Status of Nutrient and Lower Food Web Modeling for Saginaw Bay Multi-Stressor Project

Saginaw Bay Multiple Stressor Modeling Team

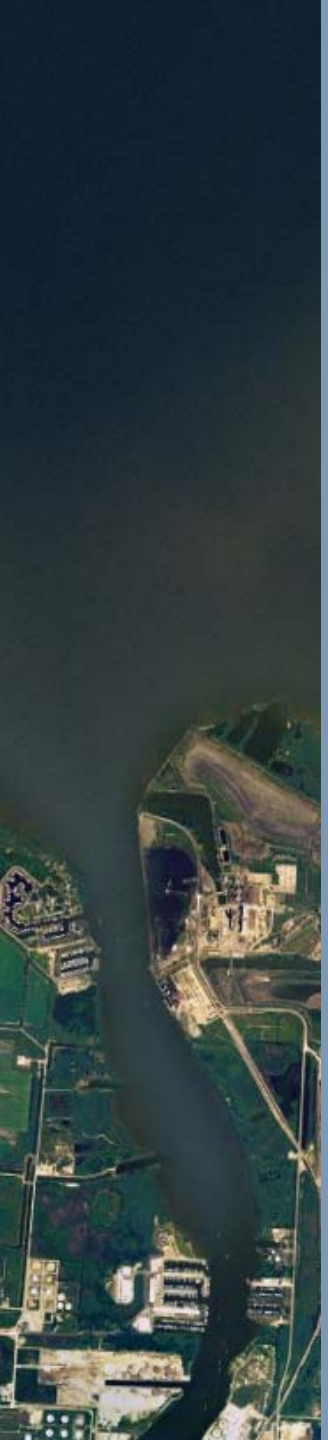
Dave Millie, University of South Florida

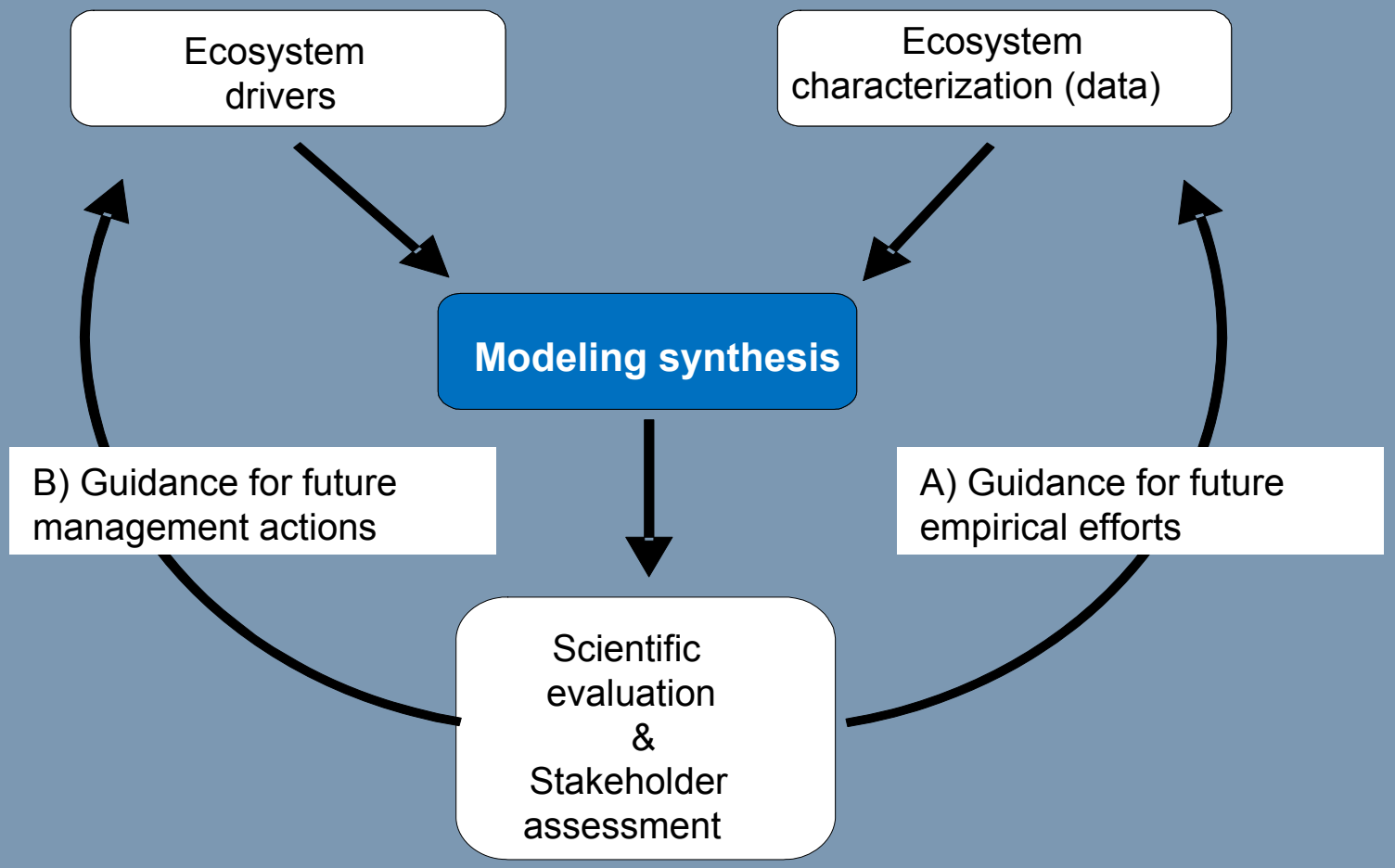
Craig Stow, GLERL

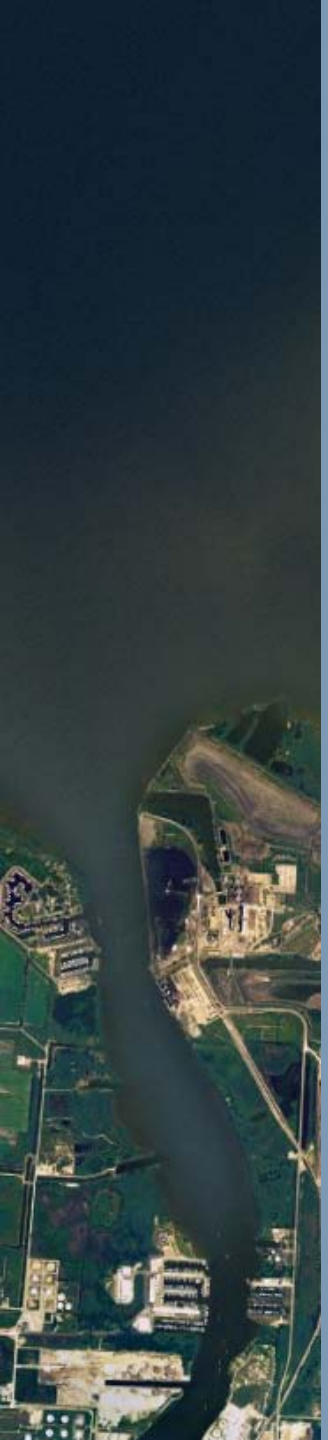
Dima Beletsky, University of Michigan – CILER

Joe DePinto, Ed Verhamme, Todd Redder, LimnoTech

Models are central to Adaptive Integrated Framework (AIF)







Three Water Quality Modeling Efforts in the Bay

- Empirically-based Statistical Modeling
  - **Dave Millie** – Non-parametric Regression Analysis
- Empirically-based Network Modeling
  - **Craig Stow** – Bayesian Probability Network
- Process-Oriented Modeling
  - **Dima Beletsky** – whole lake and nested bay-lake hydrodynamic models
  - **LimnoTech** – linked hydrodynamic – Advanced nutrient-lower food web model

Saginaw Bay *Multistressors* - Millie FY 2009 Accomplishments

Statistical-Based Characterization of Phytoplankton, 1990 - 1996

- Finalized temporal (inter-/intra-annual) and spatial (inner/outer Bay) characterization of phytoplankton dynamics, with attention to dominant and toxic species;
- Completed non-parametric modeling of *Microcystis* biovolumes incorporating *in situ* and/or meteorological predictor variables;
- Initialized manuscript preparation of above work;
- Technology Transfer, concerning *Multistressor* work:
  - *IAGLR* Annual Meeting (contributed presentation; May, 09) & University of South Carolina (invited seminar; November, 09)
  - Weckman, G., Millie, D., Ganduri, C. , Rangwala, M., Young, W., Fahnenstiel, G. 2009. Knowledge extraction from the neural 'black box' in ecological monitoring. *J. Indust. Syst. Engin.* 3: 38-55

Data-Driven Modeling of Saginaw Bay Phytoplankton

Dave Millie's Approach

- **Premise:**
- **Interacting abiotic/biotic parameters create environmental gradients responsible for transitory-patterns of assemblages,**
- **Suites of parameters serve as distribution/pattern 'predictors'**
- **Conversely:**
- **Linear associations among abiotic/biotic parameters typically do not exist - parameters combine additively or multiplicatively,**
- **Modeling success dependent upon characterizing non-linear (and often stochastic) patterns and processes.**
- **Modeling ecological (realized) rather than fundamental niches:**
- **Artificial Neural Networks: adaptive training - 'learns' any response-predictor pattern given enough data & processing capacity; enables prediction & qualitative data exploration ... BUT - I also will argue for quantitative evaluation !**
- **Non-Parametric Regression: link function between mean response & 'smoothed' predictors among data subsets; enables qualitative data exploration**
- **'Zero-Inflated' Nonlinear Mixed Models: account for both binary (presence-absence) & continuous count distributions; enables quantitative data evaluation**

Non-Parametric Multiplicative Regression (NPMR)

Creating Species Response Surfaces in Multidimensional Space

$$y_i = \alpha + f_i(x_{i1}) + f_2(x_{i2}) + f_3(x_{i1}\, x_{i2}) + \varepsilon_i$$

with $f_{i..x}$ (partial regression functions) estimated from data weighting functions

- **Components are combined multiplicatively (ecological factors do not combine additively !)**
  - **No assumption of linearity**
  - **Variable effects dependent upon effects of other variables**
  - **Easily copes with multiple dimensions (negates 'Curse of Dimensionality' - *the incre in variance with increasing number of independent variables*)**
- **Optimizes "fit' within data-subset 'neighborhoods':**
  - **Does not assume a particular response shape (e.g. linear, polynomial, etc.)**
  - **Iteratively combines multiple, linear model terms (for data-subset neighborhoods) t form a non-linear response surface**
- ✓ **Disadvantages:**
  - **Computationally intensive,**

‘Best’ Models - Non-Parametric Multiplicative Regression

Microcystis vs. Candidate *In Situ* Predictors

Local Mean Model - xR^2 = 0.69; *N = 16.1

Predictors (Tolerance)

°C (2.89)

TP (5.72)

SiO_2 (0.24)

Local Linear Model - xR^2 = 0.85; *N = 15.5

Predictors (Tolerance)

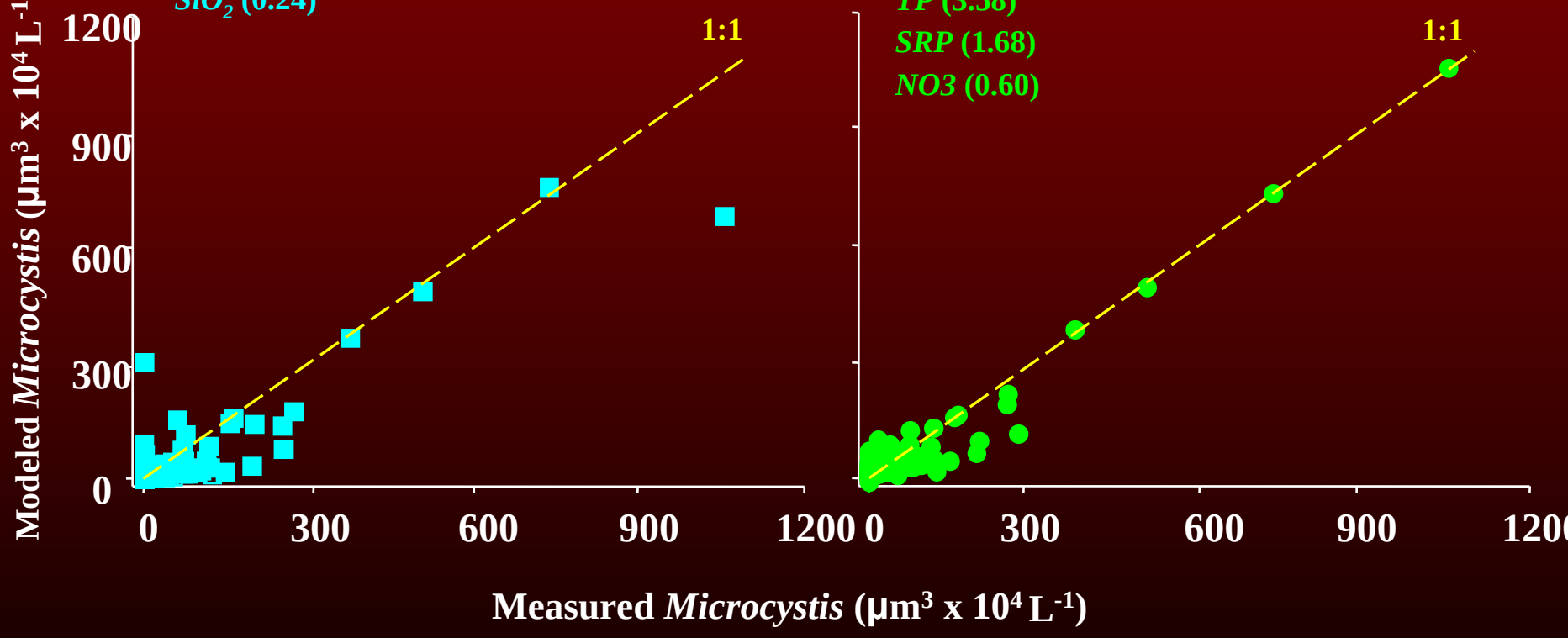
°C (1.92)

Secchi (2.75)

TP (3.58)

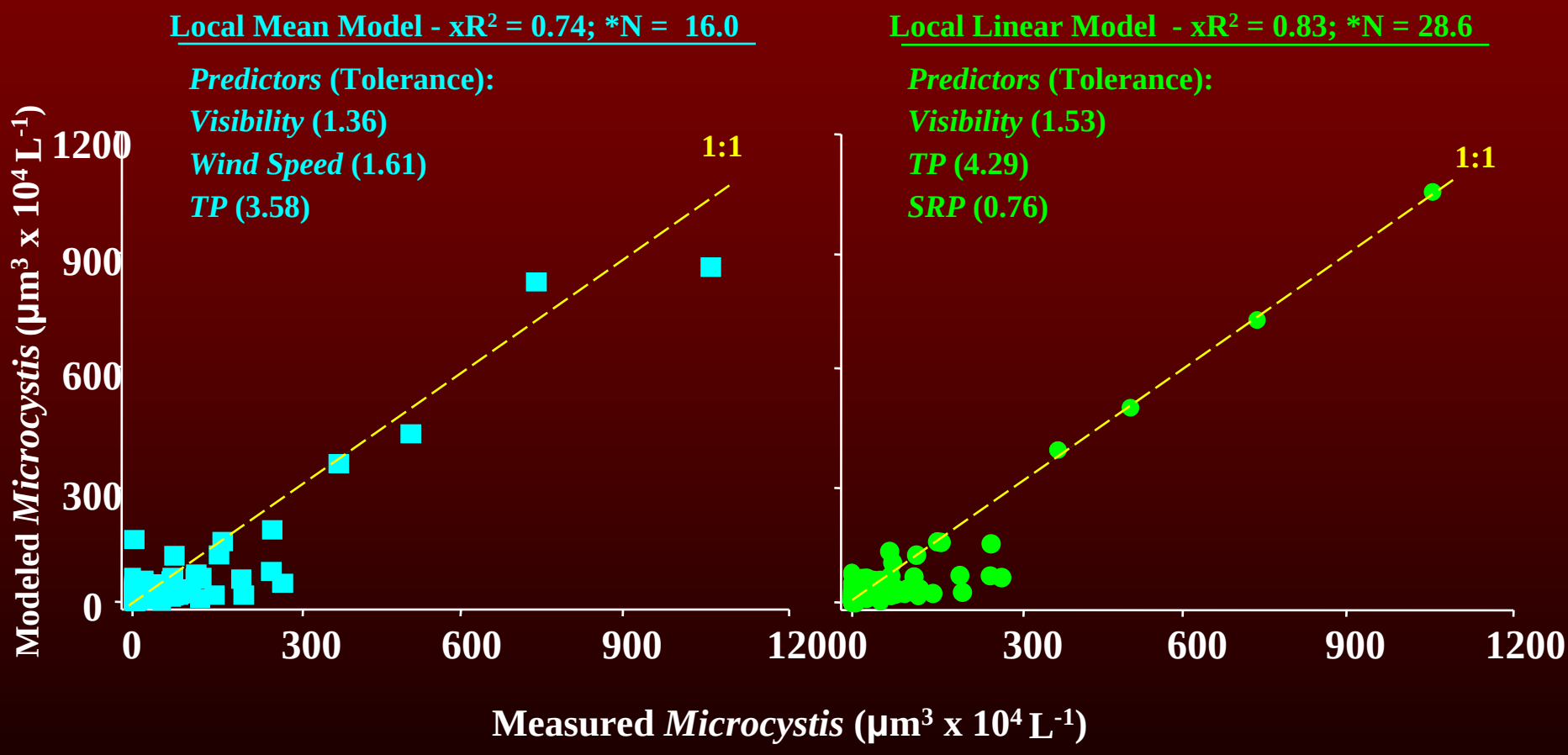
SRP (1.68)

NO3 (0.60)



‘Best’ Models - Non-Parametric Parametric Regression

Microcystis vs. Candidate *In Situ* & Meteorological Predictors



What Dave Millie is Doing Now.....

Why 'Zero-Inflated', Non-Linear Mixed Models ?

- Non-Linear mixed models – *QUANTITATIVE* regression modeling
  - Fixed (X_i) & random (R_i) predictor effects enters nonlinearly into model:

$$Y_i \sim f(X_i) + R_i + e$$

  - Accounts for overall nonlinear (mean) structure & both inter-subject variability & intra-subject correlation and heterogeneity
- However, excessive zeros in *Microcystis* count data arise, if:
  - *Microcystis* is absent due to ecological process - i.e. habitat unsuitability; a 'TRUE' ZERO (binary distribution; or presence-absence; Pr(Y=0)
  - *Microcystis* occupies site, but absent at collection or missed - e.g seasonal occurrence, inadequate sampling; a 'FALSE' ZERO (continuous count distribution; Pr ($Y \geq 0$)
- *Microcystis* modeled as a function of both binary & continuous distributions:

$$\Pr(Y_i \mid x_i, z_i) = [p_i + (1-p_i)*P(y_i \mid x_i = 0)] + (1-p_i)*[P(Y=1) + P(Y=2) + \ldots)] = 1$$

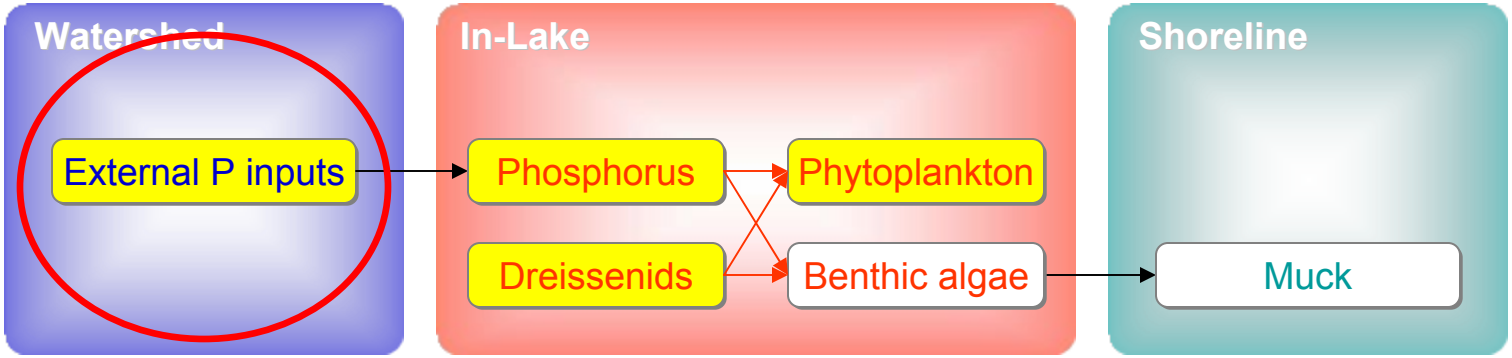
< ------ Pr(Y=0) ------ > < ---------- Pr($Y \geq 0$) ---------- >

where: p_i depends upon the predictors ($z_{1..i}$), $P(y_i \mid x_i = 0) = g(\mu_i)$ - the function of the logit distribution, and $[P(Y=1) + P(Y=2) + \ldots)] = f(\mu_i)$ - the function of the poisson (or negative binomial) distribution

after Guisan et al. 2002, *Ecol. Model* & Marten et al. 2005, *Ecol. Lett.*

Bayesian Probability Network

Conceptual Overview



Prepared by Yoonkyung Cha – *Duke University*

Bayesian Probability Network

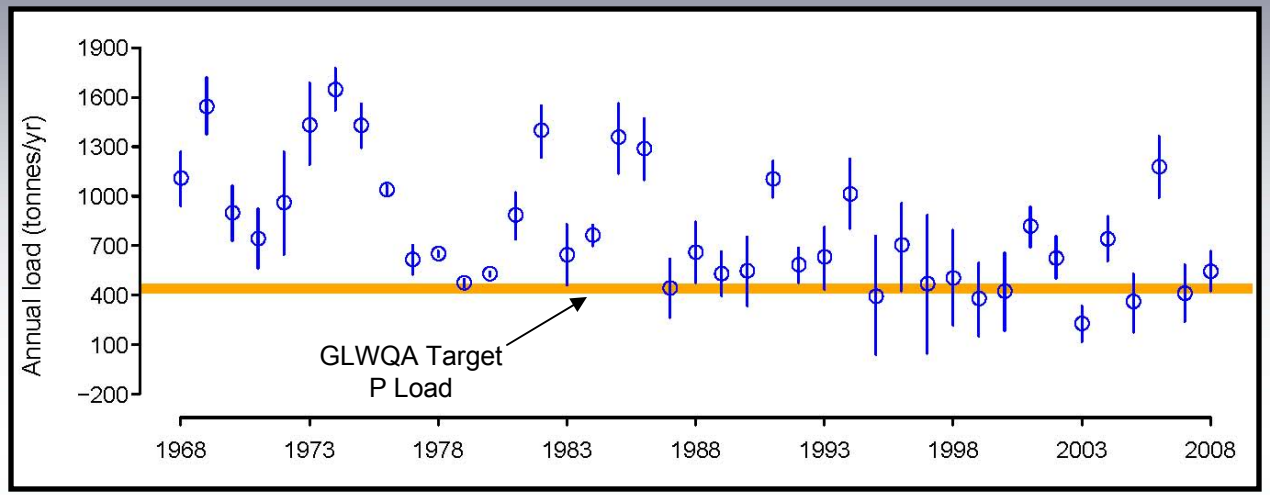
External P inputs

Saginaw River Annual TP Loads

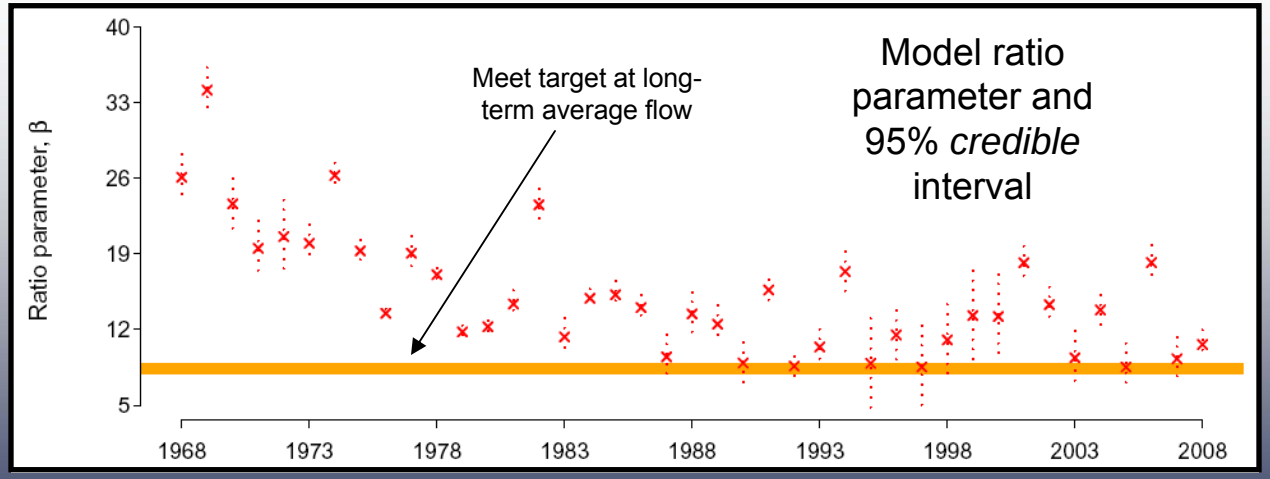
Partial-pooling across years using a Bayesian hierarchical model

Mean and 95% *credible* interval

Varying river flow partially obscures trend



Varying river flow effect removed
Trend clearer



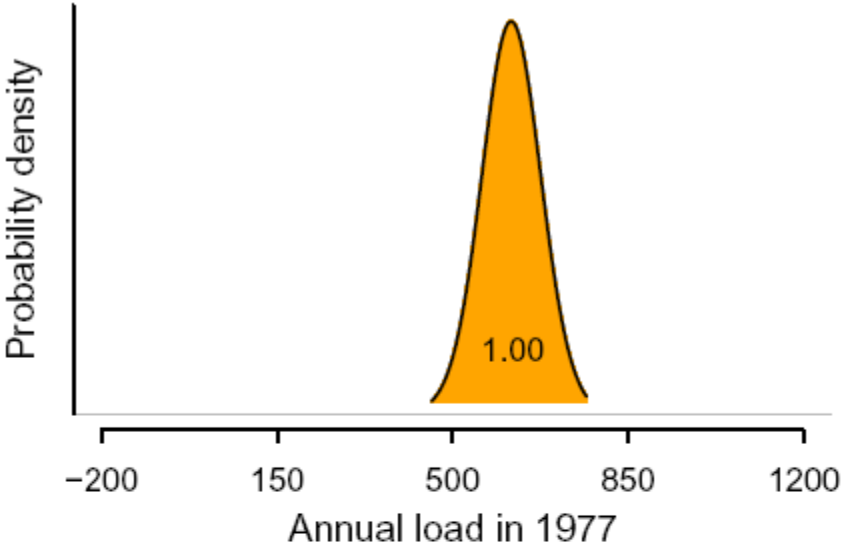
Bayesian Probability Network

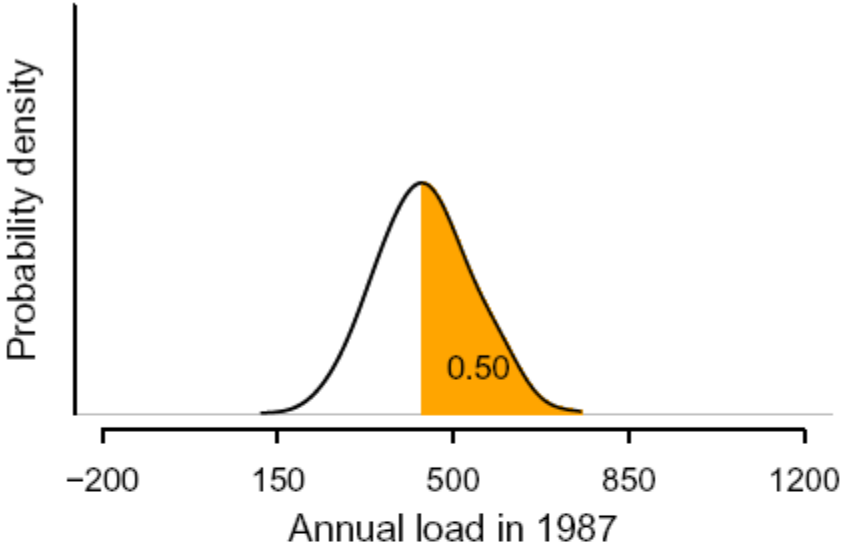
External P inputs

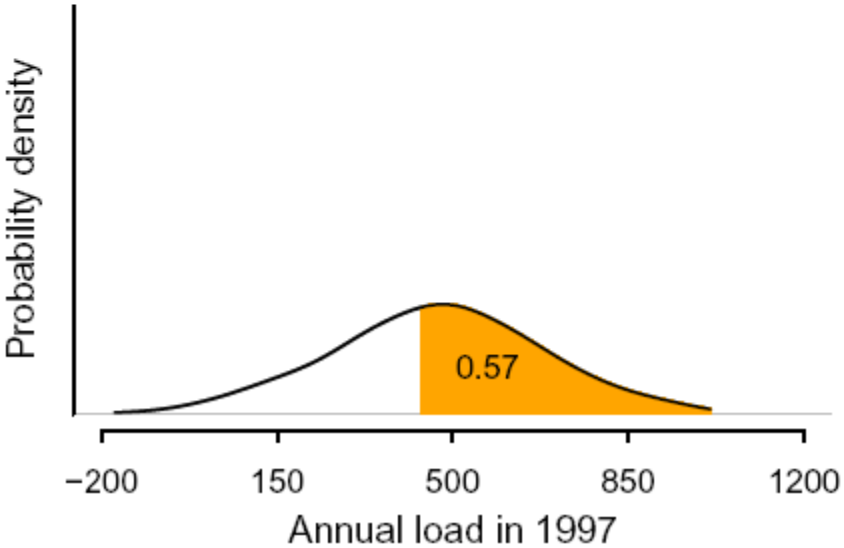
Advantage – we can evaluate

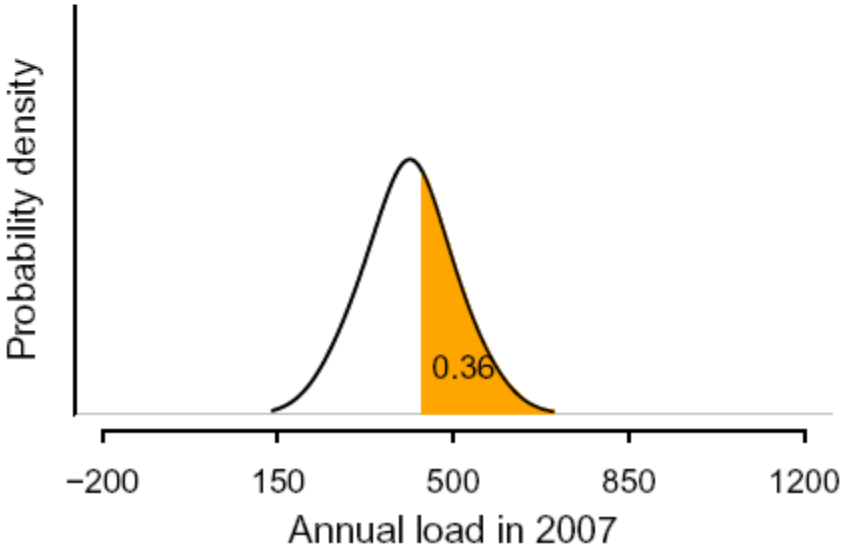
Probability Target Load Exceeded

Saginaw River Only



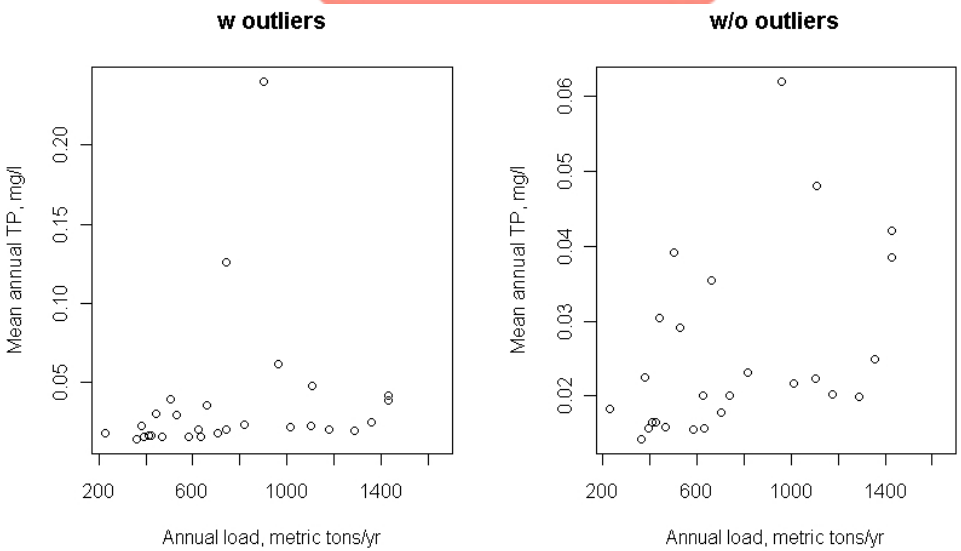






Bayesian Probability Network

Next Steps



Weak Empirical Relationship between TP Load and Concentration

Therefore, dynamic mass balance TP model

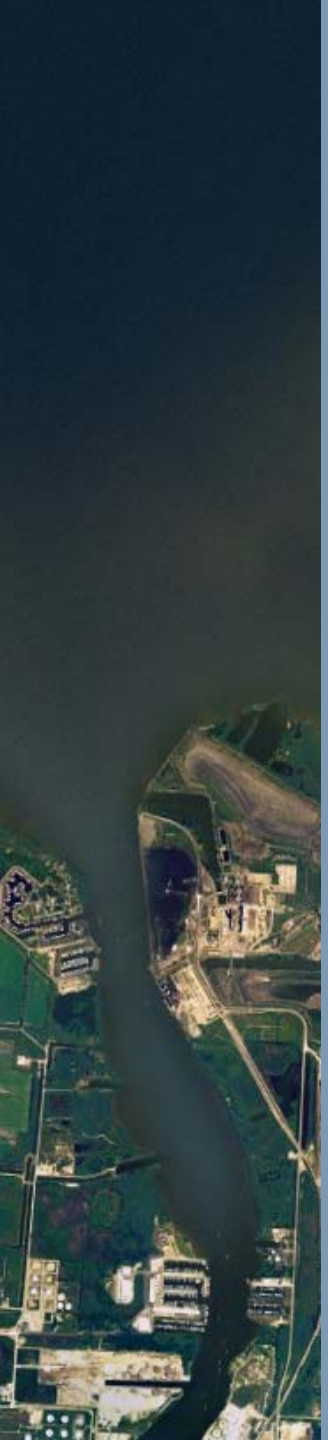
In-lake changes with time = external loading – output – (sedimentation + internal loading)

Programmed into WinBUGS

Empirical chl-a model

Phytoplankton (chl-a) ~ f (TP)

Forthcoming…



PROCESS-ORIENTED BAY MODELING

Mechanistic, deterministic modeling of the relationship between external forcing functions (loads, hydrometeorology) and *in situ* water quality and lower food web response variables

Hydrodynamic modeling program goals

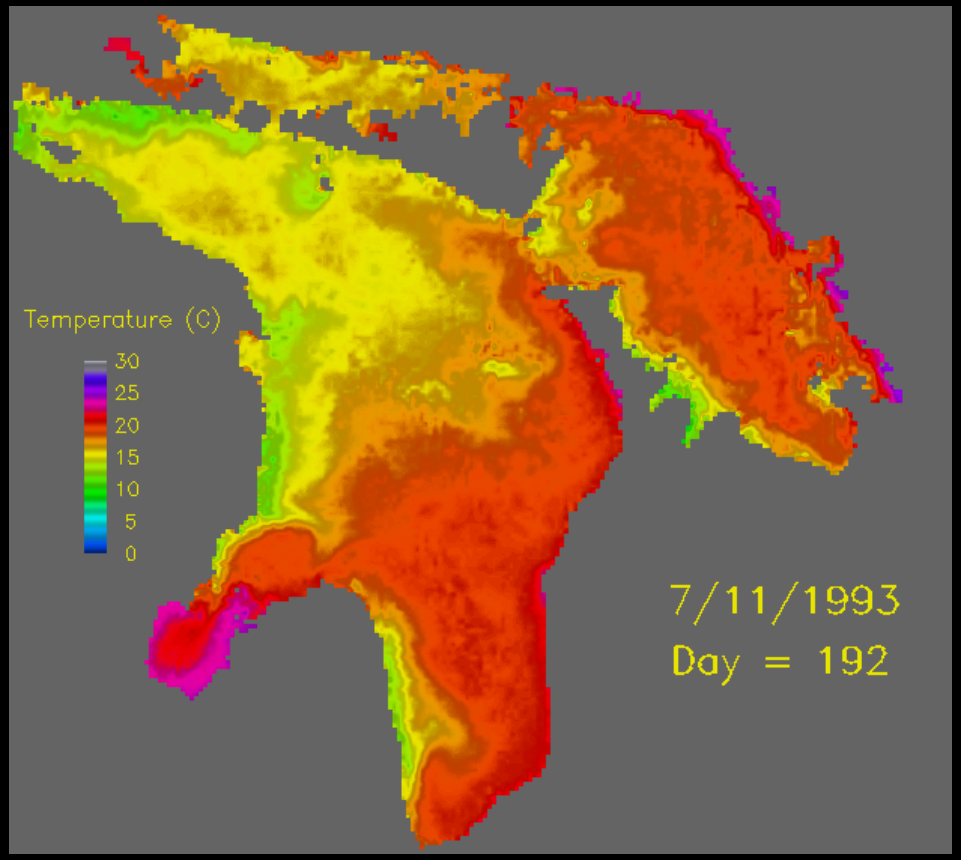
- To determine circulation patterns and residence time of Saginaw Bay
- To calculate resuspension potential
- To validate circulation patterns in the open-boundary EFDC model

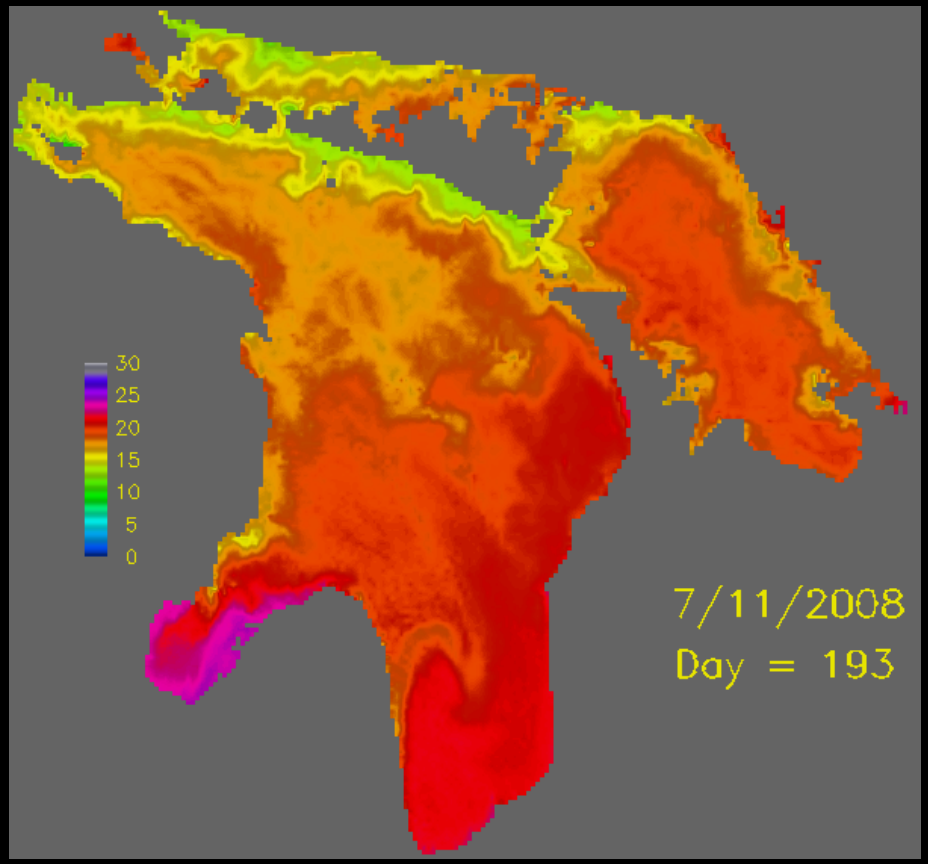
3D Hydrodynamic Model

- Lake-wide circulation model for seasonal simulations (Beletsky and Schwab 2001)
- Inputs: hourly wind stress and heat fluxes
- Horizontal resolution - 2 km
- Vertical resolution - 20 sigma levels

Model development status

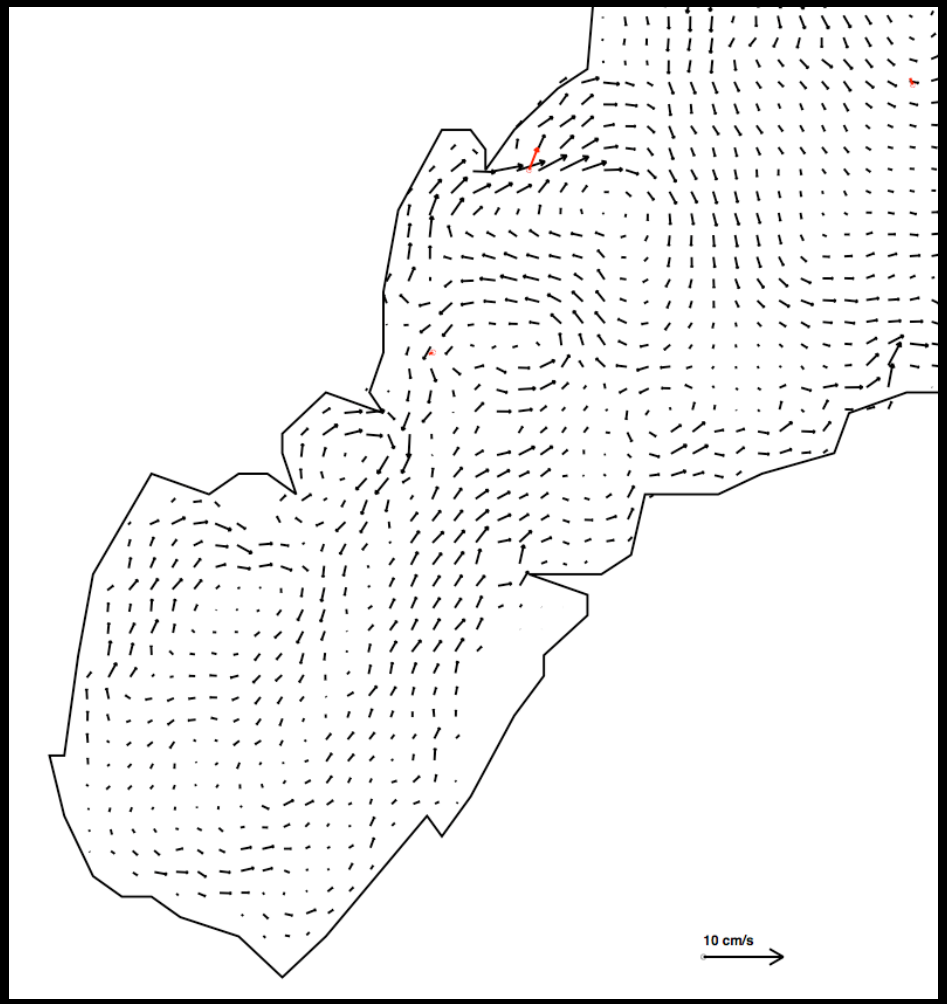
- 1993 and 2008 model runs complete
- 1991-1996 runs will begin soon



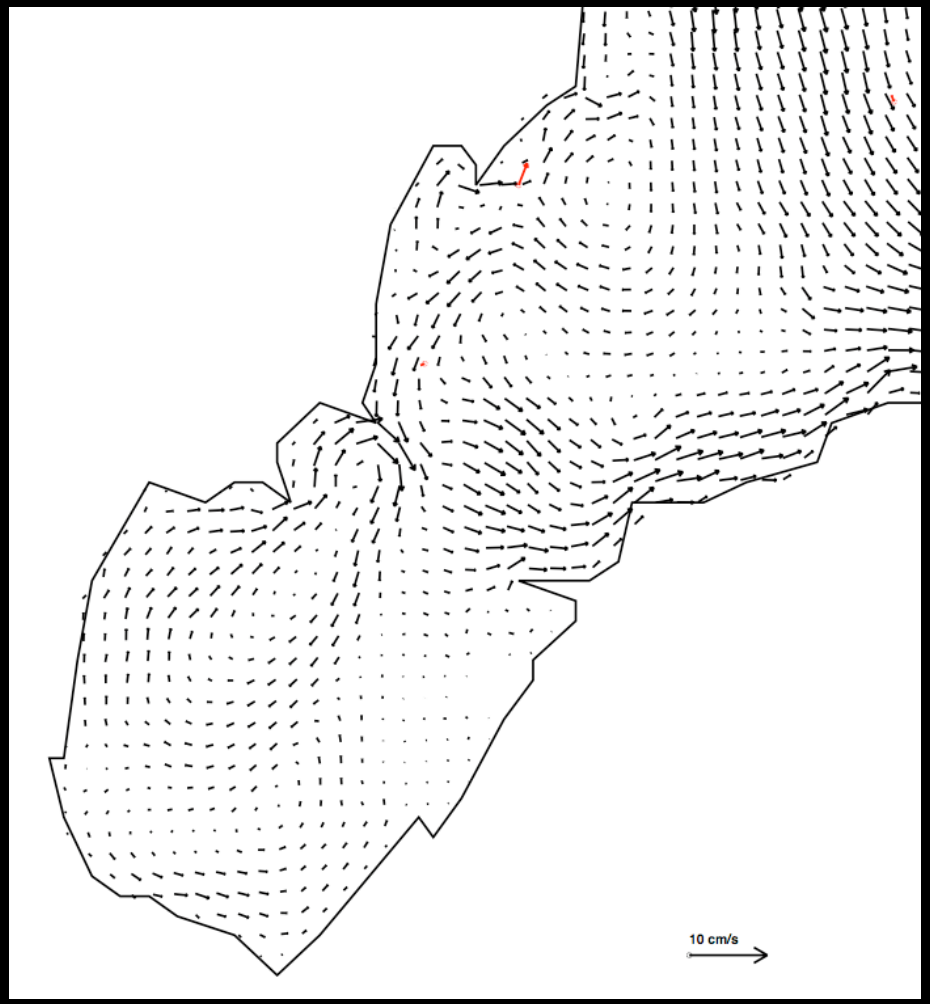


Depth-averaged currents in April-September

1993



2008



3D Nested Grid Model

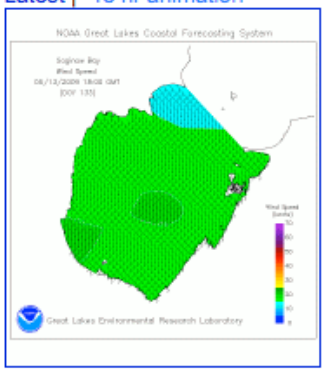
- Circulation model for seasonal simulations (Beletsky and Schwab 2001)
- Inputs: hourly wind stress and heat fluxes, currents/temperature at the open boundary, Saginaw River flow (USGS)
- Inner Bay Resolution
  - Horizontal resolution - 200 m
  - Vertical resolution - 11 levels
- Became operational (GLFS) in May 2009

Saginaw Bay Nowcast

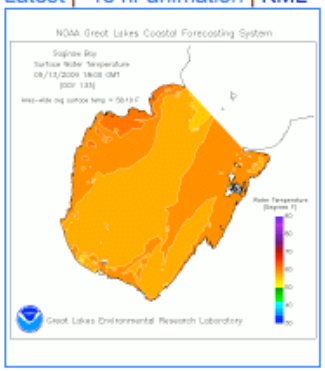
Timestamp: 05/13/2009 (DOY 133) 18:00 GMT

The products on this page are updated 4x per day at about 0100, 0700, 1300, and 1900 GMT (subtract 4 for EDT)

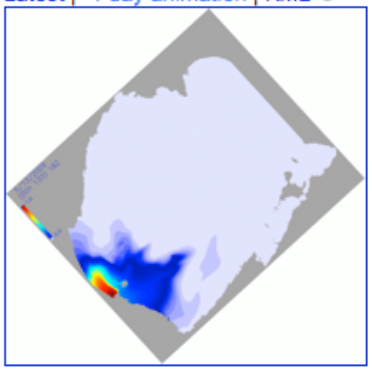
Winds:
Latest | -48 hr animation



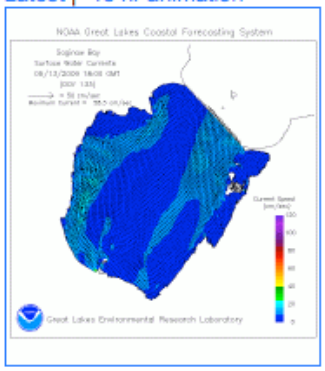
Surface Water Temps:
Latest | -48 hr animation | KML



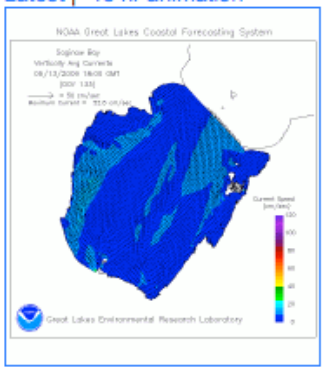
Tracer Concentration:
Latest | -4 day animation | KML



Surface Currents:
Latest | -48 hr animation



Vertically Avg Currents:
Latest | -48 hr animation



See also: grid1 | grid2 | grid3 | grid4 (KML)
Bathymetry: jpg | KML

Comments? gregory.lang@noaa.gov

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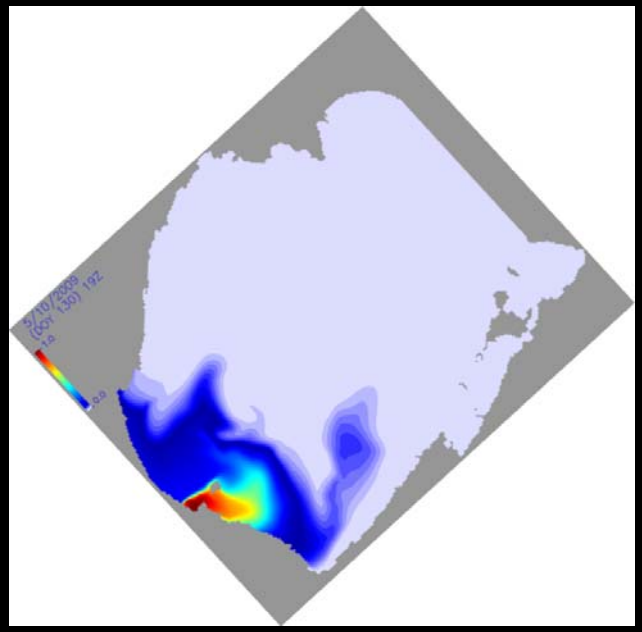
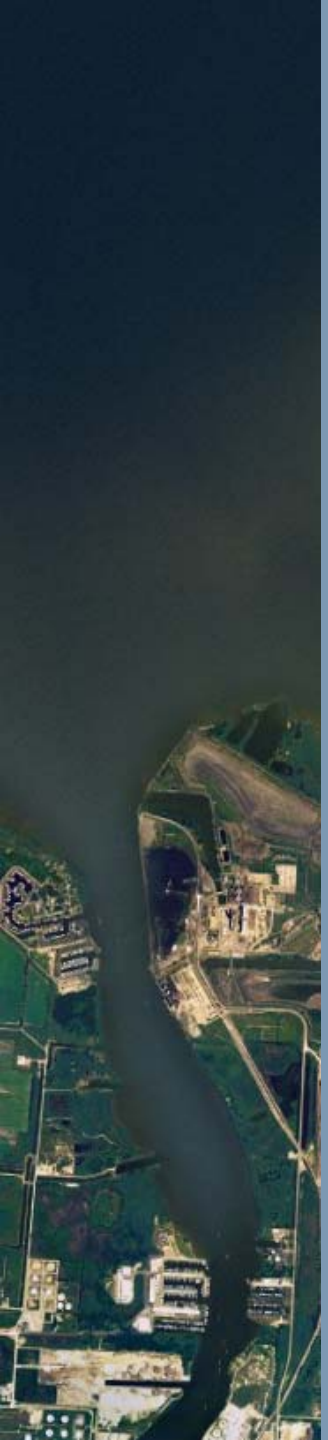
Comparison with observations (May 10, 2009)

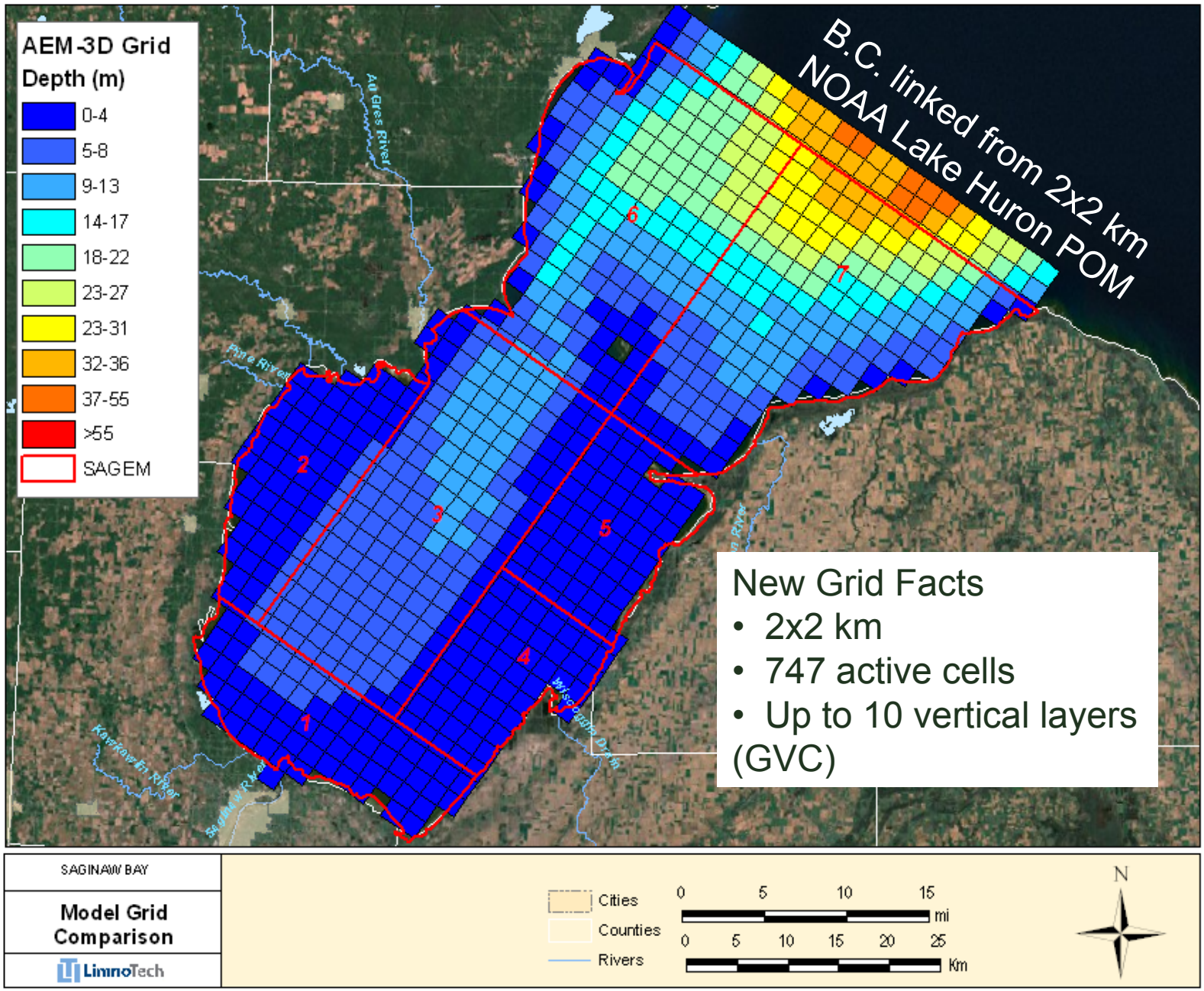




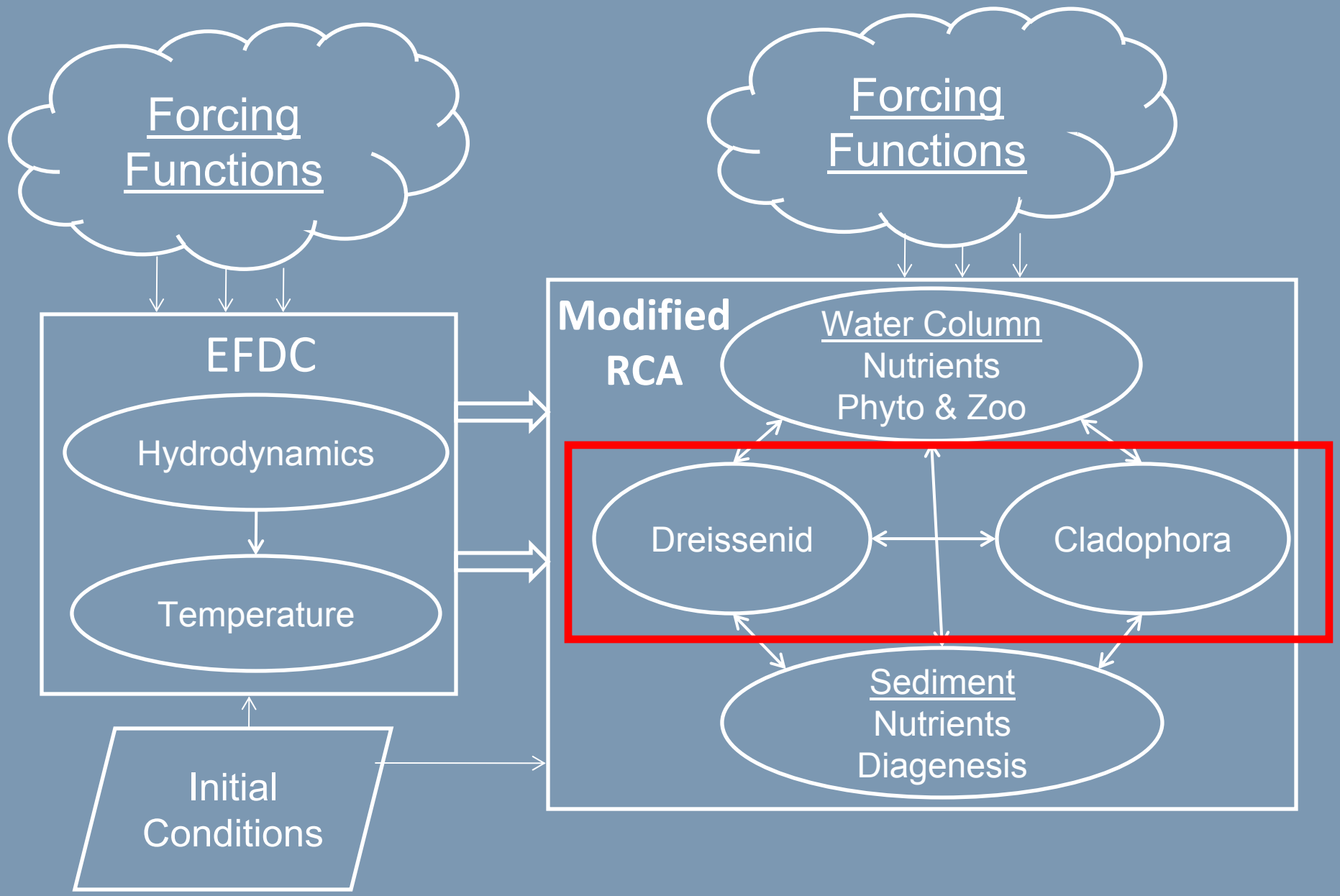
SAGEM → SAGEM2

Category	SAGEM	SAGEM2
Hydrodynamic model	2D chloride mass balance 7 segments	3D with 747 cells 10 vertical layers
Water Quality Model	Customized framework built from Bierman model	Documented and highly tested framework. Full sediment diagenesis sub-model
Benthic Algae Sub-model	Simple kinetics, attached green alga not specific to Cladophora	“Best available” Cladophora model with tracking of sloughed biomass
Filter Feeder Sub-model	1 species with 3 cohorts	2 species with 3 cohorts Complete mass balance

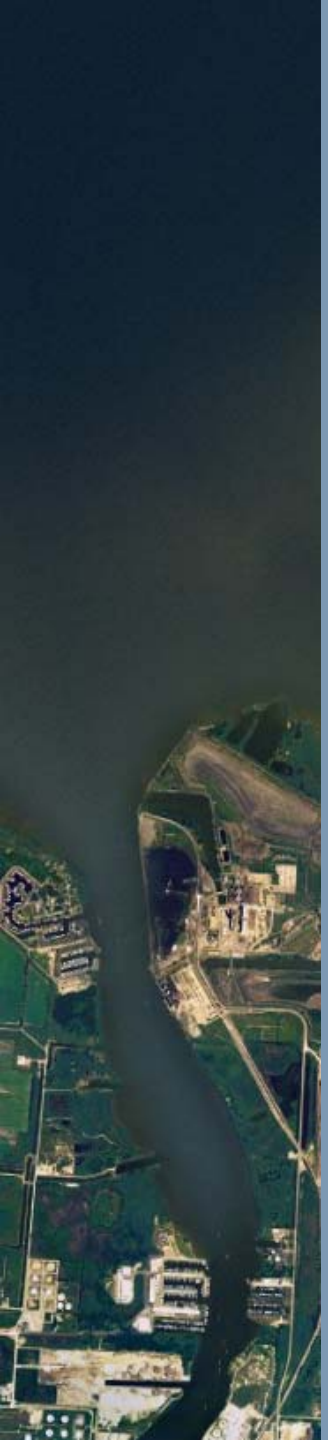
Updated Model Grid – SAGEM → SAGEM2

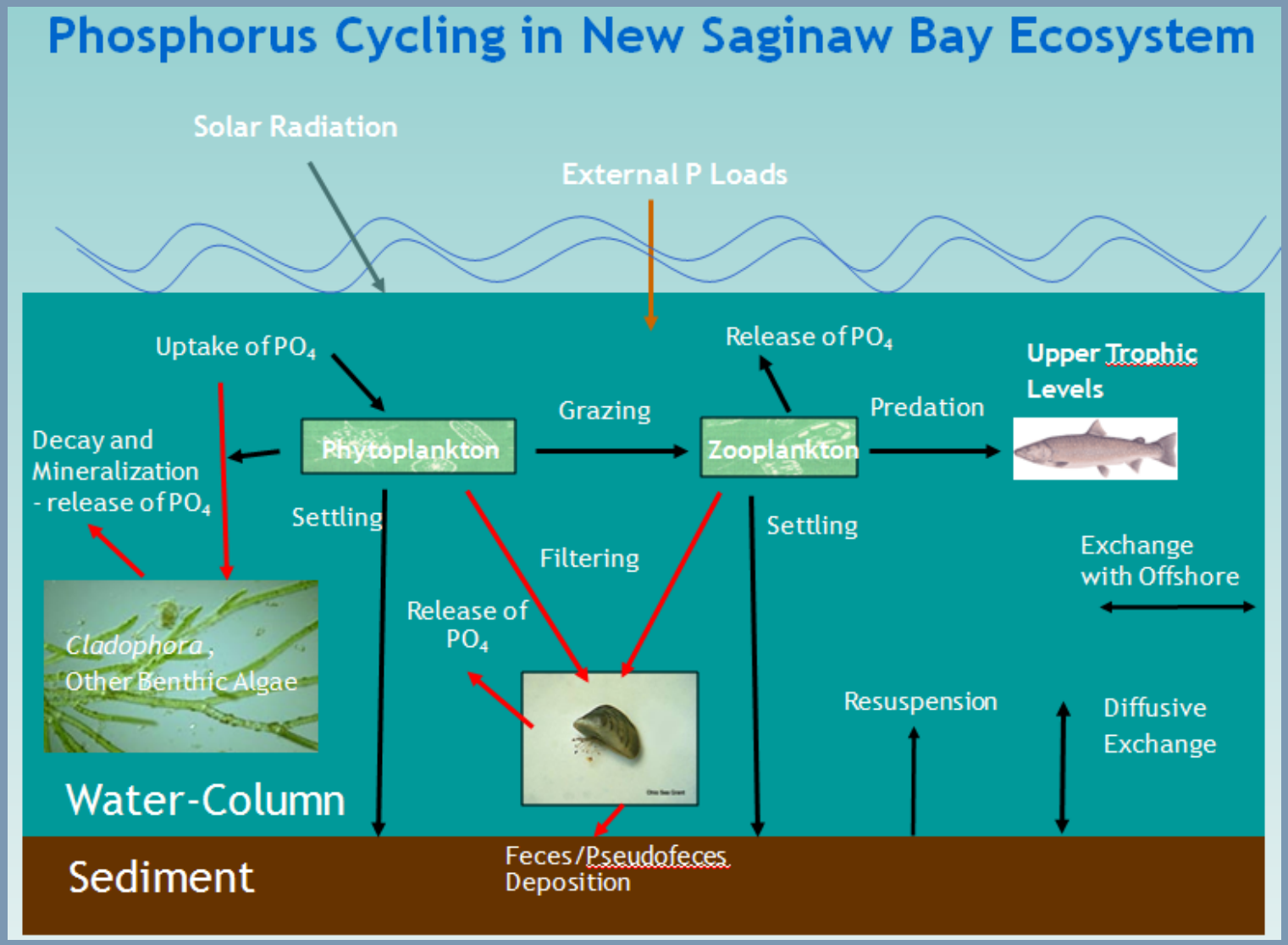


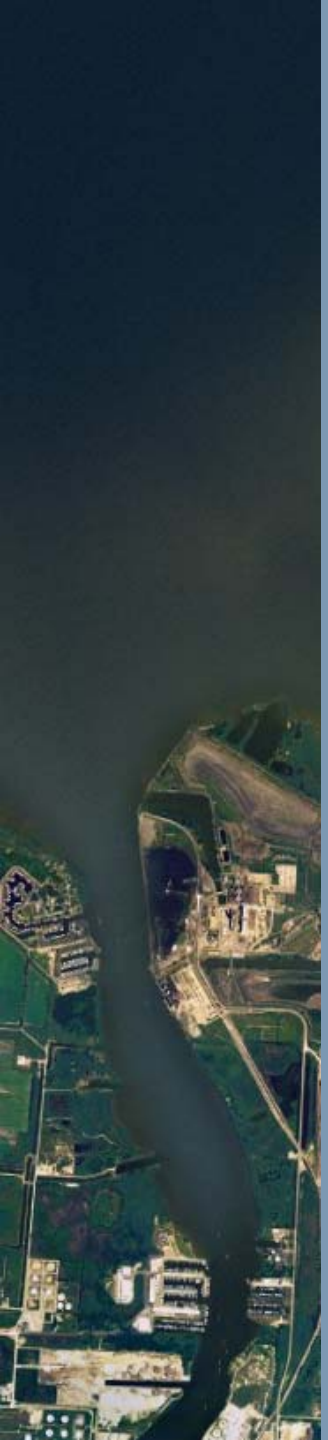
Modeling Framework: SAGEM2



SAGEM2 Phosphorus Cycling







Management Issues Addressed by SAGEM2

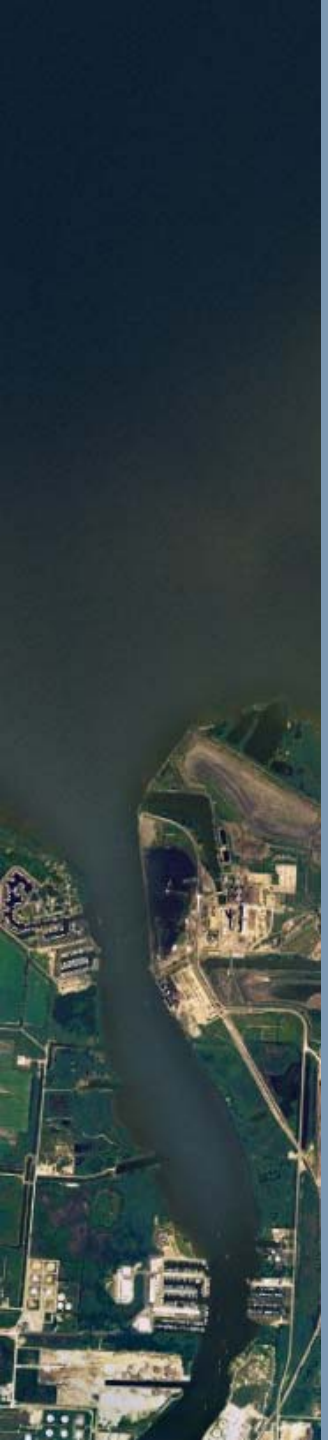
Quantify and explain the relative contribution of multiple stressors

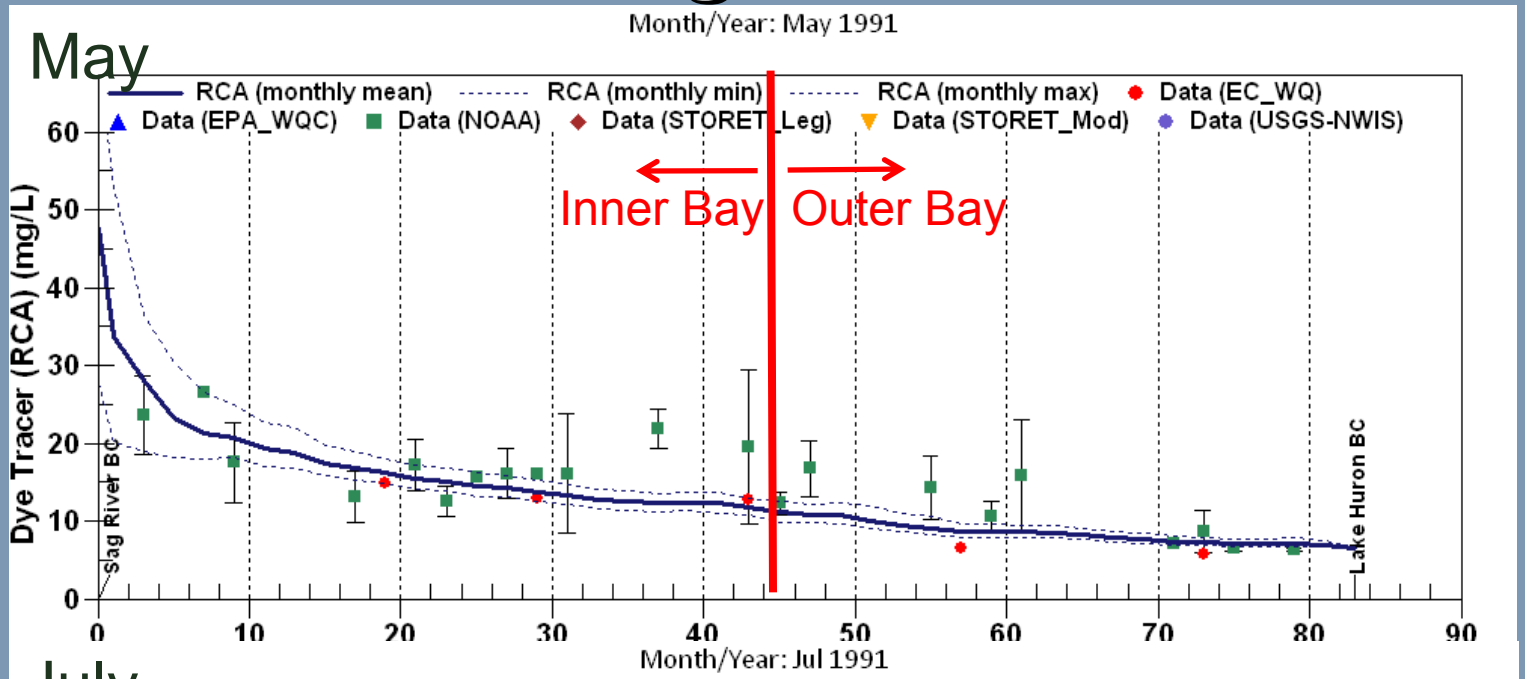
- Nutrient loads
- Solids loads
- Dreissenids
- Climate
  - Solar radiation
  - Wind
  - Temperature
  - Hydrology and water level

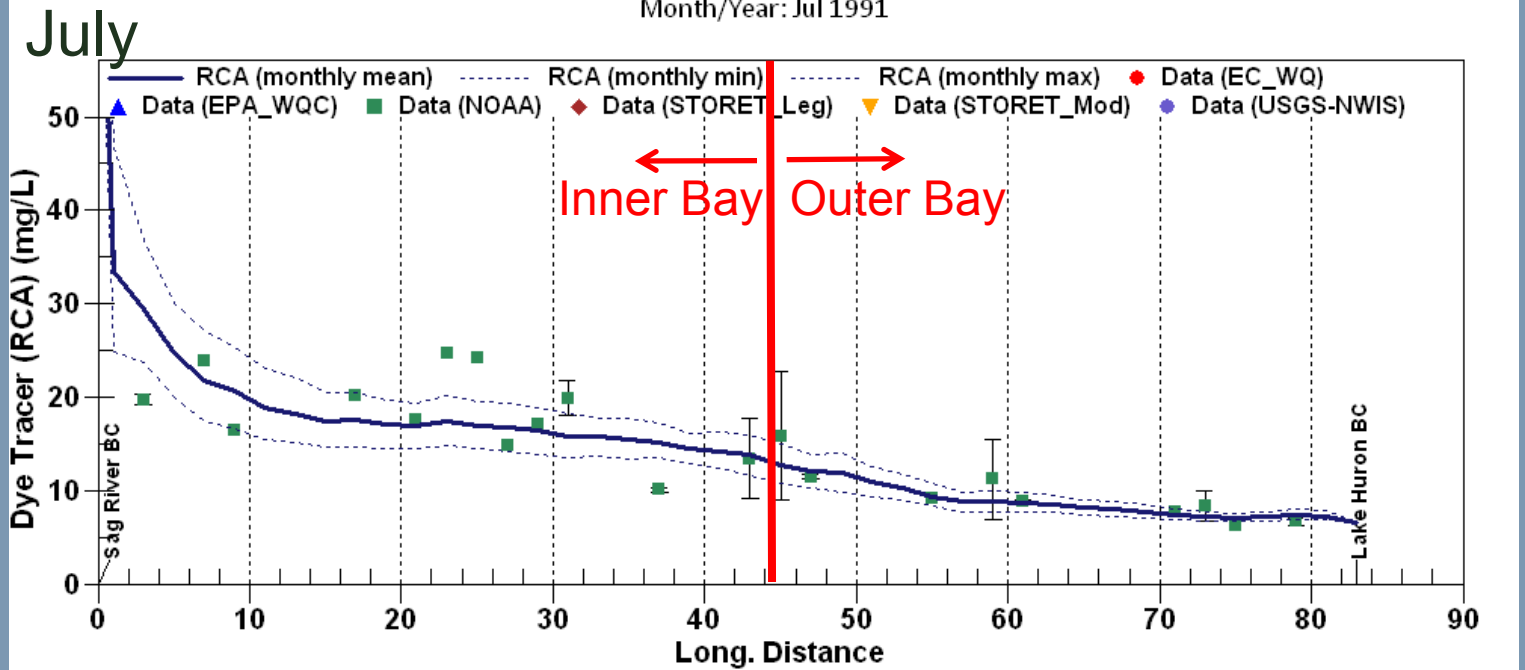
to multiple water quality endpoints of concern.

- Nutrient concentrations/budgets
- HABs (*Microcystis*)
- Benthic algae (*Cladophora* , *Spirogyra*) and “muck” distribution
- Dissolved oxygen conditions
- Carrying capacity for upper food web

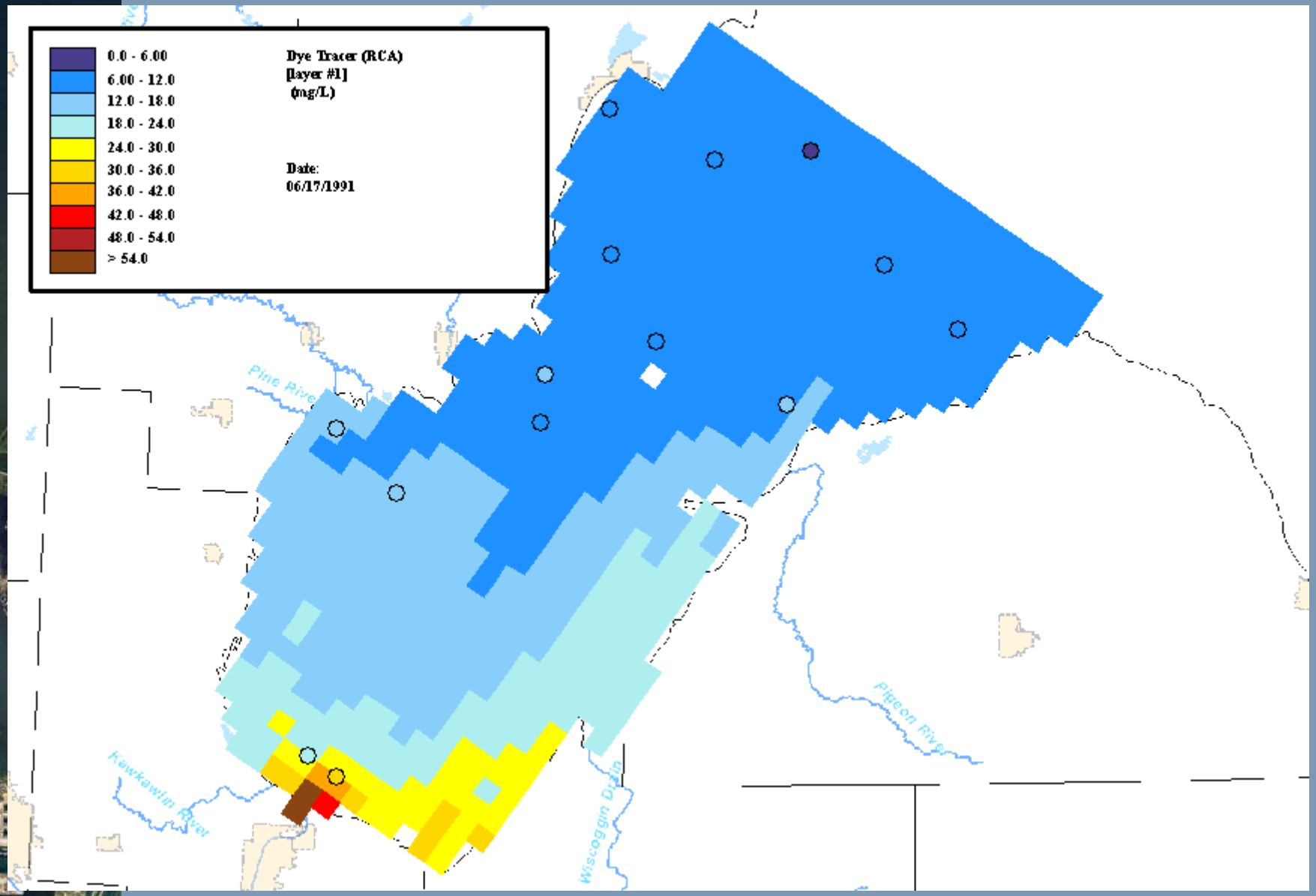
Chloride Longitudinal Profile







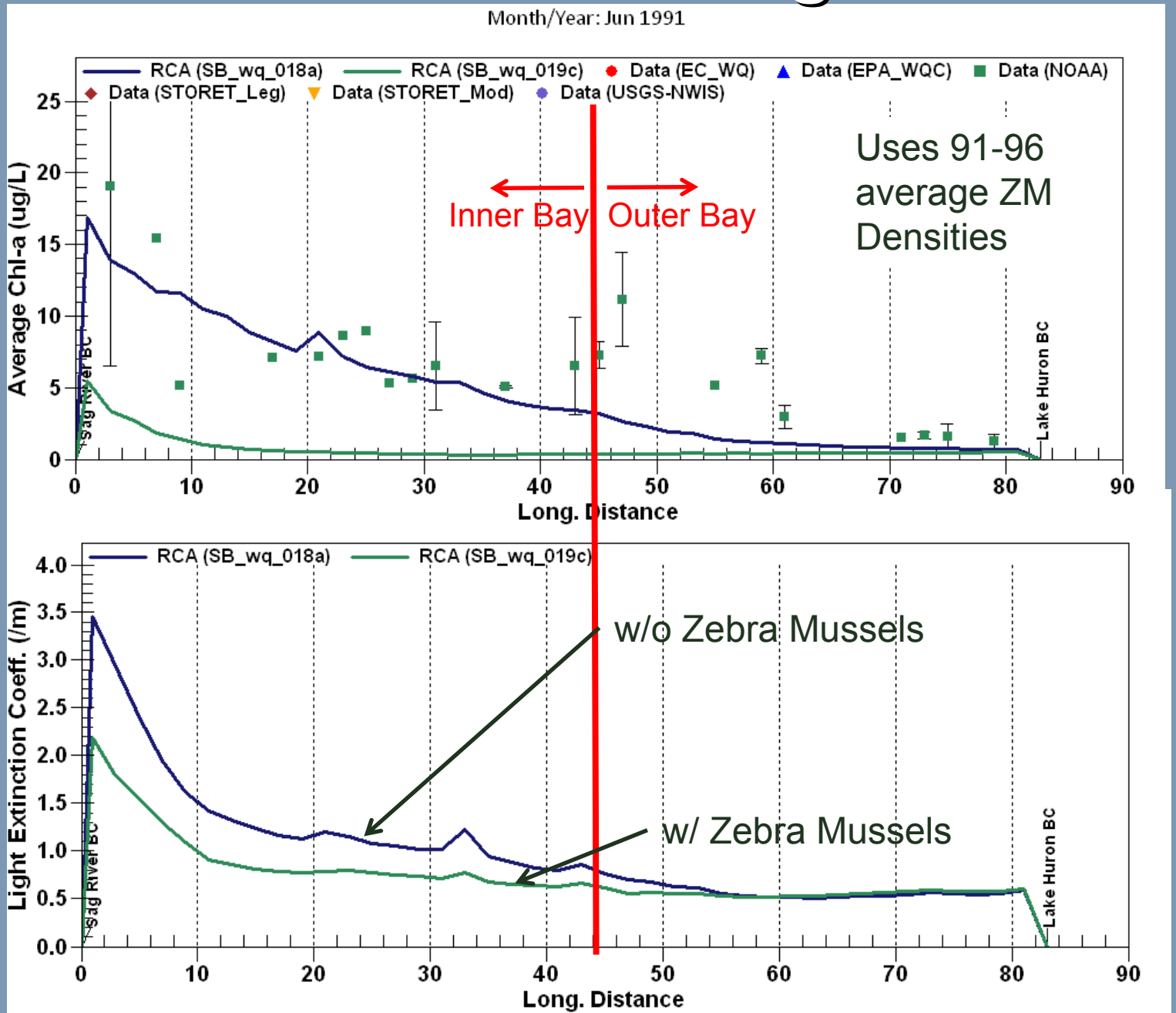
Chloride 2D Distribution



Dreissenid: 'Clearing' Effect

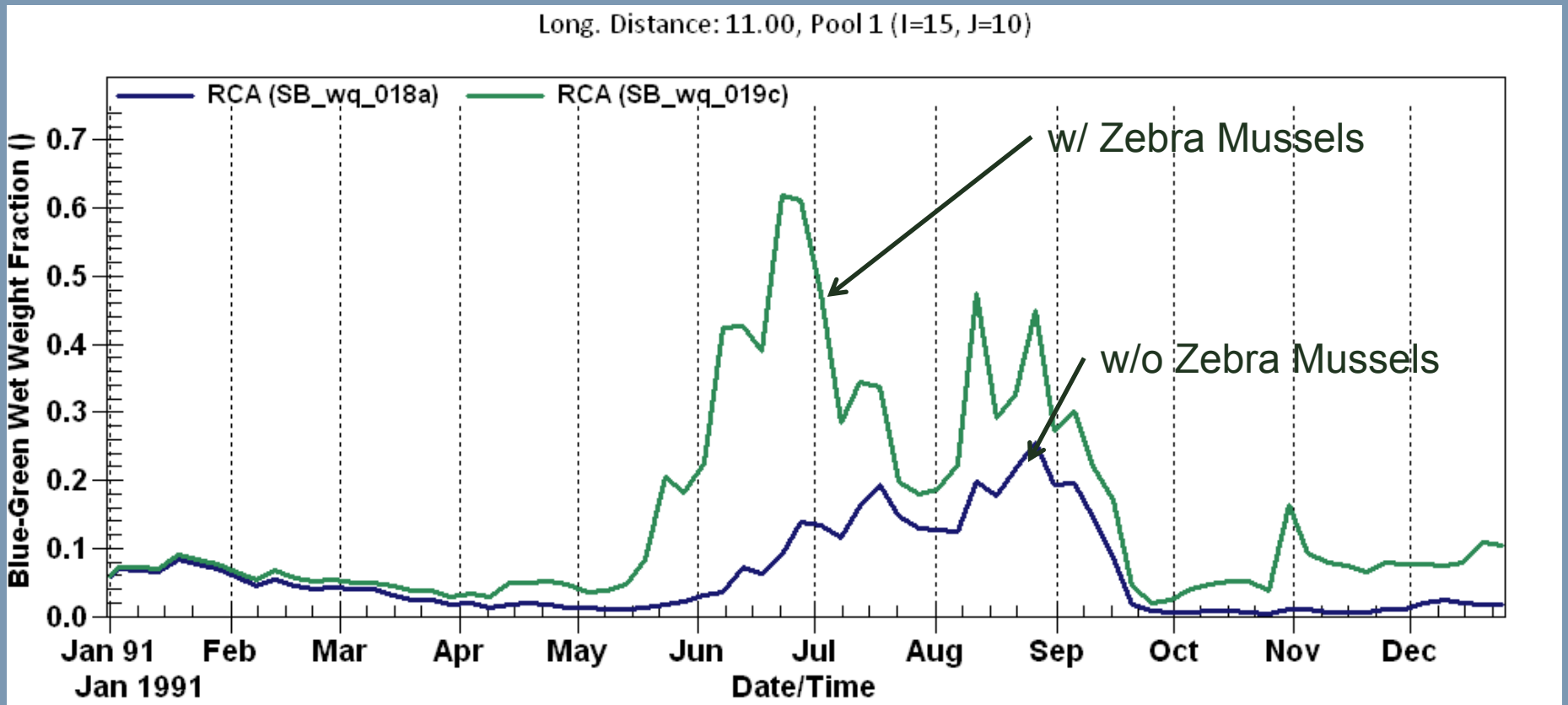
Chlorophyll

Light Extinction



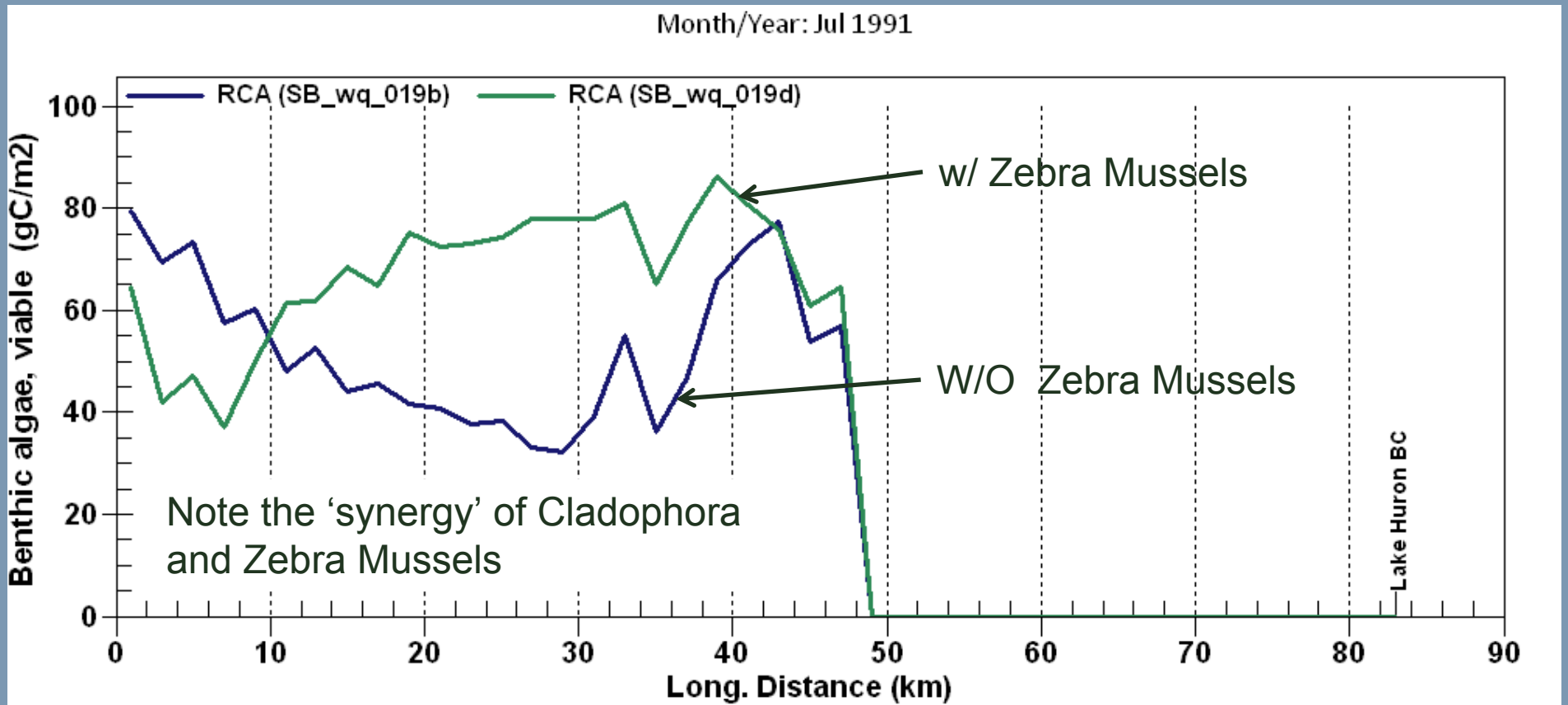
Dreissenid: Selective Filtration

- Dreissenid Filtration:
  - Phytoplankton
  - Zooplankton
  - Organic sediment (POM)
  - Inorganic sediment
  - **Reject Blue-Greens**

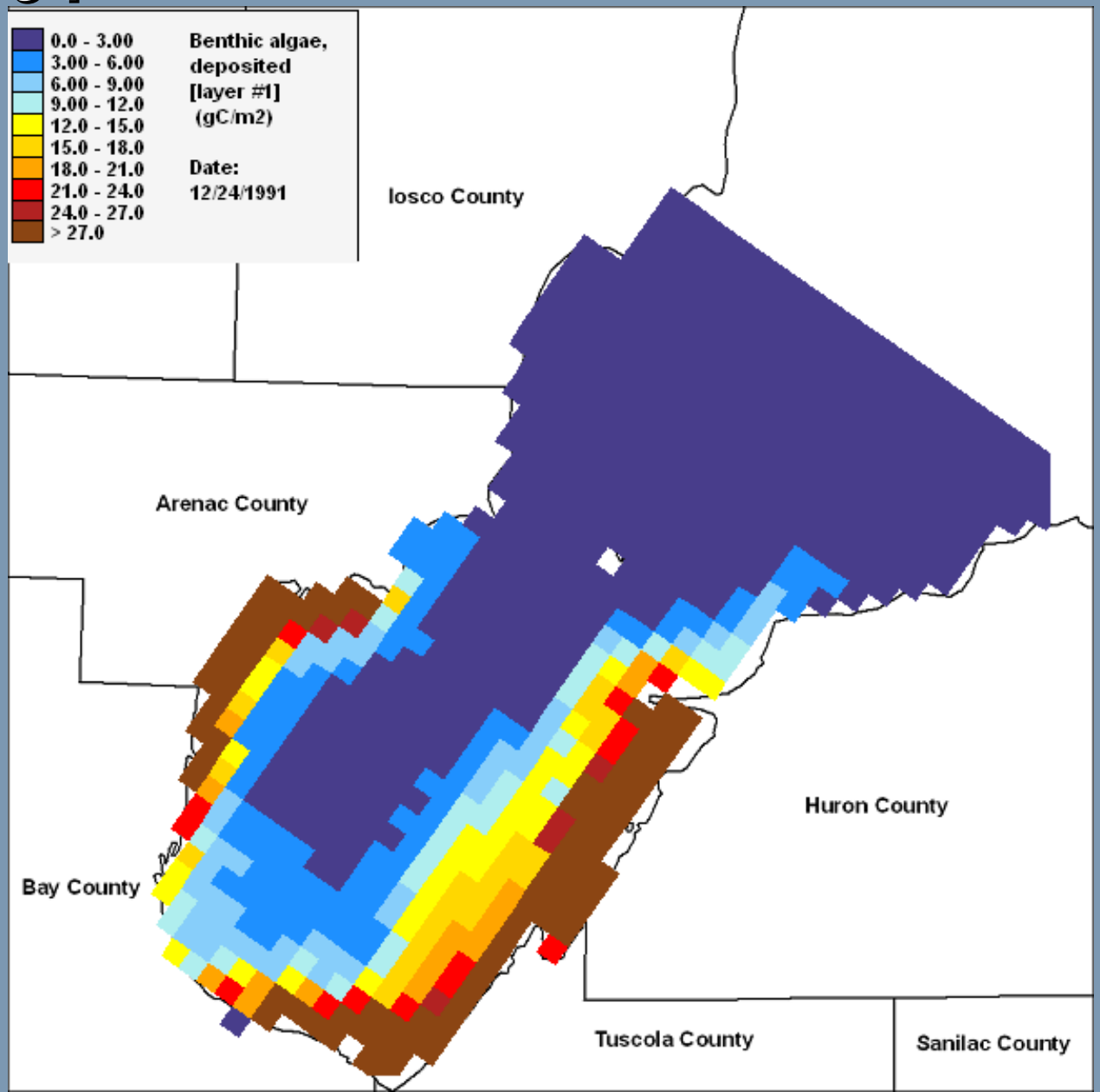


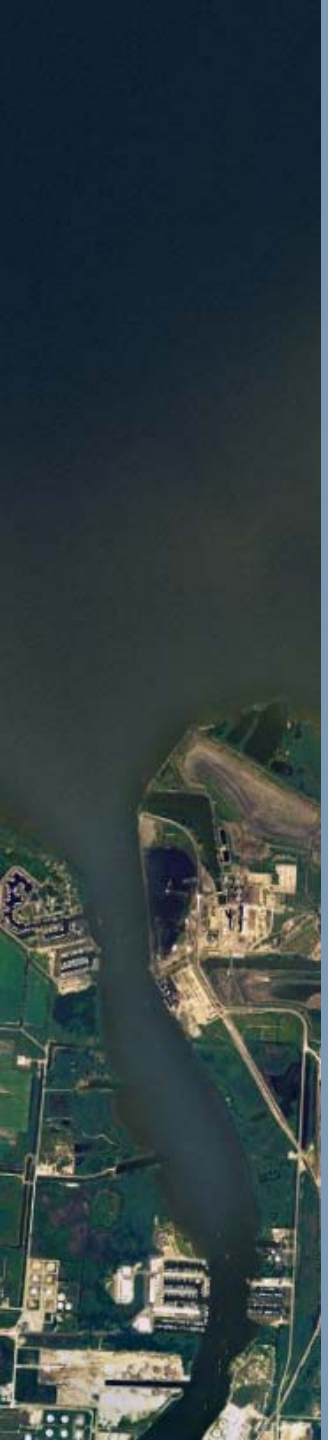
Benthic Algae Sub-model

- Based on GLCM developed by M. Auer
- Model code is flexible to model any benthic or 'semi' benthic algae



Total Detrital Deposition ("Muck") - 1991

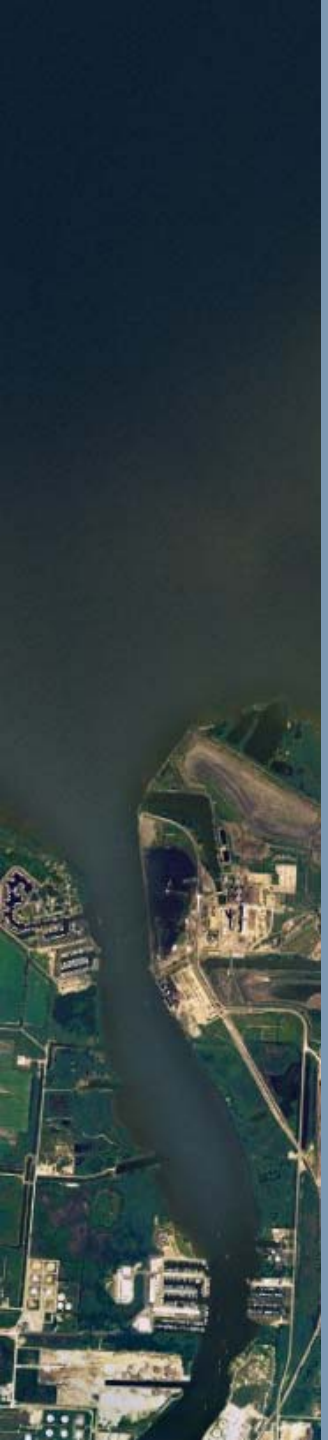




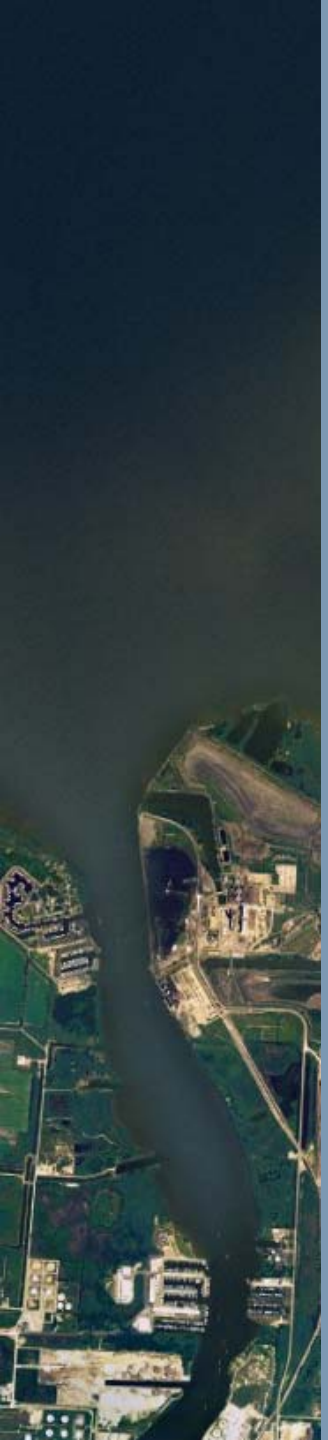
SAGEM2 Plan

- Preliminary calibration and diagnostic analysis with 1991-96 Saginaw Bay data
- Final calibration with project data
  - 2008 – 2011
- Confirm SAGEM2 with 1991 – 2011 run
- Link SAGEM2 with upper food web model (SB-IBM)
  - Produces SAGEM3
- Apply to management questions within AIF process
  - Ongoing over remainder of project

Saginaw Bay
Multiple Stressors
QUESTIONS?

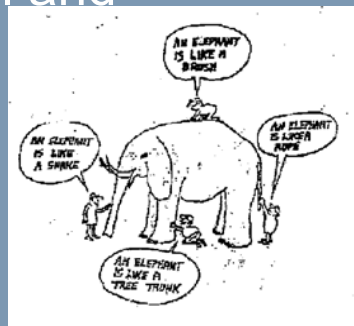


Extra Slides

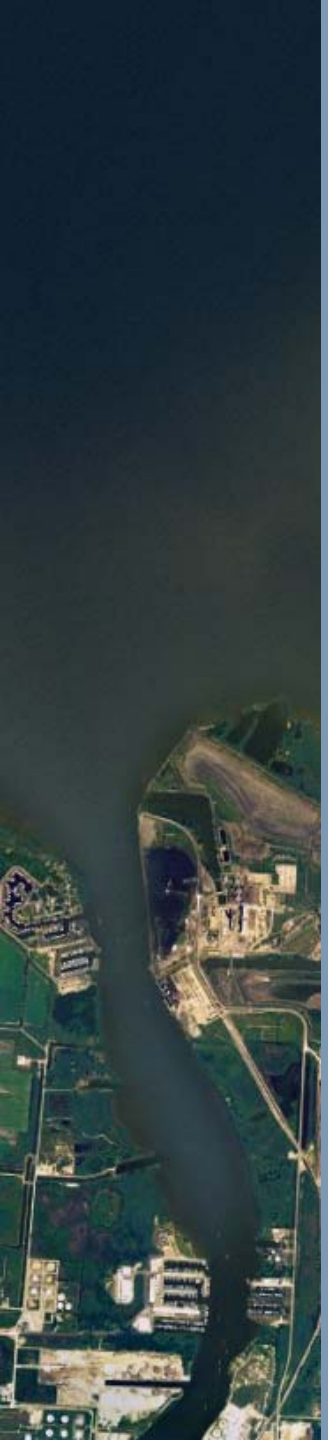


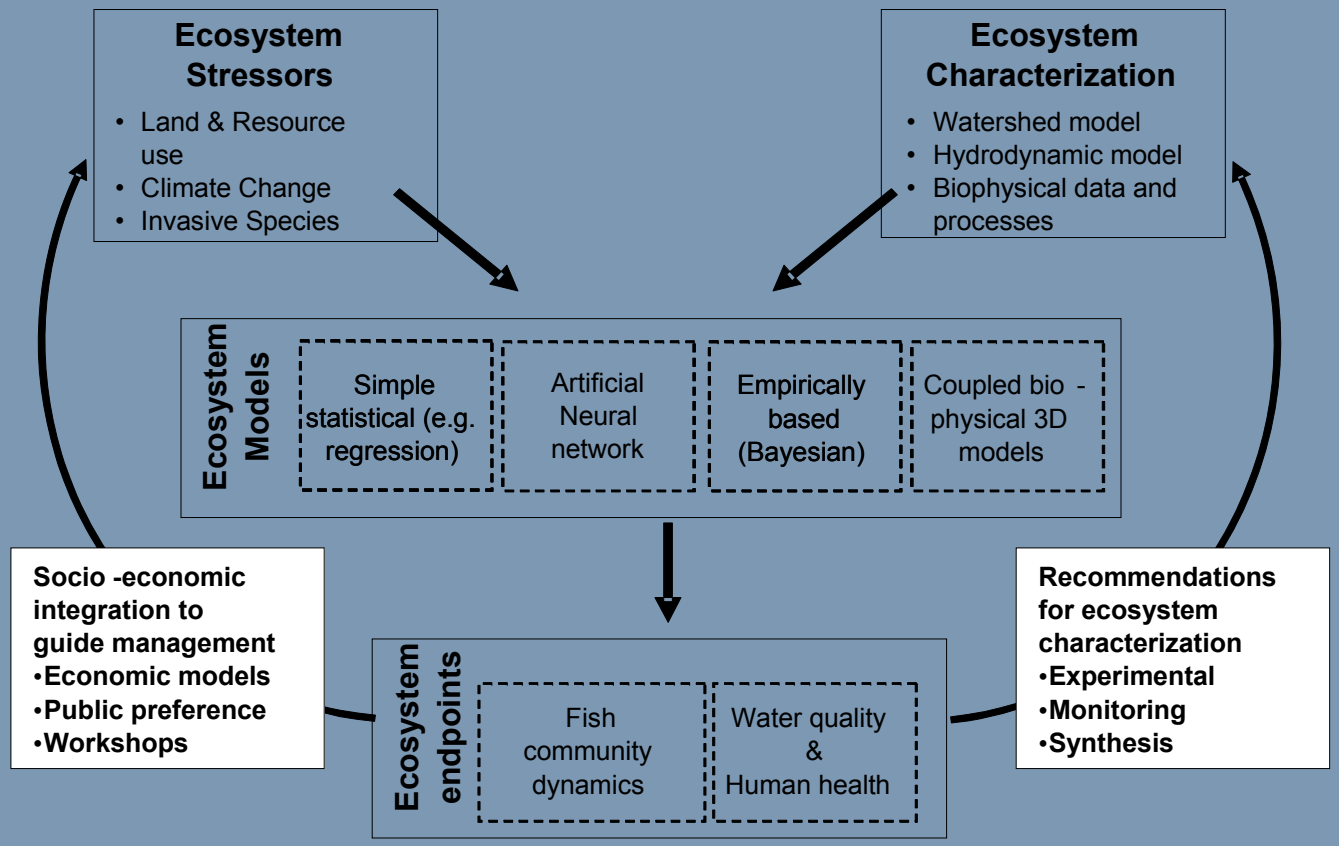
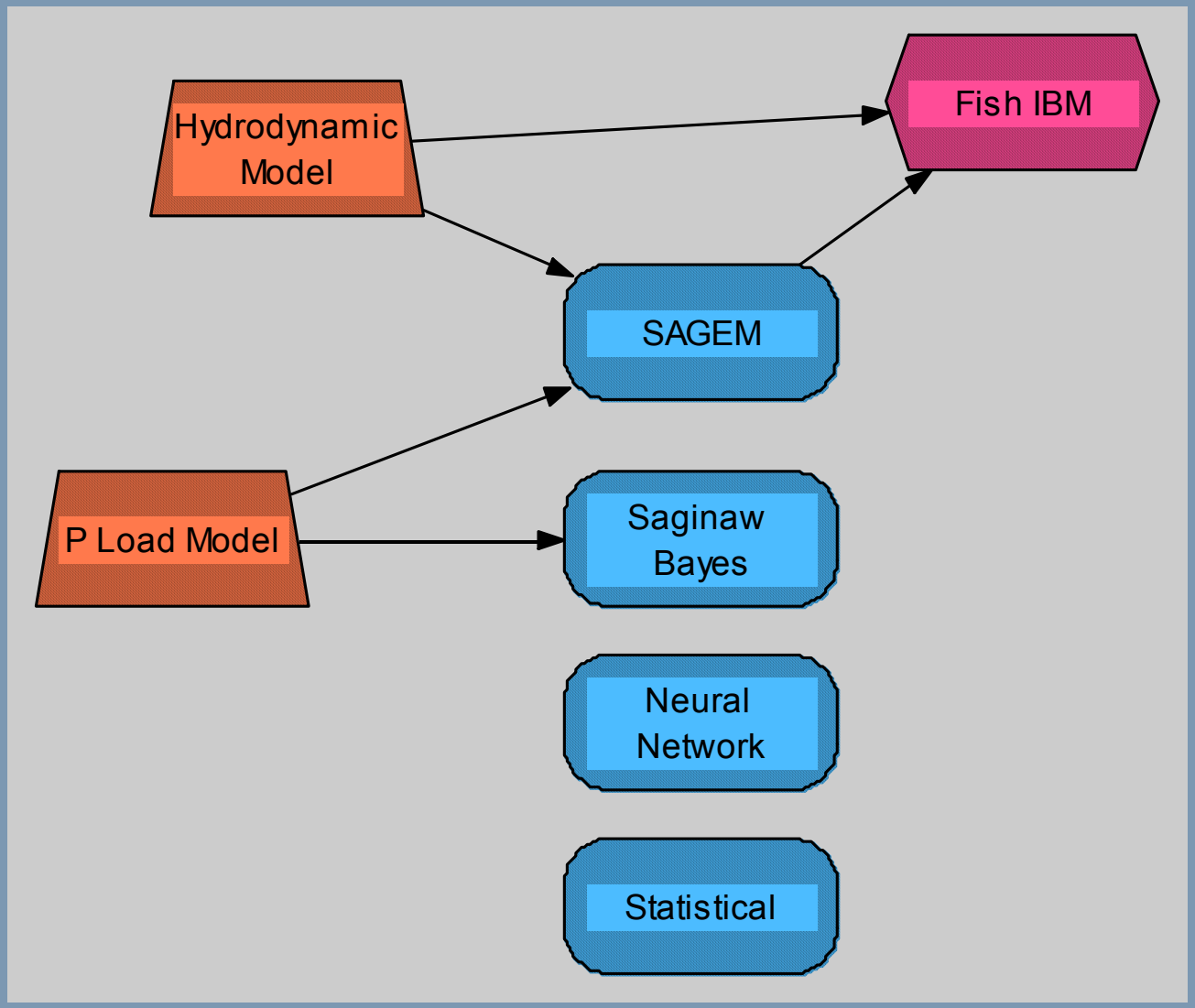
Benefits of Whole System Models

- Models provide a means of synthesizing available system data and knowledge in a given problem domain
  - Quantify the state of a system and explain how it functions
  - Identify data/knowledge gaps and help design monitoring and research programs
- Models provide a means of quantifying the relationship between key forcing functions (e.g., loads) and ecosystem responses of concern
  - Compare and evaluate management options
  - Quantify and assess outcomes of management actions
  - Forecast the system response to both natural and anthropogenic stressors



Application of Adaptive Integrated Framework to Saginaw Bay





Current Relationship Among Saginaw Bay Models