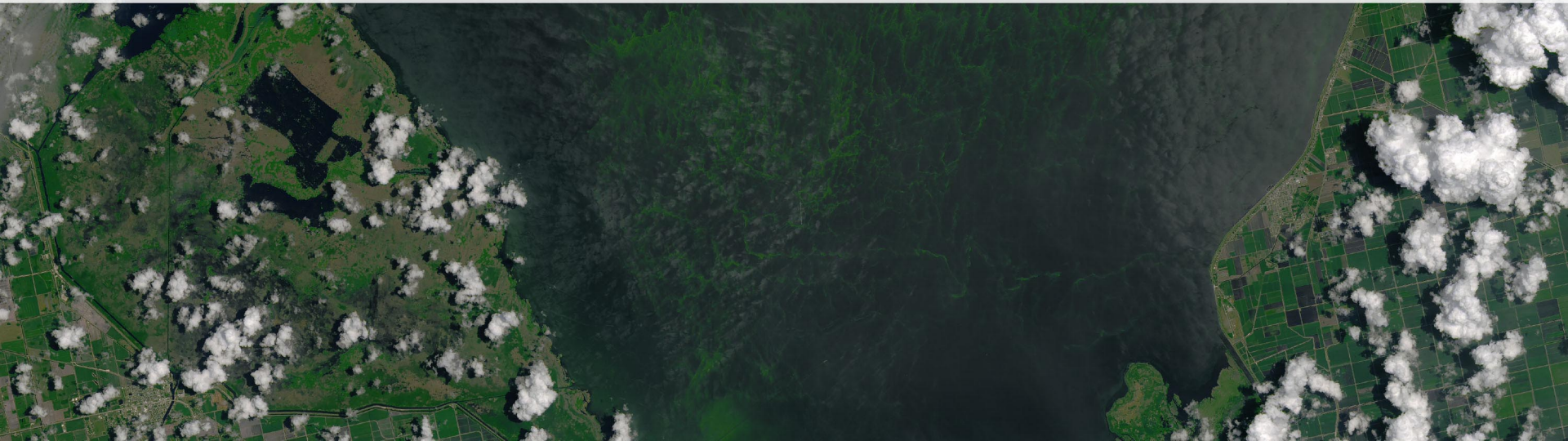
Basins to blooms: modeling drivers and consequences of nutrient loading in fresh and coastal waters

Natalie Nelson, Assistant Professor, Biological and Agricultural Eng., NC State

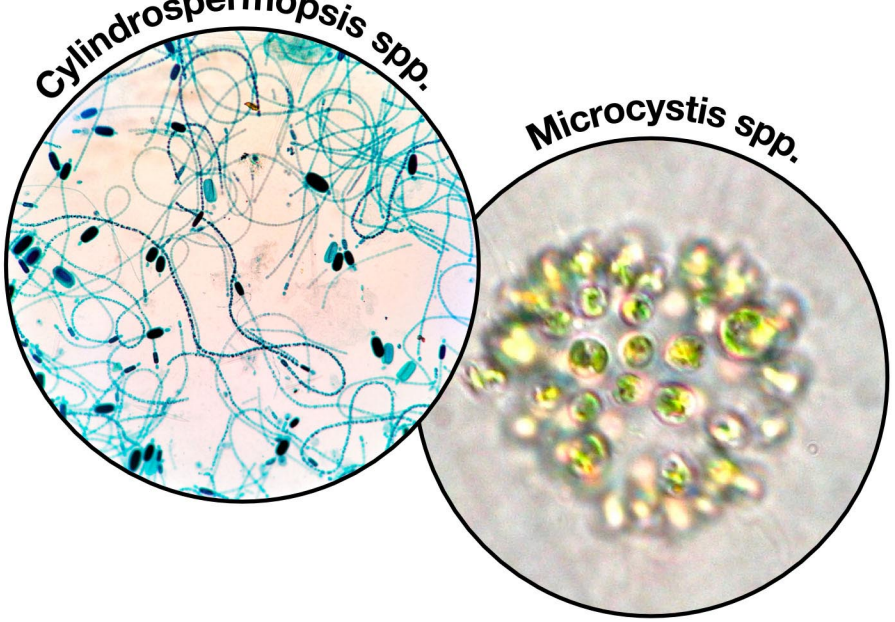
Geospatial Forum, November 29, 2018



Blooms

Cyanobacteria

- "blue-green" algae
- Photosynthetic prokaryotes
- Capable of thriving in a wide range of environmental conditions



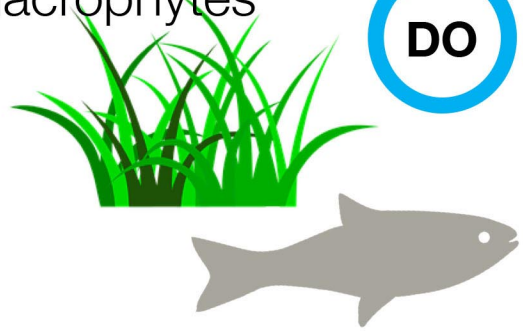
Source: Wikimedia

Source: USGS

Bloom-driven impacts

Shades out macrophytes

Hypoxia



Trophic structure

Drinking water

Tourism & recreation

Property values

Freshwater blooms → $2.2 billion per year

Conservative estimate from Dodds et al. 2008

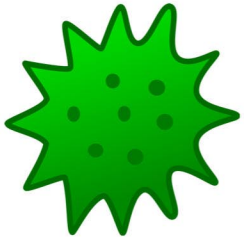
Water quality regulation

Total Maximum Daily Loads (TMDLs)

- Maximum allowable pollutant load to a waterbody
- Created for waters deemed impaired by Section 303(d) of the Clean Water Act

TMDL = ΣWLA + ΣLA + MOS

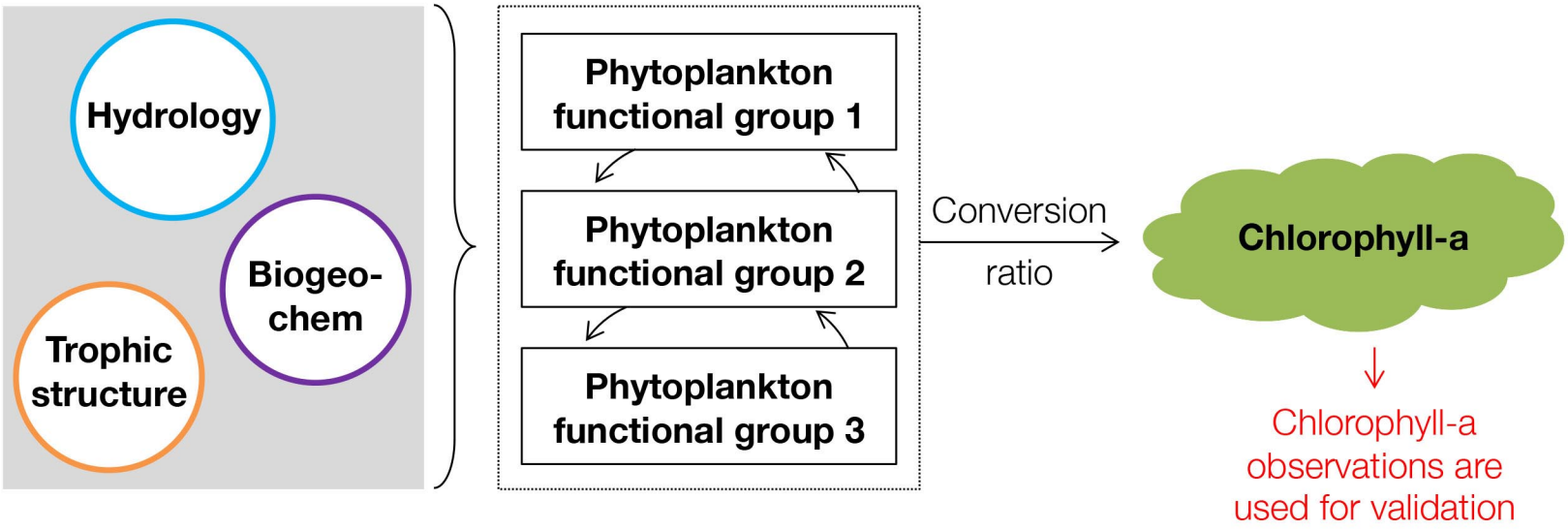
- WLA: wasteload allocations (point sources)
- LA: load allocations (nonpoint source and background levels)
- MOS: margin of safety



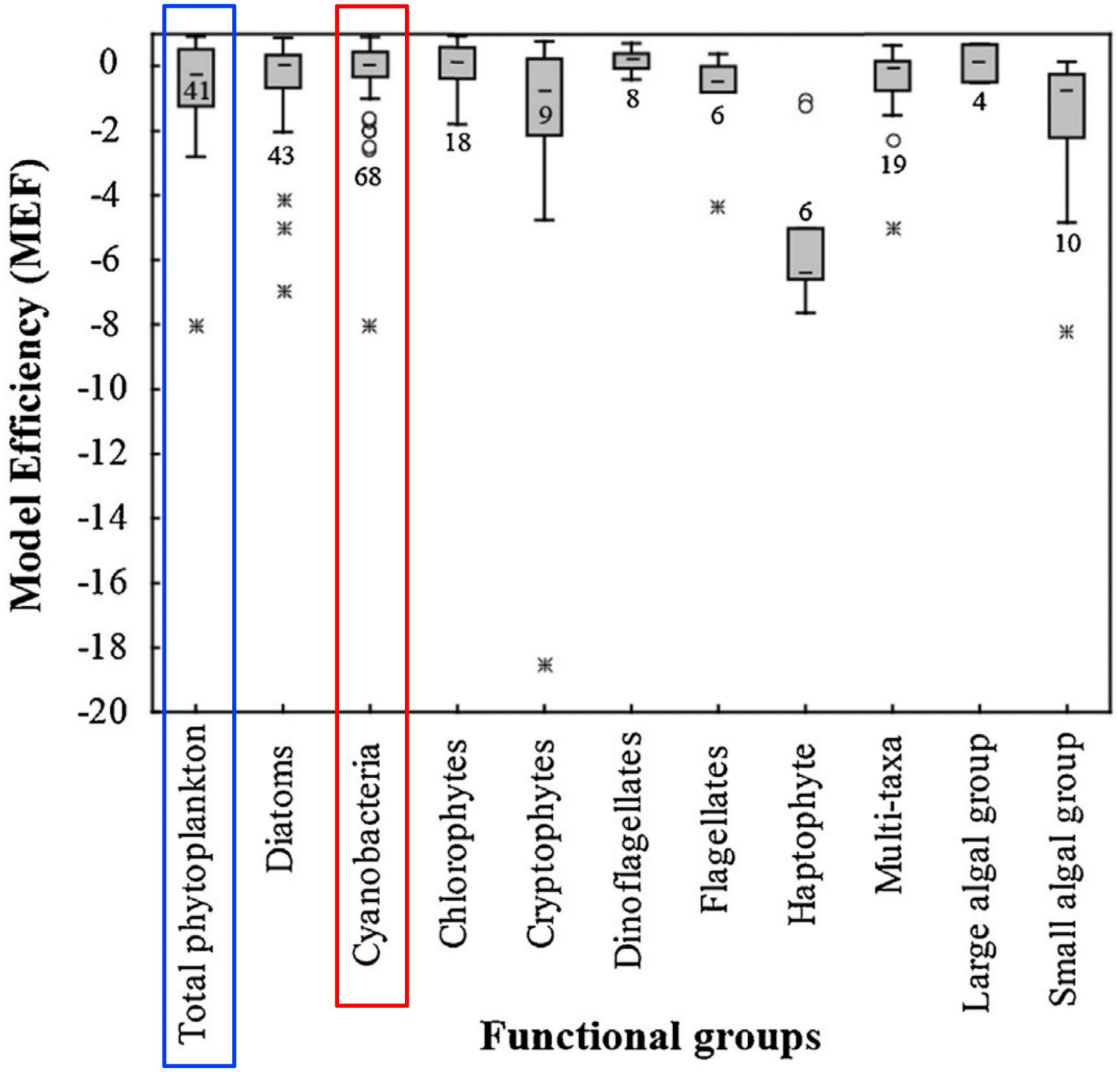
TMDLs for bloom-impacted waters typically target nitrogen and/or phosphorus

How are bloom-related TMDLs determined?

When possible, phytoplankton functional group models (WASP, LAKE2K, CE-QUAL-W2, CE-QUAL-ICM)



Phytoplankton functional group model performance



$$MEF = 1 - \frac{\sum(O - P)^2}{\sum(O - \bar{O})^2}$$

$O = observed$
$\bar{O} = mean\ of\ observed$
$P = predicted$

$Median\ MEF_{cyano} = 0.06$

$Median\ MEF_{total} = -0.2$

Shimoda and Arhonditsis (2016), Phytoplankton functional type modelling: Running before we can walk? A critical evaluation of the current state of knowledge, *Ecol. Modelling*

Which phytoplankton functional group model factors are driving output uncertainty?

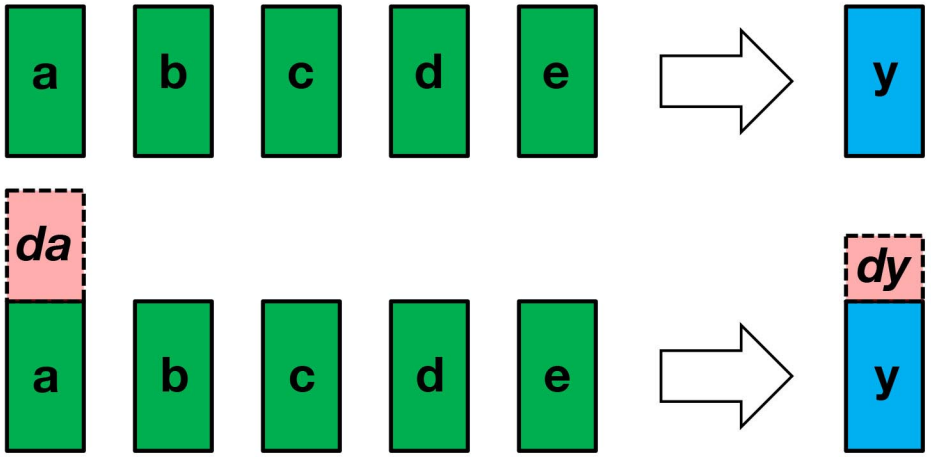
Global sensitivity analysis of CE-QUAL-ICM

Sensitivity Analysis

- Process of apportioning uncertainty in model output to individual model inputs (e.g. model parameters)
- Frequently performed one-factor-at-a-time
- Evaluate factors' direct effects on model output

$$a * (bx_1 + (c*d)x_2)^e = y$$

$$\text{Sensitivity} \quad \frac{dy}{da}$$



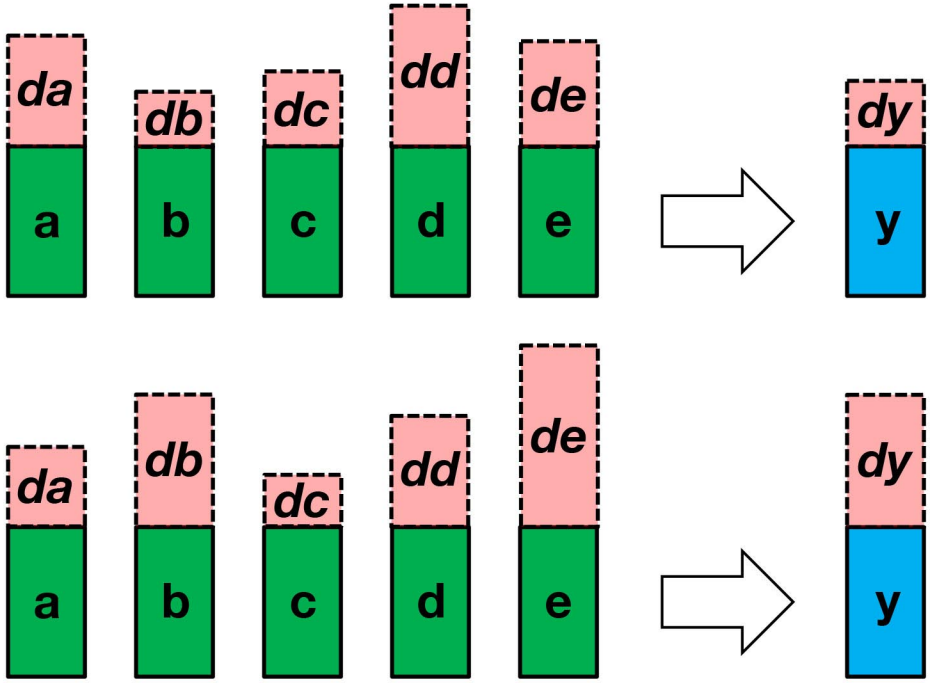
Global sensitivity analysis of CE-QUAL-ICM

Global Sensitivity Analysis – Morris Method

- Process of apportioning uncertainty in model output to individual model inputs (e.g. model parameters)
- Performed as all-factors-at-a-time
- Evaluate factors' direct and interactive effects on model output

$$a * (bx_1 + (c*d)x_2)^e = y$$

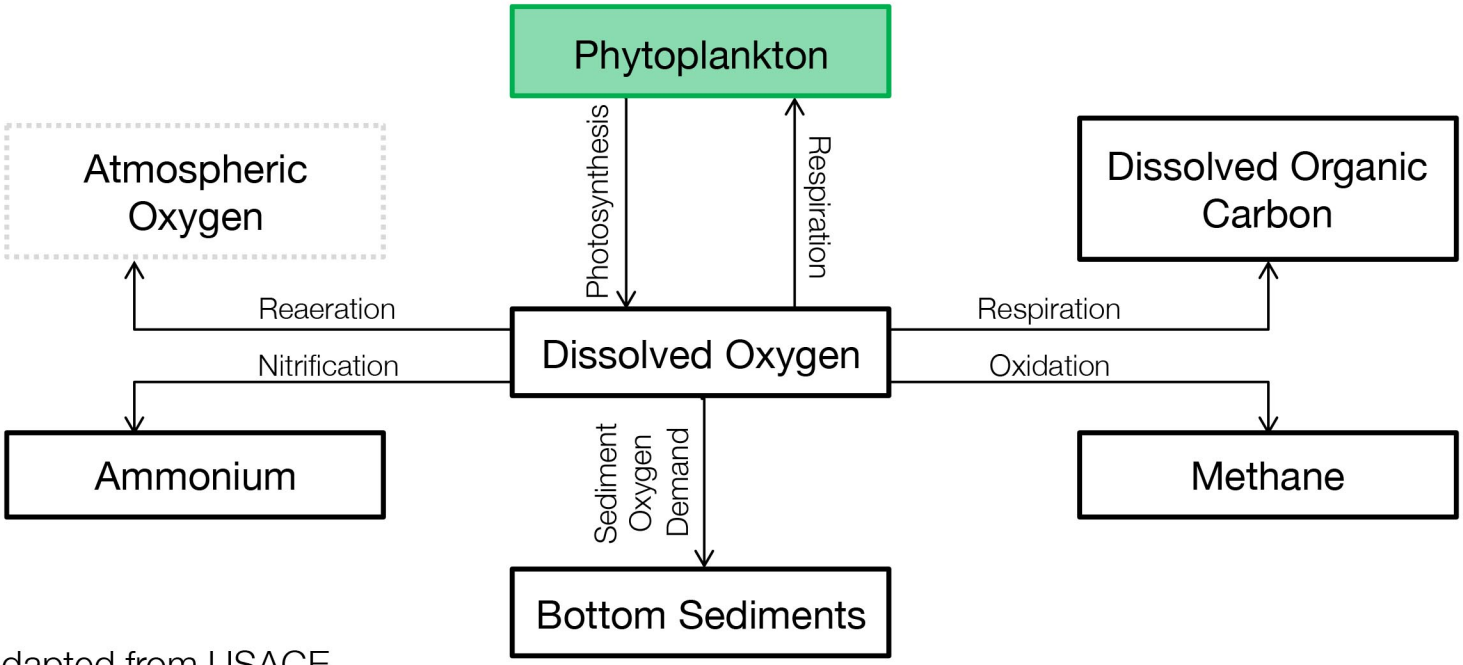
Sensitivity:
mean derivative (direct)
& standard deviation of
derivatives (interactive)



Global sensitivity analysis of CE-QUAL-ICM

CE-QUAL-ICM

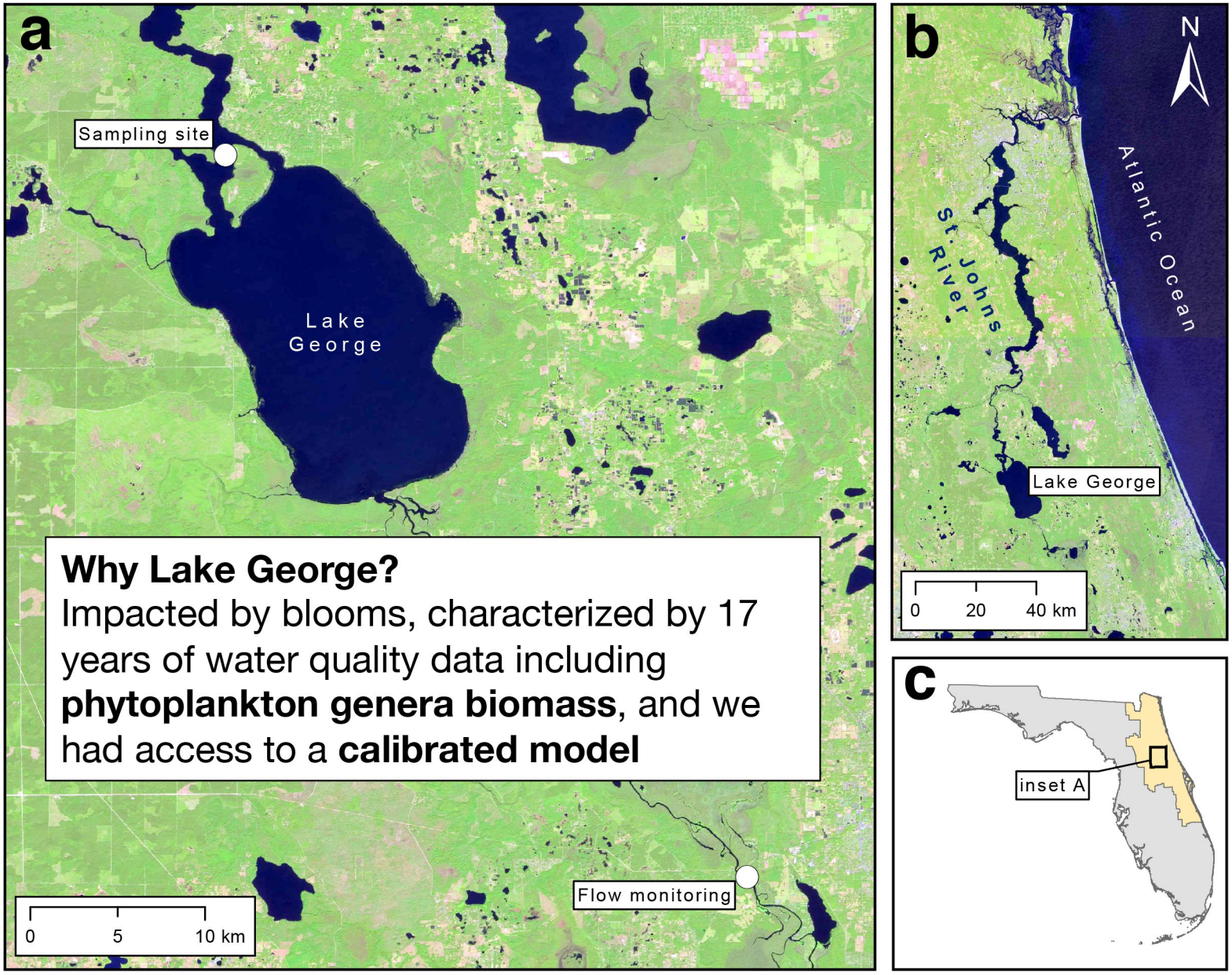
- U.S. Army Corps of Engineers
- Dozens of state variables, hundreds of parameters
- Three-dimensional water quality model
- Couples with EFDC
- Has been used for regulatory purposes (e.g. TMDL development)
  - Most notably used in the Chesapeake Bay



Source: Adapted from USACE

Global sensitivity analysis of CE-QUAL-ICM

1. Simulate two phytoplankton functional groups: cyanobacteria + eukaryotic phytoplankton
2. Vary all phytoplankton growth and loss parameters across published ranges = **42 parameters**
3. Run model **516** times, calculate model efficiency for chlorophyll, cyanobacteria biomass, and eukaryote biomass for each run
4. Quantify direct and interactive effects of parameters on model output variance

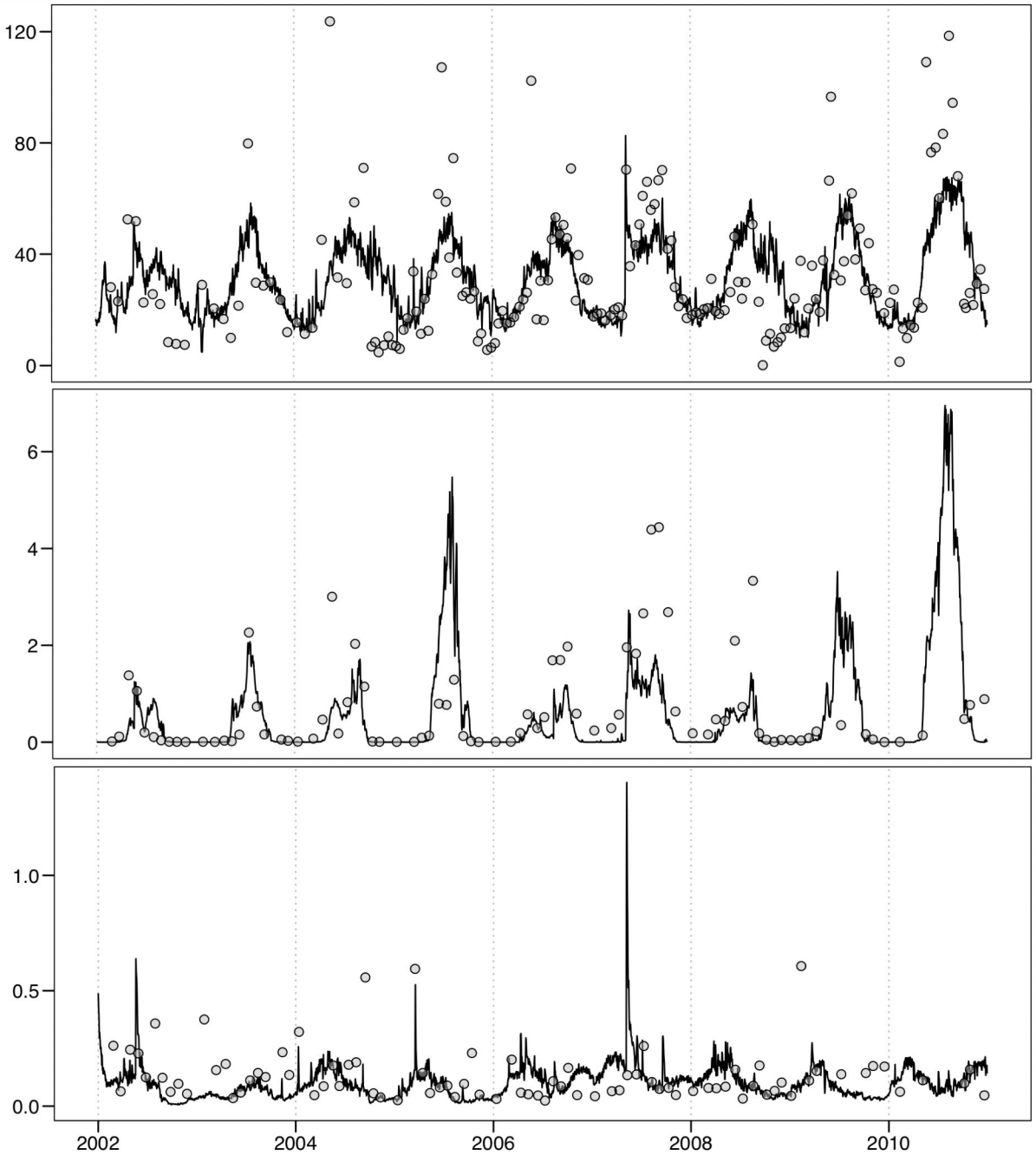


Why Lake George?
Impacted by blooms, characterized by 17 years of water quality data including **phytoplankton genera biomass**, and we had access to a **calibrated model**

Chlorophyll-a (µg L^{-1})
Model efficiency = [-1226, 0.36]
Median = -3.01

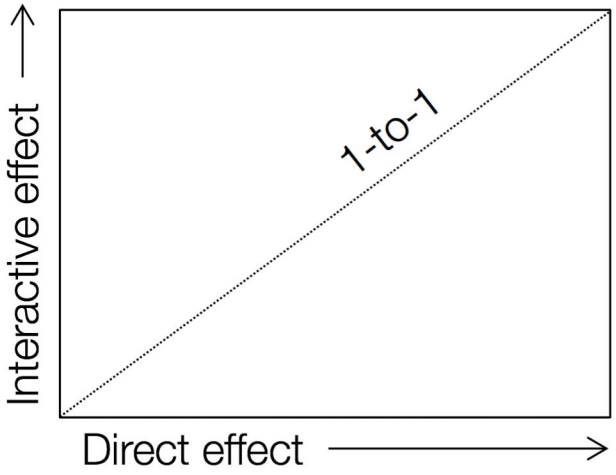
Cyanobacteria (mg C L^{-1})
Model efficiency = [-118, 0.19]
Median = -1.26

Eukaryotes (mg C L^{-1})
Model efficiency = [-58.6, -0.927]
Median = -7.58



Nelson et al., *in preparation*

Model efficiency sensitivity

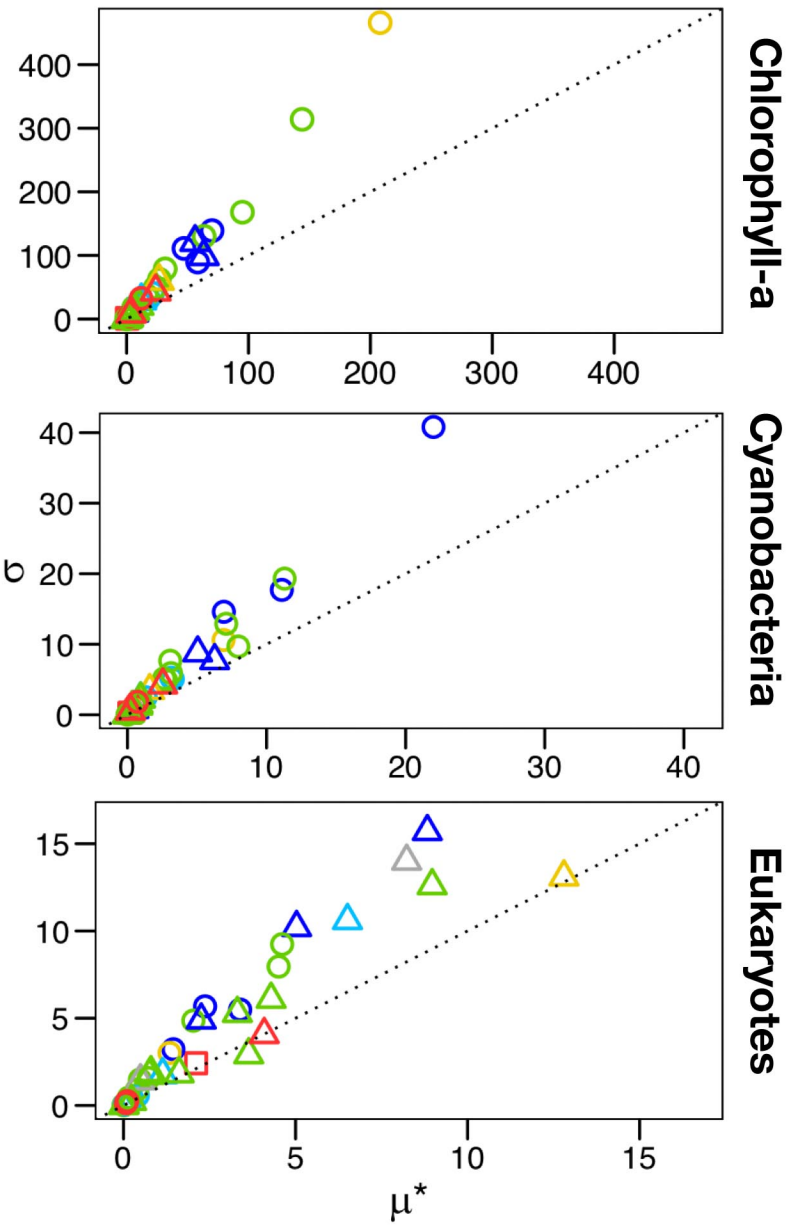


Phytoplankton classification

- ○ Cyanobacteria
- △ Eukaryotes
- □ General

Parameter type

- Chlorophyll–to–carbon ratio
- N uptake
- P uptake
- Photosynthesis and respiration
- Predation and settling
- Si uptake



Nelson et al., *in preparation*

Model efficiency sensitivity

Chlorophyll-a

$CHLA:C_{cy}$	Chlorophyll-to-carbon ratio of cyanobacteria
PM_{cy}	Rate of cyanobacteria growth under optimal growth conditions
BMR_{cy}	Basal metabolism rate of cyanobacteria

Cyanobacteria

$Q0_{cy}$	Minimum internal cell phosphorus for cyanobacteria
BMR_{cy}	Basal metabolism rate of cyanobacteria
$Vmax_{cy}$	Maximum rate of P uptake by cyanobacteria

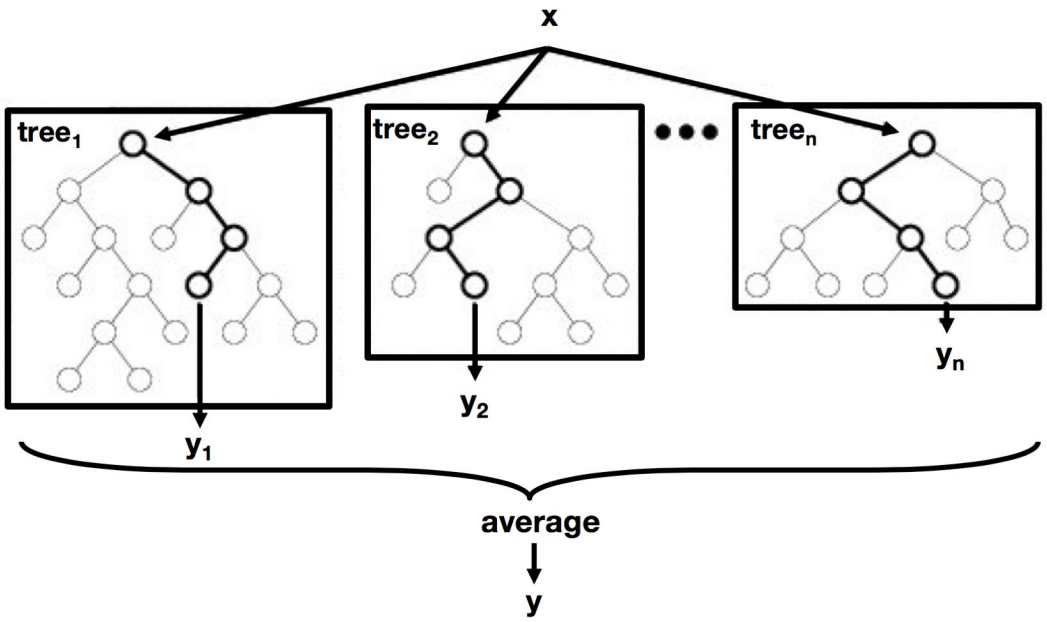
Nelson et al., *in preparation*

Phytoplankton functional group model take-aways

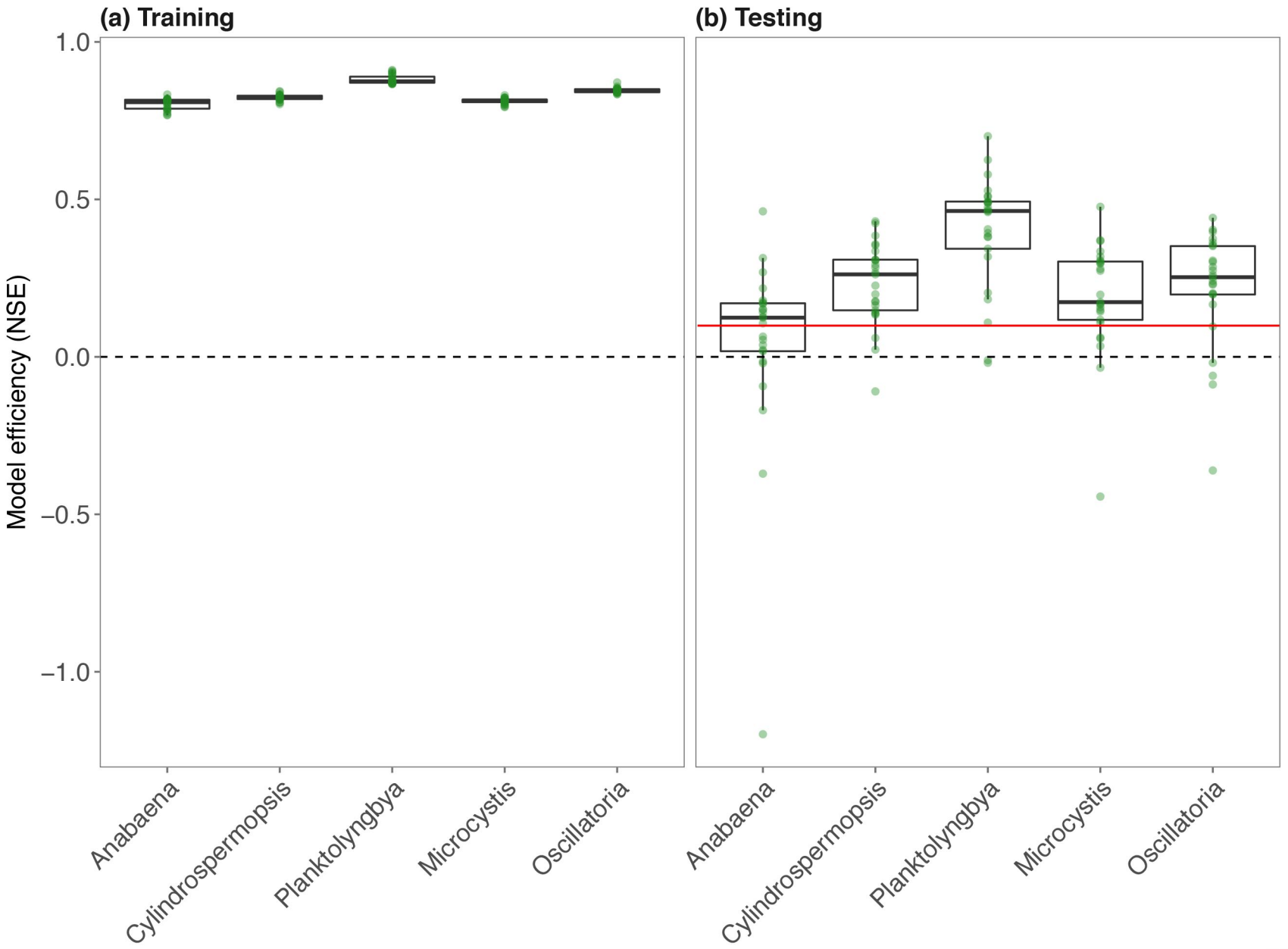
- GSA of a state-of-the-art mechanistic model demonstrates that management-relevant outputs are **very sensitive** to parameters that are **highly uncertain**
- Improvements to PFG models will require reduction in parameter uncertainty → is this possible? Who will fund this kind of work?
- In the interim, are parsimonious statistical models more appropriate?

Statistical machine learning

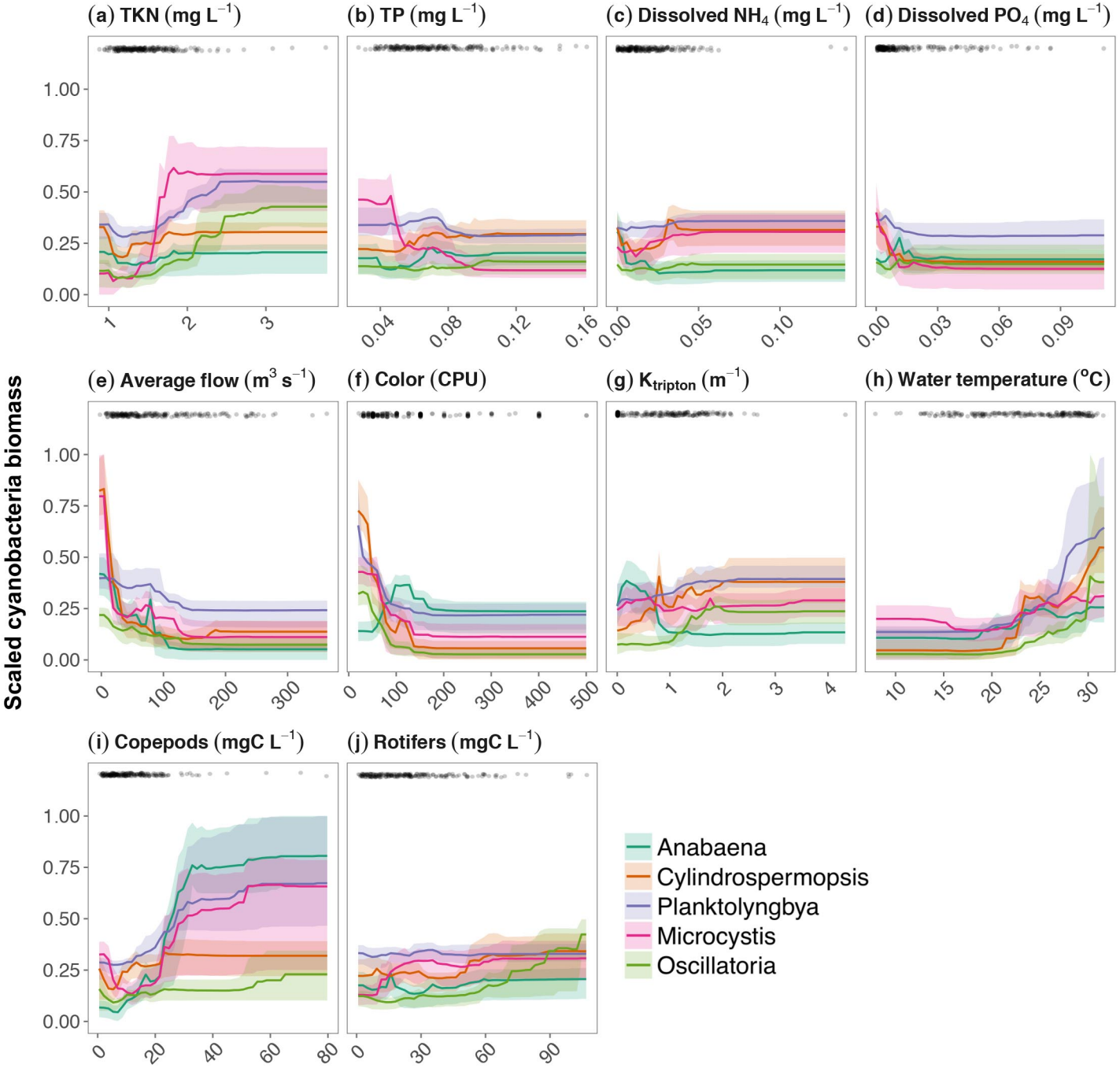
- Flexibility in model structure → ideal for modeling processes from complex/irregular systems
- Case study: applying Random Forest through 5-repeated 5-fold cross validation
  - Ensemble regression tree approach



Adapted from E. Vaicuiukynas



Nelson et al. (2018), *Environmental Science & Technology*



Nelson et al. (2018), *Environmental Science & Technology*

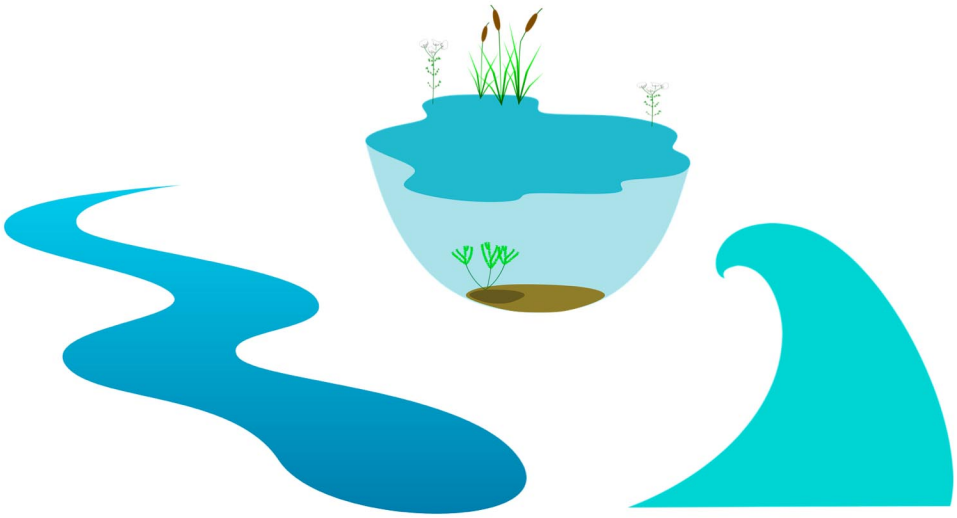
Physical-statistical modeling of phytoplankton groups?

- For TMDL development in highly dynamic systems, should we gravitate away from PFG models?
  - Physical processes (many, not all) are well represented by mechanistic models
  - Machine learning approaches seem to be effective at predicting *very detailed* phytoplankton dynamics
  - → best of both worlds with physical-statistical modeling?

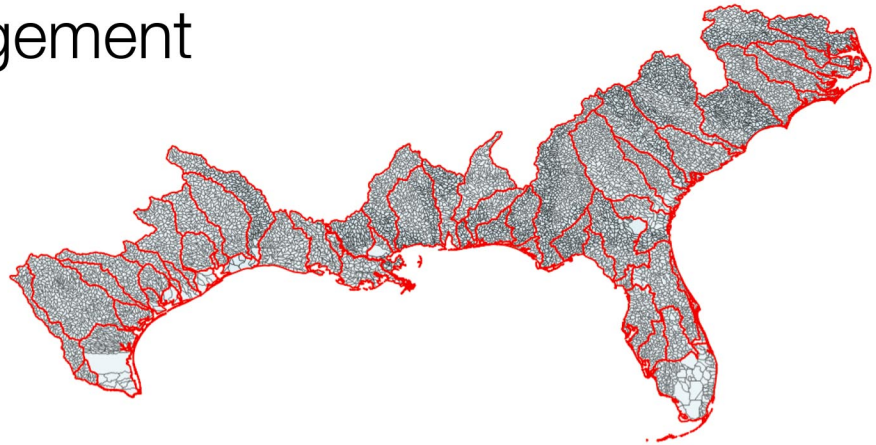
- At present, statistical models are used in TMDL development, but largely for analyzing relationships between land use and nutrient loading

Thinking “big” – spatially

Analyzing blooms at cross-system scales



Replacing reactive management with proactive planning

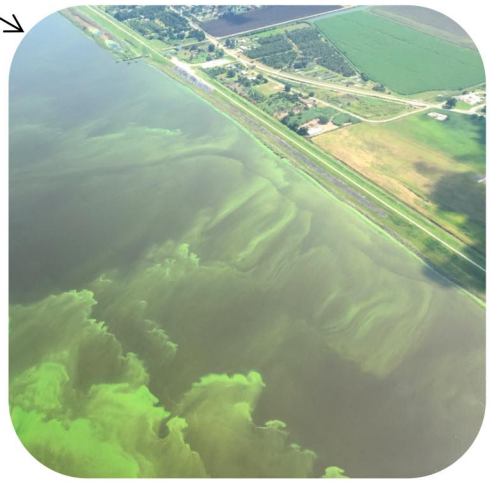


Cross-system bloom dynamics

Source: Calusa Waterkeeper, 2018

Source: J. Flannery, 2016

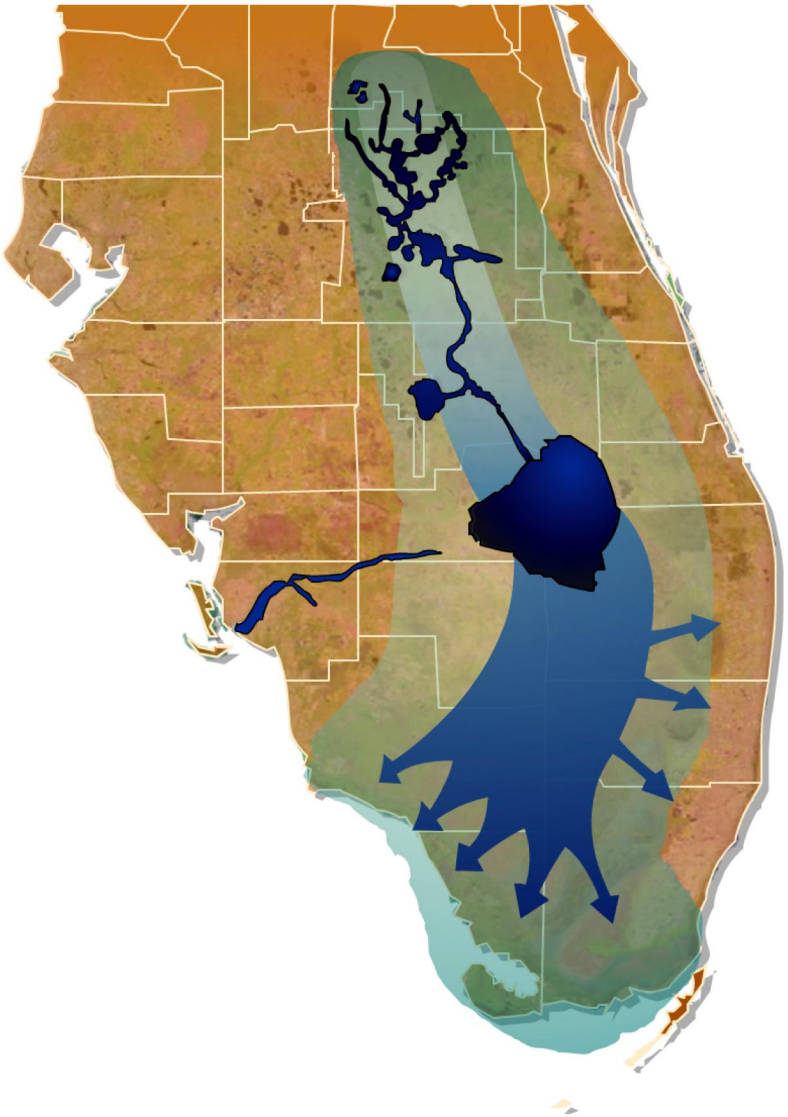
Source: Ben Depp (Nat Geo), 2018

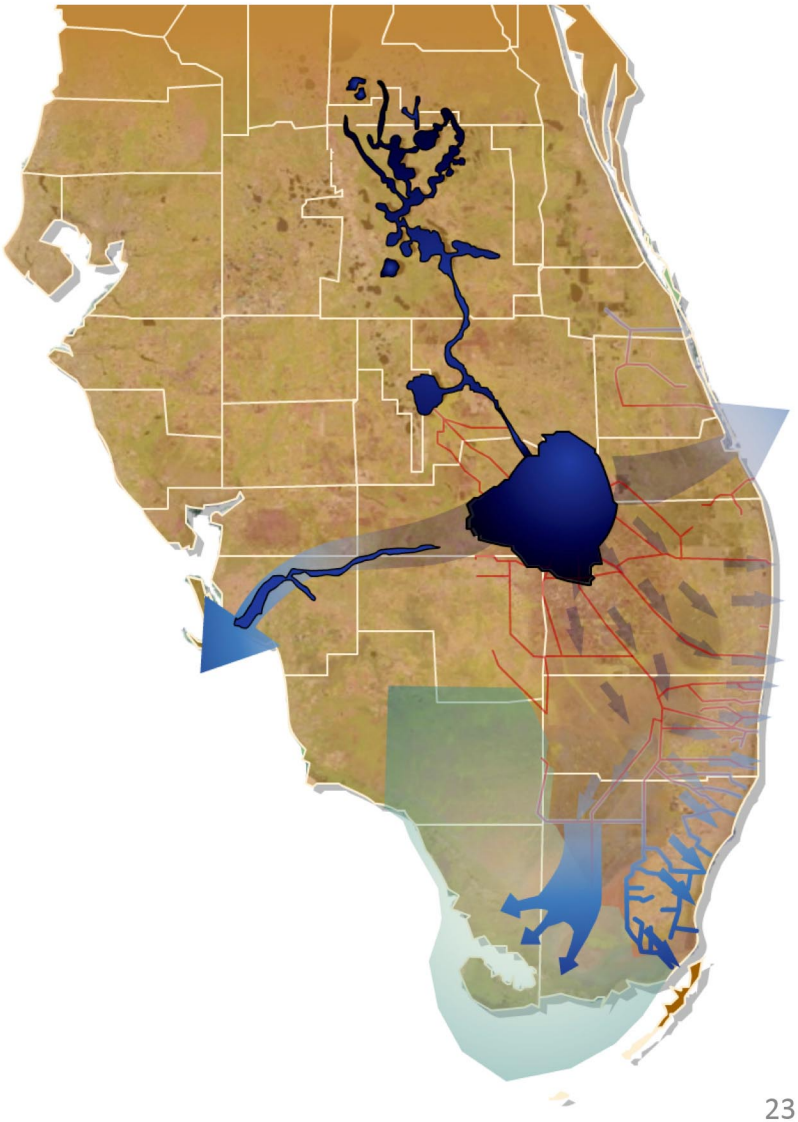


Source: USGS, 2016

Lake Okeechobee
Coastal Connections

Cross-system bloom dynamics



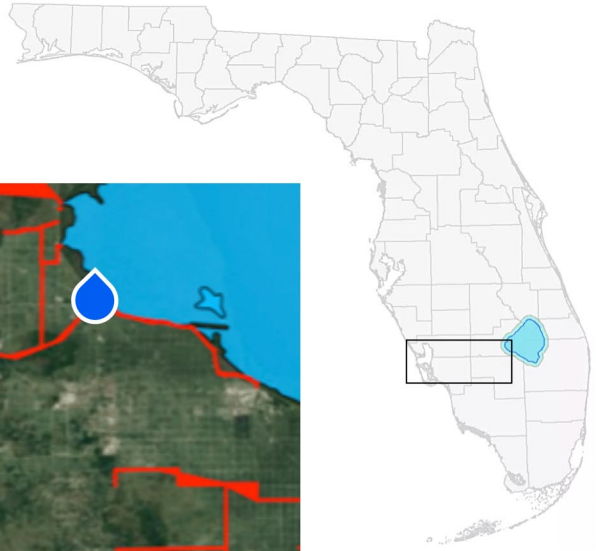


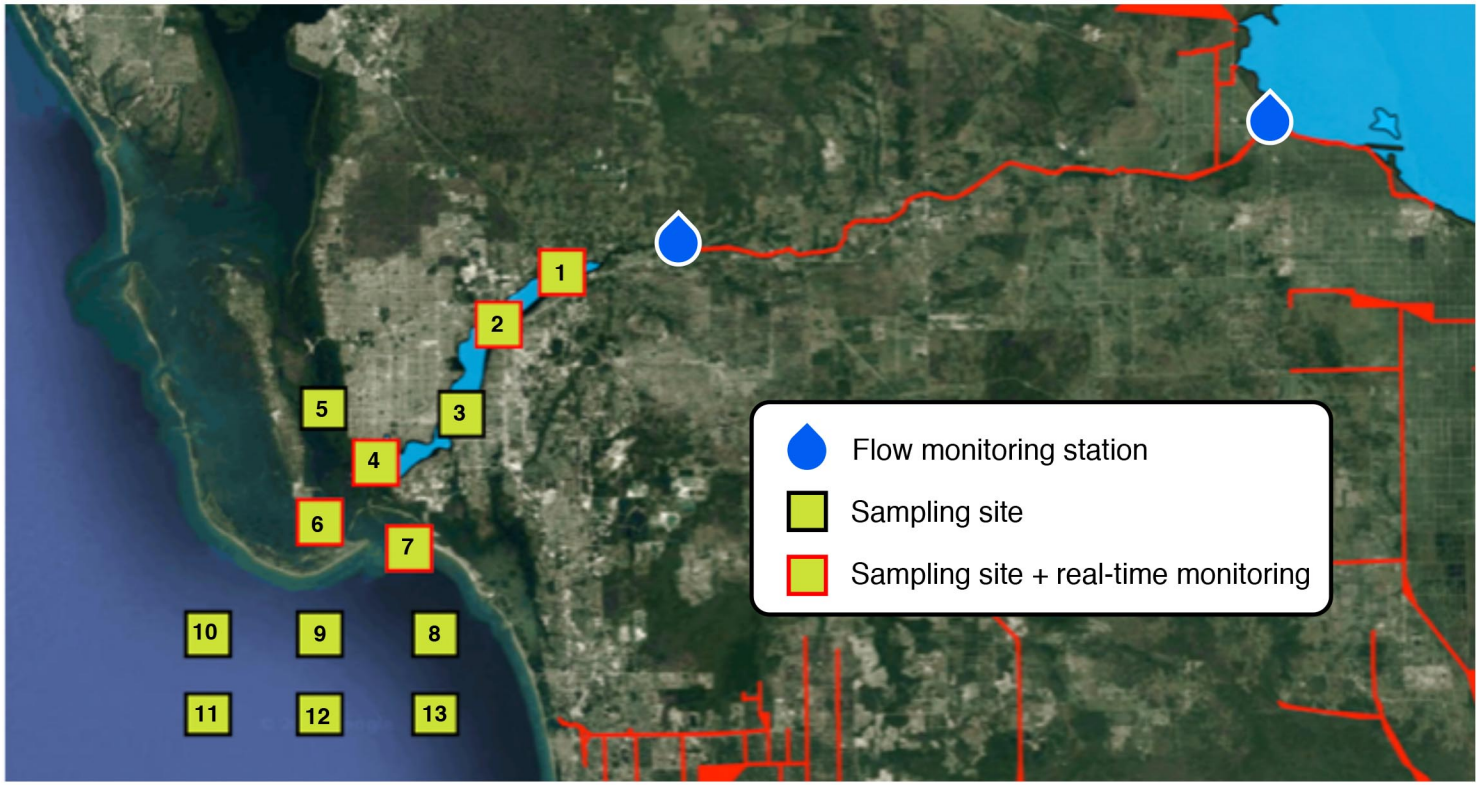
Source: SFWMD

Source: Planet Labs

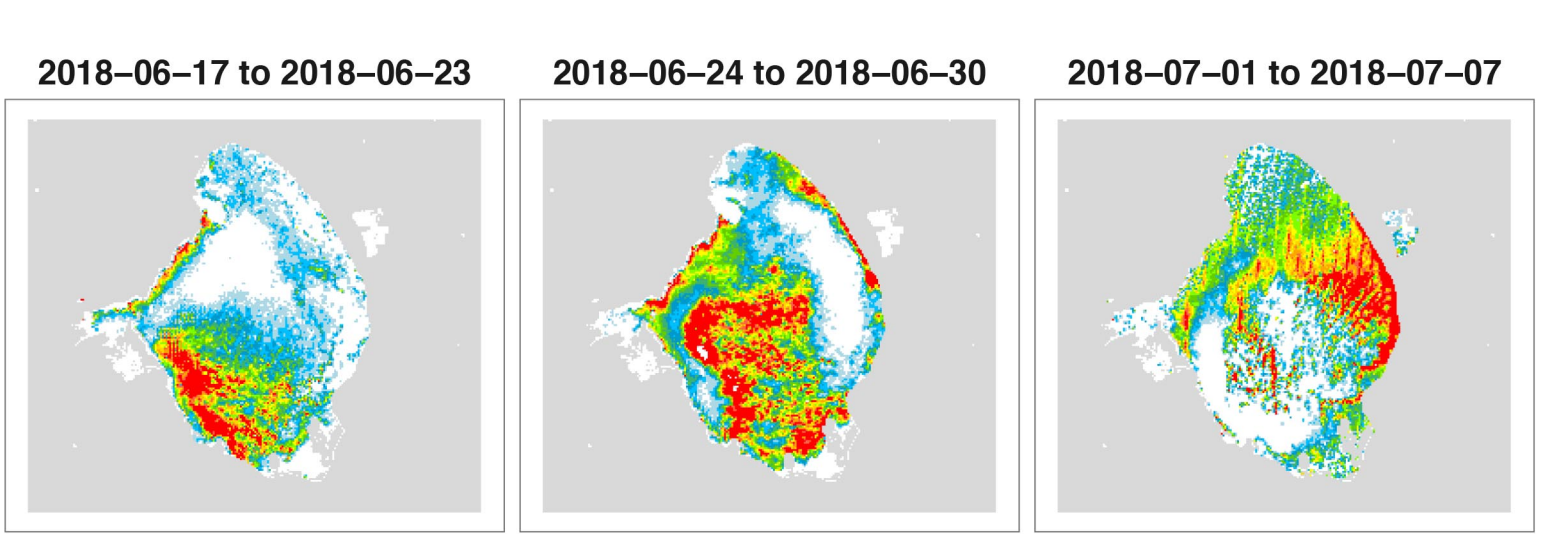
Objective: analyze multi-scale data to investigate connections between freshwater management, freshwater cyanobacteria blooms, and coastal red tides

System-scale bloom dynamics





System-scale bloom dynamics

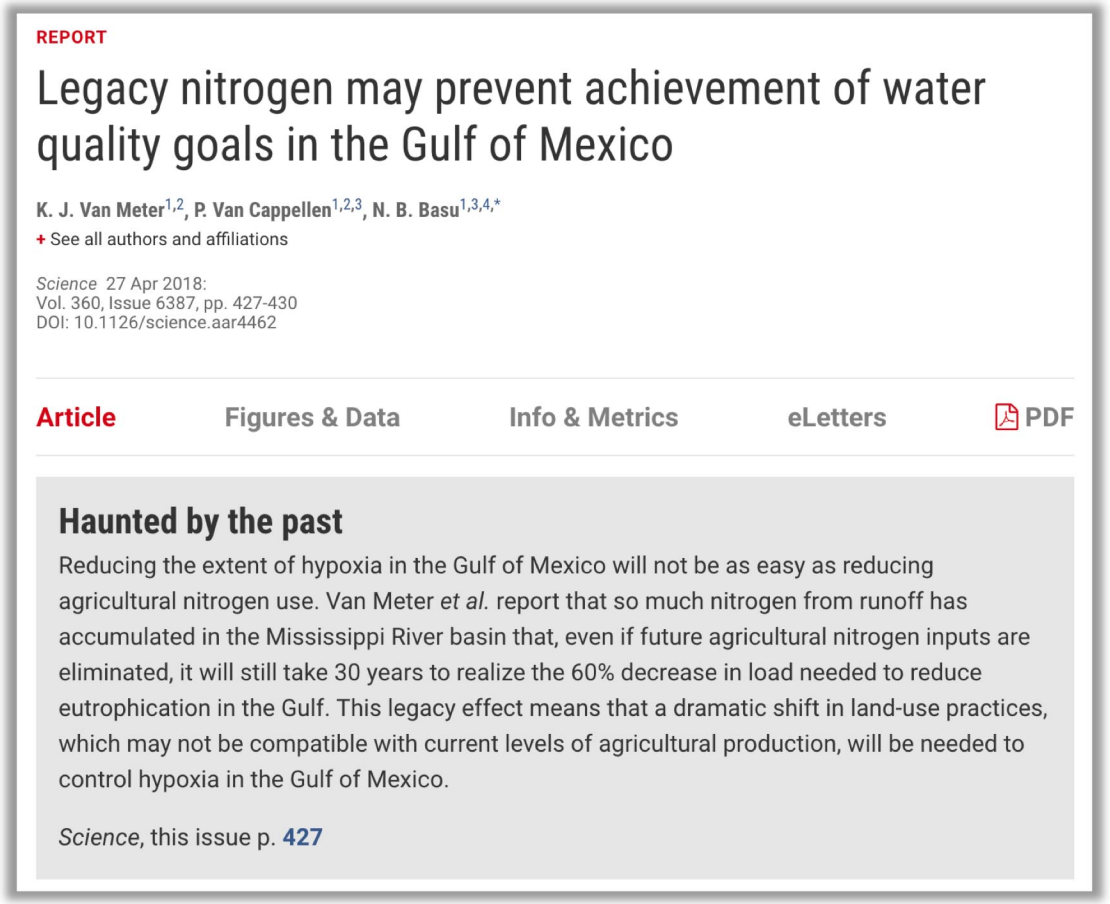


Data: Cyanobacteria Assessment Network (CyAN); EPA, NASA, NOAA, USGS

Out of the water and into the basin

In many systems, recovery from the effects of nutrient loading will take decades

What areas remain where proactive, smart planning & management can occur to avoid long-term water quality impacts?



REPORT

Legacy nitrogen may prevent achievement of water quality goals in the Gulf of Mexico

K. J. Van Meter[1,2], P. Van Cappellen[1,2,3], N. B. Basu[1,3,4,*]
+ See all authors and affiliations

Science 27 Apr 2018:
Vol. 360, Issue 6387, pp. 427-430
DOI: 10.1126/science.aar4462

Article | Figures & Data | Info & Metrics | eLetters | PDF

Haunted by the past

Reducing the extent of hypoxia in the Gulf of Mexico will not be as easy as reducing agricultural nitrogen use. Van Meter *et al.* report that so much nitrogen from runoff has accumulated in the Mississippi River basin that, even if future agricultural nitrogen inputs are eliminated, it will still take 30 years to realize the 60% decrease in load needed to reduce eutrophication in the Gulf. This legacy effect means that a dramatic shift in land-use practices, which may not be compatible with current levels of agricultural production, will be needed to control hypoxia in the Gulf of Mexico.

Science, this issue p. 427

Objective: identify basins with the greatest potential and needs for coastal eutrophication mitigation

Vulnerability of eutrophication under future conditions

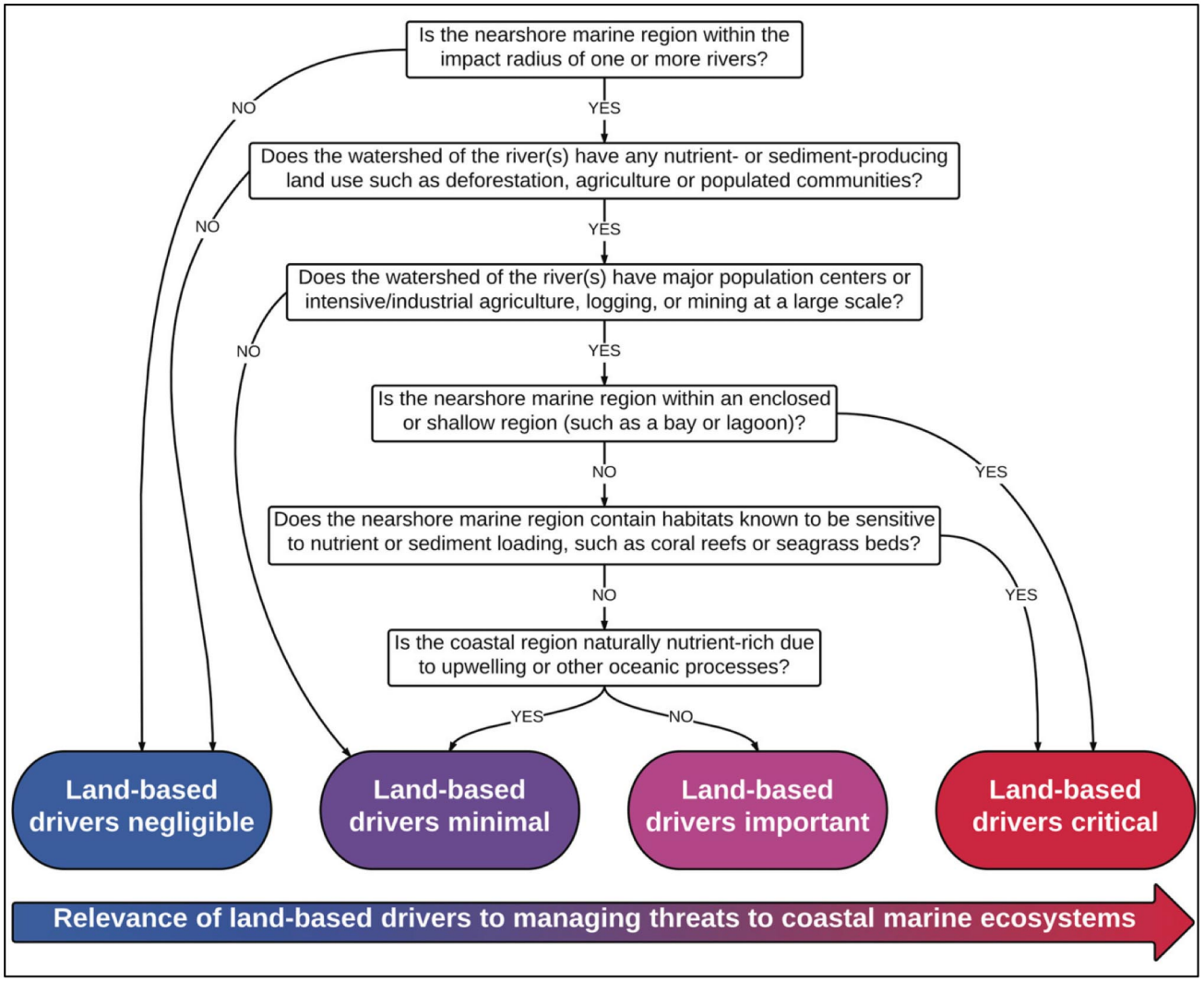
Exposure (future)

- Climate-driven changes in runoff
- Nutrient loading driven by land use change
- *Multiple scenarios*

Adaptive Capacity (present)

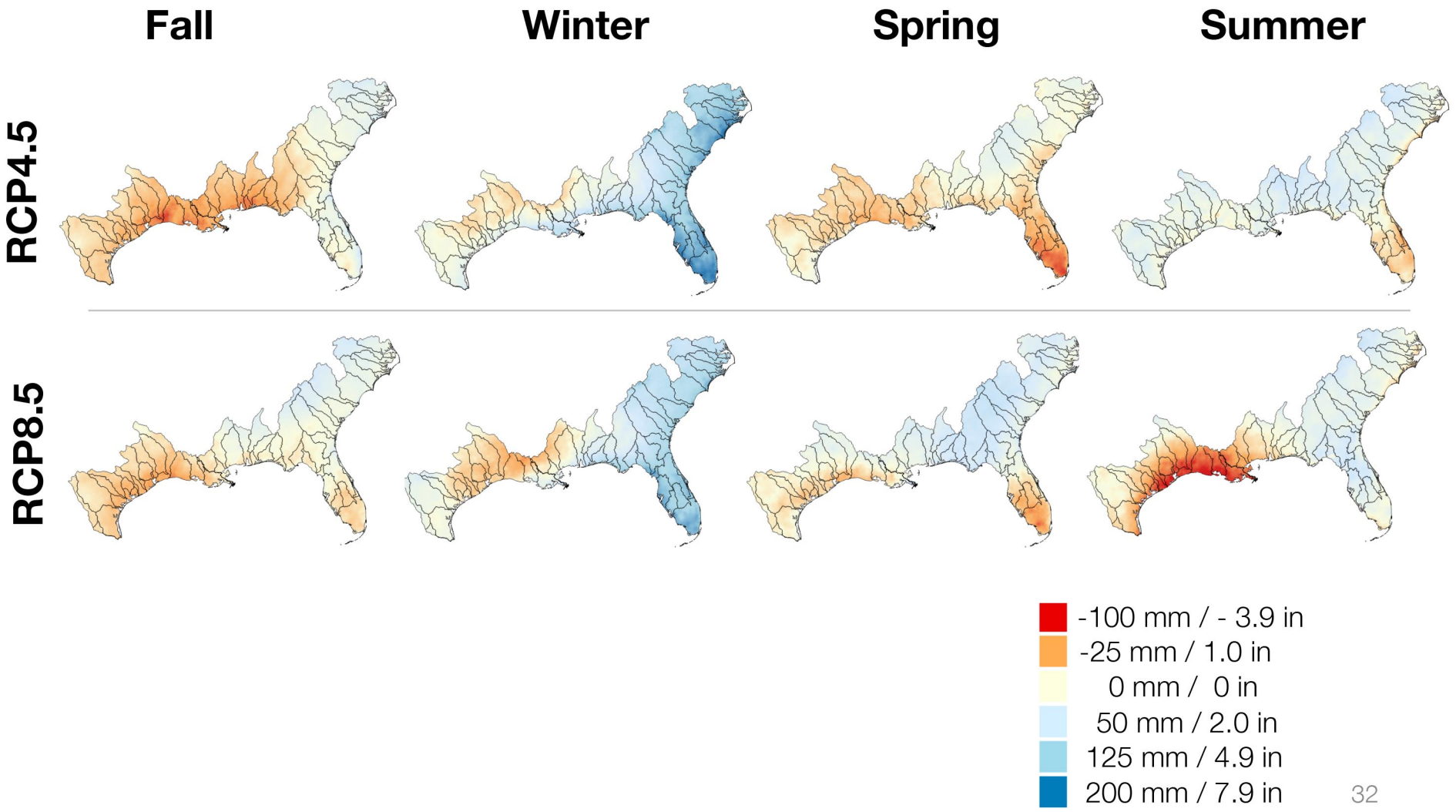
- Presence of biogeochemical activity hotspots (e.g. wetlands, floodplains)
- Public lands
- Natural or semi-natural land cover area

Focus on the Southeast U.S.

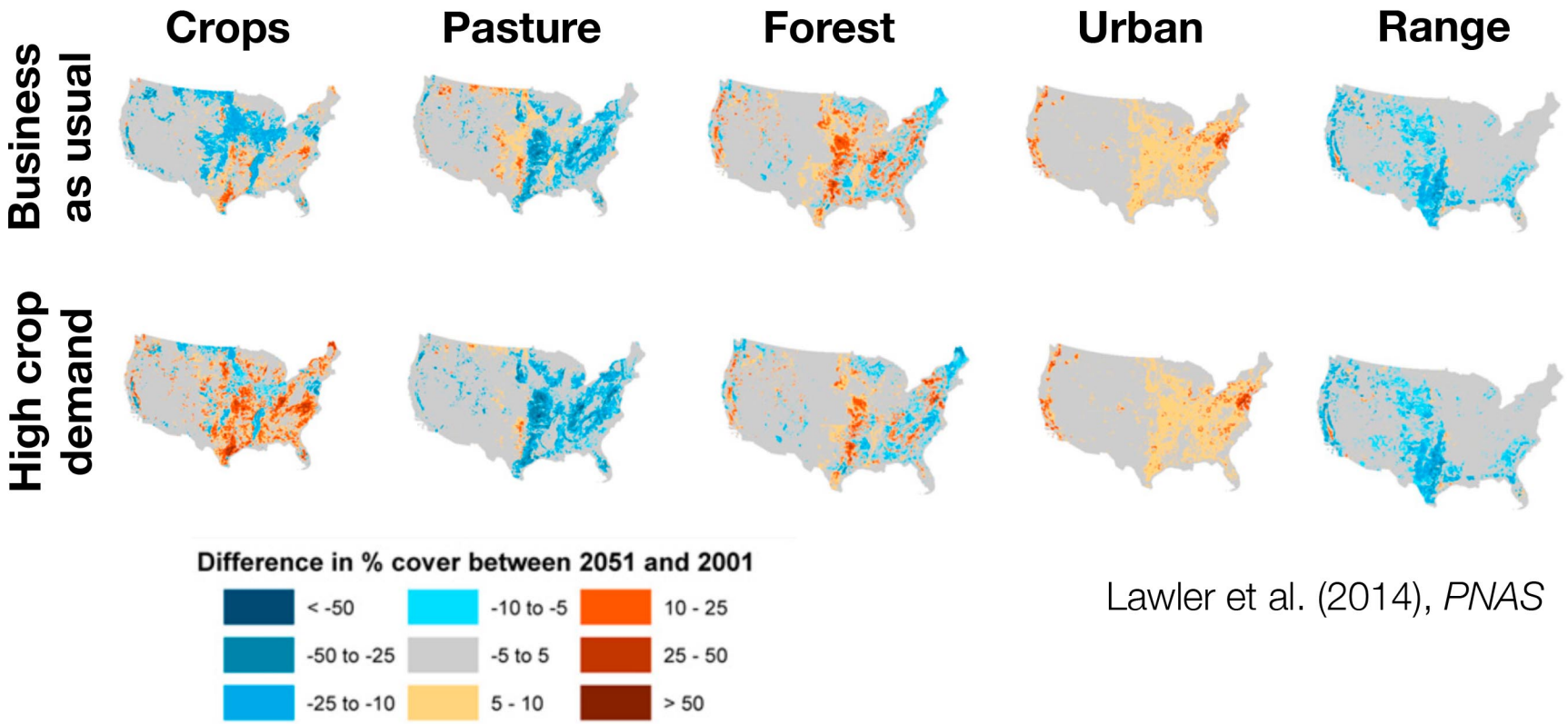


Fredston-Hermann et al. 2016

Potential runoff ($P - ET_0$): 1950-2005 vs. 2020-2050



Land use change projections (2050)

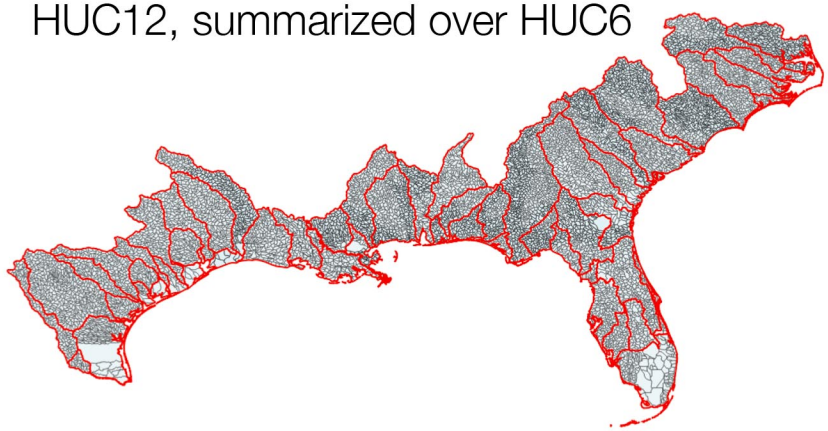


Lawler et al. (2014), *PNAS*

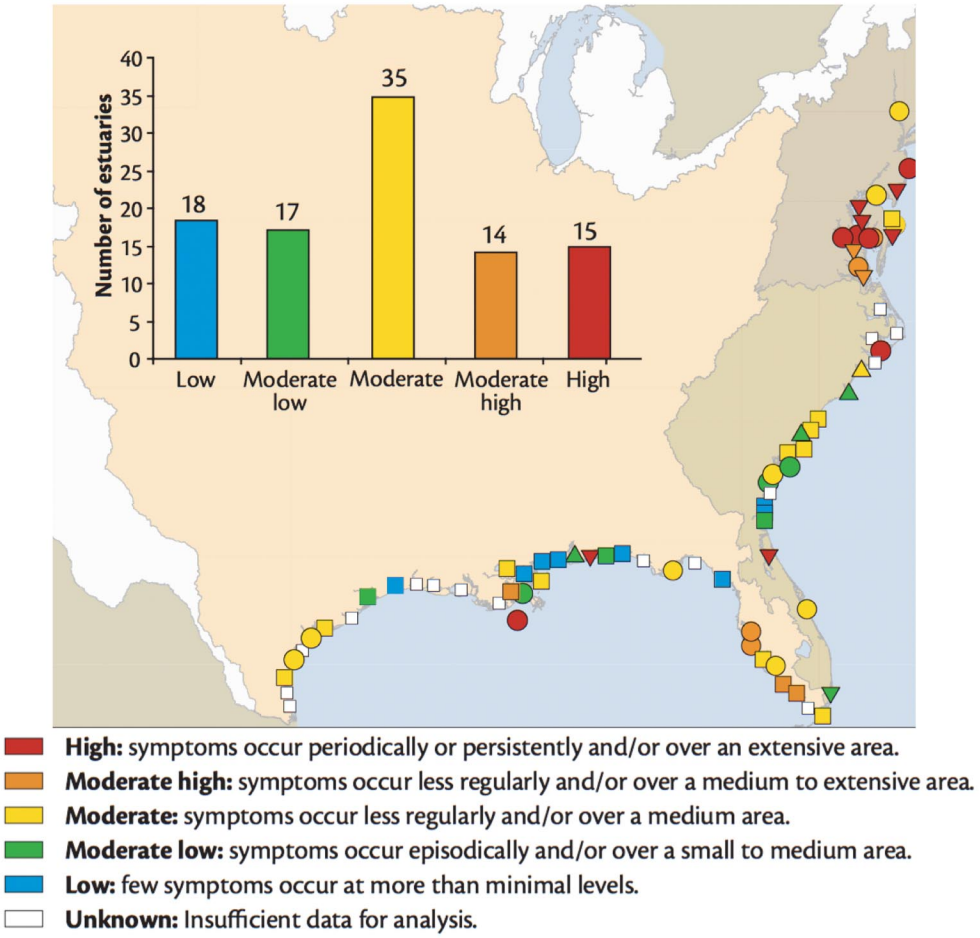
Predict nutrient loading potential

Simple runoff + nutrient loading model

EPA STEPL model applied to each HUC12, summarized over HUC6



Validate: Overall Eutrophication Condition scores



Source: National Estuarine Eutrophication Assessment

Biosystems Analytics Lab

Lise Montefiore
PhD student
Relationships between land use change and water quality: historical trends and future projections

Emine Fidan
PhD student
Flood-driven water quality dynamics across agriculturally-diverse landscapes

Sam Blackman
Undergraduate Research Assistant
Tidal creek dissolved oxygen dynamics across National Estuarine Research Reserve sites

Bio&Ag ENGINEERING

Thank you!

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