

USE OF LANDSAT IMAGERY TO DEVELOP A WATER QUALITY ATLAS OF MINNESOTA'S 10,000 LAKES

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ABSTRACT

Lakes are important environmental, economic and recreational resources and contribute significantly to the quality of life in Minnesota. However, because of expense and time requirements for monitoring, it is effectively impossible to adequately monitor more than a small fraction of this large resource by conventional field methods. The use of satellite remote sensing is a cost-effective way to gather the information needed for regional water quality assessments. Based on a strong relationship between Landsat TM bands 1 and 3 and Secchi disk transparency, we developed an image processing and classification procedure and applied it to ~40 Landsat images to classify the water clarity of over 10,000 lakes in the State of Minnesota for the ~1990 and ~2000 time periods. The resulting atlas of water clarity is being used to assess spatial and temporal patterns in lake water clarity based on surrounding land use and cover by using a geographical information system (GIS) to link the lake clarity data with land-use features.

INTRODUCTION

Minnesota is fortunate to have a large number of lakes (approximately 12,000 lakes > 4 ha). These lakes are important recreational and aesthetic resources that add to economic stability and quality of life. Protecting and monitoring lake water quality is a major concern for many local and state agencies. However, because of expense and time requirements for ground-based monitoring, it is impractical to monitor more than a small fraction of this large resource by conventional field methods. The use of satellite-based sensing is a cost-effective way to gather the information needed for regional water quality assessments in lake-rich areas like Minnesota.

For effective environmental planning and management, it is vital to have long-term water quality information on a broad regional scale. Although it is not possible to go back in time and collect additional water quality information using conventional field methods to fill gaps from previous efforts, Landsat data have been collected regularly since the early 1970s, allowing the possibility of extracting historical water quality information from Landsat images. The extraction of historic and current water quality data from satellite images, coupled with existing data collection efforts, may facilitate the development of comprehensive regional databases that can be used to evaluate regional differences and water quality trends over time. If used along with land-use data, this information can help determine the impacts different land-use practices have on lake conditions. Results of such analyses will likely aid local and state agencies to make informed decisions about development policy and improve the management of lake resources.

Although several satellite remote sensing systems have been used for water quality assessment, the relatively low cost, temporal coverage, spatial resolution, and data availability of the Landsat system make it particularly useful for assessment of inland lakes. Several studies have demonstrated a strong relationship between Landsat Multispectral Scanner (MSS) or Thematic Mapper (TM) data and ground observations of water clarity and chlorophyll *a* (e.g., Brown et al. 1977, Lillesand et al. 1983; Lathrop and Lillesand 1986; Lathrop 1992; Cox et al. 1998). However, use of satellite remote sensing for water clarity assessments as a routine application has moved slowly. This may be due to a lack of familiarity among inland aquatic scientists with remote sensing technology and a perception that the data are expensive and difficult to process. In 1999 with the launch of Landsat 7, data distribution was returned to the public sector, and the cost of data acquisition dropped significantly. Along with today's powerful desktop computers and sophisticated software, processing and analysis of satellite imagery has become relatively inexpensive and easy to perform.

In our efforts to develop a Minnesota state-wide comprehensive water quality database we have produced water clarity atlases of over 10,000 lakes that cover the entire State of Minnesota for the ~1990 and ~2000 time periods.

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These water clarity atlases are currently being used to assess spatial and temporal patterns in lake water clarity based on surrounding land use and cover by using a geographical information system (GIS) to link the lake clarity data with land use features.

METHODS

Our methods for applying Landsat imagery to regional-scale and statewide assessment of lake water quality were developed from work initiated by Olmanson (1997) and continued in subsequent studies by our group (e.g., Brezonik et al. 2002; Kloiber et al., 2002ab; Olmanson et al., 2001). The image processing procedures were developed specifically for Minnesota, but with appropriate modifications these procedures should work equally well for other regions.

Lake Reference Data

The principal objective is to perform regional assessments of lake water quality; in particular to estimate variables related to key management indicators, such as the trophic state indices of Carlson (1977). The three water quality variables that have been most commonly used to indicate trophic state are total phosphorus (TP), chlorophyll *a* (chl *a*), and Secchi disk transparency (SDT). Measurements of these water quality variables, along with various transformations such as the trophic state indices (TSIs), have been widely used by lake management agencies and organizations.

Secchi disk transparency, a measure of water clarity, is strongly related to satellite spectral-radiometric observations of lakes. For lakes whose clarity is dominated by phytoplankton abundance, chlorophyll is also highly correlated with the satellite observations. Because phosphorus is the limiting nutrient for most lakes, it is generally correlated with chlorophyll in multi-lake analyses, but it is not directly measurable by optical instruments. Moreover, there are enough exceptions and deviations in the relationships between TP, chl *a*, and SDT that we do not recommend estimating TP values for lakes from Landsat data.

The availability of lake reference data varies both over time and space within any project area. Ideally, there should be at least 20 lake reference points for each image, and they should be distributed over a wide range of water quality/clarity. Contemporary studies usually can be designed to meet these criteria, but collecting the necessary ground observation data in remote areas may be difficult. In retrospective analyses, one must work within the confines of historical sampling programs. SDT is the most consistently collected trophic state indicator, and it is strongly correlated with Landsat data (Olmanson 1997, Kloiber et. al. 2000). Because SDT is inexpensive to measure and can be determined reliably by volunteer monitoring programs, it is likely that these measurements will be collected on a regular basis throughout the Midwest and other regions.

Therefore, most of our research to date has involved calibrating Landsat TM data with ground-based SDT measurements and inferring SDT for all lakes in an image from the regression equation developed in the calibration step. The results then can be mapped directly as distributions of SDT in the lakes, or the estimated SDT can be converted to Carlson's (1977) trophic state index based on transparency TSI(SDT):

$$TSI(SDT) = 60 - 14.41 \ln(SDT)$$

It is important to recognize that other factors aside from algal turbidity (as indicated by chlorophyll levels) may affect SDT in lakes. Most important of these (non-trophic-state) factors are humic color and non-algal turbidity (including soil-derived clays and suspended sediment). For this reason, it is preferable to report Landsat results based on SDT calibrations directly as satellite-estimated SDT or to use the explicit term, TSI(SDT), which clearly identifies the value as an index based on transparency, rather than the generic term, TSI.

Satellite Image Data

Images selected for water quality assessment were high-quality, cloud-free images selected from a late summer index period. Kloiber et al. (2002b) and Stadelmann et al. (2001) determined that an index period of late July to early September was the optimal time for measuring trophic conditions in Minnesota lakes. During this period temporal and in-lake variability is at a minimum for SDT and most lakes have their minimum water clarity. In addition, for trend analysis, it is preferable to have images from near anniversary dates. This time period also correlates with high recreational use of lakes when lake users encounter impacts due to excess nutrients.

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For this large regional assessment 19 Landsat images from five Landsat paths were needed to cover the entire State of Minnesota. To date we have targeted two time periods ~1990 and ~2000 for statewide assessment. The best results were obtained when entire Landsat paths of clear imagery were available for the same day. By using paths of Landsat imagery of two to five Landsat images we are able to increase the available number of observations and range of water clarity (because water clarity in Minnesota generally increases from south to north) in the dataset used to calibrate the imagery, which is discussed in the next section. For the ~1990 time period we used August and early September 1990 and 1991 Landsat TM imagery. For the ~2000 time period we used August and early September 1999, 2000 and 2001 Landsat TM and ETM imagery.

Images were registered to the Universal Transverse Mercator (UTM) coordinate system using the NAD 83 datum and nearest neighbor resampling. Careful selection of approximately 30 well-defined, and well-distributed ground control points (GCPs) resulted in positional accuracy (RMSE) equal or smaller than ± 0.25 pixels, or 7.5 m. We found the Minnesota Department of Transportation highway map (available in ArcInfo GIS format) provides an efficient and effective means of easily finding a large number of well-distributed GCPs. Atmospheric correction or normalization of the Landsat data is not necessary for the regression method described herein. However, it may be necessary if *in-situ* data are not available for a particular scene.

Classification Procedures

This section summarizes our image classification procedures; more detail is provided by Olmanson et al. (2001), and the rationale for the procedures is described by Kloiber et al. (2002ab). ERDAS Imagine, image processing software, and ArcView, geographical information system (GIS) software, are used for the image processing steps. One of the most important steps is acquiring a representative image sample from each lake. Ideally, the sample should represent the center portion of the lake in at least 5 m of water (or twice the SDT measurement), where reflectance from vegetation, the shoreline, or the lake bottom will not affect the spectral signature.

The first step is to make a “water-only” image by performing an unsupervised classification in ERDAS Imagine. Because water features have very different spectral characteristics from terrestrial features, water is put into one or more distinct classes that can be easily identified. Terrestrial features then are masked creating a water-only image. A second unsupervised classification is performed on the water-only image. Average brightness values from the unsupervised classification of this image are graphed to show spectral signatures of each class. These signatures along with the location where the pixels occur are used to differentiate classes containing clear water, turbid water, and shallow water (where sediment and/or macrophytes affect spectral response). Based on this information classes are re-colored so that vegetation, bottom and terrestrial effects can be avoided when selecting lake sample locations or areas of interest (AOI). AOIs are the locations where brightness values from the Landsat image are obtained to develop relationships with measured SDT. For this assessment a polygon layer was used to help automate the process when delineating AOIs and is discussed in Olmanson et al. (2001). ERDAS Imagine’s signature editor is used to extract the spectral data from the image for each AOI. All available SDT data collected within a prescribed number of days (3 to 7 days depending on availability of data for a given image or path of images from same day) of the satellite image are used for calibration purposes. A data set that includes 20 or more ground observations per image, spanning a wide range of ambient conditions is considered acceptable. A multiple regression is performed using log-transformed SDT data as the dependent variable and Landsat Thematic Mapper Band 1(TM1) and the TM1:TM3 ratio as independent variables.

In our previous work, lake water clarity maps were created from the regression model by two methods. The first method used the ERDAS modeler to apply the model to each water pixel. This method creates a pixel-level lake map (Figure 1). With this map all water pixels are classified and intra-lake variability can be evaluated. The other method used the brightness values from the AOI in a spreadsheet program to calculate water clarity for each lake. The data were then linked to a lake polygon layer in ArcView or another GIS program to create a lake-level water-clarity map (Figure 2). The latter method was used in this study and has the advantage of providing a water clarity number for each lake that can be used in other analyses or used in a water clarity database.

Alternative Calibration Methods

We also evaluated other calibration methods for remote areas where ground observation data are scarce or unavailable. These methods included using data from an adjacent scene or from a different time period for the same scene to develop a regression relationship. Several preliminary studies were conducted to test the reliability of these approaches using Landsat images from central and southern Minnesota. Scenes from the same path taken on the

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same day can use the model developed from an upper or lower scene as long as atmospheric conditions are similar.

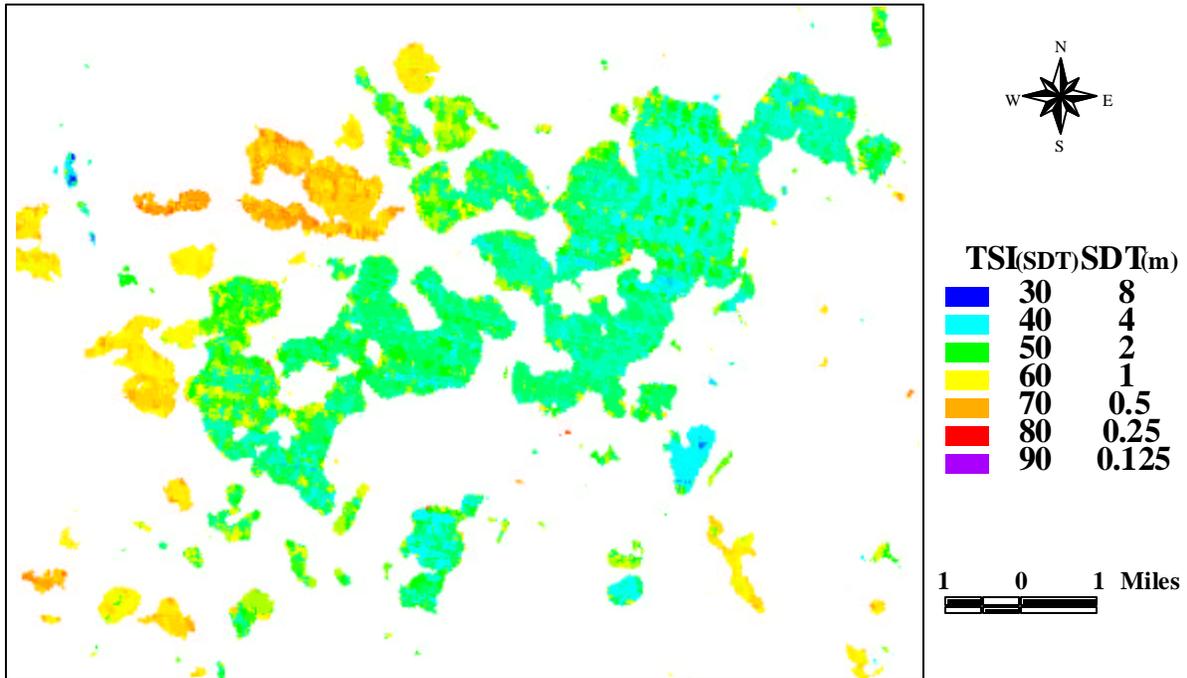


Figure 1 Pixel-Level Water Clarity Map for Lake Minnetonka and Surrounding Lakes.

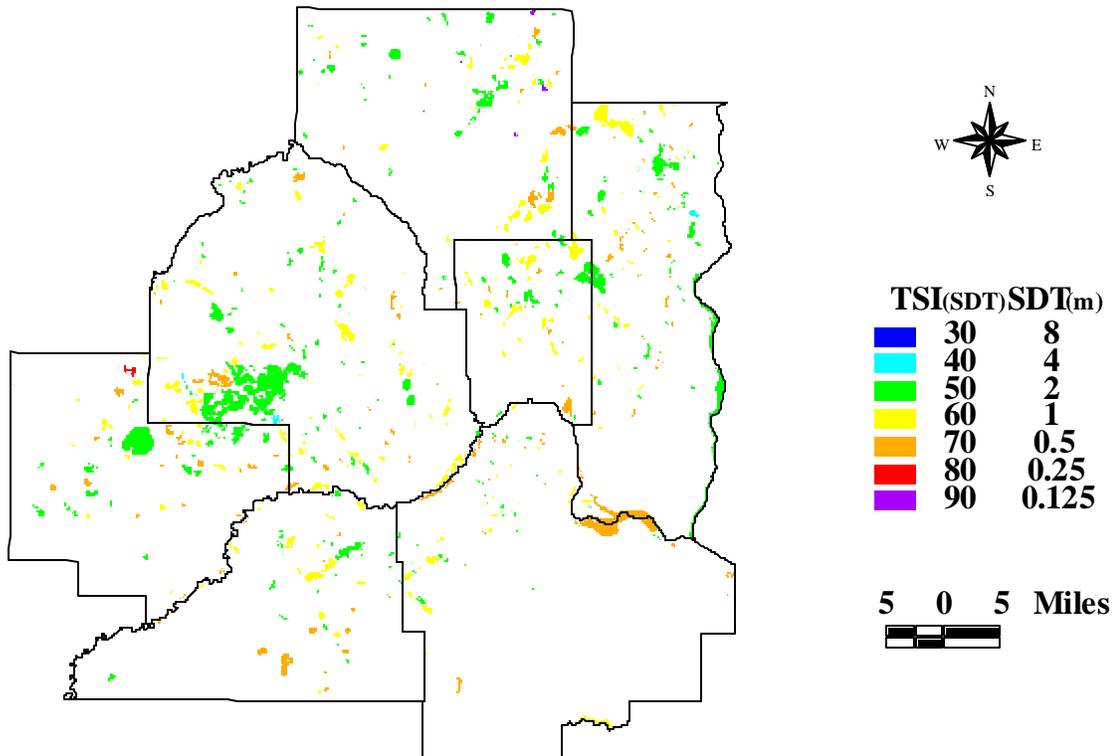


Figure 2 Lake-Level Water Clarity Map for the Twin Cities (Minneapolis St. Paul, MN) Metropolitan Area.

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For example, we classified the image for Path 28 Row 30 from August 26, 1991, which had limited reference data (nine SDT measurements, all < 1 m, within seven days of the image date) based on the model developed from the image for Path 28 Row 29 on the same date. This image had 25 SDT measurements within seven days of the image date. A comparison of the classified lakes from the overlap area of both images indicates very good agreement ($R^2 = 0.996$ and $SEE = 0.48$ TSI(SDT) units). For better results we suggest using data from both or all images in the path to increase the available number of observations and range of data used to calibrate the imagery.

We also conducted an experiment using an adjacent scene from a different path and time to calibrate a Landsat image. The first image (Path 28 Row 28 (east) from August 7, 1990) had 140 SDT measurements within 7 days of the overpass date. The regression model for $\ln(\text{SDT})$ versus Landsat spectral-radiometric data for this scene has an $R^2 = 0.81$ and $SEE = 0.31$. The adjacent scene (Path 29 Row 28 (west) from August 17, 1991) had 57 SDT measurements within seven days of the Landsat overpass date. The regression model for $\ln(\text{SDT})$ versus Landsat spectral-radiometric data for this scene has an $R^2 = 0.81$ and $SEE = 0.29$. For the experiment we used Landsat-inferred values of $\ln(\text{SDT})$ from the “east” image as reference data for the overlapping lakes of the “west” image. This resulted in 714 reference lakes and a regression model (inferred $\ln(\text{SDT})$ versus Landsat spectral-radiometric data) with an R^2 of 0.58 and $SEE = 0.50$. To improve the relationship we limited the reference lakes to those for which >100 pixels had been used to calculate the spectral mean. This reduced the number to 330 reference lakes and yielded a regression model with $R^2 = 0.67$ and $SEE = 0.48$. The latter relationship was used to calculate lake water clarity for the “west” image. A statistical comparison of water clarity results from the SDT reference data model and the adjacent scene reference data model for the “west” image indicate a very strong relationship with an R^2 of 0.95 and $SEE = 2.25$ TSI(SDT) units.

Finally, we found that use of an image from the same path and row but different time period to calibrate other images is feasible as long as some method of radiometric calibration is applied (Kloiber et al.,2002). However, the resulting predictions from this method have a greater uncertainty than those obtained using in-situ data to develop a scene-specific regression relationship. Therefore, it is preferable to develop scene-specific relationships with in-situ data whenever possible. In the future, as better atmospheric correction technologies become available, other approaches may prove to be as accurate.

RESULTS AND DISCUSSION

For this assessment we were not able to find acceptable imagery for the entire State of Minnesota for any given year, but were able to acquire clear Landsat imagery state-wide for the ~1990 and ~2000 time periods when imagery from two or three years were used. In remote areas where lake data is limited we improved our results by using two or more images from the same path and date. By using paths of connected images we were able to find enough SDT data points to calibrate the imagery while also increasing the range of available data. In this and previous studies, we found $R^2 = \sim 0.8$ and standard error = ~ 0.3 for images within the index period (July 15 – September 15). Figure 3 shows predicted versus observed TSI(SDT) for Landsat Path 29 Rows 26-28, August 28, 2001 images with $N = 124$ and $R^2 = 0.89$, and Figure 4 presents predicted versus observed TSI(SDT) for Landsat Path 27 Rows 26-30, September 12, 2000 images with $N = 229$ and $R^2 = 0.82$. The differences in R^2 appear to be due to differences in water clarity in the different regions of the State. Path 29 does not extend into the extremely eutrophic lakes of southern Minnesota and does not have a representation of data from lakes higher than around 65 to 70 TSI. Path 27 extends throughout the entire State and has a larger representation of lakes in southern Minnesota with TSI values higher than 65 to 70. The data from lakes with higher TSI values tend to have more scatter, probably because of sampling inconsistencies and more temporal and in-lake variation of eutrophic lakes. Because TSI is a logarithmic transformation of SDT, small errors in measurements of less than 0.5 feet have a much larger effect in more eutrophic lakes than in clearer lakes.

To date we have completed draft copies of the ~ 1990 and ~2000 Minnesota lake water clarity atlases. These atlases have water clarity data for over 10,000 lakes and represent the lake water clarity of the State of Minnesota for the ~1990 and ~2000 time periods. The ~2000 Minnesota water clarity map is presented as Figure 5. This map indicate that lake water clarity is relatively poor in southern and southwestern Minnesota and becomes progressively clearer toward northeastern Minnesota. We are using these water quality atlases to assess spatial and temporal patterns in lake water clarity based on surrounding land use and cover by using a GIS to link the lake clarity data with land use features.

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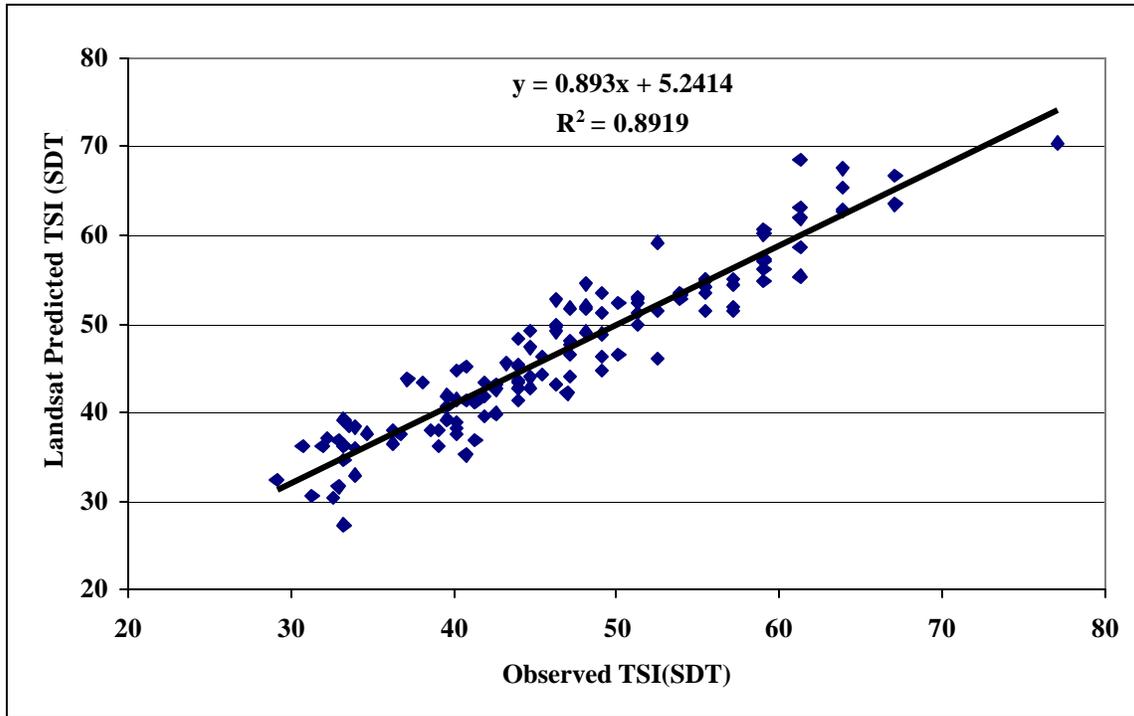


Figure 3 August 28, 2001 Landsat TM Path 29 Predicted vs. Observed TSI(SDT)

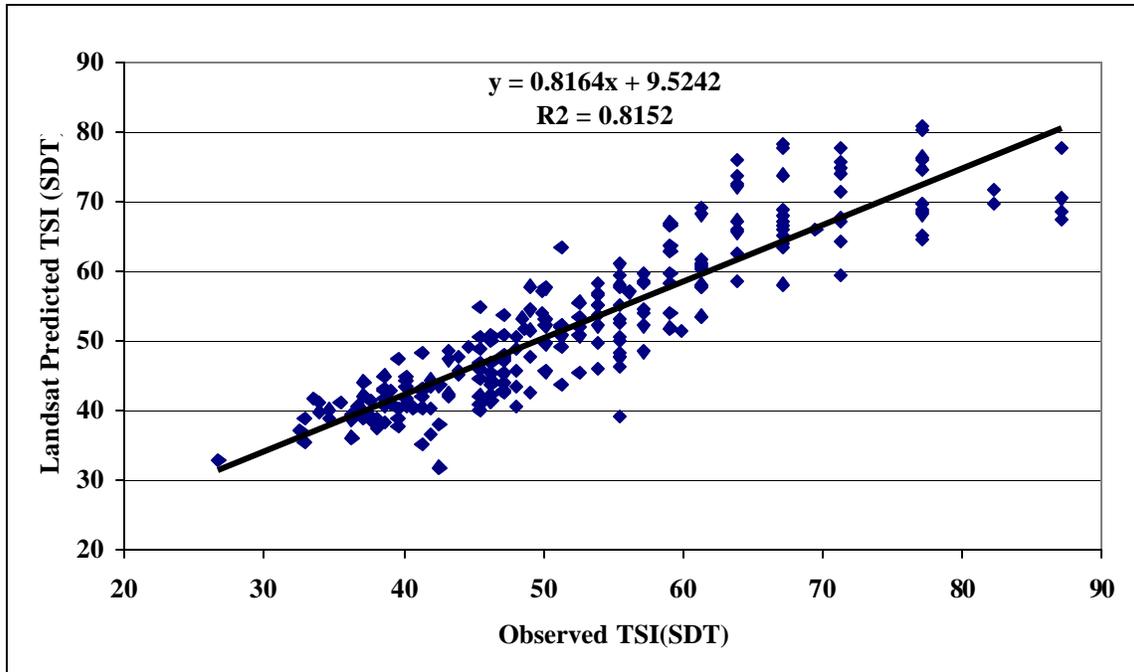


Figure 4 September 12, 2000 Landsat TM Path 27 Predicted vs. Observed TSI(SDT)

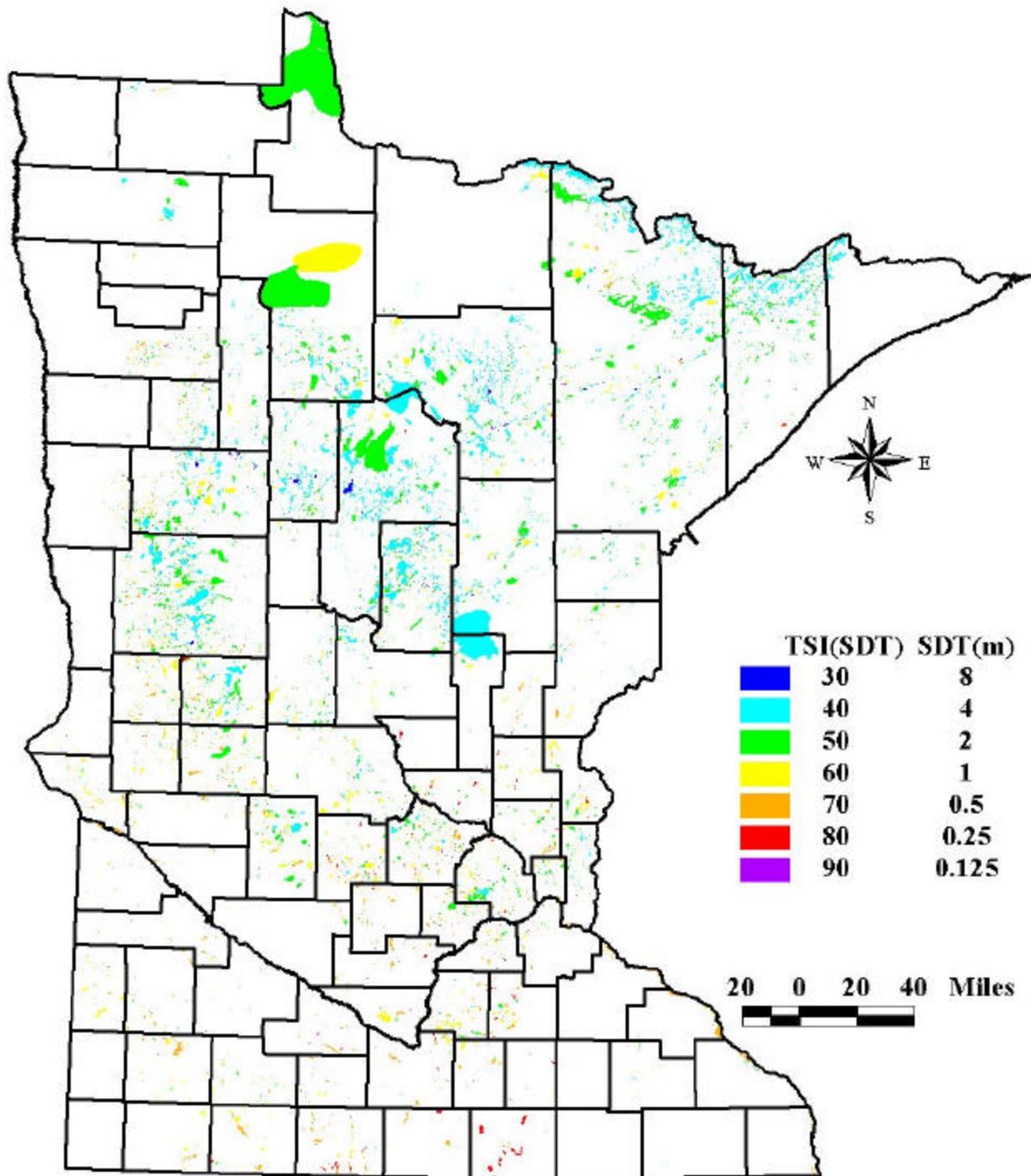


Figure 5 ~2000 Minnesota Water Clarity Map Developed from Landsat TM and ETM Imagery.

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REFERENCES

- Brezonik, P.L., Kloiber, S.M., Olmanson, L.G., and Bauer, M.E. 2002. Satellite and GIS tools to assess lake quality. Tech. Rept. 145, Water Resources Center, Univ. of Minnesota, St. Paul, 8 pp.
- Brown, D., Warwick, R. and Skaggs, R., 1977. Lake conditions in east central Minnesota. Rept. No.5022. Minnesota Land Management Information System, Center for Urban and Regional Affairs, University of Minnesota, Minneapolis, MN.
- Carlson, R.E., 1977. A trophic state index for lakes. *Limnol. Oceanogr.*, 22, 361-369.
- Cox, R.M., Forsythe, R.D., Vaughan, G.E., and Olmsted, L.L., 1998. Assessing water quality in the Catawba River reservoirs using Landsat Thematic Mapper Satellite Data. *J. Lake and Res. Manage.*, 14, 405-416.
- Kloiber, S.M., Anderle, T.H., Brezonik, P.L., Olmanson, L.G., Bauer, M.E., and Brown, D.A., 2000. Trophic state assessment of lakes in the Twin Cities (Minnesota, USA) region by satellite imagery. *Arch. Hydrobiol. Spec. Issues. Advanc. Limnol.*, 55, 137-151.
- Kloiber, S.M., Brezonik, P.L., Olmanson, L.G., and Bauer, M.E., 2002a. A procedure for regional lake water clarity assessment using Landsat multispectral data, *Remote Sens. Environ.* 82(1), 38-47.
- Kloiber, S.M., P.L. Brezonik, and M.E. Bauer. 2002b. Application of Landsat imagery to regional-scale assessments of lake clarity. *Water Research* 36: (in press).
- Lathrop, R.G., 1992. Landsat Thematic Mapper monitoring of turbid inland water quality. *Photogram. Engrg. Remote Sens.*, 58, 465-470.
- Lathrop, R.G., and Lillesand, T.M., 1986. Utility of Thematic Mapper data to assess water quality in southern Green Bay and west-central Lake Michigan. *Photogram. Engrg. Remote Sens.*, 52, 671-680.
- Lillesand, T.M., Johnson, W.L., Deuell, R.L., Lindstrom, O.M. and Meisner, D.E., 1983. Use of Landsat data to predict the trophic state of Minnesota lakes. *Photogram. Engrg. Remote Sens.*, 49, 219-229
- Olmanson, L.G., 1997. Satellite remote sensing of the trophic state conditions of the lakes in the Twin Cities Metropolitan Area. M.S. Paper, Water Resources Science, University of Minnesota, St. Paul, MN.
- Olmanson, L.G., S.M. Kloiber, M.E. Bauer, Brezonik, P.L., 2001. Image processing protocol for regional assessment of lake water quality. Water Resources Center Tech. Rept. # 14, University of Minnesota, St. Paul, Minnesota. 19 pp.
- Stadelmann, T.H., Brezonik, P.L., and Kloiber, S.M. 2001. Seasonal patterns of chlorophyll *a* and Secchi disk transparency in lakes of east-central Minnesota: implications for design of ground- and satellite-based monitoring programs. Submitted to *Lake Reserv. Manage.*