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Abstract

Ground-based measurements on 15 Minnesota lakes with wide ranges of optical properties and Landsat TM data from the same lakes were used to evaluate the effect of humic color on satellite-inferred water quality conditions. Color (C₄₄₀), as measured by absorbance at 440 nm, causes only small biases in estimates of Secchi disk transparency (SDT) from Landsat TM data, except at very high values (> ~ 300 chloroplatinate units, CPU). Similarly, when chlorophyll a (chl a) levels are moderate or high (> 10 µg/L), low-to-moderate levels of humic color have only a small influence on the relationship between SDT and chl a concentration, but it has a pronounced influence at high levels of C₄₄₀ (e.g., > ~200 CPU). However, deviations from the general chl a-SDT relationship occur at much lower C₄₄₀ values (~ 60 CPU) when chl a levels are low. Good statistical relationships were found between optical properties of lake water generally associated with algal abundance (SDT, chl a, turbidity) and measured brightness of various Landsat TM bands. The best relationships for chl a (based on R² and absence of statistical outliers or lakes with large leverage) were combinations of bands 1, 2, or 4 with the band ratio 1:3 (R² = 0.88). Although TM bands 1-4 individually or as simple ratios were poor predictors of C₄₄₀, multiple regression analyses between ln(C₄₄₀) and combinations of bands 1-4 and band ratios yielded several relationships with R² ≥ 0.70, suggesting that C₄₄₀ can be estimated with fair reliability from Landsat TM data.

Key Words: Landsat, humic color, chlorophyll, Secchi disk transparency

Landsat imagery can be used to estimate several optically related characteristics of lakes (e.g., Lillesand et al. 1983; Lathrop 1992; Dekker and Peters 1993; Cox et al. 1998; Kloiber et al. 2002a,b). The 30-m spatial resolution of these images allows measurements even on small lakes (~ 8 ha). For example, Kloiber et al. (2002a) developed a method to estimate Secchi disk transparency (SDT) from brightness data for lake surfaces from the Landsat Thematic Mapper (TM) and Multispectral Scanner (MSS) sensors. SDT, the most common measure of lake clarity, often is used as an indirect measure of algal abundance. In situ measurements are required to calibrate relationships between SDT and TM data, but results from a small number (~20-30) of lakes can be applied to all lakes in a Landsat image. Resulting reductions in manpower and travel costs make satellite remote sensing cost-effective for regional assessments of lake clarity. Kloiber et al. (2002b) used 10 Landsat images acquired over 25 years to evaluate water clarity trends in ~450 lakes across the metropolitan area of Minneapolis-St. Paul, MN. A modification of this method was used for a census-level assessment of water clarity in more than 10,000 Minnesota lakes for ~1990 and ~2000 (Olmanson et al. 2001a).

This paper extends our work on satellite-based measurements of lake clarity and investigates relationships between Landsat TM data and the two primary constituents that affect SDT in lakes of the north-central United States: chlorophyll and colored dissolved organic matter (CDOM, variously referred to as humic matter, limnohumic acids, and gilvin). CDOM is a complicated mixture of organic macromolecules

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with aromatic, carboxylic acid, and phenolic groups derived primarily from decomposition of plant material in soils and wetlands. CDOM is expressed here in terms of color ($C_{440}$) measured as absorbance at 440 nm. Our study had three objectives: (1) determine whether CDOM introduces error in satellite-inferred SDT, (2) evaluate the reliability of satellite-inferred SDT as an indirect measure of algal abundance, and (3) determine whether other optical water-quality variables, specifically color ($C_{440}$) and chlorophyll concentration, can be inferred from Landsat TM data.

**Background Information**

Landsat TM data have been acquired routinely for over two decades starting with Landsat 4 in 1982. Landsat 5, launched in 1984, continues to be operational (through mid-2004). Landsat 7, with a modified sensor (ETM+), was launched in 1999. Landsat collects and archives data for a given location every 16 days, but cloud cover on a given acquisition date results in a lower frequency of usable data, especially in regions prone to cloudy weather. The Landsat TM sensor has seven spectral bands, the first four being of primary interest in this study: (1) 450-515 nm, (2) 525-605 nm, (3) 630-690 nm, and (4) 750-900 nm. TM bands 5-7 provide measures of radiance in the mid- and thermal-infrared regions and are not used to estimate the water characteristics of interest here (SDT, chlorophyll, $C_{440}$, turbidity).

Estimating water quality characteristics using Landsat data has important limitations. First, the characteristic must be (or be related to) an “inherent optical property” (IOP) that can be measured by the satellite sensor. For example, the lake clarity work cited above relates SDT to the radiance (or brightness) measured by Landsat in several spectral bands. Potential sources of error arise from varying atmospheric conditions, which affect the amount of incoming solar radiation reaching the water surface and the fraction of light leaving the water surface that reaches the satellite sensor. TM data are measures of the radiance at the sensor and are not calibrated for the intensity of incoming solar radiation, which varies with latitude, season, and time of day. In addition, atmospheric haze scatters light (especially blue wavelengths) and causes an increase in observed radiance. Atmospheric interference over water bodies can be significant, and the potential for such interference increases as reflected radiance from the water decreases; thus, lakes with high clarity and high CDOM are most affected. Atmospheric interferences, sensor response, and incoming irradiance change with time, rendering correction for these changes difficult. These factors prevent direct comparison of data from Landsat images for different dates (Klober et al. 2002a). Hence, estimating water quality characteristics such as SDT from TM data requires nearly simultaneous ground data to calibrate equations and minimize errors.

Inherent optical properties (IOPs) of water are related to light reflectance, $R(\lambda)$, at the water surface, i.e., water-leaving radiance, $L_\omega(\lambda)$, divided by the downwelling (solar) irradiance just above the water surface, $E_\omega(\lambda,0+)$, where $\lambda$ indicates a wavelength-dependent property (Carder et al. 2003). Some new sensors (e.g., the MODIS sensor on the Terra and Aqua satellites, but not Landsat’s TM) have spectral bands at wavelengths sensitive to atmospheric conditions and thus potentially can be used to correct brightness readings at the sensor to surface reflectance values. MODIS also has more and narrower spectral bands, and these characteristics enable the development of more physically based algorithms to calculate IOPs and related water-quality characteristics from MODIS data (e.g., Carder et al. 2003). However, the large pixel size of the MODIS sensor (500 m for the same bands as Landsat TM1-4; 1 km$^2$ for other important spectral bands) renders this sensor unusable for remote sensing of most lakes (i.e., those smaller than a few thousand hectares). For example, only about 1% of Minnesota’s more than 10,000 lakes are large enough to be measured by MODIS. Consequently, Landsat and similar satellites with higher spatial resolution are likely to remain the only options for satellite-based measurements of water quality characteristics of small lakes for the near future.

The factors that affect water clarity are complicated and vary among lakes. In most lakes, clarity is controlled by algae and algal-related suspended matter. Some lakes contain high levels of light-absorbing CDOM, which also affects clarity, SDT, and satellite sensor response. Water clarity in reservoirs and lakes where soil erosion is a problem may be limited by suspended inorganic sediment. However, these cases are uncommon in lake-rich states of the Upper Midwest (Minnesota, Wisconsin, and Michigan). When estimating trophic state from SDT, we assume SDT is controlled by algal-derived turbidity. Lakes with high CDOM concentrations are a potential problem for this assumption given that CDOM can affect the intensity and spectral characteristics of upward radiance from lakes.

Suspended particles, including algal cells and suspended sediments, cause an increase in the measured response (brightness) for bands 1-4. In the band 1 region, increased reflectance from algal cells is offset partially by absorbance from algal pigments. CDOM absorbance increases exponentially with decreasing wavelength, and thus band 1 is influenced by CDOM more than the other bands. Band 2 is centered on an algal reflectance peak. Increased algal abundance increases response in TM band 2. CDOM also absorbs light in band 2, but much less than in band 1. Band 3 overlaps a region of strong absorbance by chl $a$, but reflectance from algal cells is enough to cause increased band 3 response despite absorbance by chl $a$. Chl $a$ absorbance drops and reflectance increases sharply from 680 to 690 nm (upper end of band 3 spectral range). Absorbance by CDOM is not important.

\[ E_\omega(\lambda,0+) \]
Table 1.-Limnological characteristics of lakes sampled in east-central Minnesota.

<table>
<thead>
<tr>
<th>Lake</th>
<th>County</th>
<th>Sampling Date</th>
<th>SDT (m)</th>
<th>Chl a (µg/L)</th>
<th>Turbidity (NTU)</th>
<th>TSS (mg/L)</th>
<th>(a_{440}) (m(^{-1}))</th>
<th>Color (CPU)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ann</td>
<td>Kanabec</td>
<td>9/12</td>
<td>0.6</td>
<td>68</td>
<td>19</td>
<td>8.0</td>
<td>3.6</td>
<td>66</td>
</tr>
<tr>
<td>Big Sandy</td>
<td>Aitkin</td>
<td>9/13</td>
<td>1.6</td>
<td>19.3</td>
<td>3.7</td>
<td>3.2</td>
<td>4.9</td>
<td>89</td>
</tr>
<tr>
<td>Cross</td>
<td>Pine</td>
<td>9/13</td>
<td>0.9</td>
<td>40</td>
<td>9.7</td>
<td>9.7</td>
<td>3.9</td>
<td>71</td>
</tr>
<tr>
<td>Fish</td>
<td>Kanabec</td>
<td>9/12</td>
<td>0.35</td>
<td>153</td>
<td>28</td>
<td>20</td>
<td>3.3</td>
<td>60</td>
</tr>
<tr>
<td>Francis</td>
<td>Isanti</td>
<td>9/12</td>
<td>0.15</td>
<td>279</td>
<td>154</td>
<td>88</td>
<td>4.7</td>
<td>86</td>
</tr>
<tr>
<td>Grindstone</td>
<td>Pine</td>
<td>9/13</td>
<td>4.4</td>
<td>2.1</td>
<td>0.7</td>
<td>1.0</td>
<td>1.4</td>
<td>26</td>
</tr>
<tr>
<td>Hanging Horn</td>
<td>Carlton</td>
<td>9/13</td>
<td>1.8</td>
<td>7.5</td>
<td>1.2</td>
<td>1.5</td>
<td>6.3</td>
<td>115</td>
</tr>
<tr>
<td>Hizer</td>
<td>Carlton</td>
<td>8/30</td>
<td>0.8</td>
<td>17.0</td>
<td>9.3(^a)</td>
<td>--</td>
<td>16.5</td>
<td>300</td>
</tr>
<tr>
<td>Knife</td>
<td>Kanabec</td>
<td>9/12</td>
<td>0.5</td>
<td>60</td>
<td>31</td>
<td>21</td>
<td>4.1</td>
<td>74</td>
</tr>
<tr>
<td>Munson</td>
<td>Carlton</td>
<td>8/30</td>
<td>0.7</td>
<td>9.0</td>
<td>4.9(^a)</td>
<td>--</td>
<td>19.4</td>
<td>353</td>
</tr>
<tr>
<td>Net</td>
<td>Pine</td>
<td>9/13</td>
<td>1.0</td>
<td>16.6</td>
<td>7.1</td>
<td>4.2</td>
<td>10.7</td>
<td>194</td>
</tr>
<tr>
<td>Rock</td>
<td>Aitkin</td>
<td>9/13</td>
<td>2.0</td>
<td>3.8</td>
<td>1.3</td>
<td>1.1</td>
<td>3.6</td>
<td>66</td>
</tr>
<tr>
<td>Round</td>
<td>Aitkin</td>
<td>9/13</td>
<td>4.0</td>
<td>3.1</td>
<td>0.3</td>
<td>0.4</td>
<td>0.6</td>
<td>10</td>
</tr>
<tr>
<td>Sturgeon</td>
<td>Pine</td>
<td>9/13</td>
<td>2.2</td>
<td>17.4</td>
<td>1.1</td>
<td>1.5</td>
<td>0.7</td>
<td>12</td>
</tr>
<tr>
<td>Typo</td>
<td>Isanti</td>
<td>9/12</td>
<td>0.15</td>
<td>183</td>
<td>155</td>
<td>101</td>
<td>5.1</td>
<td>92</td>
</tr>
</tbody>
</table>

\(^a\)Not measured; estimated from the regression relationship between chl \(a\) and turbidity for the remaining lakes: \(T_{\text{NTU}} = 0.545(\text{chl } a)\); \(r^2 = 0.82\).

in bands 3 and 4. Absorbance by water increases sharply in band 4, but increased reflectance by algae and suspended sediments still can be detected (Dekker and Peters 1993). In summary, TM responses for bands 1-4 increase with algal abundance, but the manner of increase varies for each band because of differences in absorbance and reflectance of algal pigments in the bands. CDOM-related color causes a decrease in TM response, especially in bands 1 and 2. Responses of lakes with low turbidity and algae should be more affected by color than those of lakes with high turbidity.

Regression equations commonly are used to “predict” water quality conditions from Landsat data. Simple regression equations relate values of water quality characteristics like chl \(a\), SDT, or total suspended solids (TSS) to TM brightness for a single band. For example, Dekker and Peters (1993) used linear regression to estimate SDT, seston dry weight, and pigment concentration (sum of chl \(a\) and phaeopigments) from the response in TM band 2 or 3. Linear regressions using band ratios also have been used (Bagheri and Dios 1990, Lavery et al. 1993). The best TM band or ratio often differs from one study to another. Equations using band ratios may offer an advantage when atmospheric interference is high (Arenz et al. 1996).

**Methods**

A Landsat 5 TM image for September 12, 2000, was obtained from EROS Data Center, Sioux Falls, SD, for path 27, rows 28-29 covering the east-central Minnesota region between Duluth and Minneapolis-St. Paul. Corresponding water quality measurements were made on September 12 or 13, 2000, on 13 lakes within the area of the image, and two additional lakes were sampled on August 30, 2000. Along with these 15 lakes (Table 1), six other lakes were sampled 2-3 times earlier in summer of 2000 in connection with Landsat overpasses that yielded unusable images (because of cloud cover). Lakes were selected to represent a wide range of optical properties resulting from varying conditions of algal abundance and CDOM. Mid-lake surface water samples were collected in 1-L Nalgene™ bottles, stored on ice in a cooler, and returned to the laboratory for analysis of chl \(a\), TSS, turbidity, and color. Lake transparency at the sampling site was measured by Secchi disk.

Chl \(a\) was analyzed according to standard methods (Eaton et al. 1995) on samples filtered through 0.7 µm GF/F glass fiber filters. TSS was determined gravimetrically (Eaton et al. 1995) by filtering water through 0.7 µm GF/F glass fiber filters and drying at 105°C. Turbidity (T\(_{\text{NTU}}\)) was measured on unfiltered samples with a Hach Company 52600 turbidimeter calibrated with a formazin standard, and results were expressed in nephelometric turbidity units (NTU). Color was measured as absorbance at 440 nm on 0.45 µm filtered water with a 4-cm quartz cell on a spectrophotometer and converted to an absorption coefficient \((a_{440})\). Color (C\(_{440}\)) expressed in chloroplatinate units (CPU) was calculated from the relationship: C\(_{440}\) = 18.22\(a_{440}\) - 0.209 (Cuthbert and del Giorgio 1992).

To aid in calibration of the relationship between SDT and Landsat brightness data, we obtained additional SDT measurements on 26 lakes in the image for dates within + 5 days of the image acquisition from the U.S. EPA’s STORET database. Kloiber et al. (2002a) showed that SDT data
The TM image was processed as described by Olmanson et al. (2001b) using ERDAS Imagine. The image was georectified using 35 ground points (primarily road intersections), which were matched with the same features in a GIS vector layer from the Minnesota Department of Transportation. Land and water features in the image were separated by unsupervised classification using all seven TM bands and specifying ten classes. Pixels of classes representing land features were masked out, and a second unsupervised classification was performed on the water-only image to identify pixels affected by aquatic macrophytes (indicated by elevated responses in bands 4 and 5). Pixels belonging to these classes were excluded during sampling of TM responses for the lakes. In the final image-processing step, the average responses were extracted for each TM band in an “area of interest” (AOI) in the middle of each lake. AOs were selected to avoid shoreline and shallow water influences on TM responses.

Distributional statistics showed that the water-quality data were skewed. Consequently, we conducted further statistical analyses using log-transformed data. Statistical analyses of the water quality data and relationships between those data and satellite measurements were performed with SYSTAT 8.0 statistical software. Cluster analyses of water-quality and TM data were done with SYSTAT 10.2 using a Euclidean distance measure and average linkage between groups as the clustering criterion.

### Results

#### Water-quality Characteristics

The 15 lakes sampled for the September 12 Landsat image varied greatly in water quality (Table 1). Grindstone Lake had the highest SDT (4.4 m) and lowest chl $a$ (2.1 mg/m$^3$). Lake Francis and Typo Lake had the lowest clarity (SDT = 0.15 m), and the highest chl $a$ concentrations (279 mg/m$^3$ for Lake Francis). Turbidity and TSS in all lakes ranged over two orders of magnitude (< 1 to 155 NTU and < 1 to 101 mg/L, respectively), but the two lakes with very high chl $a$ levels skewed the distributions for both variables. Without these lakes, the ranges were < 1 to 28 NTU and < 1 to 21 mg/L. Color ranged from 26 CPU (Grindstone Lake) to 353 CPU (Munson Lake); Hizer Lake also had very high C$_{440}$ (300 CPU). Turbidity, chl $a$, and TSS had strongly positive correlations with one another (all $r > 0.95$) and strongly negative correlations with SDT (all $r < -0.95$). In contrast, C$_{440}$ was correlated much more weakly with the other four variables (Table 2).
Cluster analysis of the 15 lakes based on four optically related water-quality variables for (chl \(a\), SDT, \(C_{440}\) turbidity) yielded readily interpretable results (Fig. 1A). For example, lakes Munson and Hizer, which had the highest color, formed a group with high internal similarity. Net Lake (with the next highest \(C_{440}\) value) joined this group at lower similarity, and the resulting three-lake cluster was highly dissimilar from the rest of the lakes. Similarly, Lakes Typo and Francis, which had the highest chl \(a\) and lowest SDT values, were joined at moderate similarity, and this cluster was highly dissimilar from the remaining lakes. Sturgeon, Round, and Grindstone lakes, which had low to moderate chl \(a\) (2-17 mg/m\(^3\)), moderate to high SDT (2.3-4.0 m), and low \(C_{440}\) (10-26 CPU), formed a cluster with the highest degree of similarity. Ann, Knife, and Cross lakes, which had high chl \(a\) (40-68 mg/m\(^3\)), low SDT (0.5-0.9 m), and moderately high \(C_{440}\) (66-74 CPU), also formed a group with high similarity. Finally, Rock, Big Sandy, and Hanging Horn lakes, which had low to moderate chl \(a\) and moderately high \(C_{440}\), also formed a distinct group.

To determine whether SDT is a reliable measure of trophic state, even for colored lakes, we plotted ln(chl \(a\)) versus ln(SDT) for 41 measurements on 20 Minnesota lakes between July 21 and September 13, 2000 (Fig. 2). The line in the graph represents the best-fit relationship between chl \(a\) and SDT used by Carlson (1977) to derive trophic state indices based on chl \(a\) and SDT. For values falling below the line, SDT-inferred trophic state is higher than that derived from chl \(a\). Many of the points below the line are from four lakes: Munson, Hizer, Net, and Rock lakes (shown as filled circles). The first three are the most highly colored ones in our study. Rock Lake had moderately high color (Table 1). The most highly colored lake (Munson) had the greatest deviation from the best-fit relationship, but not all colored lakes had major deviations from this relationship. Data for Hanging Horn Lake (\(C_{440}\) = 110-115 CPU) are close to the line of the general relationship for all three sampling dates. Data for Cross Lake (\(C_{440}\) = 71-83 CPU) consistently fell above the line, indicating that SDT in the lake was greater than that predicted by the general relationship because the dominant algae in the lake (probably Microcystis) formed globules visible to the naked eye. Packaging of algae (hence chl \(a\)) into globules results in greater transparency compared to an equivalent abundance of individual algal cells (Kirk 1994). Overall, the results in Fig. 2 indicate that high CDOM decreases SDT, but SDT depends largely on algal-derived turbidity in most of the lakes.

**Landsat TM Brightness**

Average brightness of AOIs in TM bands 1-4 for the 15 lakes are listed in Table 3, and Fig. 3 illustrates the range of responses for lakes spanning low and high algal abundance and CDOM. Hypereutrophic Lake Francis had the highest brightness in all four bands; eutrophic Round Lake had much lower brightness for all four bands. Values for eutrophic Fish Lake were intermediate. Highly colored Lake Munson had the lowest brightness for bands 1 and 2, but its band 3 response was nearly identical to that of Round Lake, and its band 4 response was slightly higher than that of Round Lake. In summary, algae increased brightness in TM bands 1-4, and CDOM decreased brightness in TM bands 1 and 2.

Hierarchical clustering based on TM data for bands 1-4 (Fig. 1B) corresponds only roughly to the results for clustering based on water-quality data. Lake Munson and Lake Hizer,
the most highly colored lakes, were the first to be grouped together (similar to the results based on water-quality data, Fig. 1A), indicating that their spectral characteristics were most similar among the 15 lakes. Similarly, Lake Francis and Typo Lake, the two most turbid lakes (SDT = 0.15 m), clustered together at fairly high similarity and were quite dissimilar from the other 13 lakes. Ann, Fish, and Knife lakes (all with moderate color, high chl $a$ and SDT < 0.7 m) also formed a group with high similarity. Hanging Horn Lake (moderately high color, low chl $a$) and Grindstone Lake (low color and chl $a$, high SDT) were joined at a high similarity, but in the clustering based on water-quality measures (Fig. 1A), these lakes were joined only at lower similarity in the hierarchical scheme. Another cluster of three lakes joined together at high similarity based on TM data (Fig. 1B) had varying water-quality characteristics: Round Lake (low color and chl $a$); Rock Lake (moderate color, low chl $a$); Big Sandy Lake (moderate color and chl $a$). Rock and Big Sandy formed a cluster with high similarity based on water-quality characteristics (Fig. 1A), but Round Lake was joined with other lakes before forming a cluster of 10 lakes (including Rock and Big Sandy) that had only moderate similarity.

**Relationships Between Landsat TM Brightness and Water Quality Variables**

Plots of ln(chl $a$) versus brightness in bands 1-4 yielded fair to good correlations. The best fits were for bands 2 ($r^2 = 0.76$) and 3 ($r^2 = 0.73$), but the linear predictive equations did not fit low chl $a$ values well (chl $a$ < ~5 mg/m$^3$). Ratios of TM bands also were related to ln(chl $a$) (Fig. 4). The ratio of band 1 to band 3 (1:3) produced the strongest relationship ($r^2 = 0.88$), but the 1:2 and 1:4 ratios also yielded high $r^2$. The 2:3 and 2:4 band ratios ($r^2 < 0.5$) were not better predictors than bands 1-4 themselves. Multiple regressions between ln(chl $a$) and various combinations of TM bands 1-4 and band ratios as independent variables yielded several relationships with high $R^2$ (Table 4). The best relationships (based on $R^2$ and absence of statistical outliers or lakes with large leverage) were combinations of bands 1, 2, or 4 with band ratio 1:3 ($R^2 = 0.88$) (Fig. 5), but similar relationships with the 1:2 ratio were almost as strong.

Turbidity (T$_{NTU}$) is a measure of light scattering by particles suspended in water; Landsat TM yields measures of upwelling radiance, which depends on light scattering in water. A positive correlation thus was expected between turbidity and TM brightness, and all four bands were correlated with ln(T$_{NTU}$). Linear fits had $r^2$ values of 0.60-0.84 (band 3 had the best fit). In all cases, the linear predictive equations did not fit low turbidity values well (T$_{NTU} < 1$ NTU). Similar relationships were found for chl $a$ and turbidity, which is not surprising given that these variables were highly correlated (Table 2).

![Figure 3](image3.png)

**Figure 3.** Landsat TM responses in bands 1-4 for four lakes of varying color and chl $a$: Munson, high color, low chl $a$; Round, low color and chl $a$; Fish, moderate color, high chl $a$; Francis, moderate color, very high chl $a$.

![Figure 4](image4.png)

**Figure 4.** Relationships between measured ln(chl $a$) and various ratios of Landsat TM bands: open diamonds, TM2:TM3; crosses, TM2:TM4; closed diamonds, TM1:TM2; open squares, TM1:TM3; closed triangles, TM1:TM4.

<table>
<thead>
<tr>
<th>Var$_1$</th>
<th>Var$_2$</th>
<th>$A_0$</th>
<th>$A_1$</th>
<th>$A_2$</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>TM1:TM2</td>
<td>TM1:TM3</td>
<td>21.79</td>
<td>-0.1675</td>
<td>-3.855</td>
<td>0.86</td>
</tr>
<tr>
<td>TM1:TM2</td>
<td>TM1:TM3</td>
<td>6.71</td>
<td>0.0537</td>
<td>-1.559</td>
<td>0.88</td>
</tr>
<tr>
<td>TM2:TM3</td>
<td>TM2:TM4</td>
<td>17.31</td>
<td>-0.1485</td>
<td>-4.017</td>
<td>0.85</td>
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<tr>
<td>TM2:TM3</td>
<td>TM2:TM4</td>
<td>7.86</td>
<td>0.0572</td>
<td>-1.481</td>
<td>0.88</td>
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<tr>
<td>TM3:TM2</td>
<td>TM3:TM4</td>
<td>10.60</td>
<td>0.0289</td>
<td>-2.633</td>
<td>0.85</td>
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<tr>
<td>TM3:TM2</td>
<td>TM3:TM4</td>
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<td>-2.179</td>
<td>0.89</td>
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<td>TM4:TM2</td>
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<td>0.0284</td>
<td>-2.648</td>
<td>0.85</td>
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<tr>
<td>TM3:TM3</td>
<td>TM4:TM2</td>
<td>9.46</td>
<td>0.0078</td>
<td>-1.680</td>
<td>0.88</td>
</tr>
</tbody>
</table>

*Lake Typo had a large leverage on the regression.

TM bands 1-4 individually were very poor predictors of \( \ln(C_{440}) \), and various band ratios also were inadequate \( (r^2 < 0.1 \) for 1:X band ratios and < 0.4 for 2:X band ratios, where X = one of the other bands). Multiple regression analyses between \( \ln(C_{440}) \) and combinations of bands 1-4 and band ratios yielded four relationships with \( R^2 > 0.70 \) (Table 5).

The combination of band 1 and the 1:4 band ratio had the best fit \( (R^2 = 0.77) \), but for reasons that are not obvious Grindstone Lake was a statistical outlier \( (\text{predicted } C_{440} = 74 \text{ CPU versus measured } C_{440} = 26 \text{ CPU}) \). The combination of band 2 and the band 1:4 ratio was almost as good. A regression prediction for \( C_{440} \) using band 1 and the band 1:3 ratio, which is the best the combination for prediction of \( \ln(\text{SDT}) \), had an \( R^2 \) of only 0.47. Predicted \( \ln(C_{440}) \) versus measured \( \ln(C_{440}) \) for the two best regression equations (Fig. 6) shows that reasonable predictive relationships can be developed for \( C_{440} \) from Landsat TM data.

Kloiber et al. (2002a) explored relationships between SDT and combinations of various TM bands for other Minnesota lakes. We applied the form of their best predictive relationship to our data set, which included 15 lakes we sampled and 26 lakes from the U.S. EPA’s STORET data base with SDT measured within 5 days of image acquisition. Two lakes (Lakes Hizer and Munson) with \( C_{440} > 300 \) CPU were not used in final regression analysis because they were found to be strong outliers. The predictive equation for SDT is:

\[
\ln(\text{SDT}) = -2.663 - 0.03191(\text{band 1}) + 1.1030(\text{band 1/band 3}); \quad R^2 = 0.91, \quad n = 39
\]

Estimated SDT from this equation is plotted versus measured SDT in Fig. 7, with different symbols for lakes with low, moderate, and high color. The low and moderately colored lakes (60-115 CPU) show little difference between TM-estimated SDT and measured SDT. The third-most colored lake, Net (194 CPU), also has comparable values using both methods. Indeed, several lakes with low color have larger deviations from the 1:1 line than Net Lake. However, TM-estimated SDT values for Lakes Hizer (300 CPU) and Munson (353 CPU) are much higher than the measured SDT.

**Discussion and Conclusions**

Chlorophyll \( a \), TSS, turbidity, and SDT are highly correlated with each other and all act as direct or indirect measures of algal abundance in Minnesota lakes. In this sense, all four characteristics could be used to measure lake trophic status. Our results demonstrate that chlorophyll and turbidity can be estimated from TM data if near-contemporaneous ground measurements are available for calibration. However, limnologists do not use turbidity and TSS as trophic state indicators because they are not direct measures of algal abundance.

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**Table 5.-** Coefficients for multiple linear regressions of \( \ln(C_{440}) \) versus Landsat TM brightness \( (\ln(C_{440}) = A_0 + A_1\text{Var}_1 + A_2\text{Var}_2) \). Only results with \( R^2 > 0.6 \) are shown \( (n = 15) \).

<table>
<thead>
<tr>
<th>Var (_1)</th>
<th>Var (_2)</th>
<th>( A_0 )</th>
<th>( A_1 )</th>
<th>( A_2 )</th>
<th>( R^2 )</th>
<th>Comments*</th>
</tr>
</thead>
<tbody>
<tr>
<td>TM1</td>
<td>TM3</td>
<td>23.59</td>
<td>-0.5735</td>
<td>0.430</td>
<td>0.60</td>
<td>Francis = O; Typo = LL</td>
</tr>
<tr>
<td>TM1</td>
<td>TM4</td>
<td>21.66</td>
<td>-0.4706</td>
<td>0.352</td>
<td>0.63</td>
<td>Grindstone = O</td>
</tr>
<tr>
<td>TM1</td>
<td>TM1:TM4</td>
<td>23.65</td>
<td>-0.3528</td>
<td>-0.657</td>
<td>0.77</td>
<td>Grindstone = O</td>
</tr>
<tr>
<td>TM1</td>
<td>TM2:TM3</td>
<td>19.42</td>
<td>-0.1642</td>
<td>-6.441</td>
<td>0.64</td>
<td></td>
</tr>
<tr>
<td>TM1</td>
<td>TM2:TM4</td>
<td>14.78</td>
<td>-0.3485</td>
<td>-0.812</td>
<td>0.75</td>
<td>Grindstone = O</td>
</tr>
<tr>
<td>TM2</td>
<td>TM1:TM4</td>
<td>17.78</td>
<td>-0.1829</td>
<td>-1.846</td>
<td>0.70</td>
<td>Grindstone = O</td>
</tr>
<tr>
<td>TM2</td>
<td>TM2:TM4</td>
<td>10.45</td>
<td>-0.1412</td>
<td>-1.905</td>
<td>0.63</td>
<td>Grindstone = O</td>
</tr>
<tr>
<td>TM4</td>
<td>TM2:TM4</td>
<td>12.07</td>
<td>-0.2145</td>
<td>-2.870</td>
<td>0.70</td>
<td>Grindstone = O; Sturgeon = LL</td>
</tr>
</tbody>
</table>

*O = outlier; LL lake had large leverage in the regression.

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**Figure 5.-** Predicted chl \( a \) for the best regression relationship from Landsat TM data (TM1; TM1:TM3; Table 3) versus measured chl \( a \).
The same problem exists with SDT, but it has been one of the most common limnological measurements for many decades, partly because it is so simple and inexpensive to obtain. SDT is amenable for use by volunteer monitors, and the development of volunteer monitoring programs has greatly expanded the availability of SDT data over the past two decades. SDT provides information that relates directly to human perceptions of lake water quality, and as Fig. 2 suggests, it is a reasonable indicator of trophic conditions (algal abundance) except in very highly colored lakes with low chl \(a\). Lakes with non-algal turbidity (clay, calcium carbonate) also would pose problems, but such lakes are uncommon in Minnesota and absent in our data set.

Our results confirm the findings of Menken et al. (submitted), who evaluated the effects of CDOM on hyperspectral reflectance of lakes. CDOM absorbs light and thus reduces the observed radiance of a lake if present in high enough concentrations. The decrease in radiance is strongest at blue wavelengths, as illustrated by comparing brightness values for bands 1-4 in lakes of differing chl \(a\) and \(C_{440}\). For example, higher algal abundance in Net Lake (Table 1) caused it to have higher brightness in TM bands 2-4 than Grindstone Lake, but higher absorbance by CDOM in Net Lake caused it to have a lower response for band 1.

The effects of CDOM are most evident in lakes with low abundance of algae. The lakes with the lowest brightness values in the blue and green portion of the spectrum (TM bands 1 and 2) had high CDOM concentrations and low algal abundance. As algal abundance increases, CDOM has less influence on observed brightness, and lakes with high algal abundance have high brightness across the spectrum. Even if CDOM concentration is high in such lakes, its absorbance may not be sufficient to offset the high radiance caused by algal cells, especially at higher wavelengths. For example, eutrophic Lake Francis and Typo Lake (279 and 183 mg/m\(^3\) chl \(a\)) had the highest TM responses for bands 1-4 despite having \(C_{440}\) measurements of 86 and 92 CPU, respectively. Moreover, the moderately high chl \(a\) (17 mg/m\(^3\)) in highly colored Hizer Lake apparently caused sufficient light to be

![Figure 6](image-url)

**Figure 6.** Predicted ln(\(C_{440}\)) versus measured ln(\(C_{440}\)) for two regression relationships involving TM data as independent variables (see Table 4 for coefficient values): (a) TM1 and TM1:TM4; and (b) TM2 and TM1:TM4.

![Figure 7](image-url)

**Figure 7.** Natural log of Landsat-inferred SDT for lakes in east-central Minnesota versus natural log of measured SDT. Closed diamonds: low color lakes; open diamonds: moderate color lakes; open squares: high color lakes; M = Munson; H = Hizer; N = Net.
reflected that the lake was not an outlier in the relationship between ln(SDT) and ln(chl a) (Fig. 2). In contrast, Munson Lake, with half the chl a and only 20% more color, was a strong outlier in that relationship.

Although most variability in TM responses for bands 1-4 can be attributed to differences in algal abundance, results of our regression analyses show that it is possible in some circumstances to predict ln(C_{440}) from TM data. A combination of band 1 and the band 1:4 ratio or band 2 and the band 1:4 ratio gave the best results. Grindstone Lake, a high-transparency lake with low color (SDT = 4.4 m, C_{440} = 26 CPU), was an outlier in five of the six these relationships; predicted ln(C_{440}) was much greater than measured ln(C_{440}) in each case. It would be beneficial to investigate the above relationships further with a larger data set.

Another issue that could also be addressed in such a study is atmospheric interference, which becomes increasingly significant as the radiance of the lake decreases (a potential problem because highly colored lakes have the lowest radiance of all lakes). A portion of the radiance that TM measures is a result of backscattering from the atmosphere, making it more difficult to distinguish relatively small changes in radiance caused by differences in CDOM.

Landsat data also could be used to identify lakes high in CDOM (rather than attempt to quantify CDOM). If a lake with unknown water-quality characteristics has low TM brightness in bands 1 and 2, its data can be compared with that for lakes with known characteristics—in particular, low color and high clarity (SDT > 4-5 m). If the lake in question has lower TM band 1 response than a lake with low color and high clarity, the lake is likely high in CDOM. Examining the Landsat image for the presence of wetlands in the watershed would provide further evidence. Kallio et al. (2001) suggested a similar approach using the shape of a lake’s brightness spectra, historical water quality data, soil type, and watershed land use to identify CDOM-rich lakes.

Finally, although our results show that CDOM influences the observed brightness of Minnesota lakes, CDOM does not appear to interfere with Landsat TM estimates of SDT for lakes with C_{440} < ~200 CPU. There does not appear to be a systematic error between TM-estimated SDT and measured SDT for such lakes, and Landsat TM data are therefore appropriate as a basis for estimating SDT. Inspection of Minnesota lake water quality data (MPCA 1998) yielded ~1250 Minnesota lakes (~10% of all lakes in the state) with color data. Only three of the lakes had C_{440} values much above 200 CPU, and an additional 12 had C_{440} values around 200 CPU. The frequency with which color would seriously interfere with Landsat-based estimation of SDT in Minnesota lakes thus appears to be relatively low. However, because lakes with color data are not a random sample of lakes in the state, these statistics should not be extrapolated quantitatively to the whole population.

Acknowledgments

This work was supported in part by NASA RESAC project and a grant from the Minnesota Department of Natural Resources. We thank David Wright, MDNR project officer, for his interest and assistance. KDM was supported in part by a Department of Civil Engineering Sommerfeld Fellowship.

References