Quantitative approaches to evaluate surface water quality: Examples from Minnesota Lakes to Florida Estuaries

Marcus W. Beck

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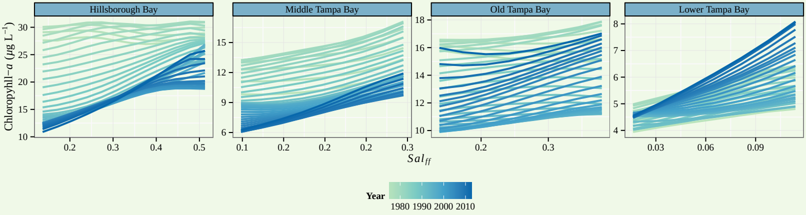
Sep. 22, 2015



Assessing environmental condition

How do we collect and use data?

The foundation of environmental management is a strong monitoring network [National Research Council, 1990]

Monitoring provides information for decision-making based on apparent trends...

What are the changes in environmental condition over time?

Are these changes 'good' or 'bad' based on our management objectives?

What may have caused these changes?

Assessing environmental condition

How do we collect and use data?

The good news: We are getting better at monitoring - standardized, automated, increased coverage, real-time/continuous

The bad news: Our ability to use these data for decision-making has not kept pace with availability!

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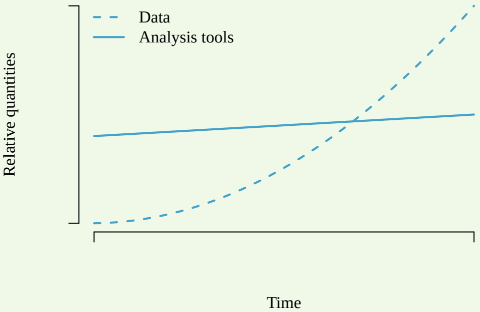

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> *Eutrophication (noun) - an* ***increase*** *in the rate of supply of* ***organic matter*** *to an ecosystem*
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Nutrient Loading

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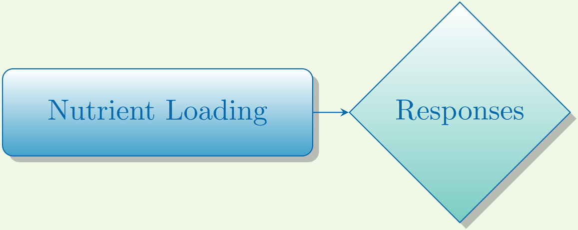

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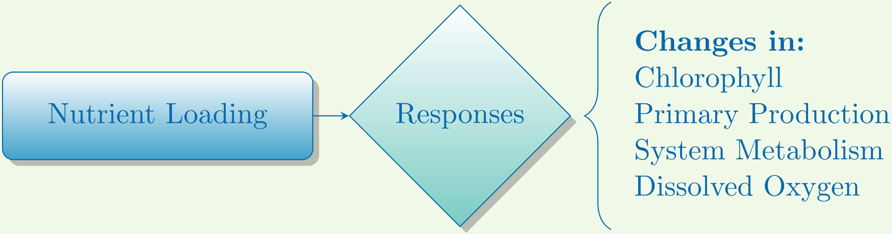

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Assessing environmental condition

How do we collect and use data?

Today's talk: My experience synthesizing and evaluating monitoring data to inform our understanding of the eutrophication paradigm

- ***Case 1***: Understanding response of a biotic index for Minnesota lakes
- ***Case 2***: Evaluating long-term datasets of chlorophyll in Tampa Bay
- ***Case 3***: Development of 'open-science' tools for the National Estuarine Research Reserve System

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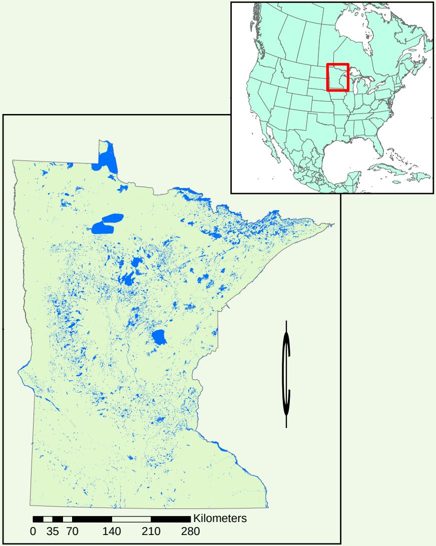
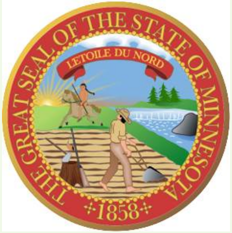
Each case addresses the challenges of ***understanding nutrient dynamics*** and ***developing quantitative tools*** for assessment

Case 1: Minnesota lakes

Evaluating biological response





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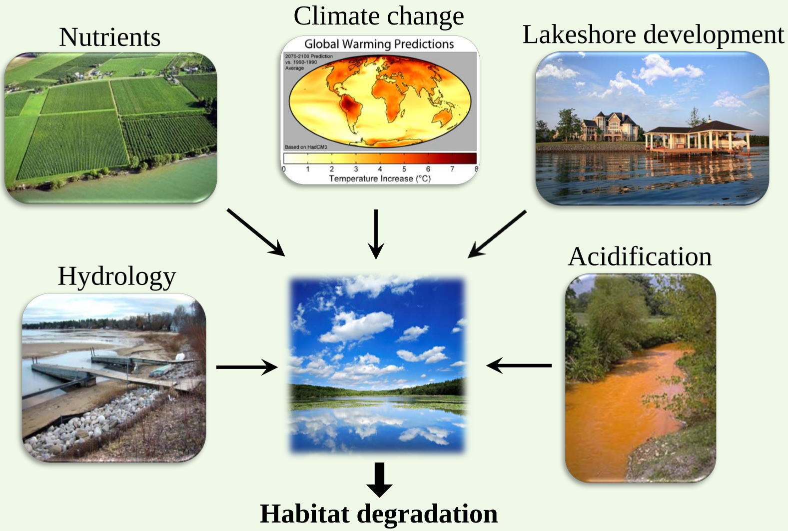

Water Quality Act Amendments of 1972

- Federal mandates to protect and restore the chemical, physical, and ***biological*** integrity of surface waters
- Protection and restoration requires monitoring

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Index of biotic integrity (IBI) [Karr, 1981, Karr et al., 1986]

- Monitoring framework for definition and evaluation of biotic integrity
- Uses aquatic organisms as indicators of ecosystem health
- A multimetric index that is regionally specific

Case 1: Minnesota lakes

Evaluating biological response

The macrophyte IBI can be used to evaluate relative lake condition by monitoring and evaluating aquatic plant metrics [Beck et al., 2010]

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Evaluating biological response

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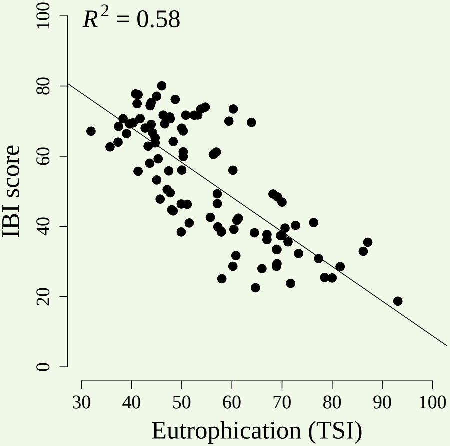
Composed of eight metrics, summed to get one IBI score per lake

- MAXD: Maximum depth of plant growth
- LITT: Percentage of littoral zone vegetated
- OVER: Number of species with frequency occurrence >10%
- EMFL: Relative frequency of emergent-floating species
- SUBM: Relative frequency of submersed species
- SENS: Relative frequency of sensitive species
- TOLR: Relative frequency of tolerant species
- TAXA: Number of native taxa

Related to changes in water quality



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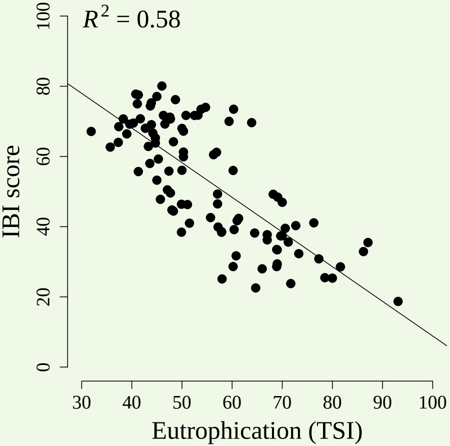
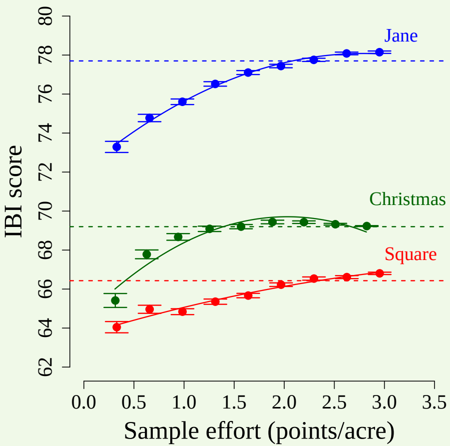


High precision given sampling effort



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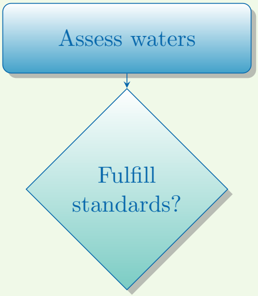

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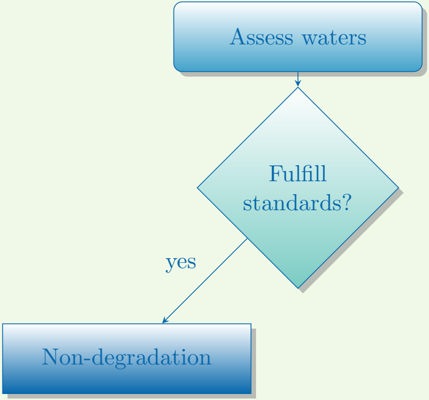

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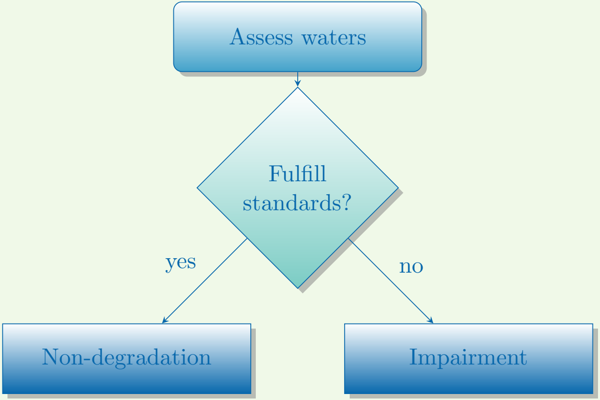

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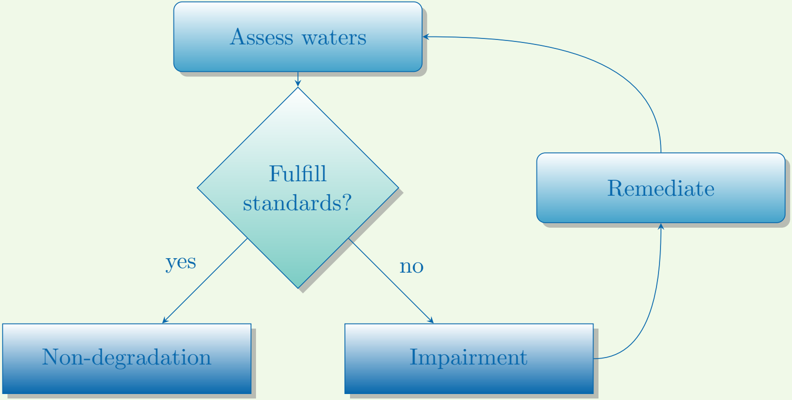

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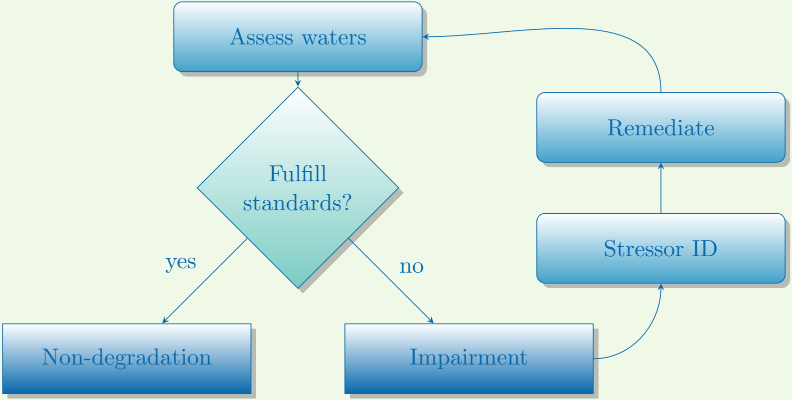

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Evaluating biological response

Consider an IBI with 12 metrics, each scored 1, 3, or 5

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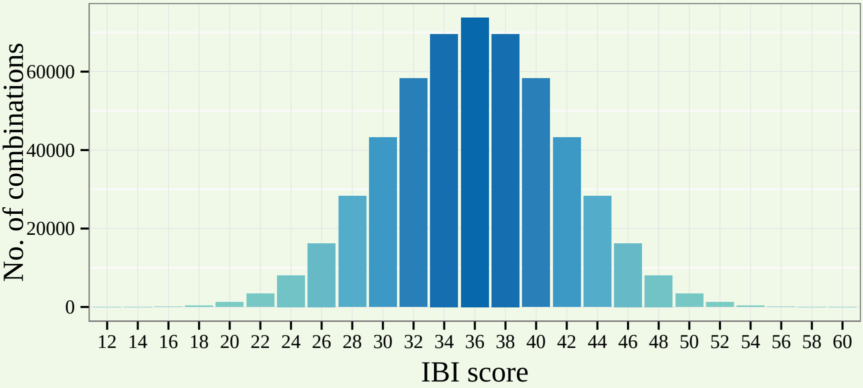

Develop and implement a framework for evaluating the macrophyte IBI to inform its use in biological monitoring:

Case 1: Minnesota lakes

Evaluating biological response

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Develop and implement a framework for evaluating the macrophyte IBI to inform its use in biological monitoring:

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Develop and implement a framework for evaluating the macrophyte IBI to inform its use in biological monitoring:

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Case 1: Minnesota lakes

Evaluating biological response

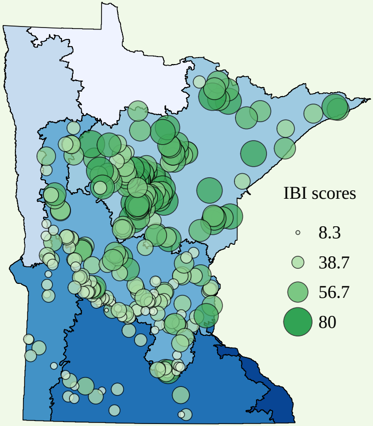
Develop and implement a framework for evaluating the macrophyte IBI to inform its use in biological monitoring:

1. How well does the index distinguish between signal and noise?
2. Can information on stressors and their effects be quantified with certainty?
3. What stressors primarily influence index response?
4. How appropriate is a multimetric index for characterizing effects of multiple stressors?

Case 1: Minnesota lakes

Evaluating biological response

- Dataset of 332 vegetation surveys, courtesy of MNDNR
- Numerous covariates describing lake characteristics and anthropogenic stressors



- lake surface area
- maximum lake depth
- trophic state index
- growing degree days
- percent agriculture in wshed
- percent impervious surfaces in wshed
- density of groundwater wells in wshed
- wshed area to lake area
- crop productivity index of wshed
- dock density
- ...

Case 1: Minnesota lakes

Evaluating biological response

Ecological and numerical complexity warrants the use of creative solutions

Neural networks to model IBI response

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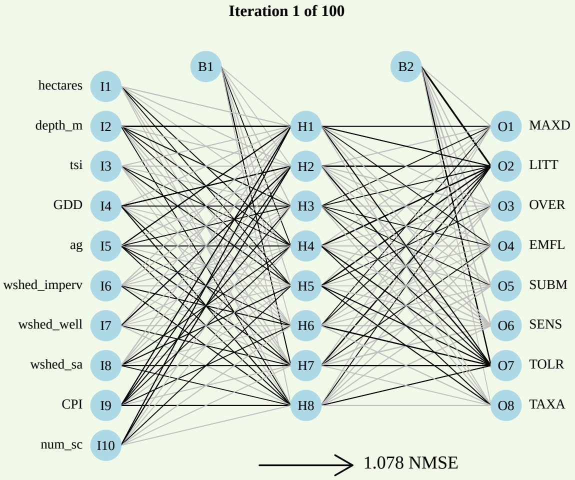
Neural networks to model IBI response

- Essentially a large, non-linear regression model free of assumptions that can handle multivariate response
- Models relationships among variables using a network that mimics neuronal structure of the human brain
- 'Supervised' neural networks are meant for prediction but network information can be used to infer causation

Case 1: Minnesota lakes

Evaluating biological response



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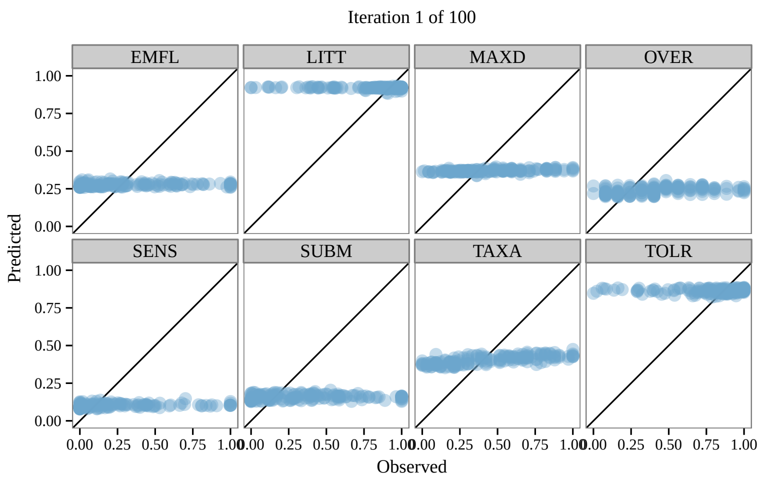
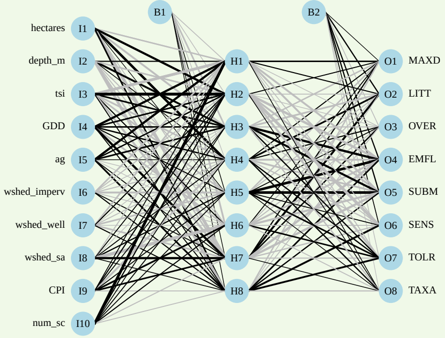
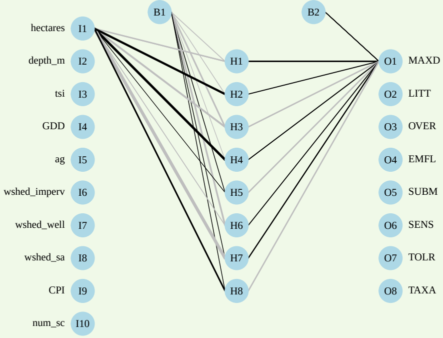


Modification of Garson's algorithm to determine relative importance of variables [Garson, 1991]





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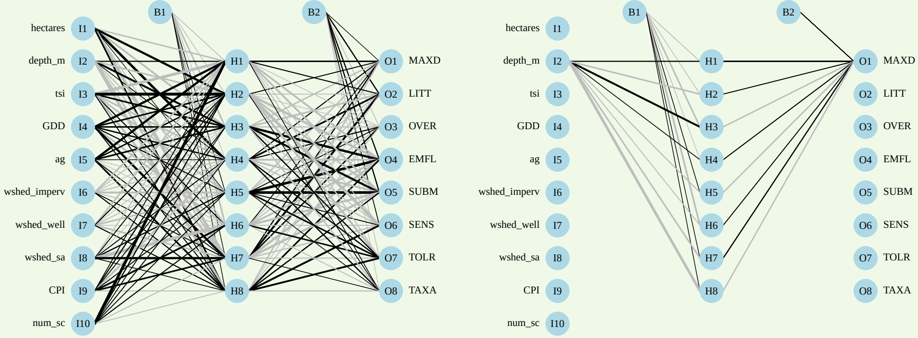

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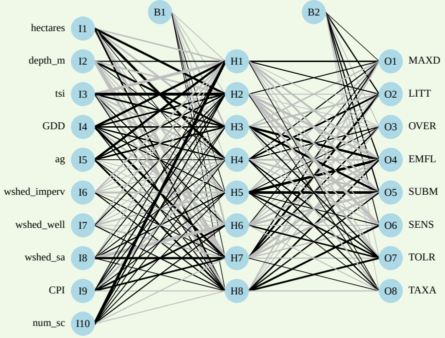

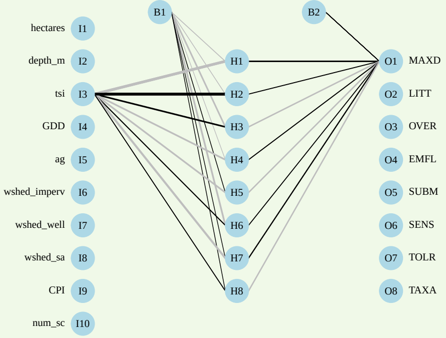

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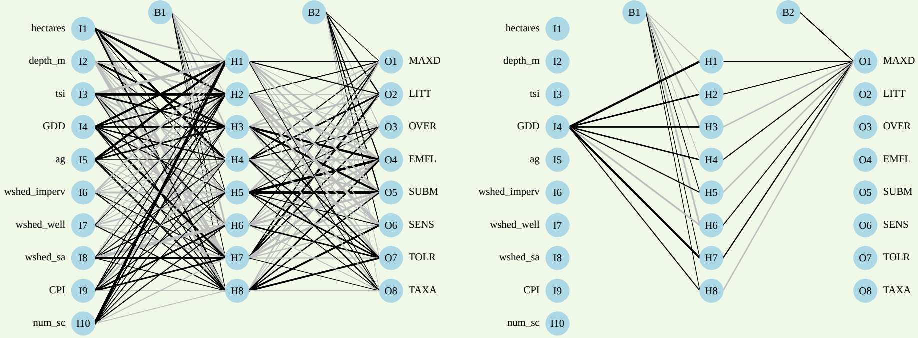

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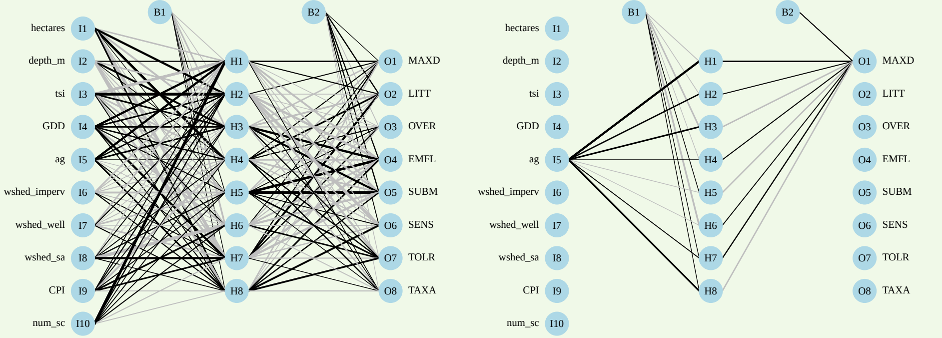

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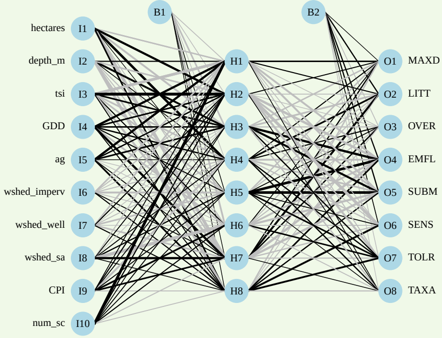

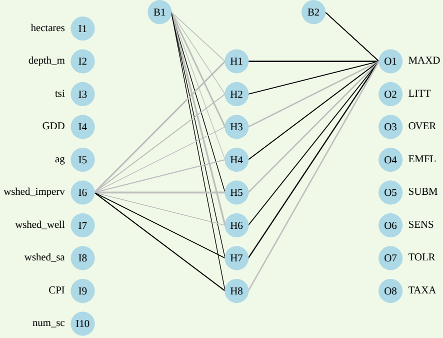

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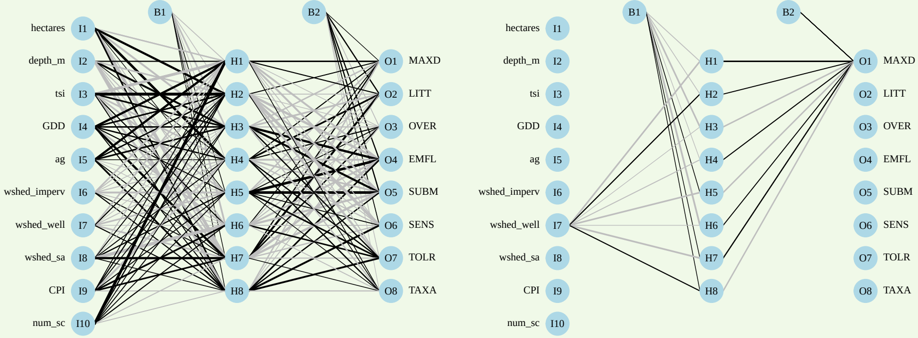

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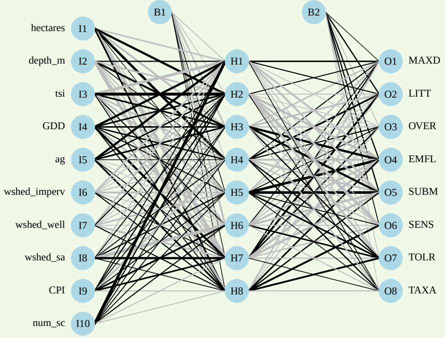

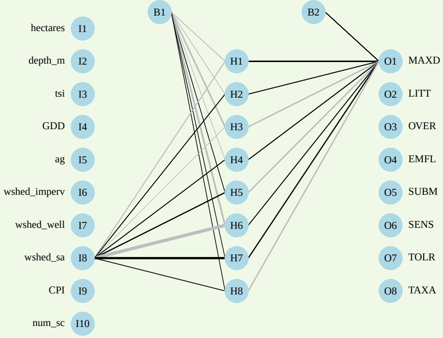

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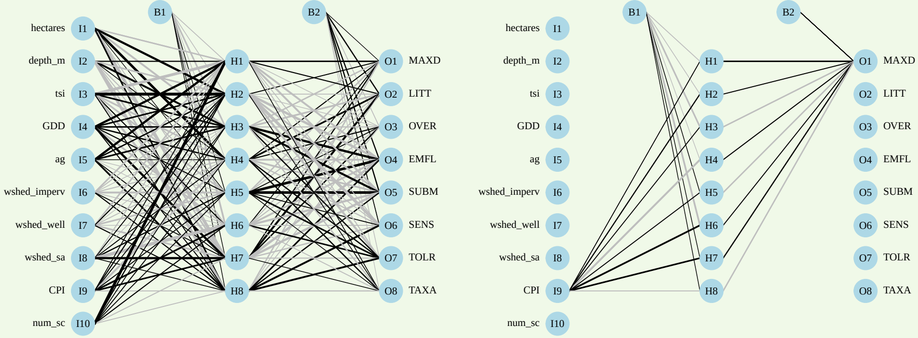

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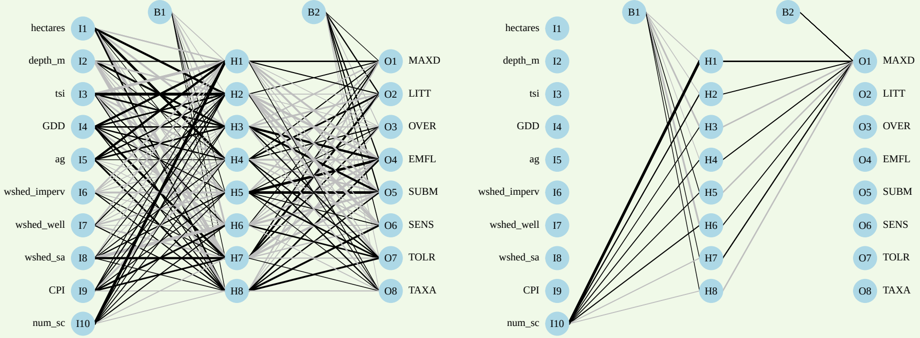

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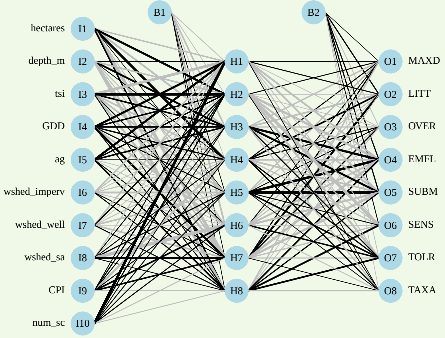

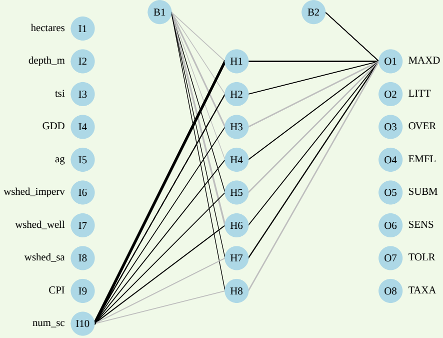

Relative importance is summation of product of weights between layers

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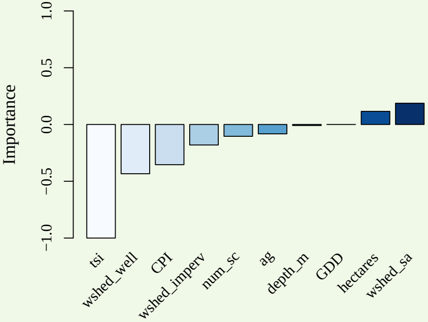
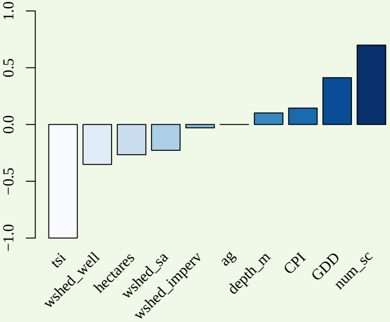


(a) IBI scores



(b) MAXD metric

Figure : Examples of relative importance of explanatory variables based on weights between layers in optimal neural networks.

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Evaluating biological response

Neural networks are powerful enough to model noise in the data

The model may be specific to peculiarities the training dataset

Uncertainty of variable importance must be quantified - bootstrap!

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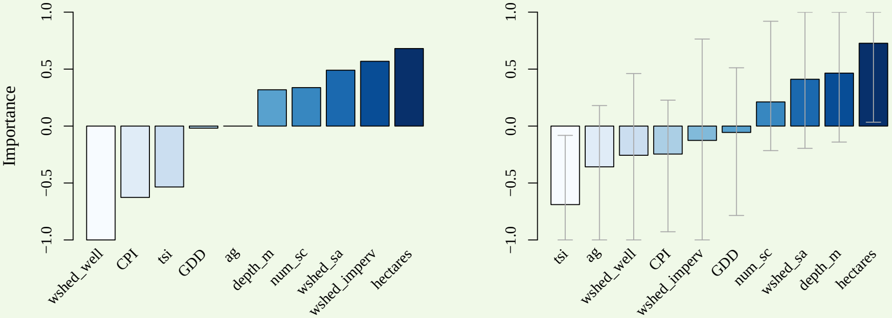

Case 1: Minnesota lakes

Evaluating biological response

Lots of uncertainty associated with input contributions...

- One of ten relationships for IBI scores with explanatory variables
- Four of 80 relationships for metrics with explanatory variables

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What is the source of this uncertainty? Sample sizes, method, neural network?

Potentially competing objectives of an IBI: certainty vs simplicity

Case 1: Minnesota lakes

Evaluating biological response

Potentially competing objectives of an IBI: certainty vs simplicity

> *IBI relies on multiparameters, a requirement when the system to be evaluated is complex. [Karr et al., 1986]*

> *The resulting index allows people without specialized expertise to understand overall condition and to make informed decisions that will then affect the health of those resources. [Karr and Chu, 1999]*

Potentially competing objectives of an IBI: certainty vs simplicity

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Combining responses into an index hides the component responses, thereby obscuring causation. [Suter, 1993]

Case 2: Florida estuaries

Evaluating long-term chlorophyll datasets

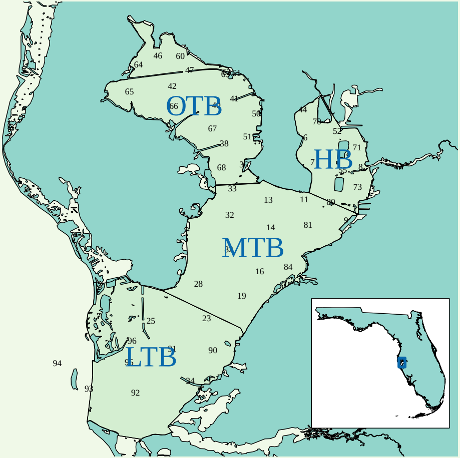
USEPA Gulf Ecology Division - guidance to Florida DEP and others on criteria development for estuaries

Case 2: Florida estuaries

Evaluating long-term chlorophyll datasets

- Four bay segments
- Monthly wq data at 50 stations from 1974 to present
- Longitudinal profile of nutrient load and salinity

Data from [TBEP (Tampa Bay Estuary Program), 2011]



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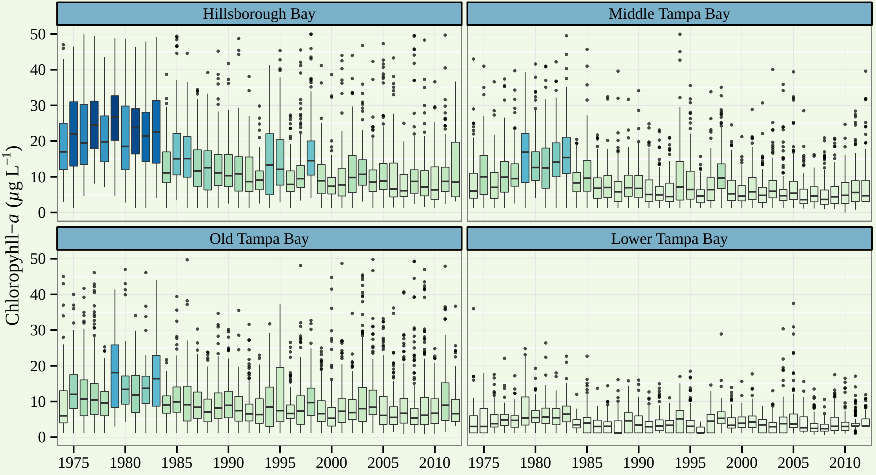

Figure : Annual trends in chlorophyll for each bay segment.

Case 2: Florida estuaries

Evaluating long-term chlorophyll datasets

What affects our interpretation of chlorophyll response to nutrients?

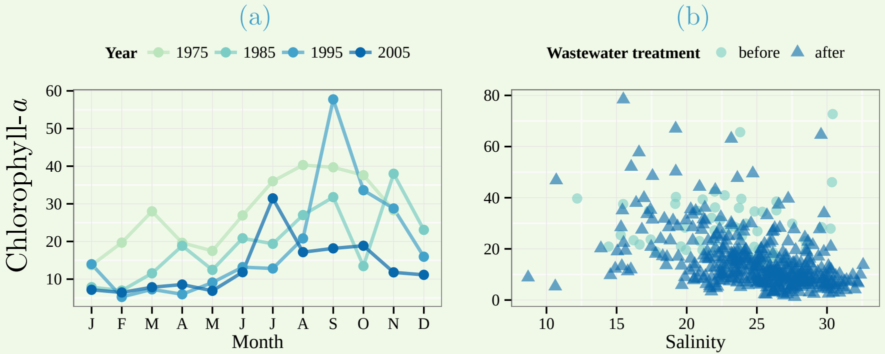

Figure : Variation in chlorophyll by (a) time and (b) salinity and management in Hillsborough Bay. Panel (a) is colored before and after wastewater treatment in 1979.

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Evaluating long-term chlorophyll datasets

Study objective

Adapt and apply nutrient response model for estuaries that leverages the descriptive capabilities of large datasets [Beck and Hagy III, 2015]

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- ...provide a natural history of water quality that is temporally consistent with drivers of change?
- ...characterize changes in extreme events in addition to describing the mean response?
- ...improve our understanding of the nutrient-response paradigm in estuaries?

Case 2: Florida estuaries

Evaluating long-term chlorophyll datasets

The ***weighted regression (WRTDS)*** model is being developed by USGS for pollutant modelling in rivers [Hirsch et al., 2010]

Based on the idea that pollution concentration is a function of ***time***, ***discharge***, and ***season***

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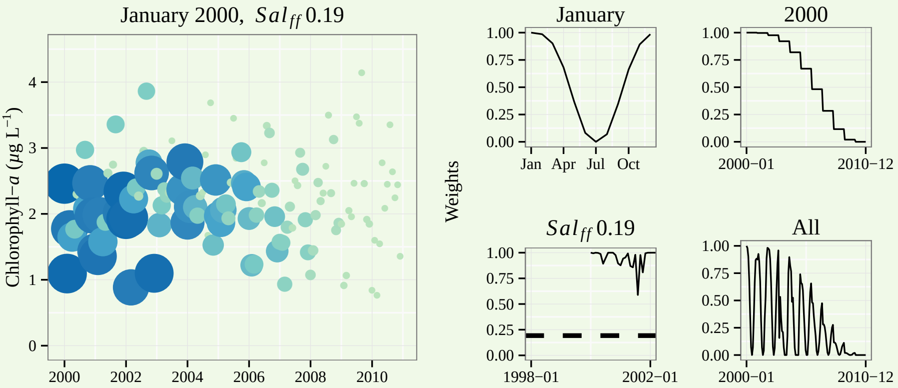
Adaptation: Can this approach be used to evaluate chlorophyll trends in Tampa Bay?

How does weighted regression work?



Case 2: Florida estuaries

Evaluating long-term chlorophyll datasets

This gives us improved predictions of chlorophyll dynamics...

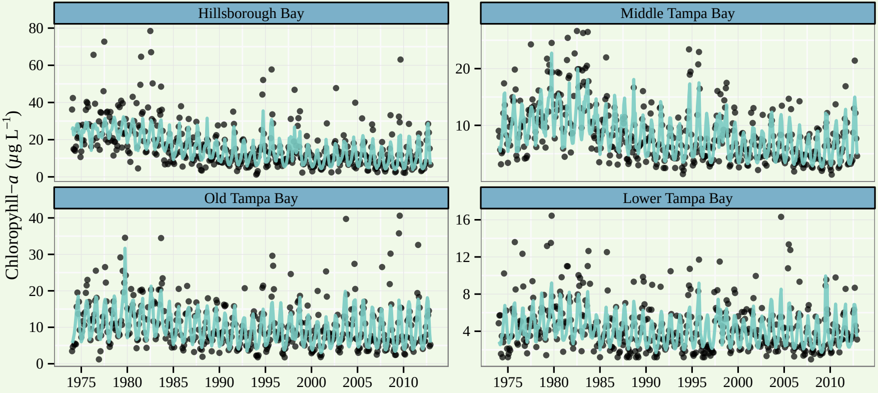
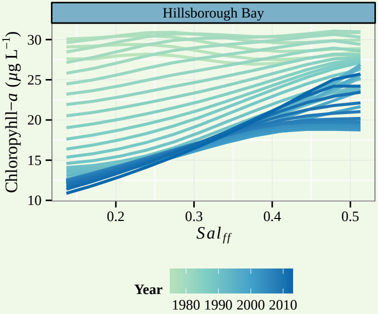


Figure : Predicted and observed monthly chlorophyll by segment.

Case 2: Florida estuaries
Evaluating long-term chlorophyll datasets

Because the model is dynamic, we have parameters describing the relationship of chlorophyll with other factors specific to different time periods



- Early period (light blue) - point-sources
- Late period (dark blue) - non-point sources
- Chlorophyll shows increasing response to freshwater input in recent years

Case 2: Florida estuaries

Evaluating long-term chlorophyll datasets

What does this mean for Tampa Bay and elsewhere?

- Predictions followed observed chlorophyll – but increased clarity in the description
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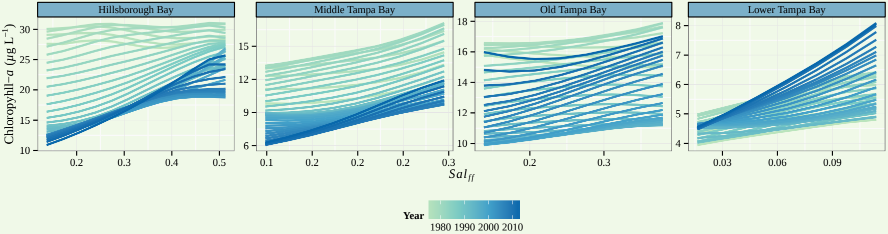
The model parameters show us a picture...



Case 3: Open-source science

Analysis tools for water quality data

Progress in science is incremental and builds on past work

This requires accurate reproduction of methods

The ability to reproduce methods will always be a challenge...

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Analysis tools for water quality data

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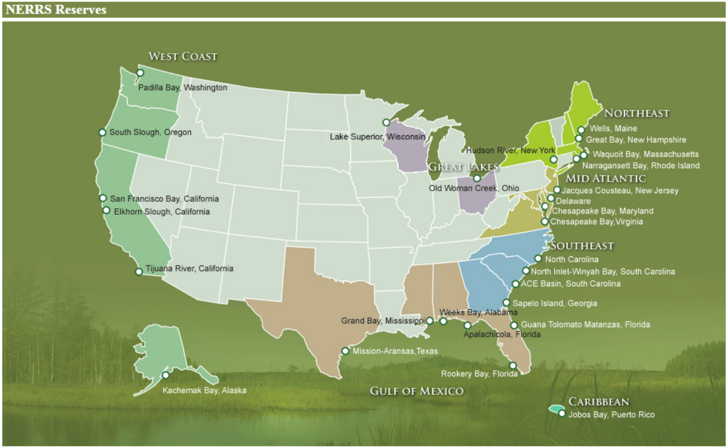
The ability to reproduce methods will always be a challenge...

...digital tools have proliferated to ***facilitate sharing***

Case 3: Open-source science

Analysis tools for water quality data

The NERRS System-Wide Monitoring Program...



Case 3: Open-source science

Analysis tools for water quality data

The SWMP database and others like it represent incredible opportunities to further our knowledge of natural systems...

...including the effects of eutrophication

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The SWMP database and others like it represent incredible opportunities to further our knowledge of natural systems...

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Problem: These data are numerous and not easily compared

Solution: Develop open-source tools that address the challenges of large-scale comparative analyses with continuous monitoring data

The benefits include:

- Free for use by anyone
- Free to collaborate
- Facilitation of analysis with 'under-the-hood' functionality

Case 3: Open-source science

Analysis tools for water quality data

Each reserve has fixed, continuous monitoring stations for ***water quality*** (15 min), ***meteorology*** (15 min), and ***nutrients*** (monthly)

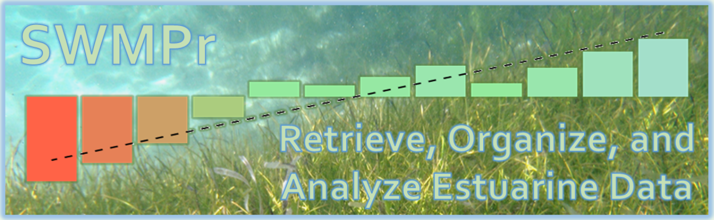
As of this month, > 60 million records available online

Raw data look like this:

	A	B	C	D	E	F	G	H	I	J	K	L
1	StationCo	isSWMP	DateTimeStamp	Historical	Provisiona	CollMetho	REP	F_Record	PO4F	F_PO4F	NH4F	F_NH4F
2	apacpnut	P	1/10/2012 10:20	0	1	1	1		0.003	<-4> [SBL]	0.03	<0>
3	apacpnut	P	2/7/2012 11:41	0	1	1	1		0.005	<0>	0.019	<0>
4	apacpnut	P	3/5/2012 11:51	0	1	1	1		0.003	<-4> [SBL]	0.041	<0>
5	apacpnut	P	4/4/2012 10:30	0	1	1	1		0.003	<-4> [SBL]	0.043	<0>
6	apacpnut	P	5/9/2012 10:12	0	1	1	1		0.003	<0>	0.053	<0>
7	apacpnut	P	5/9/2012 10:15	0	1	1	2		0.003	<-4> [SBL]	0.022	<0>
8	apacpnut	P	5/9/2012 10:20	0	1	1	3		0.003	<0>	0.016	<0>
9	apacpnut	P	6/5/2012 8:30	0	1	1	1		0.003	<-4> [SBL]	0.04	<0>
10	apacpnut	P	7/3/2012 9:58	0	1	1	1	{CSM}	0.004	<0>	0.094	<0>
11	apacpnut	P	7/3/2012 9:59	0	1	1	2	{CSM}	0.004	<0>	0.066	<0>

Case 3: Open-source science

Analysis tools for water quality data



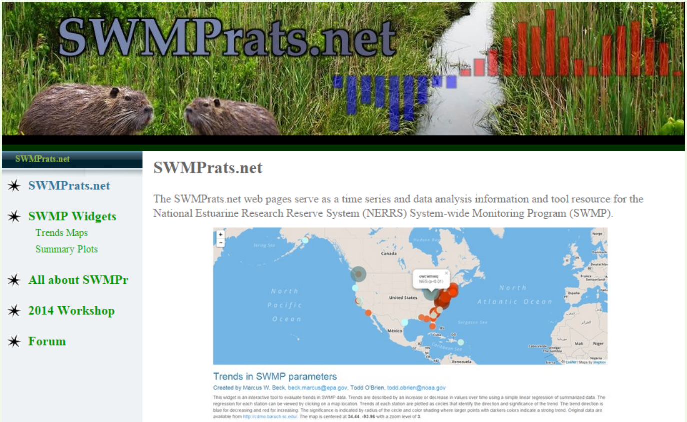
SWMPr is a freely available package for use with R

- ***Retrieve*** SWMP data for any site and date combination
- ***Organize*** the data using standard pre-processing techniques
- ***Analyze*** the data using a suite of exploratory and graphical analysis tools

Case 3: Open-source science

Analysis tools for water quality data

SWMPrats.net: ***S***ystem-***W***ide ***M***onitoring ***P***rogram ***R***esources for the ***A***nalysis of ***T***ime ***S***eries

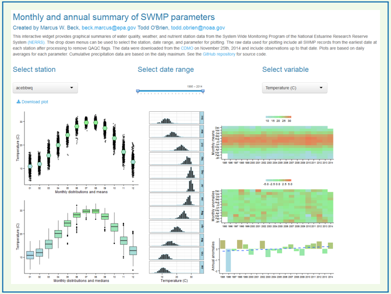


Case 3: Open-source science

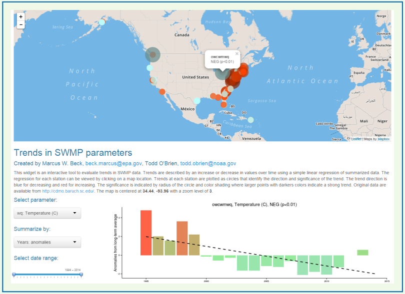
Analysis tools for water quality data

Two online applications can help visualize trends

Summary plots



Trends map



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Tools in the SWMPr package have facilitated comparative analyses of millions of water quality records from NERRS

These tools can help improve our understanding of nutrient pollution and eutrophication

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Analysis tools for water quality data

Tools in the SWMPr package have facilitated comparative analyses of millions of water quality records from NERRS

These tools can help improve our understanding of nutrient pollution and eutrophication

Potential for many other applications... actively being developed

Conclusions

The analysis of water quality will continue to require the use of novel techniques to interpret the data

These needs are motivated by:

- The continued relevance of stressors that influence ecosystem conditions
- Our increasing ability to gather raw, uninterpreted data

Our methods must be able to make sense of ***historical trends***, as well as predict ***future conditions***

Conclusions

Our ability to ***share***, ***reproduce***, and ***collaborate*** is essential

SWMPr package: https://github.com/fawda123/SWMPr

Summaries of SWMP parameters:
https://beckmw.shinyapps.io/swmp_summary

Trends in SWMP parameters:
https://beckmw.shinyapps.io/swmp_comp

This presentation: https://github.com/fawda123/ncea_pres

Github: github.com/fawda123/

Blog: beckmw.wordpress.com/

Acknowledgments:

Research staff and employees at USEPA Gulf Ecology Division - especially J. Hagy, M. Murrell

Field staff and data managers at Hillsborough County Environmental Protection Commission

Research coordinators, technicians, and field staff of the National Estuarine Research Reserve System

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