

Big data informing lake ecology: Case study on nutrient and water color effects on lake primary production

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Wagner

Michigan Inland Lakes Convention

April 2016



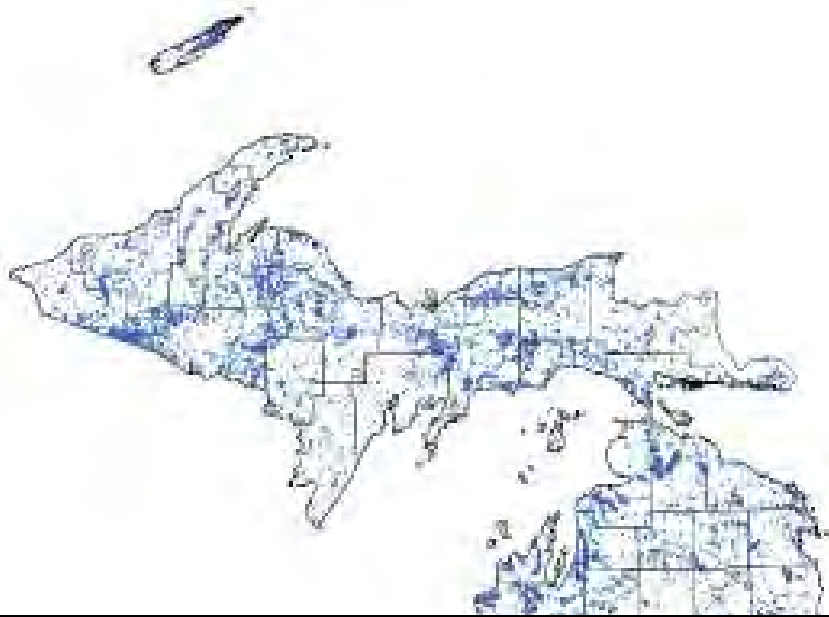
Lakes in the landscape



Michigan over 10,000 inland lakes (>4 ha in size)

U.S. estimated over 120,000 inland lakes

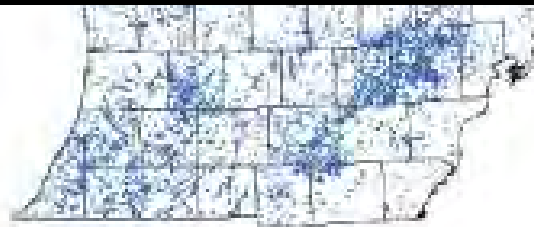
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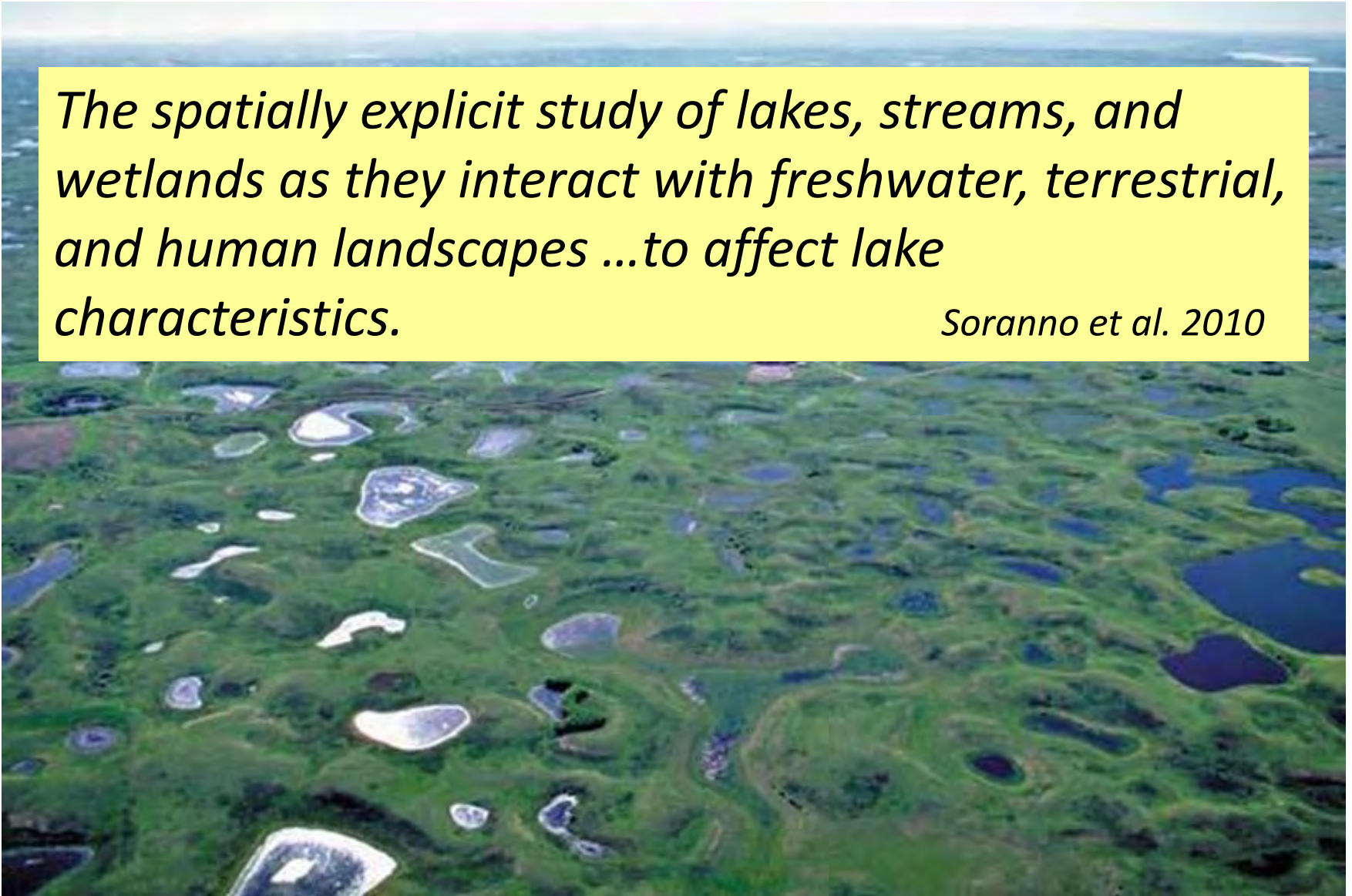
How can we effectively study and manage them?



Landscape limnology

The spatially explicit study of lakes, streams, and wetlands as they interact with freshwater, terrestrial, and human landscapes ...to affect lake characteristics.

Soranno et al. 2010



Landscape limnology

Principles

Patch characteristics



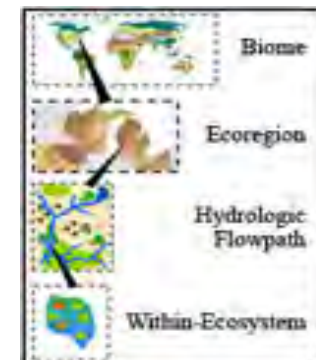
Patch context



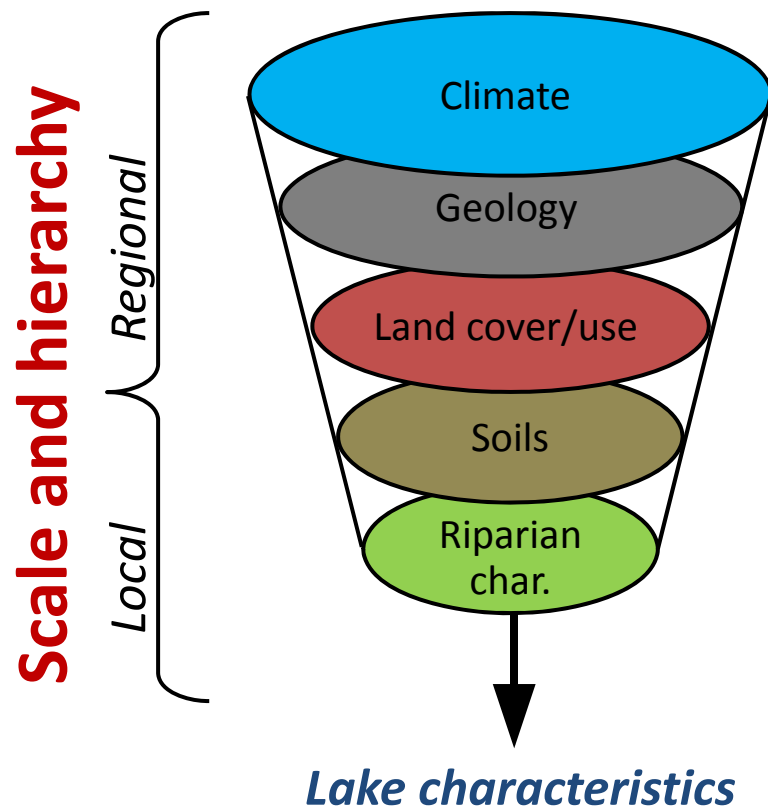
Patch connectivity & directionality



Spatial scale & hierarchy



Landscape limnology



Novel questions and perspectives

- Regional variation
- Broad-scale disturbance effects
- Prediction
- Temporal trends



Harnessing 'Big Data' to address lake questions



Harnessing 'Big Data' to address lake questions



Indiana
Clean Lakes Program



Minnesota Pollution Control Agency

Overall Goals

- More holistic understanding of lake ecology
- Provide information to guide management and conservation action



Case study

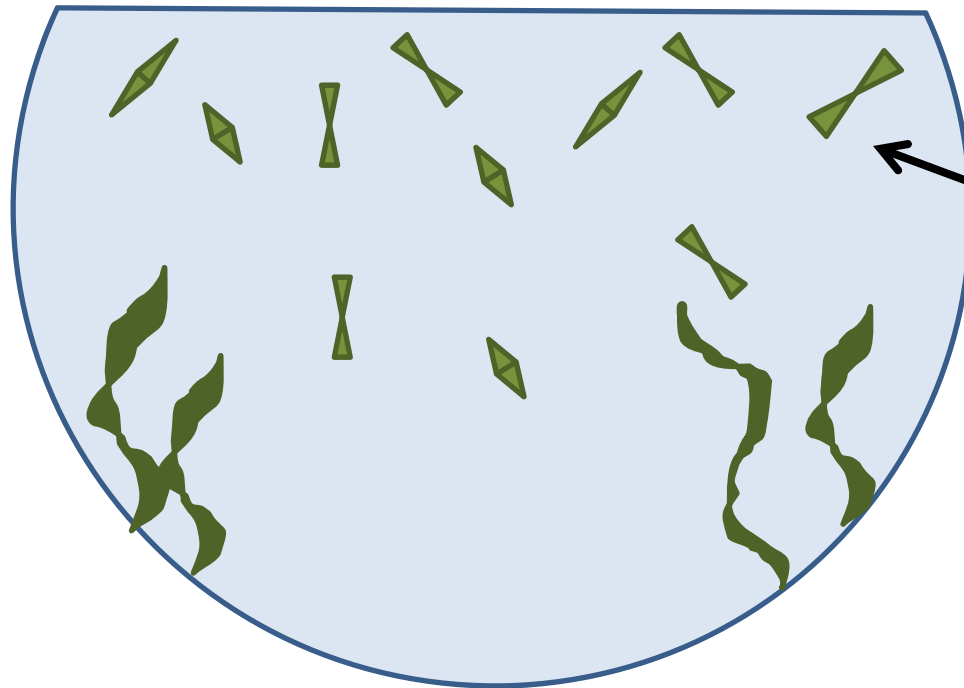
Lake nutrient and water color effects on lake primary production



Drivers of lake primary production

Nutrients

Light



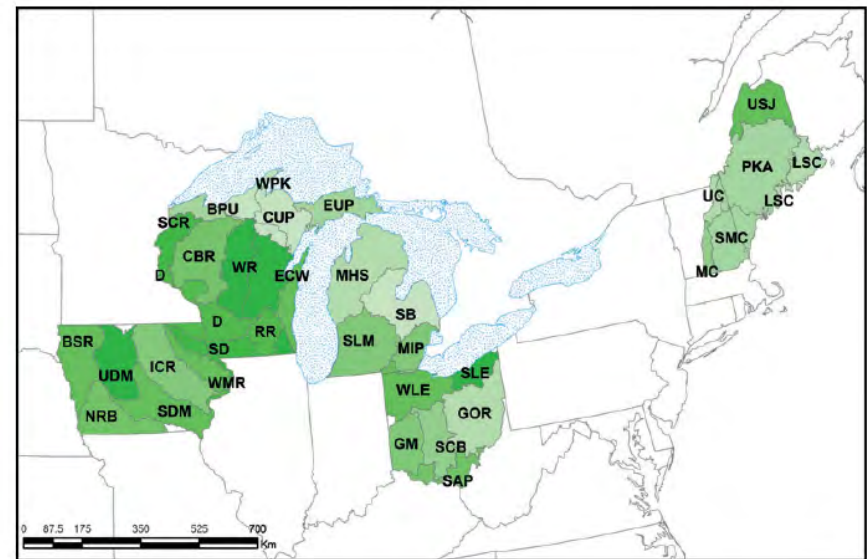
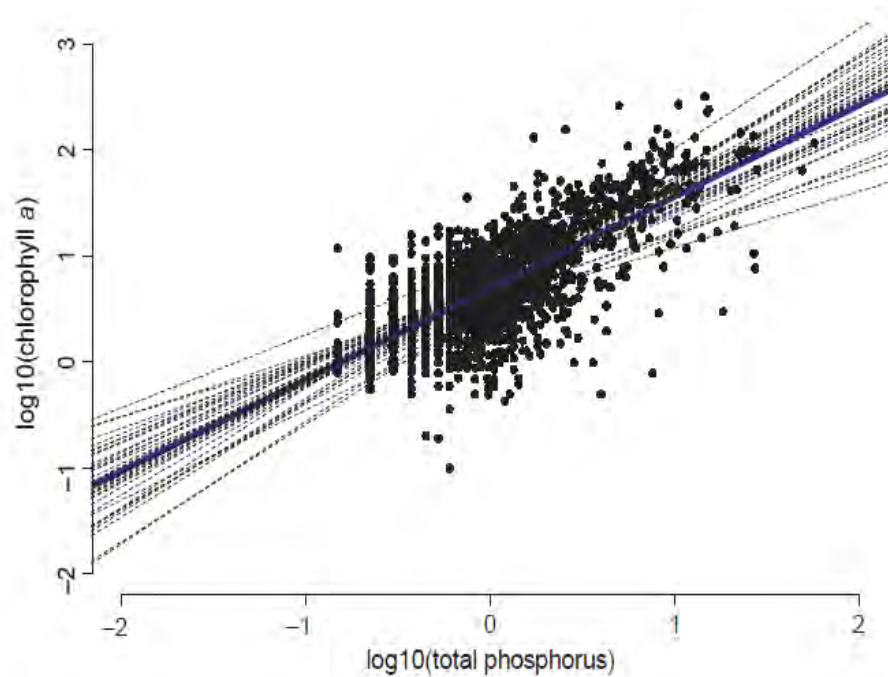
Phytoplankton
Bulk of 1°
production in lakes

TP ~ Chlorophyll a relationship



Revisiting the TP ~ Chlorophyll relationship

TP ~ CHL

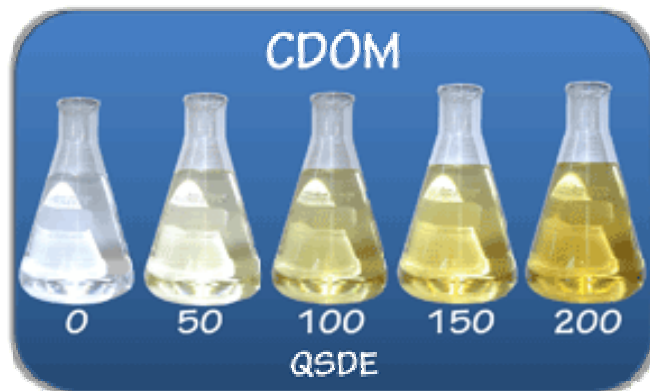


Spatial variation in relationships

Colored dissolved organic carbon (water color)

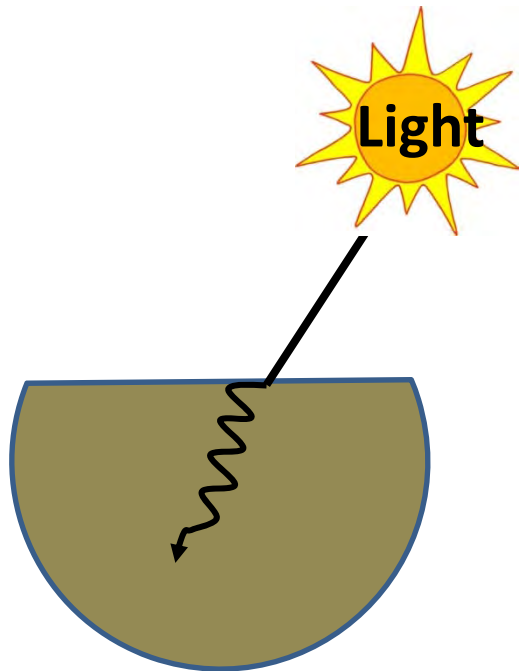


- Humic substances primarily from surrounding landscape
- Alters physical, chemical, and biological environment



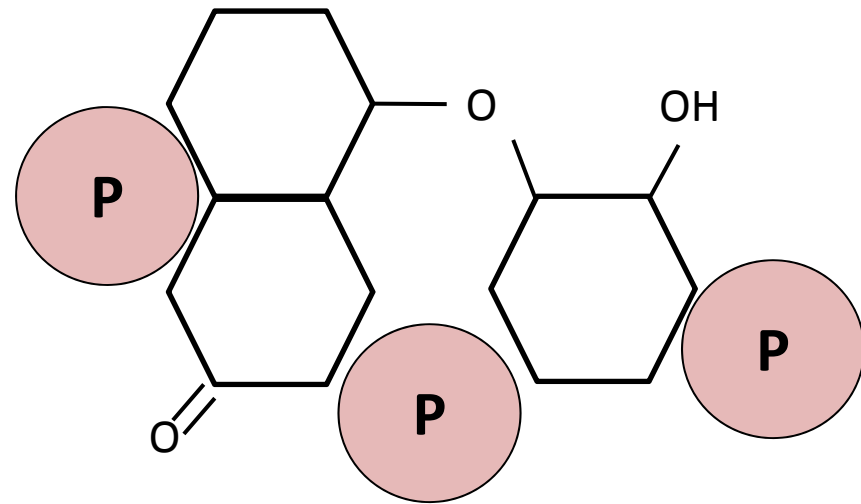
Colored dissolved organic carbon (Water Color)

Negative effects



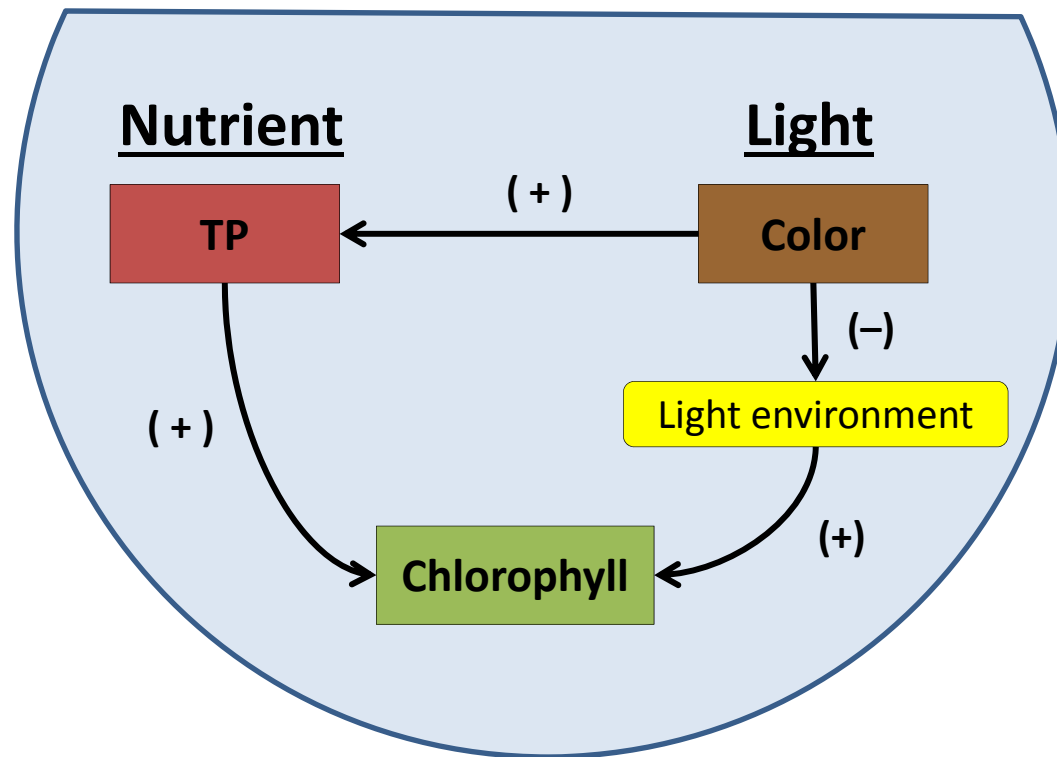
- Weakens light
- Shades algae

Positive effects



- Nutrients bound to humic compounds

Nutrient-water color paradigm



Important to understand in time of global change

ENVIRONMENTAL
Science & Technology



Article

pubs.acs.org/est

Continental-Scale Increase in Lake and Stream Phosphorus: Are Oligotrophic Systems Disappearing in the United States?

John L. Stoddard,^{*,†} John Van Sickle,^{†,‡} Alan T. Herlihy,[§] Janice Brahney,^{||} Steven Paulsen,[†]
David V. Peck,[†] Richard Mitchell,[⊥] and Amina I. Pollard[⊥]



Nutrient

Freshwater Biology

Freshwater Biology (2014) 59, 325–336

doi:10.1111/fwb.12267

Warming and browning of lakes: consequences for pelagic carbon metabolism and sediment delivery

EMMA S. KRITZBERG, WILHELM GRANÉLI, JESSICA BJÖRK, CHRISTER BRÖNMARK, PER HALLGREN, ALICE NICOLLE, ANDERS PERSSON AND LARS-ANDERS HANSSON
Department of Biology, Aquatic Ecology, Lund University, Lund, Sweden



DOC



<http://www.peak-light.com/black-clough>

Landscape nutrient and carbon sources

- **Agriculture** –
nutrient source
- **Wetlands &
Forest** –
carbon source

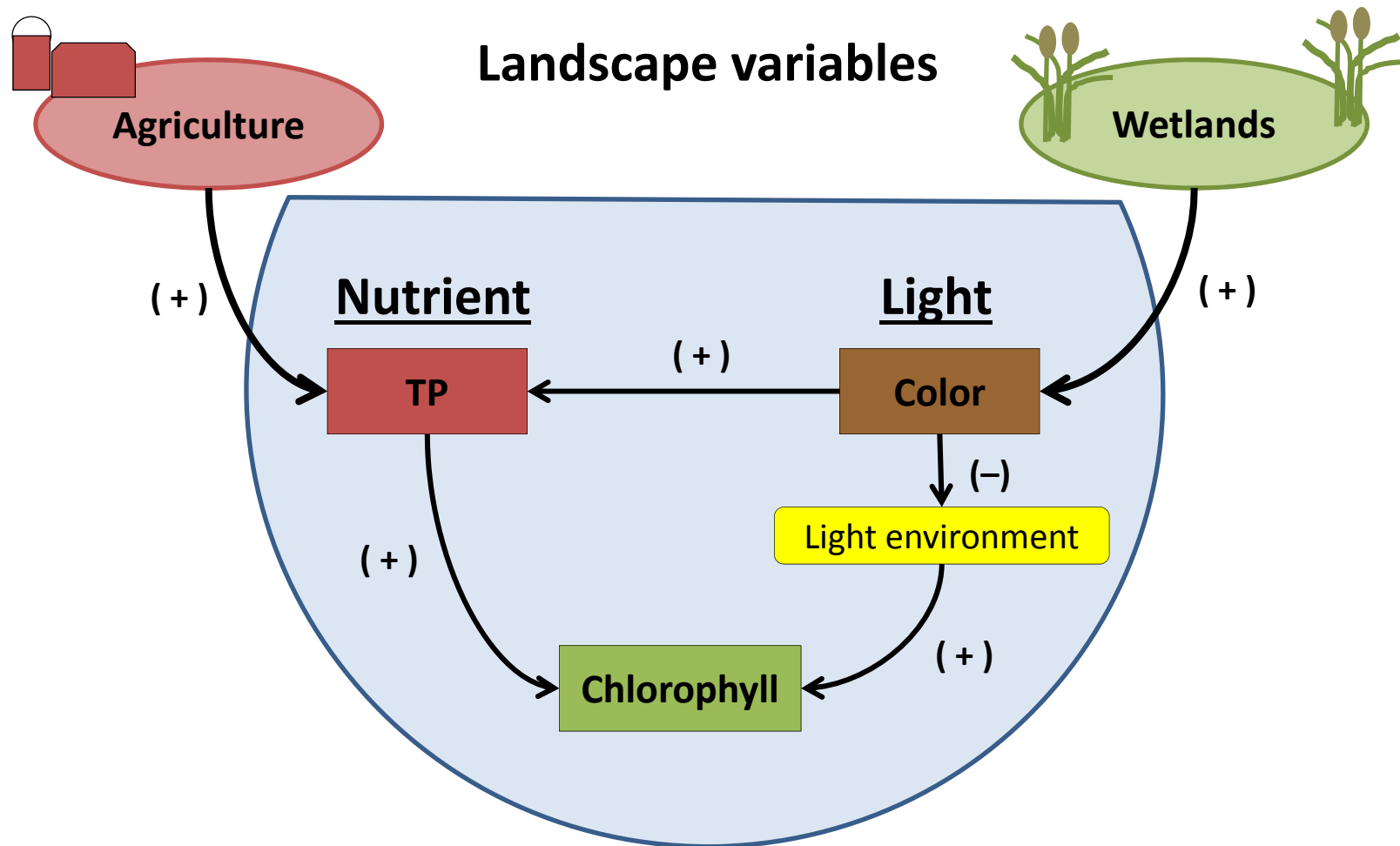


<http://www.garthlenz.com/industrial-landscape/agriculture/Ches-Lancaster-8436>

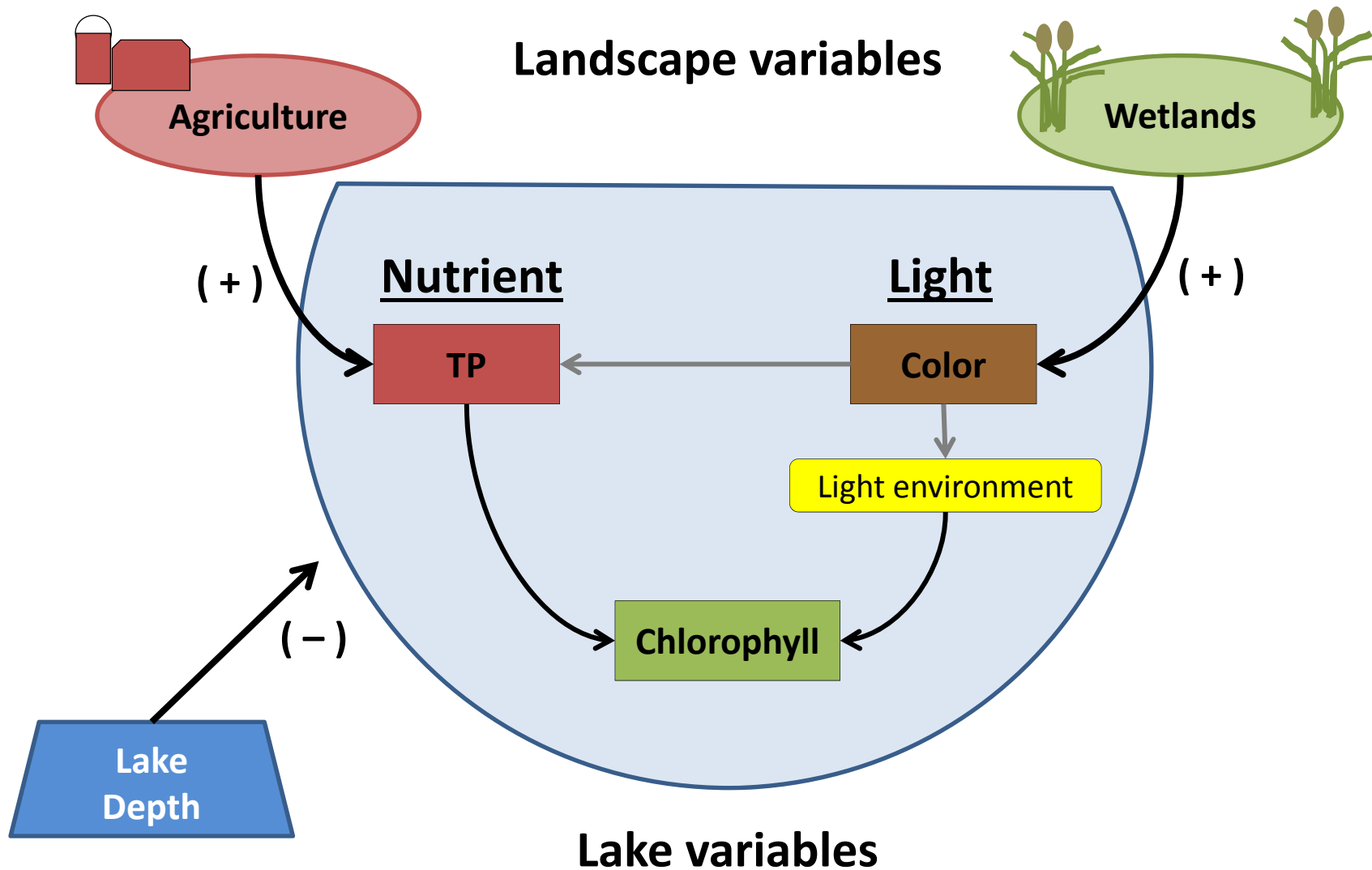


<http://blogs.ubc.ca/theardgers/2015/05/03/impacts-of-climate-change-on-carbon-emissions-from-canadian-peatlands/>

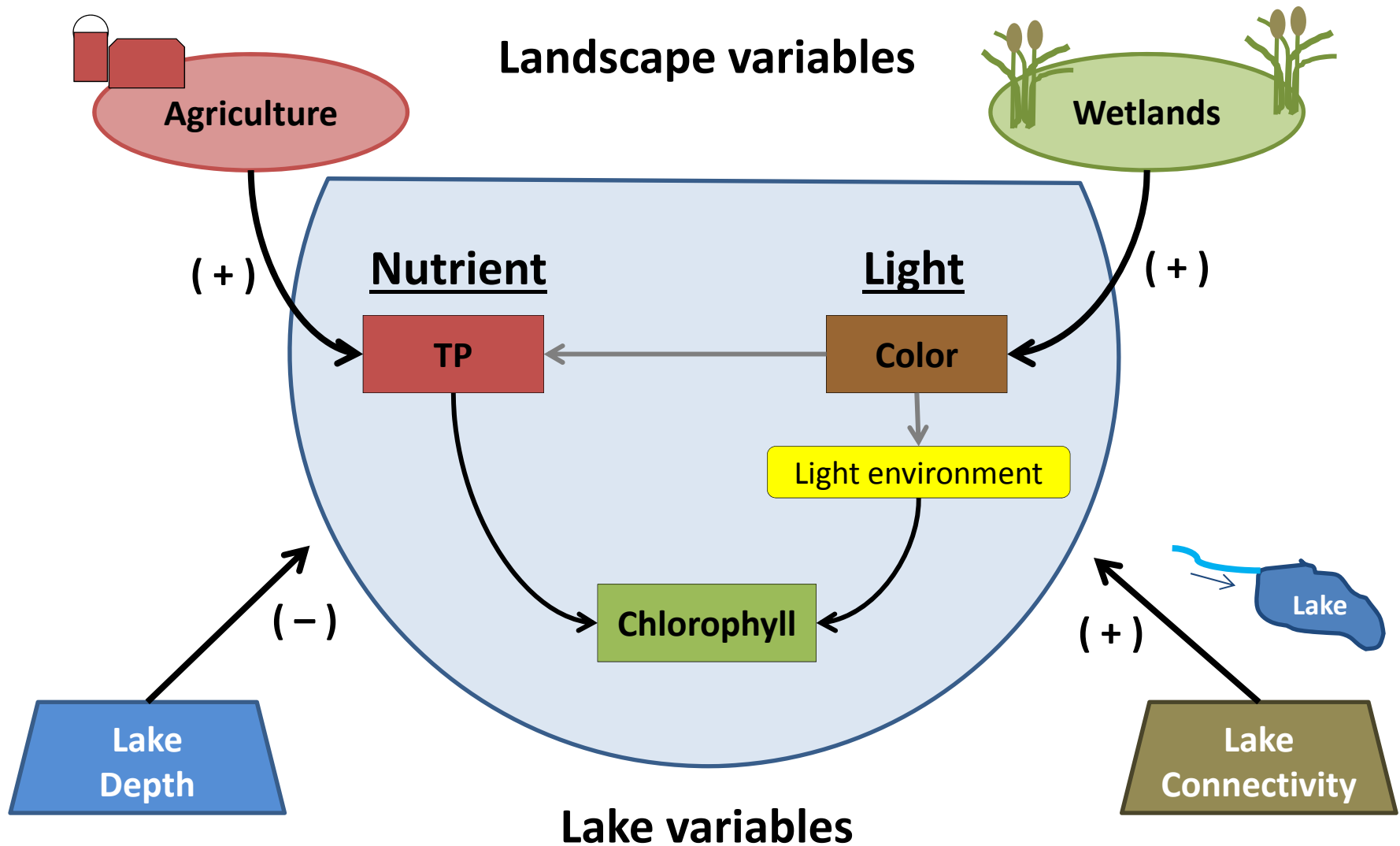
Spatial Nutrient-water color paradigm



Spatial Nutrient-water color paradigm



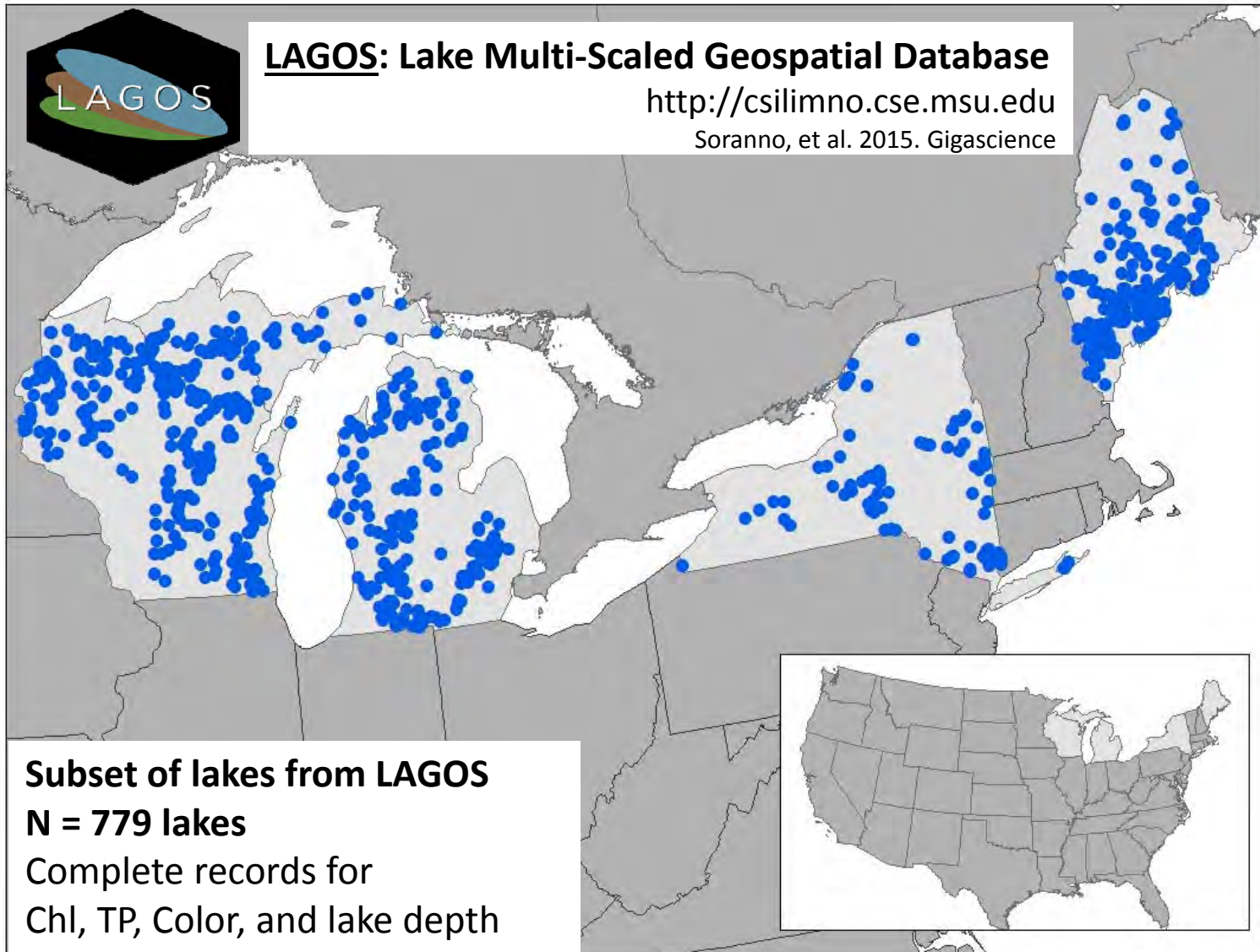
Spatial Nutrient-water color paradigm



Research questions

- 1) Do TP and Water Color effects on Chlorophyll vary over space?**
- 2) If so, are there lake and landscape variables that account for variation in these relationships?**

Lake database

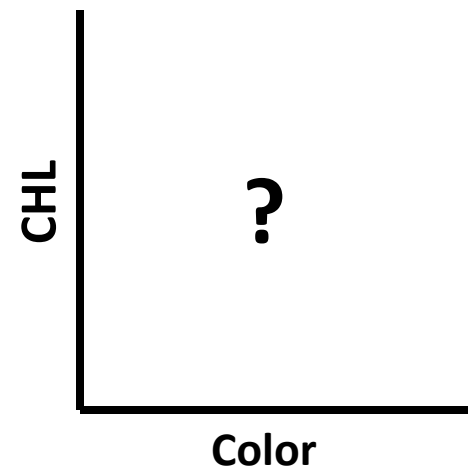
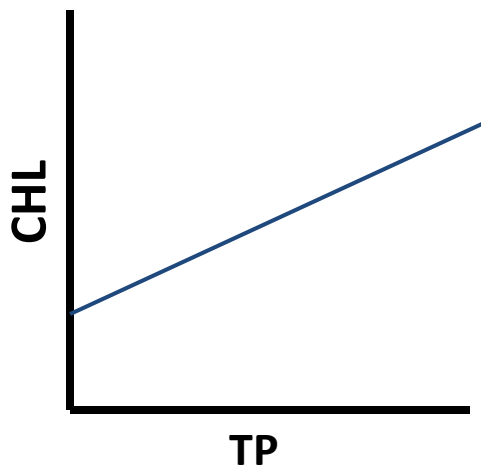


Spatially-varying coefficient model

Co-authors: quantitative ecologists
with mad statistical skills



$$Chl_t(s) = \tilde{x}_t(s)\tilde{\beta}(s) + x_t(s)\beta + \epsilon_t(s)$$

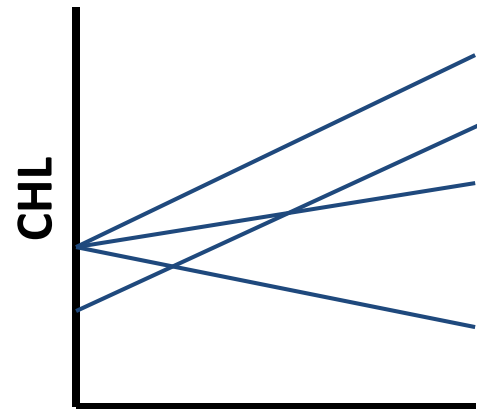
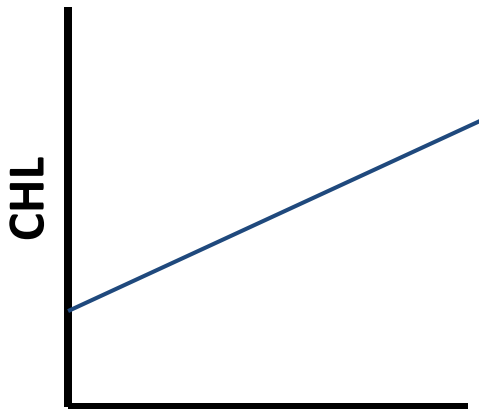


Spatially-varying coefficient model

Spatially-varying
coefficients

$$Chl_t(s) = \tilde{x}_t(s) \tilde{\beta}(s) + x_t(s) \beta + \epsilon_t(s)$$

$\tilde{\beta}(s)$ = Intercept, TP, and Water Color



Spatially-varying coefficient model

Spatially-varying
coefficients

Stationary
coefficients

$$Chl_t(s) = \tilde{x}_t(s)\tilde{\beta}(s) + x_t(s)\beta + \epsilon_t(s)$$

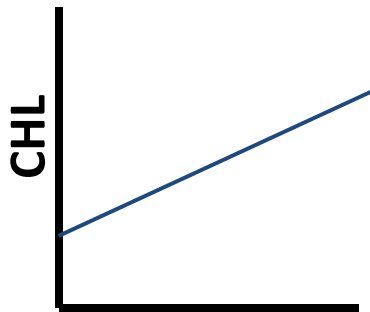
Hypothesized landscape & lake variables

- Lake depth
- Catchment: Lake Area ratio
- Agriculture
- Wetland
- Lake connectivity type (isolated vs. drainage)

Q1) Spatial variation in TP & Color effects?

Non-spatial

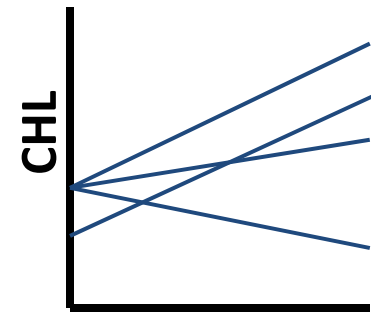
M_{NULL} : CHL \sim Intercept + TP + Color



Vs.

Spatially-varying

M_1 : CHL \sim *Intercept* + *TP* + *Color*



Evaluated using model fit criteria

G = goodness of fit; **P** = penalty; **D** = model criteria

Gelfand and Gohosh 1998

Results: Q1

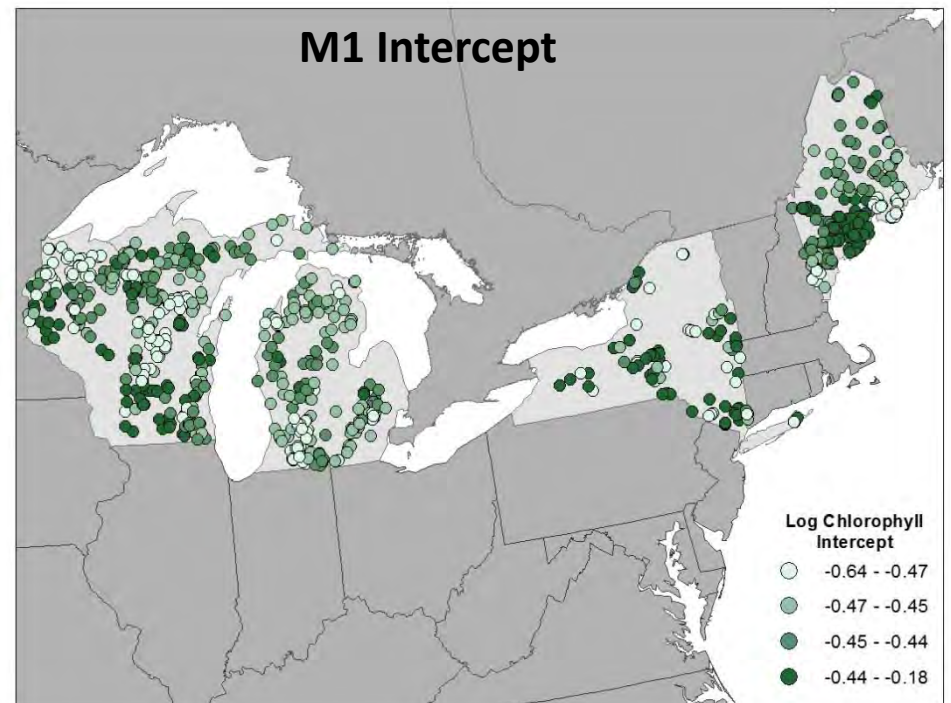
| Model | G | P | D |
|-------------|--------|--------|---------|
| Null | 5456.0 | 5435.2 | 10891.3 |
| 1 | 4736.4 | 4502.9 | 9239.4 |

Lower is
better

Results: Q1

| Model | G | P | D |
|----------|--------|--------|---------|
| Null | 5456.0 | 5435.2 | 10891.3 |
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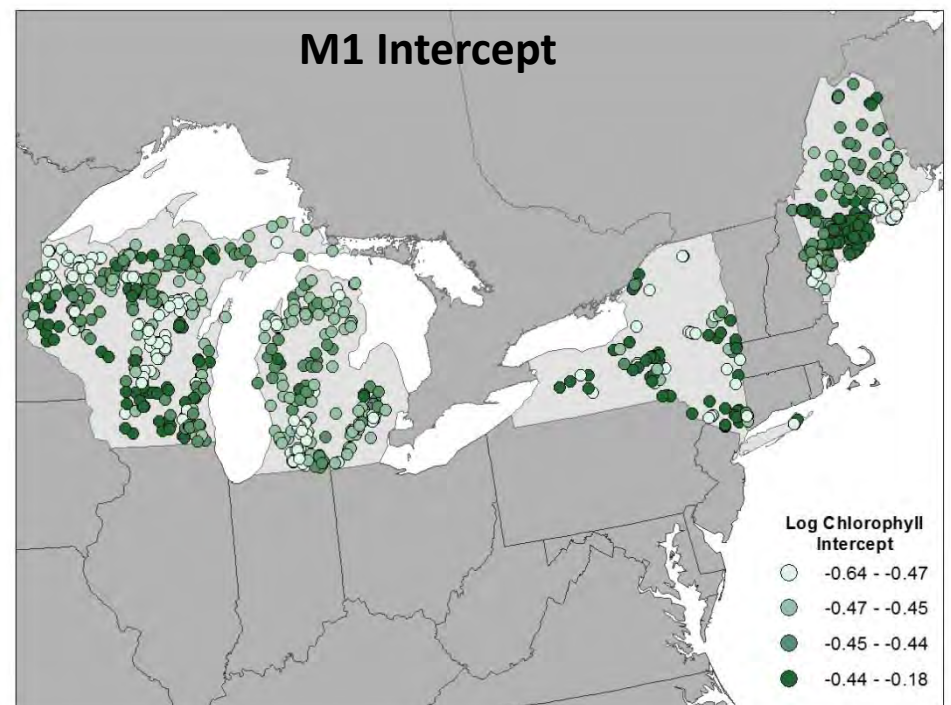
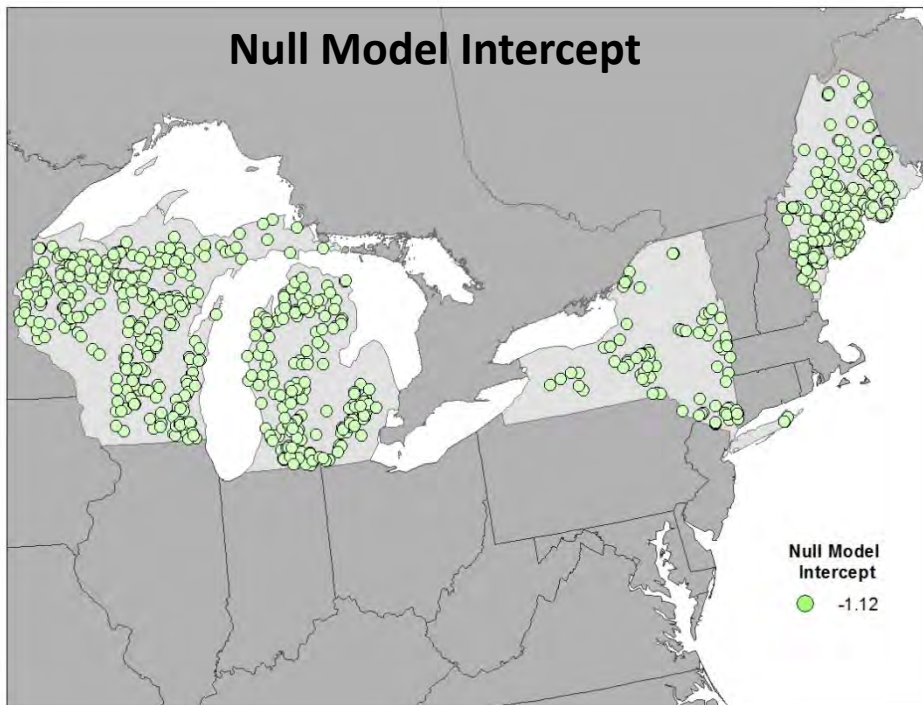
Lower is better



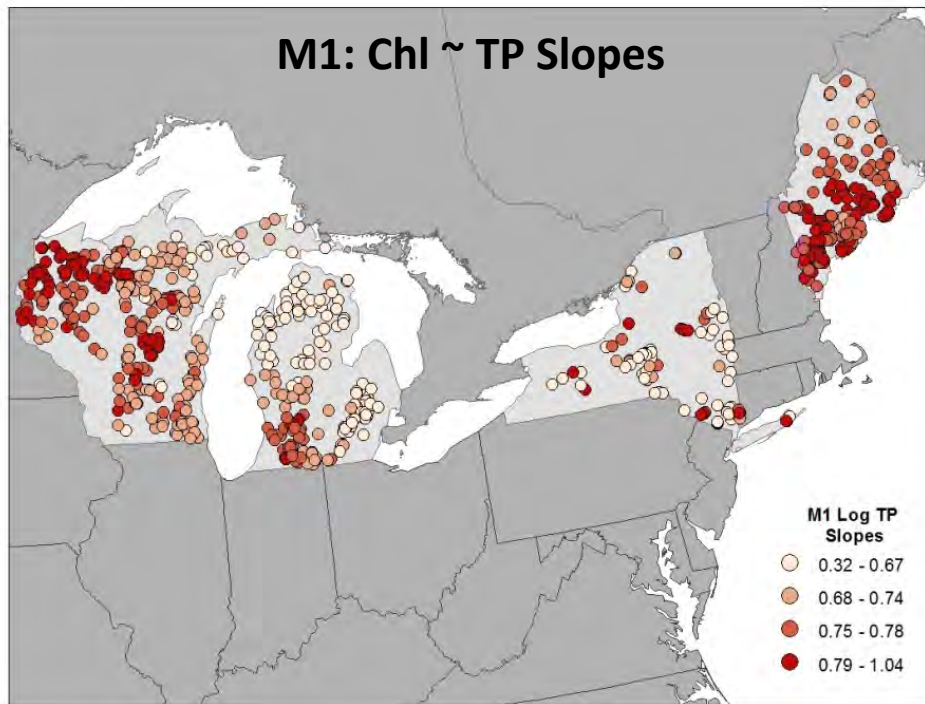
Results: Q1

| Model | G | P | D |
|----------|---------------|---------------|---------------|
| Null | 5456.0 | 5435.2 | 10891.3 |
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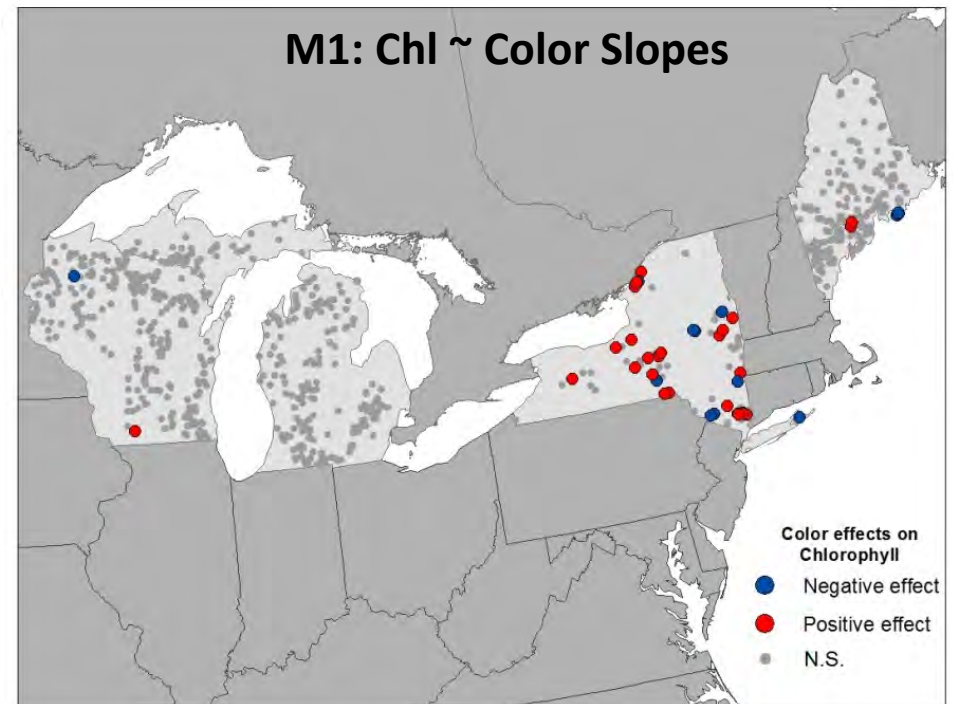
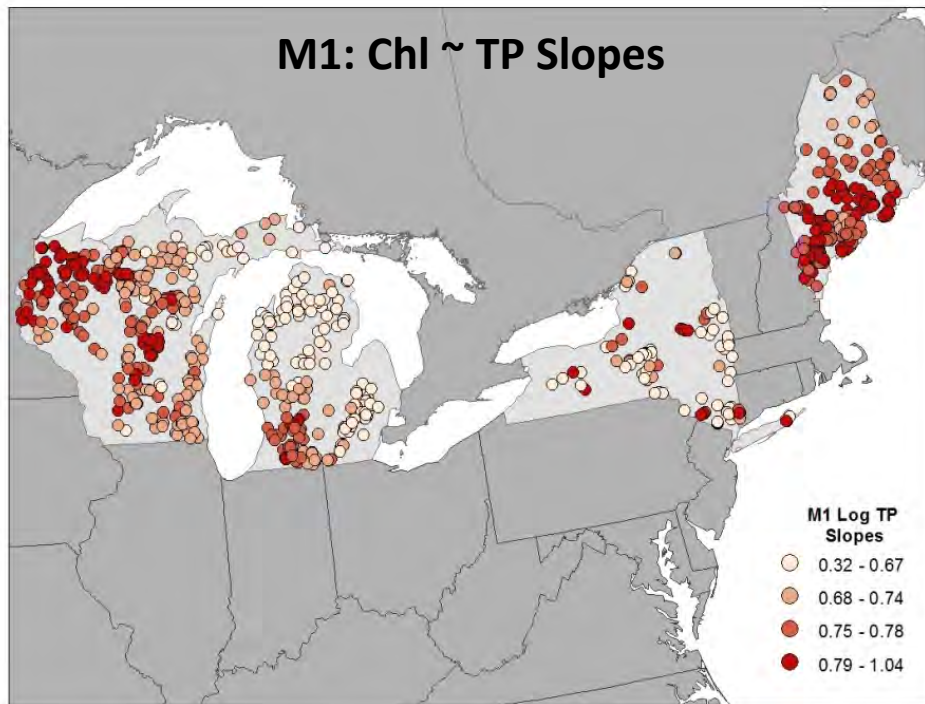
Lower is better



Results: Q1



Results: Q1



Conclusions: Q1

Lake Chlorophyll exhibits spatial variation even after accounting for TP & Color

- Landscape, lake, & other spatial variables may explain remaining spatial variation

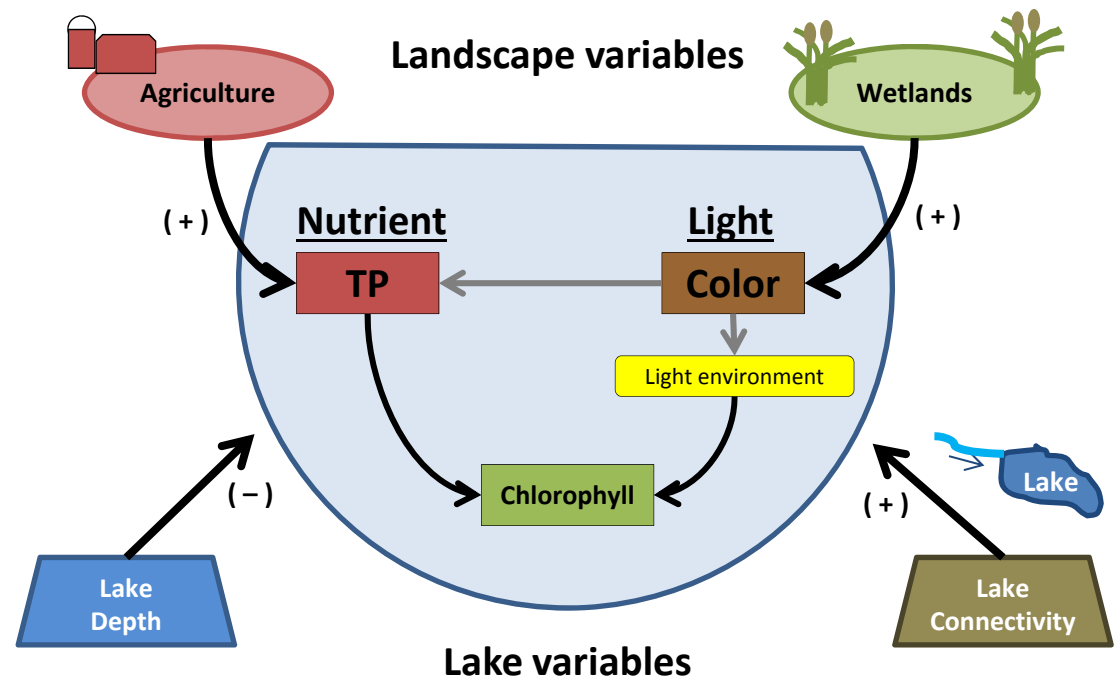
TP effects on Chlorophyll vary over space but Color effects were not significant for most lakes

- TP is primary driver of lake productivity in Upper Midwest and NE U.S.

Q2) Lake & landscape drivers of variation

Spatially-varying

$M_1: \text{CHL} \sim \text{Intercept} + \text{TP} + \text{Color}$

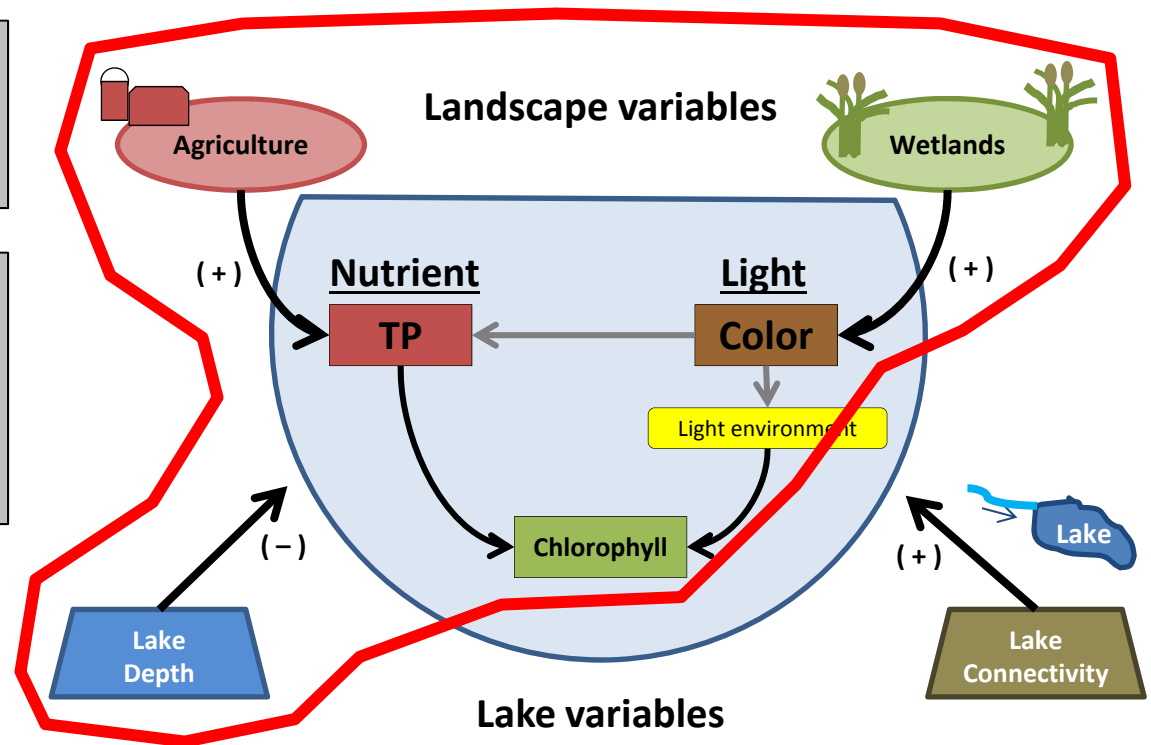


Q2) Lake & landscape drivers of variation

Spatially-varying

$M_1: \text{CHL} \sim \text{Intercept} + \text{TP} + \text{Color}$

$M_2: \text{CHL} \sim \text{Intercept} + \text{TP} + \text{Color} + \text{Depth} + \text{CA:LK} + \text{AGR} + \text{WET}$



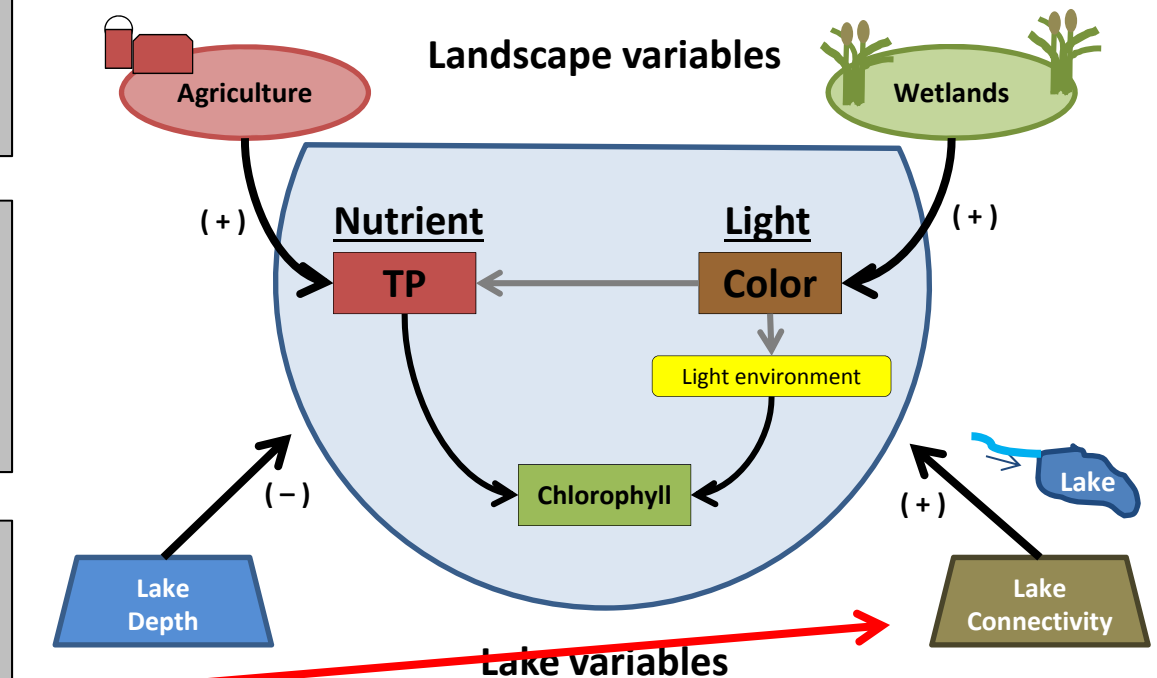
Q2) Lake & landscape drivers of variation

Spatially-varying

M_1 : CHL \sim Intercept + TP + Color

M_2 : CHL \sim Intercept + TP + Color + Depth + CA:LK + AGR + WET

M_3 : CHL \sim Intercept + TP + Color + Depth + CA:LK + AGR + WET + Connectivity



Results: Q2

Spatially-varying

M₁: CHL ~ *Intercept* + *TP*
+ *Color*

M₂: CHL ~ *Intercept* + *TP*
+ *Color* + *Depth* + *CA:LK*
+ *AGR* + *WET*

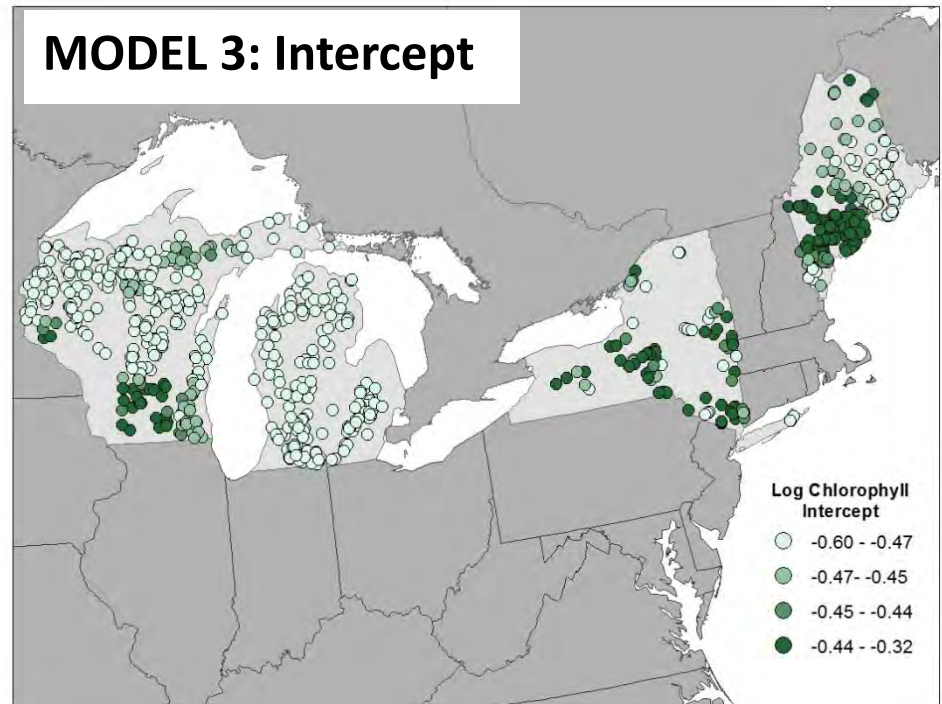
M₃: CHL ~ *Intercept* + *TP*
+ *Color* + *Depth* + *CA:LK*
+ *AGR* + *WET* +
Connectivity

| M | G | P | D |
|---|--------|--------|--------|
| 1 | 4736.4 | 4502.9 | 9239.4 |
| 2 | 4667.8 | 4508.4 | 9176.2 |
| 3 | 4593.7 | 4495.0 | 9088.8 |

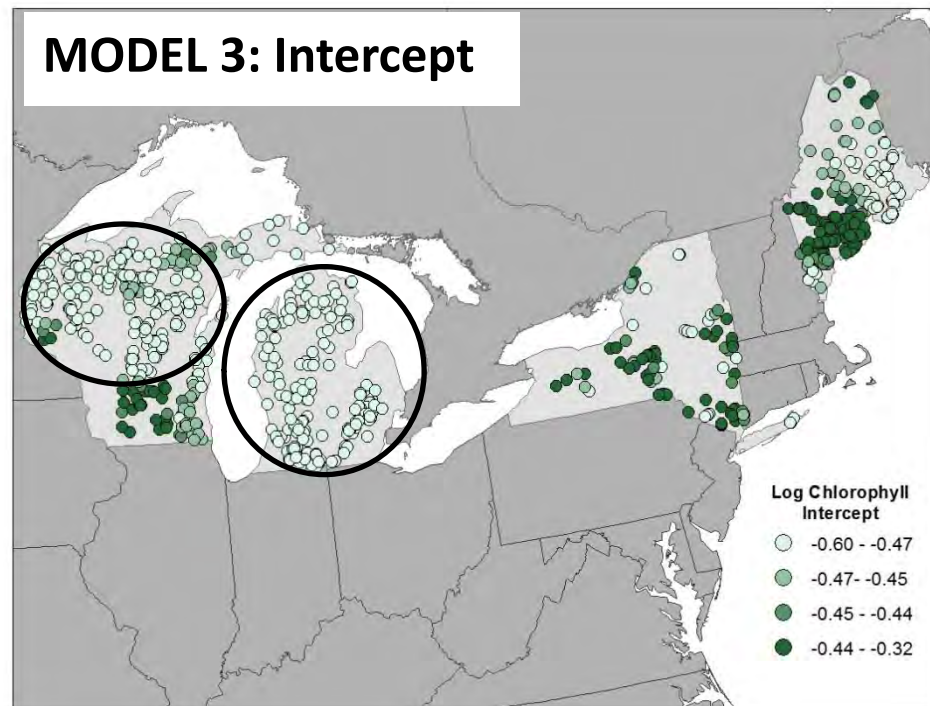
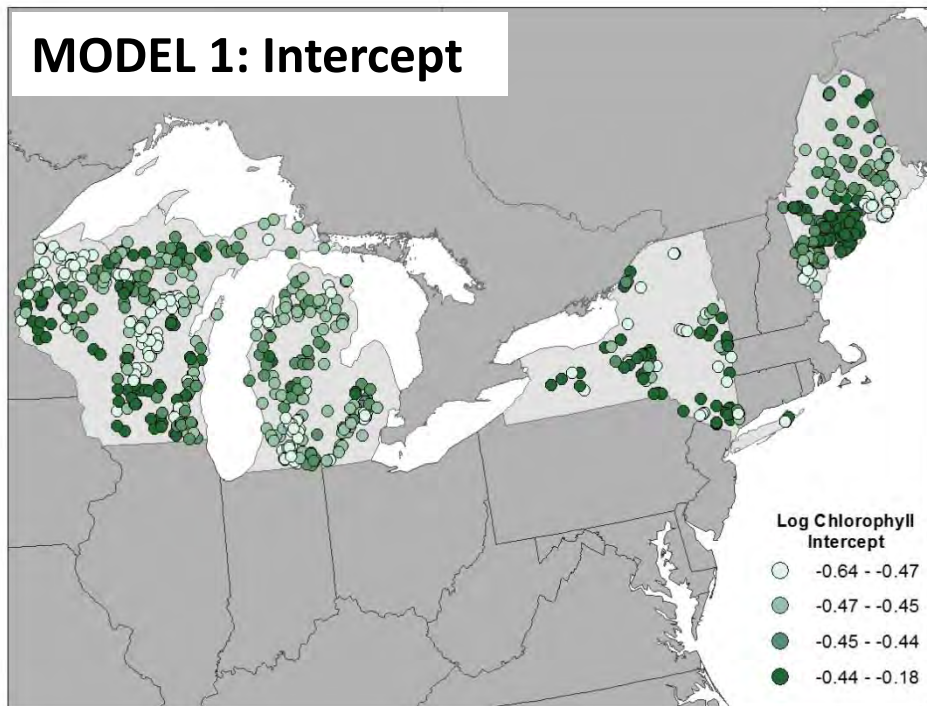
Model 3: Global parameter estimates

| Spatially-varying | | | Fixed over space | | | | |
|-------------------------------|----------------------------|------------------------|---------------------------------|---------------------------------------|----------------------------|------------------------|----------------------------|
| β_0 | TP β_1 | Color β_2 | Depth β_3 | CA:LK β_4 | AGR β_5 | WET β_6 | Lake Type β_7 |
| -0.48 (-0.6 – -0.3) | 0.68 (0.5 – 0.7) | 0.01 (-0.09 – 0.13) | -0.01 (-0.01 – -0.01) | -0.0003 (-0.0005 – -0.0001) | 0.51 (0.2 – 0.8) | 0.13 (-0.34 – 0.65) | 0.22 (0.1 – 0.3) |

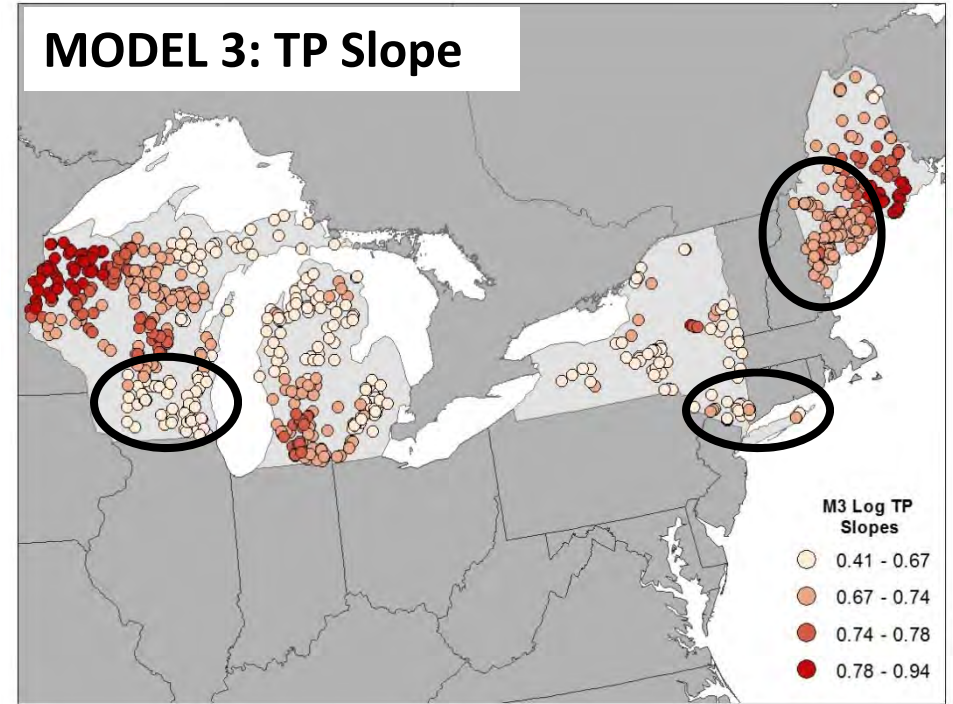
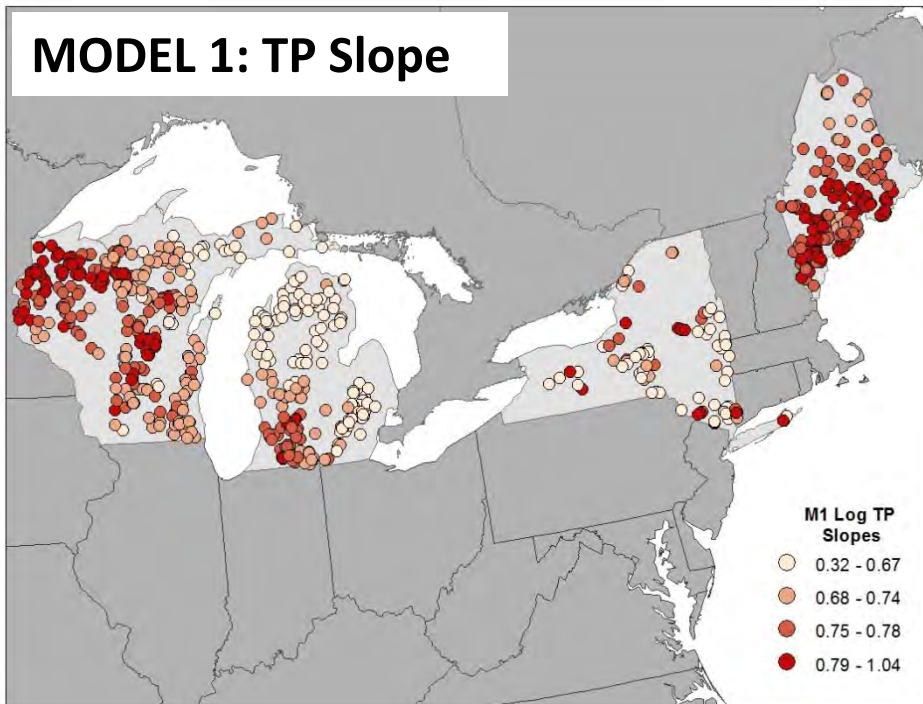
Comparing model with lake & landscape covariates



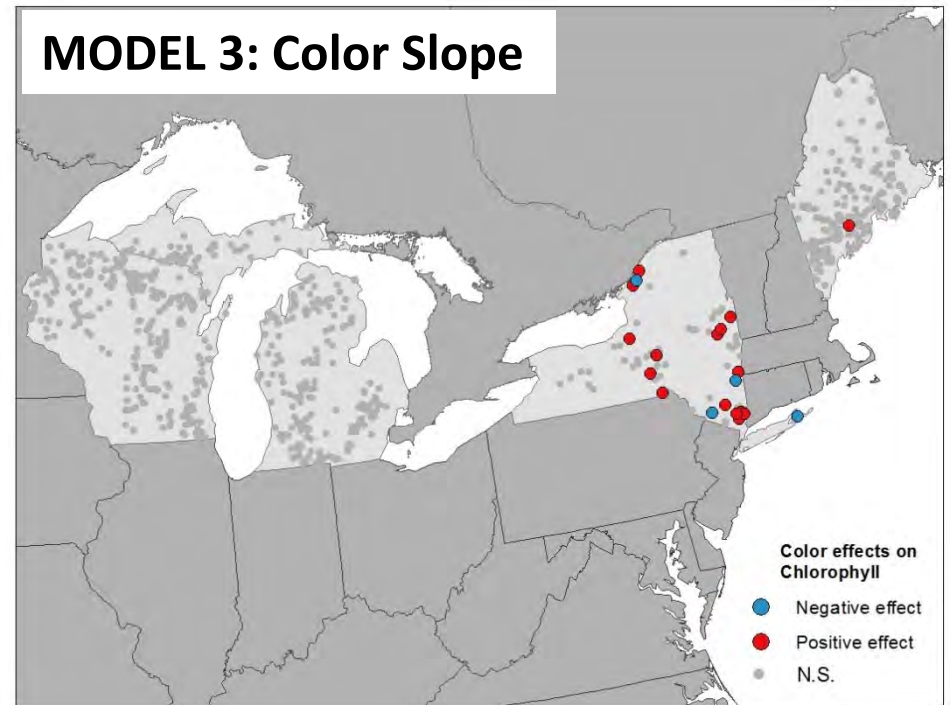
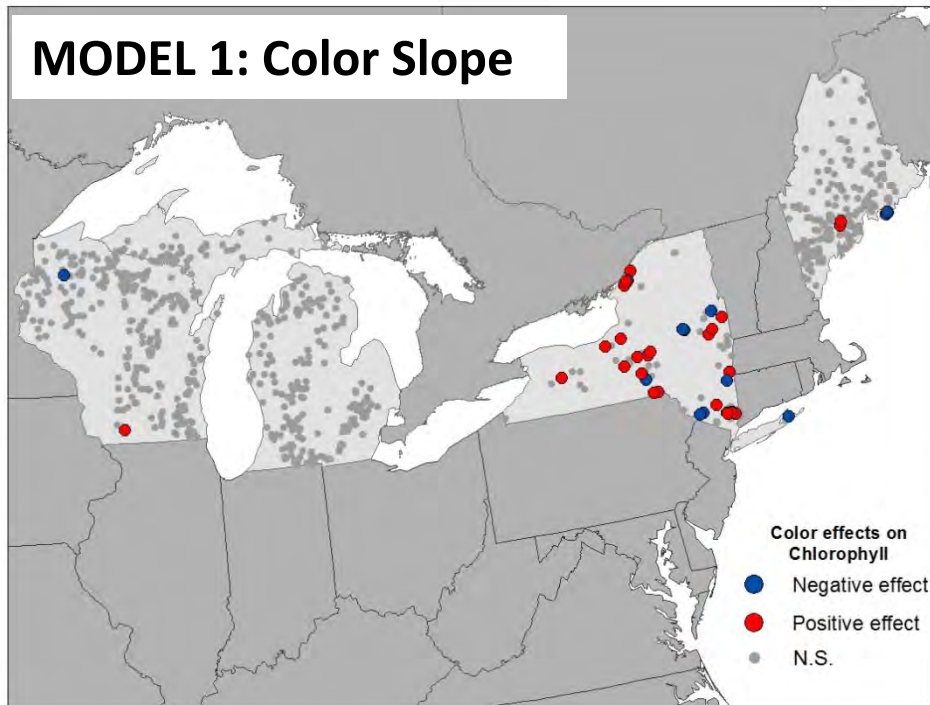
Comparing model with lake & landscape covariates



Comparing model with lake & landscape covariates



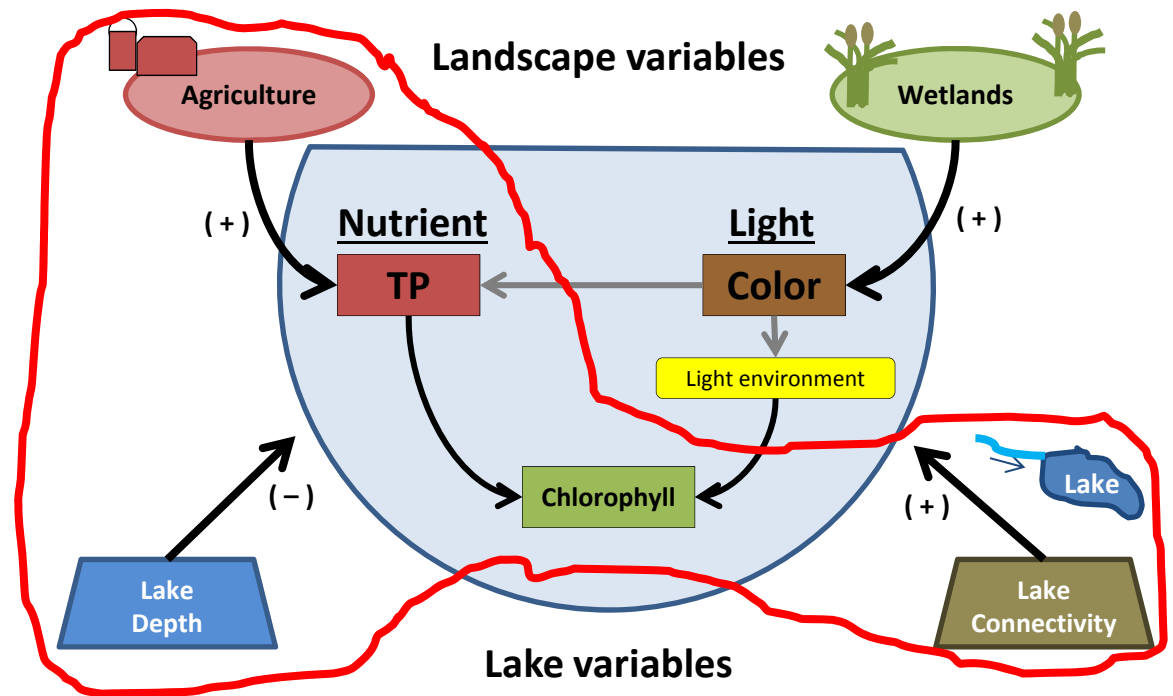
Comparing model with lake & landscape covariates



Conclusions: Q2

Hypothesized lake and landscape variables account for spatial variation

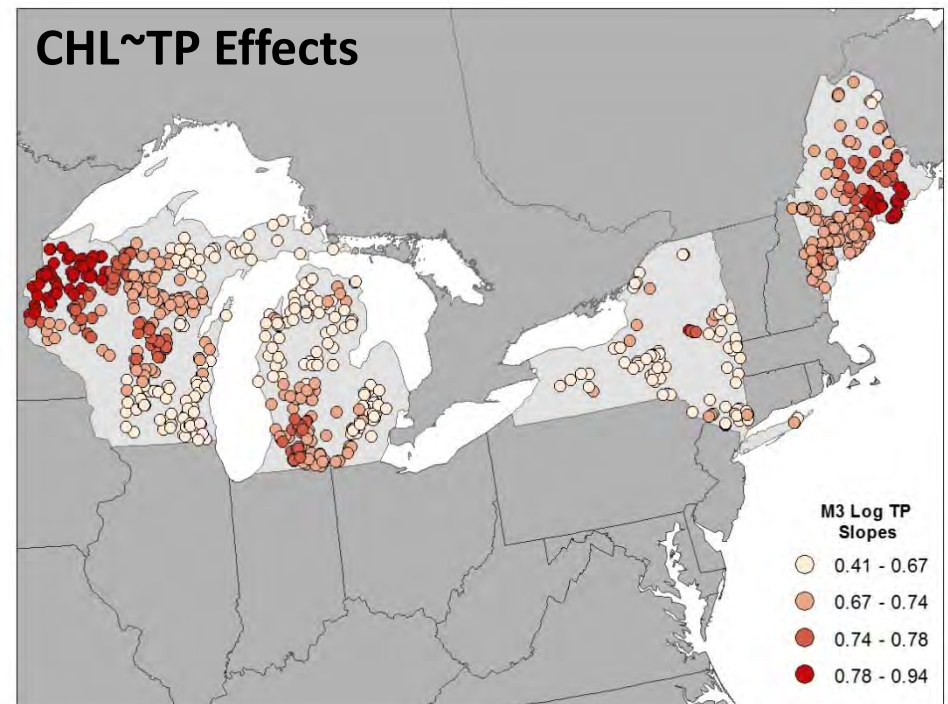
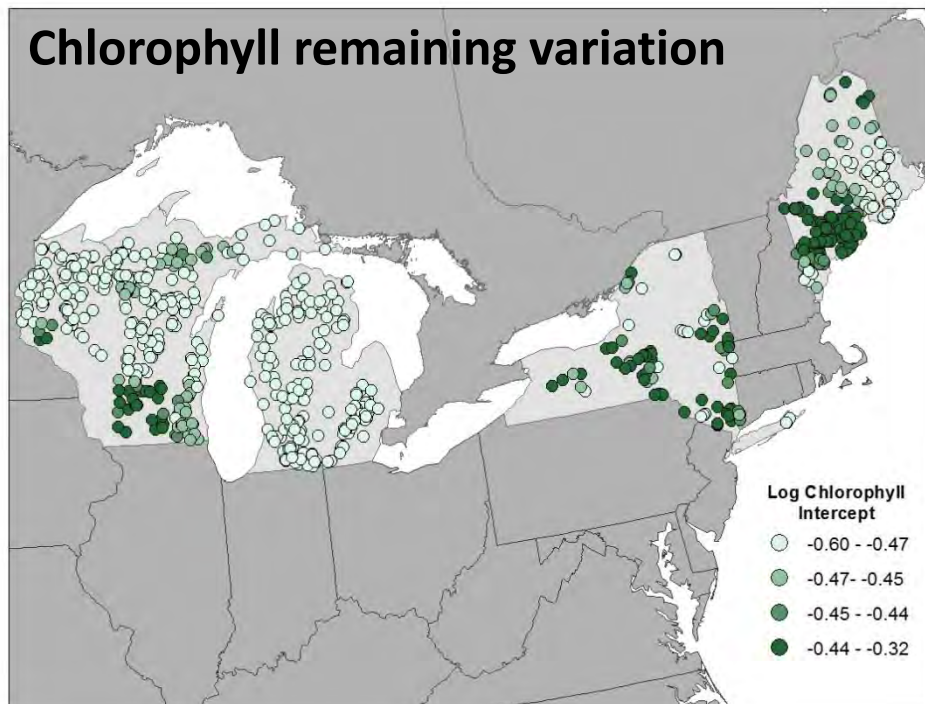
- To a great deal for Chlorophyll
- Moderately for CHL~TP
- And less for CHL~Color



Conclusions: Q2

BUT spatial variation remains

- Scale of variation remaining – help identify potential predictors to consider for future models



Big data informing lake ecology

- Evaluate existing theory
- Help meet management and conservation goals
 - Assess lake water quality and ecological health
 - Set regional restoration targets





Acknowledgements

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Database support: Ed Bissell

Special thanks: CSI Limnology Team, MSU
Limnology Lab