Zooplankton from Space

Predicting, Validating And Understanding Zooplankton Distributions From Space In An Eddy Rich Ocean

Nazanin Chaichitehrani, Victoria Coles – Physical Oceanography and modeling

Jamie Pierson – Zooplankton Ecologist

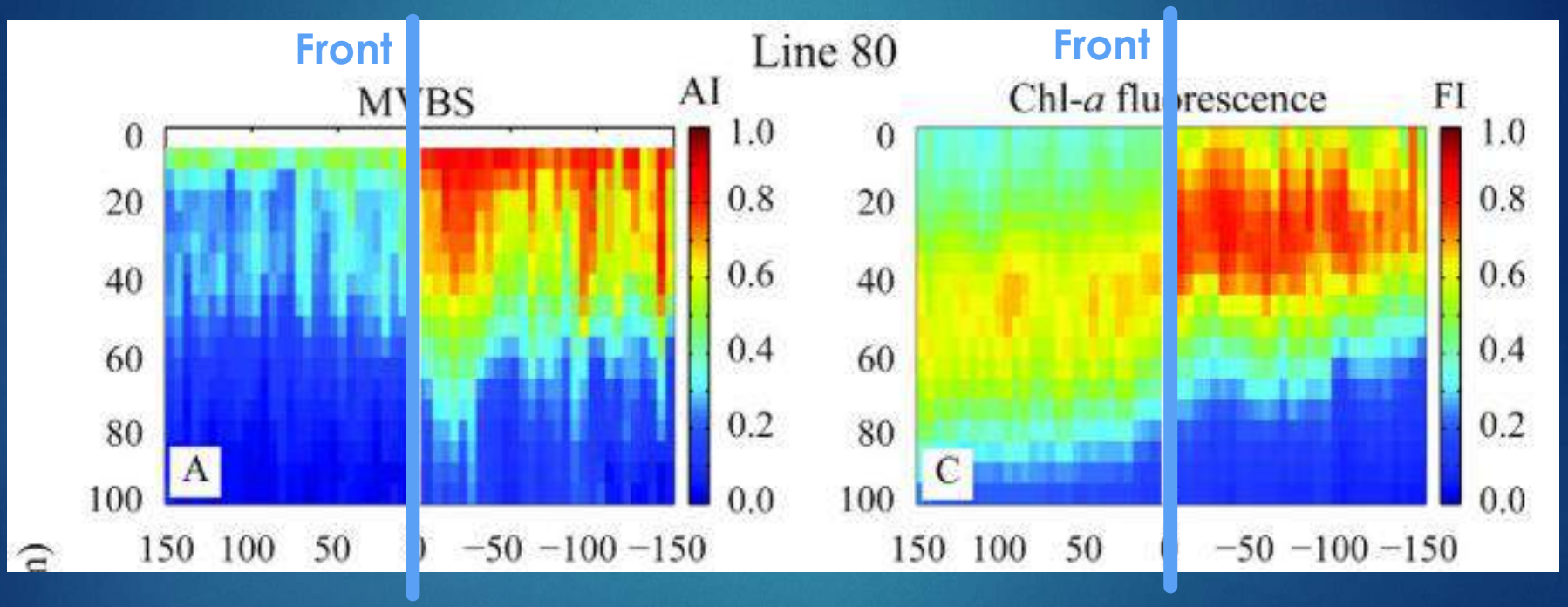
Mike Stukel, Taylor Shropshire – Zooplankton Ecologist And Modelers

Greg Silsbe – Remote Sensing And Phytoplankton Physiology

Kenny Rose – Fisheries

Who, Why, How, What

- Our goal is to use space-based, high resolution spatial and temporal observations of the ocean to predict zooplankton and grazing dynamics in relation to mesoscale eddy features.

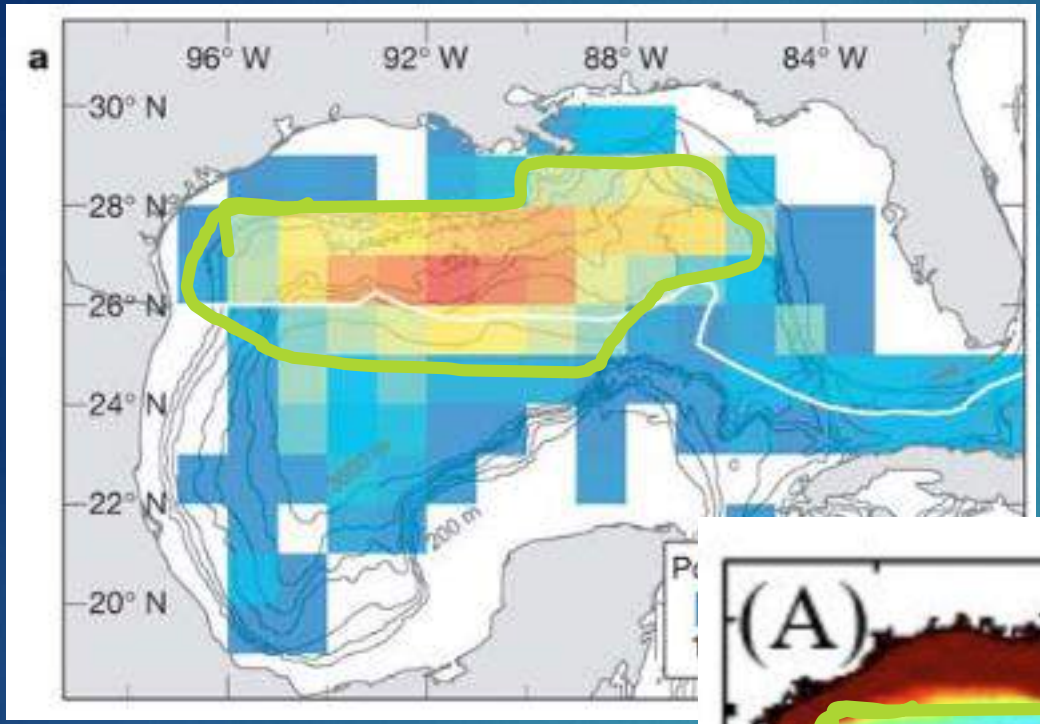


Measure of Zooplankton abundance

Measure of Phytoplankton abundance

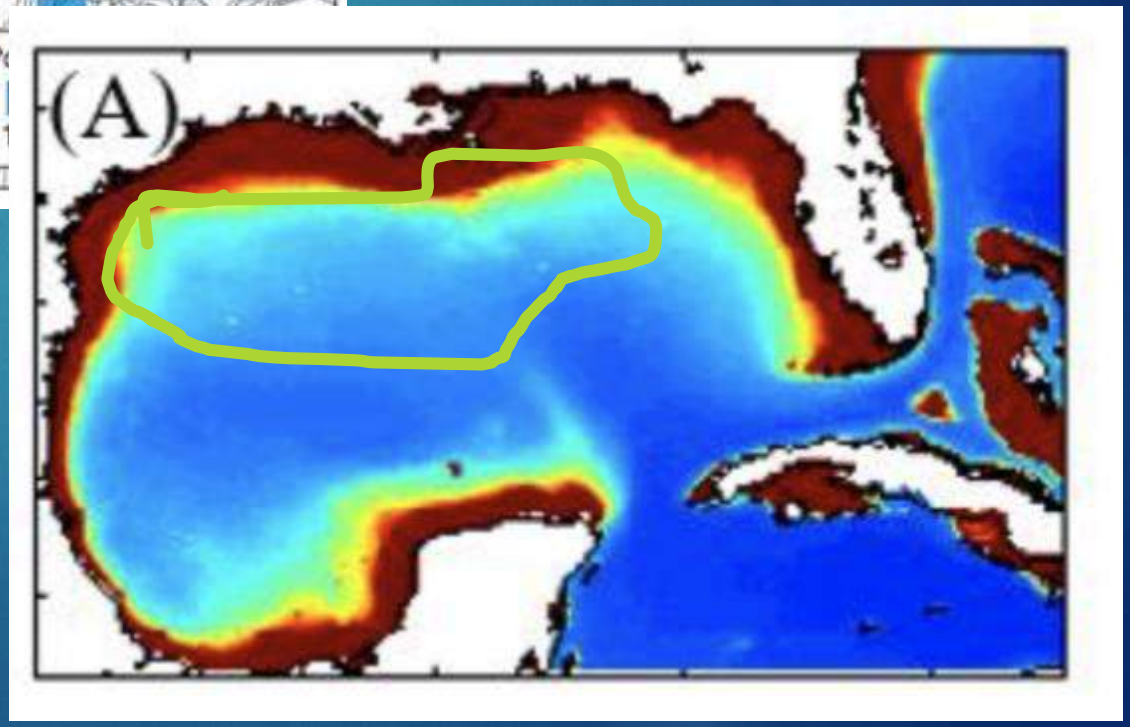
Powell and Ohman, 2015 Prog. Oceanogr.

Bluefin Tuna spawning locations do not co-occur with annual mean phytoplankton biomass



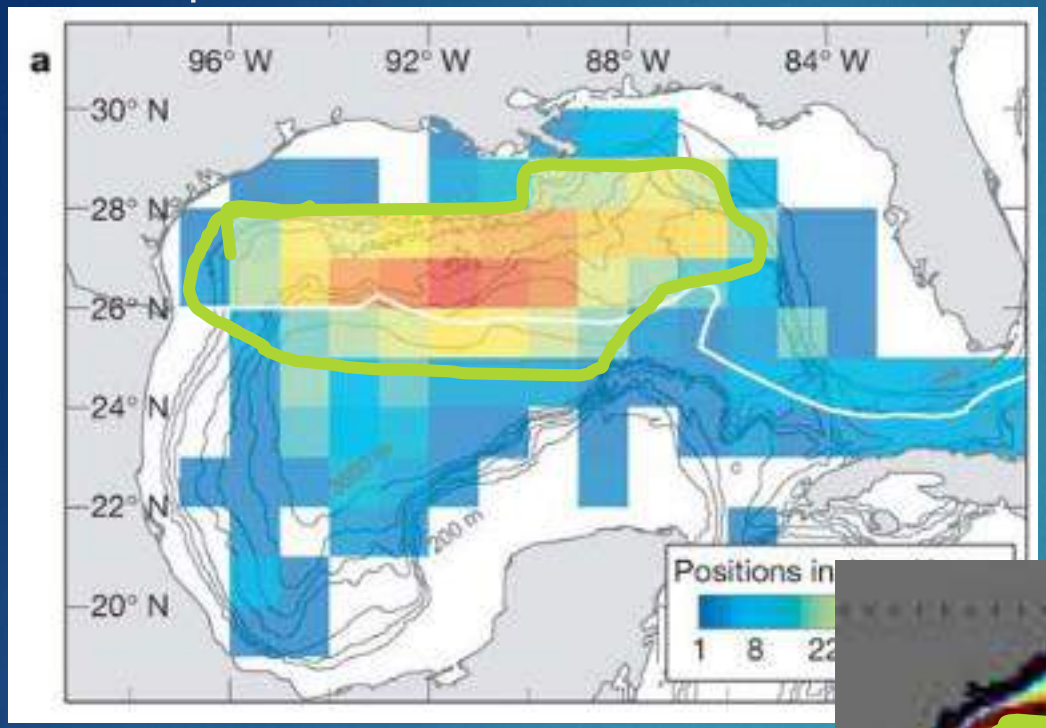
Observed locations of Atlantic bluefin tuna – spawning thought to occur April, May, June

Annual average surface chlorophyll



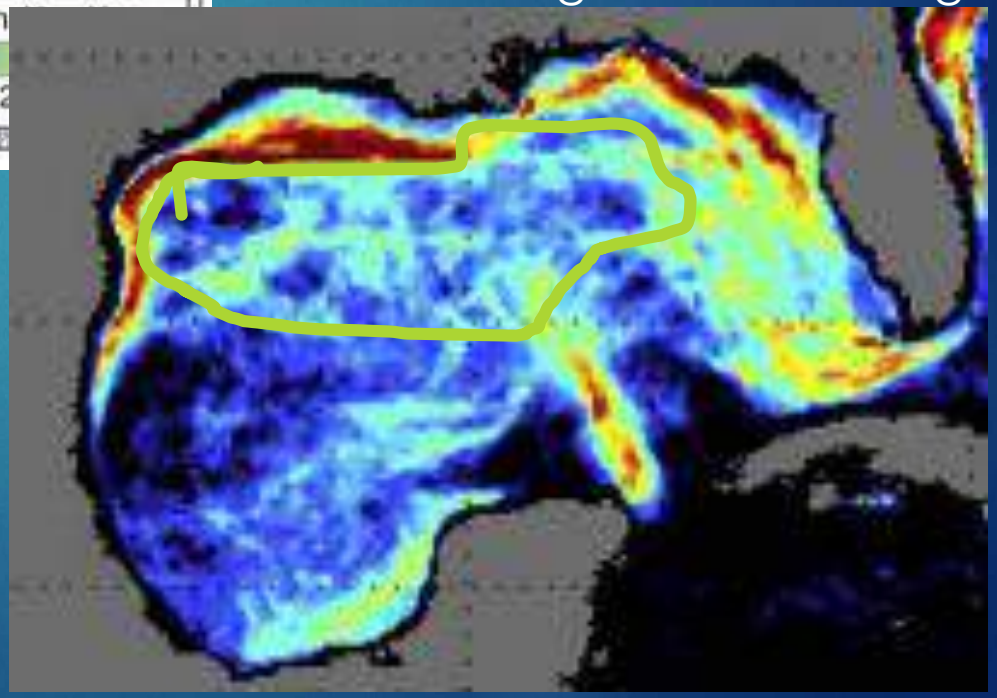
Block et al, 2005 Nature

Bluefin Tuna spawning locations do co-occur with frontal positions.



Observed locations of Atlantic bluefin tuna – spawning thought to occur April, May, June
Block et al, 2005 Nature

Long term mean March frontal structures
Belkin et al, 2009 Progress in Oceanogr.



Who, Why, How, What

Model simulation of physical and biological quantities that can be determined from satellites – Temporary Truth

Test approaches on remote sensing to estimate Zooplankton biomass and grazing in different size classes

Characterize errors in approaches

Surface mass balance

Inverted ecological model equations

Machine Learning

Theoretical ecological size scaling

Validate using *in situ* data

Apply to California Current region

Apply to Gulf of Mexico region

What is the role of fronts and eddies in mediating trophic transfer from plants to fish

Siegel et al. 2013 Glob. Biogeochem. Cycles

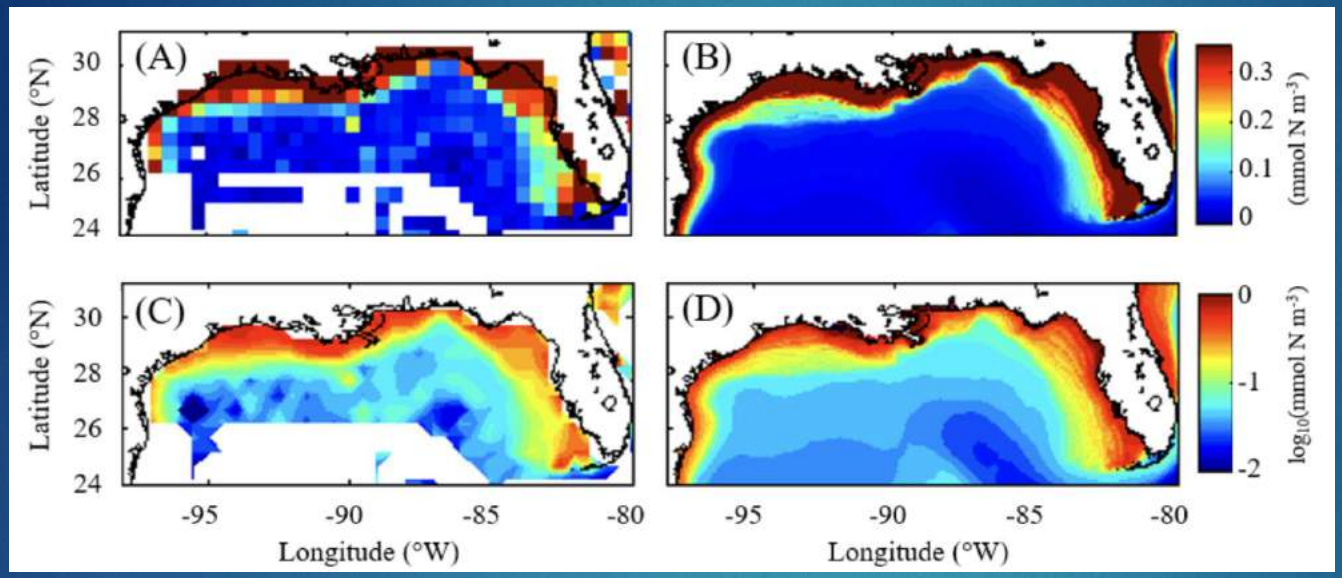
Remote sensing and model inputs

- Large and Small phytoplankton biomass (Graff et al 2015, Deep Sea Res. + Mouw and Yoder, 2010 J. Geophys. Res.)
- Large and small phytoplankton net primary productivity (Silsbe et al. 2016, Global. Biochem. Cycles. + Mouw and Yoder, 2010 J. Geophys. Res.)
- Sea Surface Temperature
- Euphotic Depth (light penetration depth)
- Mixed layer depth

The NEMURO model (our "truth") simulates reasonable zooplankton biomass in the Gulf of Mexico

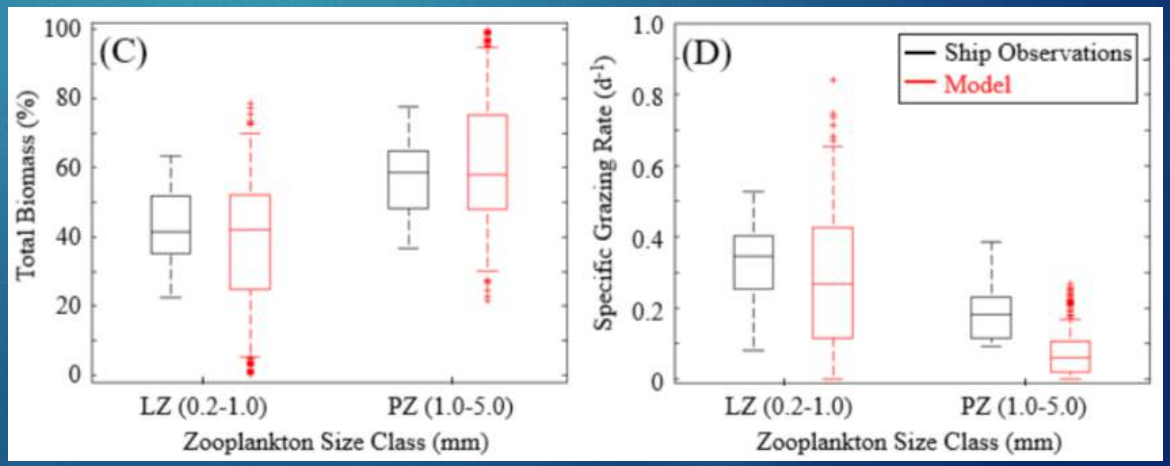
SeaMap Dataset

Gulf of Mexico NEMURO Model (Stukel and Shropshire)



Modelled biomass fraction and growth rates are consistent with observations in the Gulf of Mexico

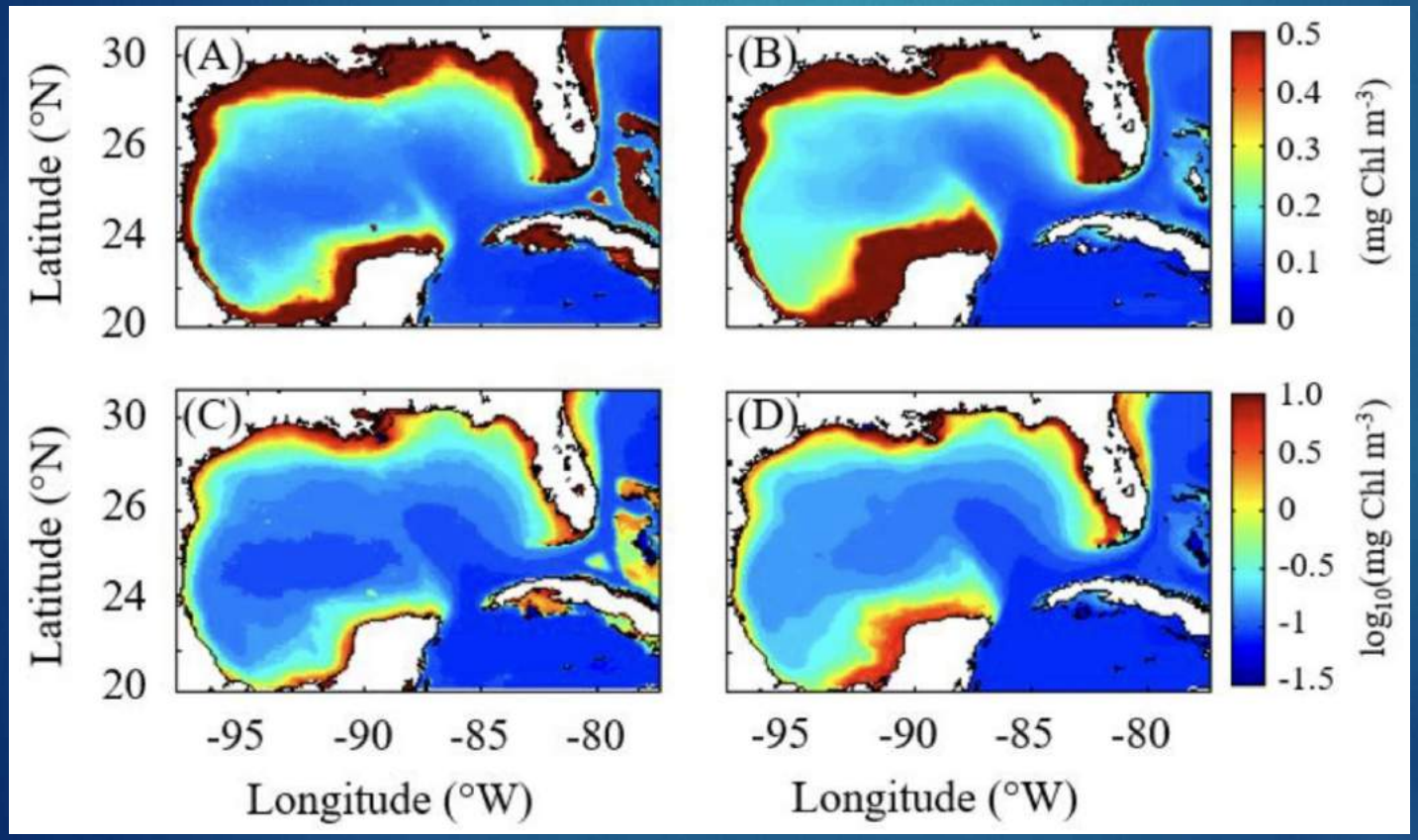
(Stukel and Shropshire)



The model simulates reasonable chlorophyll-a. Thus, we have a reasonable variance for tuning the zooplankton algorithm.

SeaWiFS Chlorophyl-a

NEMURO Model
(Stukel and Shropshire)



4 methods for estimating zooplankton biomass

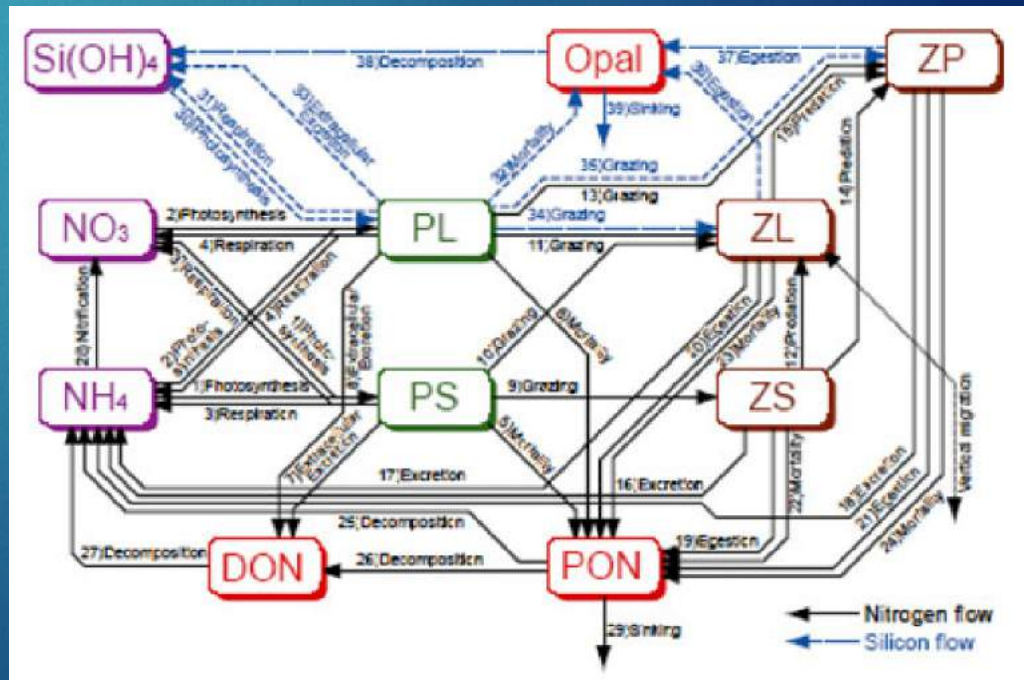
1. ~~Slope of the biomass spectrum – ecological theory.~~

2. Siegel et al mass balance algorithm –

$$\frac{dP}{dt} = \frac{NPP}{Zeu} - Grazing - mortality - sinking - entrainment$$

3. NEMURO model inversion –
ODEs for state variables. Invert for zooplankton given Ps, PL, NPP_PS, NPP_PL, dPS/dt, dPL/dt

4. Machine learning approaches e.g. GLM, Neural Net

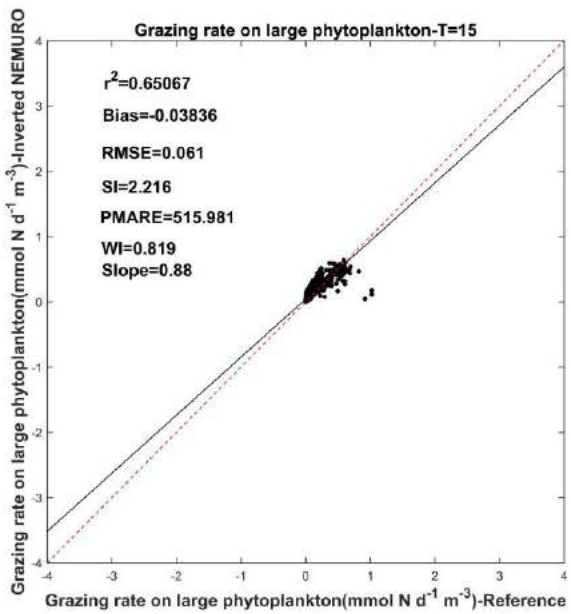


Kishi et al, 2011

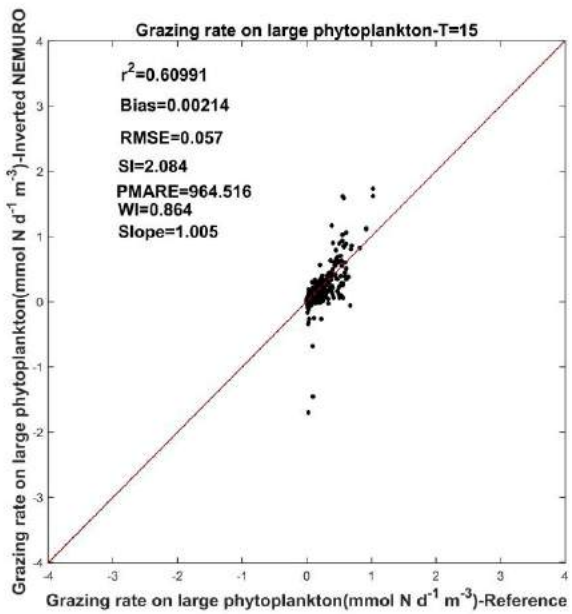
The models for Zooplankton grazing are sensitive to physics (entrainment) and biological disequilibrium

Grazing on Large Phytoplankton – Equilibrium Method (dp/dt=0)

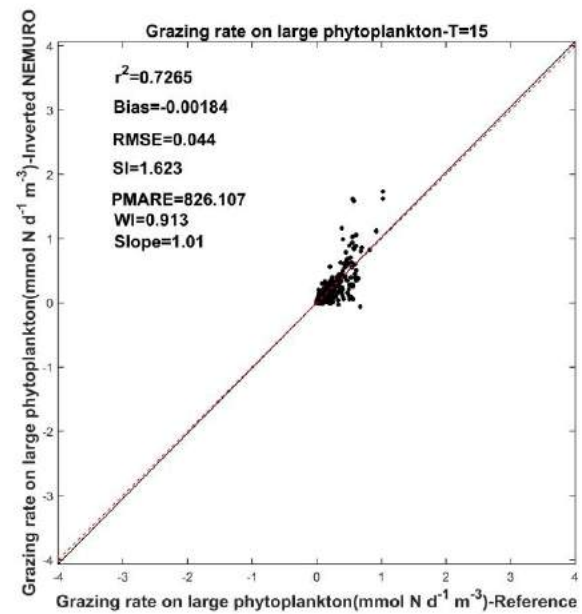
Inverted Model



Siegel Model-Entrainment Included



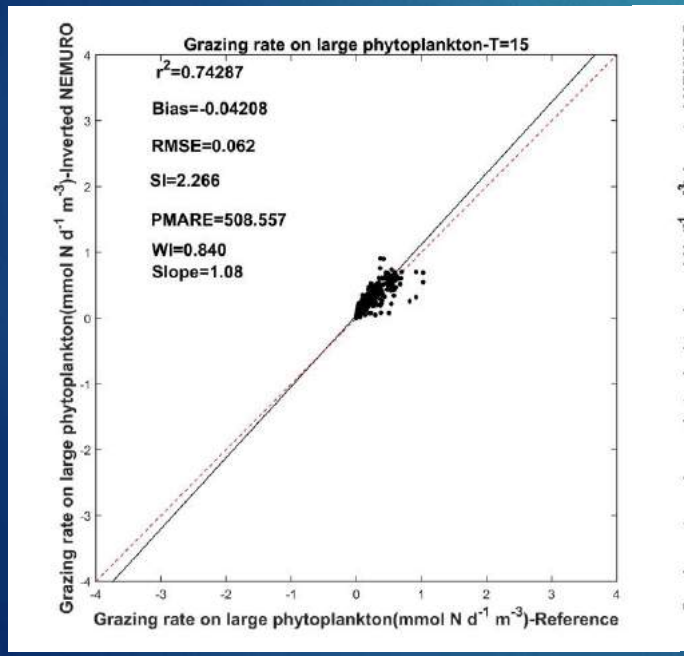
Siegel Model-Entrainment excluded



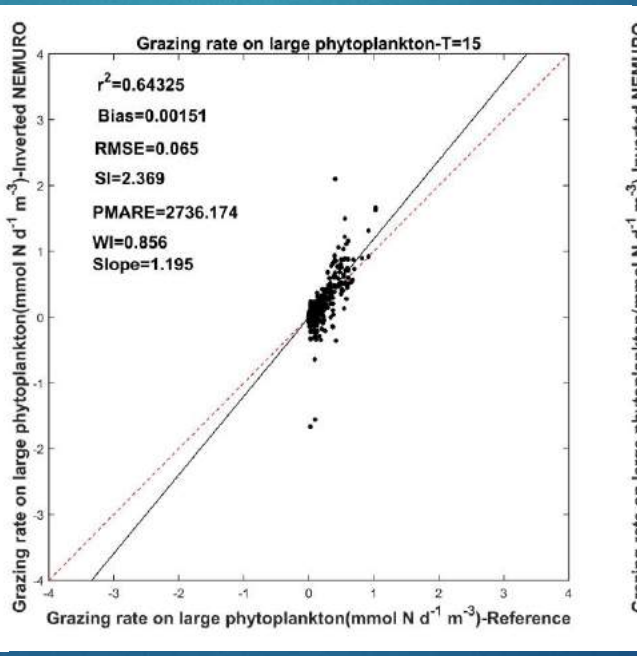
Grazing on Large Phytoplankton is more accurate with inclusion of time dependence

Grazing on Large Phytoplankton $$\frac{dP}{dt} = \frac{(P_2 - P_1)}{\Delta t}$$

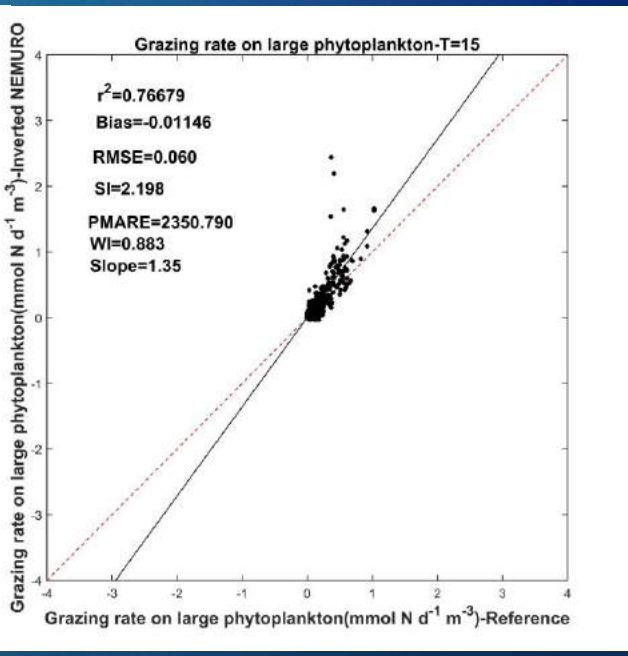
Inverted Model



Siegel Model-Entrainment Included



Siegel Model-Entrainment excluded



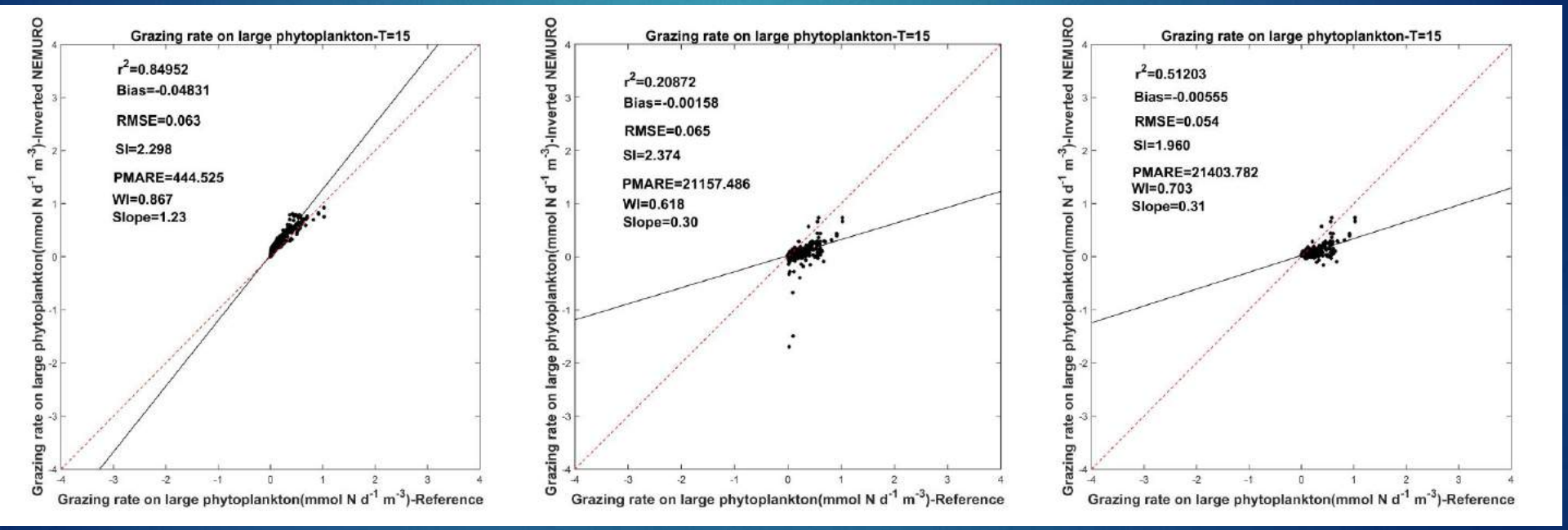
Grazing on Large Phytoplankton can be more accurate when using empirical relationships for time dependence

Grazing on Large Phytoplankton – (dp/dt= function of NPP)

Inverted Model

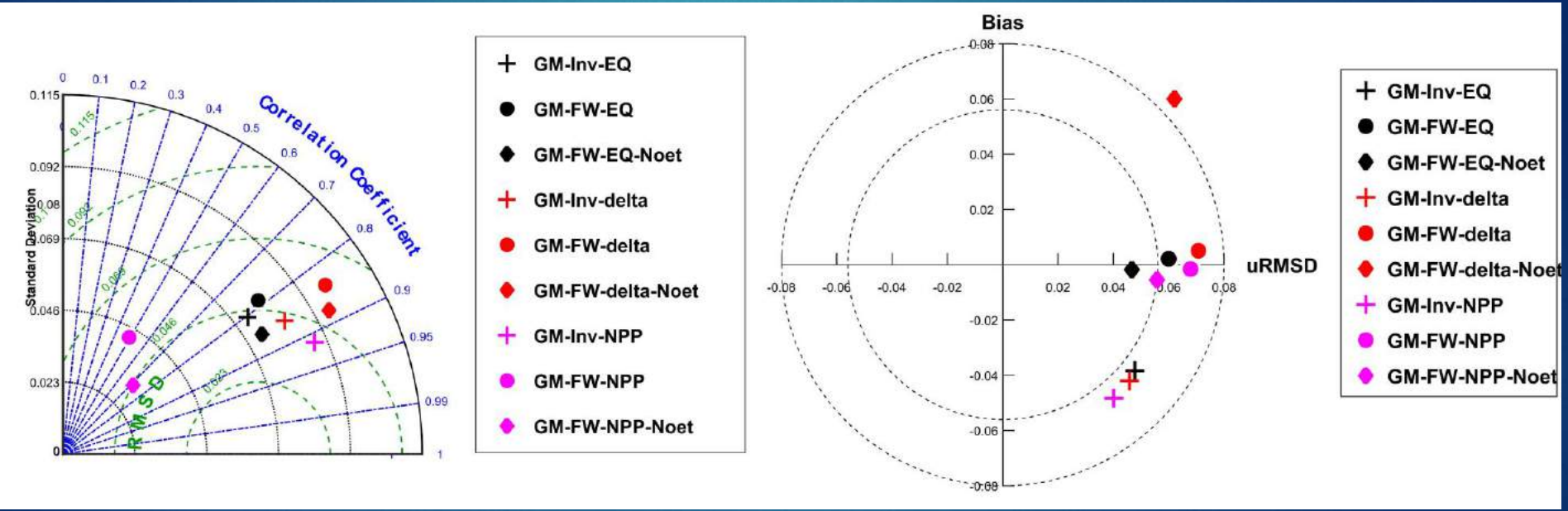
Siegel Model-Entrainment Included

Siegel Model-Entrainment excluded

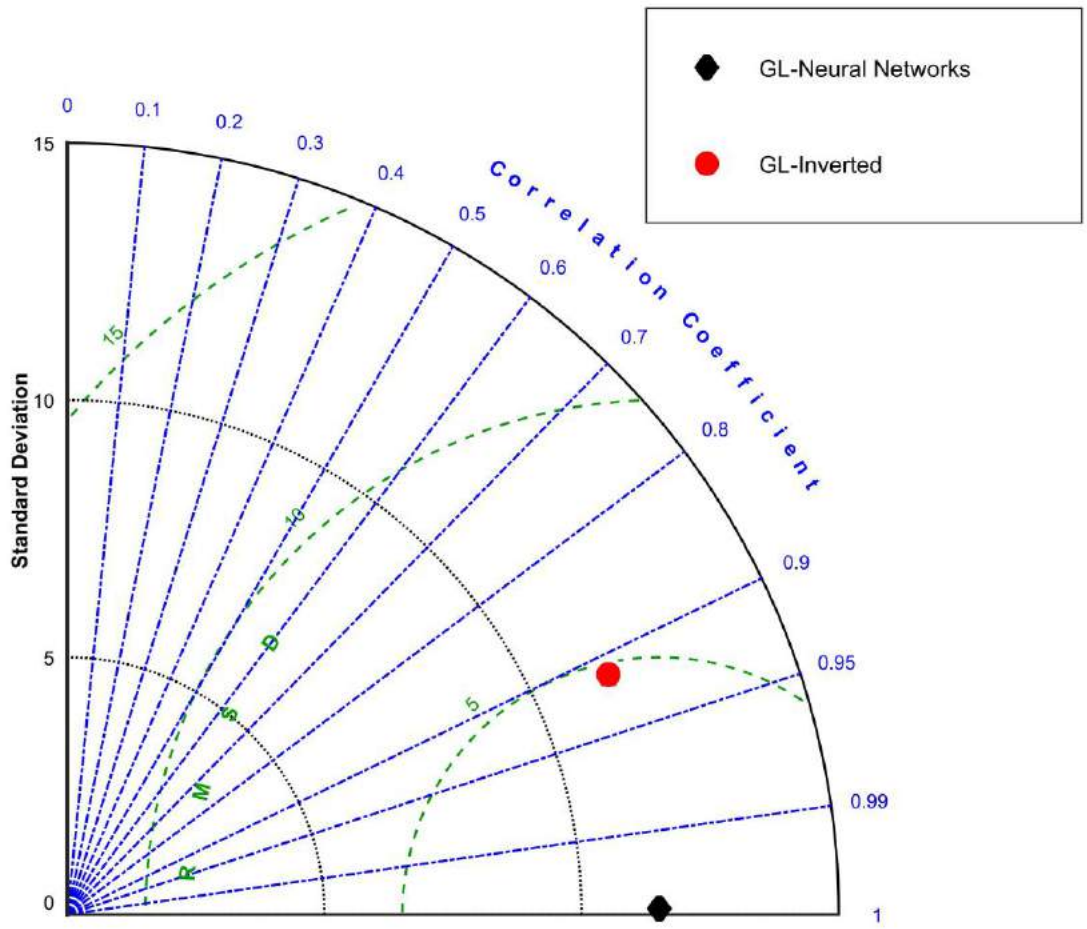


Reference model

Grazing on Large Phytoplankton is reasonably estimated by both the Siegel (FW) and Nemuro inversions (Inv).



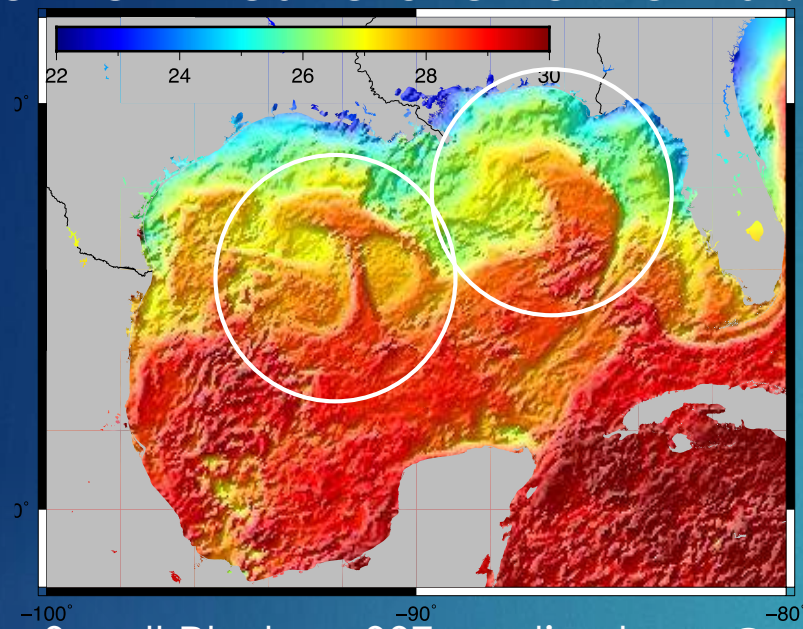
Machine learning techniques are very effective, but give little mechanistic information on the causal links or temporal variation.



Takeaway

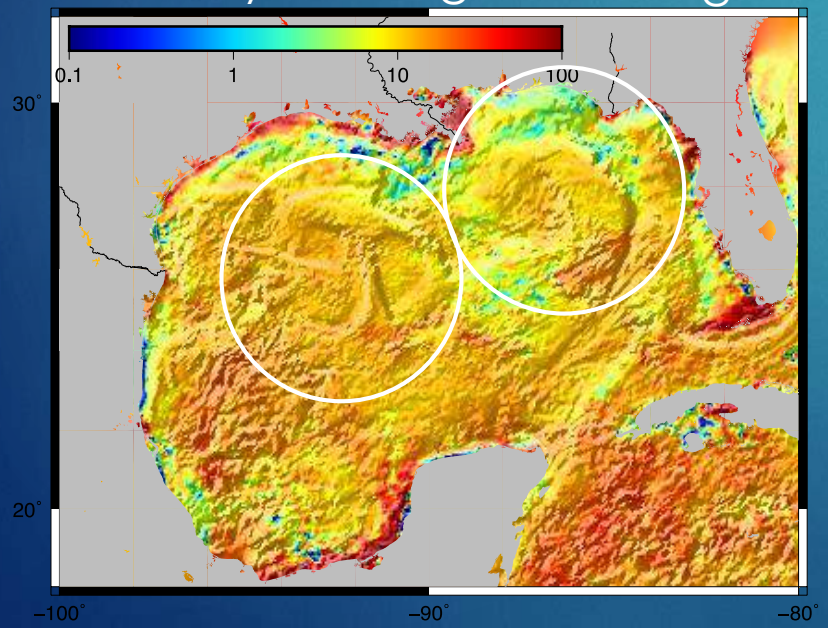
- In the Gulf of Mexico, conditions are typically close to equilibrium except where Net Primary Production is high (particularly large phytoplankton).
- Estimating entrainment typically degrades results in stratified regions, (consistent with Stukel et al, 2017)
- Simple Siegel food web model works as well as the more complex model for grazing rate, but does not yield the full complement of outputs available to an ecological model inversion.
- Machine learning approaches could be locally powerful where the answer is more important than the underlying mechanisms… and where sufficient data exists for training

Large scale patterns of Phytoplankton Biomass sometimes relate to fronts … but not always.

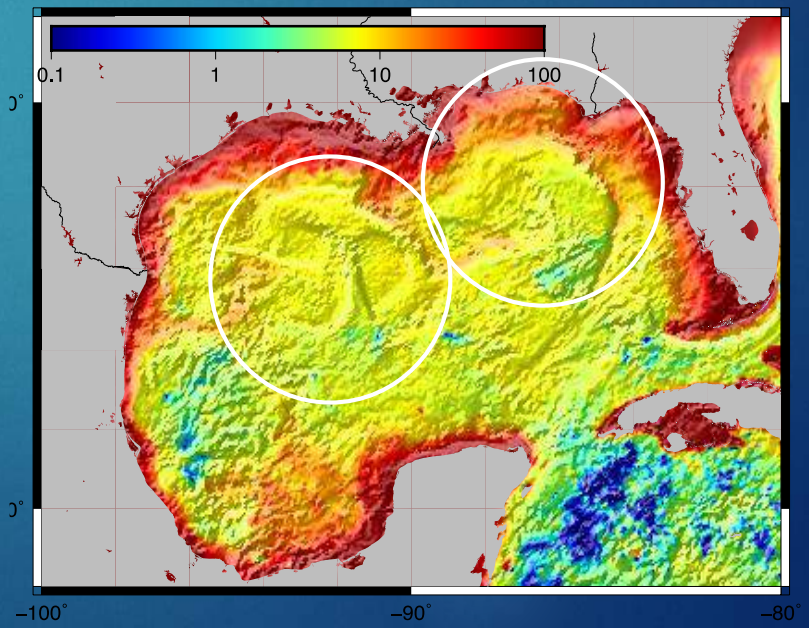


SST +SSTgradient

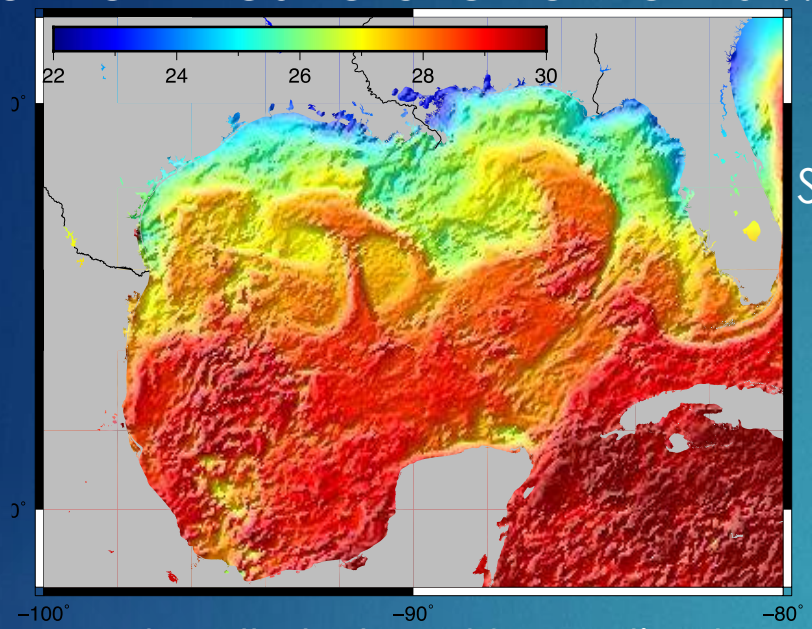
Small Phyto + SSTgradient mgC m^{-3}



Large Phyto + SSTgradient

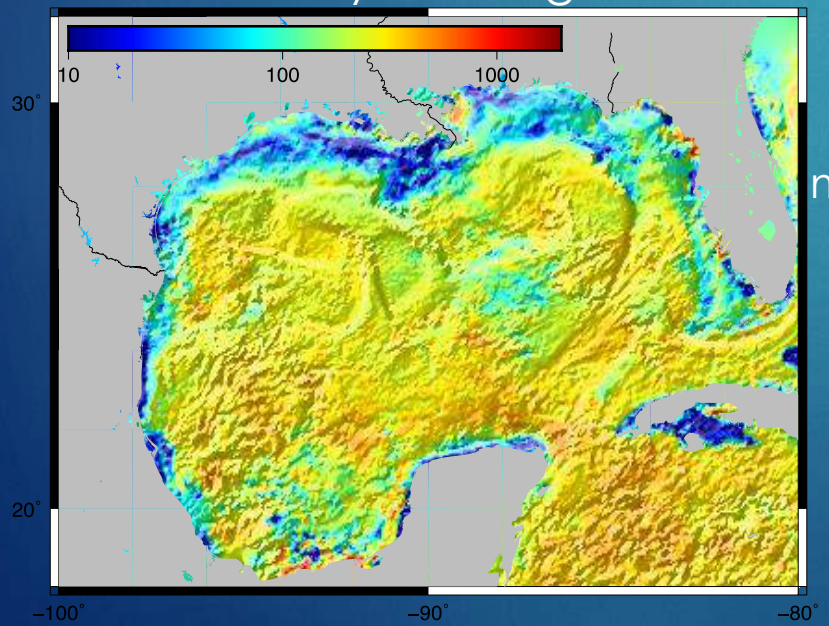


Large scale patterns of Phytoplankton Production sometimes relate to fronts … but not always.



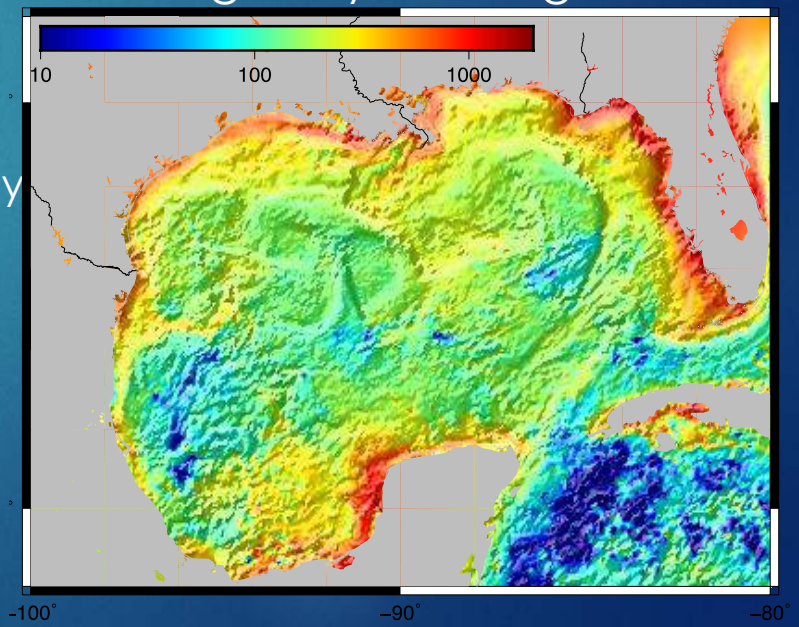
SST +SSTgradient

NPP Small Phyto + SSTgradient

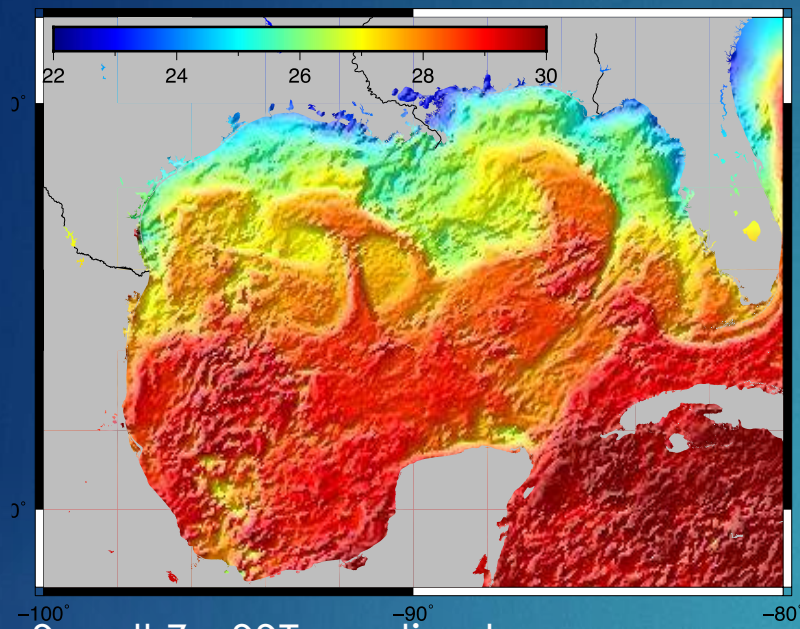


mgC m^{-2}day

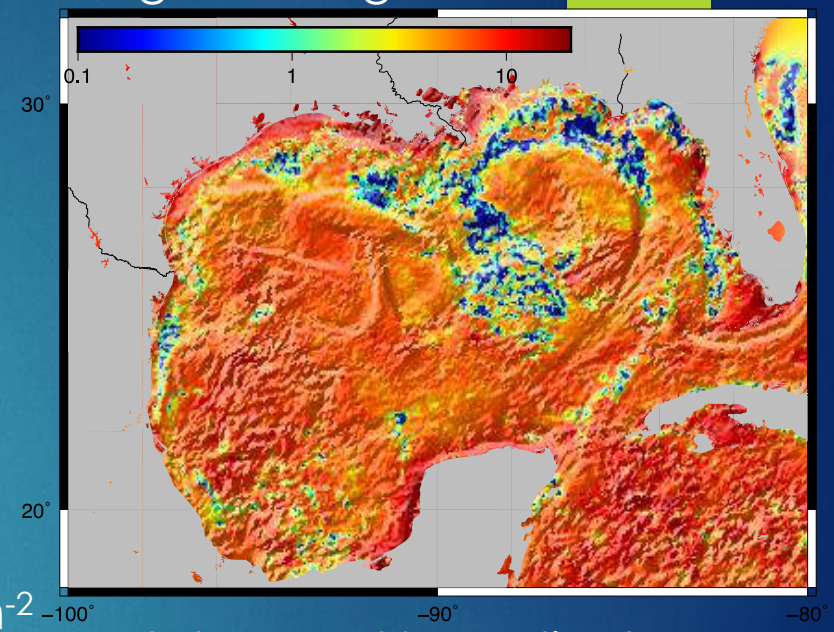
NPP Large Phyto + SSTgradient



Large scale patterns of Zooplankton sometimes relate to fronts … but not always.

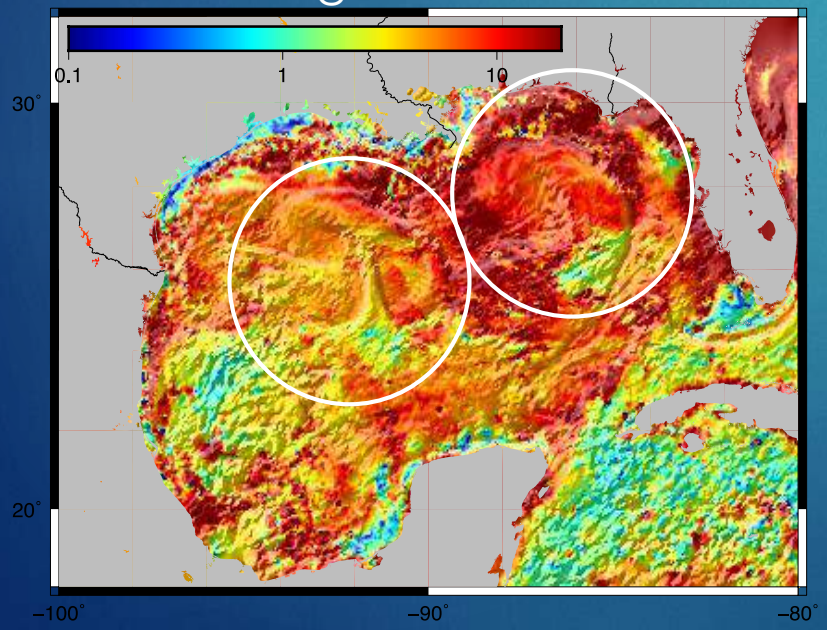


Large Z + SSTgradient

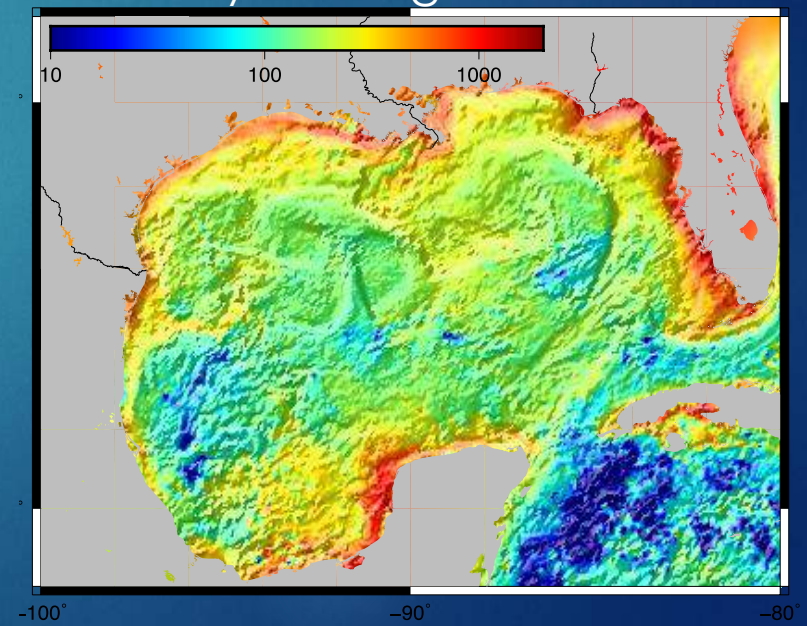


mgC m^{-2} day^{-1}

Small Z+ SSTgradient

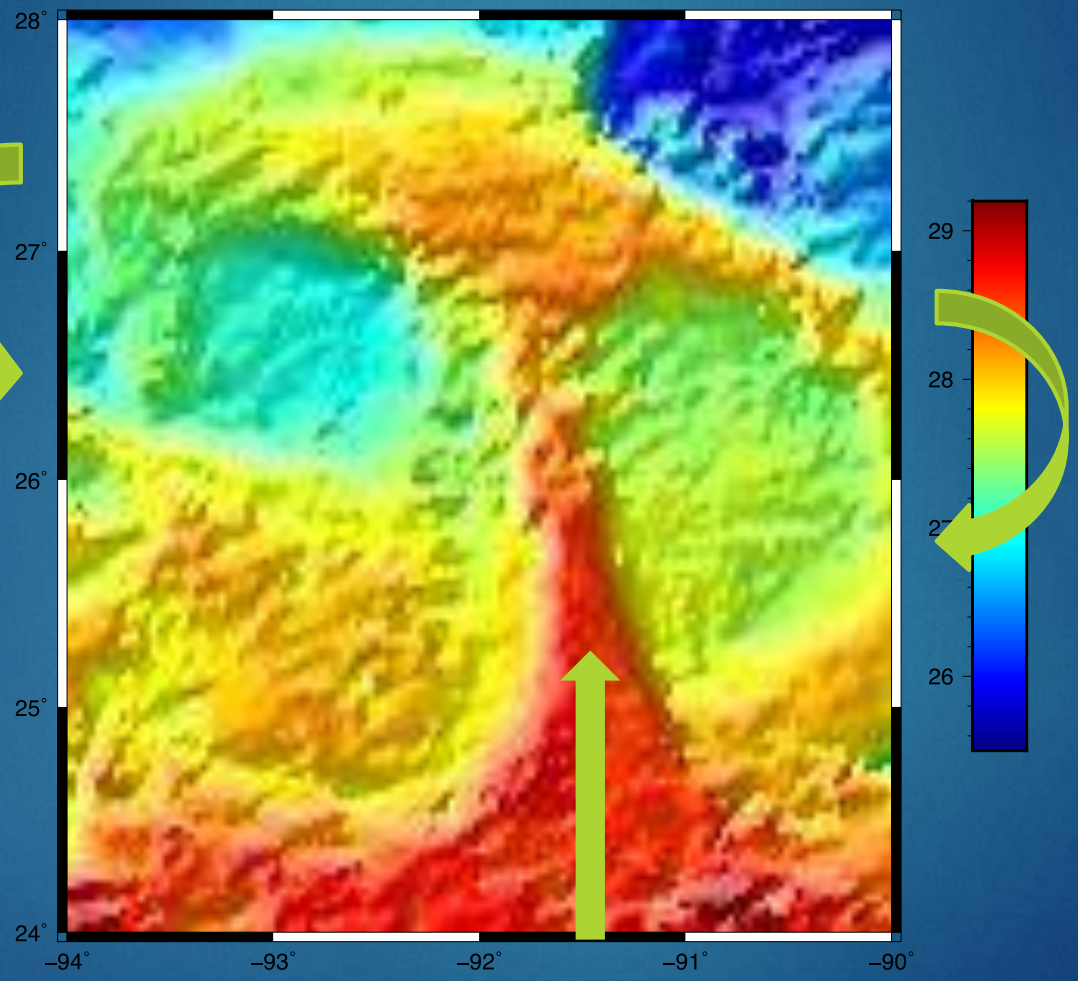


Predatory Z + SSTgradient



Hammerhead frontal structure results in two eddies with differing dynamics, but likely similar initial conditions.

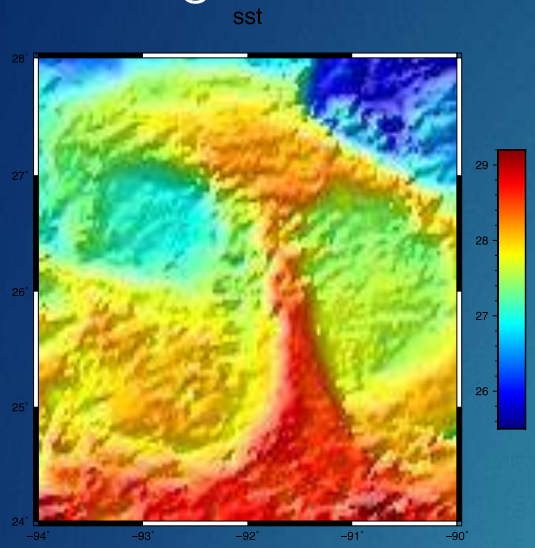
SST +SSTgradient



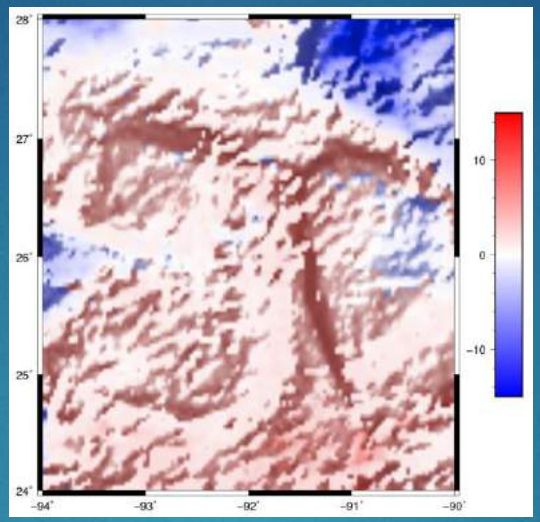
Shallow thermocline -> Nutrients closer to surface

Deep thermocline -> less nutrient transfer to surface

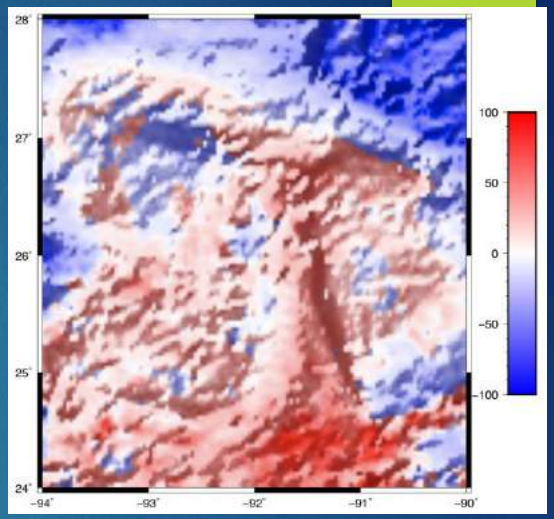
SST +SSTgradient



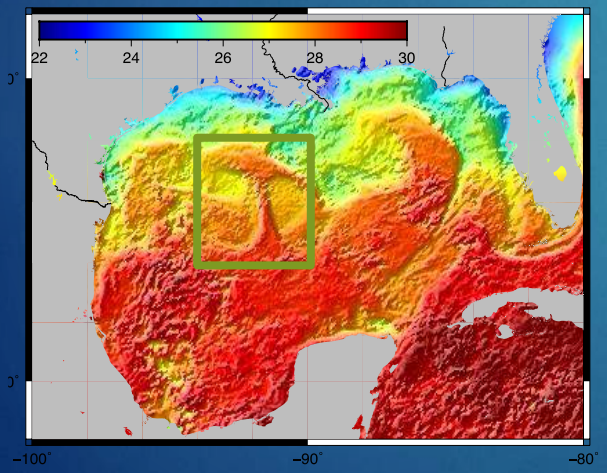
Large Phyto+SSTgradient



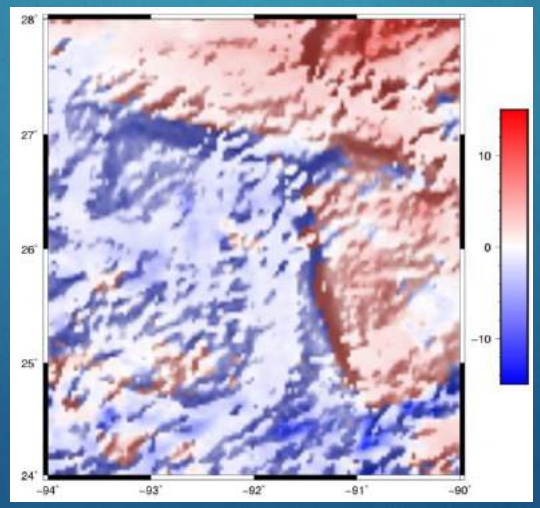
NPP Large Phyto +SSTgradient



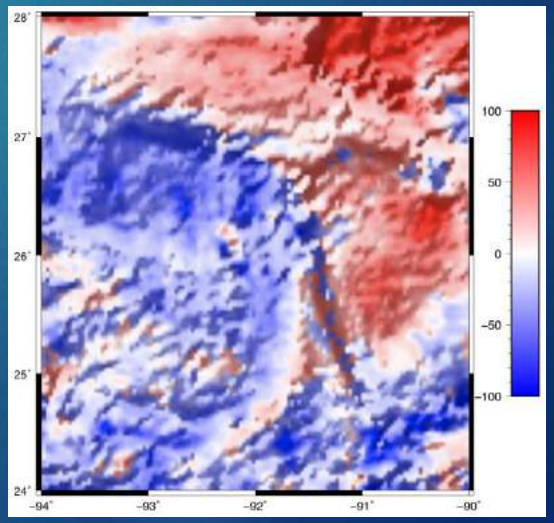
mgC m^{-3} and mgC m^{-2}day^{-1}



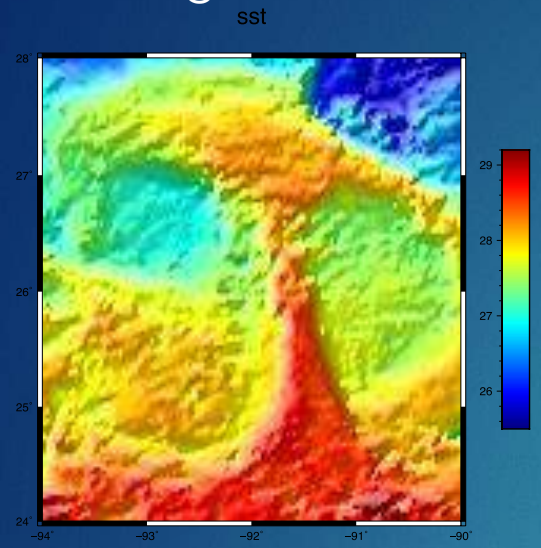
Small Phyto+SSTgradient



NPP Small Phyto +SSTgradient

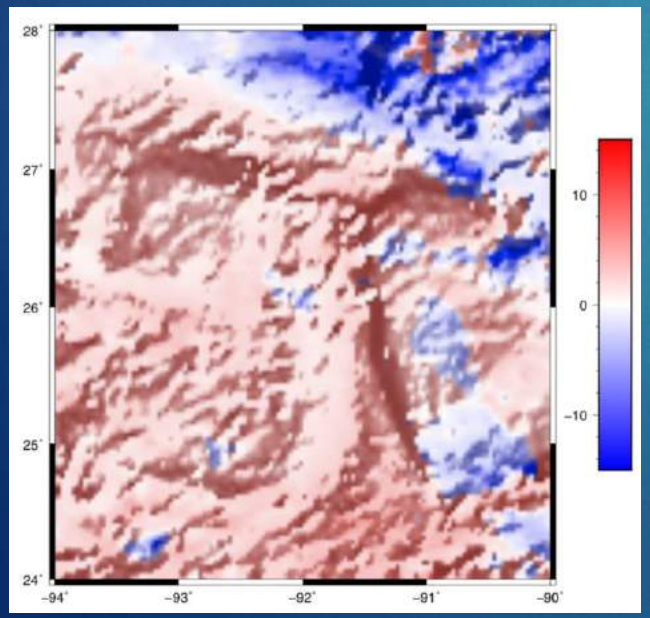


SST +SSTgradient

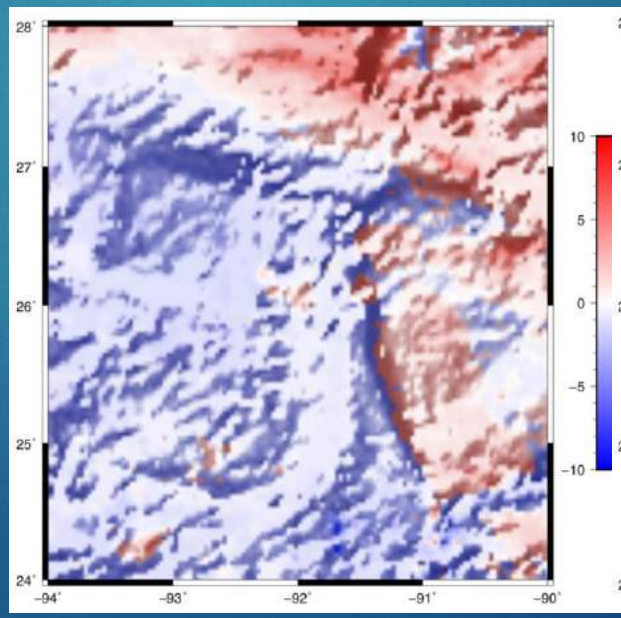


mgC m^{-3} and mgC $m^{-2}day^{-1}$

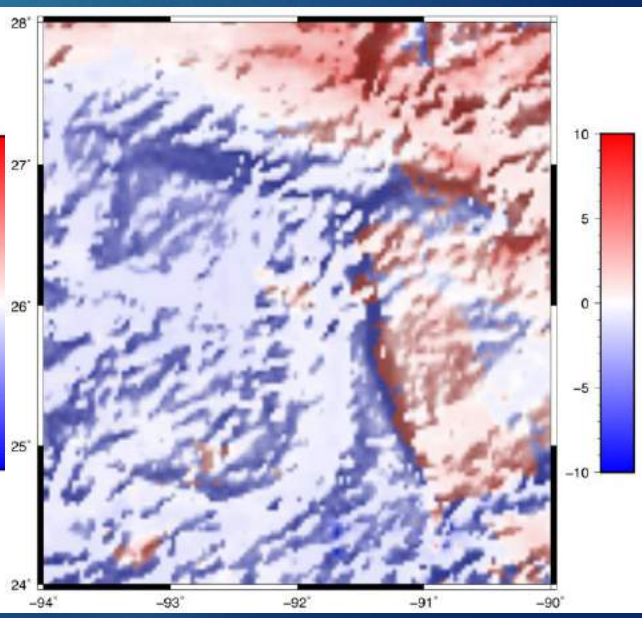
Small Z+SSTgradient



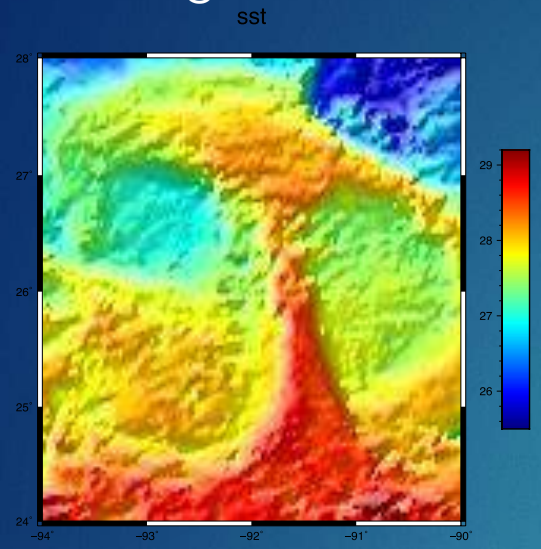
Large Z+SSTgradient



Predatory Z+SSTgradient

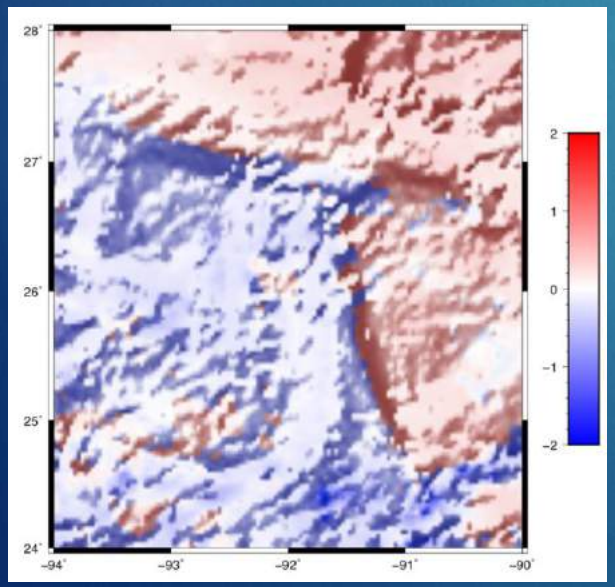


SST +SSTgradient

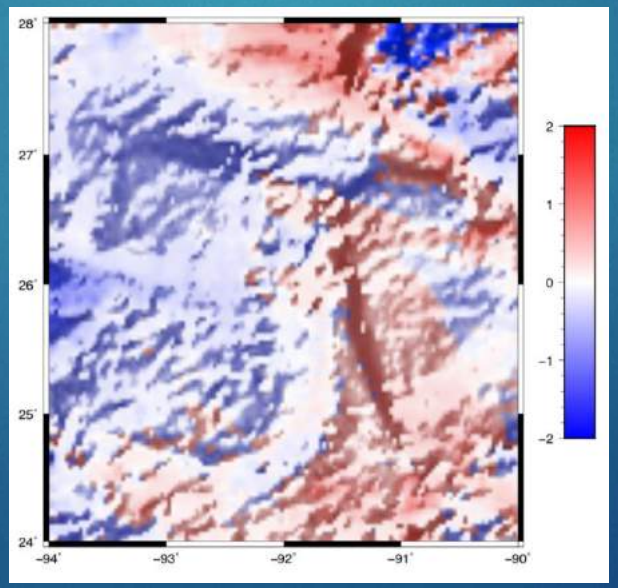


mgC m^{-3} and mgC $m^{-2}day^{-1}$

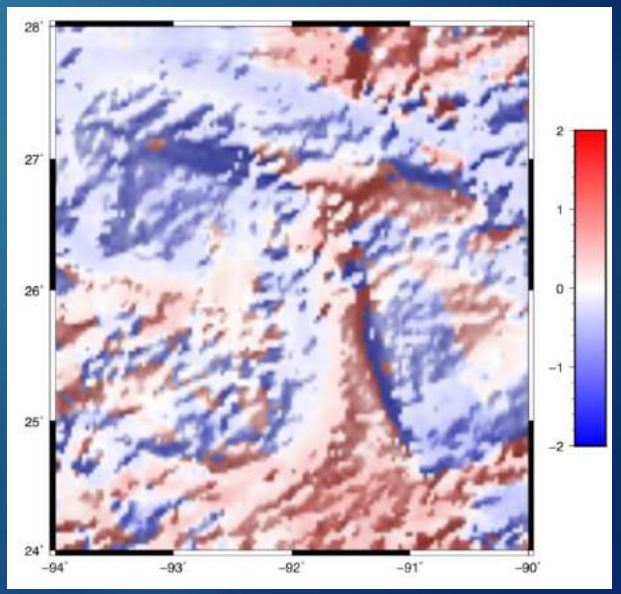
Large Z grazing on Small P +SSTgradient



Large Z grazing on Large P +SSTgradient



Large Z grazing on Small Z +SSTgradient

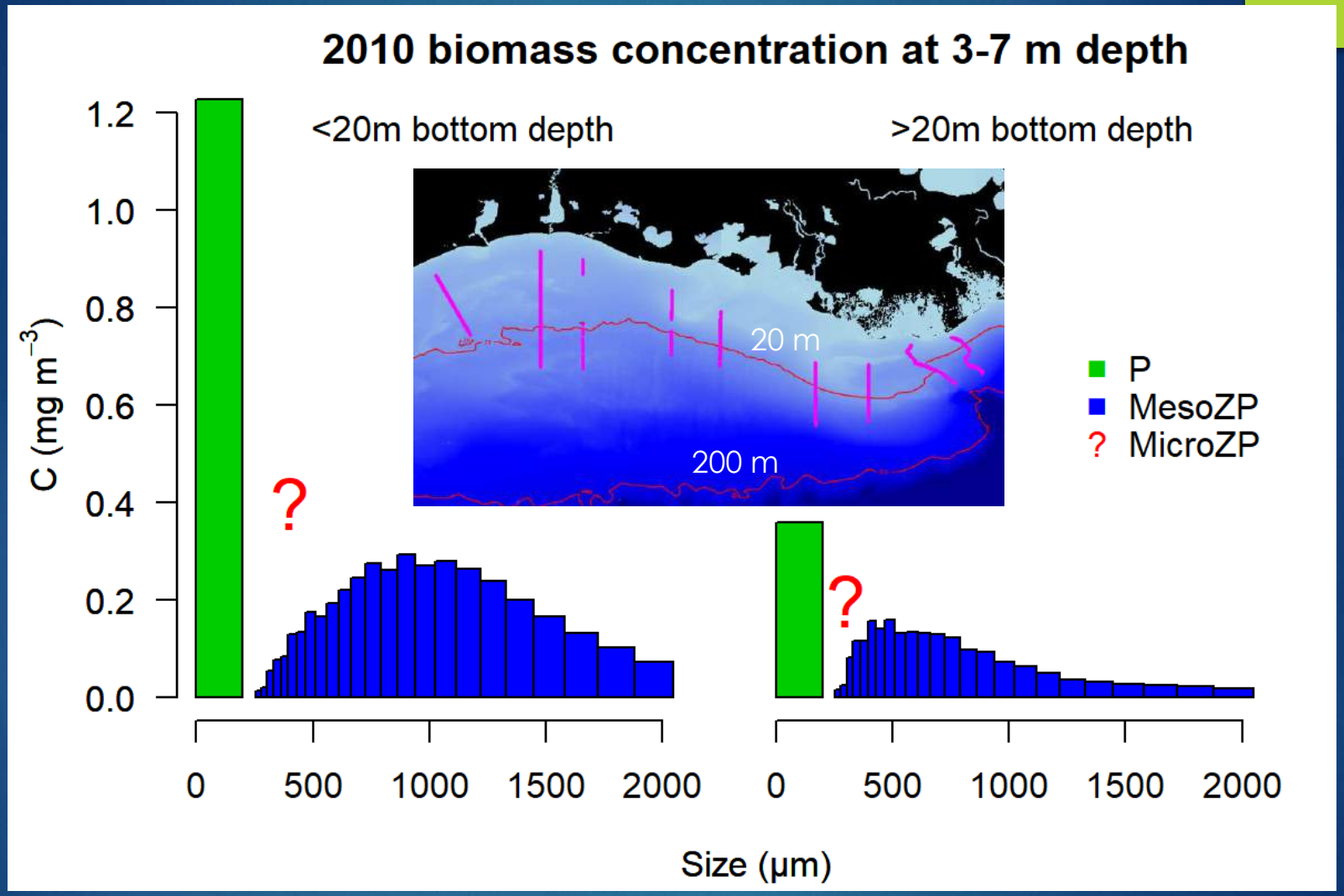


Next Steps

1. Characterize sensitivity of the methods to errors in the input data, e.g. MLD variability.
2. Characterize sensitivity of the methods to the temporal interval of the data.
3. Integrate Individual based zooplankton model into the methods to include behaviors such as diel vertical migration
4. Apply methods to other regions with data – e.g. California Current.

Potential applications

1. Parameterize models as a function of underlying seascapes / biomes
2. Use for data assimilation and prediction as a complete ecosystem solution


2010 biomass concentration at 3-7 m depth
<20m bottom depth
>20m bottom depth
20 m
200 m
P
MesoZP
? MicroZP
?
?
C (mg m^{-3})
1.2
1.0
0.8
0.6
0.4
0.2
0.0
0
500
1000
1500
2000
0
500
1000
1500
2000
Size (µm)