text{x}10^{-2}$ (Band 1) + $2.18\text{x}10^{-2}$ (Band 3) + 0.866	0.7204	3	17
9/9/2001	Terra	$-7.91\text{x}10^{-3}$ (Band 1) + 2.21	0.7403	3	22
8/1/2001	Terra	$-1.42\text{x}10^{-2}$ (Band 1) + $1.11\text{x}10^{-2}$ (Band 3) + $5.48\text{x}10^{-3}$ (AvgDepth) + 1.80	0.7742	7	31
7/20/2001	Terra	$-6.24\text{x}10^{-3}$ (Band 1) + $5.31\text{x}10^{-3}$ (Band 3) + $4.83\text{x}10^{-3}$ (AvgDepth) + 2.47	0.7064	3	18
5/25/2001	Terra	$-1.11\text{x}10^{-2}$ (Band 1) + $1.50\text{x}10^{-2}$ (Band 3) - $3.58\text{x}10^{-4}$ (Wetland) + 1.70	0.8910	3	13
5/8/2001	Terra	$-9.29\text{x}10^{-3}$ (Band 1) + $2.16\text{x}10^{-2}$ (Band 3) - $5.37\text{x}10^{-4}$ (Wetland) - 0.877	0.7194	3	13

[a] Band 1 = visible red (620-670 nm), [b] AvgDepth = average lake depth, [c] Band 3 = visible blue (459-479 nm), [d] Wetland = proportion of watershed covered by wetland. We failed to create models for imagery captured 5/9/2004, 10/20/2004 and 10/5/2010 owing to lack of calibration data.

Table 3.2. Average absolute difference (m) between MODIS-estimated and observed SDD by lake trophic state[a]

Date	Satellite	Eutrophic	Mesotrophic	Oligotrophic	Overall
9/18/2010	Terra	0.36	0.67	1.21	0.67
8/29/2010	Terra	0.77	0.96	1.64	1.09
8/19/2010	Terra	0.68	1.07	1.39	1.12
6/15/2010	Terra	0.43	0.83	1.29	0.91
5/21/2010	Terra	1.42	0.65	2.14	1.17
Average		0.64	0.86	1.47	0.98
Std Dev		0.58	0.61	0.93	0.78
9/14/2004	Aqua	0.53	1.23	1.15	0.99
9/2/2004	Aqua	0.30	0.89	1.70	1.17
8/24/2004	Aqua	0.55	0.94	1.78	1.11
7/7/2004	Aqua	0.16	0.92	1.48	0.83
6/5/2004	Aqua	0.49	0.66	1.82	0.81
Average		0.45	0.92	1.57	1.00
Std Dev		0.47	0.62	1.08	0.86
9/9/2001	Terra	0.76	0.86	2.43	1.41
8/1/2001	Terra	0.61	1.64	1.57	1.38
7/20/2001	Terra	1.10	0.85	1.17	0.94
5/25/2001	Terra	0.42	0.83	1.12	0.83
5/8/2001	Terra	1.04	0.95	1.91	1.28
Average		0.77	1.09	1.50	1.13
Std Dev		0.97	0.67	1.21	0.97

[a] Eutrophic SDD < 4 m, Mesotrophic SDD = 4-7 m, Oligotrophic SDD > 7 m

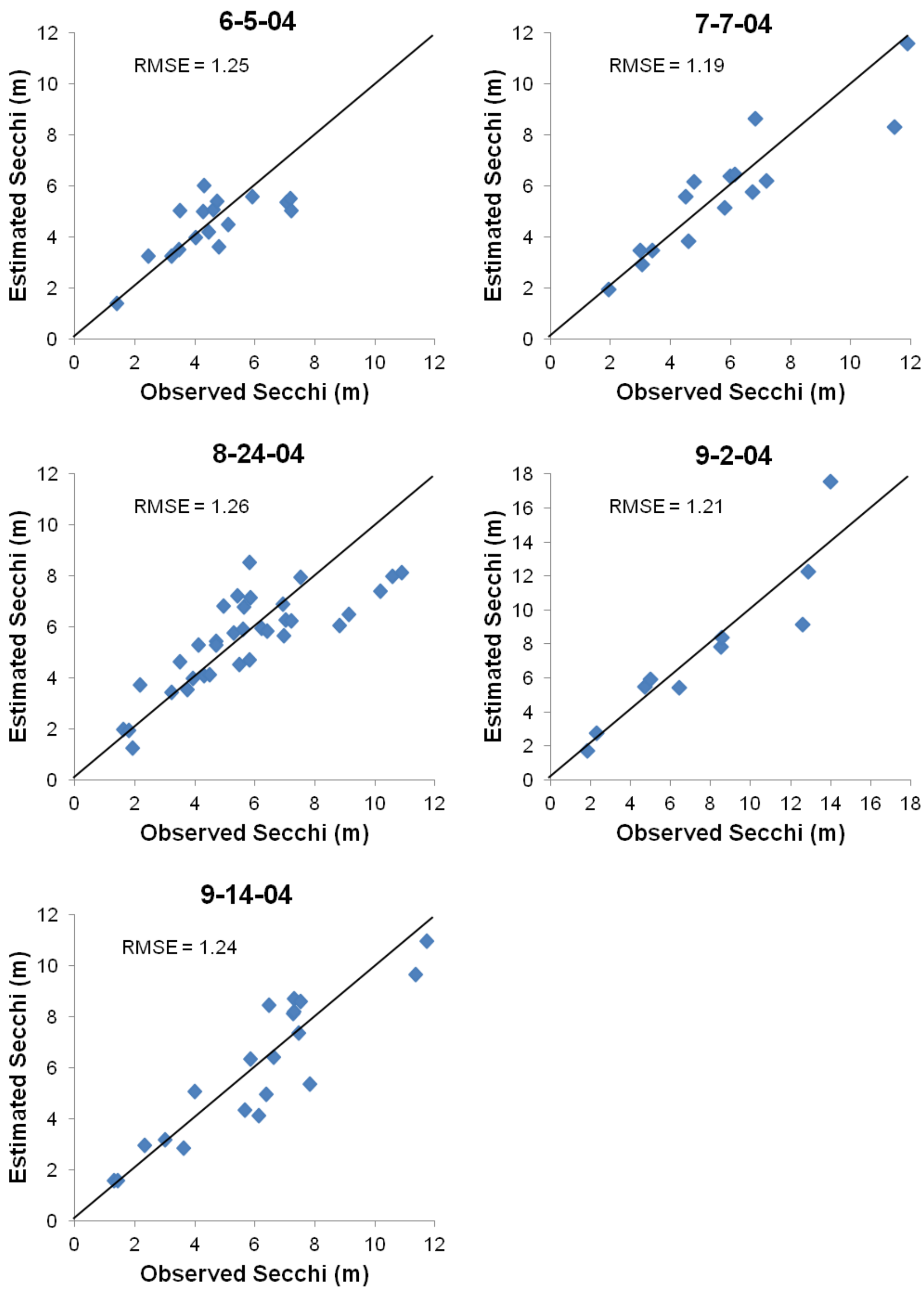

Fig. 3.2. Plotted relationships between observed and estimated secchi disk depth (m) for 2004 MODIS models with 1:1 fit line. Observed values are based on field data gathered by the Maine Volunteer Lake Monitoring Program (VLMP) ± 3-7 days of satellite overpass. RMSE = root mean squared error.

3.4.2. Comparison to same-date Landsat models

Predictive capacities (R^2) were greater for Landsat than MODIS models on three of four occasions, except on 14 September 2004 (Table 3.3). Significant predictors generally were similar in corresponding models (Table 3.3). Similarly, the average absolute difference between model-estimated and field-collected SDD measurements consistently was less in Landsat models, except on 14 September 2004. The window of days for usable calibration data varied in all years except 2009 based on calibration data availability (Table 3.3). The same calibration datasets could not be used in respective MODIS and Landsat models owing to lake size/shape requirements for MODIS models and the larger geographic extent of MODIS imagery. SDD estimates from MODIS and concurrently collected Landsat data were not different across all years (n=279; paired t-test, p=0.243), nor in any individual year (Table 3.4). The absolute difference between annual average MODIS and Landsat SDD estimates ranged 0.06-0.33 m across all four years (Table 3.4).

Table 3.3. Comparison of MODIS and Landsat models predicting SDD on coincident dates

Date	Satellite	Model	R^2	± Days	n	Abs Diff (m)[g]
8/30/2010	Aqua	$-8.08x10^{-3}$ (Band 1[a]) + $7.71x10^{-4}$ (AvgDepth[b]) + 2.52	0.6528	3	22	1.51
8/30/2010	Landsat	-0.244 (TM3[c]) + $8.39x10^{-3}$ (AvgDepth) + 5.22	0.7305	1	65	1.03
9/5/2009	Terra	$-1.31x10^{-2}$ (Band 1) + $1.62x10^{-2}$ (Band 3[d]) - $3.41x10^{-4}$ (Wetland[e]) + 1.95	0.7667	3	22	1.45
9/5/2009	Landsat	$-3.20x10^{-1}$ (TM3) + $3.72x10^{-2}$ (TM1[f]) + $7.78x10^{-3}$ (AvgDepth) - $3.61x10^{-4}$ (Wetland) + 5.51	0.8631	3	66	0.73
9/14/2004	Aqua	$-8.63x10^{-3}$ (Band 1) + 2.60	0.8797	3	20	0.99
9/14/2004	Landsat	-0.298 (TM3) + 6.44	0.6693	1	44	1.27
8/9/2002	Terra	$-1.13x10^{-2}$ (Band 1) + $8.26x10^{-3}$ (Band 3) + $1.06x10^{-3}$ (AvgDepth) + 1.57	0.7787	3	16	1.37
8/9/2002	Landsat	$-3.22x10^{-2}$ (TM3) + $1.29x10^{-2}$ (AvgDepth) - $7.51x10^{-4}$ (Wetland) + 4.25	0.9010	1	36	0.65

[a] Band 1 = MODIS visible red, [b] AvgDepth = average lake depth, [c] TM3 = Landsat visible red, [d] Band 3 = MODIS visible blue, [e] Wetland = proportion of watershed covered by wetlands, [f] TM1 = Landsat visible blue, [g] Avg Abs Diff = average absolute difference between observed and satellite-estimated SDD values.

Table 3.4. Paired t-test comparisons of MODIS and Landsat estimates

Date	Abs diff (m)[a]	p value	n
2010	0.06	0.779	72
2009	0.07	0.828	47
2004	0.33	0.106	81
2002	0.11	0.555	79
All	0.13	0.243	279

[a] Abs diff (m) = absolute difference between annual average MODIS and Landsat SDD estimates

3.5. DISCUSSION

3.5.1. Application of MODIS imagery in remote lake clarity monitoring

MODIS 500 m imagery is usable for regional remote clarity estimation of large lakes from late spring through late summer; however, MODIS predictions of lake clarity are more consistently accurate in mid-late summer. Inconsistency during late spring and early summer likely reflects seasonally unstable, unpredictable lake conditions that result from annual fluctuations in algal community development. Algal growth peaks consistently cause water clarity to be at its lowest in late summer, creating conditions most easily detectable by remote platforms sensitive to the visible portions of the electromagnetic spectrum correlated with lake water clarity (Kloiber et al. 2002a, Chipman et al. 2004, Olmanson et al. 2008). Given seasonally dynamic clarity conditions, mid-late summer estimates potentially are more valuable indicators than estimates outside this window. Furthermore, volunteers gather more calibration data in summer than in spring or fall, accounting for our inability to calibrate models for October or consistently for May.

Various combinations of MODIS bands 1 and 3 and physical lake parameters provided best-fitting models across years and seasons, which can be explained by seasonal lake dynamics and fluctuations in weather. The short wavelength of the visible blue band (band 3) poorly penetrates turbid or productive water and is less strongly correlated with ln(SDD) than the visible red band (band 1) (Lathrop 1991). Consequently, we would expect band 3 to be a weak predictor of water clarity during periods of high algal biomass, which typically occurs in late summer. This was the case in our study in

2001 and 2004, but not in 2010, which experienced an unusually dry and warm summer (June-August) (NOAA 2011) that likely lowered lake levels and concentrated algal productivity in lake water columns. Statewide lake clarity was at a 15 year low in August 2010 (McCullough et al. in review), which coupled with weather likely explains the lack of predictive capacity of band 3 after late May. Average depth is a major determining factor in lake water clarity during the stratified period, which begins between late April and early June and typically lasts 4-6 months in Maine (Davis et al. 1978). Therefore, we would expect that average depth would not be a consistent predictor of SDD during May, early June and early-mid September, which our results confirm (Table 3.1). Wetlands contain the most water in spring as a result of snowmelt and decrease in volume later during the year. Consequently, we would expect the effects of wetlands on lake water clarity to be most pronounced in May, which our results also confirm; however, 2009 experienced record summer rainfall (NOAA 2011), which explains the significance of wetlands in our 5 September 2009 MODIS model (Table 3.3). Although we found wetlands to be a consistent predictor of late summer lake clarity only in eastern Maine in our Landsat-based study (McCullough et al. in press), it is likely that the 500 m resolution, inclusion of additional months, and the wider geographic extent of this study accounted for the lack of similar findings.

The temporal resolution of MODIS data makes annual and intra-annual lake clarity estimation possible, whereas retrieving cloud-free Landsat imagery at these frequencies is less likely, particularly in areas with frequent cloud cover. Many cloud-free MODIS images of Maine were available during mid-late summer 2001-2010, whereas few cloud-free Landsat images were available during this period. Given that cloud-free imagery may not be available for several weeks at a time, the greater temporal resolution of MODIS increases the probability that high-quality imagery would be available at some point each summer, which represents a considerable advantage over Landsat. Although we proposed that pre-conversion to surface reflectance was a similar advantage over Landsat, loss of spatial resolution may negate potential benefits, which are unproven at this time. MODIS Level 1B corrections were designed to improve analyses of land features and research is needed to evaluate potential effects on water quality assessment. Although Olmanson et al. (2011) found uncorrected MODIS imagery performed as well, if not better than corrected MODIS imagery in estimation of SDD, we hypothesize that the use of cloud-free imagery may mask potential effects of atmospheric correction. Comparative analyses of cloud-free and marginally usable imagery may clarify the effects of MODIS atmospheric corrections on water quality estimation; however, the temporal resolution of MODIS potentially eliminates the need for use of all but the best quality imagery with minimal atmospheric interference.

3.5.2. Limitations of MODIS for lake clarity estimation

MODIS visible red data (band 1) consistently provided stronger predictions of SDD than visible blue data (band 3). MODIS data at 250 m resolution are not available at the visible blue wavelength (459-479 nm); however, the smaller resolution would considerably increase the number of lakes that could be remotely monitored, though at the expense spectral sensitivity. As the blue band is a relatively weak predictor of lake clarity in late summer or in productive waters in Maine, 250 m imagery may be particularly useful under these conditions. Chen et al. (2007) used 250 m Level 1B imagery to map turbidity in Tampa Bay with strong accuracy (R^2=0.73), conditions in which we would expect little penetration of visible blue radiation. Olmanson et al. (2011) successfully estimated SDD of 1,257 lakes > 125 ha using 250 m MODIS imagery captured in August, however, further research is needed to evaluate the utility of MODIS 250 m imagery during other months. Inclusion of additional lakes would increase calibration data availability. Model predictions potentially are affected by the selected lake calibration dataset, including sample size, and geographic and numeric distribution of SDD values. The numeric distribution of lake water clarity values may be reduced when fewer lakes are included in the model-building dataset, which subsequently affects model fitness (Nelson et al. 2003).

Average lake depth and wetland area seasonally improve accuracy of lake clarity estimation models; however, these variables may not be readily available in other locations and may require site-based sampling, which potentially is difficult in inaccessible areas. Lake depth and wetland area likely are sufficiently stable year-to-year at the landscape scale such that reassessment is unnecessary. Knowledge of lake depth relativizes the proportion of the water column penetrable by light and is useful regardless of predictive capacity. We have shown that average lake depth and wetland area improve model fitness in some cases; however, SDD estimates with reduced accuracy are useful when these variables are not available (McCullough et al. in press). Average depth and wetland area were strong predictors of Maine lake clarity; however, other ancillary variables may be better predictors in other regions based on the landscape and season of interest.

Utility of remote sensing data for lake water clarity monitoring is affected by cloud cover. Although daily MODIS imagery potentially provides multiple opportunities for cloud-free imagery each year, cloud cover remains a major limitation of satellite remote sensing. Despite the temporal frequency of MODIS image capture, availability of cloud-free imagery on specific dates is unlikely, especially in frequently clouded areas, requiring that remote monitoring protocols be flexible with regard to image selection.

3.5.3. Comparison of MODIS and Landsat models

Although we found no significant differences between SDD estimates from Landsat and MODIS models across all dates and models, the generally better accuracy of Landsat models can be attributed to finer resolution and smaller scale (individual TM paths). Olmanson et al. (2011) found that Landsat imagery performed better in terms of R^2 than concurrent MODIS 250, 500 and 1,000 m imagery, and different band combinations provided best-fitting models across image products. These findings are consistent with ours. The difference in scale accounts for differences in significant predictor variables in 2009 and 2002 MODIS and Landsat models. Landsat models contained lakes located in individual TM paths, whereas MODIS models encompassed all of Maine. It was not practical to use common calibration datasets owing to the small number of MODIS-eligible lakes; differences in resolution affected calibration data availability.

Landsat and MODIS imagery can be used to estimate SDD accurately despite differences in resolution and scale; however, Landsat and MODIS models have entirely different applications in remote water clarity monitoring. The 83 lakes in Maine that can be monitored simultaneously with 500 m MODIS imagery constitute $< 10\%$ of the approximately 1,000 lakes (≥ 8 ha) that potentially can be monitored with either Landsat path 11 or 12 (McCullough et al. in press). In Wisconsin, 60% of lakes > 400 ha can be reliably monitored with MODIS 500 m imagery, (Chipman et al. 2009), whereas the 83 MODIS-eligible Maine lakes represent 49% of lakes > 400 ha. Although Landsat data provide generally more accurate water clarity assessments, an important advantage of MODIS data is the ability to assess water clarity multiple times during spring and summer over a considerably larger geographic area. The 16 day temporal resolution of Landsat may require the use of marginal imagery when short time windows are of interest (e.g., late summer), whereas use of MODIS data substantially increases the probability of obtaining high-quality imagery.

3.6. CONCLUSION

MODIS 500 m imagery is a reliable tool in characterizing water clarity of large lakes from late spring through late summer and the frequency of MODIS image capture potentially enables assessment of lake clarity change during this period. MODIS-based lake monitoring is less dependable in May, however, owing to model calibration data availability and seasonally unstable lake dynamics that result in inconsistent relationships between spectral reflectance and water clarity. Average lake depth and watershed wetland area improved model accuracy for Maine lakes when knowledge of seasonal lake dynamics and recent weather are considered in model calibration. Only large lakes (83 in Maine) can be reliably assessed with MODIS 500 m data; considerably more lakes can be monitored with Landsat. The effects of MODIS atmospheric corrections on water clarity assessment are unknown; however, the temporal resolution of MODIS increases the probability of obtaining clear imagery with minimal atmospheric interference. Although the utility of MODIS data is biased toward large lakes, frequency of image capture is a notable advantage of MODIS over Landsat and allows selection of only the best quality imagery. A comprehensive lake water clarity monitoring program combines MODIS and Landsat TM data with rigorous field sampling programs that capture the ground-truthed SDD data on which a satellite-based monitoring program depends.

CHAPTER 3 REFERENCES

Boyle, K. J., Poor, P.J. and Taylor, L. O. (1999). Estimating the demand for protecting freshwater lakes from eutrophication. *American Journal of Agricultural Economics* 81 (5): 1118-1122.

Carlson, R. E. (1977). A trophic state index for lakes. *Limnology and Oceanography* 22(2): 361-369.

Chen, Z., Hu, C. and Muller-Karger, F. (2007). Monitoring turbidity in Tampa Bay using MODIS/Aqua 250-m imagery. *Remote Sensing of Environment* 109(2): 207-220.

Chipman, J. W., Lillesand, T. M., Schmaltz, J. E., Leale, J. E. and Nordheim, M. J. (2004). Mapping lake clarity with Landsat images in Wisconsin, U.S.A. *Canadian Journal of Remote Sensing* 30(1): 1-7.

Chipman, J. W., Olmanson, L. G., and Gitelson, A. A. (2009). Remote sensing methods for lake management: a guide for resource managers and decision-makers. Developed by the North American Lake Management Society in collaboration with Dartmouth College, University of Minnesota, University of Nebraska and University of Wisconsin for the United States Environmental Protection Agency.

Dall'Olmo, G., Gitelson, A. A., Rundquist, D. C., Leavit, B., Barrow, T. and Hulz, J. C. (2005). Assessing the potential of SeaWiFS and MODIS for estimating chlorophyll concentration in turbid productive waters using red and near-infrared bands. *Remote Sensing of Environment* 96(2): 176-187.

Davis, R. B., Bailey, J. H., Scott, M, Hunt, G., and Norton, S. A. (1978). Descriptive and comparative studies of Maine lakes. Life Sciences and Agricultural Experiment Station. NTIS. Technical Bulletin 88.

Gibbs, J. P., Halstead, J. M., Boyle, K. J., and Huang, J. (2002). An hedonic analysis of the effects of lake water clarity on New Hampshire lakefront properties. *Agricultural and Resource Economics Review* 31(1): 39-46.

Heiskary, S. A. and Walker, W. W. (1988). Developing phosphorus criteria for Minnesota lakes. *Lake and Reservoir Management* 4(1): 1-9.

Houston, B. (2008). Coastal Maine updates. U.S. Fish and Wildlife Service. Gulf of Maine Coastal Program. Falmouth, ME 04105.

Kloiber, S. M., Brezonik, P. L. and Bauer, M. E. (2002a). Application of Landsat imagery to regional-scale assessments of lake clarity. *Water Research* 36: 4330-4340.

Kloiber, S. M., Brezonik, P. L., Olmanson, L. G. and Bauer, M. E. (2002b). A procedure for regional lake water clarity assessment using Landsat multispectral data. *Remote Sensing of Environment* 82: 38-47.

Lathrop, R. G. (1991). Testing the utility of simple multi-date Thematic Mapper calibration algorithms for monitoring turbid inland waters. *International Journal of Remote Sensing* 12(10): 2045-2063.

Lillesand, T. M. (2002). Combining satellite remote sensing and volunteer secchi disk measurement for lake transparency monitoring. Environmental Remote Sensing Center, University of Wisconsin, 1225 W Dayton St, Madison, WI 53706 USA.

Maine PEARL. (2011). Lakes Guide. Senator George J. Mitchell Center for Environmental Research, University of Maine, Orono. http://www.pearl.maine.edu/windows/community/default.htm. Accessed 1/18/11.

Maine Volunteer Lake Monitoring Program. (2010). http://www.mainevolunteerlakemonitors.org. Accessed 12/17/10.

McCullough, I. M., Loftin, C. S. and Sader, S. A. In press. Combining lake and watershed characteristics with Landsat TM data for remote estimation of regional lake clarity. *Remote Sensing of Environment*.

McCullough, I. M., Loftin, C. S. and Sader, S. A. In review. Application of Landsat TM imagery reveals declining clarity of Maine's lakes during 1995-2010.

MDEP; Bacon, L. (2010). Maine Department of Environmental Protection. Augusta, ME 04333.

MDEP; Suitor, D. (2011). Maine Department of Environmental Protection. Augusta, ME. 04333.

Michael, H. J., Boyle, K. J. and Bouchard, R. (1996). Water quality affects property prices: a case study of selected Maine lakes. Maine Agricultural and Forest Experiment Station, University of Maine, Orono, ME.

NOAA. (2011). National Oceanic and Atmospheric Administration, National Weather Service Forecast Office. Gray, ME. http://www.erh.noaa.gov/er/gyx/climate_f6.shtml. Accessed 11/11/11.

Nelson, S. A. C., Soranno, P. A., Cheruvelil, K. S., Batzli, S. A. and Skole, D. L. (2003). Regional assessment of lake water clarity using satellite remote sensing. *Limnology* 62(1): 27-32.

Olmanson, L. G., Bauer, M. E. and Brezonik, P. L. (2008). A 20-year Landsat water clarity census of Minnesota's 10,000 lakes. *Remote Sensing of Environment* 112: 4086-4097.

Olmanson, L. G., Brezonik, P. L. and Bauer, M. E. (2011). Evaluation of medium to low resolution satellite imagery for regional lake water quality assessments. *Water Resources Research* 47: 1-14.

Omernik, J. M. (1987). Ecoregions of the conterminous United States. *Annals of the Association of American Geographers* 77(1): 118-125.

Sahinler, S. and Topuz, D. (2007). Bootstrap and jackknife resampling algorithms for estimation of regression parameters. *Journal of Applied Quantitative Methods* 2(2): 188-199.

Stadelmann, T. H., Brezonik, P. L. and Kloiber, S. M. (2002). Seasonal patterns of chlorophyll a and Secchi disk transparency in lakes of East-Central Minnesota: Implications for design of ground- and satellite-based monitoring programs. *Lake and Reservoir Management*, 17(4): 299-314.

Tiner, R. W. (1998). Wetland indicators: a guide to wetland identification, delineation, classification and mapping. Boca Raton: CRC Press. 293 pp.

U.S. EPA. (2010). Primary distinguishing characteristics of Level III Ecoregions of the continental United States. United States Environmental Protection Agency. Washington, D.C. 20460. http://www.epa.gov/wed/pages/ecoregions/level_iii_iv.htm. Accessed 12/28/11.

Wu, M., Zhang, W., Wang, X. and Luo, D. (2009). Application of MODIS satellite data in monitoring water quality parameters of Chaohu Lake in China. *Environmental Monitoring and Assessment* 148: 255-264.

Zhu, L., Wang, S., Zhou, Y., Yan, F. and Wang, L. (2005). Determination of chlorophyll a concentration changes in Taihu Lake, China using multi-temporal MODIS image data. Geosciences and Remote Sensing Symposium, 2005. IGARSS 2005. Proceedings. 2005 IEEE International. 7:4535-4538.

REFERENCES

Bacon, L. and Bouchard, R. (1997). Geographic analysis and categorization of Maine lakes: a trial of the draft bioassessment and biocriteria technical guidance. Maine Department of Environmental Protection, Augusta, ME 04333.

Boyle, K. J., Poor, P.J. and Taylor, L. O. (1999). Estimating the demand for protecting freshwater lakes from eutrophication. *American Journal of Agricultural Economics* 81 (5): 1118-1122.

Carlson, R. E. (1977). A trophic state index for lakes. *Limnology and Oceanography* 22(2): 361-369.

Chen, Z., Hu, C. and Muller-Karger, F. (2007). Monitoring turbidity in Tampa Bay using MODIS/Aqua 250-m imagery. *Remote Sensing of Environment* 109(2): 207-220.

Chipman, J. W., Lillesand, T. M., Schmaltz, J. E., Leale, J. E. and Nordheim, M. J. (2004). Mapping lake clarity with Landsat images in Wisconsin, U.S.A. *Canadian Journal of Remote Sensing* 30(1): 1-7.

Chipman, J. W., Olmanson, L. G., and Gitelson, A. A. (2009). Remote sensing methods for lake management: a guide for resource managers and decision-makers. Developed by the North American Lake Management Society in collaboration with Dartmouth College, University of Minnesota, University of Nebraska and University of Wisconsin for the United States Environmental Protection Agency.

Dall'Olmo, G., Gitelson, A. A., Rundquist, D. C., Leavit, B., Barrow, T. and Hulz, J. C. (2005). Assessing the potential of SeaWiFS and MODIS for estimating chlorophyll concentration in turbid productive waters using red and near-infrared bands. *Remote Sensing of Environment* 96(2): 176-187.

Davis, R. B., Bailey, J. H., Scott, M, Hunt, G., and Norton, S. A. (1978). Descriptive and comparative studies of Maine lakes. Life Sciences and Agricultural Experiment Station. NTIS. Technical Bulletin 88.

Detenbeck, N. E., Johnston, C. A. and Niemi, G. J. 1993. Wetland effects on lake water quality in the Minneapolis/St. Paul metropolitan area. *Landscape Ecology* 8(1): 39-61.

Gibbs, J. P., Halstead, J. M., Boyle, K. J., and Huang, J. (2002). An hedonic analysis of the effects of lake water clarity on New Hampshire lakefront properties. *Agricultural and Resource Economics Review* 31(1): 39-46.

Gunn, J. M., Snucins, E., Yan, N. D. and Arts, M. T. (2001). Use of water clarity to monitor the effects of climate change and other stressors on oligotrophic lakes. *Environmental Monitoring and Assessment* 67: 69-88.

Heiskary, S. A. and Walker, W. W. (1988). Developing phosphorus criteria for Minnesota lakes. *Lake and Reservoir Management* 4(1): 1-9.

Houston, B. (2008). Coastal Maine updates. U.S. Fish and Wildlife Service. Gulf of Maine Coastal Program. Falmouth, ME 04105.

Kloiber, S. M., Brezonik, P. L. and Bauer, M. E. (2002a). Application of Landsat imagery to regional-scale assessments of lake clarity. *Water Research* 36: 4330-4340.

Kloiber, S. M., Brezonik, P. L., Olmanson, L. G. and Bauer, M. E. (2002b). A procedure for regional lake water clarity assessment using Landsat multispectral data. *Remote Sensing of Environment* 82: 38-47.

Krohn, W. B., Boone, R. B. and Painton, S. L. (1999). Quantitative delineation and characterization of hierarchical biophysical regions on Maine. *Northeastern Naturalist* 6: 139-164.

Lathrop, R. G. (1991). Testing the utility of simple multi-date Thematic Mapper calibration algorithms for monitoring turbid inland waters. *International Journal of Remote Sensing* 12(10): 2045-2063.

Lathrop, R. G. (1992). Landsat thematic mapper monitoring of turbid inland water quality. *Photogrammetric Engineering and Remote Sensing* 58(4): 465-470.

Lillesand, T. M. (2002). Combining satellite remote sensing and volunteer secchi disk measurement for lake transparency monitoring. Environmental Remote Sensing Center, University of Wisconsin, 1225 W Dayton St, Madison, WI 53706 USA.

Maine PEARL. (2011). Lakes Guide. Senator George J. Mitchell Center for Environmental Research, University of Maine, Orono. http://www.pearl.maine.edu/windows/community/default.htm. Accessed 1/18/11.

Maine Volunteer Lake Monitoring Program. (2010). http://www.mainevolunteerlakemonitors.org. Accessed 12/17/10.

McCullough, I. M., Loftin, C. S. and Sader, S. A. In press. Combining lake and watershed characteristics with Landsat TM data for remote estimation of regional lake clarity. *Remote Sensing of Environment*.

McCullough, I. M., Loftin, C. S. and Sader, S. A. In review. Application of Landsat TM imagery reveals declining clarity of Maine's lakes during 1995-2010.

McCullough, I. M., Loftin, C. S. and Sader, S. A. In review. High-frequency remote monitoring of large lakes with MODIS 500 m imagery. *Remote Sensing of Environment.*

MDEP; Bacon, L. (2010). Maine Department of Environmental Protection. Augusta, ME 04333.

MDEP; Bacon, L. (2011). Maine Department of Environmental Protection. Augusta, ME 04333.

MDEP; Suitor, D. (2011). Maine Department of Environmental Protection. Augusta, ME. 04333.

MEGIS. (2010). Maine Office of GIS Data Catalog. http://www.maine.gov/megis/catalog/. Accessed 10/15/10.

Michael, H. J., Boyle, K. J. and Bouchard, R. (1996). Water quality affects property prices: a case study of selected Maine lakes. Maine Agricultural and Forest Experiment Station, University of Maine, Orono, ME.

Nelson, S. A. C., Soranno, P. A., Cheruvelil, K. S., Batzli, S. A. and Skole, D. L. (2003). Regional assessment of lake water clarity using satellite remote sensing. *Limnology* 62(1): 27-32.

NOAA. (2011). National Oceanic and Atmospheric Administration, National Weather Service Forecast Office. Gray, ME. http://www.erh.noaa.gov/er/gyx/climate_f6.shtml. Accessed 11/11/11.

Noone, M. D. and Sader, S. A. In press. Are forest disturbances influenced by ownership change, conservation easement status, and land certification? *Forest Science*.

Olmanson, L. G., Bauer, M. E. and Brezonik, P. L. (2008). A 20-year Landsat water clarity census of Minnesota's 10,000 lakes. *Remote Sensing of Environment* 112: 4086-4097.

Olmanson, L. G., Brezonik, P. L. and Bauer, M. E. (2011). Evaluation of medium to low resolution satellite imagery for regional lake water quality assessments. *Water Resources Research* 47: 1-14.

Olmanson, L. G., Kloiber, S. M., Bauer, M. E. and Brezonik, P. L. (2001). Image processing protocol for regional assessments of lake water quality. Water resources center and remote sensing laboratory, University of Minnesota, St. Paul, MN, 55108, October 2001.

Omernik, J. M. (1987). Ecoregions of the conterminous United States. *Annals of the Association of American Geographers* 77(1): 118-125.

Peckham, S. D. and Lillesand, T. M. (2006). Detection of spatial and temporal trends in Wisconsin lake water clarity using Landsat-derived estimates of secchi depth. *Lake and Reservoir Management* 22(4): 331-341.

Sahinler, S. and Topuz, D. (2007). Bootstrap and jackknife resampling algorithms for estimation of regression parameters. *Journal of Applied Quantitative Methods* 2(2): 188-199.

Stadelmann, T. H., Brezonik, P. L. and Kloiber, S. M. (2002). Seasonal patterns of chlorophyll a and Secchi disk transparency in lakes of East-Central Minnesota: Implications for design of ground- and satellite-based monitoring programs. *Lake and Reservoir Management*, 17(4): 299-314.

Tiner, R. W. (1998). Wetland indicators: a guide to wetland identification, delineation, classification and mapping. Boca Raton: CRC Press. 293 pp.

U.S. EPA. (2010). Primary distinguishing characteristics of Level III Ecoregions of the continental United States. United States Environmental Protection Agency. Washington, D.C. 20460. http://www.epa.gov/wed/pages/ecoregions/level_iii_iv.htm. Accessed 12/28/11.

Wu, M., Zhang, W., Wang, X. and Luo, D. (2009). Application of MODIS satellite data in monitoring water quality parameters of Chaohu Lake in China. *Environmental Monitoring and Assessment* 148: 255-264.

Zhu, L., Wang, S., Zhou, Y., Yan, F. and Wang, L. (2005). Determination of chlorophyll a concentration changes in Taihu Lake, China using multi-temporal MODIS image data. Geosciences and Remote Sensing Symposium, 2005. IGARSS 2005. Proceedings. 2005 IEEE International. 7:4535-4538.

BIOGRAPHY OF THE AUTHOR

Ian M. McCullough was born in Ann Arbor, Michigan on November 13, 1987. He was raised in McLean, Virginia, where he graduated from Langley High School in 2006. He attended Colby College in Waterville, Maine and graduated in 2010 with a B.A. with honors in Environmental Studies. At Colby, Ian served as a resident advisor in campus dormitories and a research assistant in the Department of Biology. He studied the effects of land use and residential development on biogeochemistry of the Belgrade Lakes of central Maine and authored an honors thesis forecasting the effects of different future residential development scenarios on phosphorus loading in the Belgrade Lakes. Ian's research on Maine lakes landed him at the University of Maine in fall 2010. He is a candidate for the Master of Science degree in Ecology and Environmental Science from The University of Maine in May, 2012.