The Hydrologic Cycle of the Great Lakes (and a few other water topics)

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Great Lakes Environmental Research Laboratory
National Oceanic and Atmospheric Administration
and
Department of Civil and Environmental Engineering
University of Michigan

April 2017

Outline

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1. Introduction
2. Statistical modeling and water quality
3. Hydrologic cycle of the Great Lakes
   - Water levels
   - Water balance components

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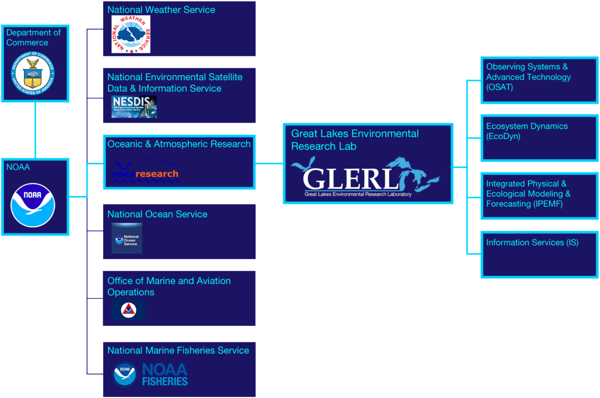
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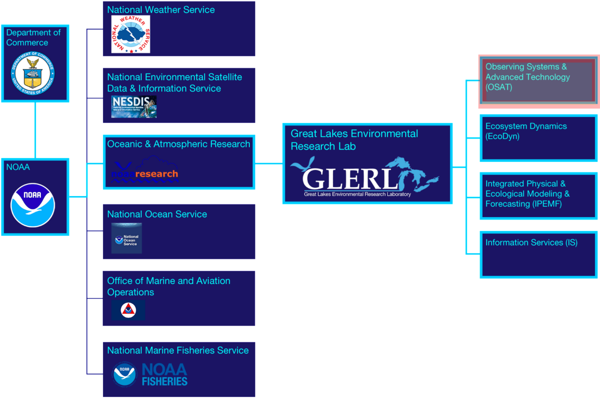
Great Lakes Environmental Research Lab
GLERL
Great Lakes Environmental Research Laboratory
Observing Systems & Advanced Technology (OSAT)
Ecosystem Dynamics (EcoDyn)
Integrated Physical & Ecological Modeling & Forecasting (IPEMF)
Information Services (IS)



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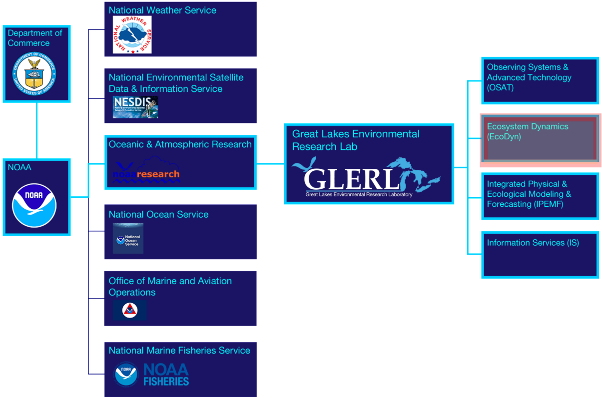
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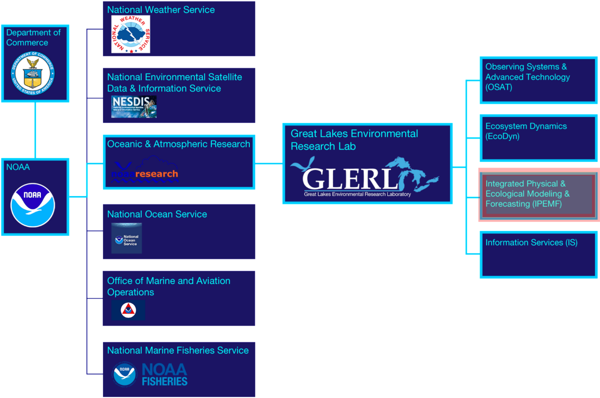
Asian Carp Studies at GLERL

Understanding the Impacts of an Invasive Species

Forecasting the effects of silver and bighead carp on food webs

A collaborative team of NOAA Great Lakes Environmental Research Laboratory (GLERL) scientists and their partners developed a model to identify potential effects of Asian carp on the food webs in Lake Erie and other Great Lakes. Food webs are the feeding interactions of aquatic life. Prior efforts to predict Asian carp effects on the Great Lakes focused on potential suitability of Great Lakes habitats for Asian carp spawning, establishment or growth, but had not investigated Asian carp effects on food webs and fisheries. This information is critical to assess potential control measures and management options. The models used by GLERL and CILER (Cooperative Institute for Limnology and Ecosystems Research) researchers simulate Asian carp population dynamics (growth and shrinkage over time, as controlled by birth, death and migration), ecosystem impacts, and food webs, and can help inform state and federal agencies working together to control the spread of Asian carp.


Department of Commerce
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NESDIS
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Probabilistic modeling:

Probabilistic modeling: MPN vs. CFU

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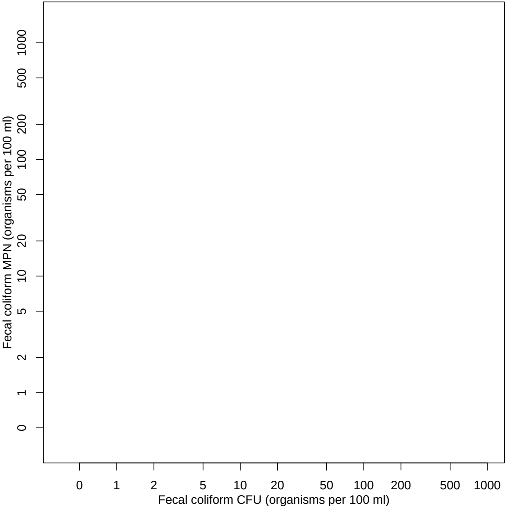
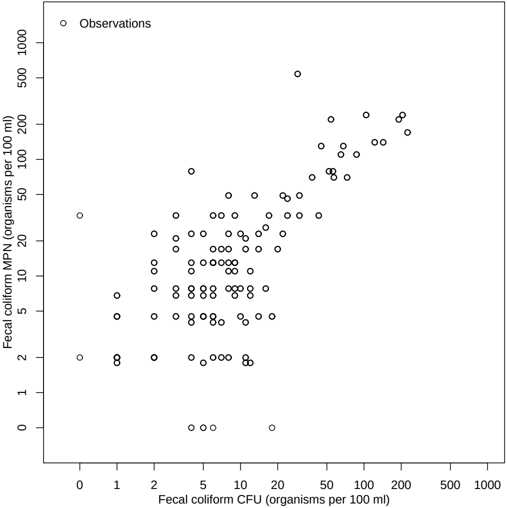


Probabilistic modeling: MPN vs. CFU



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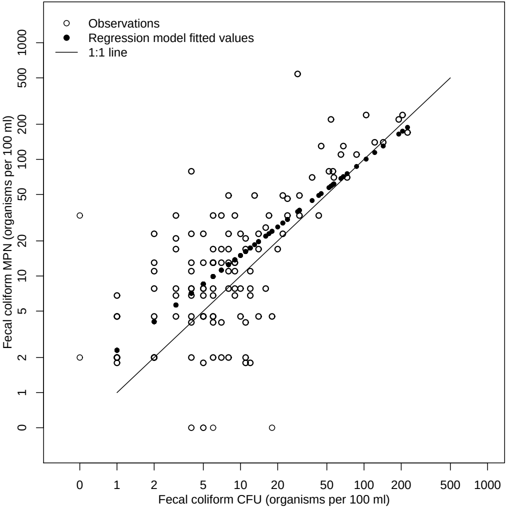

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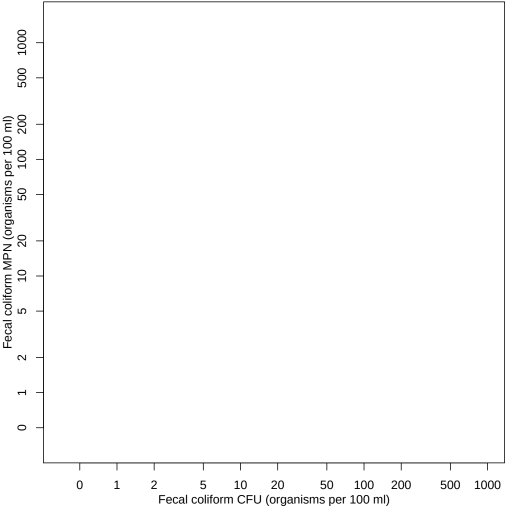

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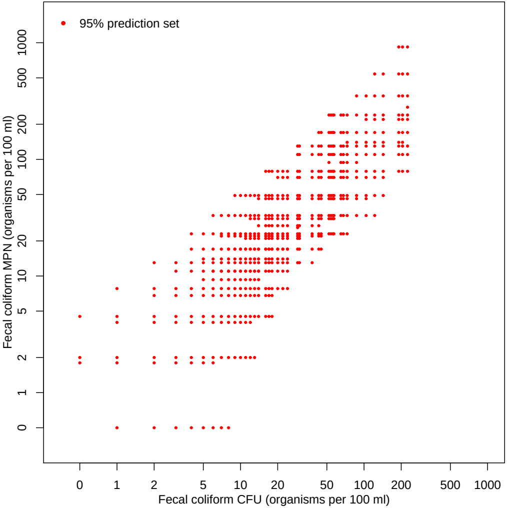

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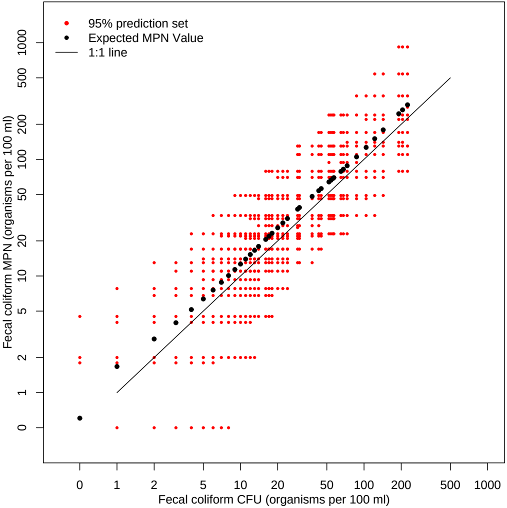

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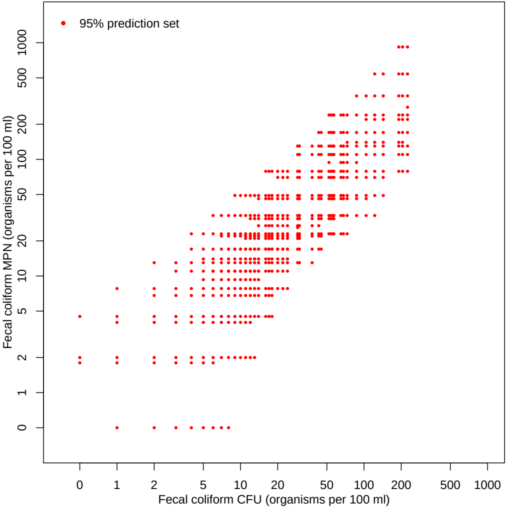

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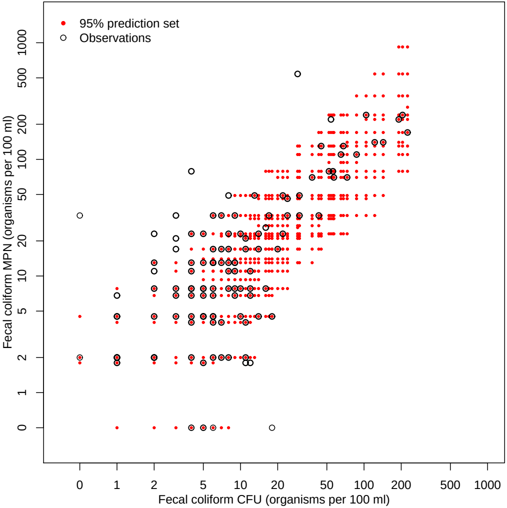

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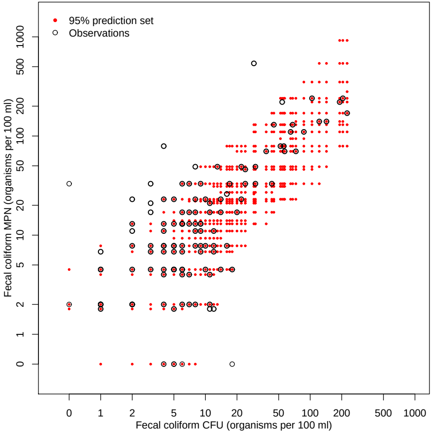
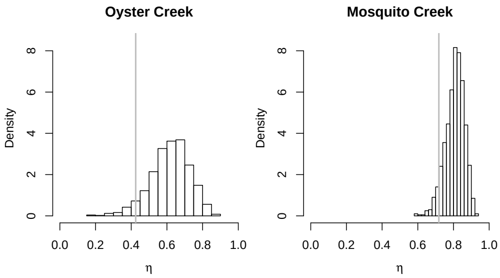


A. D. Gronewold and R. L. Wolpert, 2008. *Water Research*.

Bayesian inference:

Bayesian inference: improving management decisions



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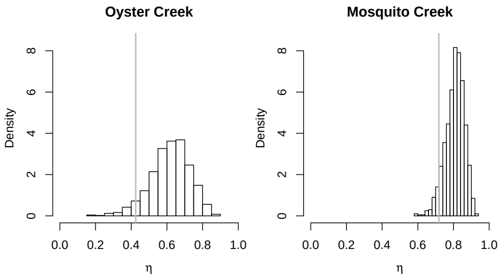

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A. D. Gronewold, S. S. Qian , R. L. Wolpert and K. H. Reckhow, 2009. *Water Research*.

A. D. Gronewold and M. E. Borsuk, 2009. *Environmental Modelling & Software*.

A. D. Gronewold, L. Myers, J. L. Swall, and R. T. Noble, 2011. *Water Research*.

A. D. Gronewold, C.A. Stow, K. Vijayavel, M.A. Moynihan, D.R. Kashian, 2013. *Water Research*.

J. Wu, A.D. Gronewold, R.A. Rodriguez, J.R. Stewart, M.D. Sobsey, 2014. *Science of the Total Environment*.

D. Obenour, A.D. Gronewold, C.A. Stow, D. Scavia, 2014. *Water Resources Research*.

A. D. Gronewold, M.D. Sobsey, L. McMahan, 2017. *Science of the Total Environment*.

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A.D. Gronewold, M.E. Borsuk, R.L. Wolpert, R.L., and K.H. Reckhow, 2008. *ES&T*

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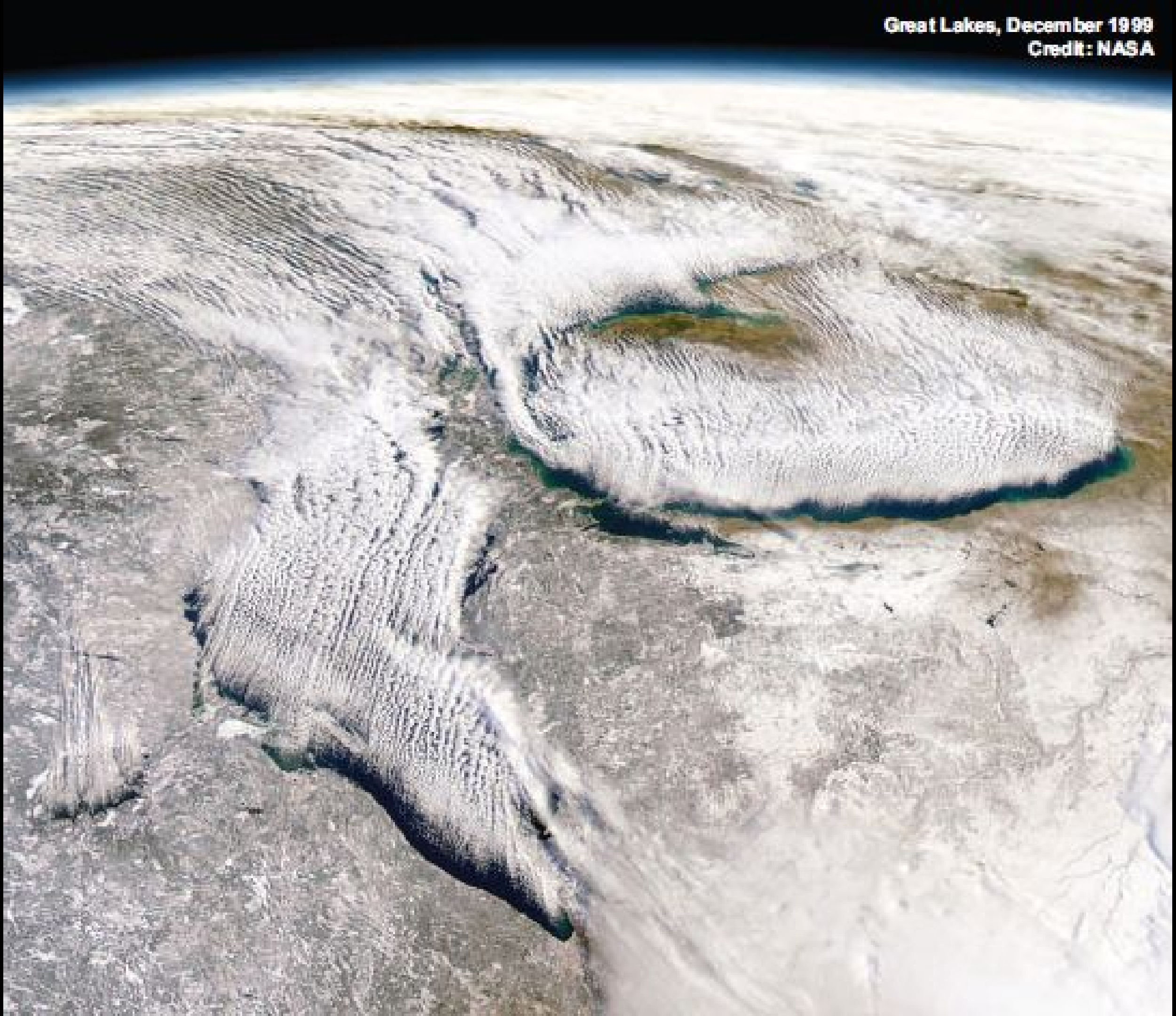
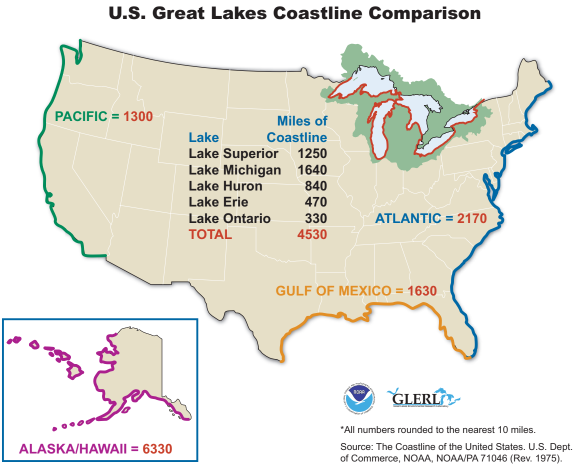

Great Lakes, December 1999
Credit: NASA



From: Gronewold, Fortin, Lofgren, Clites, Stow, and Quinn (2013). *Climatic Change*.

Name	Country	Surface area (km^2)	Surface area (mi^2)	Volume (km^3)	Volume (mi^3)
Michigan–Huron	U.S. and Canada	117,702	45,445	8,458	2,029
Superior	U.S. and Canada	82,414	31,820	12,100	2,900
Victoria	Multiple	69,485	26,828	2,750	660
Tanganyika	Multiple	32,893	12,700	18,900	4,500
Baikal	Russia	31,500	12,200	23,600	5,700
Great Bear Lake	Canada	31,080	12,000	2,236	536
Malawi	Multiple	30,044	11,600	8,400	2,000
Great Slave Lake	Canada	28,930	11,170	2,090	500
Erie	U.S. and Canada	25,719	9,930	489	117
Winnipeg	Canada	23,553	9,094	283	68
Ontario	U.S. and Canada	19,477	7,520	1,639	393

Table: Water volume and surface area of Earth's largest (ranked by surface area) fresh surface waters.

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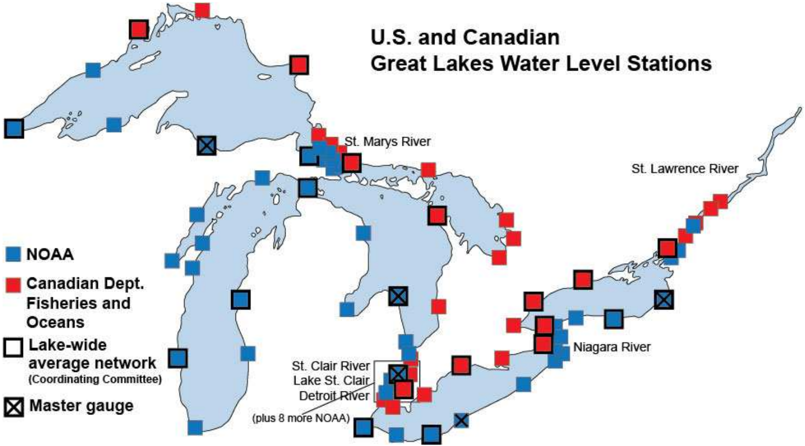
U.S. and Canadian Great Lakes Water Level Stations



From: NOAA National Ocean Service (CO-OPs) and NOAA-GLERL.

Great Lakes Water Levels

Long-term and seasonal variability

Great Lakes Water Levels

Long-term and seasonal variability

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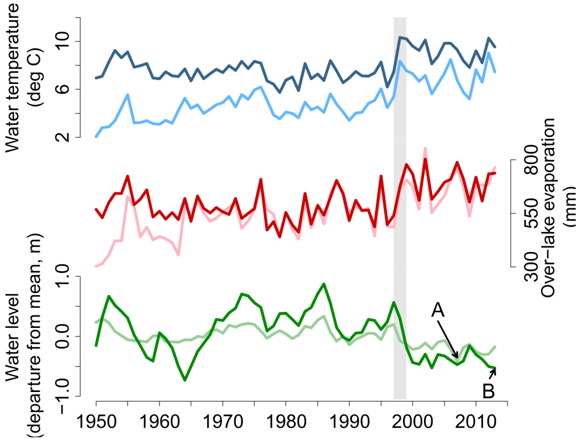

From: Gronewold & Stow (2014), *Science*

See also: Sellinger, Stow, Lamon, and Qian (2007), *ES&T*

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Earth & Space Science News

GREAT LAKES WATER LEVELS SURGE

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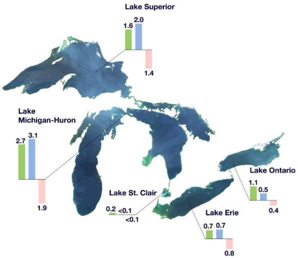
Runoff
Overlake Precipitation
Overlake Evaporation

All values are averaged over the period 1950-2010 and are in thousands of cubic meters per second.



- Runoff
- Overlake Precipitation
- Overlake Evaporation
- Flow Between Lakes
- Diversions

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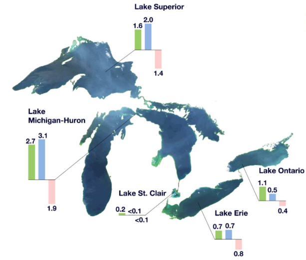

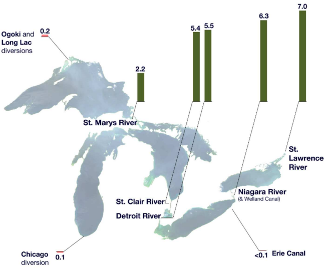


White Shoal Lighthouse: Lake Michigan
Photo courtesy Dick Moehl (Lighthouse Keepers Association)

Great Lakes Water Levels

Ice and evaporation interactions

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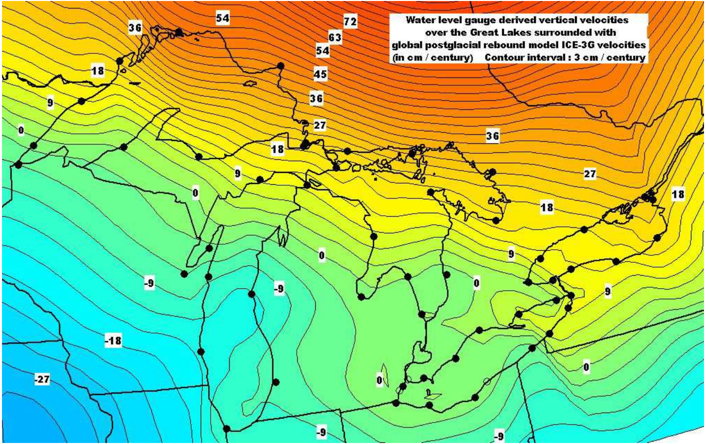

From: Mainville and Craymer (2005), *GSA Bulletin*.

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Multi-decadal projections

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Concluding remarks

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- Uncertainty quantification: simple or complex models?

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- Projections: prediction or insight?

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- Uncertainty quantification: simple or complex models?
- Projections: prediction or insight?
- Value of continuous monitoring programs

Acknowledgements

- Marie Biron, Heng Zhang, and MWRD
- Joe Smith, Kaye Lafond, Anne Clites, Tim Hunter
- NOAA, USACE, USGS, and Environment and Climate Change Canada

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Seasonal projections

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Great Lakes Water Levels

Seasonal and interannual variability

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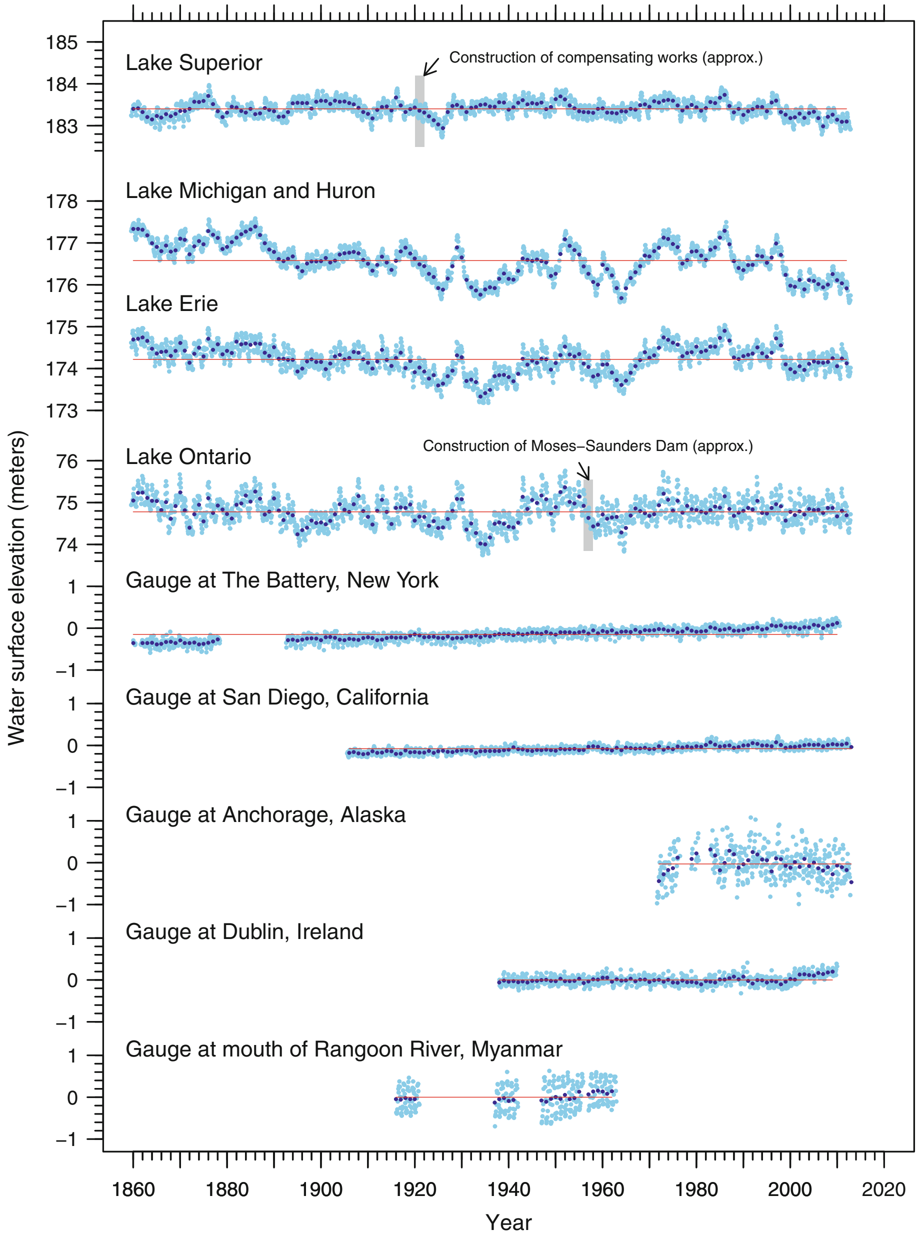
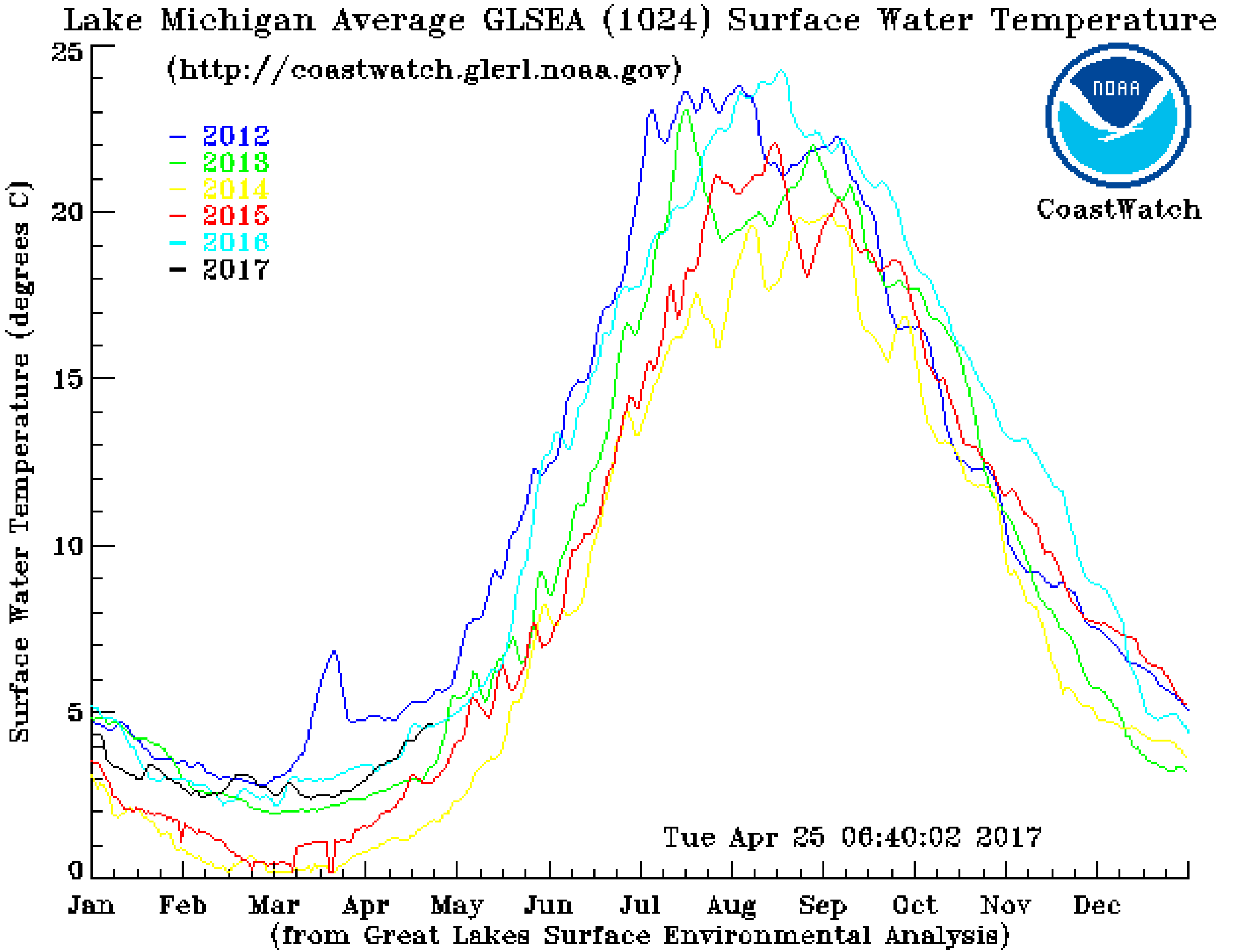
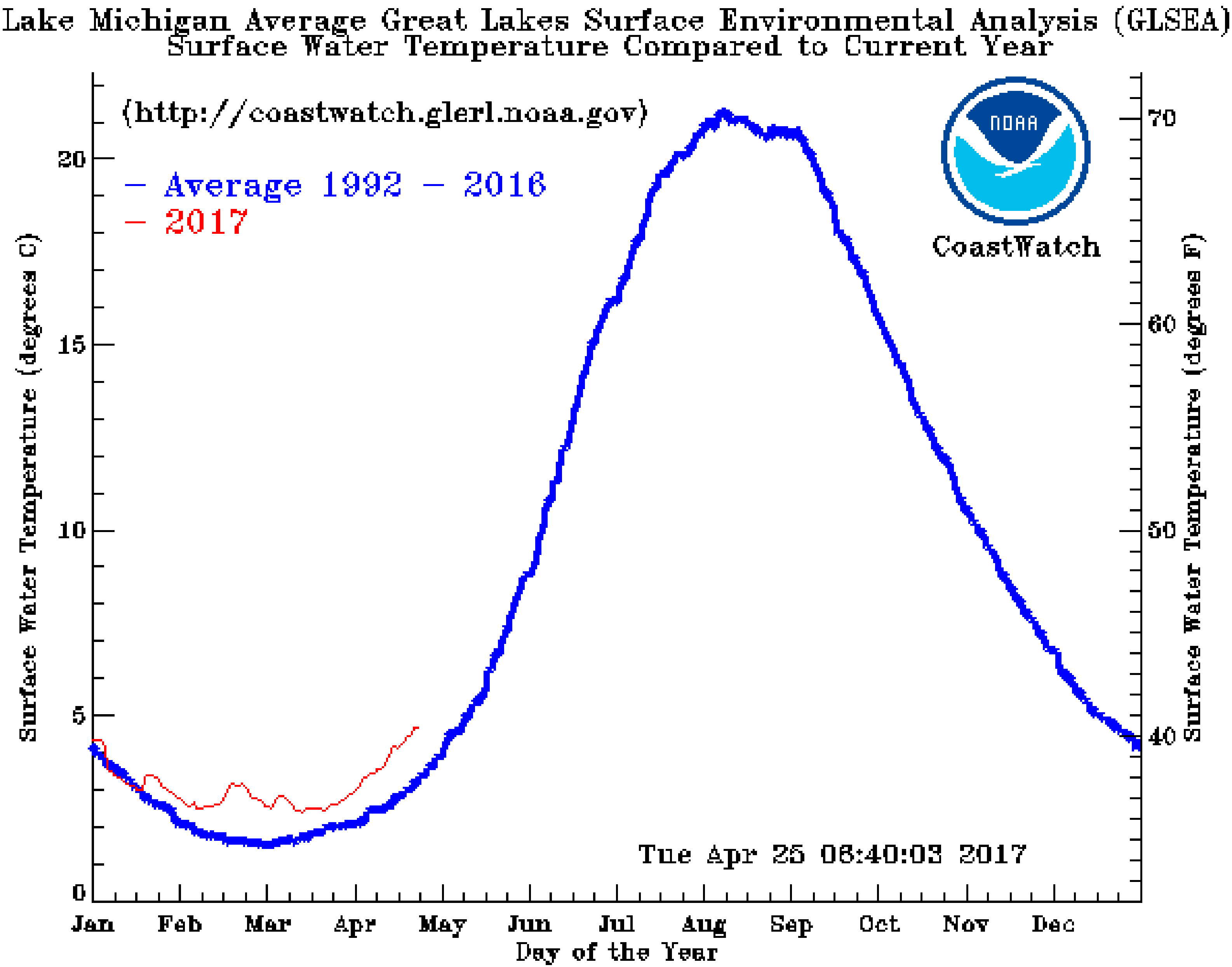

Lake Superior
Construction of compensating works (approx.)
Lake Michigan and Huron
Lake Erie
Lake Ontario
Construction of Moses–Saunders Dam (approx.)
Gauge at The Battery, New York
Gauge at San Diego, California
Gauge at Anchorage, Alaska
Gauge at Dublin, Ireland
Gauge at mouth of Rangoon River, Myanmar
Water surface elevation (meters)
185
184
183
178
177
176
175
174
173
76
75
74
1
0
−1
1860
1880
1900
1920
1940
1960
1980
2000
2020
Year


Lake Michigan Average GLSEA (1024) Surface Water Temperature
(http://coastwatch.glerl.noaa.gov)
2012
2013
2014
2015
2016
2017
NOAA
CoastWatch
Surface Water Temperature (degrees C)
25
20
15
10
5
0
Tue Apr 25 06:40:02 2017
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
(from Great Lakes Surface Environmental Analysis)


Lake Michigan Average Great Lakes Surface Environmental Analysis (GLSEA)
Surface Water Temperature Compared to Current Year
(http://coastwatch.glerl.noaa.gov)
— Average 1992 – 2016
— 2017
NOAA
CoastWatch
Tue Apr 25 06:40:03 2017
Surface Water Temperature (degrees C)
Surface Water Temperature (degrees F)
0
5
10
15
20
40
50
60
70
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Day of the Year

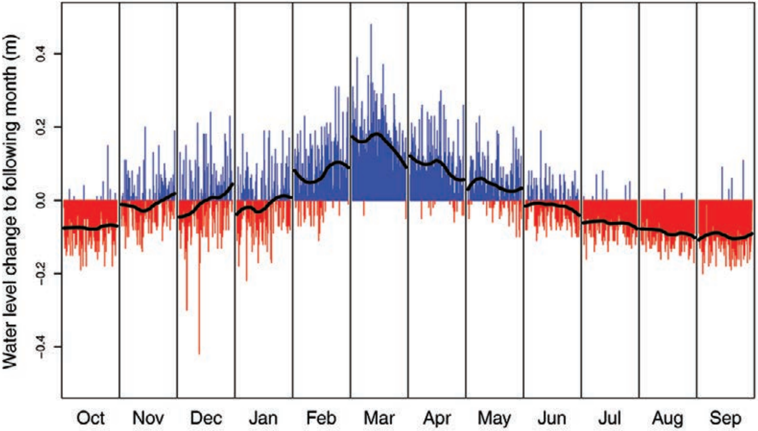
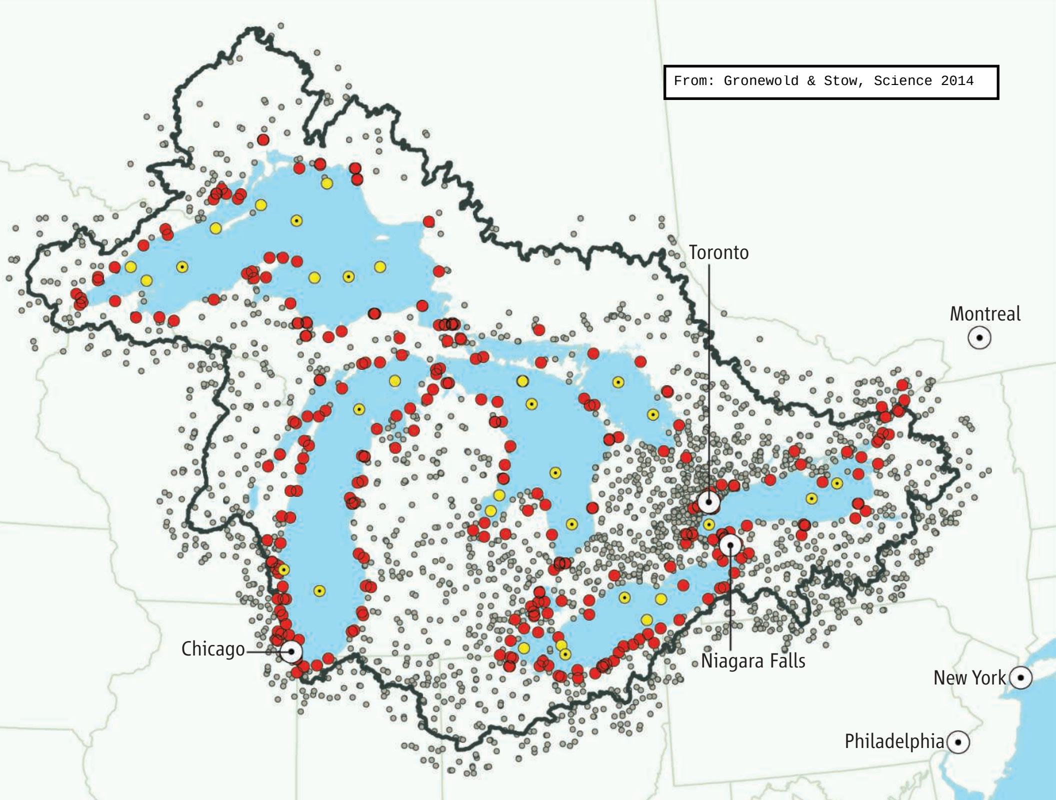
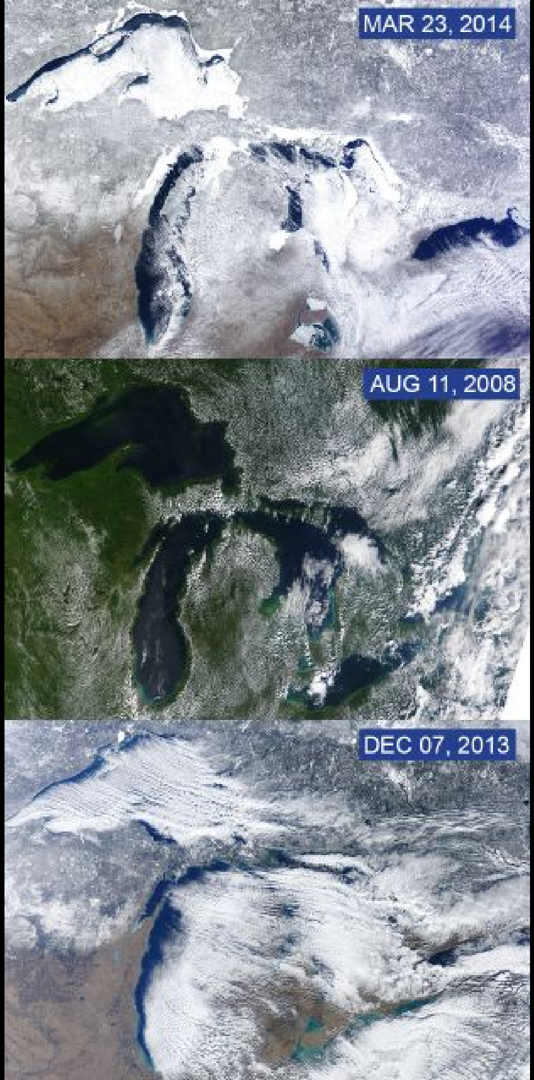


Fig. 2. Month-to-month changes in Lake Erie monthly average water levels. Vertical bars in each panel (one panel for each month) represent the water-level change (m) from the month indicated at the bottom of the panel to the following month for each year from 1860 to 2012. The left-most panel, for example, includes water-level changes from Oct to Nov. Blue vertical bars indicate an increase in monthly water level; red vertical bars indicate a decrease in monthly water level. The black line within each panel indicates the long-term trend.


From: Gronewold & Stow, Science 2014
Toronto
Montreal
Chicago
Niagara Falls
New York
Philadelphia


MAR 23, 2014
AUG 11, 2008
DEC 07, 2013

EDITORIAL

On the Need for Uncertainty Assessment in TMDL Modeling and Implementation

K. H. Reckhow
Duke University; UNC Water Resources Research Institute.

Will TMDL decisions be improved with knowledge of the uncertainty in outcomes from proposed pollutant load reductions? That is, will our decisions generally be better if we have some idea of the range of possible outcomes that might result? I believe that the answer is yes; and yet current practice in water quality assessment and management suggests that others may believe that decision making may be undermined with full disclosure of uncertainties, or perhaps believe that uncertainty is small enough that it can be safely ignored.

Despite these reservations, it is noteworthy that the U.S. EPA also believes the answer is "yes," although their reasoning is unclear. EPA's perspective is implicit in their technical requirement for an uncertainty-based "margin of safety" (MOS) in a TMDL application; however, absent from EPA guidance is an explanation as to why decisions improve with an uncertainty analysis.

Despite the requirement for an uncertainty-based MOS estimate, few TMDLs are accompanied by actual estimates of forecast uncertainty. Instead, TMDLs are typically proposed with either "conservative" modeling assumptions or an arbitrarily chosen MOS. Neither approach explicitly links the MOS to TMDL forecast uncertainty. However, by hedging the TMDL decision in the direction of environmental protection, the MOS effectively increases the assurance that water quality standards will be achieved. This may seem reasonable and even desirable, but it must be noted that this hedging comes at a cost, and the basis for the hedging cost is totally arbitrary in most cases.

The National Research Council Committee to Assess the Scientific Basis of the Total Maximum Daily Load Approach to Water Pollution Reduction has recognized the arbitrary way in which the margin of safety has been applied. Specifically, their Executive Summary contains the following recommendation (NRC 2001):

> The TMDL program currently accounts for the uncertainty embedded in the modeling exercise by applying a Margin of Safety (MOS); EPA should end the practice of arbitrary selection of the MOS and instead require uncertainty analysis as the basis for MOS determination.

However, acknowledging and computing model prediction uncertainty is not without challenges, as I learned several years ago. While in graduate school, I became involved in a proposed consulting venture in New Hampshire focusing on 208 planning. As a young scientist, I was eager to apply my new scientific knowledge, so I suggested to my consulting colleagues that we add uncertainty analysis to our proposed 208 study. Everyone agreed; thus we proposed that uncertainty analysis be a key component of the water quality modeling task for the 208 planning process. Well, after we made our presentation to the client, the client's first question was, "The previous consultants didn't have any uncertainty in their modeling study, what's wrong with your model?" This experience made me realize that I had much to learn about the role of science in decision making and about effective presentations!

While this story may give the impression that I'm being critical of the client for not recognizing the ubiquitous uncertainty in environmental forecasts, in fact I believe the fault to lie primarily with the scientists and engineers who fail to fully inform clients of the uncertainty in their assessments. Partially in their defense, water quality modelers may fail to see why decision makers are better off knowing the forecast uncertainty, and perhaps modelers may not want to be forced to answer the embarrassing question like the one posed to me years ago in New Hampshire.

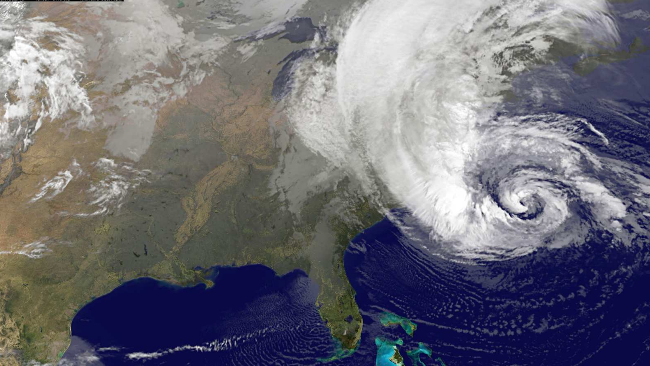
For this situation to change, that is, for decision makers to demand estimates of forecast error, decision makers first need (1) motivation—that is, they must become aware of the substantial magnitude of forecast error in many water quality assessments, and (2) guidance—ideally, they need relatively simple heuristics that will allow them to use this knowledge of forecast error to improve decision making in the long run. Once this happens, and decision makers demand that water quality forecasts be accompanied with error estimates, water quality modelers can support this need through distinct short-term and long-term strategies.

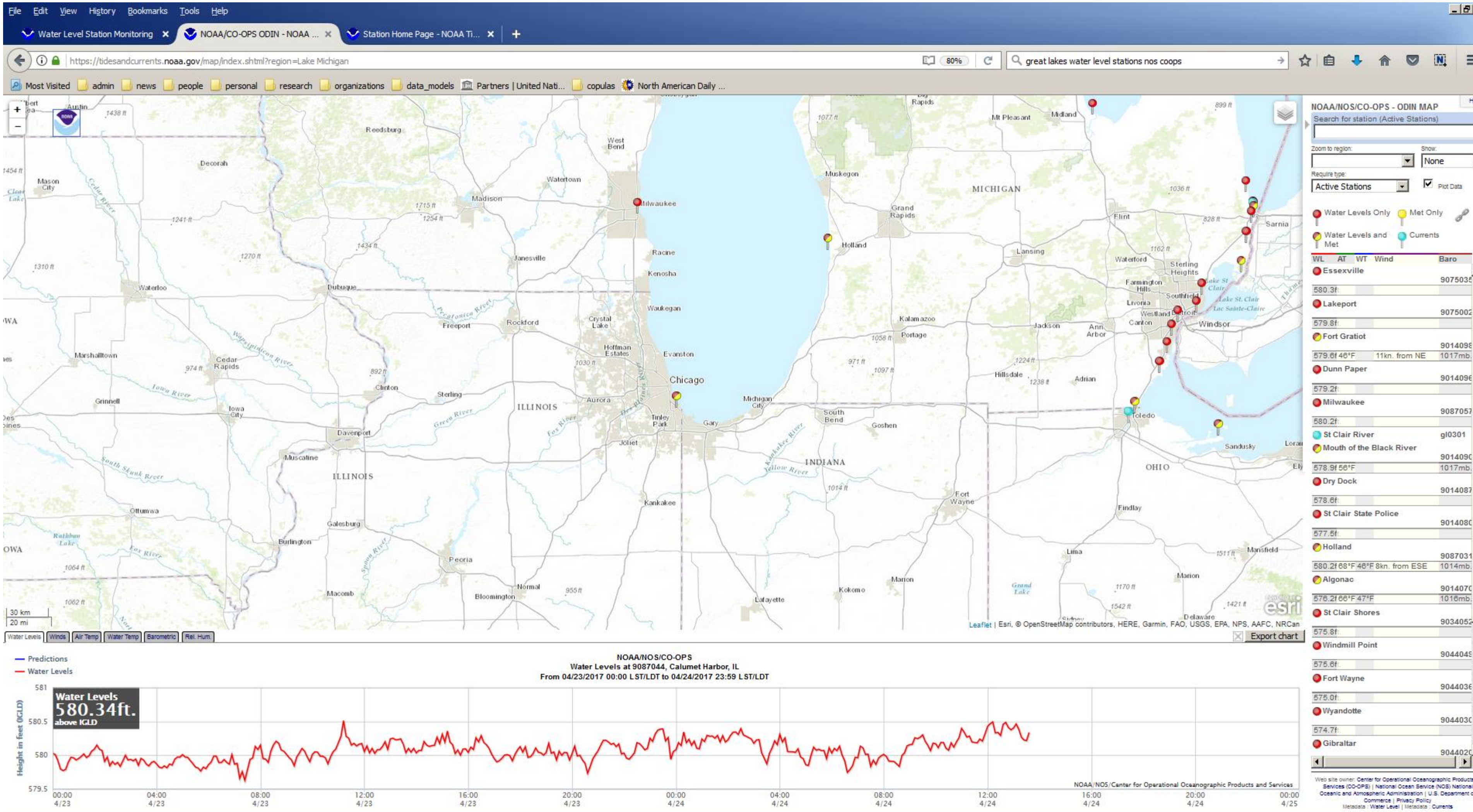
Short-term approaches are necessary since most existing water quality models are not supportive of complete error analysis; thus procedures are needed to immediately (1) conduct an informative, but incomplete error analysis, and (2) use that incomplete error analysis to improve decision making. In the long term, recommendations can be made to (1) restructure the models so that a relatively complete error analysis is feasible, and (2) employ Bayesian approaches that are compatible with adaptive assessment techniques that provide the best approach for improving forecasts over time.

In the short term, if knowledge, data, or model structure prevents uncertainty analysis from being complete, is there any value in conducting an incomplete uncertainty analysis? Stated another way, is it reasonable that decision making will be improved with even partial information on uncertainties, in comparison to current practice with no reporting of prediction uncertainties? Often, but not always, the answer is "yes," although the usefulness of incomplete uncertainty characterization, like the analysis itself, is limited.

Using decision analysis as a prescriptive model, we know that uncertainty analysis can improve decision making when prediction uncertainty is integrated with the utility (or loss, damage, net benefits) function to allow decision makers to maximize expected utility (or maximize net benefits). When uncertainty analysis is incomplete (and perhaps more likely, the utility function is poorly characterized) the concepts of decision analysis may still provide a useful guide.

For example, triangular distributions could be assessed for all uncertain model terms, assuming that correlation is negligible, and then limited systematic sampling (e.g., Latin hypercube)

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Water Levels Winds Air Temp Water Temp Barometric Rel. Hum.
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Zoom to region:
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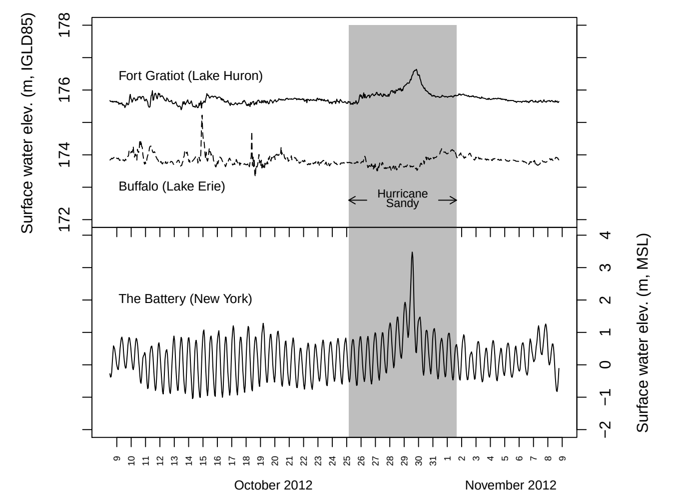
Require type:
Active Stations
Plot Data
Water Levels Only
Met Only
Water Levels and Met
Currents
WL AT WT Wind Baro
Essexville 580.3ft
Lakeport 579.8ft
Fort Gratiot 579.6ft 46°F 11kn. from NE 1017mb.
Dunn Paper 579.2ft
Milwaukee 580.2ft
St Clair River gl0301
Mouth of the Black River 578.9ft 56°F 1017mb.
Dry Dock 578.6ft
St Clair State Police 577.5ft
Holland 580.2ft 68°F 46°F 8kn. from ESE 1014mb.
Algonac 576.2ft 66°F 47°F 1016mb.
St Clair Shores 575.8ft
Windmill Point 575.6ft
Fort Wayne 575.0ft
Wyandotte 574.7ft
Gibraltar
Predictions
Water Levels
NOAA/NOS/CO-OPS
Water Levels at 9087044, Calumet Harbor, IL
From 04/23/2017 00:00 LST/LDT to 04/24/2017 23:59 LST/LDT
Water Levels
580.34ft.
above IGLD
Height in feet (IGLD)
NOAA/NOS/Center for Operational Oceanographic Products and Services



Surface water elev. (m, IGLD85)
178
176
174
172
Fort Gratiot (Lake Huron)
Buffalo (Lake Erie)
Hurricane
Sandy
The Battery (New York)
Surface water elev. (m, MSL)
4
3
2
1
0
−1
−2
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
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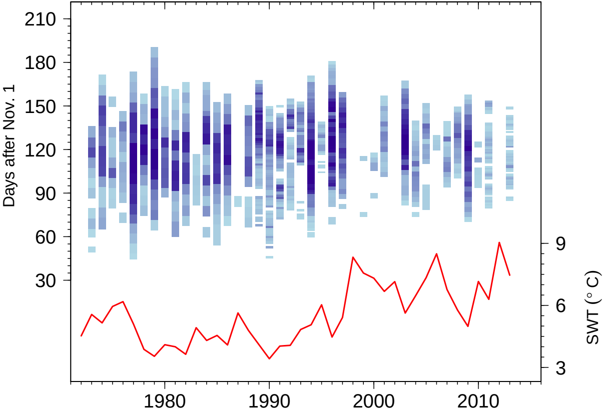
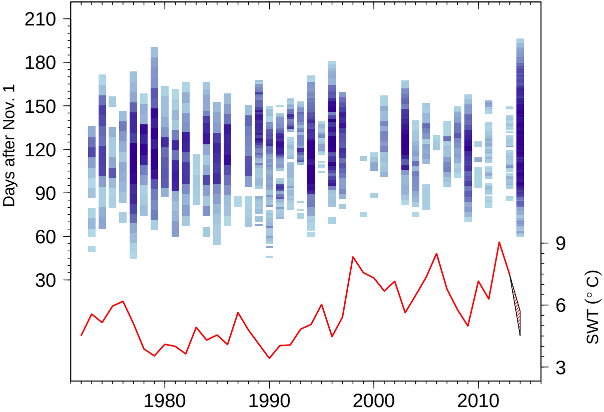
9
October 2012
November 2012



From: Clites et al. (2014), *Eos, transactions of AGU*.
See also: Van Cleave et al. (2014), *L&O*.



From: Clites et al. (2014), *Eos, transactions of AGU*.
See also: Van Cleave et al. (2014), *L&O*.