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

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Abstract

Remote sensing has been effectively used to measure water clarity in several single-lake studies. However, there are still many challenges to applying these approaches to large numbers of lakes within a large geographic region. Our objectives were to: (1) develop a model to predict lake water clarity from Landsat data based on 93 calibration lakes across the state of Michigan, and (2) examine how the distribution of water clarity across the 93 lakes, as measured by Secchi disk transparency (SDT), influenced the model. We hypothesized that the distribution of SDT in the calibration dataset would influence model calibration, and that it is necessary to include a complete range of calibration SDT values to achieve a better regional model. Our regression model of field-collected SDT data and Landsat-7 ETM+ data for the 93 lakes resulted in an r^2 of 0.43 ($p < 0.001$), which was substantially lower than many previous single-lake studies. We simulated a calibration dataset with a different SDT distribution similar to previous studies to examine the role of lake SDT distribution in the model fit. The percent of lakes that had a SDT value less than 1.5 m was increased from 8.6% (original dataset) to 47% (subsampled dataset). The regression model for the subsampled dataset resulted in an r^2 of 0.82 ($p < 0.001$). Our results show that Landsat can be used to measure water clarity across a large number of lakes with a wide range of SDT values. However, we found the regression model to be sensitive to the distribution of SDT values used in the calibrated dataset, and conclude this distribution must be taken into account when developing regional models to predict lake water clarity using remote sensing.

1. Introduction

Monitoring the status of inland lakes is critical because they provide an important recreational, commercial and aesthetic resource to the public. The water quality monitoring of lakes often includes the monitoring of water clarity using a Secchi disk. Although more sophisticated measurement techniques exist, Secchi disk transparency (SDT) appears to be a relatively good coarse measure of water clarity, partly because it is easy and inexpensive to use. The use of SDT has been widely adopted in many lake monitoring programs worldwide (Bukata, Jerome, & Burton, 1988; Wallin & Hakanson, 1992; Lee, Jones-Lee, & Rast, 1995). Several studies have found SDT to correlate well with a number of other water quality variables, such as trophic status, phosphorus loads, planktonic chlorophyll concentrations, hypolimnetic oxygen concentrations, suspended sediment concentrations, and fish yields (Oglesby, 1977; Lorenza, 1980; Lee, Jones-Lee, & Rast, 1995). Despite the ease of collecting Secchi data, collecting SDT on large numbers of lakes can be costly and challenging for monitoring agencies, especially in states with thousands of lakes. However, in the past several decades, citizen-volunteer lake monitoring programs using SDT measurements have allowed data collection over larger regions than capable through local and state agencies alone. The accuracy of volunteer collected data has been reported by several authors to be comparable to data collected by professional monitoring personnel and have shown no statistical difference in summer averages of SDT compared to professional measurements (Heiskary, Lindbloom, & Wilson, 1994; Kerr, Ely, Lee, & Mayio, 1994; Obrecht, Milanick, Perkins, Ready, & Jones, 1998, Canfield, Brown, Bachmann, & Hoyer, 2002). However, extending volunteer collection programs to thousands of lakes, on a statewide level, is currently still cost and logistically prohibitive in many areas.

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

For inland lakes, the relationship between field observations of SDT and satellite spectral values has been examined through simple linear regression analysis of *in-situ* measurements of SDT and spectral brightness values from the sensor (Lillesand, Johnson, Deuell, Linstrom, & Meisner, 1983; Lathrop & Lillesand, 1986; Kloiber, Brezonik, Olmanson, & Bauer, 2002). Regression models developed for single water bodies using a single image have resulted in high r^2 values (0.80 – 0.90, $p < 0.05$) (Lathrop & Lillesand, 1986; Lavery, Pattiaratchi, Wyllie, & Hick, 1993; Giardino, Pepe, Brivio, Ghezzi, & Zilioli, 2001). These strong relationships developed for single water body studies suggest that remote sensing may be useful for measuring

SDT in a large number of lakes across larger spatial scales. However, fewer studies have used Landsat to measure SDT of multiple lakes, over a large area, or covering multiple images (Table 1). In a recent study, Kloiber, Anderle, Brezonik, Olmanson, Bauer, & Brown (2000), developed regressions between data acquired from a single Landsat TM image and field observations of SDT from 47 lakes, in Minnesota, USA. They also found high r^2 values (0.72 – 0.86). Previous studies have shown that several factors influence the reliability and the strength of regression relationships between field-observed SDT and satellite data. For example, Kloiber, Brezonik, Olmanson, & Bauer (2002) suggest that reliable SDT relationships can be developed with field SDT data collected within $\pm$ 7 days of the satellite over-flight and using pixels extracted only from within the pelagic areas of the lakes. However, it is unclear from the current literature if the relationships developed in previous studies can be applied to a large number of lakes within a large geographic region, which include a broad range of SDT values. Before we can apply these methods to a statewide scale, further research is needed.

Our objectives in this study were to determine if we could use Landsat-7 data to measure lake water clarity across a large region of lakes within three images in a single path (94,350 km^2), and to determine how the regional distribution of SDT affects models of regional lake water clarity. We regressed field observations of SDT against Landsat spectral values of 93 lakes from three images in Michigan, USA.

2. Methods

2.1. Study area

The state of Michigan has approximately 3,500 inland lakes < 10 ha in size and many thousands of smaller lakes (unpublished data from the Michigan Department of Environmental Quality). Our study lakes include 93 lakes in the lower peninsula of Michigan (Figure 1). The

lakes are distributed throughout an area of 94,350 km^2, which makes up approximately 80% of the lower peninsula of the state. Our lakes range in surface area from 12 – 4125 ha with a mean Secchi depth of 3.1 m (Table 2).

2.2. Field Observations

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

2.3. Satellite image data

We used three Landsat-7 Enhanced Thematic Mapper Plus (ETM+) scenes from August 28, 2001 from ground track Path 21 (Worldwide Reference System-2) that covered the lower peninsula of Michigan (Figure 1). Spectral digital number (DN) values were extracted for each lake within the pelagic region of each lake, identified by creating an area of interest (AOI) using ERDAS Imagine version 8.4 image processing software. The pelagic region of each lake was defined within an area > 4.5 m in depth. We used bathymetric maps to identify the 4.5 m depth contour within the 80 sample lakes for which we had maps, to ensure that each AOI would be free of reflections from the lake bottom or submerged macrophytes. Bathymetric maps were not available for 13 sample lakes. For the 13 lakes without bathymetric maps, we created an AOI for each lake from groups of pixels within the center of each lake, avoiding any shoreline or shallow

areas. From each lake AOI, we extracted the mean DN for each spectral band to use in all subsequent analyses. Our AOI values ranged from 8 to 1012 pixels (± 183 pixels).

2.4. Statistical analysis

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

To examine the role of lake SDT distribution in our regression model, we developed an additional regression model based on a subsample of our complete dataset with a different SDT distribution. We used a manual selection technique to create a subsampled dataset that matched a previous study that found a strong relationship between multiple lake SDT values and Landsat (Kloiber et al., 2000). To compare the regressions of the complete and subsampled datasets, we used a slope heterogeneity test and analysis of covariance (ANCOVA). We also performed an F-test on the residual values to determine if there was a significant difference between the variances of the residuals of each dataset, and to ensure that the residual distributions about the mean of each dataset were simply not an effect of the complete model having a larger sample size than the subsampled model.

2.5 SDT distributions

We extracted values of SDT in Figure 5 of Kloiber et al. (2000) to compare the distribution of our complete dataset to the Kloiber et al. (2000) distribution. We also compiled a distribution of statewide Michigan summer lake SDT data, available from the US EPA Storage and Retrieval (STORET) database. These data included 675 lakes (>20 ha) sampled from the 1970's through the 1980's. Data from some lakes were averaged across sample years if multiple years were sampled.

3. Results

Our regression of SDT and ETM1/ETM3 produced an r^2 value of 0.43 ($p < 0.001$; Figure 2). To examine why our models explained much less variation than previous studies, we compared the SDT distribution of the 47 lakes included in the Kloiber et al. (2000) study to the distribution of our 93 lakes. We found that approximately 62% of the lakes used in the Kloiber et al. (2000) study had a SDT of 1.5 m or less (Figure 3). For the 93 lakes used in our study, only 9% had a SDT of 1.5 m or less (Figure 3). According to the lake trophic state index definition developed by Forsberg & Ryding (1980), the lakes included in Kloiber et al. (2000) are predominantly eutrophic. The lakes included in our study would be considered largely mesotrophic to oligotrophic (Figure 3). To examine the effect these different distributions may have on SDT prediction, we manually adjusted our SDT sample distribution to have a mean Secchi depth of 1.8 meters and a distribution with 47% of the lakes having a SDT of $\leq$ 1.5m. This subsample included 17 lakes and resembled the sample distribution found in the Kloiber et al. (2000) study (Figure 4). The regression for this subsampled dataset had an r^2 value of 0.82 ($p < 0.001$; Figure 5).

We compared the trend lines from the regressions of our two models, the complete dataset model (n = 93) and the subsampled dataset model (n = 17), and found that the difference in the slopes of the two models was not statistically significant (ANCOVA $p = 0.247$; Figure 6). We also examined the residuals against their predicted fitted value (Figure 7). This analysis suggests that there is less variability in the residuals about the mean for the subsampled dataset than the complete dataset, thus leading to the lower r^2 value of the complete dataset model. We used an F-test to determine that the variance of the residuals of the two datasets were not significantly different. This test indicated that there is a significant probability that the residual variances in the two datasets are statistically different ($F = 2.86$, $p = 0.0099$).

Finally, we further explored the models by plotting the residuals against the observed Secchi values to determine if the residual errors differed in closeness of fit about the mean at different SDT values (Figure 8). This analysis suggests that the complete dataset model may provide better SDT predictions, as its confidence intervals for the predicted mean are narrower for both shallower and deeper Secchi depths than for the subsampled dataset with much wider confidence intervals.

4. Discussion

Our results show that we can use a standard regression model for 93 lakes within a large geographic region, encompassing multiple Landsat scenes, to predict SDT. These results are in agreement with authors such as Lathrop and Lillesand (1986) who recommended the establishment of common statistical models (e.g. standardized regressions) to use remote sensing for monitoring water quality parameters and enhance the development of future sensors tailored to freshwater lake systems. Currently there are still many challenges to applying these

approaches to large numbers of lakes within a large geographic region. For example, several previous studies have developed successful statistical relationships between a single Landsat imagery and a single lake or water bodies within very localized areas. However, to our knowledge only Kloiber et al. (2000) has examined this relationship on a much larger scale, using 47 lakes within a 7,700 km^2 area. The results from Kloiber et al. (2000) show promise in developing even larger scale satellite-based water clarity monitoring protocols using our current systems. Our study expands on this work by examining almost twice the number of lakes within an area of approximately twelve times the areal extent of the Kloiber et al. (2000) study. However, the result of our regression using our complete dataset was substantially lower than those in the Kloiber et al. (2000) study. Other previous single-lake studies using similar Landsat bands also have higher regression results than we did (Lathrop, 1992; Pattiaratchi et al., 1994; Cox et al. 1998). This discrepancy may have been a result of our SDT distribution included in our complete dataset. Our complete dataset model consisted of a broad range of SDT values, including deeper SDT lakes. Lakes with deeper SDT values return less signal reflectance from algal turbidity in the water column to the Landsat sensor and, thus, may not be well detected using current sensors. In contrast, the Kloiber et al. (2000) study was based on a cluster of lakes within the metropolitan area of Minneapolis and St. Paul, Minnesota, USA, where over 60% of the lakes included in this study are eutrophic (Forsberg & Ryding, 1980). Our subsampled dataset incorporated a larger percentage of eutrophic lakes, which yielded a comparable r^2 result to the Kloiber et al. (2000) study. This suggests that inter-lake variably plays an important role in influencing the strength and reliability of regression models of Landsat and lake SDT.

Two remaining questions include: (1) what are the best ranges of SDT that can predicted from Landsat; and (2) what are the best regression models for regions with a wide range of

Secchi depth values? To address the first question, we explored the residual plots of each dataset against the predicted ETM values (Figure 7). This analysis is useful to determine how the residual errors differed in closeness of fit about the mean for both models. The confidence intervals may provide an estimate of the range of values (the upper and lower limits) within which the true distribution is likely to lie. The confidence intervals of the subsampled dataset were wider in both shallow and deep Secchi depth locations than the intervals of the complete dataset. Although a wider interval in the subsampled dataset may partially be related to the much smaller sample size of the subsampled dataset, the wider interval may also indicate a higher overall degree of uncertainty, or possibly inconstant variance throughout the residual terms (Van Belle, 2002). We also explored the possible relationships between the residuals in each dataset and the observed SDT values to determine how the residual errors differed in closeness of fit about the mean at different SDT values for both models (Figure 8). Both the complete and subsampled dataset plots show a distinct cluster of residual values within the 2 – 3 m Secchi range and a narrowing of the confidence intervals within this range. This may suggest that our models are better suited for predicting Secchi depths within these ranges than they are at predicting Secchi depth at the shallow or deep end of the distribution. Thus the implication is that our models may be more useful for predicting Secchi depths within a specific range (e.g. 2-3 m) but may become increasingly uncertain at shallower or deeper Secchi depths as the residual relationship becomes more poorly defined and the confidence intervals widen. Overall, our residual analyses showed a much larger spread of the confidence intervals in the subsampled dataset compared to the complete dataset. This suggests the complete model may be better at predicting Secchi depth than the subsampled dataset with the higher r^2 value.

To address the question of which regression model is better for predicting SDT, we first need to consider the goal of the study in question. For shallow SDT lake studies within a moderate-scale geographic region, models such as our subsampled dataset and the Kloiber et al (2000) study should provide desirable results. This type of investigation could be particularly useful in urban watershed remote sensing studies where water clarity of eutrophic lakes is of particular interest to lake managers. However, if the goal is to examine SDT at a statewide level, a broader range of inter-lake variability must be considered. For example, our complete model, with a lower r^2 result, incorporated a wide range of SDT. A wider range of SDT should be expected when modeling many lakes throughout a large geographic region. In fact, the range of the SDT data included in our complete dataset model is comparable to the existing range of SDT collected within state of Michigan, based on 675 lakes sampled from the 1970's to the 1980's (US EPA STORET; Figure 9).

Remote sensing can play a vital role in reducing the cost, labor, and time required to develop statewide water clarity assessments that are currently impossible by traditional field operations. However, caution should be used in developing assessment criteria based on remotely sensed data. Current sensors may be able to effectively measure shallow Secchi depth lakes, but may not do as well for lakes with deeper Secchi depths. Without accounting for the complete distribution of Secchi within the state, it may be complicated to ability to apply a regression model based on Landsat-SDT relationships to a statewide assessment of Secchi. For example, the lake STORET data for Secchi in the state of Michigan ranges from 0.5 – 8.0 m, with a mean of 3.0 m. Our complete dataset captures this range, from 0.9 – 7.6 m with a mean 3.1 m (Figure 9). Therefore, it is important to recognize that a regression model based on SDT

reflectance data may produce lower r^2 values once deeper SDT values are included to resemble a statewide distribution.

Developing a general statewide assessment of water clarity using Landsat satellite data needs to be simple and require limited sampling operations. However, development of models is limited by ground data since the SDT and Landsat relationship must be based on sampling that is difficult to obtain on a statewide level. Although we included ground observations from a number of reliable sources in an effort to increase our ability to relate SDT over a large area, such as the lower peninsula of Michigan, we were still somewhat limited in developing a dataset of over 100 lakes for this purpose. For example, during this study, we experienced a large number of days with a high percentage of cloud cover that resulted in few available cloud free scenes. In addition, we experienced difficulties in creating a single regression relationship which included lakes from multiple paths. We suspect the poor result from this model was caused by increased path to path atmospheric variations. Within the three contiguous Landsat scenes used in this study, atmospheric corrections were not necessary for sampling SDT as a result of this imagery being on the same relative temporal scale, a single date (Song et al., 2001).

Finally, we felt that although a standard equation relating Landsat data and water clarity over a large area can be used to predict SDT, the sensitivity of the regression model to the distribution of lake calibration data must be taken into consideration. The SDT distribution influences the reliability and the strength of regression relationships based on ground observation and satellite data, such as the relationships previously identified by Kloiber, Brezonik, Olmanson, & Bauer (2002). Further research is required to determine the optimal ranges in which Secchi depth can be predicted from Landsat data, the reliability of predictive models in

shallow as well as deep SDT lakes, and the best regression estimates for states with a wide range of Secchi depth values.

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Table 1. Landsat remote sensing studies of Secchi depth using multiple inland lakes.

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

Table 2. Information for the 93 study lakes used to collect field observations.

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

[1]Citizens Lake Monitoring Program

[2]Michigan Department of Environmental Quality

[3]Michigan State University

Figure Legend

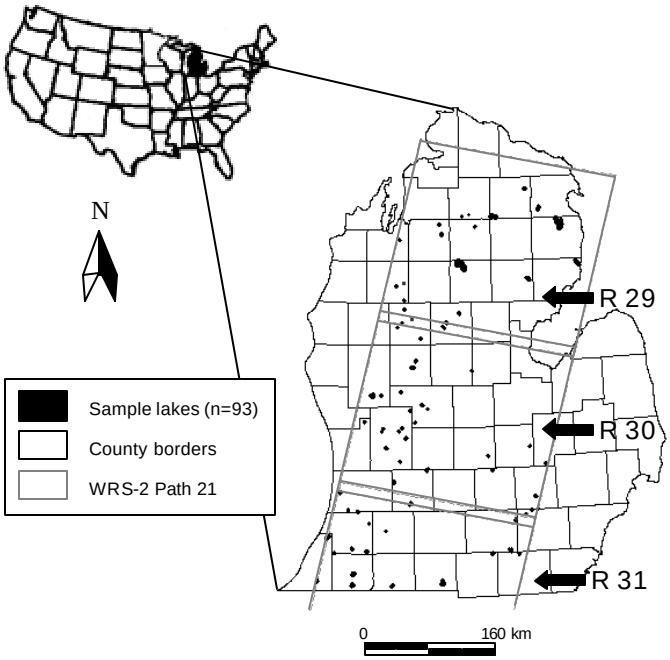

Figure 1.

Figure 1. The study area within Path 21 of the Landsat Worldwide Reference System-2 (WRS) in Michigan, USA. The three individual scene rows within Path 21 used in this study are designated as R29, R30, and R31. All images are from the same acquisition date, 28 August 2001.

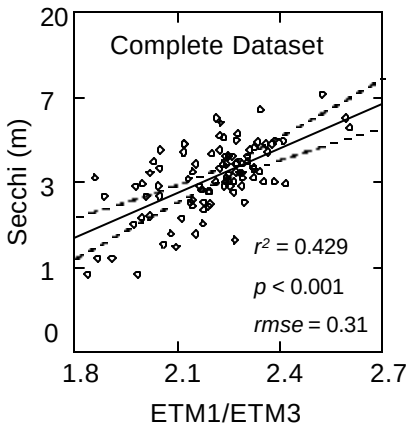

Figure 2.

Figure 2. Regression of Landsat-7 ETM+ data (ratio of two bands, ETM1 and ETM3) and field measured Secchi depth transparency (natural log transformed) for 93 study lakes. The regression model is ln(Secchi) = 1.830 (ETM1/ETM3) - 2.976. The rmse residual value (standard error of estimate) has the same units as the predicted ETM values and represented our standard deviation. The dashed lines represent the 95% confidence interval.

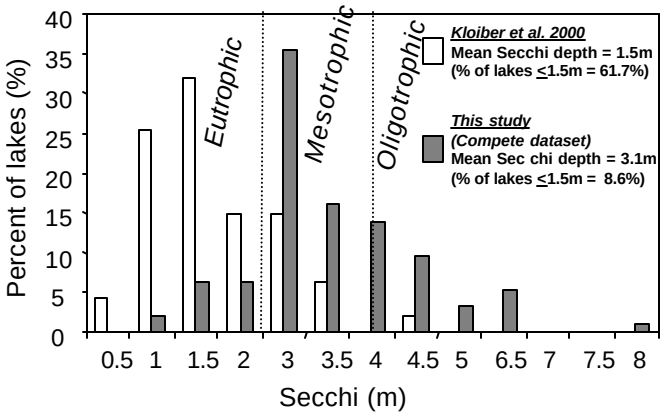

Figure 3.

Figure 3. Histogram of the percent of lakes in each 0.5 m Secchi depth category for the 47 lakes in Kloiber et al. (2000), and for the 93 MI study lakes (complete dataset). Vertical dashed lines represent the limits of the three trophic state categories (Forsberg & Ryding, 1980).

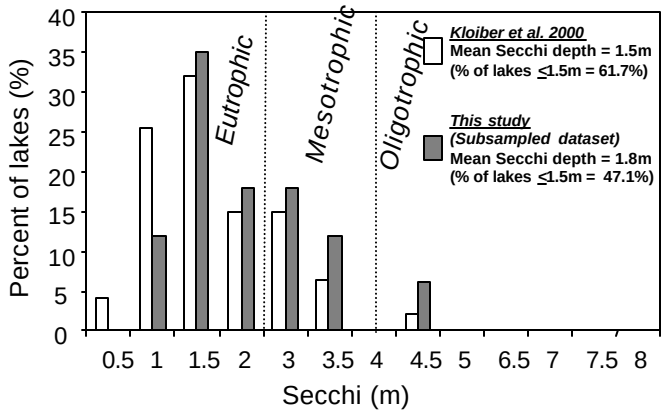

Figure 4.

Figure 4. Histogram of the percent of lakes in each 0.5 m Secchi depth category for the 47 lakes in Kloiber et al. (2000), and for the MI subsampled dataset (n=17). Vertical dashed lines represent the limits of the three trophic state categories (Forsberg & Ryding, 1980).

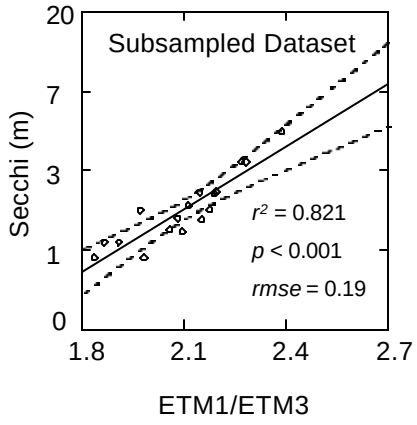

Figure 5.

Figure 5. Regression of Landsat-7 ETM+ data (ratio of two bands, ETM1 and ETM3) and field measured Secchi depth transparency (natural log transformed) for the MI subsampled dataset. The regression model is ln(Secchi) = 2.630 (ETM1/ETM3) - 5.009. The rmse residual value (standard error of estimate) has the same units as the predicted ETM values and represented our standard deviation. The dashed lines represent the 95% confidence interval.

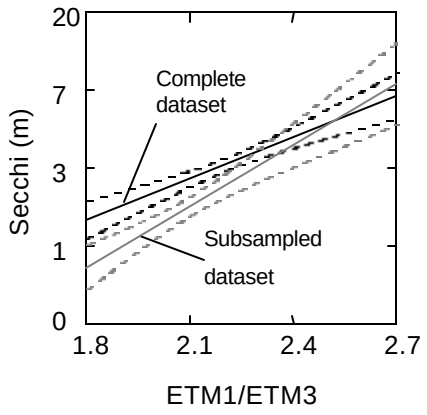

Figure 6.

Figure 6. Regression of Landsat-7 ETM+ data (ratio of two bands, ETM1 and ETM3) and field measured Secchi depth transparency (natural log transformed) for the MI complete and subsampled dataset for slope comparison of each of the dataset regressions. The difference between the two slopes was not statistically significant (ANCOVA, p=0.247). The dashed lines represent the 95% confidence intervals around each regression.

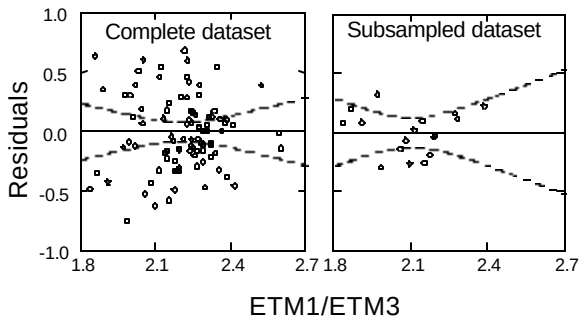

Figure 7.

Figure 7. Scatter plots of the residuals for the complete and subsampled datasets against the predicted fitted value. The dashed lines represent the 95% confidence intervals.

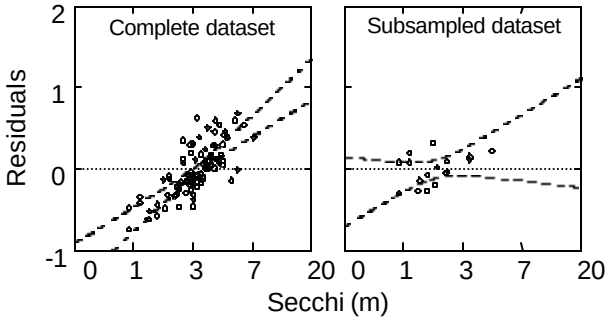

Figure 8.

Figure 8. Scatter plots of the residuals for the complete and subsampled datasets against the observed Secchi values. The dashed lines represent the 95% confidence intervals.

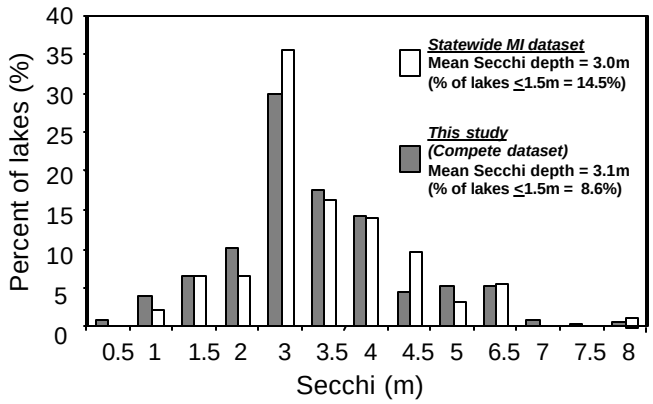

Figure 9.

Figure 9. Histogram of the percent of lakes in each 0.5 m Secchi depth category from a statewide lake database (n=675) and for the 93 MI study lakes (complete dataset).