Use of open science to inform restoration projects in estuaries: A Tampa Bay example

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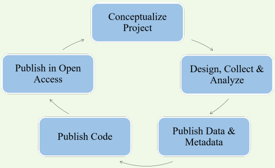
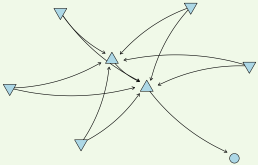
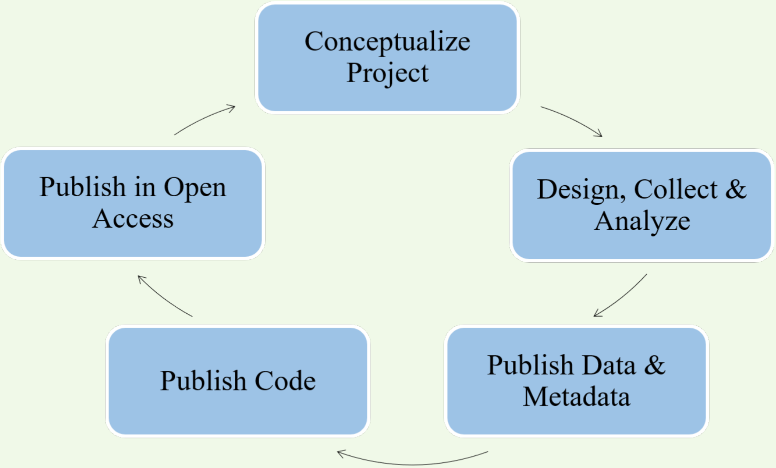




Open science workflow

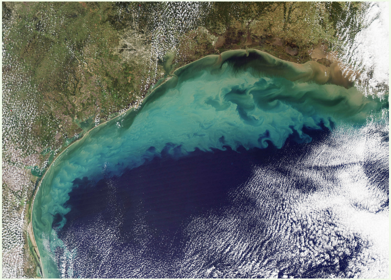


Modified from Hampton et al. 2015. The Tao of open science for ecology. Ecosphere 6(7):1-13.

Open Science for Synthesis: Gulf Research Program

July 10 - July 28, 2017
NCEAS, Santa Barbara, CA

NCEAS
National Center for Ecological Analysis and Synthesis



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https://nceas.github.io/oss-2017/lessons.html

- Collaboration modes and technologies, virtual collaboration
- Data management, preservation, and sharing
- Data manipulation, integration, and exploration
- Scientific workflows and reproducible research
- Programming using agile and sustainable software practices
- Data analysis and modeling
- Communicating results to broad communities

Today's talk

Our experience using the open science workflow to inform restoration projects in estuaries

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- ***Develop*** a decision support tool with empirical observations to evaluate likelihood of potential outcomes

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- ***Synthesize*** data in space and time to evaluate cumulative effects of restoration projects
- ***Develop*** a decision support tool with empirical observations to evaluate likelihood of potential outcomes
- ***Apply*** the tool to guide expectations for future restoration projects

Tampa Bay - from gross to less gross

Past:

- Mid-1970s N load 8.2×10^6 yr^{-1} [Greening and Janicki, 2006]
- Elevated chl-a concentrations
- Increased occurrence of HABs

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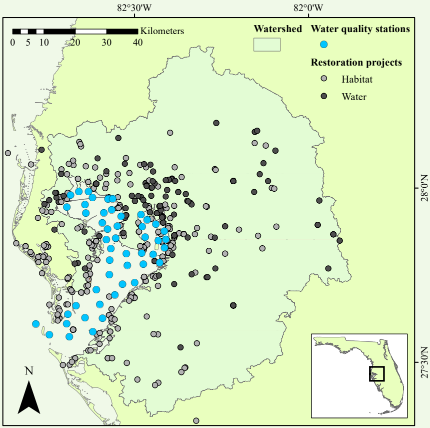
Present:

- 2016 seagrass at ˜17k ha [Sherwood et al., 2017]
- Reductions in nutrient load, chlorophyll
- Increase in water clarity [Morrison et al., 2006, Beck et al., 2017]

Tampa Bay - open data sources



- *Water quality* monitoring dataset: 1974 to present, ~500 obs. per site

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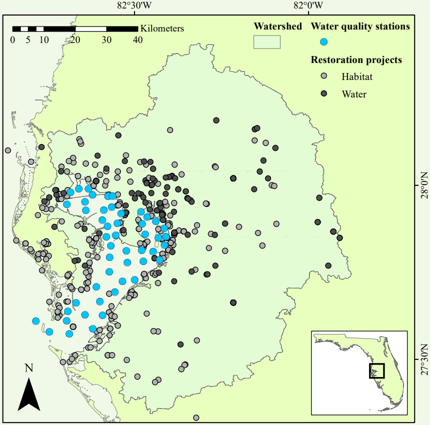

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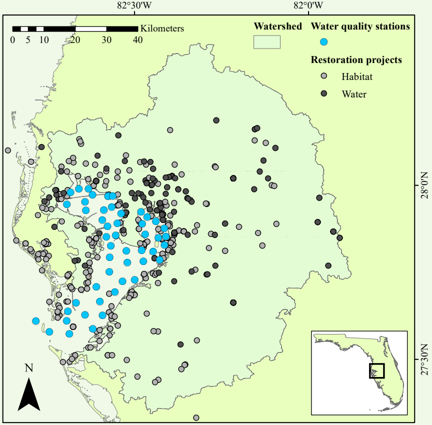

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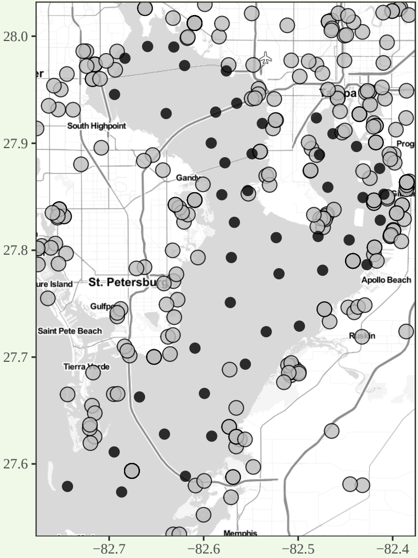
Despite considerable *investments* in restoration, *effectiveness evaluation* continues to elude practitioners at geographic scales [Diefenderfer et al., 2016]

Data munging with open source tools

Task 1: Can we empirically link 500 restoration projects to chlorophyll changes at water quality stations over a forty year period?

Data munging with open source tools



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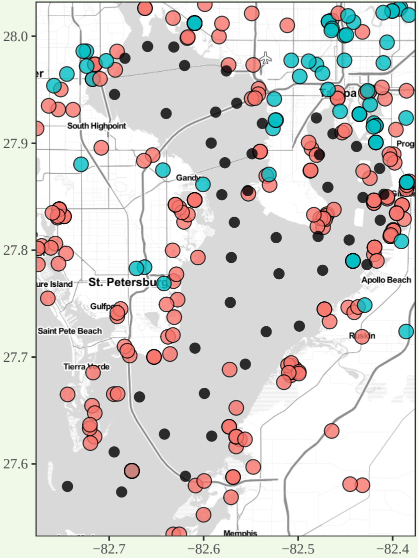

Can we link 500 restoration projects to chlorophyll changes over a forty year period?

- Consider an effect of restoration ***site type***?

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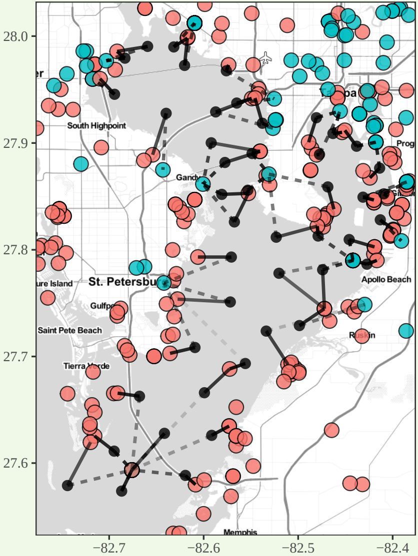

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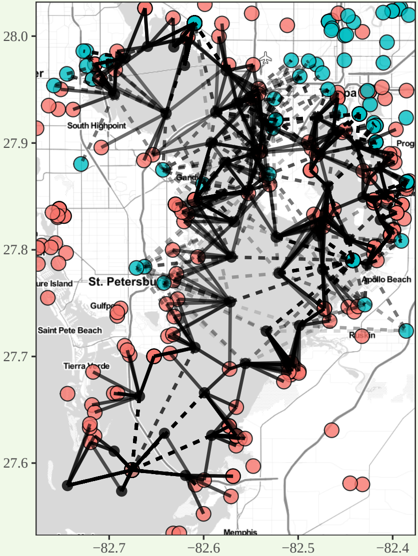
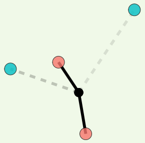


Can we link 500 restoration projects to chlorophyll changes over a forty year period?

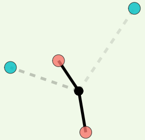
- Consider an effect of restoration ***site type***?
- Consider ***distance*** of sites from water quality stations?
- Consider ***cumulative effects***?

WQ and restoration sites: ***spatial join***

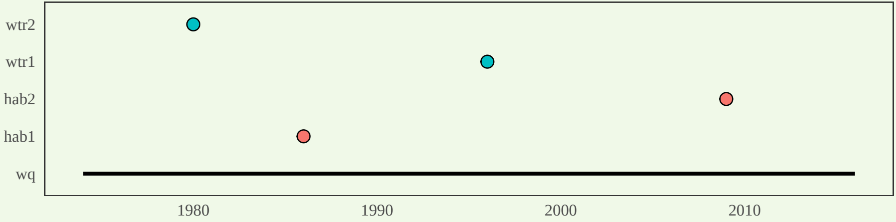


Data munging with open source tools

WQ and restoration sites: *spatial join*



WQ and restoration sites: *temporal join*



Data munging with open source tools

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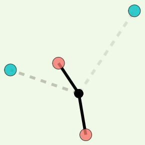
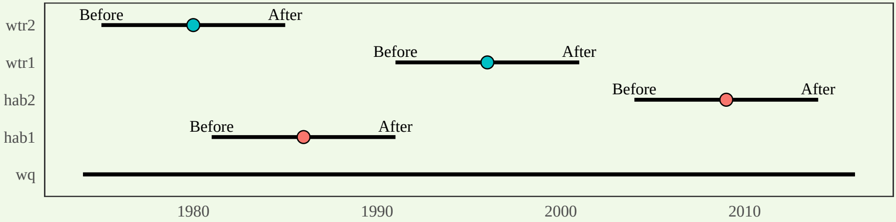
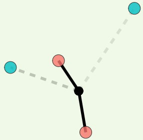


WQ and restoration sites: *temporal join, before/after*

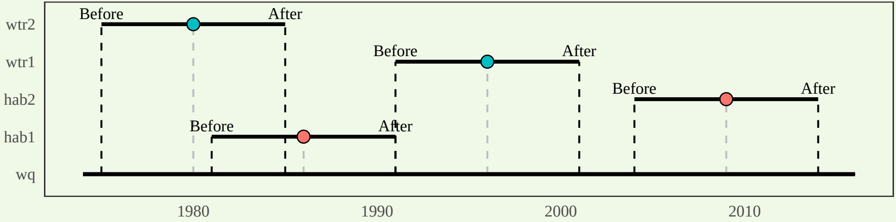


Data munging with open source tools

WQ and restoration sites: *spatial join*

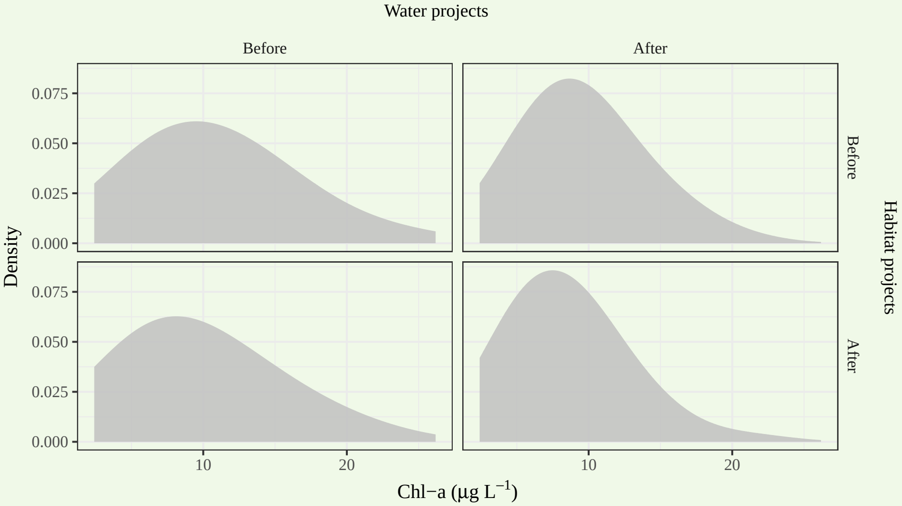


WQ and restoration sites: *temporal join, before/after, slice*



Data munging with open source tools

For *many* water quality stations matched to *many* restoration sites...



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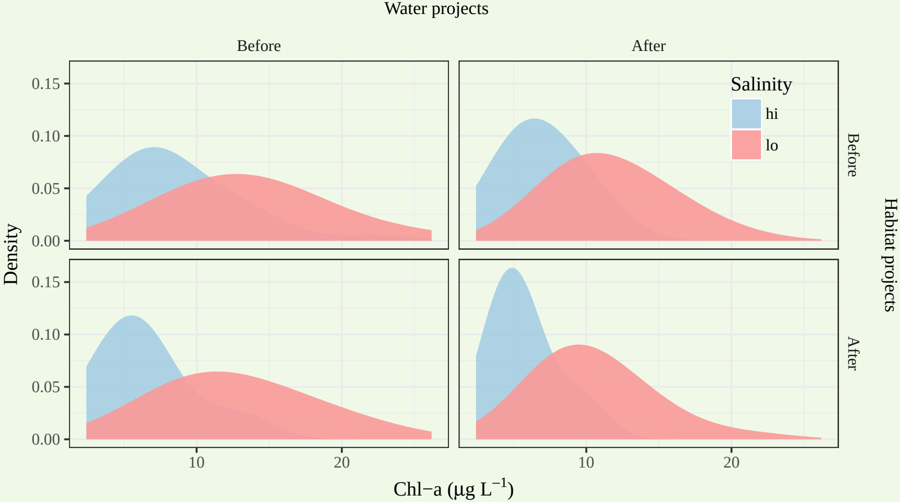

Data munging with open source tools

What is the probability of low/high chlorophyll given other events?

$$P\left(Chl \mid Event\right) = \frac{P(Event|Chl) \cdot P(Chl)}{P(Event)}$$

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- Do water quality conditions differ by ***restoration type***?
- Does it differ by low/high ***salinity*** as a natural covariate?

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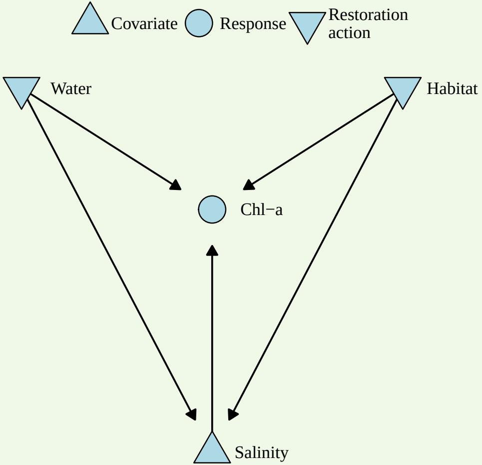
Bayesian models let us evaluate likelihood of potential outcomes given conditional distributions

Using the *conditional probabilities* from the *empirical response*, what's the probability of low chlorophyll...



Data munging with open source tools

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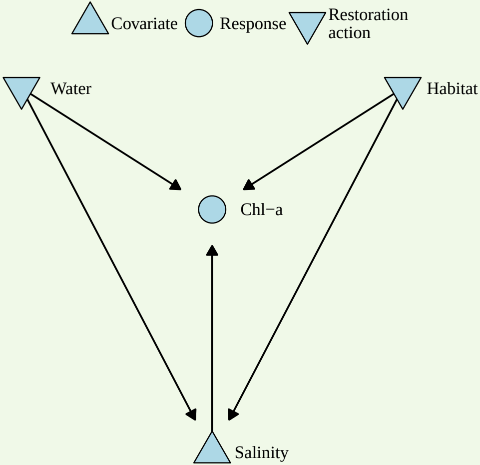

- from water projects

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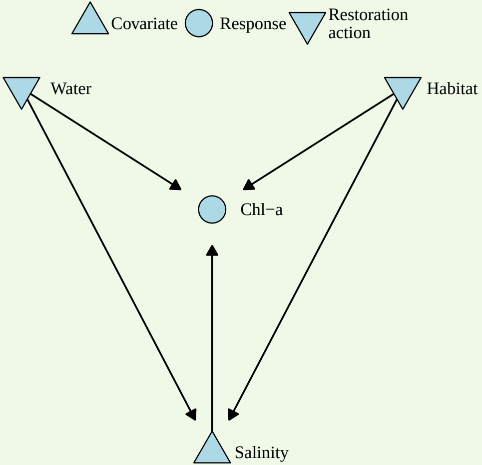

- from water projects
- from habitat projects

Data munging with open source tools

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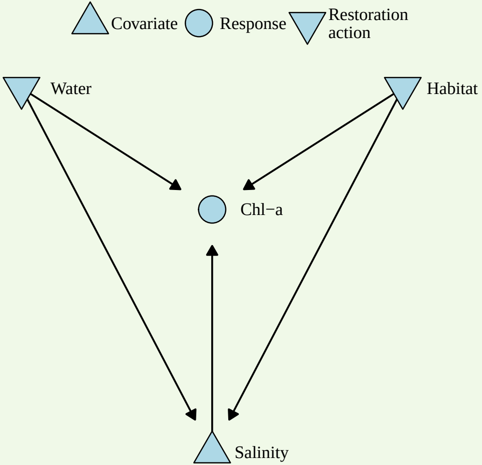

- from water projects
- from habitat projects
- from all projects

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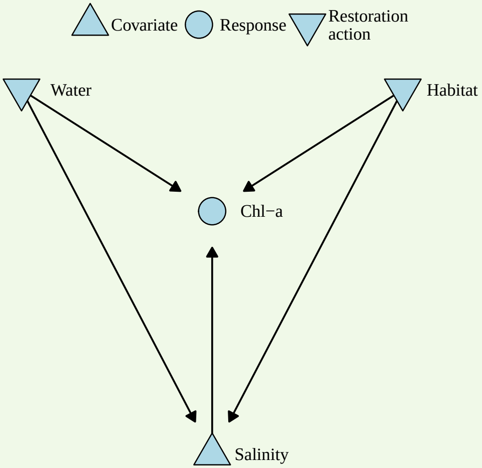
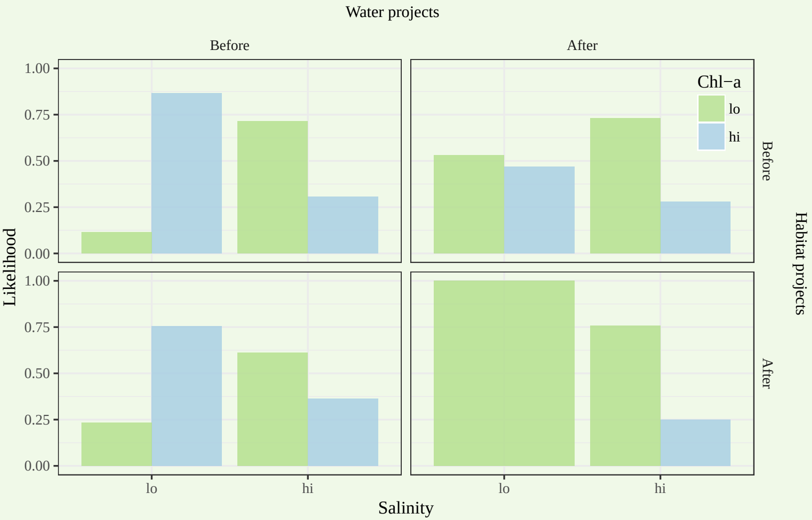


- from water projects
- from habitat projects
- from all projects
- by salinity regime

All possible scenarios:



Invidividual scenarios: Probability of **high** chlorophyll

Water projects:

- Before: 53%
- After: 26%

Habitat projects:

- Before: 50%
- After: 50%

Data munging with open source tools

Invidividual scenarios: Probability of **high** chlorophyll

Water projects:

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- After: 26%

Habitat projects:

- Before: 50%
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Invidividual scenarios: Probability of **low** chlorophyll

Water projects:

- Before: 46%
- After: 77%

Habitat projects:

- Before: 49%
- After: 51%

Data munging with open source tools

Where is the sweet spot?

Probability of low chlorophyll before/after **both project types** by **low/high salinity**

Data munging with open source tools

Where is the sweet spot?

Probability of low chlorophyll before/after **both project types** by **low/high salinity**

Low salinity:

- Before both projects: 13%
- After both projects: 100%

High salinity:

- Before both projects: 69%
- After both projects: 75%

Data munging with open source tools

Take home:

- Water infastructure projects had the largest effect

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Data munging with open source tools

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- Depends on year, distance combinations

Data munging with open source tools

Take home:

- Water infastructure projects had the largest effect
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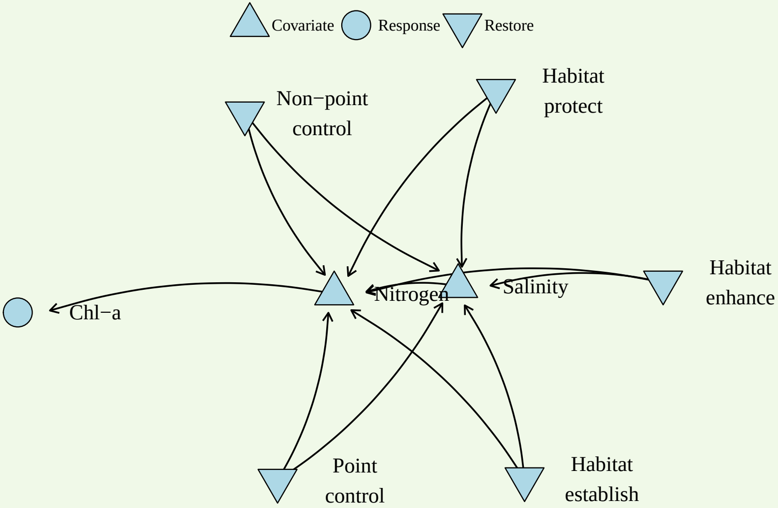
But...

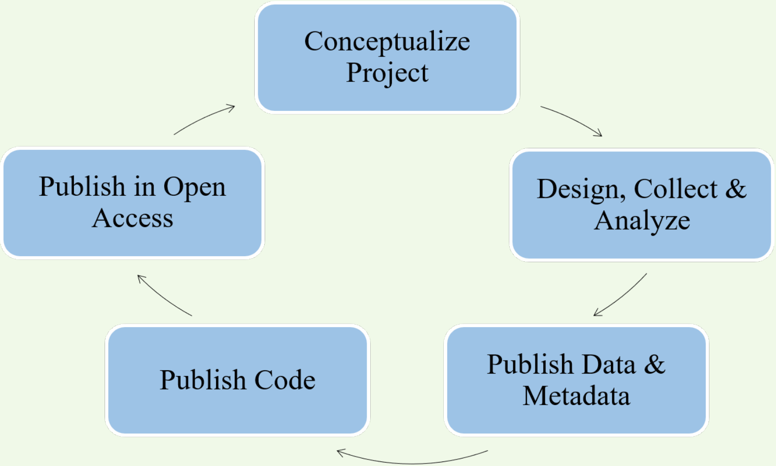
- Depends on year, distance combinations
- This is a simple model

Data munging with open source tools

The holy grail:



Open science workflow



Modified from [Hampton et al., 2015]

Open science workflow

What aspects of our project used and benefitted from open science?

- Early idea conception
- Long distance collaboration
- Transparent and reproducible analysis

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... but the circle is not complete

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GULF RESEARCH PROGRAM

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GitHub (project): https://github.com/fawda123/restorebayes

GitHub (presentation): https://github.com/fawda123/AWRA_2018

Twitter: @fawda123

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