ERDC/EL TR-11-13

US Army Corps of Engineers®
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Water Operations Technical Support Program

Remote Sensing for Inland Water Quality Monitoring: A U.S. Army Corps of Engineers Perspective

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October 2011

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Final report

Prepared for U.S. Army Corps of Engineers
Washington, DC 20314-1000

Abstract: Many agencies, including the U.S. Army Corps of Engineers, are responsible for ensuring that national water quality standards are met. The Corps manages and monitors water quality of all waters within Corps jurisdictions outlined in Water Quality Management Plans, including traditional field sampling (water, sediment, and biological) and measurement of physical parameters. However, these traditional approaches can be labor-intensive and expensive, often providing discrete data at a single point in space and time and making it difficult to characterize a larger waterbody.

During the last three decades, remote sensing has experienced an increasing role in water quality studies, largely due to technological advances, including instrument/sensor and algorithm/image processing improvements. The primary strength of remote sensing over traditional techniques includes the ability to provide a synoptic view of water quality for more effective monitoring of spatial and temporal variation. In addition, remote sensing offers capabilities for viewing water quality in multiple waterbodies over a large region at one time, a more comprehensive historical record or trend analysis, a planning tool for prioritizing field surveying and sampling, and accurate estimations of optically active constituents used to characterize water quality. Furthermore, when utilized in water quality management planning, remote sensing can help reduce costs through minimizing and targeting the collection and processing of thousands of water samples. Although the technology is still emerging, there is abundant evidence of the usefulness of remote sensing in water quality management and monitoring.

This report examines a variety of remote sensing-related studies in which a suite of capabilities are presented. It is intended to serve as a guide for determining how remote sensing can complement and enhance traditional water quality monitoring and the appropriate level of remote sensing to incorporate in a management plan.

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Preface

This technical report provides an overview of remote sensing capabilities and limitations for water quality assessment of inland lakes and reservoirs managed by the U.S. Army Corps of Engineers (USACE). The reported research was conducted as part of the Water Operations Technical Support (WOTS) Program. The WOTS Program is sponsored by Headquarters, USACE, and is assigned to the U.S. Army Engineer Research and Development Center (ERDC) under the purview of the Environmental Laboratory (EL), Vicksburg, MS. The WOTS Program is managed by Dr. Patrick Deliman.

The research was conducted by Ms. Molly Reif, Environmental Systems Branch (EE-C), Environmental Engineering Division (EE), EL, ERDC located at the Joint Airborne Lidar Bathymetry Technical Center of eXpertise (JALBTCX), Kiln, MS. A special thank you is extended to Erich Emery, Water Quality Specialist, Water Management Division, Great Lakes and Ohio River Division, Cincinnati, OH, who helped formulate the direction and purpose of this research, as well as provided technical feedback and guidance.

This work was performed under the general supervision of Dr. Beth C. Fleming, Director, EL; Dr. Edmond Russo, Chief, EE; Mark Graves, Chief, EE-C; and Jennifer Wozencraft, Director, JALBTCX. At the time of publication, Dr. Jeffery P. Holland was Director of ERDC. COL Kevin J. Wilson was Commander.

Unit Conversion Factors

Multiply	By	To Obtain
acres	4,046.873	square meters
hectares	1.0 E+04	square meters
miles (nautical)	1,852	meters
miles (U.S. statute)	1,609.347	meters

1 Introduction

Water quality and the U.S. Army Corps of Engineers

Water quality monitoring is a fundamental component to the Civil Works mission of the U.S. Army Corps of Engineers (USACE). The Corps must meet federal, state, and local mandates for water quality standards and stewardship responsibilities as described in Engineer Regulation 1110-2-8154, *Water Quality and Environmental Management for Corps Civil Works Projects* (U.S. Army Corps of Engineers 1995). In addition, Corps policy also provides guidance for addressing water quality issues using a holistic watershed approach in the Policy Guidance Letter 61, *Application of Watershed Perspective to Corps of Engineers Civil Works Programs and Activities, CECW-AA* (USACE 1999) to emphasize watershed perspectives with regional dimensions and multipurpose planning within individual Civil Works projects. Through the establishment of individual Water Quality Programs, the Corps manages and monitors water quality of all waters within Corps district jurisdictions outlined in Water Quality Management Plans (WQMPs). For example, the Ohio River Water Quality Program is responsible for water quality monitoring and management in reservoirs, lakes, tributaries, and rivers with Corps-operated flood control and navigation structures, which are ultimately conducted by the four districts within the Great Lakes and Ohio River Division. The division provides 34% of the Corps' total outdoor recreational opportunities, managing more than 16,000 miles of shoreline along 128 lakes and navigation pools, as well as maintaining 83 flood control lakes and reservoirs for flood risk management.

Primary monitoring activities include field measurements of physical parameters and the collection and laboratory testing of water, sediment, and biological samples to ensure compliance with federal, state, and local standards, as well as examination of short-and long-term trends related to watershed management practices and regulation and operation practices in reservoirs, locks, and dams. Periodic collection of samples provides historical information to evaluate variations under a wide range of environmental, weather, and climate conditions, allowing project planners to better understand factors influencing water quality within a watershed. At each project site, periodic field visits and samples are collected from inflow streams, tributaries, reservoirs or lake bodies, headwaters, and tailwaters to

ensure that water quality management objectives determined for a specific project are being met. Although each project site is different, generally samples are collected at a minimum of annually or bi-annually; however, more intensive sampling may be conducted monthly to multiple times a year, budgets permitting. Seasonal considerations are another important factor and typically, samples are collected in spring, early summer, late summer, and fall to include a wide array of environmental conditions and seasonal impacts, such as mid-to late summer during increased eutrophication, maximum algal concentrations, and minimum water clarity due to increased environmental stressors. To accomplish water quality management objectives detailed in WQMPs, the Corps collaborates with other agencies and organizations participating in water quality monitoring and watershed management. Coordination with others allows for full consideration of interests and views affecting plans and data requirements. This is especially useful for sharing costly and labor-intensive water quality data useful for multi-objective project planning. Typical objectives determined in WQMPs may include the development and maintenance of a customer-responsive program and establishment and maintenance of water quality and watershed partners within the district. More specifically, the goals include monitoring water quality trends, assessment of surface water quality conditions, quantification of water quality concerns, development of collaborative teams for restoration when applicable, provision of data to support reservoir operations, collaboration for communicating and sharing data and resources with other Corps districts and divisions, implementation of chemical, biological, etc. teams within the program, and preparation of annual technical reports for implementation and direction.

Specific approaches for water quality sampling include sampling to establish baseline conditions at lakes and reservoirs, monitoring for priority pollutants, assessing compliance with water quality regulations, developing a database for analysis and sharing, investigating water management problems, designing modifications, improving procedures, support for reservoir regulation, participating in design and engineering of aquatic ecosystems and restoration projects, and maintaining environmental awareness for watershed management and environmental stewardship. Typical samples for water quality monitoring and other field surveying may include, but are not limited to, the following:

- <u>Biological samples</u>: This includes phytoplankton, chlorophyll-a, and macroinvertebrate samples, which may be collected throughout the

water column and representative sites throughout the project area (i.e. macroinvertebrate samples, at inflow and tailwater locations to compare with other project sites within the watershed).

- Water samples: This includes water samples collected at varying depths in the water column at select sites throughout the project area and year when possible.
- Field data: This includes measurement of physical parameters such as temperature, dissolved oxygen, specific conductivity, pH, turbidity, and Secchi depth, which are collected in profile format at water and biological sampling locations within the project area.
- Sediment samples: This includes sediment samples at upper, middle, and lower reservoir base sites within the larger reservoir body on a multi-year schedule.

Key parameters affecting water quality in waterbodies are suspended sediments (turbidity), algae (i.e. chlorphylls, carotenoids, etc.), chemicals, (i.e. nutrients, pesticides, metals, etc.), dissolved organic matter (DOM), thermal releases, aquatic vascular plants, pathogens, and oils (Ritchie et al. 2003). Of these, the U.S. Environmental Protection Agency (USEPA) concludes that suspended sediments, algae, aquatic vascular plants, and temperature are related to the major water quality problems (USEPA 1998). Other special water quality issues in lakes and reservoirs include algal blooms (due to increased nutrients), bacterial contamination (i.e. fecal coliform bacteria), toxic contaminants (i.e. fish tissue contaminants), and invasive species (i.e. hydrilla).

Real-time proximal and remote monitoring

Aside from manual field surveying and sampling techniques, other approaches to monitor water quality include proximal sensing and remote monitoring through specialized equipment and monitoring stations. Real-time remote monitoring (RTRM) is conducted through in situ monitoring stations established at many Corps project sites, such as at the pool above dams (headwater), major tributaries and inflows, releases at the dam, and tailwaters downstream of the dam. These data are continuously recorded and monitored (either onsite or sent to another location) to assist with determination of dam and hydropower facility operation and maintenance or restoration of water quality conditions. Advances in sensor technologies, mobile computing, and wireless communications have led to enhanced RTRM (Glasgow et al. 2004). Advantages associated with these improved systems include real-time alert notifications during spills or other high-risk

events, data streamlining and minimization of human error, time and cost reductions, and data quality and quantity improvements. Typically the sensors include both meteorological and hydrological sensors coupled with advanced computer hardware and software; new systems can be transferred via web-based applications within the RTRM network (Glasgow et al. 2004).

An example of an RTRM system is the network of stations and automated platforms in the Neuse River Estuary Monitoring and Research Program, providing real-time data and a web-based warning notification for harmful algal bloom, fish kill, and oxygen deficiency monitoring via sophisticated sensors and cellular telemetry data download (Glasgow et al. 2004). Other examples include RTRM systems for fish detection, fish behavior, and automated platforms and autonomous underwater vehicles (AUVs). The Corps uses real-time proximal sensing in addition to RTRM stations, which refers to the use of instruments to measure phenomena in close proximity to a target. An example is a spectroradiometer, which is used to measure light reflected and absorbed by components of the water column in different wavelengths of the electromagnetic spectrum. These in situ measurements include reflectance values collected at a single location and are often indicative or characteristic of individual targets or constituents. These data can be useful for determining concentrations of water column components within the water column and can be collected above and below the water surface (Chipman et al. 2009). Furthermore, they are also useful for comparison with remotely sensed imagery, and ultimately image processing to estimate water quality parameters.

Remote sensing and water quality

Conventional in situ water sampling conducted by the Corps is labor-intensive and costly. Many agencies charged with monitoring water quality are facing challenges associated with monitoring more areas with less resources and decreased budgets. Therefore, collaboration and data sharing with other agencies and organizations are increasingly essential to maximize resources. However, in situ measurements are limited because they only provide information at a single point in space and time, which may not provide the spatial and temporal variation and view of water quality in a larger waterbody (Ritchie et al. 2003), and may be especially inadequate for characterizing heterogenous waterbodies, such as complex Case 2 waters including coastal and inland waters (Liu et al. 2003). For more than three decades the use of remote sensing has illustrated a variety

of capabilities for assessing water quality through strong correlations between remote sensing bands and band ratios (i.e. visible and near infrared channels of the electromagnetic spectrum) and optically active constituents in complex inland lakes and reservoirs (Chipman et al. 2009; Gitelson et al. 1993, 2008; Kallio 2000; Kennedy et al. 1994; Knaeps et al. 2010; Kloiber et al. 2002a; LaPotin et al. 2001; Olmanson et al. 2008; Ritchie et al. 2003; Sawaya et al. 2003; Schiebe et al. 1992; Shafique et al. 2003; Wang et al. 2004). Although remote sensing has proven useful for water quality monitoring, it will never replace traditional field surveying and sampling. However, when coupled with such techniques, remote sensing can enhance and complement existing approaches to maximize resources and cost-effectiveness. Additional advantages of incorporating remote sensing in water quality monitoring programs include the following:

1. a synoptic view of a waterbody for more effective monitoring of the spatial and temporal variation,
2. a simultaneous view of water quality in multiple lakes over a large area at one time,
3. a more comprehensive historical record of water quality showing trends over time,
4. a planning tool to prioritize field surveying and sampling locations and times, and
5. an accurate estimation of optically active constituents used to characterize water quality (Kallio 2000).

Many factors affecting water quality can be measured with remote sensing, including optically active constituents, referring to those that interact with light, thus changing the energy spectra of reflected solar radiation emitted from surface waters (Ritchie et al. 2003). These include phytoplankton pigments (chlorophylls, carotenoids, phycocyanin, etc.), colored dissolved organic matter (CDOM), and inorganic and non-living suspended matter, which coincide well with the previously mentioned parameters determining the majority of water quality issues in inland waters. In contrast, parameters that cannot be measured directly with remote sensing include chemicals, pathogens, and acidity because they do not affect spectral properties, although they may be inferred from other parameters associated with those conditions (Kallio 2000, Ritchie et al. 2003).

Remote sensors include airborne (i.e. fixed-wing aircraft) and spaceborne (i.e. earth orbiting satellites) platforms, which have both been routinely used to assess and interpret water quality in lakes, rivers, and coastal estuaries, representing heterogeneous Case 2 waters. These sensors measure upwelling radiance from a waterbody at various wavelength ranges and spatial resolutions. Often, radiance is converted to reflectance in order to compare image scenes acquired under different conditions and derive values that are less dependent on weather and illumination (i.e. the ratio of upwelling radiance, or light reflected from a waterbody, to the downwelling irradiance, or incoming sunlight). In general terms, remote sensing of components in the water column is based on how light in different wavelengths of the electromagnetic spectrum is absorbed or reflected by those components. Solar radiation penetrating the water column can be absorbed and scattered by the water, as well as optically active constituents (i.e. inherent optical properties of the water column). Therefore, the radiation measured by the sensor includes volume information from scattering within the water, surface reflection, and radiation from optically active constituents reacting within specific wavelengths.

Interpretation approaches

There are two types of approaches for interpreting water quality from remotely sensed imagery: the (semi-)empirical approach and the (semi-)analytical approach (Cannizzaro and Carder 2006, Giardino et al. 2007, Kallio 2000, Knaeps et al. 2010, Ritchie et al. 2003). Semi-empirical and empirical based approaches are the most common and are determined through statistical relationships between measured spectral properties (i.e. radiance or reflectance) and the measured water quality parameter of interest (Ritchie et al. 2003). Examples can be found in many ocean color algorithms for derivation of chlorophyll-a concentrations (Chl), which illustrate strong correlations between Chl and the blue and green spectral regions (i.e. Chl has absorption maxima at 430-450 and 660-680 nanometers, nm). However, these spectral regions typically do not work well for retrieval of Chl in Case 2 waters, which have increased turbidity and overlapping absorption of dissolved organic matter and tripton (Gitelson et al. 2008). Wavelengths are typically analyzed and selected from regions in the spectrum in which reflectance and absorption are strongly impacted by the parameter of interest (Kallio 2000). For turbid water environments, many algorithms have been developed to retrieve Chl, which are primarily based on a band ratio between a reflectance peak near 700 and an absorption peak (red Chl absorption band) around 670 - 680 nm

(Dall'Olmo and Gitelson 2005). Improvements to this approach have examined ways to subtract the effects of other factors on reflectance around the peak at 670 nm using a three-band reflectance model (Dall'Olmo et al. 2003; Gitelson et al. 2003, 2008). In empirical approaches, statistical regressions (i.e. linear or multiple) are established between reflectance values extracted from the imagery (individual bands, band combinations, or ratios) with concurrent in situ water quality measurements for correlation and validation (Figure 1).

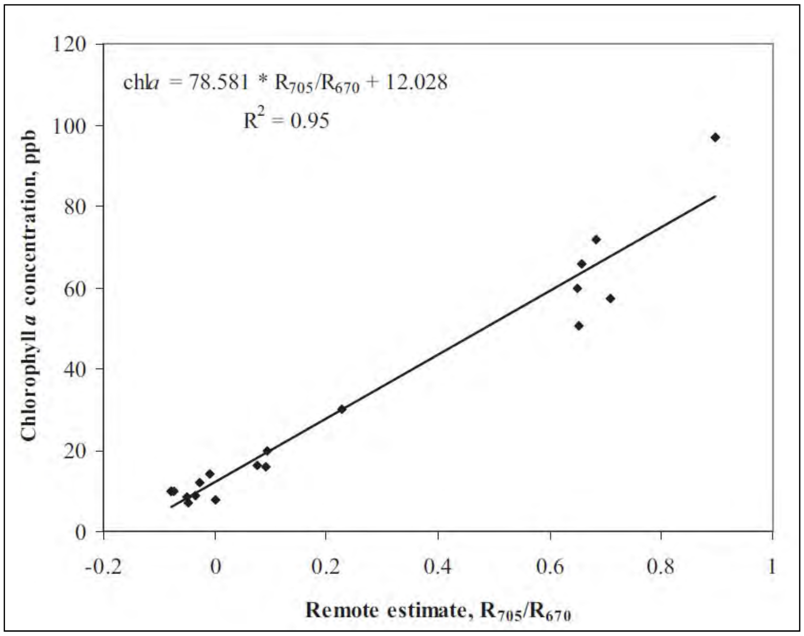

Figure 1. Example of a linear regression between laboratory-measured Chl concentrations in Lake Minnetonka, MN in 2005 with predicted Chl estimates using a common near infrared (NIR)/red band ratio (705/670 nm); the model illustrates strong correlation between measured and predicted estimations with high statistical significance, $R^2 = 0.95$, which is a common measure of goodness of fit (Chipman et al. 2009).

Although empirical approaches have been successfully illustrated in many studies and are easy to use and apply, the disadvantages are that they require in situ sampling for testing and validation and they tend to be scene dependent, applying locally to the specific data from which they were derived (Giardino et al. 2007, Kallio 2000, Lathrop 1992, Ritchie et al. 2003). Therefore, application of successful relationships in one project site may not apply to a lake or reservoir with different conditions in another project site, thus making the results site-specific and not applicable on a regional basis. However, regional lake assessments taking advantage of more statistically robust models such as the three-band model or semi-

empirical approaches that involve focusing or tuning spectral regions and bands in the statistical analysis (when the spectral characteristics of parameters are known) have been successfully conducted for assessment of lake water clarity over a large geographic area (Chipman et al. 2009; Kloiber et al. 2002a, 2002b; Olmanson et al. 2008). Therefore, in order to successfully interpret water quality for a large geographic area in many lakes and reservoirs with varying conditions and optical properties, a semi-empirical approach, positioning spectral bands and widths is useful (Chipman et al. 2009, Dall'Olmo and Gitelson 2005, Gitelson et al. 2008).

Analytical and semi-analytical approaches refer to more complex modeling in which water parameter concentrations are physically related to the measured reflectance spectra by evaluating their absorption and scatter coefficients at multiple wavelengths. Through the use of sophisticated radiative transfer equations, relationships between water reflectance and the concentration of constituents and their Specified Inherent Optical Properties (SIOPS) are established (Giardino et al. 2007, Kallio 2000, Knaeps et al. 2010, Ritchie et al. 2003). The process involves inverting the radiative transfer equation (typically using hyperspectral imagery) to determine water quality parameters. Numerous inversion processes have been developed for this purpose (Lee et al. 1999; Mobley et al. 2005) and have been shown to optimize unknown parameters when measured input are not available (Giardino et al. 2007, Kim et al. 2010, Lee et al. 1999; Santini et al. 2010); other attempts have employed the use of look-up tables (LUT) (Mobley et al. 2005) and neural network analysis (Doerffer and Schiller 1999). Inversion models have been particularly useful for separating bottom reflectance from water column spectra, which is especially important in shallow waters where the water-leaving radiance/reflectance likely contains some spectral information from the bottom reflectance as well as the water column (Cannizzaro and Carder 2006; Kim et al. 2010). Often, more simple interpretation approaches applied in optically shallow waters can lead to overestimation of water column constituents due to the increased reflectance values primarily from the bottom reflectance (Lee et al. 2001). Therefore, many studies employing empirical approaches remove shoreline and shallow-water pixels from consideration (leaving only optically deep waters) to avoid this problem (Chipman et al. 2009). Analytical and semi-analytical approaches offer the following distinct advantages over empirical approaches: 1) they can be used to estimate properties of the optical constituents in the water column (for both optically deep and shallow waters) and bottom (for optically shallow waters) using

physics-based modeling, 2) they can be applied in the absence of in situ water quality measurements, making the approach more independent, and 3) they can be more regionally applied in multiple lakes and reservoirs with heterogeneous conditions. Despite these advantages, however, they are computationally intensive, making them more expensive and difficult to use and requiring knowledge of the inherent optical properties of the waterbody. In addition, they typically do not work well with the broad spectral bands inherent in multispectral imagery, potentially limiting their use. Nevertheless, ongoing research and development in this area is focused on making these techniques better suited to operational instruments that cover large geographic areas for long-term monitoring (Giardino et al. 2007) and easier to use, especially with advancements in computer technology.

Many factors contribute to the selection of appropriate imagery and analytical methods specific to the goals of individual projects. Selecting appropriate sensors, bands, and methods is largely dependent on the size of the study area, desired mapping unit/scale/resolution, water quality objectives and parameters of interest, cost of imagery and analysis, project timelines, and level of expertise. The purpose of this report is to provide a review of sensor platforms, analysis methods, and the ability to measure or estimate a variety of common, optically active water quality constituents that may be useful to address water quality objectives defined by the Corps. Included in this review is specific information about the various types of sensors, associated costs of the imagery, the types of water quality parameters that can be measured with the corresponding sensor, the type of processing and methods used to analyze the data, limitations of the corresponding sensor, and examples from scientific literature and agency reports.

2 Airborne Sensors

Airborne sensors for water quality monitoring

In the case of water quality monitoring, the primary airborne sensor used is a hyperspectral imager, although some studies have utilized aerial photography to assess water quality conditions, such as the study done in a Wisconsin lake estimating turbidity via suspended solids using aerial photos and in situ measurements (Klooster and Scherz 1973). Hyperspectral sensors measure upwelling radiance (i.e. from solar radiation) over a geographic area in a series of narrow spectral bands. One example is the Itres Compact Airborne Spectrographic Imager (CASI)-1500, which is a pushbroom sensor featuring up to 288 spectral bands measuring in the 375-to 1050-nm range at 1.9-nm intervals. Other examples are the Airborne Imaging Spectrometer for Application (AISA), which is also a pushbroom sensor measuring radiance in the visible and near infrared portions of the spectrum (with as many as 512 discrete bands) and HyMap (HyVista Corporation), which is a whiskbroom sensor offering 128 bands in the 450-to 2500-nm range at a 15-to 20-nm bandwidth. Typically these sensors are configured to collect fewer bands, which is an advantage of this sensor type since bands and band centers can be configured to meet specific project needs. Raw data values are generally converted to at-sensor radiance (i.e. reflectance at the satellite sensor) using calibration techniques and information supplied with the data. Additional information collected onboard the aircraft (Global Positioning System and Inertial Navigation Sensor) are used for georeferencing and correcting position and orientation (Chipman et al. 2009).

Although radiance data can and have been used to interpret water quality, in order to conduct multitemporal comparisons across different flight lines and image sets, it is necessary to remove atmospheric effects (Hadjimitsis and Clayton 2009, Thiemann and Kaufmann 2002). This process involves converting the radiance data to reflectance and removing atmospheric effects of light passing from the sun to the image scene and back to the aircraft. Accurate atmospheric models make it possible to determine surface reflectance from the sensor. There are many models for atmospheric correction procedures and generally the process is conducted in remote sensing software such as in ITT Visual Information Solutions (ITT VIS) ENVI and ERDAS Imagine software programs. They include

empirical approaches, such as the empirical line approach, requiring field spectra for a bright and dark target, atmosphere removal algorithms (ATREM) in which no field data are required (common ones developed for land include HATCH, ACORN, FLAASH, ISDAS, and ATCOR, which are comparable although some include advanced spectral smoothing and topographic correction), and lastly, corrections for ocean applications employing radiative transfer equations, such as Tafkaa developed by the Naval Research Laboratory and WATCOR developed for coastal and lake waters (Gao et al. 2009).

Other considerations for hyperspectral imagery include area of coverage (swath) and spatial and spectral resolutions, all of which can be configured during mission planning (i.e. pre-planning before a flight to determine appropriate survey windows). As previously mentioned, one of the main advantages of airborne hyperspectral imagers is that they can be configured to match specific project needs. For example, if a specific target is being analyzed in a project area, such as a plant species, a priori knowledge of the spectral characteristics of that species may be used to program the sensor to corresponding band centers or spectral ranges in which that species is most sensitive. For water quality, studies have shown that sufficient spectral resolution, especially in certain portions of the spectrum (i.e. near infrared, 700 to 740 nm), is important for determining which parameter can be measured, or conversely, which sensor is most appropriate to measure a parameter (Gitelson et al. 2008, Kallio 2000). Although wide bandwidths have improved signal-to-noise ratios, they may not be appropriate for detection of certain water quality parameters that require finer spectral detail; therefore, it may be best to determine which water quality parameters are to be measured with the imagery ahead of time, otherwise, the imagery may dictate which parameters are possible to measure. For hyperspectral sensors having both high spatial and spectral resolutions, this is generally not a problem and is another advantage of these systems.

Swath width and spatial resolution are determined by the flying altitude of the aircraft. In general, lower altitudes will result in higher spatial resolution and a smaller area of coverage, whereas higher altitudes will result in lower spatial resolution and a larger area of coverage. These specifications are decided during mission planning and are often dictated by project requirements and budget constraints. They may also be determined by programmatic considerations. Many airborne sensors are

utilized in various research efforts and agency programs, such as the U.S. Army Corps of Engineers National Coastal Mapping Program (NCMP), which uses the Compact Hydrographic Airborne Rapid Total Survey (CHARTS) system (Figure 2). CHARTS is an integrated sensor suite, featuring a CASI-1500 hyperspectral imager, as well as a topographic and bathymetric light detection and ranging (lidar) and RGB digital camera (Wozencraft and Lillycrop 2006). The Joint Airborne Lidar Bathymetry Technical Center of eXpertise (JALBTCX) uses this system to collect lidar elevation data and imagery for a 1-mile swath along the coastal United States on a recurring basis to support NMCP activities, such as regional sediment management, navigation, environmental restoration, regulatory enforcement, asset management, and emergency response activities in the coastal zone. Typical CASI configuration in the NMCP includes 36 spectral bands with 18-nm bandwith, operating in the 380-to 1050-nm spectral range at a 1-m spatial resolution (i.e. 750-m swath width at a flying altitude of 700 m); however, these specifications are flexible and can change to meet Corps district requirements for a specific project.

Figure 2. Beechcraft King Air 200 (left) and CHARTS instrument in the aircraft (right).

Airborne case studies

Many studies have been conducted using airborne hyperspectral sensors to interpret water quality in lakes and reservoirs with a variety of environmental conditions. One example is a study that was done to assess a series of lakes with a wide range of land use and development in Fremont, Nebraska. In this study, the AISA sensor was used to acquire imagery (Figure 3) in late summer 2005 (2-m spatial resolution, 97 bands, at a 3000-m altitude, and clear skies). The recommended band centers for aquatic studies are presented in Appendix A.

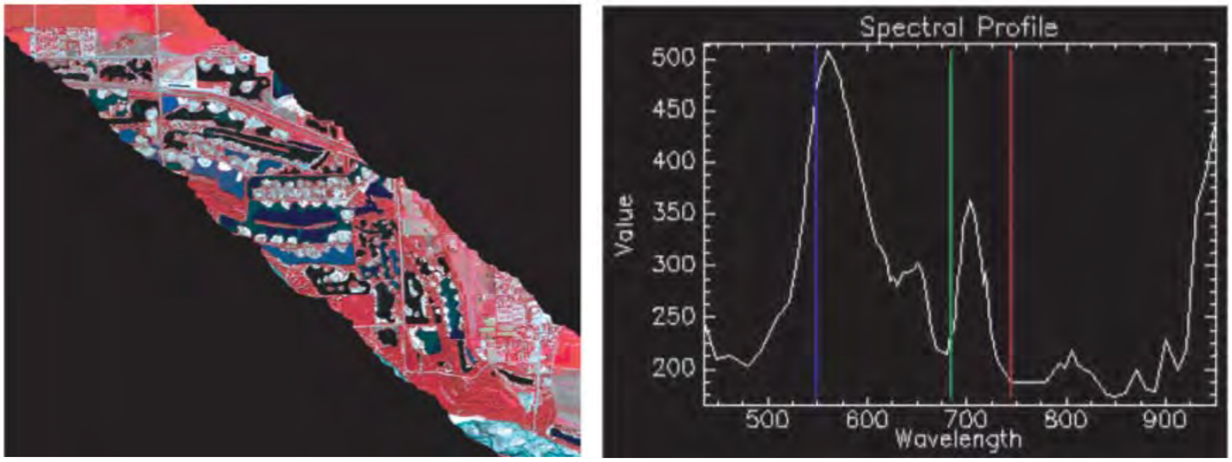

Figure 3. AISA hyperspectral image (false color) over Fremont, NE (left) and a spectral profile of a water pixel from the image (right) (Chipman et al. 2009).

Using a three-band model to estimate Chl and a two-band model to estimate total suspended solids (TSS), thematic maps illustrating relative concentrations were generated. Equations are as follows:

$$\text{Chlorophyll concentration: } \alpha\ [R^{-1}(\lambda_1) - R^{-1}(\lambda_2)] \times R(\lambda_3) \quad (1)$$

$$\text{Total Suspended Solids: } \alpha\ [R(\lambda_3)/\ R(\lambda_4)] \quad (2)$$

A detailed description of these equations can be found in Chipman et al. (2009) and Gitelson et al. (2008); however, α refers to the total absorption and backscattering coefficients, R^{-1} is the reciprocal of reflectance (absorption feature) at wavelengths λ_1 and λ_2, R is reflectance at wavelengths λ_3 and λ_4, and where λ_1 = 665–675 nm, λ_2 = 700–710 nm, λ_3 = 730–740 nm, λ_4 = 540–560 nm. Figure 4 illustrates the results from Equation 1.

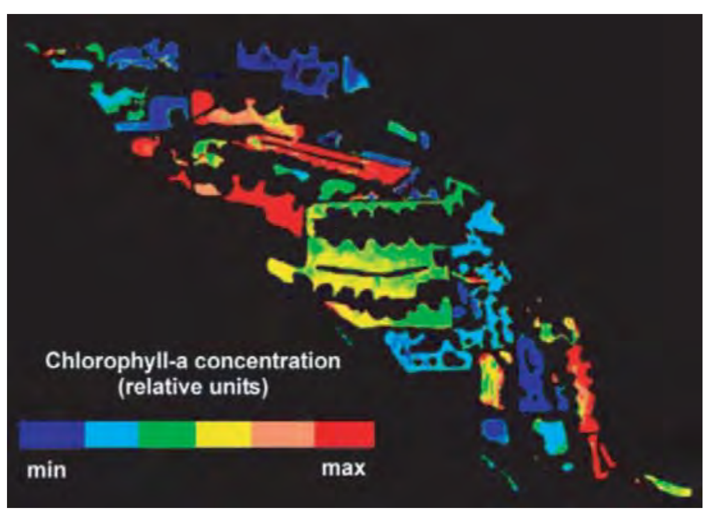

Figure 4. Chl concentration in Fremont Lakes, NE (Chipman et al. 2009).

Another study conducted in Germany used CASI and HyMap airborne hyperspectral imagery to map Secchi disk transparency and Chl using a semi-empirical approach for a range of lakes (Secchi disk transparency ranged between 0.25 and 8.5 m and depths ranged between 3 and 36 m) (Thiemann and Kaufmann 2002). CASI and HyMap imagery were acquired in 1997 to 1999 along with in situ field measurements (water samples for Chl analysis and Secchi disk transparency). CASI imagery included 17 bands at 6-to 25-nm spectral resolution and 3-m spatial resolution, whereas the HyMap imagery included 28 bands (400- to 750-nm range) at a 15-nm bandwidth and 10-m spatial resolution; both were atmospherically corrected (using the empirical line approach and the ATCOR program). For Secchi disk depth transparency (SD), a regression was calculated between the in situ SD and the spectral coefficient determined from the imagery (spectral fitting approach at the local minima, 430 nm, and longer wavelengths, 750 nm). A high correlation of R^2 = 0.85 was determined from the regression analysis) (Thiemann and Kaufmann 2002). Figure 5 is an example of the map results for the study.

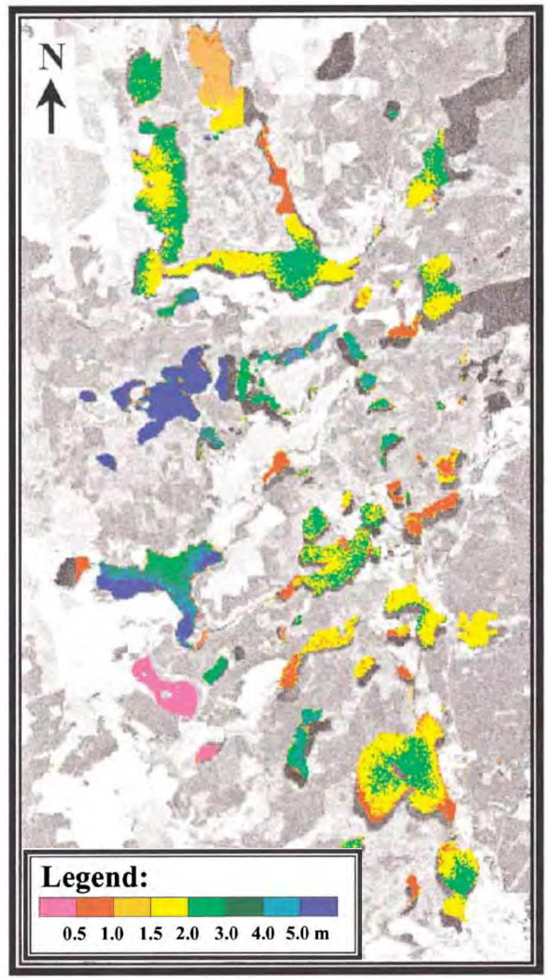

Figure 5. SD estimations from HyMap and CASI in Germany, 1997-1999 (Thiemann and Kaufmann 2002).

A final example of airborne hyperspectral imagery comes from a recent study done in Italy to measure concentrations of Chl, CDOM, and tripton (i.e. the non-living component of total suspended matter) in highly turbid lagoon waters (Santini et al. 2010). In this study an analytical approach using a nonlinear relationship is determined through a refined physics-based model. As mentioned previously, the inversion technique is used to determine water quality parameters from the hyperspectral imagery – in this case, through a two-step optimization method. A bio-optical model is further used in optically shallow waters to separate water column versus

bottom cover information. Both data sets can be useful in assessing water quality and in this case are used to develop optical waterbody classifications, monitor sea/lagoon water mass exchange and river discharge plumes, and track the effects of infrastructure to protect areas from sea level rise (Santini et al. 2010). Yearly Chl values range between 0.5 and 10.5 mg/m^3 (with summer peaks above 30 mg/m^3); the lagoon is characterized as hydrologically complex with heavy river discharges of nutrients, causing gradients of plankton, Chl, and suspended matter. The airborne hyperspectral imagery acquired for this project included CASI and the Multispectral Infrared Visible Imaging Spectrometer (MIVIS). CASI data were collected in May 2005 with a 6-m spatial resolution (41 bands in the 472-to 700-nm range), while MIVIS data were collected in July 2001 with an 8-m spatial resolution (12 bands in the 480-to 700-nm range). Field data were simultaneously collected including water surface radiometric data (spectroradiometer) for pre-processing of the hyperspectral imagery, as well as water samples (i.e. laboratory determination of Chl, CDOM, and tripton), and water optical property measurements (i.e. measurement of attenuation and absorption coefficients). After atmospheric and geometric corrections were made to the imagery, the equations/models for inversion processing were applied to determine the parameters (equation descriptions in Santini et al. (2010)); however, it consisted of identifying the absorption and backscattering spectral coefficients of each parameter and the final result illustrating the estimation of the constituents obtained from the corrected water leaving reflectance. The optical parameters used in the model were derived from the in situ data as well as from the scientific literature (Chl absorption feature centered at 673 nm). Figure 6 illustrates the spectral results of the in situ derived tripton value versus the model.

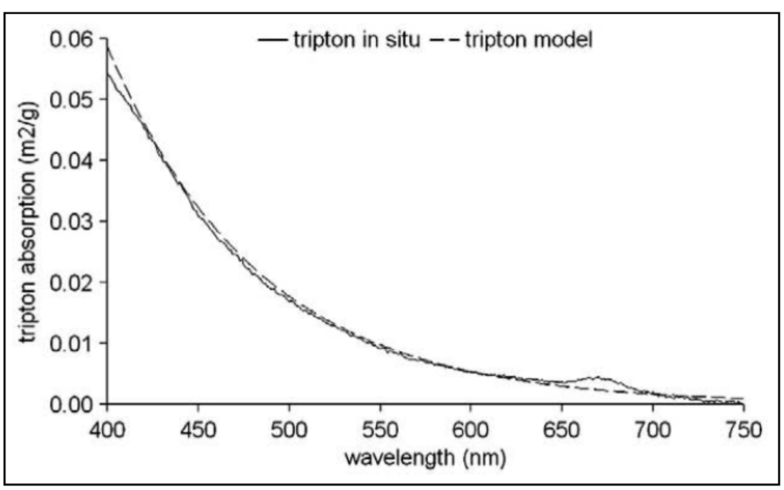

Figure 6. Tripton spectral coefficient (in situ vs. model) (Santini et al. 2010).

Hydrolight software was used for the processing in which the bio-optical model inputs were used to assess the parameters in more than 500 simulations (simulations account for the variance of in situ measurements). The quadratic regression using the CASI data only resulted in an R^2 value of 0.9974 (Santini et al. 2010). Lastly, the two-step optimization (nonlinear least squares method) was run using IDL programming language and constituent concentration values were estimated for each image pixel to produce the maps in Figure 7.

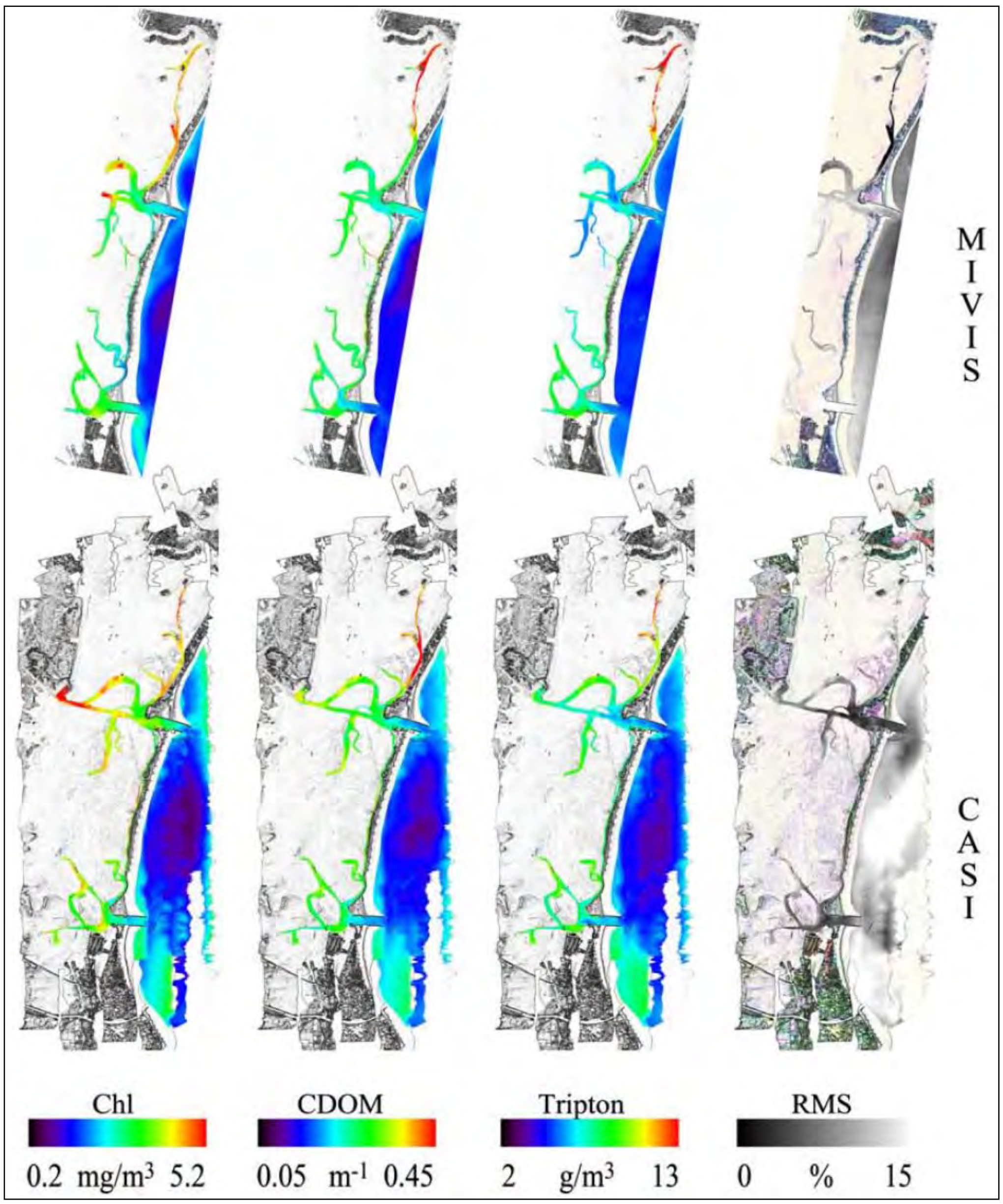

Figure 7. Water constituents (Chl, CDOM, and tripton) from MVIS and CASI (Santini et al. 2010).

Airborne hyperspectral advantages:

- Airborne hyperspectral sensors are highly flexible and can be tailored, including time/date of survey and sensor configuration (bandwidth, spectral range, number of bands, spatial resolution, etc.) to meet specific project goals, budget constraints, and water quality parameters and specific issues; this flexibility is also useful for planning surveying in which flights can be scheduled under optimal weather and other conditions.
- When compared to many commercially available satellite sensors, airborne hyperspectral sensors have the higher spatial and spectral resolutions necessary to identify water quality parameters (Chl, CDOM, Tripton, Secchi disk transparency, suspended solids, etc.).
- Airborne hyperspectral sensors provide sufficient detail to map and measure water quality in small waterbodies and contributing tributaries.
- Airborne hyperspectral sensors can be used in both empirical and analytical interpretation approaches.
- Airborne hyperspectral sensors are ideally suited for locally focused or comparatively small geographic areas requiring relatively detailed spatial resolution with the ability to discern small or complex features/parameters; however, they are also feasible in regional assessments when flown at higher altitudes to cover larger geographic areas.

Airborne hyperspectral disadvantages:

- Although capabilities for processing hyperspectral imagery have greatly improved, when compared to other image types, processing of hyperspectral images is more complex and requires specific skills.
- Airborne surveys can be challenging to plan, involving many factors such as solar conditions, tides, flight line orientation, air traffic restrictions, and weather.
- When compared to other commercially available satellite sensors, airborne hyperspectral sensors cover smaller geographic areas due to a lower altitude of acquisition.
- Airborne surveys are typically expensive; one study cited average costs of $350 per square mile (Chipman et al. 2009).

3 Spaceborne Sensors

Spaceborne sensors for water quality monitoring

Like airborne sensors, spaceborne sensors are passive and measure reflected solar radiation; however, these sensors tend to have comparatively coarser spatial and spectral resolutions, covering larger geographic areas. Many satellite remote sensing systems are commercially available ranging from expensive for higher resolution systems (i.e. $2-10K per scene) to low-cost or free for moderate (i.e. Landsat) and global systems (i.e. MODIS and MERIS). One major advantage is that many spaceborne sensors have consistently frequent coverage (i.e. revisit frequency) of the earth's surface because they rely on orbital patterns of the satellite. Although subject to cloud cover constraints (most providers consider 20% cloud cover or less acceptable), the increased temporal frequency of the sensors works well for studies requiring regular coverage for monitoring water quality trends. Most of these sensors are referred to as multispectral because they measure relatively few, broad spectral bands when compared to hyperspectral sensors; however, there is currently one commercially available hyper-spectral sensor (Earth Observing – 1 Hyperion Imager, 30-m spatial resolution). Some of the more common multispectral sensors suitable for water quality monitoring are listed in Table 1. Most of these sensors were developed for terrestrial-based applications; however, newer sensors like WorldView-2 and MERIS have included "coastal" bands, which are beneficial for aquatic studies and have been used in various studies to illustrate successful interpretation of water quality parameters (Gitelson et al. 2008; Kallio et al. 2005; Marchisio et al. 2010). Note that some of these sensors lack blue bands or middle infrared and thermal bands, which can be useful for estimating water clarity and improving classification accuracy (Chipman et al.2009). The high resolution sensors provide the advantage of high spatial resolution making it possible to identify pond and wetland features as small as 1 ha; yet, there is a tradeoff with limited spatial coverage in which case these sensors may be better suited for project-scale analysis rather than regional. Furthermore, all of these systems have the disadvan-tage of decreased spectral resolution as compared to any hyperspectral system. Also, all of these sensors have predetermined lifespans (i.e. Landsat 7 was launched in 1999 with a 5-year lifespan), although many have outlived these lifespans (i.e. Landsat 5 was launched in 1984 with a 3-year lifespan and is celebrating more than 25 years of operation). To continue such

efforts, NASA and the U.S. Geological Survey have partnered to form the Landsat Data Continuity Mission ensuring future Landsat satellite missions. Other upcoming sensors include GeoEye-2 with a 0.25-m spatial resolution and expected launch in 2013, as well as Digital Globe's Worldview-3 with very high spatial resolution measuring eight bands and expected to launch in 2014.

Table 1. List of common multispectral sensors including high resolution (pink), moderate resolution (blue), and regional/global resolution (green). Note that "Pan" refers to a panchromatic band, which is a higher resolution grayscale image covering the red, green, and blue portions of the spectrum and is used in combination with multispectral bands to sharpen the image. Units are as follows: nm = nanometers, m=meters, and km=kilometers.

Satellite/Sensor	Spectral Bands	Spatial Resolution	Swath Width	Repeat Orbit
Digital Globe WorldView-1	Pan (400 - 900nm)	0.5m	17.7km	1.7 days
Digital Globe WorldView-2	8 (400-1040nm)/1 Pan(450-800nm)	1.85m/0.46m	16.4km	1.1 days
Digital Globe Quickbird	4 (430-918)/1 Pan (450-900nm)	2.62m/0.65m	18km	2.5 days
GeoEye Geoeye-1	4 (450-920nm)/1 Pan (450-800nm)	1.65m/0.41m	15.2km	<3 days
GeoEye IKONOS	4 (445-853nm)/1 Pan (526-929nm)	3.2m/0.82m	11.3km	~3 days
Spot Image SPOT-5	3 (500-890nm)/1 Pan (480-710nm) /1 SWIR (1580-1750nm)	5m/10m/20m	60km	2-3 days
Landsat-7 ETM+	6 (450-1750m)/1 Pan (520-900nm) /1 (2090-2350nm)/1 (1040-1250nm)	15m/30m/60m	183km	16 days
Landsat-5 TM	5 (450-1750m)/1 (2080-2350nm) /1 (1040-1250nm)	30m/60m	185km	16 days
MODIS	2 (620-876nm)/5 (459-2155nm) /29 (405-877nm and thermal)	250m/500m/1000m	2330km	daily
MERIS	15 (390-1040nm)	300m	1150km	daily

Specific costs of the imagery are not provided in Table 1 because many of the archived data are available to the Corps at no costs, as dictated in policy guidance (Army Regulation 115-11, *Geospatial Information and Services*, which directs the Corps to submit imagery requirements to the Army Geospatial Center (AGC)). The AGC Imagery Office serves as the Army's Executive Agent for commercial imagery and has an agreement with the National Geospatial-Intelligence Agency (NGA), allowing for the acquisition of archived, unclassified imagery at no cost to the services and intelligence communities. The NGA awards contracts to high-resolution commercial data providers, such as GeoEye and Digital Globe, making much of this data free to the Corps. This agreement does not include

airborne hyperspectral or low-resolution data providers. Some of these sensors can be "tasked," meaning that requests can be made to the AGC to request acquisitions in designated locations in advance of a project; however, national security concerns override civil priorities.

Spaceborne case studies

Many studies have proven that Landsat imagery can be used to assess water quality using empirical based approaches (Kloiber et al. 2002a, 2002b; Mancino et al. 2009; Olmanson et al. 2008; Wang et al. 2004); however, some have illustrated that these approaches may be limited to the data from which they were derived and thus, may not be applicable to other lakes (Giardino et al. 2007, Kallio 2000, Lathrop 1992, Ritchie et al. 2003). Successful regional approaches were demonstrated by Kloiber et al. (2002a, 2002b) and Olmanson et al. (2008) in which Landsat imagery was used to assess thousands of lakes in Minnesota. This work culminated in a 20-year historical perspective of water clarity in over 10,000 lakes (larger than 8 ha) in Minnesota (1985-2005) and was conducted in cooperation with the University of Minnesota Remote Sensing and Geospatial Laboratory and the Minnesota Pollution Control Agency and is available online, http://water.umn.edu/ (Chipman et al. 2009, Olmanson et al. 2008). Similar statewide efforts have occurred in Wisconsin in cooperation with the University of Wisconsin and the Wisconsin Department of Natural Resources (http://www.lakesat.org/), as well as in Michigan in cooperation with the U.S. Geological Survey and the Michigan Department of Environmental Quality (http://pubs.usgs.gov/fs/2007/3022/). The statewide efforts provide a good example of regional water quality assessments conducted with inexpensive techniques and free imagery; archived Landsat imagery is free and can be acquired from the U.S. Geological Survey's EROS Data Center website.

In Minnesota lakes as in many areas, the prime issue is trophic state, which can be indicated by chlorophyll-a (Chl), total phosphorous (TP), and Secchi disk transparency (SD) (Olmanson et al. 2008). This study involved calibrating Landsat TM imagery with in situ field measurements of SD to estimate Landsat-derived SD using a regression equation. The mapped distributions and estimates were converted to a Trophic State Index based on the transparency TSI(SD) (Carlson 1977). It is noted that factors other than phytoplankton abundance measured by Chl can affect SD (e.g., humic color, non-phytoplankton turbidity, and suspended sediments). Therefore, this study reported results based on the SD calibrations as Landsat-derived estimates or TSI(SD), which is an index based on transparency

(Olmanson et al. 2008). Imagery for this study included Landsat 4, 5, and 7 over a 20-year period, including mostly cloud-free scenes between July and September. Note that Landsat 7 (since 2003) has the scan-line corrector turned off due to a malfunction; however, this is not an issue for regional water quality studies requiring only a representative number of pixels from a waterbody. The summer timeframe is often targeted for water quality studies because variability in lake clarity is at a minimum and water clarity is usually the worst (Olmanson et al. 2008). In general, paths of consecutive imagery were chosen because they were collected at the same time affording advantages with image processing and model accuracy. Over 100 scenes were analyzed. In situ data were obtained from water quality measurements collected through statewide programs and volunteer efforts, and data collected within ±3 days of satellite overpass were used in the regression (Olmanson et al. 2008). Image samples were taken from each lake, focusing on lake centers where reflectance from the bottom, shoreline, and other targets would not impact the signal. Image scenes were mosaicked and haze was removed to create an "open-water-only" image (an unsupervised classification technique was used to group land versus water pixels). Spectral information from the open water only pixels was used to develop relationships with SD. Log-transformed SD data were treated as the dependent variable and Landsat TM band 1 and a TM1:TM3 ratio were treated as the independent variable in a least-squares multiple regression:

$$\ln(SD) = a(TM1/TM3) + b(TM1) + c \tag{3}$$

where a, b, and c are coefficients fit to the calibration data by the regression analysis, $ln(SD)$ is the natural logarithm of SD for a lake, and $TM1$ and $TM3$ are the Landsat brightness values (digital numbers) for the chosen lake pixels in the blue and red bands, respectively (Olmanson et al. 2008). Although a pixel-based map could have been generated for each lake, a single Landsat-derived SD value was assigned to a lake polygon (i.e. as a representative value for each lake). Regression models were generated for each Landsat path and showed strong relationships between in situ measurements and imagery-derived values (R^2 values ranged from 0.71 to 0.96). Figure 8 shows the map results for the state of Minnesota. This study illustrates that it is possible to accurately estimate water clarity using moderate resolution, multitemporal imagery over a large geographic area with a wide variety of lake conditions without collecting any new in situ data. Furthermore, it was conducted using free imagery and simple, robust techniques that do not require advanced computing power.

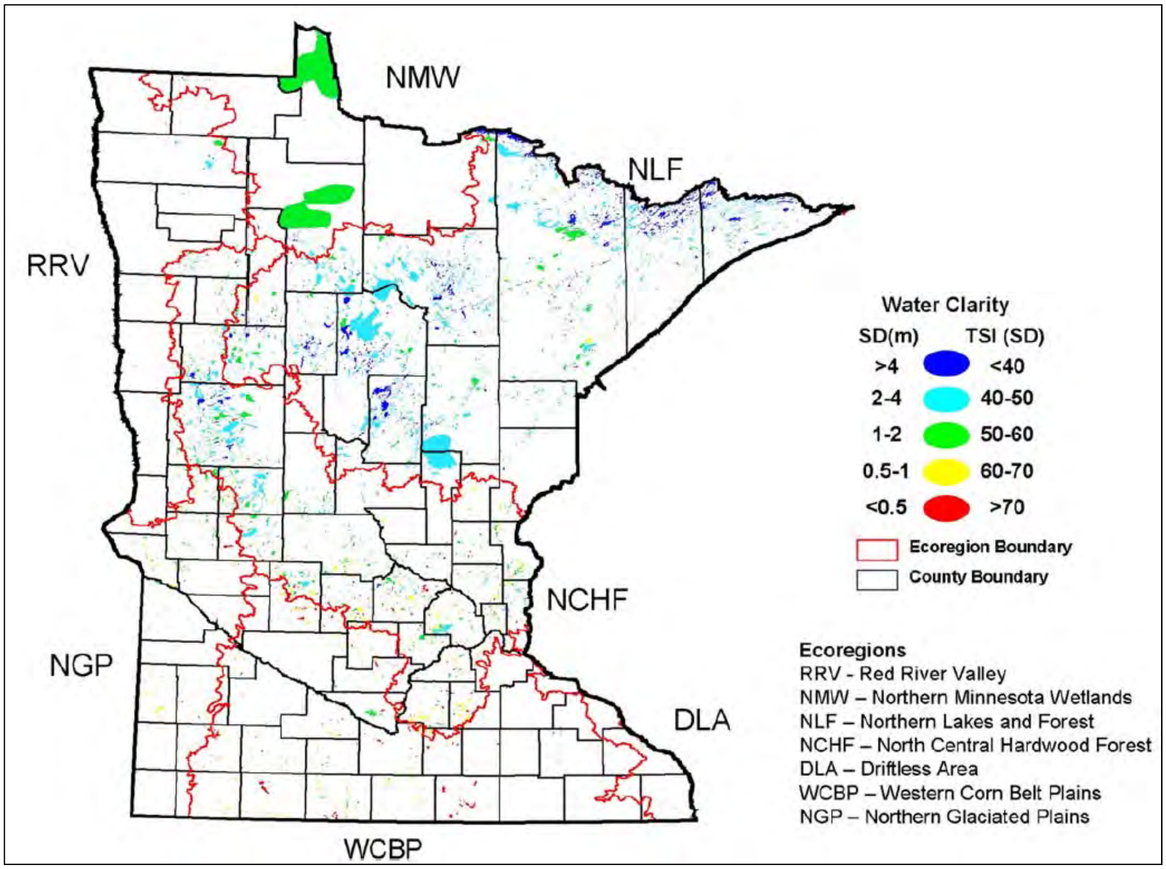

Figure 8. Water clarity estimates in Minnesota derived from Landsat imagery (Olmanson et al. 2008).

Other studies to assess water quality have been conducted with high-resolution remote sensing systems, such as IKONOS (Ekercin 2007, Ormeci et al. 2009, Sawaya et al. 2003). Similar empirical methods can be applied to high-resolution imagery as moderate resolution imagery, although these data have the added advantage of improved spatial resolution and thus, can resolve water quality in small lakes, ponds, rivers, etc. Even though these sensors have limited spectral ranges and resolutions (i.e. IKONOS has four broad multispectral bands measuring in the 445-to 853-nm range), their spectral resolution is sufficient for measuring concentrations of such parameters as SD, Chl, and TSS. One example study conducted in a region of Turkey successfully illustrated the use of IKONOS imagery to retrieve such parameters over a large water area in Istanbul (Ekercin 2007). IKONOS-2 imagery from June 2005 was radiometrically corrected and converted to radiance units in ERDAS Imagine software. Multiple regressions were established with the radiance data and collected water quality data using the following equation:

$$\text{WQPs} = A0 + \sum_{i=1}^{k} A_i^* (IKONOS_i) \quad (4)$$

where WQP = water quality parameter, $IKONOS$ = radiance of 4 bands, k = IKONOS band number, and A_0 and A_i = empirical regression coefficients derived from in situ observations. Individual bands used in the analyses were B1 (445-530nm), B2 (520-610nm), B3 (640-720nm), and B4 (770-880nm) with a 5 X 5 filter to obtain average radiance values in close proximity to in situ measurements. In situ measurements (SD, Chl, and TSS) were collected from nine stations located in the Golden Horn area in Istanbul during the image acquisition. Relationships were established for all four bands of IKONOS data: for SD, B1-3 resulted in an $R^2 = 0.9893$, for Chl all bands resulted in an $R^2 = 0.9924$, and for TSS all bands resulted in an $R^2 = 0.9724$. Table 2 shows in situ measurements as compared to those extracted from the IKONOS imagery for all nine stations. Figure 9 shows the map results for Chl and TSS estimations in the Golden Horn.

Other studies have utilized regional and global sensors (MODIS and MERIS) (Chipman et al. 2009, Gitelson et al. 2008, Koponen et al. 2002). These sensors have limited spectral resolution and coarse spatial resolution (Table 1) ranging from 250 to 1000 m, so they are only appropriate for large aquatic systems (200 to 1000 ha or larger); however, they have frequent coverage that is daily and are either low-cost or free. They are subject to the same cloud cover constraints as other spaceborne systems, yet the MERIS system operates in an "on demand" mode in which imagery is collected based upon request rather than continuously (Chipman et al. 2009). The most useful MODIS bands are 1 to 5 and 8 to 16, and the 1000-m spatial resolution for bands 8 to 16 makes only the largest lakes in the upper

Table 2. In situ SD, Chl, and TSS compared to IKONOS-derived estimations (Ekercin 2007).

Station name	Secchi Disc Depth (SDD) (m)		Chlorophyll-a (Chl-a) (μg/l)		Total Suspended Sediment (TSS) (mg/l)	
	In-situ	Estimated	In-situ	Estimated	In-situ	Estimated
GK	6,500	6,517	2,316	2,271	23,800	23,832
KP	3,000	2,903	8,912	8,634	28,000	28,701
CA	2,500	2,814	10,598	11,376	25,200	24,247
VS	2,500	2,418	15,288	13,686	23,400	23,508
HK	2,000	1,770	23,021	23,055	29,000	28,487
ES	2,000	1,843	22,681	23,563	25,200	26,870
AA	1,000	1,045	53,769	58,455	33,000	31,670
AS	0,800	0,998	51,376	50,074	40,300	40,535
UK[a]	3,000	3,210	3,750	4,204	22,400	24,301

[a] External check point.

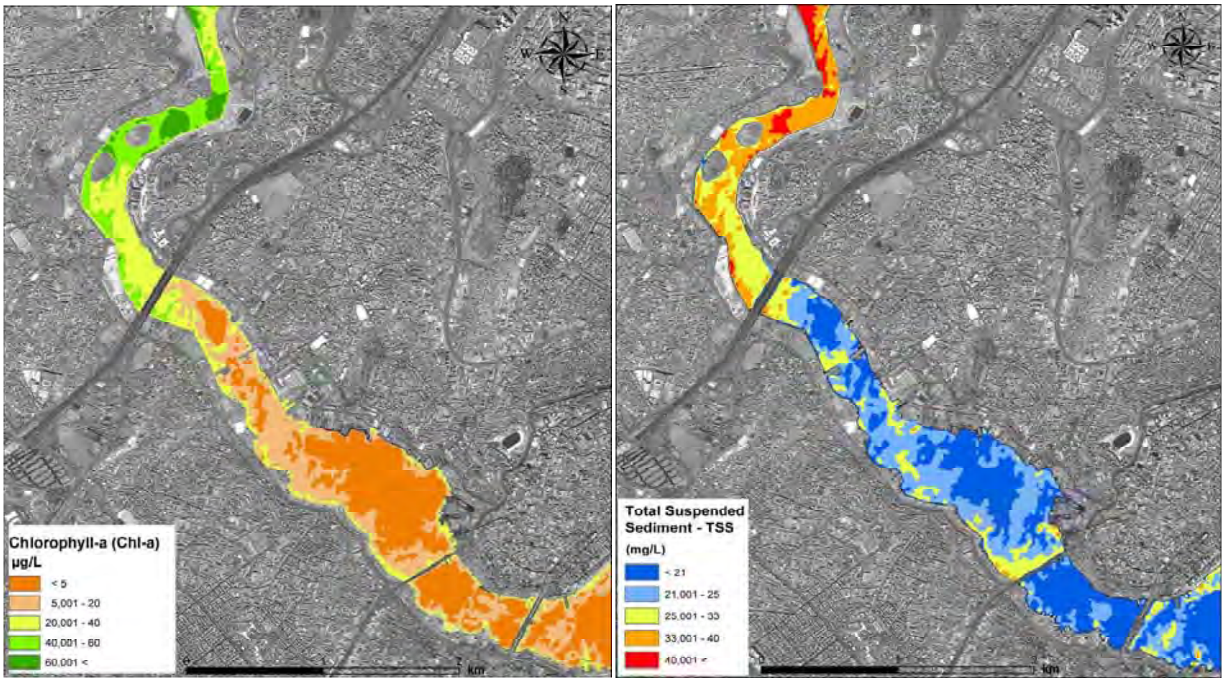

Figure 9. Water quality constituents measured with IKONOS imagery in Istanbul (Ekercin 2007).

Midwest suitable for this sensor (Chipman et al. 2009). Like Landsat, MODIS data are freely available online and served by a number of sources (such as the NASA Earth Observing System Data Gateway website); furthermore, an atmospherically corrected image product is also available. For a study in Minnesota and western Ontario, MODIS imagery was acquired in 2005 (both the radiance and atmospherically corrected reflectance products) to coincide with a large field sampling effort, collecting over 100 samples to measure Chl and water clarity (Chipman et al. 2009). The lakes in the region cover a wide variety of Chl, CDOM, SS, and water clarity conditions. Image processing included unsupervised classifications to eliminate cloud and haze as well as separate land versus water pixels. A buffer was applied to water pixels in order to eliminate those pixels in shallow-water areas or close to the shoreline. At each in situ sample site, the spectral signatures were extracted from the MODIS products. Then, regression models were run to correlate MODIS bands and band ratios with the natural logarithm of Chl concentration. Lastly, the models were applied to individual pixels to predict Chl concentration. The best results were achieved with the Terra MODIS radiance product and the blue/red ratio (MODIS band 3 divided by band 1), $R^2 = 0.79$. This was improved to an $R^2 = 0.84$ when two additional band ratios were included (band 3/band 2 and band 3/band4). A subset of the region is shown in Figure 10, illustrating Chl concentrations estimated from the Terra MODIS imagery.

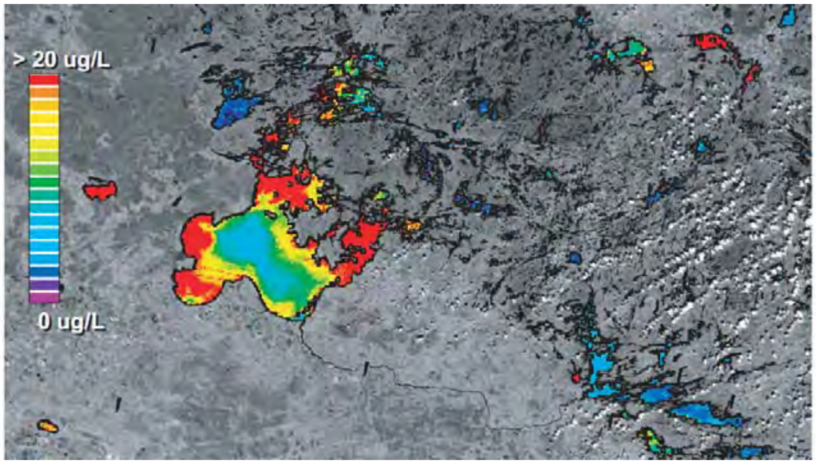

Figure 10. Estimated Chl concentration for an area along the Minnesota/Ontario border from MODIS imagery (Chipman et al. 2009).

Spaceborne advantages:

- Spaceborne sensors have a high revisit frequency ranging from daily to monthly, making multitemporal water quality studies to examine trends and patterns possible (cloud constraints can render scenes useless, so scenes must be examined to determine acceptable use).
- Many commercially available sensors have very high spatial resolutions, ranging from 0.5 m to 10 m (Worldview-2, Woldview-1, Quickbird, GeoEye-1, IKONOS, SPOT-5, etc.), which make it possible to examine water quality in small waterbodies and tributaries; thus, these sensors are typically better suited to local or project level applications.
- Moderate, regional, and global sensors cover large geographic areas in one scene and are better suited to regional water quality studies.
- When compared to hyperspectral sensors, image processing tends to be less complex with spaceborne sensors, requiring a more basic remote sensing knowledge level.
- Moderate, regional, and global spaceborne sensors are typically low-cost or free, making remote sensing of water quality a more viable and cost-effective option.

Spaceborne disadvantages:

- Multispectral spaceborne sensors have coarse spectral resolutions and some have limited coverage of the electromagnetic spectrum, eliminating the important blue band; this may mean that some sensors are not suitable for a particular water quality parameter measurement.

- High spatial resolution imagery can be very expensive (~ $2-10K per scene); however, the Corps has agreements in place making much of this imagery freely available.
- In general, empirical-and semi-empirical-based approaches can be used to analyze multispectral imagery (excluding spaceborne hyperspectral sensors); this can be problematic in optically shallow waters, in which reflectance from the bottom contributes to the water-leaving reflectance, potentially resulting in over-estimation of water quality parameter concentration.
- Although some sensors can be “tasked” through requests to the Army Geospatial Center (national security concerns have priority), project managers and researchers are limited to the coverage schedule of the satellite, including weather/cloud constraints; this can be challenging when trying to conduct water quality monitoring at a certain time of the year or dealing with project schedules.

4 Considerations in Collecting Data

In situ data considerations

The studies described in this report as well as most remote sensing-based studies detailed in scientific literature involve the use of in situ water sample data to either calibrate models or verify results. This is especially true for studies employing empirical-and semi-empirical-based approaches in which in situ data are required (whereas analytical approaches can be used without in situ data, although in situ data are often used to validate results). This may be seen as a limitation because collection of samples is time-consuming and they are costly to process; however, these studies have also shown that it can take few in situ samples to characterize a large waterbody (Ekercin 2007). There is no set standard for the number of samples required to adequately interpret an image scene or characterize a waterbody, yet some have suggested appropriate schemes for lakes (Karabork 2010). Some studies have utilized fewer than 10 samples to characterize a single waterbody, while others have used hundreds to characterize thousands of lakes. While there is no rule for the number of samples required, studies described in this report illustrate the importance of collecting samples that adequately cover the range of water quality conditions to capture the variety. Studies such as Nelson et al. (2003) have illustrated that remotely sensed imagery (in this case, Landsat) to measure water quality can be sensitive to the distribution of water clarity used in the calibration process. Therefore, emphasis should be placed on the number of samples to capture the variability of a waterbody or waterbodies; in highly variable systems this may mean that more samples are required and will depend on the project area or region under study. The other important aspect of in situ sampling is the timing of samples. In order to use in situ measurements in the image calibration process, they must be collected around the time of image acquisition. There is no set standard for the number of days within a satellite overpass a sample must be taken. One study cited in this report (Olmanson et al. 2008) tested samples taken within 3 days versus 10 days and found that samples taken 10 days out yielded unacceptable R^2 results. The timing of samples will vary with any project and is determined by the short-term variability of the system in question, as well as the range of variability within multiple waterbodies for regional assessments. Although sample collection is time-consuming and expensive, many studies take advantage of the increasing number of water sampling activities, volunteer

efforts, and state-run programs to monitor water quality including the regular collection of samples. Since the 1980s many programs to monitor water quality have been established and make their data freely available. The use of these data in place of newly acquired samples can keep costs low, although there are limitations, such as the types of parameters measured and when they are collected, which may not fit with the goals and schedule of a remote sensing study. In situ samples for use in remote sensing studies should include measurement of chlorophyll-a, total suspended solids, turbidity, and Secchi disk depth/transparency (Kallio 2000). Additional sampling could include algae biomass, species composition, mineral suspended solids, dissolved organic matter, and the absorption coefficients from filtered samples as a result of aquatic humus (Kallio 2000). Most remote sensing approaches are empirically based; therefore, sampling at the surface (0 to 0.5 m) is typically sufficient. However, if analytical approaches are used, samples from varying depths in the water column may be useful.

Special water quality events

Water quality events such as harmful algal blooms (HABs) have attracted recent attention within the Corps due to their widespread impacts (Linkov et al. 2009). In the event of an HAB, algae multiply and, in the case of freshwater, commonly consist of cyanobacteral algae (blue-green). These events can cause reductions in dissolved oxygen and release toxins, which can cause fish kills and are becoming an increasing concern in Corps Civil Works projects (Linkov et al. 2009). Linkov's 2009 technical note found that reservoirs can be conducive to HABs for the following reasons:
1) residence time affects turnover rates of algae and nutrients in which algal accumulation is the result of growth rate outpacing flushing rate,
2) stratification can increase algal growth when it takes advantage of vertical temperature gradients to promote growth, 3) light can promote growth when the intensity of light striking the surface is greatest, and 4) certain temperature ranges can be favorable for individual species. Chemical factors can also influence the growth rate of algae, such as nitrogen and phosphorous loading, especially in freshwater systems (Linkov et al. 2009). The Corps manages factors influencing HAB development by altering water flow, increasing shear forces, enhancing mixing, and controlling water intake and mixing to influence stratification in the water column. The report also includes input from Corps districts, recommending management of the upper watershed to reduce nutrient loading as well as other management practices (Linkov et al. 2009). Remote sensing can be useful in these integrated management strategies to assist with short- and long-term

monitoring. Early warning systems and identification and quantification of land use and cover within the watershed are two ways in which remote sensing can be coupled with existing management strategies; these methods are further described in the following section.

Remote sensing studies have focused on using imagery to identify the optical signature of cyanobacteria, which is strongly influenced by the photosynthetic biomarker pigment, C-phycocyanin (C-PC), having an absorption maximum near 615 nm (Hunter et al. 2008). In this case, C-PC can be used as an index of cyanobacterial abundance, estimating C-PC concentration in lakes where phytoplankton assemblages are dominated by phycocyanin-rich cyanobacteria using semi-analytical and semi-empirical approaches (Hunter et al. 2008; Simis et al. 2005). These studies illustrate the wide range of capabilities of remote sensing to monitor cyanobacteria, ranging from the use of airborne hyperspectral (CASI) imagery in a series of small lakes in England (Hunter et al. 2008) to the use of global MERIS imagery in large turbid lakes in the Netherlands (Simis et al. 2005). Figure 11 depicts a time-series estimating C-PC in England using CASI imagery.

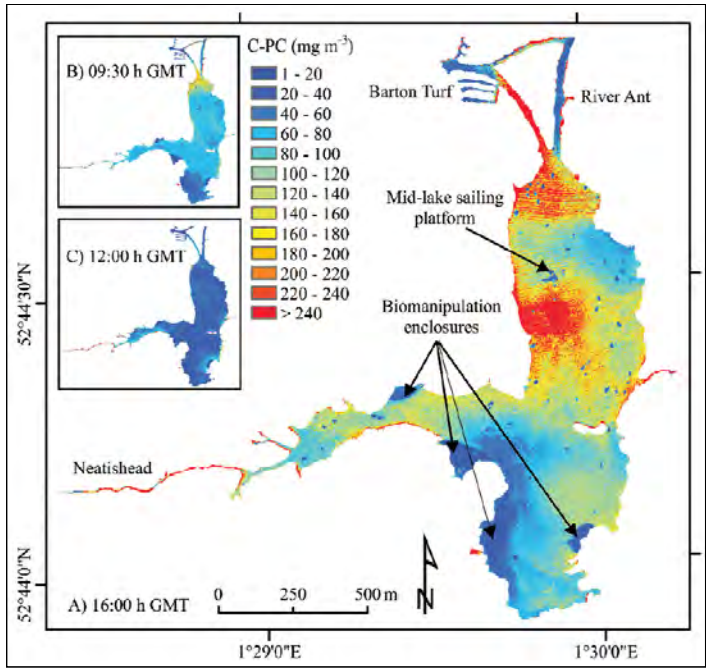

Figure 11. CASI-derived time series illustrating C-PC distribution in England, 2005 (Hunter et al. 2008).

Other uses for remote sensing in water quality monitoring

Remote sensing of water quality includes more than just examining the waterbody in question. It is well-known that water quality is directly tied to the surrounding land use and cover (LULC) within a watershed (Basnyat et al. 1999). Remote sensing can be especially useful to assess watershed conditions on a regional scale, especially for examining the effects of non-point source pollution (Griffith 2002). Updated LULC data derived from remote sensing are essential for developing landscape-scale

analyses that can be directly tied to physical changes, patterns of discharge, temperature and light regimes, chemistry, and input of nutrients and sediments (Griffith 2002). Many studies have illustrated the integration of remote sensing to study the impacts on water quality (Herlihy et al. 1998, Griffith et al. 2000). For example, studies have mapped impervious surfaces in a watershed and related water quality issues (Sawaya et al. 2003). When coupled with Geographic Information Systems (GIS), land cover can be accurately quantified for a better understanding of landscape patterns and spatial heterogeneity (Turner and Carpenter 1998). Landscape metrics are computed to quantify landscape patterns such as habitat fragmentation or contiguity; in turn, these metrics are indicative of landscape dynamics contributing to water quality. Furthermore, LULC changes can be analyzed over time to better understand the relationship of landscape metrics to water quality. Simple band ratios such as the Normalized Difference Vegetation Index (NDVI), NDVI = (NIR –Red)/(NIR + Red), have shown sensitivity to biophysical characteristics of vegetation, such as net primary production, and can be useful in assessing watershed health (Jones et al. 1996).

Other studies focus on identifying surrounding wetland and submerged aquatic vegetation (SAV) habitat, which are known to be indicators of ecological health and subsequently respond to subtle changes in hydrologic regime due to corresponding changes in LULC (i.e. increased stormwater runoff as a result of increased impervious surface). Traditional field surveys can be difficult, as these habitats may be inaccessible and time-consuming. Remote sensing offers an alternative to identify habitats and assess condition and diversity. One such study used high-resolution IKONOS imagery in Swan Lake in Minnesota, which is a deep freshwater marsh with a variety of emergent and submergent aquatic vegetation providing wildlife and fish habitat (Sawaya et al. 2003). Field reference data were collected with a Global Positioning System (GPS) shortly after the 2001 imagery were acquired to identify the aquatic vegetation types directly on the IKONOS imagery. Spectral signatures of the aquatic vegetation were also analyzed to identify potentially different types prior to field investigation, especially targeting emergent vegetation types. A hydroacoustic survey was used to collect depth and plant depth for SAV (118 sites were surveyed). Similar methods developed at the U.S. Army Engineer Research and Development Center (ERDC) illustrate the use of the patented Submersed Aquatic Vegetation Early Warning System (SAVEWS) to measure canopy geometry using a digital signal processing

algorithm; the system has been used to identify SAV, early infestations of nuisance aquatic plants, and bathymetry beneath the canopy (Sabol et al. 2002). The imagery was classified to mask out terrestrial features, leaving water and wetlands only (using spectral differences), followed by separation of submergent and emergent wetlands using an unsupervised classification approach (10 classes). A second unsupervised classification was conducted on the emergent vegetation only (100 classes); however, due to some confusion between vegetation types, further stratification was conducted (Sawaya et al. 2003). This third unsupervised classification focused on separating thick submergent from emergent confused classes. The field data were used to validate the presence of five emergent, two submergent, and one thick submergent vegetation types to classify the images with an overall accuracy of 79.5%. Figure 12 illustrates the results. New techniques using hyperspectral imagery fused with lidar bathymetry are being explored at the ERDC to detect and discriminate SAV and macroalgae species (Reif et al., in preparation).

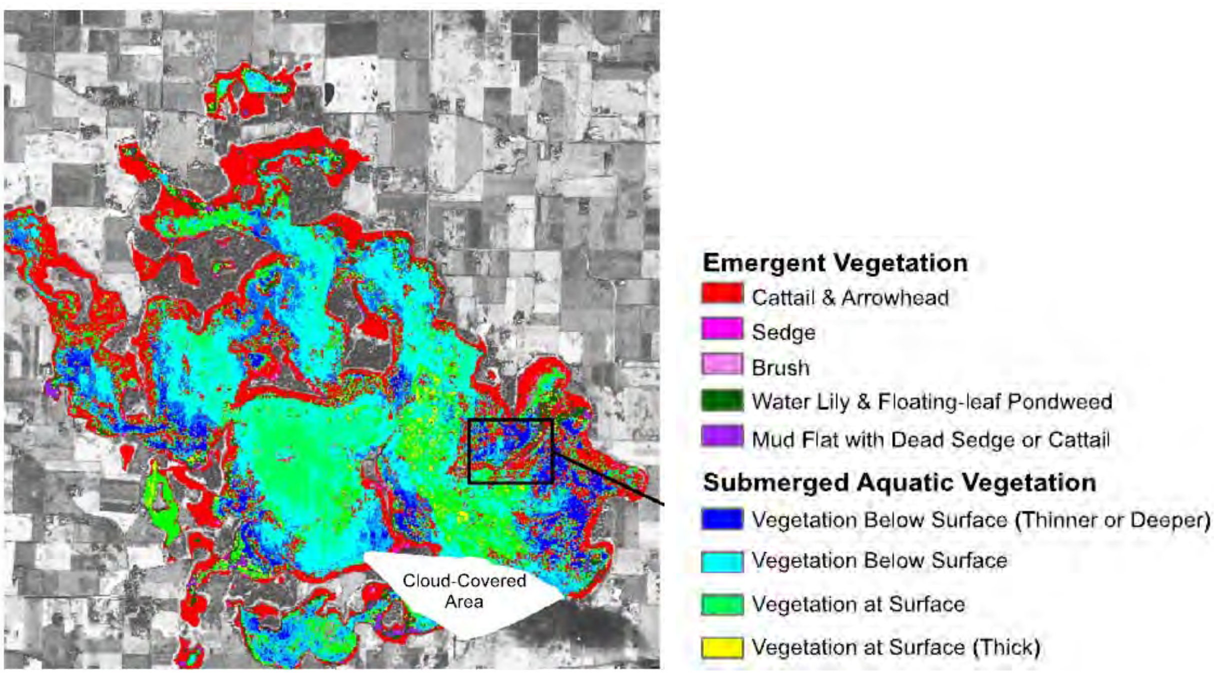

Figure 12. Submergent and emergent aquatic vegetation mapped using IKONOS imagery in Swan Lake, MN, 2001 (Sawaya et al. 2003).

Nuisance aquatic vegetation (weeds) is also commonly monitored in lakes and reservoirs (Ritchie et al. 2003). Such vegetation can either be rooted or free-floating, causing such problems as clogging reservoirs and reducing recreational usage. A study conducted by the U.S. Department of Agriculture, Kika de al Garza Agricultural Research Laboratory, used GIS,

GPS, and remote sensing to detect noxious aquatic weeds (i.e. hyacinth, hydrilla, and giant salvinia) in Texas. These species have replaced native plant populations, adversely affecting fish habitat and populations, as well as impacting drainage and reducing recreation. Airborne and field-based methods were employed in this study (Everitt et al. 1999); however, multispectral and hyperspectral imagery are increasingly used to detect aquatic vegetation taking advantage of high spatial and spectral resolutions (Everitt et al. 2008; Phinn et al. 2008; Pinnel et al. 2004; Reif et al., in preparation). The studies in Texas revealed spectral differences in the near-infrared region of the spectrum, which are used to identify the various species. An updated study in 2008 utilized Quickbird imagery to successfully identify giant salvinia infestation in the Toledo Bend Reservoir in east Texas (Figure 13) (Everitt et al. 2008).

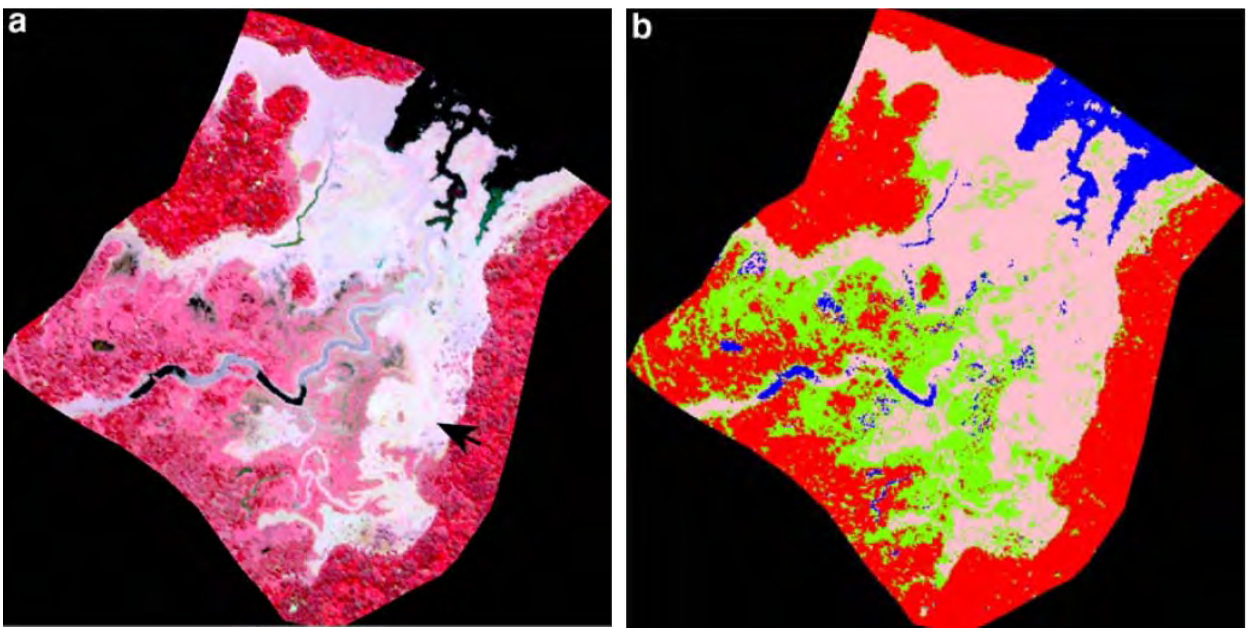

Figure 13. Quickbird false-color image (a) and unsupervised classification map (b), showing giant salvinia (pink), mixed woody vegetation (red), mixed aquatic vegetation (green), and water (blue) in Toledo Bend Reservoir, TX (Everitt et al. 2008).

Topographic and bathymetric elevation characteristics are also important for understanding water quality. In the case of watershed assessments, Digital Elevation Models (DEMs) are used to calculate slope and identify erosion potential. When combined with LULC, DEMs can also be used to highlight problems such as clear cuts on steep slopes, agricultural practices on steep slopes, and other practices around stream headwaters that might contribute to runoff and nutrient loading within a tributary, and eventually a waterbody. These data can also be used in hydrologic

models to delineate catchments within watersheds and model runoff when combined with LULC. The ERDC has developed a suite of hydrologic modeling tools useful for examining water quality. One example is the Trophic Assessment Screening Tool for Reservoirs (TASTR), which provides a rapid, initial estimation of water quality conditions that can be expected at a project site as a result of LULC, climate, or reservoir operational (i.e. water level) changes. This GIS-based management tool provides a way of evaluating management approaches under various alternatives. Another example is the Adaptive Hydraulics-Comprehensive Aquatic Systems Model (ADH-CASM), which is an integrated model featuring hydrological and ecological frameworks. It has a variety of potential uses, such as examining potential ecological impacts due to restoration or diversion projects, as well as calculating flows, velocities, depths, and transported and non-transported constituents, showing bioenergetic parameters and trophic relationships.

Bathymetric data are important for understanding water quality issues, especially in cases where parameters may be depth-dependent. In analytical and semi-analytical approaches, bathymetric data or depth can be used as a fixed constraint in the inversion of the radiative transfer equation for improved optimization (Kim et al. 2010). A study conducted in Hawaii by the JALBTCX used airborne CHARTS data (see *Airborne Sensors for Water Quality Monitoring*) to collect topographic lidar for characterizing topography as well as bathymetric lidar and hyperspectral imagery for characterizing shallow coastal areas including depth, bottom reflectance, $a+b_b$ measuring absorption and backscattering in the water column, and water column volume reflectance (Wozencraft et al. 2008). In addition, Liu et al. (2003) explain that bathymetry is a commonly used ancillary data type that is useful in water quality modeling. When combined in a GIS, remote sensing imagery, water sampling data, and bathymetry can be integrated for better quantification and visualization of water quality parameters (Liu et al. 2003). Furthermore, including bathymetric data is important for understanding the movement and transport of water constituents and for estimating constituents in complex Case 2 waters (Liu et al. 2003).

Temperature is another parameter that can be detected using remote sensing and can play a role in water quality monitoring. In the case of thermal pollution, anthropogenic activities, such as discharge from a power plant, can change the temperature of a waterbody and impact

biological activities. Remote sensing is used to map that discharge, providing information about the spatial and temporal variation of thermal releases, which in turn can be used to provide estimates useful for interpreting results of mathematical models of thermal plumes (Ritchie et al. 2003). The MODIS sensor has thermal infrared bands for measuring surface water temperature (Chipman et al. 2009). Landsat-5 TM imagery has also been used to derive surface temperature in lakes in Italy using a scene-independent procedure, whereby the Planck law (describing radiation emitted from a black body) is inverted using the atmospherically corrected radiances in TM band 6 (Giardino et al. 2001). The Landsat-derived temperature had a root mean square error (RMSE) of 0.328°C as compared to the in situ measurements. Figure 14 shows the mapping results of both the MODIS-and Landsat-5 TM-based studies.

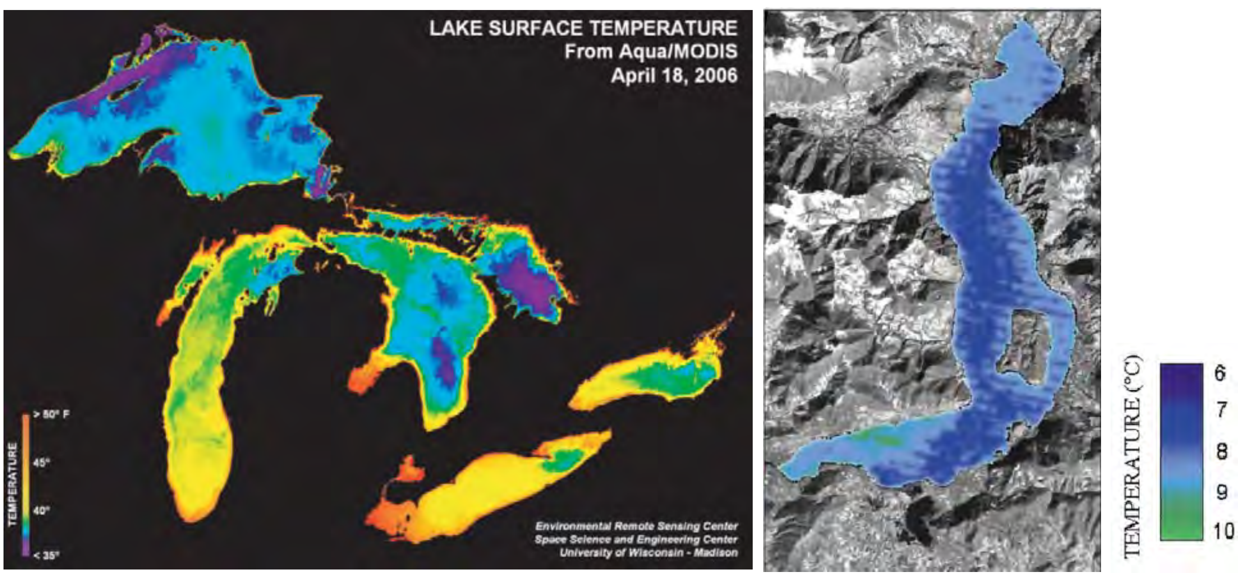

Figure 14. MODIS-derived (left) and Landsat-5 TM-derived (right) surface temperatures (Chipman et al. 2009; Giardino et al. 2001, respectively).

5 Summary and Conclusions

The role of remote sensing in water quality studies has increased over the last 30 years, paralleling its technological advances, including both instrument/sensor and algorithm/image processing improvements, and illustrating its evolutionary development in water quality studies. Many agencies, including the Corps of Engineers, have responsibilities to ensure that water quality standards are met. For example, the USEPA not only develops regulations to ensure those standards, but also administers the National Aquatic Resource Surveys, providing conditional reports of the nation's coasts, lakes, rivers, streams, wetlands, and wadeable streams. Furthermore, the USEPA (Ecological Exposure Research Division) contributes to technological advances, such as the development of water quality indicators using remote sensing (Frohn and Autrey, draft internal report; Shafique et al. 2003). In this initiative, the agency develops and tests models used for monitoring, assessing, and quantifying the spatial and temporal distribution of parameters with remotely sensed imagery, and develops a library of indicators estimable with remotely sensed data. The U.S. Geological Survey also develops remote sensing techniques for water quality measurement, such as predicting water clarity in Michigan's inland lakes (greater than 25 acres). This study (in cooperation with the Michigan Department of Environmental Quality), uses techniques modeled after Olmanson et al. (2008) to assess water clarity through the Lake Water Quality Assessment Monitoring Program (Fuller and Minnerick 2007). The Michigan maps and data are available online through an Internet Mapping Service (IMS) interactive website, showing secchi-disk, chlorophyll-a, and trophic state index values for Michigan lakes between 2001 and 2006. The growing number of agency initiatives and cooperatives are important for continued development of remote sensing technology in water quality monitoring as the techniques continue to evolve. Although research and development continue to prove that this technology is still emerging, evidence for the usefulness of remote sensing in water quality management and monitoring is abundant.

Traditional sampling schemes are time-consuming and expensive. Other disadvantages can include inaccessibility and the limitation of providing discrete data at only a single point in space and time, making it hard to characterize a larger waterbody. Although remote sensing can never fully

replace field sampling methods, many studies have proven the successful utility of remote sensing in water quality monitoring using a variety of sensor types, interpretation techniques, and geographic areas for potential use in both project-level (i.e. Corps Civil Works projects) and regional assessment efforts (i.e., USEPA National Aquatic Resource Surveys). The primary strengths of remote sensing over traditional techniques are two-fold:

1. Spatial variability: Remote sensing can be used to illustrate and measure the spatial variability of water quality over an entire waterbody using limited, but appropriate, in situ sampling data (i.e. the samples do not necessarily have to be numerous, but must represent the full range of water quality conditions present in the imagery being assessed).[1]
2. Temporal variability: Remote sensing can be used to illustrate and measure temporal variability using limited, but appropriate, in situ sampling for multiple image scenes, providing trend analyses (i.e. the ability to model water quality for as many time sequences from which data and imagery are available).

In the case of these two primary strengths, remote sensing offers the capability to be more cost-effective and time-efficient because thousands of samples do not have to be collected and processed to compare with modeled remote sensing results (derived using fewer samples), and multiple field survey efforts throughout the year do not have to be conducted to compare with the more frequently modeled remote sensing results that can be derived from a wide array of available satellite and airborne sensors (with a frequent revisiting cycle, historical archive, and flexible collection, respectively). Considering these two advantages alone, remote sensing offers capabilities that cannot be duplicated with traditional sampling methods.

This report examines a variety of remote sensing-related studies in which a suite of capabilities were presented; however, they may not represent the full range of capabilities in a growing body of scientific literature and programmatic efforts to use remote sensing to assess complex Case 2 waters. Many considerations must be weighed to determine the appropriate use of remote sensing in any water quality management initiative. Some of these considerations include project budget and timeline, staff skill level

[1] Personal Communication. 2010. Brad Autrey, USEPA Ecological Exposure Research Division.

and ability to collaborate with other technical groups (i.e. for remote sensing software/hardware), water quality management goals, and the ability to integrate with other water quality sampling activities (i.e. for sharing and acquiring existing in situ data). These considerations can help determine the appropriate level of remote sensing to incorporate in a management plan. Alternative approaches for the use of remote sensing may include monitoring land use and land cover practices in a watershed, mapping indicator and nuisance vegetation species, targeting or prioritizing field sampling locations using imagery as a first pass to monitoring quality, integrating topographic and bathymetric data, and using sophisticated modeling techniques for early warning and alternative scenario-based planning. This report should serve as a guide for determining how remote sensing, in cooperation with the Civil Works mission of the Corps, can complement and enhance traditional water quality monitoring.

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Appendix A: AISA Spectral Band Configuration

AISA spectral band configuration for a 97-bandset recommended for using in aquatic studies (Chipman et al.2009)

Band #	Band center (nm)	Band width (nm)	Band #	Band center (nm)	Band width (nm)	Band #	Band center (nm)	Band width (nm)
1	950.39	9.64	34	693.42	2.35	67	580.60	2.35
2	940.77	9.64	35	691.07	2.35	68	578.26	2.34
3	931.14	9.64	36	688.72	2.35	69	575.93	2.32
4	921.52	9.64	37	686.37	2.35	70	573.61	2.32
5	911.90	9.61	38	684.02	2.35	71	571.29	2.32
6	899.92	9.61	39	679.32	2.35	72	568.97	2.32
7	890.34	9.60	40	674.62	2.35	73	566.65	2.32
8	880.76	9.60	41	669.92	2.35	74	564.33	2.32
9	871.18	9.60	42	665.22	2.35	75	562.01	2.32
10	859.20	9.60	43	660.52	2.35	76	559.69	2.32
11	849.62	9.60	44	655.82	2.35	77	557.37	2.32
12	840.03	9.60	45	651.12	2.35	78	555.05	2.32
13	830.45	9.60	46	646.42	2.35	79	552.73	2.32
14	818.45	9.60	47	641.72	2.35	80	550.41	2.32
15	806.44	9.60	48	637.01	2.35	81	548.09	2.32
16	794.43	9.60	49	632.31	2.35	82	545.79	2.28
17	780.01	9.60	50	629.96	2.35	83	543.52	2.26
18	744.10	9.44	51	627.61	2.35	84	541.26	2.26
19	733.49	2.36	52	625.26	2.35	85	539.00	2.26
20	728.77	2.36	53	622.91	2.35	86	536.74	2.26
21	724.06	2.36	54	620.56	2.35	87	534.48	2.26
22	721.70	2.36	55	618.21	2.35	88	532.23	2.26
23	719.34	2.36	56	613.51	2.35	89	529.97	2.26
24	716.99	2.36	57	608.81	2.35	90	520.93	2.26
25	714.63	2.36	58	604.11	2.35	91	509.63	2.26
26	712.27	2.36	59	599.41	2.35	92	500.59	2.26
27	709.92	2.36	60	597.06	2.35	93	491.55	2.26
28	707.56	2.36	61	594.71	2.35	94	480.26	2.26
29	705.20	2.36	62	592.36	2.35	95	462.18	2.26
30	702.84	2.36	63	590.01	2.35	96	448.62	2.26
31	700.49	2.36	64	587.66	2.35	97	435.09	2.20
32	698.13	2.36	65	585.30	2.35			
33	695.78	2.35	66	582.95	2.35			

REPORT DOCUMENTATION PAGE

Form Approved
OMB No. 0704-0188

1. REPORT DATE *(DD-MM-YYYY)*	2. REPORT TYPE	3. DATES COVERED *(From - To)*
October 2011	Final report	

4. TITLE AND SUBTITLE
Remote Sensing for Inland Water Quality Monitoring: A U.S. Army Corps of Engineers Perspective

5a. CONTRACT NUMBER

5b. GRANT NUMBER

5c. PROGRAM ELEMENT NUMBER

6. AUTHOR(S)
Molly Reif

5d. PROJECT NUMBER

5e. TASK NUMBER

5f. WORK UNIT NUMBER

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)
U.S. Army Engineer Research and Development Center
Environmental Laboratory
3909 Halls Ferry Road
Vicksburg, MS 39180-6199

8. PERFORMING ORGANIZATION REPORT NUMBER
ERDC/EL TR-11-13

9. SPONSORING / MONITORING AGENCY NAME(S) AND ADDRESS(ES)
U.S. Army Corps of Engineers
Washington, DC 20314-1000

10. SPONSOR/MONITOR'S ACRONYM(S)

11. SPONSOR/MONITOR'S REPORT NUMBER(S)

12. DISTRIBUTION / AVAILABILITY STATEMENT
Approved for public release; distribution is unlimited.

13. SUPPLEMENTARY NOTES

14. ABSTRACT
Many agencies, including the U.S. Army Corps of Engineers, are responsible for ensuring that national water quality standards are met. The Corps manages and monitors water quality of all waters within Corps jurisdictions outlined in Water Quality Management Plans, including traditional field sampling (water, sediment, and biological) and measurement of physical parameters. However, these traditional approaches can be labor-intensive and expensive, often providing discrete data at a single point in space and time and making it difficult to characterize a larger waterbody.

During the last three decades, remote sensing has experienced an increasing role in water quality studies, largely due to technological advances, including instrument/sensor and algorithm/image processing improvements. The primary strength of remote sensing over traditional techniques includes the ability to provide a synoptic view of water quality for more effective monitoring of spatial and temporal variation. In addition, remote sensing offers capabilities for viewing water quality in multiple waterbodies over a large region at one time, a more comprehensive historical record or trend analysis, a planning tool for prioritizing field surveying and sampling, and accurate estimations of optically active constituents used to characterize water quality. Furthermore, when utilized in water quality management planning, remote sensing can help reduce costs through minimizing and targeting the collection and processing of thousands of water samples. Although the technology is still emerging, there is abundant evidence of the usefulness of remote sensing in water quality management and monitoring.

This report examines a variety of remote sensing-related studies in which a suite of capabilities are presented. It is intended to serve as a guide for determining how remote sensing can complement and enhance traditional water quality monitoring and the appropriate level of remote sensing to incorporate in a management plan.

15. SUBJECT TERMS
Remote sensing
Water quality management plan
Water quality monitoring
Watershed management

16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON
a. REPORT	b. ABSTRACT	c. THIS PAGE			19b. TELEPHONE NUMBER *(include area code)*
UNCLASSIFIED	UNCLASSIFIED	UNCLASSIFIED		51	