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Combining lake and watershed characteristics with Landsat TM data for remote estimation of regional lake clarity

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ABSTRACT

Water clarity is a reliable indicator of lake productivity and an ideal metric of regional water quality. Clarity is an indicator of other water quality variables including chlorophyll-a, total phosphorus and trophic status; however, unlike these metrics, clarity can be accurately and efficiently estimated remotely on a regional scale. Remote sensing is useful in regions containing a large number of lakes that are cost prohibitive to monitor regularly using traditional field methods. Field-assessed lakes generally are easily accessible and may represent a spatially irregular, non-random sample of a region. We developed a remote monitoring program for Maine lakes > 8 ha (1511 lakes) to supplement existing field monitoring programs. We combined Landsat 5 Thematic Mapper (TM) and Landsat 7 Enhanced Thematic Mapper Plus (ETM+) brightness values for TM bands 1 (blue) and 3 (red) to estimate water clarity (secchi disk depth) during 1990–2010. Although similar procedures have been applied to Minnesota and Wisconsin lakes, neither state incorporates physical lake variables or watershed characteristics that potentially affect clarity into their models. Average lake depth consistently improved model fitness, and the proportion of wetland area in lake watersheds also explained variability in clarity in some cases. Nine regression models predicted water clarity (R^2 = 0.69–0.90) during 1990–2010, with separate models for eastern (TM path 11; four models) and western Maine (TM path 12; five models that captured differences in topography and landscape disturbance. Average absolute difference between model-estimated and observed secchi depth ranged 0.65–1.03 m. Eutrophic and mesotrophic lakes consistently were estimated more accurately than oligotrophic lakes. Our results show that TM bands 1 and 3 can be used to estimate regional lake water clarity outside the Great Lakes Region and that the accuracy of estimates is improved with additional model variables that reflect physical lake characteristics and watershed conditions.

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 (Boyle et al., 1999; Michael et al., 1996) and New Hampshire (Gibbs et al., 2002) and also enhances user-perception of Minnesota lake water quality (Heiskary & 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

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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., 2001, 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.

2. Methods

2.1. Description of study area

Located in the northeastern United States, Maine contains over 5500 lakes and ponds >1 ha in surface area across a total area of approximately 90,000 km^2 (Fig. 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.

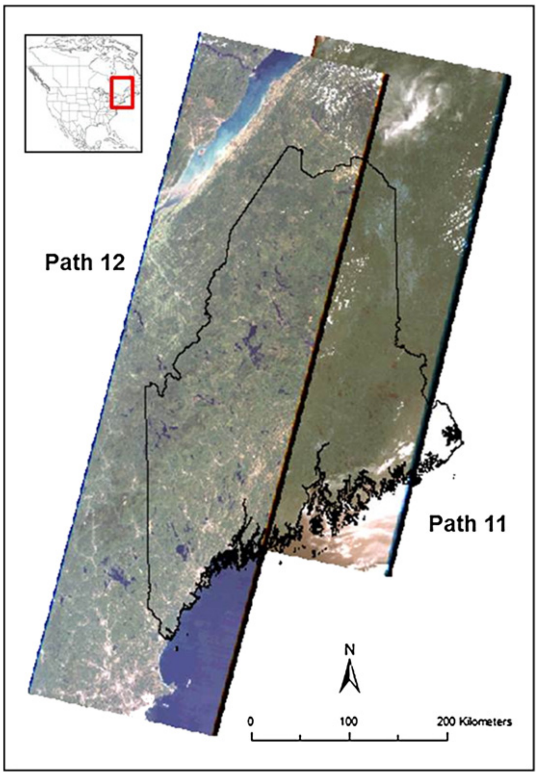

Fig. 1. Landsat TM paths 11 and 12 over Maine, USA.

2.2. Landsat data selection

Most of Maine is covered by Landsat paths 11–12, rows 27–30 (Fig. 1). Paths of images captured during mid-late summer were selected every 3–7 years from 1990 to 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). 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.

2.3. Supplementary lake data

Although satellite imagery previously has been used to monitor lake water clarity (Chipman et al., 2004; Kloiber et al., 2002a; 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).

Table 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.

2.4. 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.

2.5. Data extraction and model development

2.5.1. 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.

2.5.2. 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 (Chipman et al., 2004; Kloiber et al., 2002a, 2002b; Nelson et al., 2003; 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.

3. 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 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

Table 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 + (8.389×10^{-3}) AvgDepth + 5.220	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 + (4.480×10^{-3}) AvgDepth + 6.202	0.8939	1	31
9/6/1995	12	27–30	(6.280×10^{-2}) TM1 − (0.361) TM3 + (1.029×10^{-2}) AvgDepth + 7.960	0.8439	3	73
9/8/1990	12	27–30	(0.145) TM1 − (0.436) TM3 + (6.403×10^{-3}) AvgDepth + 2.930	0.6916	7	117
9/5/2009	11	28–29	(3.715×10^{-2}) TM1 − (0.320) TM3 + (7.766×10^{-3}) AvgDepth − (3.609×10^{-4}) Wetland + 5.513	0.8631	3	65
8/9/2005	11	27–29	(0.113) TM1 − (0.315) TM3 + (7.888×10^{-3}) AvgDepth − (3.697×10^{-4}) Wetland − 0.8681	0.8244	3	55
8/9/2002	11	27–29	(-3.217×10^{-2}) TM3 + (1.291×10^{-2}) AvgDepth − (7.511×10^{-4}) Wetland + 4.252	0.9010	1	35
8/14/1995	11	27–29	(9.347×10^{-3}) TM1 − (5.869×10^{-2}) TM3 + (9.825×10^{-3}) AvgDepth − (3.059×10^{-4}) Wetland + 3.906	0.7919	7	119

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

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 4). Estimates consistently were more accurate for eutrophic (SDD ≤ 4 m) and mesotrophic (SDD = 4–7 m) than oligotrophic lakes (SDD ≥ 7 m) (Table 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 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 3, 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.

4. Discussion

4.1. 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

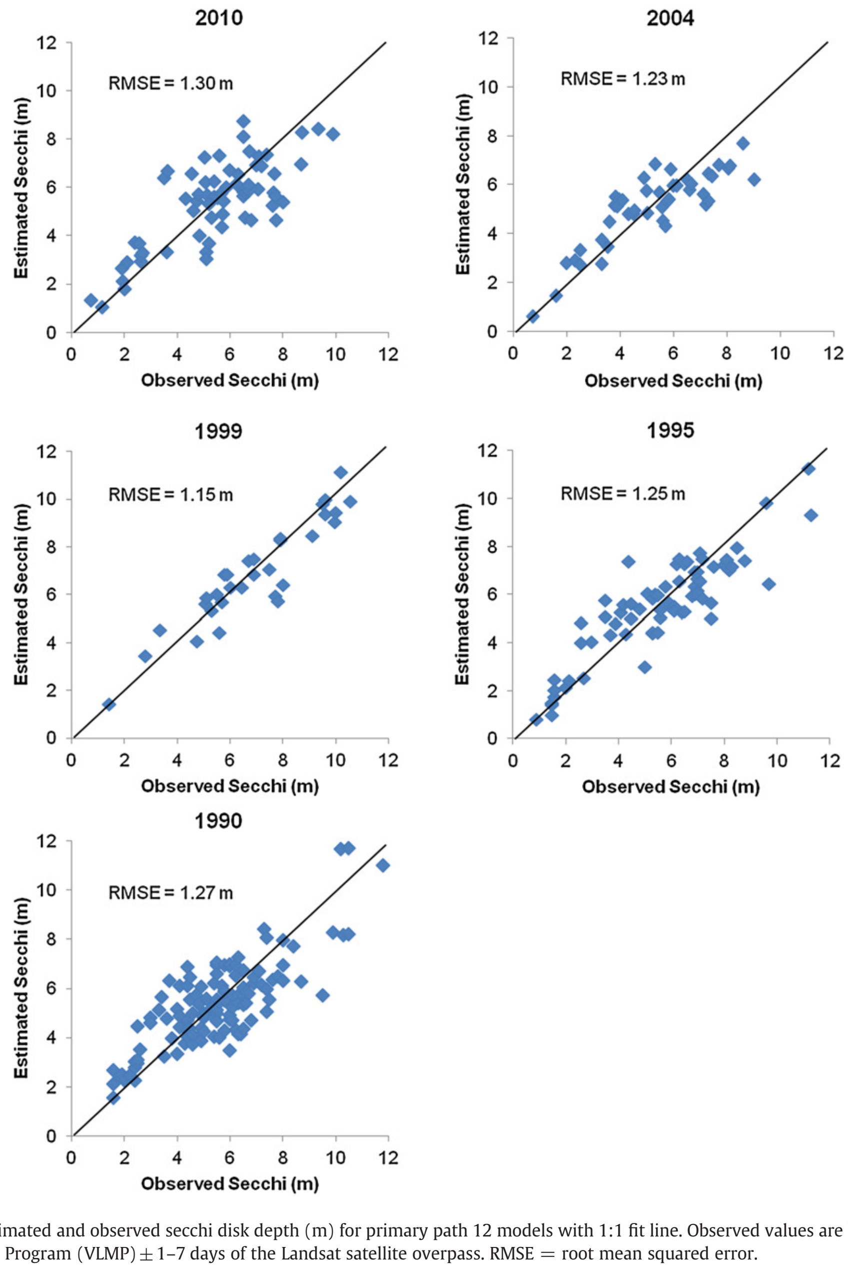

Fig. 2. Scatter plots of Landsat-estimated and observed secchi disk depth (m) for primary path 12 models with 1:1 fit line. Observed values are based on field data gathered by the Maine Volunteer Lake Monitoring Program (VLMP) ± 1–7 days of the Landsat satellite overpass. RMSE = root mean squared error.

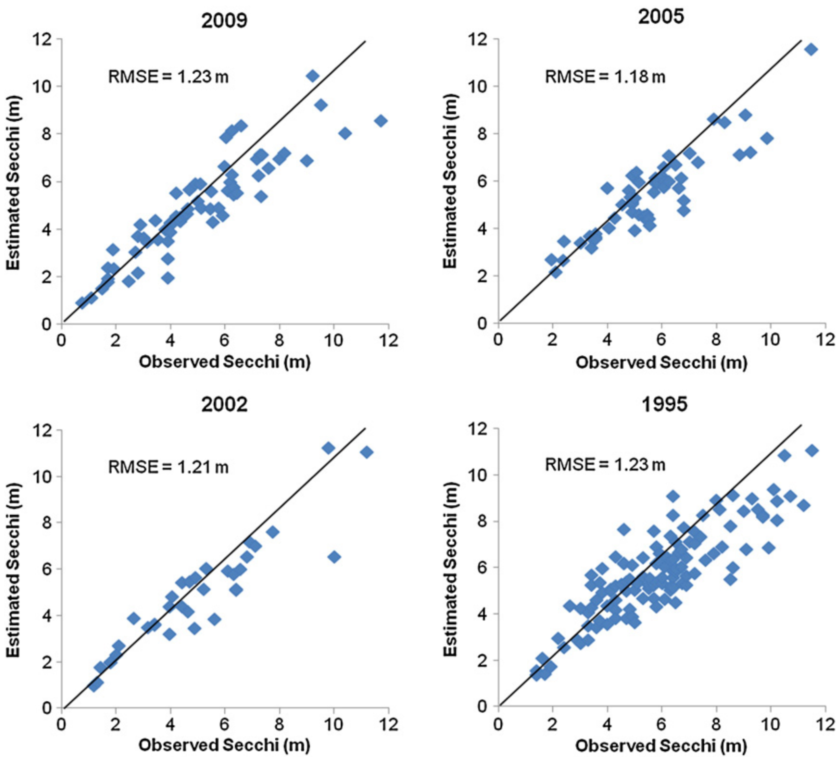

Fig. 3. Scatter plots of Landsat-estimated and observed secchi disk depth (m) for primary path 11 models with 1:1 fit line. Observed values are based on field data gathered by the Maine Volunteer Lake Monitoring Program (VLMP) ± 1–7 days of the Landsat satellite overpass. RMSE = root mean squared error.

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.

4.2. 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 & Lillesand, 2006) and Minnesota (Olmanson et al., 2008), suggesting there is a recognition of regional lake clarity variation. It may not be

Table 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 + 5.567	0.7018	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	(-0.479) TM3 + 6.901	0.8248	1	31
9/6/1995	12	27–30	(6.368×10^{-2}) TM1 − (0.366) TM3 + 8.252	0.8168	3	73
9/8/1990	12	27–30	(0.157) TM1 − (0.467) TM3 + 3.101	0.6313	7	117
9/5/2009	11	28–29	(4.299×10^{-2}) TM1 − (0.334) TM3 − (4.290×10^{-4}) Wetland + 5.561	0.8273	3	65
8/9/2005	11	27–29	(0.135) TM1 − (0.364) TM3 − (4.072×10^{-4}) Wetland − 1.396	0.7019	3	55
8/9/2002	11	27–29	(-3.104×10^{-2}) TM3 − (8.897×10^{-4}) Wetland + 4.537	0.8642	1	35
8/14/1995	11	27–29	(1.304×10^{-2}) TM1 − (6.753×10^{-2}) TM3 − (3.456×10^{-4}) Wetland + 3.948	0.7412	7	119

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

Table 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 SDD < 4 m, Mesotrophic SDD = 4–7 m, Oligotrophic SDD ≥ 7 m.

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.

4.3. 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., submitted for publication). 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 SDD = 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.

Table 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 SDD < 4 m, Mesotrophic SDD = 4–7 m, Oligotrophic SDD ≥ 7 m.

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.

5. 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/).

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