

# Lake Monitoring in Wisconsin using Satellite Remote Sensing



D. Gurlin and S. Greb  
Wisconsin Department of Natural Resources  
2015 Wisconsin Lakes Partnership Convention  
April 23-25, 2105  
Holiday Inn Convention Center, Stevens Point

LDCM artist's rendering: NASA/Goddard  
Space Flight Center Conceptual Image Lab

# Remote sensing applications for environmental monitoring

## Satellite-based water quality monitoring for improved spatial and temporal retrieval of chlorophyll-a in coastal waters

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## Improved algorithm for routine monitoring of cyanobacteria and eutrophication in inland and near-coastal waters

Mark William Matthews <sup>a,b</sup>, Daniel Odermatt <sup>b,c</sup>

<sup>a</sup> Department of Geography, University of Cape Town, Rondebosch, 7700, Cape Town, South Africa  
<sup>b</sup> Brockmann Umwelt GmbH, Graf-Plath-Stra. 2, 27332, Cuxhaven, Germany  
<sup>c</sup> Oerlemans IT & Remote Sensing, c/o the HES, Association, Finkenstrasse 21-25, 8005 Zurich, Switzerland

## Monitoring selective logging in western Amazonia with repeat lidar flights

Hans-Erik Andersen <sup>a</sup>, Stephen E. Reutebuch <sup>a,\*</sup>, Robert J. McGaughey <sup>a</sup>,  
Marcus V.N. d'Oliveira <sup>b</sup>, Michael Keller <sup>c,d</sup>

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<sup>c</sup> USDA Forest Service, International Institute of Tropical Forestry, San Juan, PR, USA  
<sup>d</sup> EMBRAPA-CNPq, Campinas, São Paulo, Brazil

## Multi-resolution time series imagery for forest disturbance and regrowth monitoring in Queensland, Australia

Michael Schmidt <sup>a,b,\*</sup>, Richard Lucas <sup>c</sup>, Peter Bunting <sup>d</sup>, Jan Verbesselt <sup>e</sup>, John Armston <sup>a,b</sup>

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<sup>d</sup> Institute of Geography and Earth Sciences, the University of Wales, Aberystwyth, Ceredigion SY23 3DA, United Kingdom  
<sup>e</sup> Laboratory of Geo-Information Science and Remote Sensing, Wageningen University, Droevendaalsesteeg 3, 6500 HB Wageningen, Netherlands

## Estimating lake carbon fractions from remote sensing data

Tiit Kutser <sup>a,b,\*</sup>, Charles Verpoorter <sup>c,b</sup>, Birgit Paavel <sup>a</sup>, Lars J. Tranvik <sup>b</sup>

<sup>a</sup> Estonian Marine Institute, University of Tartu, Mõisaku 14, Tallinn, 12618, Estonia  
<sup>b</sup> Evolutionary Biology Centre, University of Uppsala, Norbyvägen 18D, 75236, Uppsala, Sweden  
<sup>c</sup> INSU-CNRS, UMR 8187, LOC, Laboratoire d'Océanologie et des Glaciologies, Université de Lille Nord de France, ULR 1157, 59630 Villeneuve, France

## Tree cover and forest cover dynamics in the Mekong Basin from 2001 to 2011

Patrick Leinenkugel <sup>a,\*</sup>, Michel J. Wolters <sup>a</sup>, Natascha Oppelt <sup>b</sup>, Claudia Kuenzer <sup>a</sup>

<sup>a</sup> German Aerospace Establishment (DLR), Earth Observation Center (EOC), German Remote Sensing Data Center (GRSC), 62331 University of Applied Sciences, Germany  
<sup>b</sup> Christian Albrecht-Universität zu Kiel, Institute for Geography, Leibniz-Strasse 24, 24109 Kiel, Germany

## Quantification of two decades of shallow-water coral reef habitat decline in the Florida Keys National Marine Sanctuary using Landsat data (1984–2002)

David A. Palandro <sup>a,b</sup>, Serge Andréfouët <sup>b</sup>, Chunmin Hu <sup>a</sup>, Pamela Hallock <sup>c</sup>, Frank E. Müller-Karger <sup>a</sup>,  
Phillip Dustan <sup>d</sup>, Michael K. Callaban <sup>e</sup>, Christine Kranenburg <sup>a</sup>, Carl R. Beaver <sup>c,f</sup>

<sup>a</sup> Institute for Marine Remote Sensing, College of Marine Science, University of South Florida, St. Petersburg, FL, USA  
<sup>b</sup> IREO Centre - Institut de Recherche pour le Développement, Noumea cedex, New Caledonia  
<sup>c</sup> Reef Invertebrate Lab, College of Marine Science, University of South Florida, St. Petersburg, FL, USA  
<sup>d</sup> Biology Department, College of Charleston, Charleston, SC, 29424  
<sup>e</sup> Fish and Wildlife Research Institute, Florida Fish and Wildlife Conservation Commission, 100 8th Ave. SE, St. Petersburg, FL 33708, USA  
<sup>f</sup> USFWS, 100 8th Ave. SE, St. Petersburg, FL 33708, USA

## Ice sheet change detection by satellite image differencing

Robert A. Bindshadler <sup>a,\*</sup>, Ted A. Scambos <sup>b</sup>, Hyeungu Choi <sup>c</sup>, Terry M. Haran <sup>b</sup>

<sup>a</sup> Hydrographic and Synthetic Science Laboratory, NASA-Goddard Space Flight Center, Code 916, Greenbelt, MD 20771, United States  
<sup>b</sup> National Snow and Ice Data Center, Cooperative Institute for Research in Environmental Sciences, 1540 20th Street, University of Colorado, Boulder, Boulder, CO 80309-0489, United States  
<sup>c</sup> SNC, 4600 Powder Mill Road, Suite 400, Bethesda, Maryland 20814-2175, United States

# Advantages and disadvantages of remote sensing for lake monitoring

## Advantages

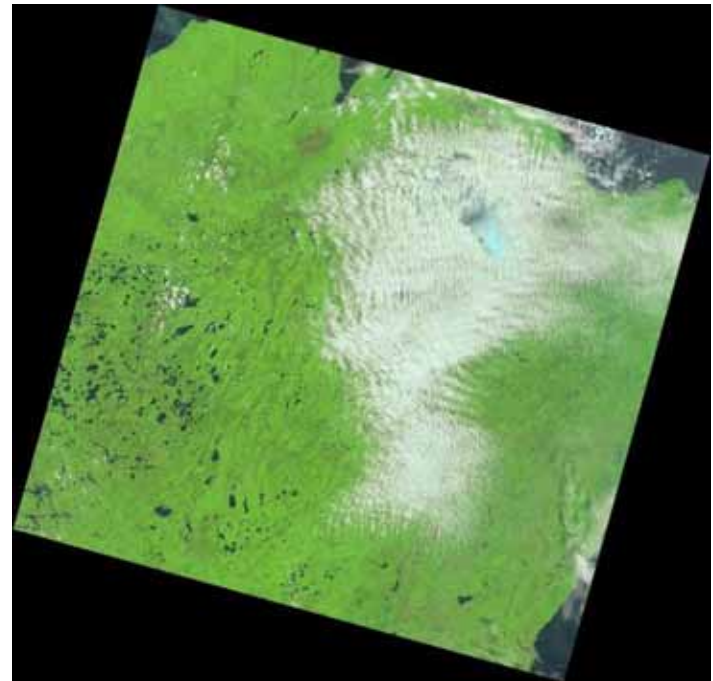
- Water quality data with a high spatial and temporal resolution for thousands of lakes at a time
- Evaluation of environmental problems and potential health risks
- Historical data for studies of trends in water quality
- Real time data for integration into early warning systems to protect the public from harmful algal blooms

## Disadvantages

- Optically complex conditions found in lakes
- Potential interference from the lake bottom in shallow lakes
- Dynamic changes in water quality
- Limited number of water quality parameters
- Calibration and validation of models typically requires the collection of ground truth data

## Remote sensing activities at the Wisconsin DNR

- Systematic processing of Landsat 7 ETM+ and Landsat 8 OLI data for the retrieval of water clarity
- Studies of the major drivers of lake water clarity, their interactions, and the potential impacts of land use and climate on water clarity
- Increase in Earth observation monitoring capabilities through the optical and biogeochemical characterization of lakes in support of algorithm calibration, refinement, and validation



Landsat 8 OLI image courtesy of the U.S. Geological Survey

# Remote sensing activities at the Wisconsin DNR

## EO sensors suitable for water quality assessment with public access data policy

	Pixel Size (m)	Bands (400-900 nm)	Revisit cycle	CHL	CYP	TSM	CDOM	SD	K <sub>d</sub>
<i>Low res.</i>									
MODIS	1000	9	Daily	●	●	●	●	●	●
MODIS	500	2	Daily	●	●	●	●	●	●
MODIS	250	2	Daily	●	●	●	●	●	●
MERIS & OCM2	300	15	2-3 days	●	●	●	●	●	●
VIIRS	750	7	2x/day	●	●	●	●	●	●
<i>Med res.</i>									
Landsat	30	4	16	●	●	●	●	●	●
<i>Future</i>									
Sentinel-3	300	21	Daily	●	●	●	●	●	●
LDCM	30	5	16	●	●	●	●	●	●
Sentinel-2	10-60	10	3-5 days	●	●	●	●	●	●
HySpIRI	60	60	19 days	●	●	●	●	●	●

● Highly suited ● Suited ● Potential ● Not suited

CHL=Chlorophyll; CYP=Cyanophycocyanin; TSM=Total Suspended Matter; CDOM=Coloured Dissolved Organic Matter; SD= Secchi Disk Transparency; K<sub>d</sub>=Vertical Attenuation of Light

Table from Dekker, A.G. & Hestir, E. L. (2012) *Evaluating the Feasibility of Systematic Inland Water Quality Monitoring with Satellite Remote Sensing*. CSIRO: Water for a Healthy Country National Research Flagship

## Landsat 8 OLI and TIRS (02/11/2013)

### OLI

- Eight multispectral bands and one panchromatic band
- Pixel size 30 m for multispectral bands and 15 m for panchromatic band

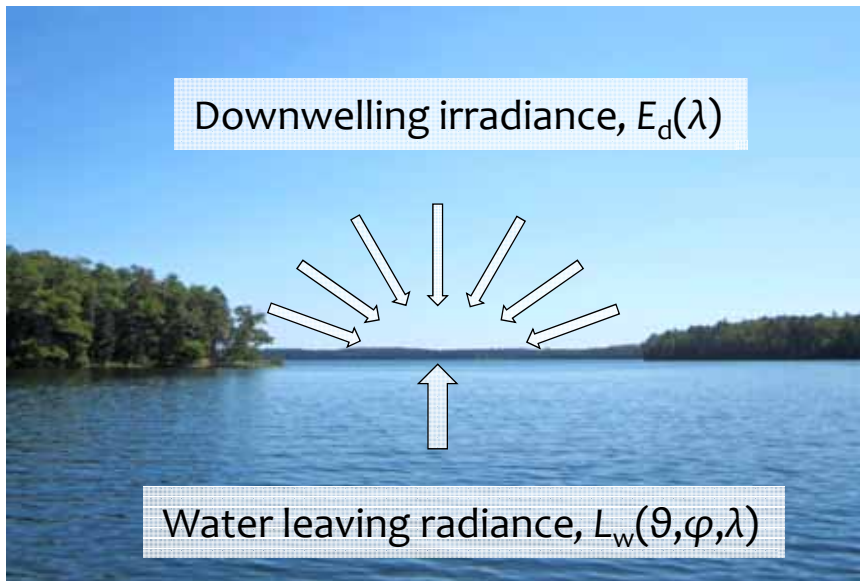
- Scene size 170 x 180 km
- Repeat cycle 16 days

### TIRS

- Two thermal bands
- Pixel size 100 m

# Remote sensing of water quality

## Remote sensing reflectance



Trout Lake

$$R_{rs}(\vartheta, \varphi, \lambda) = \frac{L_w(\vartheta, \varphi, \lambda)}{E_d(\lambda)}$$

Water leaving radiance

Downwelling irradiance



# Remote sensing of water quality

## Absorption and scattering coefficients

Sensitivity of the reflectance to variations in the solar zenith angle

$$R_{rs}(\vartheta, \varphi, \lambda) = \frac{f(\lambda)}{Q(\lambda)} \frac{b_b(\lambda)}{a(\lambda) + b_b(\lambda)}$$

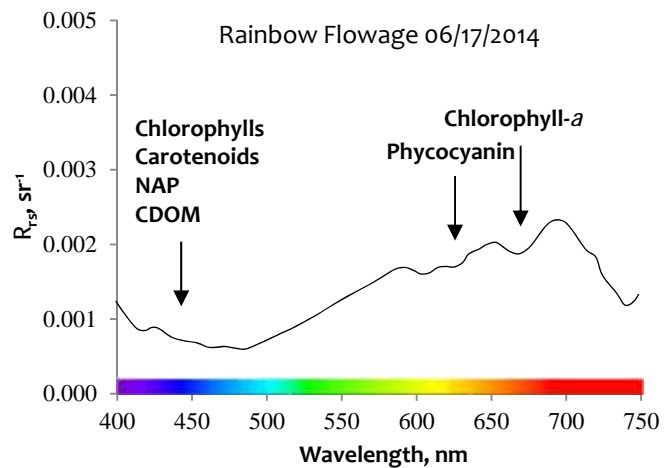
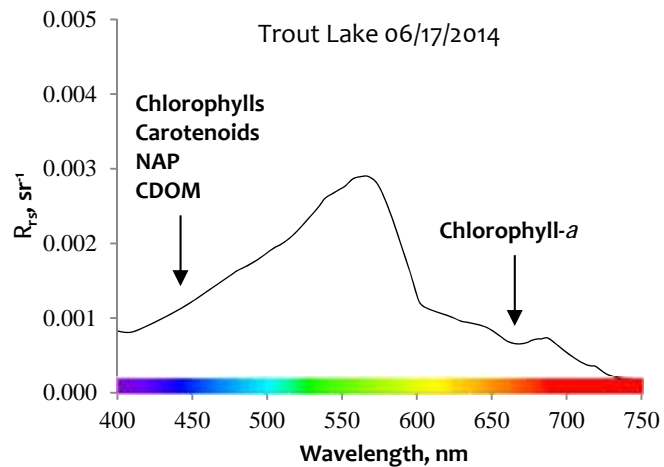
Bidirectional properties of the reflectance

Absorption coefficient

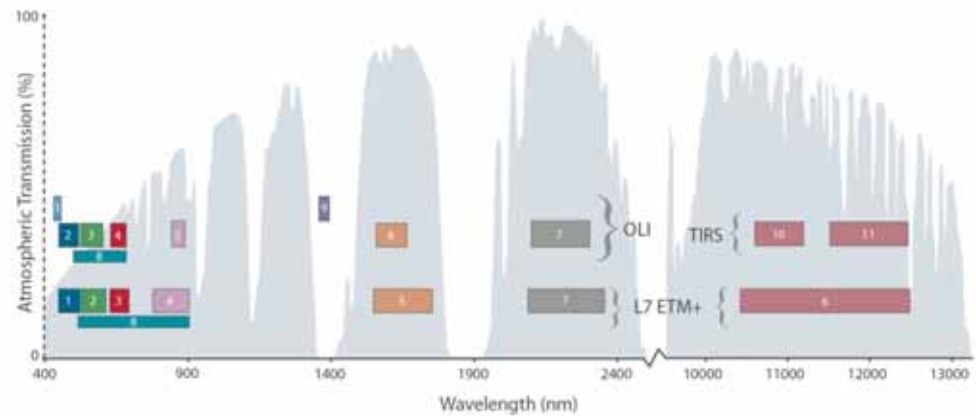
Backscattering coefficient

$$a(\lambda) = a_{\varphi}(\lambda) + a_{\text{NAP}}(\lambda) + a_{\text{CDOM}}(\lambda) + a_{\text{w}}(\lambda)$$

# Remote sensing of water quality



## Landsat 8 spectral bands



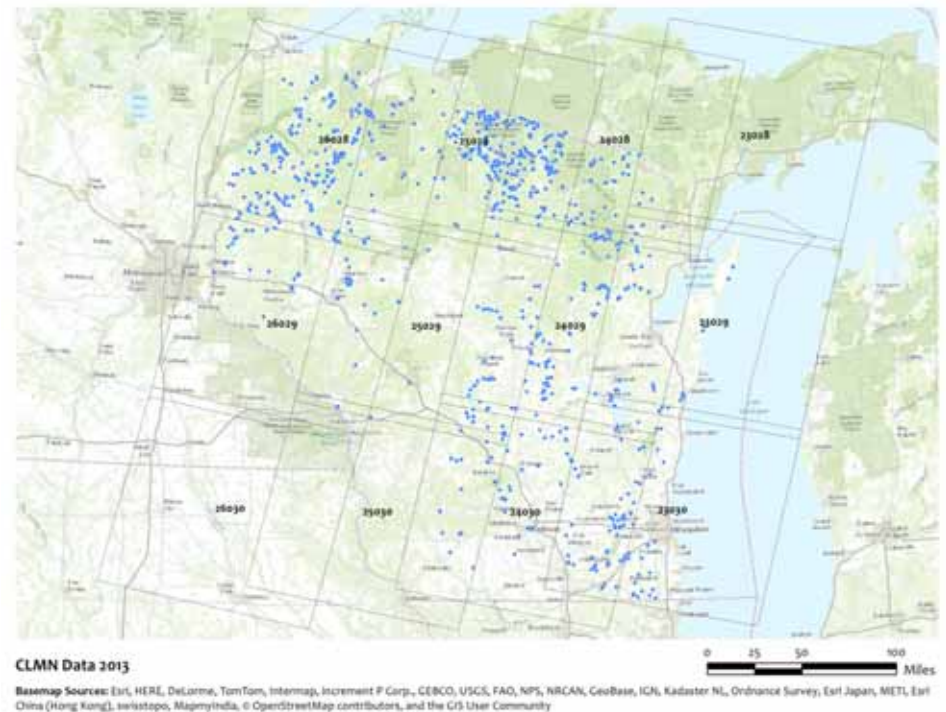
Landsat 8 spectral bands graph from <http://landsat.gsfc.nasa.gov>



# Systematic processing of satellite data for water clarity

## 2013 water clarity estimation

- 54 satellite images
- 3992 ground truth measurements
- 32 data processing steps
- 9 image mosaics for algorithm development
- 475 ground truth measurements for algorithm development
- 8561 water clarity estimates
- 3788 files
- 0.94 TB of data



# Systematic processing of satellite data for water clarity

## Image processing steps

- Conversion of data to TOA spectral radiance
- Reprojection of images to WTM
- Removal of cirrus clouds
- Removal of land
- Removal of shallow waters and aquatic vegetation
- Mosaicking
- Extraction of radiance values for CLMN stations with data collected within one week from image acquisition date



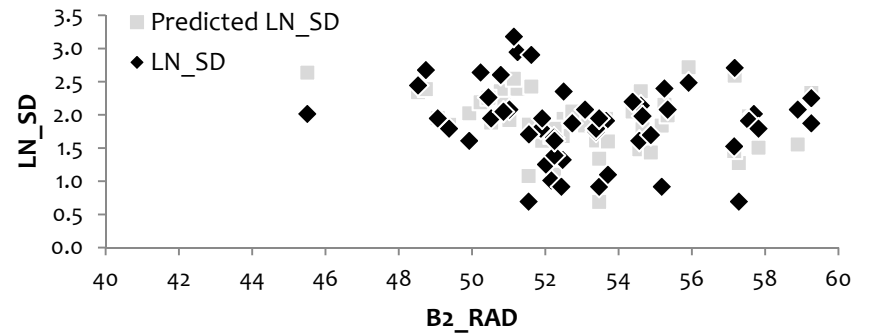
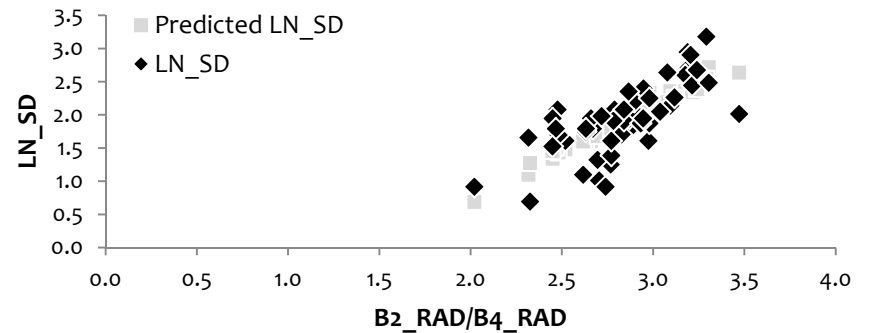
Landsat 8 OLI image of Lake Winnebago  
07/18/2013

0 2.5 5 10 Miles

# Systematic processing of satellite data for water clarity

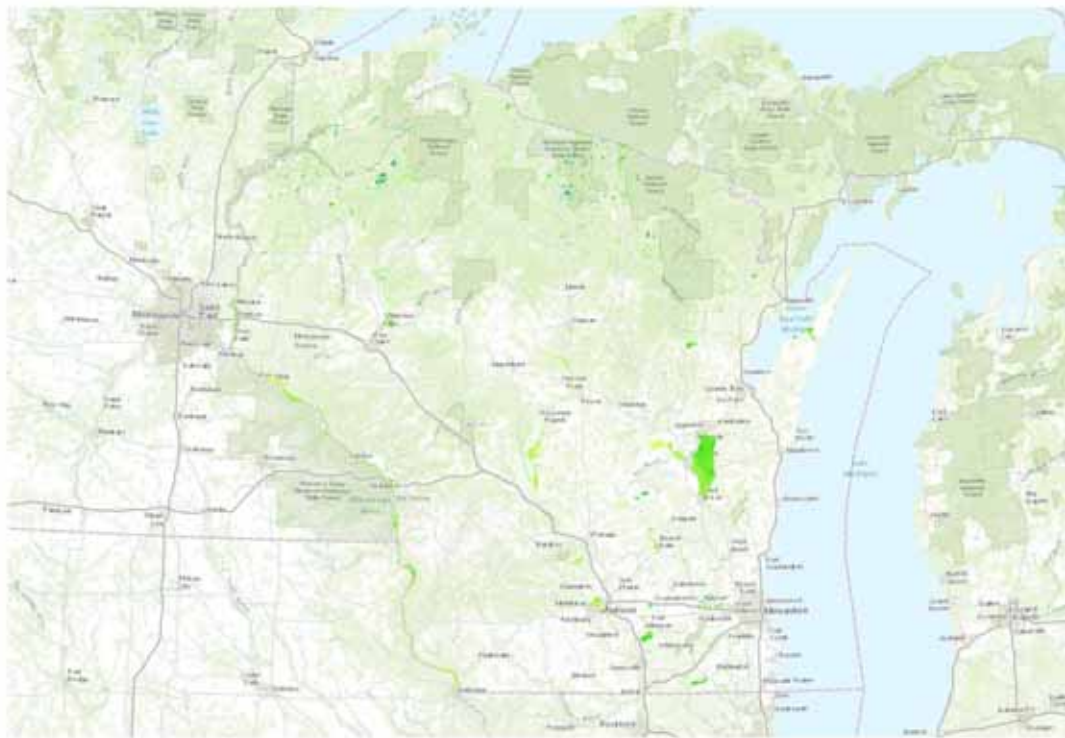
## Algorithm calibration

$$\ln(\text{SD}) = a + b \times \frac{\text{OLI}_{\text{B}_2}}{\text{OLI}_{\text{B}_4}} + c \times \text{OLI}_{\text{B}_2}$$





# 2013 preliminary water clarity composite

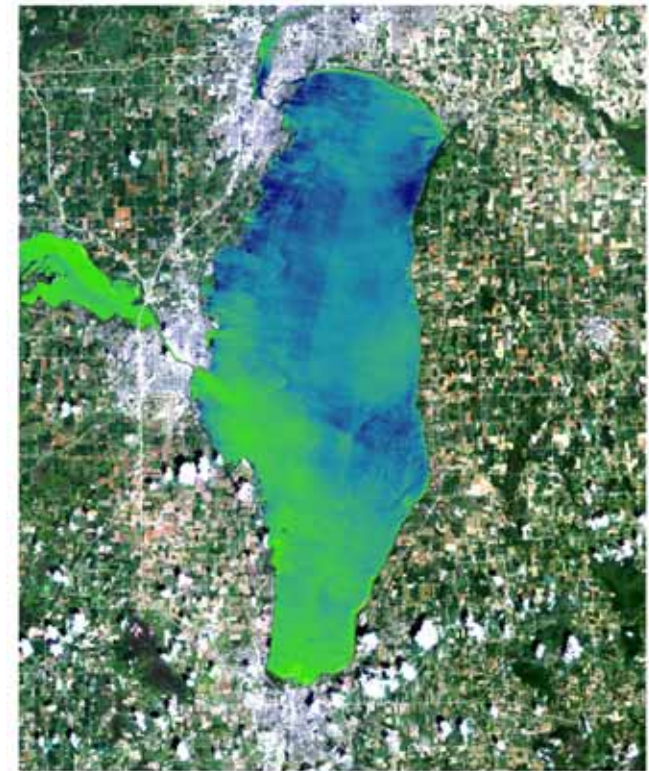


Preliminary Water Clarity Composite 2013

High: 32 ft Low: 0 ft

0 25 50 100 Miles

Basemap Sources: Esri, HERE, DeLorme, TomTom, Intermap, increment P Corp., GEBCO, USGS, FAO, NPS, NRCAN, GeoBase, IGN, Kadaster NL, Ordnance Survey, Esri Japan, METI, Esri China (Hong Kong), swisstopo, MapmyIndia, © OpenStreetMap contributors, and the GIS User Community

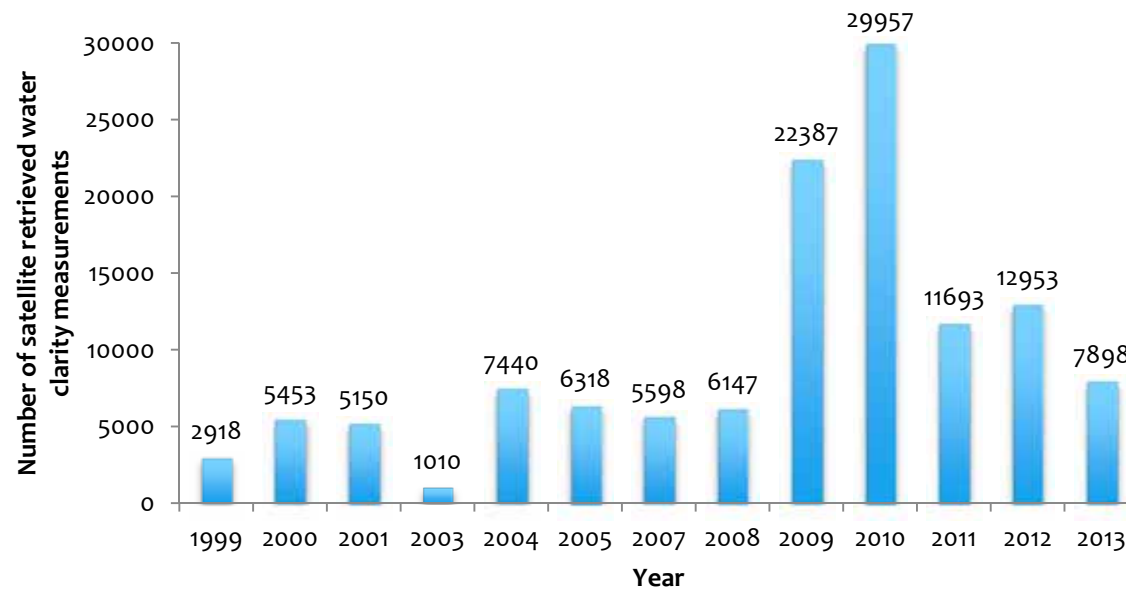


Water clarity composite for Lake Winnebago 06/16/2013 and 07/18/2013

High: 12 ft Low: 0 ft

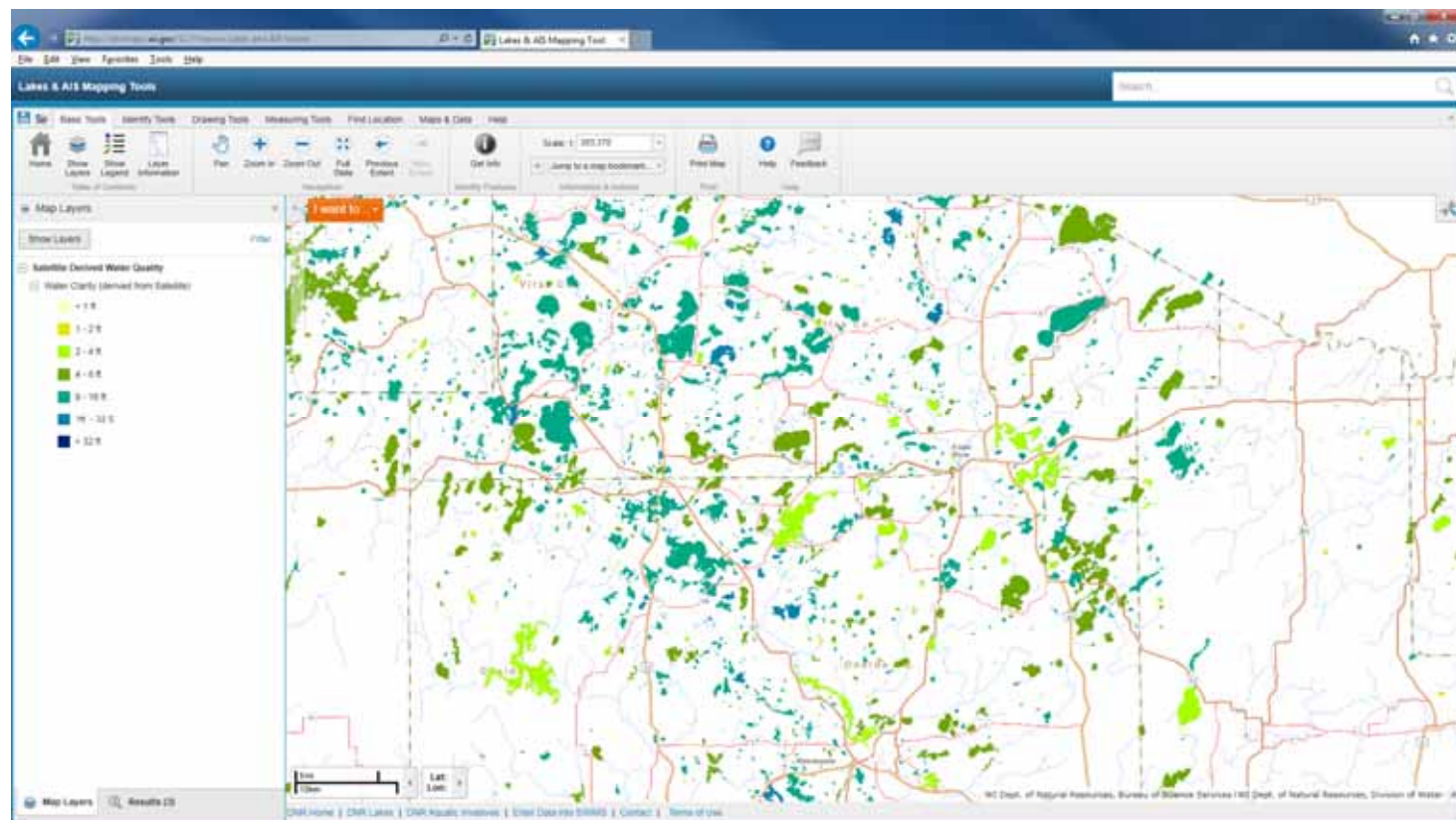
0 2.5 5 10 Miles

# Systematic processing of satellite data for water clarity



# Lakes and Aquatic Invasive Species (AIS) Mapping Tool

<http://dnr.wi.gov/lakes/viewer/>

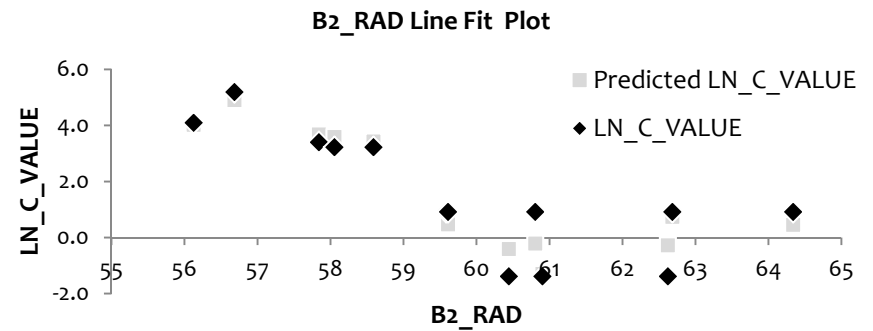
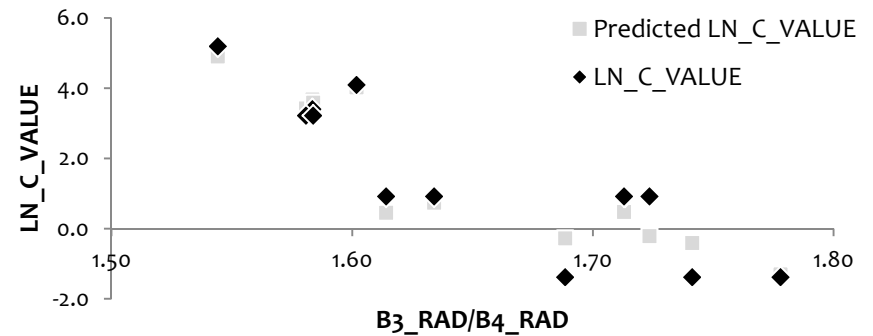




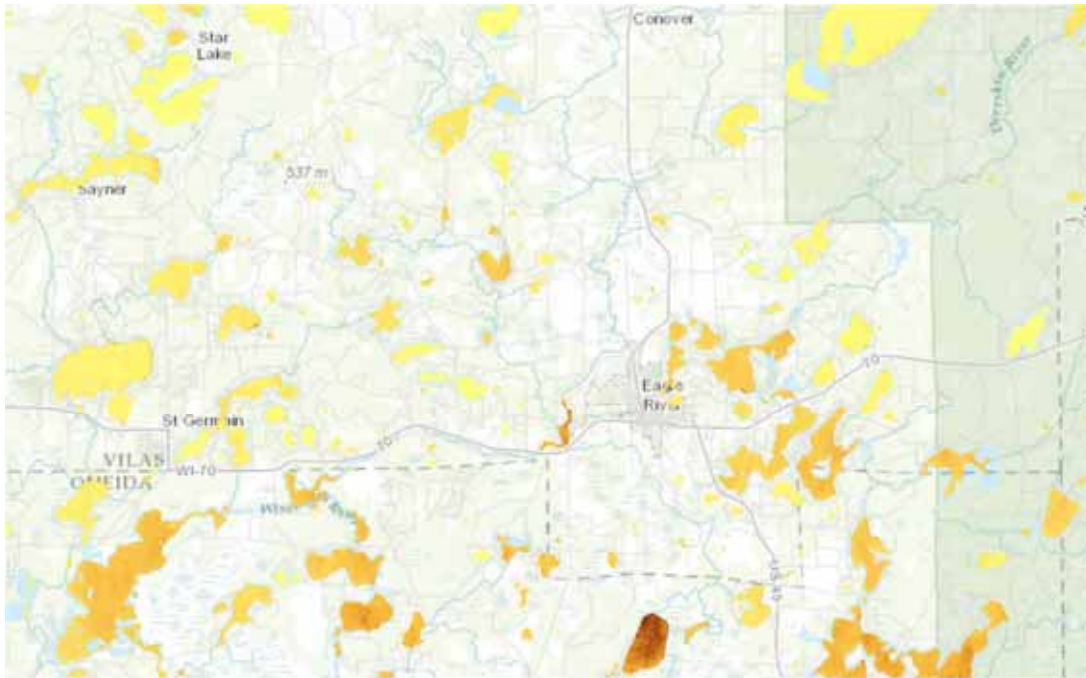
# Systematic processing of satellite data for water color

## Algorithm calibration

$$\ln(C) = a + b \times \frac{OLI_{B3}}{OLI_{B4}} + c \times OLI_{B2}$$



# 2013 preliminary water color product



Landsat 8 OLI Water Color  
06/23/2013

High: 200 PCU Low: 0 PCU



Basemap Sources: Esri, HERE, DeLorme, TomTom, Intermap, increment P Corp., GEBCO, USGS, FAO, NPS, NRCAN, Geobase, IGN, Kalasiter NL, Ordnance Survey, Esri Japan, METI, Esri China (Hong Kong), Swisstopo, MapboxIndia, © OpenStreetMap contributors, and the GIS User Community

## Average Water Color

Big Saint Germain Lake

- 5.5 PCU

Rainbow Flowage

- 33.0 PCU

Pickerel Lake

- 13.3 PCU

# Major drivers of lake water clarity

## Focus on

- Explained variance
- Response distributions

## Predictor categories

- Climate
- Land use/land cover
- Surficial geology
- Water chemistry
- Lake morphology & position
- Runoff potential

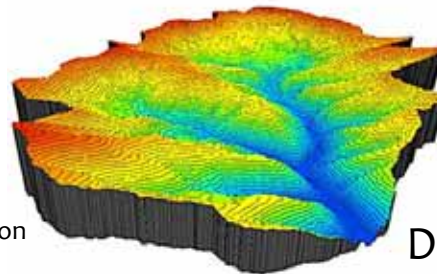
National Land Cover Database



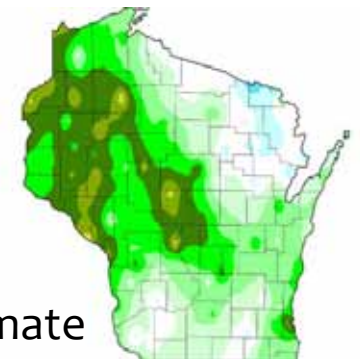
USDA National Soil Survey



Water chemistry



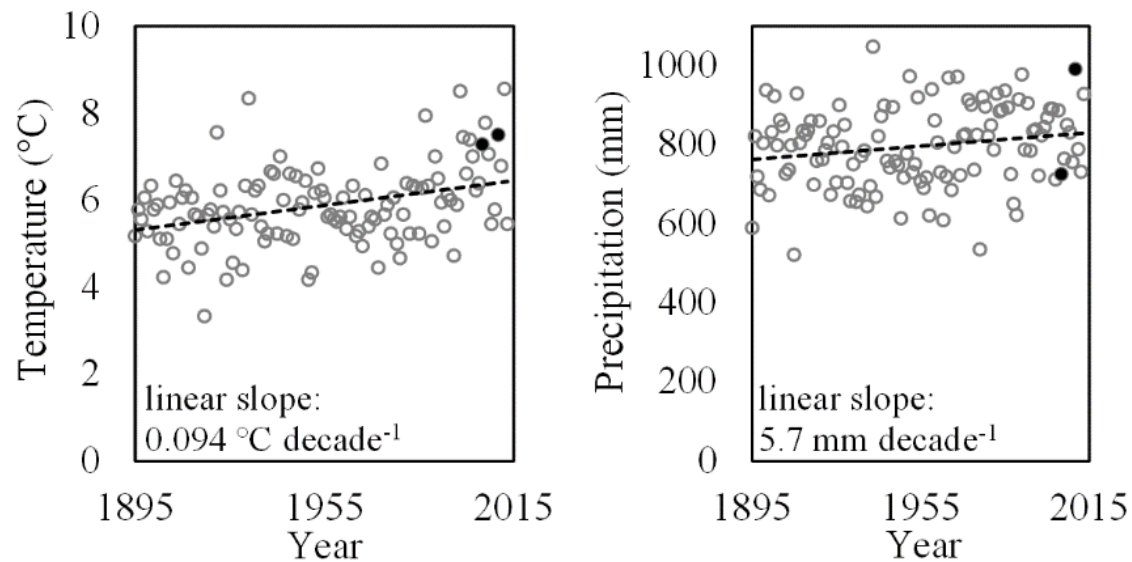
Gridded climate



Digital elevation models

## Major drivers of lake water clarity

What are the implications of long term trends in temperature and precipitation?



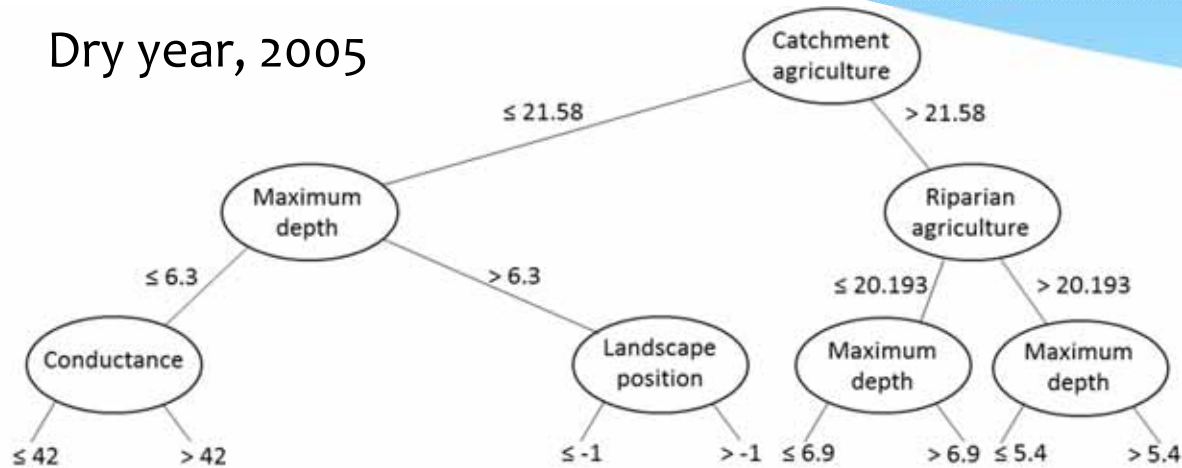
## Major drivers of lake water clarity

Water clarity is regulated by many different drivers.

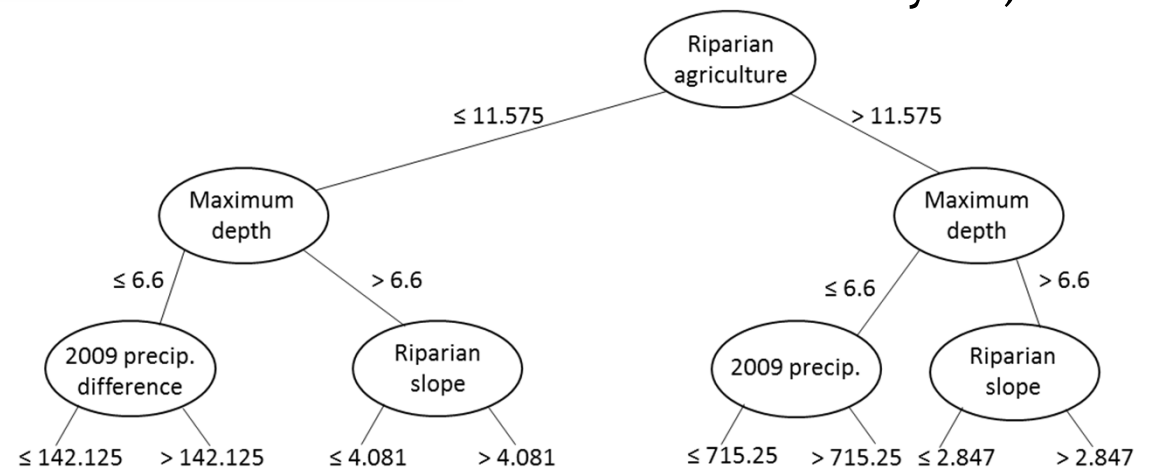
	Predictor category	Predictors (#)	2005 variance explained	2010 variance explained
Dry year, 2005	Climate	13	30.0	23.1
Wet year, 2010	Land use/land cover	26	28.5	21.3
	Lake morphometry	4	27.5	23.7
	Run-off potential	5	18.8	11.7
	Catchment morphometry	11	17.9	12.0
	Water chemistry	3	12.8	2.1
	Geology	18	4.3	3.6
	Total	80	64.4	52.4

# Major drivers of lake water clarity

Dry year, 2005



Wet year, 2010



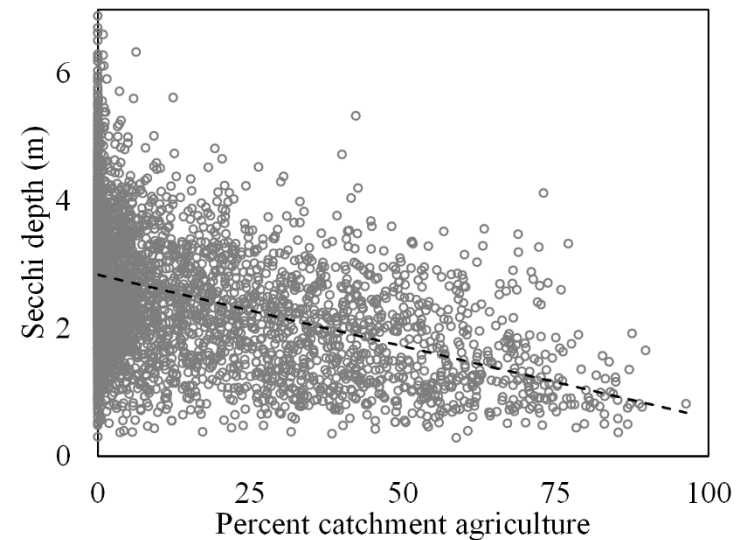
Data courtesy of Kevin Rose, University of Wisconsin-Madison



# Major drivers of lake water clarity

## Regulators of lake water clarity

- Deep lakes high in the landscape tend to be the clearest
- Agricultural land use is the best land use predictor of water clarity
- High precipitation is associated with lower water clarity



# Increase in Earth observation monitoring capabilities

## Optical and biogeochemical characterization of lakes

- Field data collection in summer and fall 2014 for algorithm development
- 24 lakes in Wisconsin

## Field and laboratory measurements

- Water temperature, dissolved oxygen, conductivity, and Secchi depth
- Reflectance
- Water color and turbidity
- TSS, ISS, and OSS
- Absorption and backscattering coefficients



Return from field data collection at Lake Geneva

# Thank you!



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