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A Landsat-based evaluation of lake water clarity in Maine lakes

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Temporal trends in water clarity and land-use/land-cover (LULC), as well as the relationship between changes in water clarity and LULC, were analyzed using water clarity values extracted from Landsat images from 1986 to 2008, acquired for east-central Maine. Of 40 lakes identified using satellite imagery, our analysis found one lake with a significant decrease in water clarity. In a second data-set, with 99 lakes, we identified two lakes with a significant increase in water clarity. Analyses of the relationship between temporal changes in the water clarity and LULC did not identify any clear, consistent, relationships between changes in the water quality variables and LULC. Overall, the results of this study aid in the identification of the relationship between water clarity and LULC, and identify temporal changes in water clarity. The findings of this study support the previous research that demonstrates the ability of satellite imagery to be used in assessments of water clarity, thus enabling evaluation at broader spatial scales and longer temporal scales than assessments that rely solely on ground-based data.

Keywords: water quality; Landsat; lakes; land-use/land-cover; Maine

Introduction

Freshwater lakes support both diverse biological communities (Bronmark & Hansson, 2005) and are a valuable resource for humans as they provide recreational opportunities, support fishery operations, and are reservoirs of freshwater for drinking water and crop irrigation (O'Sullivan, 2005). Recognizing the value of not only lakes, but of all surface waters of the United States, the United States Government has taken regulatory action to protect surface water quality. One measure of water quality is water clarity. Water clarity is an important indicator of the general health of a lake system, including the amounts of sediment present, algal biomass, and the trophic condition of the lake (Bronmark & Hansson, 2005; Dodson, 2005).

One of the greatest threats to lakes in Maine, USA, is the nutrient enrichment. Sources that contribute to nutrient enrichment include fertilizers, storm water and agricultural runoff, and land-use/land-cover (LULC) change. While nutrients are necessary for the healthy functioning of aquatic ecosystems, excessive nutrient loads may cause lake water to become more biologically productive. The result is the increased growth of algae and other aquatic plants, which ultimately disturbs the natural equilibrium of the lake ecosystem and can contribute to considerable economic and

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ecological problems over time. One measure of change in the biological productivity of surface waters is water clarity; however, "many years" of data are generally needed to monitor and assess such changes (Maine VLMP, 2013). In Maine, water clarity has been monitored in selected lakes since the early 1950s and yet, though the number of lakes monitored has increased over time, many lakes within the State lack this valuable information (University of Maine George J. Mitchell Center for Environmental and Water Research, 2011).

Traditional methods of measuring lake water quality involve direct, *in situ* measurements. While *in situ* measurements are accurate for a single point and time, they often do not provide a spatial or temporal view of water quality (Ritchie, Zimba, & Everitt, 2003). Alternatively, satellite remote sensing allows for assessment of large areas and greater temporal coverage of lake water quality, making possible the assessment of multiple water bodies effectively, efficiently, and at a reduced cost. Moreover, monitoring lake water quality and LULC using satellite remote sensing enables managers to be retrospective and investigate the relationship between the landscape and lake water quality (Kloiber, Brezonik, & Bauer, 2002).

The use of remote sensing imagery has been well documented for water clarity studies. Early research demonstrated the utility of Landsat imagery to classify lakes within a predefined trophic class (Scarpace, Holmquist, & Fisher, 1979) and predict Secchi disk depths (SDDs) (Lillesand, Johnson, Deuell, Lindstrom, & Meisner, 1983). A more recent study of approximately 500 lakes in Minnesota using Landsat imagery from 1973 through 1998 found "excellent agreement between satellite-estimated and ground-observed [Secchi disk transparencies] can be achieved" (Kloiber et al., 2002). Research by Chipman, Lillesand, Schmaltz, Leale, and Nordheim (2004) resulted in a statewide database for Wisconsin of lake transparencies based on water clarity data derived from Landsat imagery, and, in Minnesota, a 20-year assessment of over 10,000 lakes resulted in a consistently strong relationship between water clarity values derived from Landsat data and field-measured Secchi disk values (Olmanson, Bauer, & Brezonik, 2008).

Given that many lakes within Maine lack sufficient monitoring of water clarity, our study objectives were to use approximately 25 years (1984 to 2008) of Landsat data to (1) determine if satellite-based spectral data could be used to estimate water clarity, (2) determine if water clarity in east-central Maine exhibited a systematic change over time, and (3) determine whether changes in water clarity could be attributed to LULC change in the study area. The ability to accurately estimate water clarity with satellite data and evaluate connections with LULC will enable land managers to effectively characterize ecosystem processes and monitor trajectories of change.

Study area and methods

Study area

Maine, the northeastern-most state in the United States, has nearly 6000 lakes. Ninety percent of lakes in Maine are drainage lakes, in which most of the water flowing into and out of the lake is surface water (Hasbrouck, 1995). Lakes in Maine are well-distributed geographically and vary in size from less than 1.0 ha to greater than 30,350 ha. For this research, the study area was limited to one Landsat 5 scene (approximately 32,000 km^2) with coverage of eastern and central Maine (Figure 1). This area is located primarily within EPA Ecoregion 82, identified as the Laurentian Plains and Hills, a region where

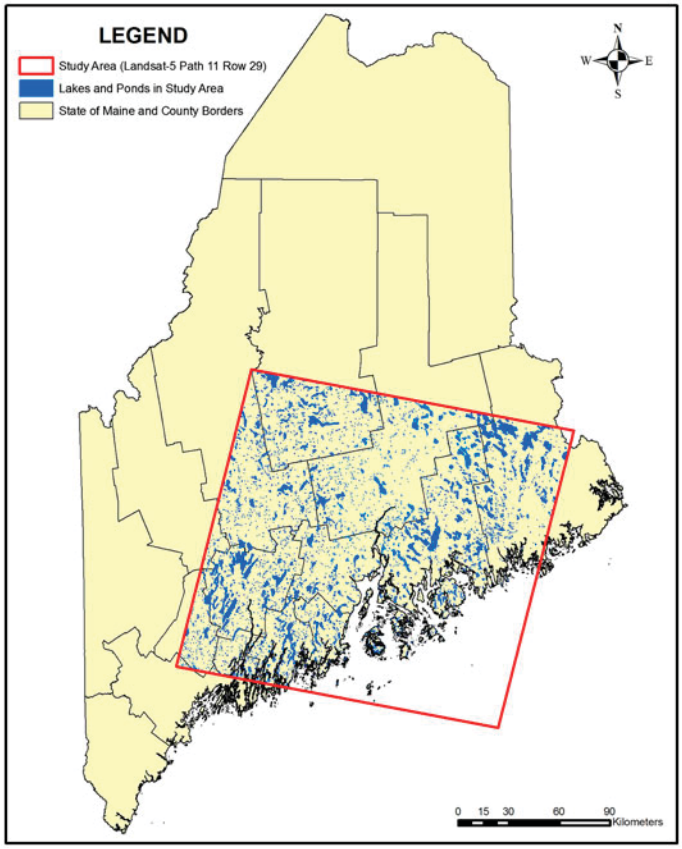

Figure 1. Study area extent in east-central Maine. Color figures are available in the online version of this article.

glacial processes created numerous lakes and wetlands. The United States Geological Survey (USGS) and EPA Land Cover Trends Project reported a 9.5% change in the region's land cover between 1972 and 2000, with forest cover as the consistent dominant land-cover class. (Moreland, [n.d.]).

In situ water clarity data

In situ water clarity data for more than 800 lakes in Maine from 1952 through 2008 (availability varies by lake and year) were compiled by the University of Maine George J. Mitchell Center for Environmental and Water Research (2011). Water clarity was measured using Secchi disks and reported in feet. Use of these data allowed water clarity values to be determined for lakes within each Landsat 5 image. The availability of *in situ* data varied by lake and by year. Lakes in the database with water clarity values within +/−7 days of each Landsat 5 image date (Table 1) were selected. If more than one value was available, the SDD measured closest to the image date was used. Following methods described by Kloiber, Brezonik, Olmanson, and Bauer (2002), Landsat 5 spectral bands that best correlated with *in situ* SDD values were identified through use of Pearson correlation coefficients and stepwise multiple regression analysis. A

Table 1. List of Landsat 5 images included in the study. All images were acquired between 10:23 am and 11:08 am local time.

Year	Date	Cloud cover* (%)
1986	August 5	10
1995	August 14	2
1999	August 25	0
2000	July 26	0
2005	August 9	15
2008	July 16	0

*As reported by USGS GloVis (USGS, 2014).

technical document by Olmanson, Kloiber, Bauer, and Brezonik (2001) provided additional information and step-by-step guidelines for Landsat image processing to extract lake water clarity values. The availability of *in situ* data enabled the extraction of water quality values from Landsat 5 imagery. Once the values were extracted, the *in situ* data were not included in further analysis.

Remote sensing data-sets and image processing

Six Landsat 5 TM scenes (Path 11 Row 29) between 1984 and 2011 were analyzed for our study (Table 1). Preference was given to images acquired between 15 July and 15 September, with a preference for August (Olmanson, Bauer, & Brezonik, 2008) as water clarity was most stable during that time period.

Classification of LULC for each Landsat image enabled the identification of individual land-use classes for each image as well as open-water areas from which to extract water quality values for individual lakes. Prior to LULC classification, each Landsat scene was processed to convert reflective wavelength bands from digital numbers to top-of-atmosphere (TOA) reflectance using calibration coefficients and associated equations provided by Chander, Markham, and Helder (2009). To maintain consistency with nationally recognized land-cover databases, the LULC classification system used by the Multi-Resolution Land Characteristics Consortium 2001 National Land Cover Data-set was used for this study (Homer, Huang, Yang, Wylie, & Coan, 2004). Only primary (i.e., Level 1) classes present within the study area were used. They included water (identified as open water), developed land, barren land, forest, planted/cultivated areas, and wetlands. A maximum likelihood algorithm was applied to each image data-set, where training sites were identified from high resolution aerial imagery acquired between 1996 and 2005. Accuracy assessments for each LULC image were performed to determine overall, the user, and producer LULC classification accuracies. Validation points for each accuracy assessment followed a stratified random sampling framework, and the reference data employed a combination of the original Landsat and high-resolution aerial imagery. Following the methods outlined by Jensen (2005), a sample size based on a multi-nomial distribution with an 85% confidence interval was used, resulting in 362 accuracy assessment points with a minimum of 30 points within each class once points affected by clouds or haze were excluded. The number of accuracy assessment points per class varied such that land-cover classes with a smaller footprint on the ground had fewer points than land-cover classes that occupied a greater proportion of the landscape.

Identification of lake catchments and areas of interest (AOI) for analysis

The immediate catchments for each lake in the study were identified using existing drainage divide polygons available from the Maine Office of GIS (USGS and MGS, 1994). The immediate catchment was used, as opposed to an entire catchment, since lakes in Maine are often drainage lakes that connect to other lakes through a series of rivers or streams. The connection between multiple lakes creates overlapping catchments for lakes within the region; thus, using only the immediate catchment resulted in each lake having a unique catchment. AOIs within each lake were used to extract reflectance values from the Landsat scenes.

AOIs were created using the classified images, where polygons were first generated based on the boundary between open-water and non-open-water class pixels. Then, to mitigate the possibility of selecting open-water pixels influenced by land or vegetation (i.e., mixed pixels), each AOI was offset inward by 120 m. These intermediate AOIs were used with the Landsat TOA reflectance data in an unsupervised classification. The ISODATA algorithm was implemented to identify spectral signatures for open water and to eliminate shallow water areas where sediment and/or the presence of aquatic plants may influence spectral response (Olmanson et al., 2001) and thus influence water clarity modeling. The area remaining within a given lake AOI after the 120-m offset and eliminating pixels indicative of shallow water was refined one final time based on lake depth (MEDEP and MEIFW, 2011). Lake depth was used to ensure that water clarity values were stable over the spatial extent for which satellite reflectance values were modeled. The deepest point for each lake was selected, and a buffer of 535 m (the buffer width required to select an area containing a maximum of 1000 pixels) was created around each point. The intersection of this buffer and the AOI for each lake was used as the final AOI for spectral data extraction. If no information regarding lake depth was available, the approximate center of the lake was used. Lakes with a final AOI less than 120 m in width or length were eliminated from further study as well as lakes with an AOI of less than nine pixels (Kloiber et al., 2002). A series of images that illustrate the process of AOI selection for a single lake are provided in Figure 2. An example of a single lake within the study area, the lake catchment, the 100- and 500-m buffer areas around the lake perimeter (addressed in following sections), LULC classifications, and the lake AOI is provided in Figure 3.

Water clarity modeling

Since the raw *in situ* SDD data exhibited a non-normal distribution, a natural log (ln) data transformation was applied prior to regression analysis. Landsat 5 TOA reflectance values for bands 1–5 and 7 were extracted based on the final AOIs delineated for each lake in the study. Mean reflectance values for each AOI were used as independent variables in a stepwise multiple regression to estimate SDD.

Analysis of change in water clarity over time

Individual multi-variate regression analyses were used to determine if a systematic, statistically significant ($p \leq 0.05$) change in water clarity had occurred over the time period of analysis (1984–2011). The independent variable (time) was identified as the study year of the Landsat 5 image, while the dependent variable was SDD data obtained *in situ*. The regression analyses were completed using all lakes in the study area that had data for all study years. First, regression analyses were performed for individual

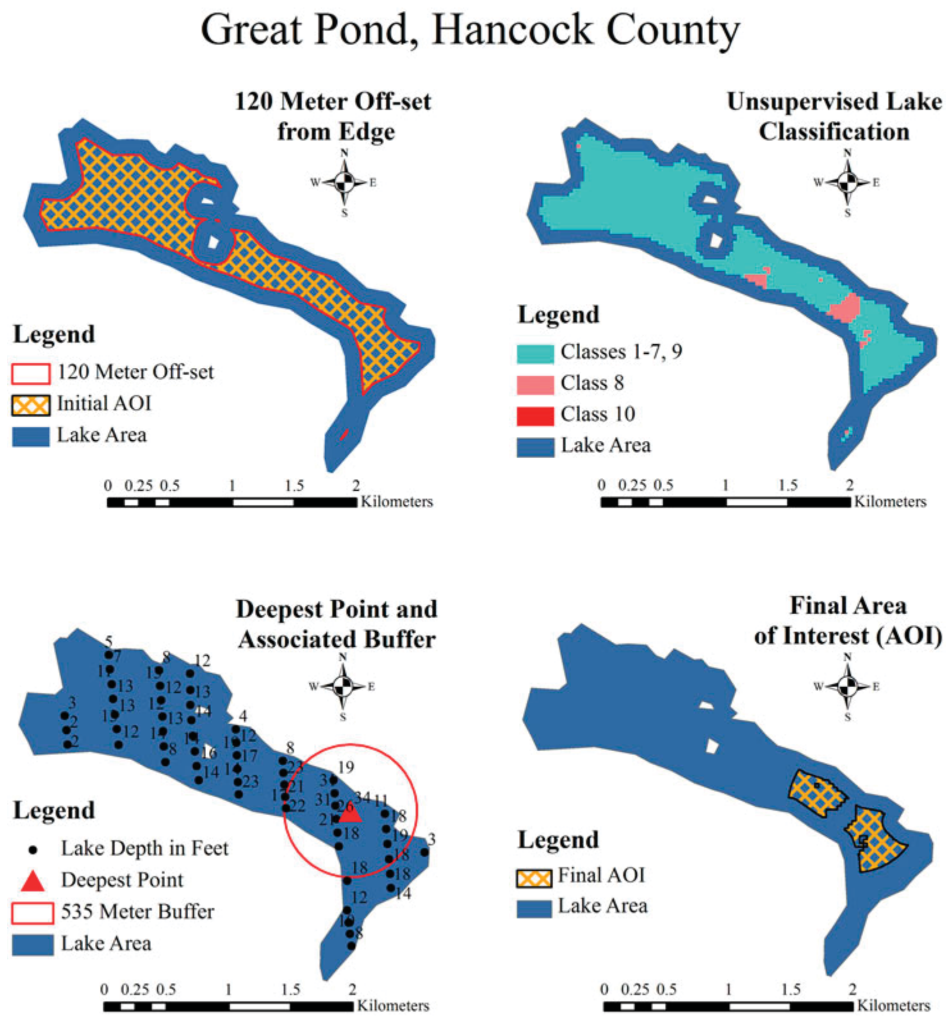

Figure 2. Image illustrating the process of AOI selection for a single lake.

lakes. Next, similar analyses were performed using the average water clarity values for all lakes within each study year to determine if there was a significant change over time in the region as a whole.

Evaluation of effect of LULC on water quality change

For lakes that exhibited a statistically significant change in water clarity, the LULC class proportions were summarized by 100- and 500-m buffers surrounding each lake and by immediate catchment for individual study years. Again, regression analyses were performed to determine if any of the lakes with a statistically significant change in water clarity during the study period also exhibited a change in one or more LULC class within the same time period. Separate regressions for each lake and each LULC class enabled the identification of lakes and their associated catchment and or/buffers that exhibited both changes during the study period.

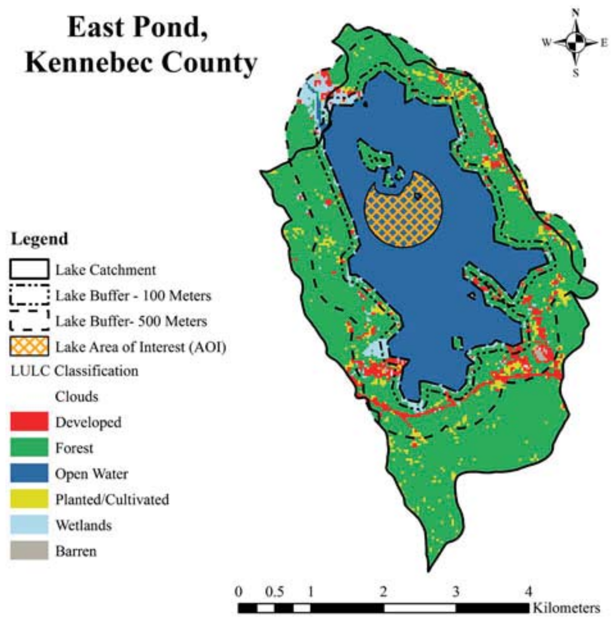

Figure 3. Example of a single lake within the study area, the lake catchment, the 100-m and 500-m buffer areas around the lake perimeter, LULC classifications, and the lake AOI.

Results

LULC classifications

The overall accuracies associated with the supervised classifications ranged from 79 to 85%, with Kappa statistic values of 0.74–0.80 (Table 2). Producer and user accuracy values varied between LULC classes as well as images. Producer accuracy indicates the probability of an accuracy assessment point or pixel being correctly classified; user accuracy indicates the probability that a classified pixel actually represents that LULC class on the ground (Jensen, 2005).

Water clarity estimates

Regression analyses between SDD and Landsat 5 TOA reflectance values explained between 70% (year 2000) and 89% (year 2008) of measured variation. The ratio between blue (B1) and red wavelengths (B3) was consistently selected as a strong explanatory variable, as was the shortwave infrared band (B7). Refer to Table 3 for the best-fit model equations, R-squared, and F values associated with each equation. Refer to Figure 4 for scatter plots of the *in situ* water clarity values and estimated water clarity values.

Temporal changes in water clarity

Forty lakes were examined after implementing the criterion that all lakes had complete regression-modeled water clarity for each of the six study years; no other additional lakes had data available for all six study years. Results of the linear regression analysis with time as the independent variable and water clarity as the dependent variable found that only one lake (Unity Pond in Waldo County) exhibited a significant change in

Table 2. Summary of supervised LULC classification accuracy assessments.

LULC class	1986 Image		1995 Image		1999 Image		2000 Image		2005 Image		2008 Image	
	User accuracy	Producer accuracy	User accuracy	Producer accuracy	User accuracy	Producer accuracy	User accuracy	Producer accuracy	User accuracy	Producer accuracy	User accuracy	Producer accuracy
Water	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Developed	0.66	0.85	0.63	0.87	0.67	0.85	0.69	0.86	0.75	0.96	0.79	0.57
Barren	0.77	0.96	0.93	0.90	0.63	0.90	0.60	0.82	0.83	0.65	0.70	0.77
Forest	0.96	0.83	0.94	0.83	0.88	0.84	0.86	0.87	0.88	0.89	0.70	0.86
Planted/cult.	0.59	0.69	0.64	0.84	0.72	0.79	0.79	0.77	0.68	0.93	0.73	0.65
Wetland	0.55	0.64	0.61	0.66	0.69	0.52	0.74	0.49	0.67	0.53	0.76	0.73
Overall	0.84		0.85		0.83		0.83		0.84		0.79	
Kappa	0.78		0.80		0.77		0.77		0.79		0.74	

Table 3. Summary of best-fit model equations for estimation of lake water clarity values using Landsat 5 spectral data.

Year	Equation: ln(SDD) =	R^2 ($p \leq 0.001$)	F value	n	Days
1986	−12.669 + 4.199(B1:B3) + 217.813(B7) + 88.686(B3)	0.73	47.83	56	+/−5
1995	−4.931 + 2.309(B1:B3) + 157.857(B7)	0.81	148.44	71	+/−5
1999	−5.858 + 2.666(B1:B3) + 380.539(B7)	0.83	144.49	64	+/−3
2000	0.936 + 1.564(B1:B3) + 58.380(B7)−45.608(B1)	0.70	32.39	46	+/−3
2005	−16.044 + 4.133(B1:B3) + 194.081(B7) + 80.070(B1)	0.81	29.25	24	+/−7
2008	−4.064 + 1.961(B1:B3) + 166.400(B7)	0.89	216.56	55	+/−5

Note: Equations in Table 3 include values associated with Landsat 5 TM bands, where B1 = blue, B3 = red, B7 = shortwave infrared, and B1:B3 represents a ratio between the blue and red bands. "*n*" indicates the number of lakes with *in situ* data used to create best-fit model and "Days" refers to the timeframe of *in situ* data used based on days before or after the Landsat 5 image date.

water clarity based on water clarity values extracted from the six Landsat 5 images. For Unity Pond, the overall water clarity, as modeled by regression analysis, decreased 1.21 m over the study period. When all lakes in the study year were evaluated together, the average change in water clarity was not found to be statistically significant.

To increase the sample size, an analysis was also run without data from 2005 since that particular scene exhibited extensive cloud cover. With data from 2005 removed, the number of lakes with water clarity data available for all years increased from 40 to 99. Even with a sample size of 99, only two lakes (Stafford Pond in Somerset County and Black Pond in Hancock County) exhibited a substantial change in water clarity over the study period. In both cases, the lakes were identified as having exhibited an increase in water clarity; Stafford Pond had an overall increase of 1.47 m and Black Pond had an overall increase of 2.61 m. Average water clarity values for the 99 lakes did not exhibit a statistically significant regional change over the time period of analysis.

Relationship between water quality and LULC change

A linear regression between water clarity and percent cover for each LULC class was completed for Unity Pond, the only lake in our study that exhibited a significant decrease in water clarity over the entire study period (1984–2011). Results of the regression analyses indicated that LULC change within the lake catchment was not significant; however, a 6.74% increase in the percent cover of developed land within the 100-m buffer and a 6.64% decrease in percent cover of open water may have contributed to the decrease in water clarity.

When data from 2005 were excluded from the analysis, Stafford Pond was the only lake that exhibited a significant change in any LULC class. Within 100 m of Stafford Pond, planted/cultivated land decreased by 5.48%. Finally, while water quality values extracted from Landsat imagery for Black Pond indicated an increase in water clarity by a depth of 2.61 m, no relationship between LULC class change and clarity were evident.

Discussion

Applicability of satellite data to estimate water clarity

Our results indicate that lake water clarity values, represented by SDD, can be successfully modeled with Landsat 5 TOA reflectance data. *R*-squared values associated with

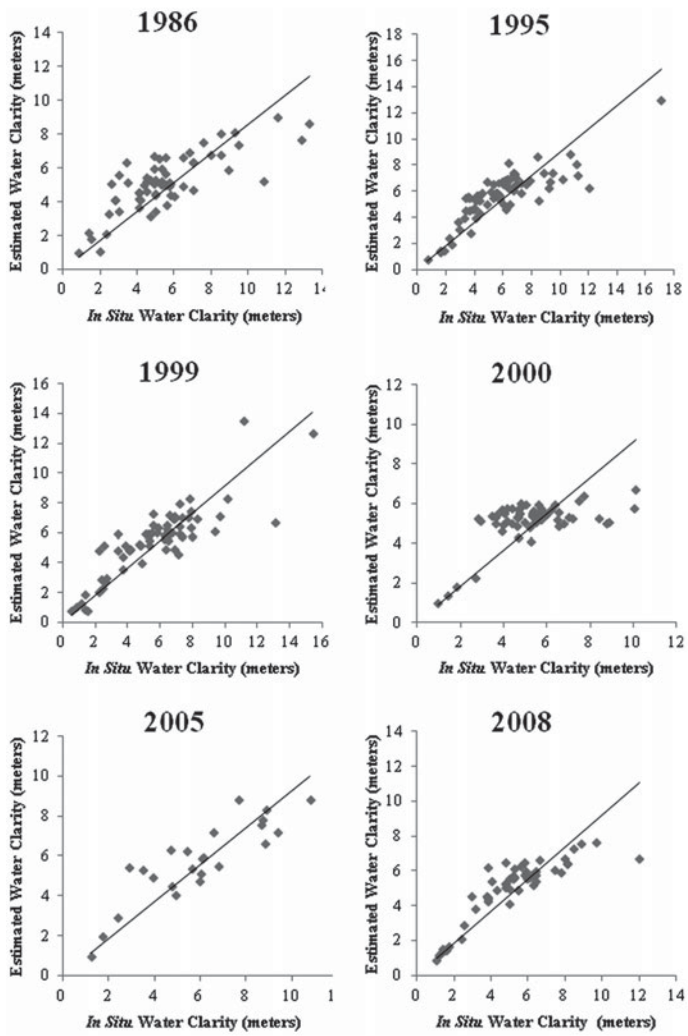

Figure 4. Scatter plots showing the *in situ* (observed) water clarity values measured as SDDs in meters (*x*-axis) and the water clarity values estimated from Landsat 5 TOA reflectance (*y*-axis).

the models ranged from 0.70 to 0.89, indicating that the models explain most of the variation in water clarity sampled in the field. Moreover, our estimates and the associated *R*-squared values are consistent with those reported by other researchers modeling water clarity values based on Landsat imagery (Kloiber, et al., 2002; McCullough, Loftin, & Sader, 2012).

Challenges associated with accurate estimation of water clarity involve the physical interactions of energy and constituents within a water column. For example, McCullough, Loftin, and Sader (2012) performed a similar analysis of satellite-based water clarity estimates and found that the trophic state of the lake influenced model estimates such that the common predictor variable B3 (red wavelength) performed poorly for clearer water bodies than lakes with higher concentrations of suspended materials or algae. Although our study does not differentiate between trophic states, exploration in future studies is warranted. Another challenge associated with establishing a relationship between satellite spectral data and *in situ* Secchi disk data involves the temporal discrepancy between when data are collected in the field and the frequency of satellite overpass. Past research has determined that *in situ* data collected within 7 days of a satellite overpass are generally acceptable for determining lake water clarity values (Kloiber, Brezonik, Olmanson, et al., 2002), however, Landsat 5 had a temporal resolution of 16 days. While the use of *in situ* data collected closer to the time of satellite overpass reduces error when estimating water clarity values, increasing the time frame (i.e., using *in situ* data collected greater than +/−7 days from the date of overpass) would have increased our overall sample size as well as the geographical area from which the data were collected. In addition to an increased number of observations for training, a larger sample size would have facilitated model validation as well.

Temporal trends in water quality and LULC change

Based on water quality data extracted from Landsat imagery, out of 40 lakes with data for all six study years, only one lake exhibited a significant change in water clarity. When study year 2005 was removed from the analysis, there were a total of 99 lakes with data for the remaining five study years, yet only two lakes exhibited a statistically significant change in water clarity based on the Landsat-based water quality estimates. Moreover, based on our analysis of the Landsat water quality estimates of the lakes and dates examined as part of this study, we found that overall water clarity remained relatively constant since 1986, with few lakes experiencing a significant increase or decrease in water clarity. Although previous research in other regions supports our findings of overall stable water clarity values when assessing multiple lakes within a region (Bruhn & Soranno, 2005; Kloiber, Brezonik, Olmanson, et al., 2002; Olmanson, Bauer, & Brezonik, 2008; Terrell, Watson, Hoyer, Allen, & Canfield, 2000), these results should be interpreted in the context of imagery collected during the summer (i.e., typically stable water clarity) and three to nine years apart over a period of 22 years. Thus, water clarity fluctuations due to seasonal changes or over very short time periods are not captured in this analysis.

Our findings with regard to the relationships between lakes with increased or decreased water clarity and LULC changes indicate that no clear relationship is evident. It should be noted, however, that a major limitation to this component of the analysis was that very few lakes in the region exhibited substantial changes in water clarity. Future research may benefit from a focus specifically on additional lakes with known changes in water clarity to assess whether a consistent relationship with LULC change can be detected. Alternately, future research could focus on areas where considerable LULC change has occurred to determine if such changes affect water clarity. Focusing on fewer lakes with known changes in either water clarity or LULC would provide a finer spatial extent and facilitate a more detailed LULC classification. For this study, the lakes and their associated lake catchments and buffers were contained within an entire Landsat 5 scene (approximately 32,000 km^2), of which the lake catchments and buffers occupied about 6500 km^2. Moreover, it is worth noting that, where change does occur, there are other potential causes besides changes in LULC. For example, the introduction of zebra mussels (*Dreissena polymorpha*) to the Great Lakes ecosystem has affected water clarity within the Great Lakes. Point-source discharges and nutrient loading may also lead to algal blooms that impact water clarity (Binding, Jerome, Bukata, & Booty, 2007) and, while related, may not directly show up as changes in LULC.

Influence of satellite image classification and associated accuracies

The overall accuracy of the supervised classifications varied from 79 to 85% over the six study years. When evaluating the accuracy of a single LULC class between years, the accuracy varied even more. A variation in accuracy between images inherently adds uncertainty to any analysis that compares changes in LULC between years. For example, the 6.64% decrease in percent cover of open water associated with LULC change surrounding Unity Pond may be attributed to classification differences of deep, dark water and near-shore water, particularly if the water near shore exhibited increased sedimentation for later image dates and those pixels were attributed to a different land-cover classes. If future assessments focused specifically on lakes with known changes in water quality or on lake catchments/buffers with known changes in LULC, the accuracy of the LULC classification could be improved, especially if the classified areas were smaller. Unfortunately, a more focused study area would eliminate the regional perspective that studies such as this sought to provide.

Overall, the examination of the relationship between changes in water clarity and changes in LULC did not identify any clear, consistent, or potentially causal relationships. The sample size for lakes that exhibited a significant change in water clarity was not large enough to indicate a clear, consistent, relationship with LULC change. As previously stated, future research regarding the effect of LULC change on water clarity would likely benefit from focusing on lakes or lake catchments/buffers with known changes.

Conclusion

This study evaluated the utility of Landsat spectral data to estimate *in situ* Secchi disk measurements of water clarity for lakes located in east-central Maine using six specific image dates over an analysis period of 22 years (1986–2008). Using multiple linear regressions, we found models that incorporated the blue, red, and mid-infrared spectral bands accounted for 70–89% of Secchi measured water clarity. Landsat-estimated water quality values for the six image dates were then evaluated to determine if water clarity exhibited a systematic change over time. Results suggest that for our specific study period of six summer dates, that only 1 of 40 lakes exhibited a significant change in water clarity. To increase sample size, one image date (2005) was excluded from analysis, resulting in a sample data-set of 99 lakes. Temporal analysis of this larger data-set resulted in two different lakes exhibiting statistically significant changes in water clarity. These results suggest that, while satellite imagery can be used to assess water clarity over time, the image dates selected for analysis can influence analysis results.

Land-cover classifications were also completed for each image date of analysis using a maximum likelihood classification. Overall classification accuracies ranged from 79 to 85% for 2008 and 1995, respectively. LULC changes over the 22-year analysis period were evaluated to determine if changes in lake water clarity could be attributed to LULC change within the catchments for lakes that exhibited significant changes in water clarity. Analyses regarding the relationship between temporal changes in water clarity and LULC identified some statistically significant relationships (e.g., increase in urban cover, decrease in planted/cultivated land); however, the relationships were not consistent among catchments and are likely attributed to LULC classification error.

Overall, the results of this study lend support to the utility of Landsat imagery to monitor and assess water clarity for individual lakes and open-water bodies within a larger region and support previous research in proving the ability of satellite imagery to enable evaluation of larger spatial and longer temporal scales than assessments that rely solely on the existence of *in situ* data.

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