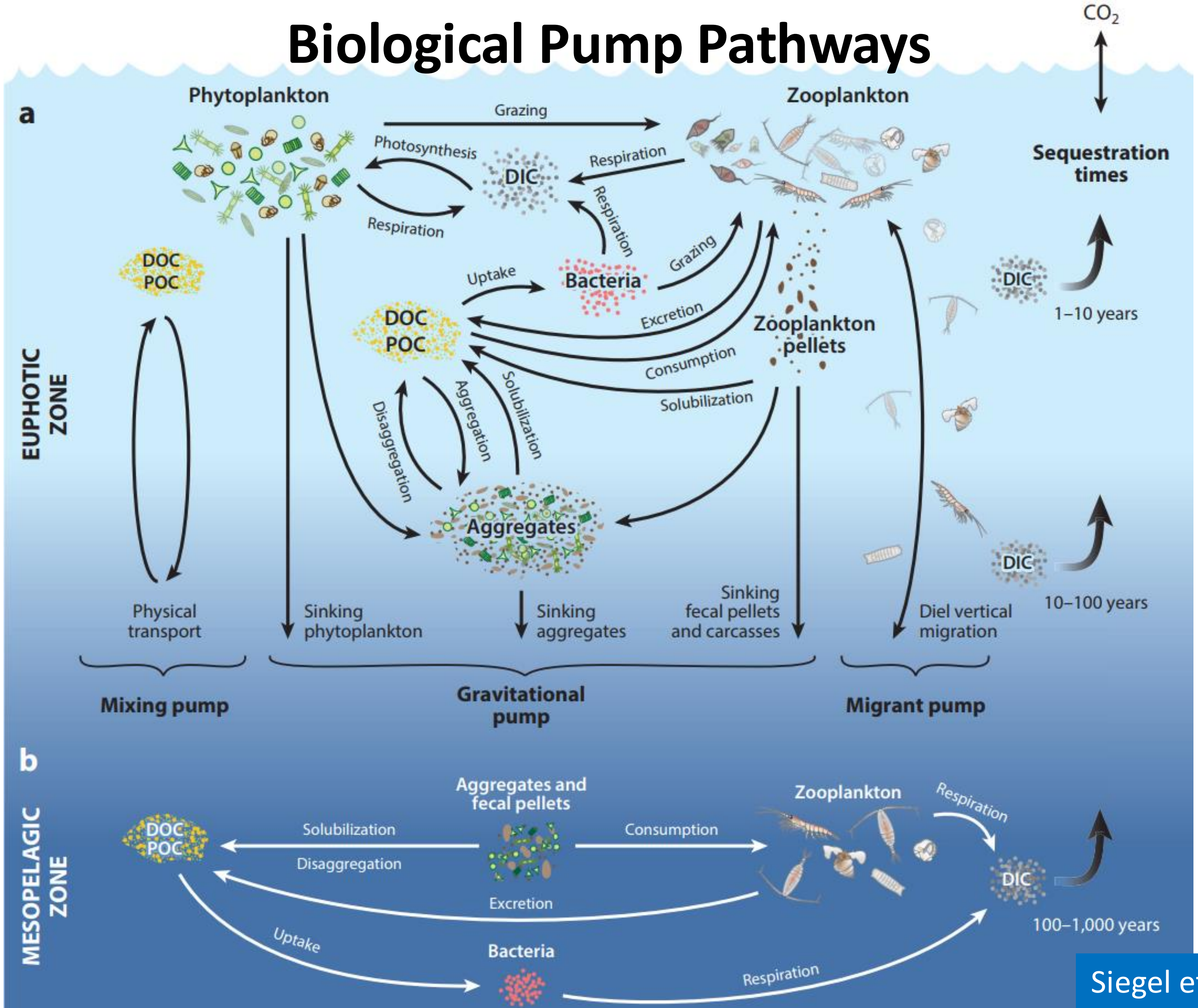
Ocean Biology and Biogeochemistry: Our Science I

Seasonality in Marine Organic Carbon Export and Sequestration Pathways

Renjian Li and Tim DeVries
University of California, Santa Barbara

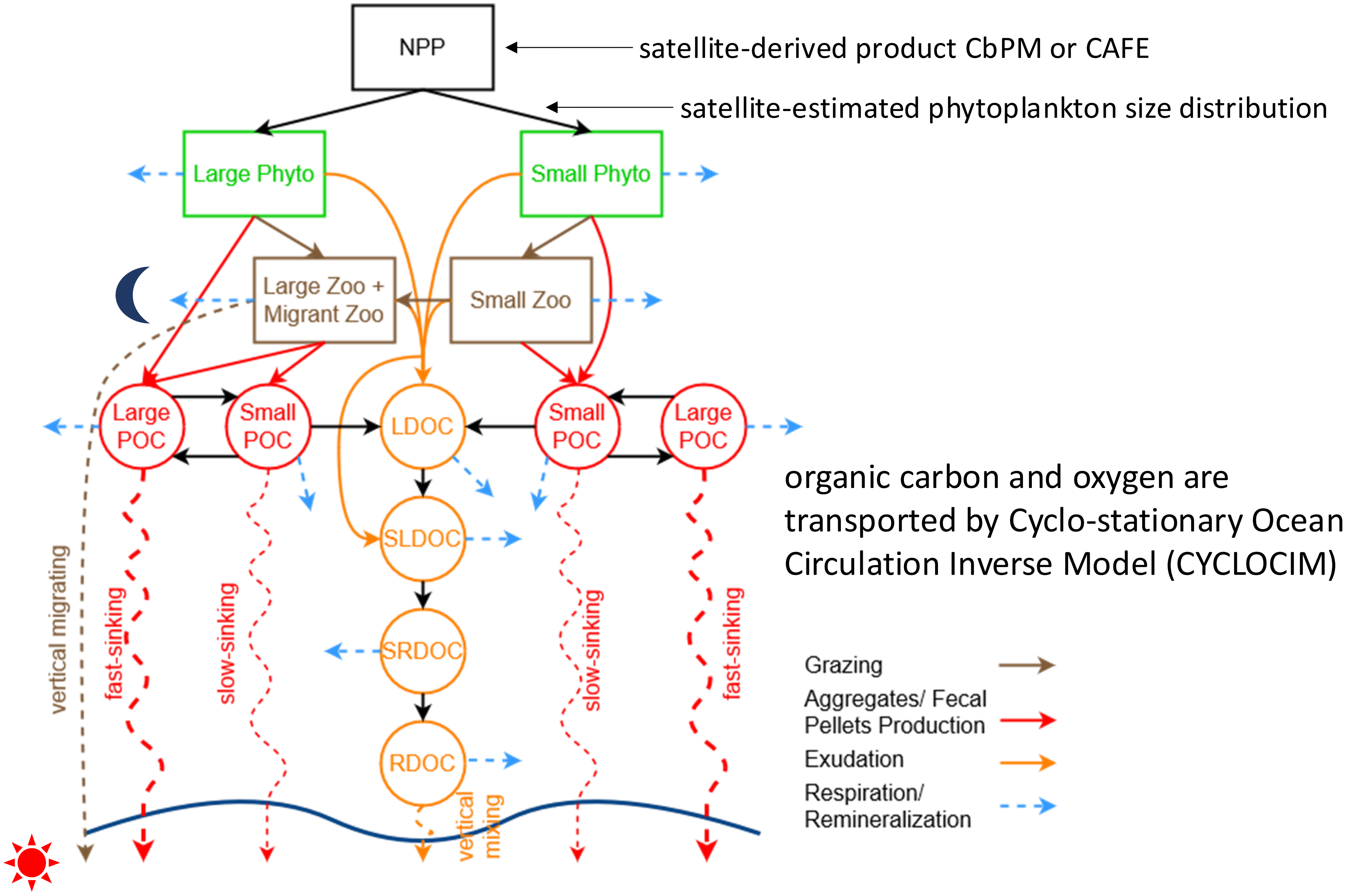
Biological Pump Pathways



Siegel et al. (AnnuRev, 2023)

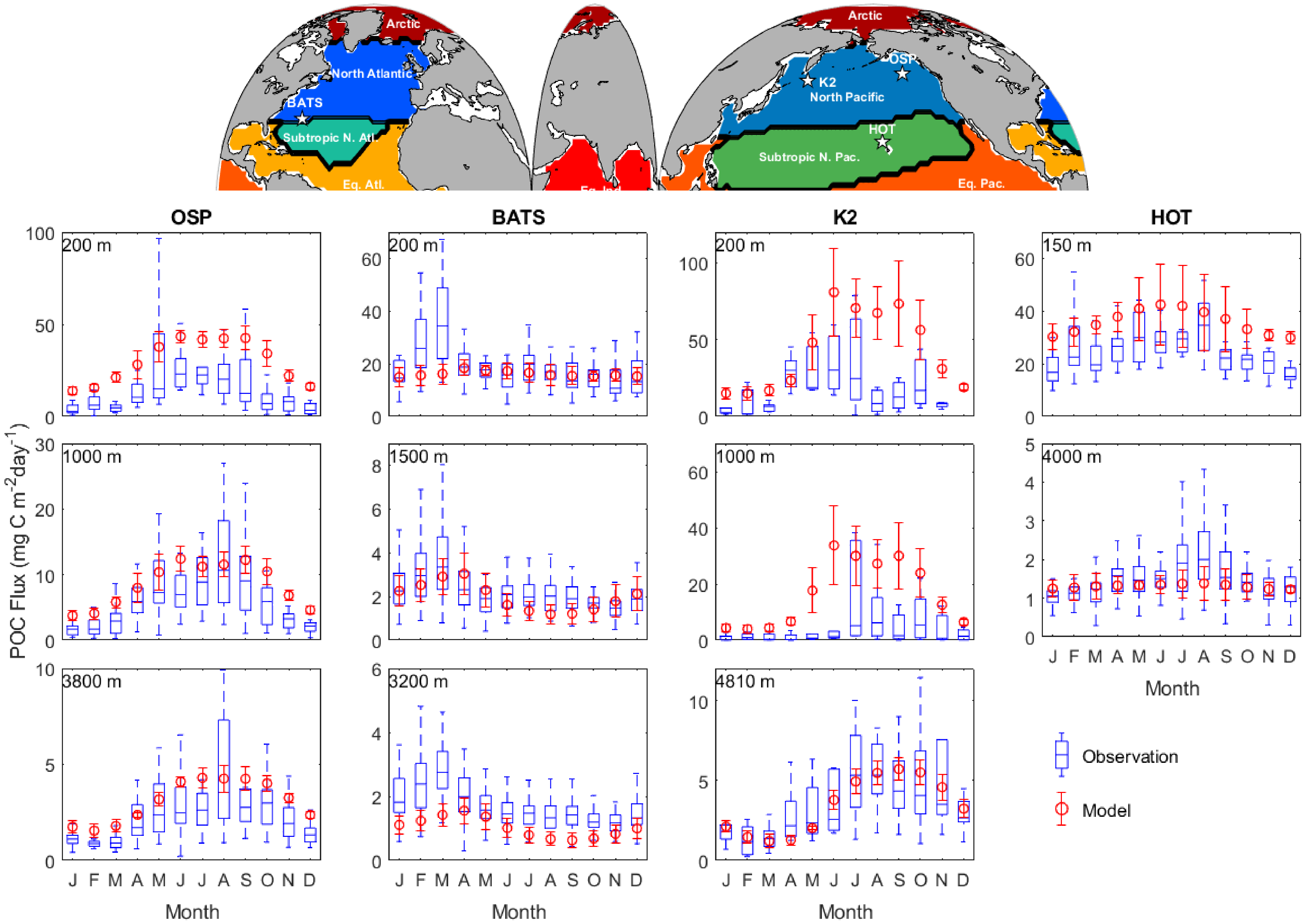
Model Implementation

Data Constrains	
surface phyto biomass	climatological-monthly
depth-integrated zoo biomass	climatological-monthly
DOC concentration	climatological-monthly
O_2 concentration	climatological-monthly
magnitude of POC flux	annual mean
magnitude of migrant flux	transient observation

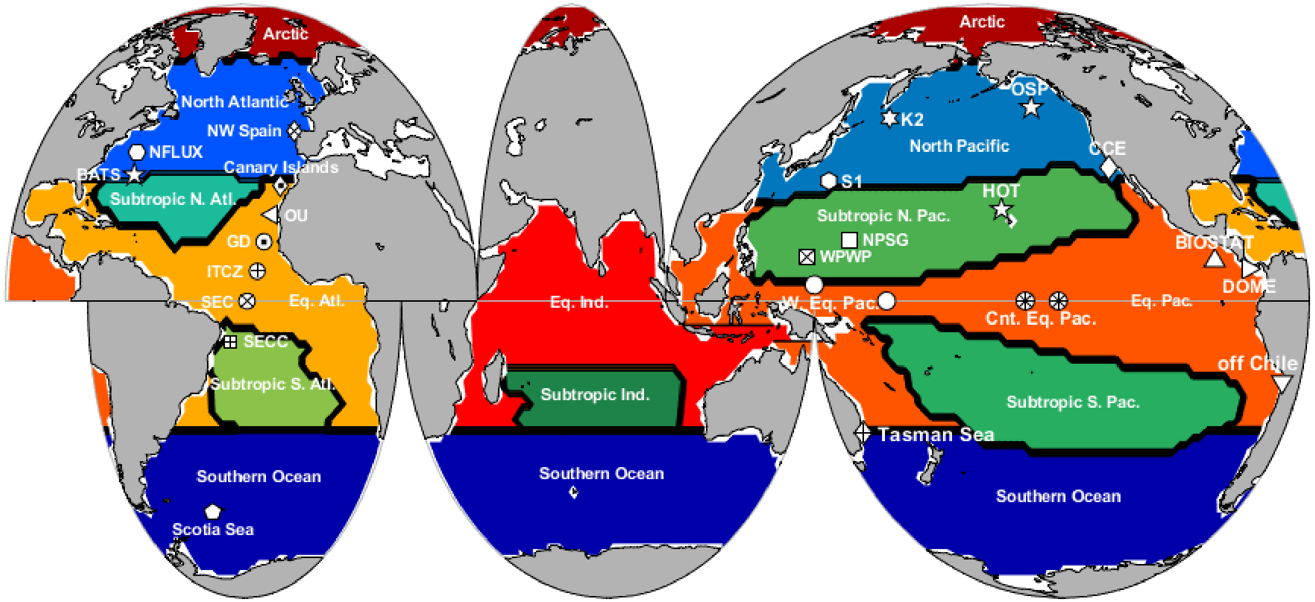


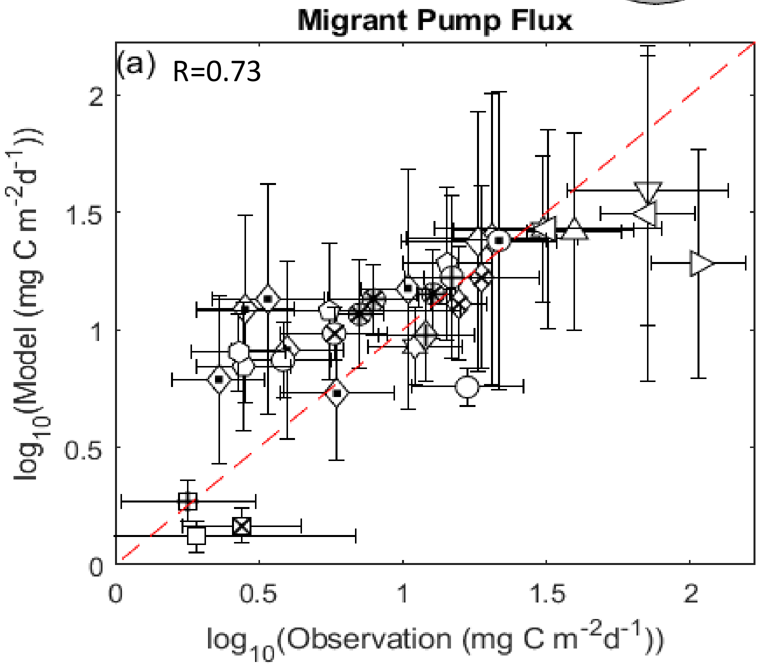
organic carbon and oxygen are transported by Cyclo-stationary Ocean Circulation Inverse Model (CYCLOCIM)

Model Performance

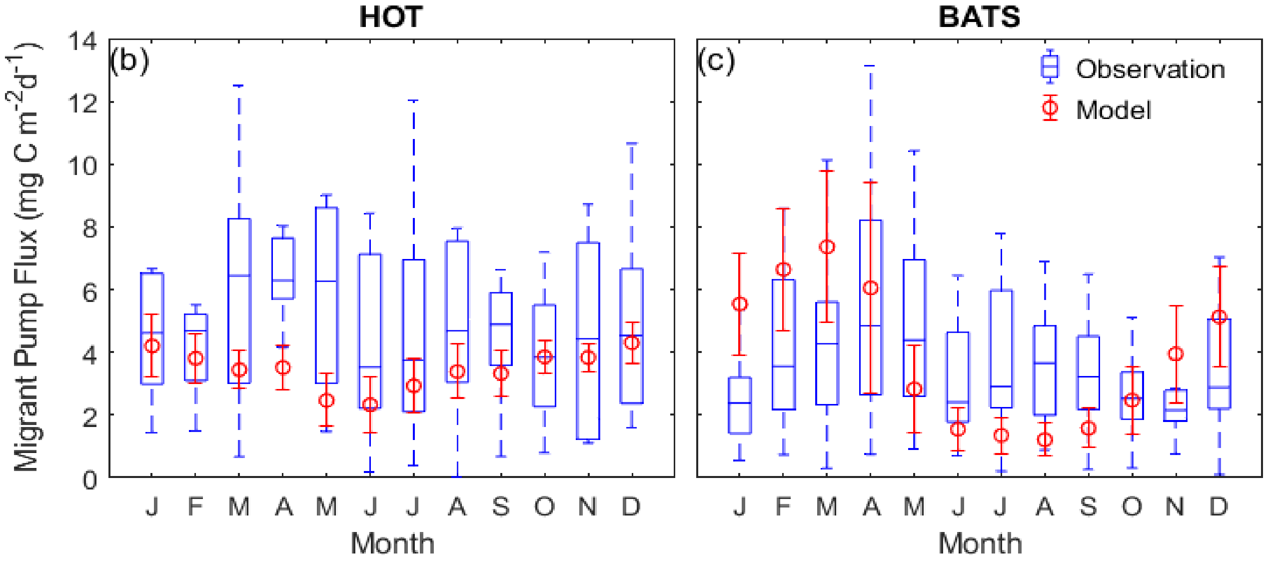


Model Performance



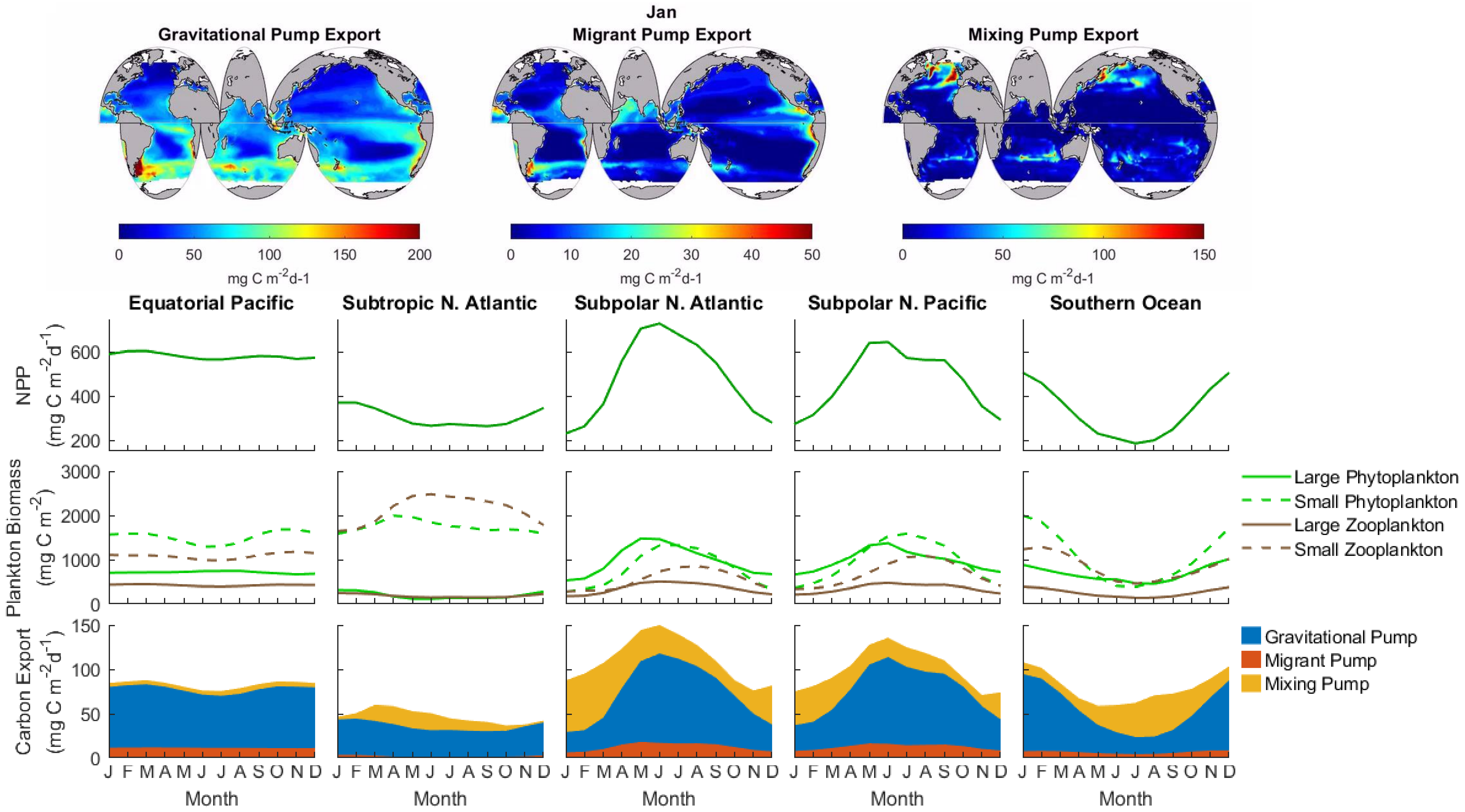


Transient Observation

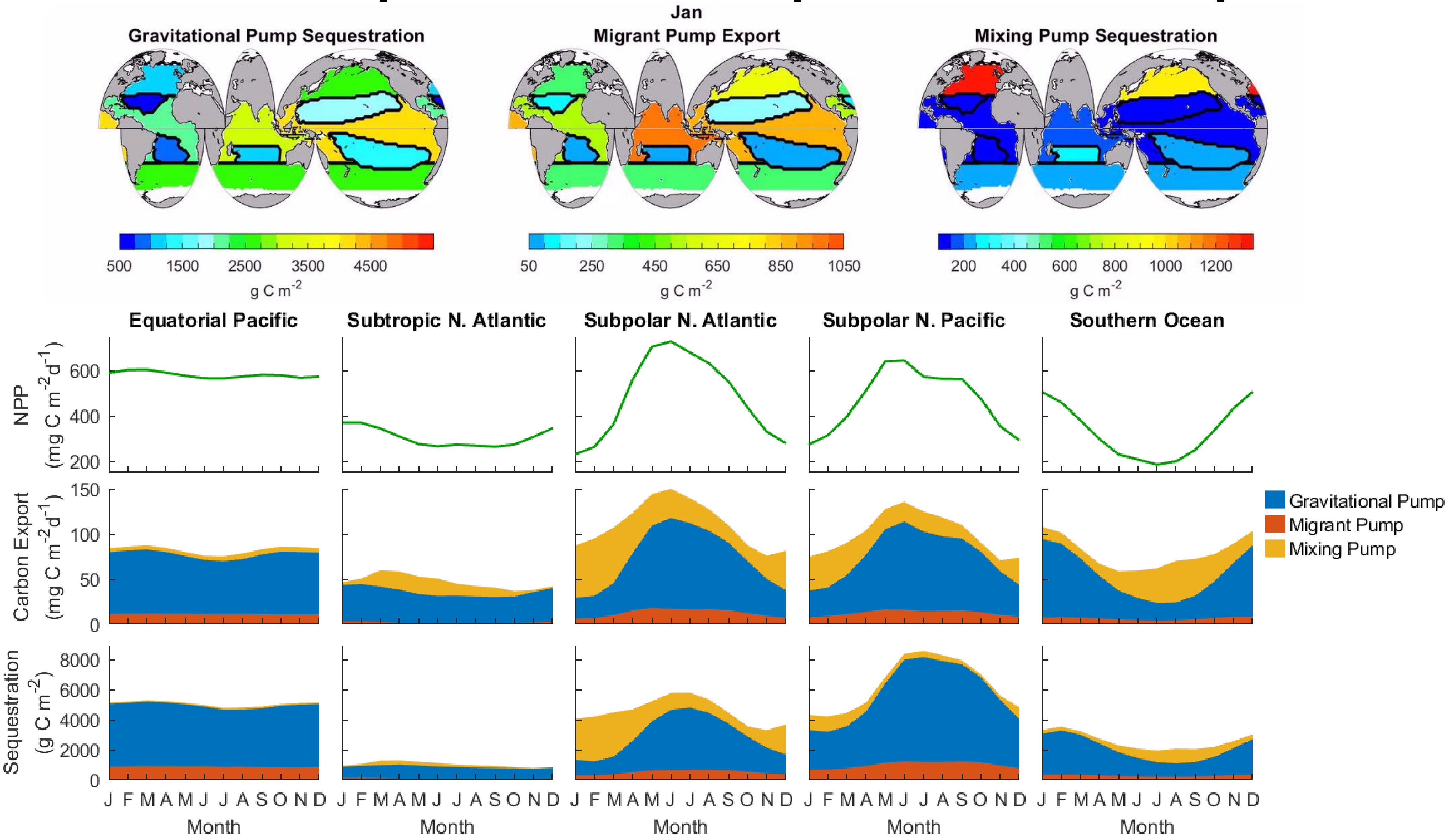


Long-term Observation Time Series

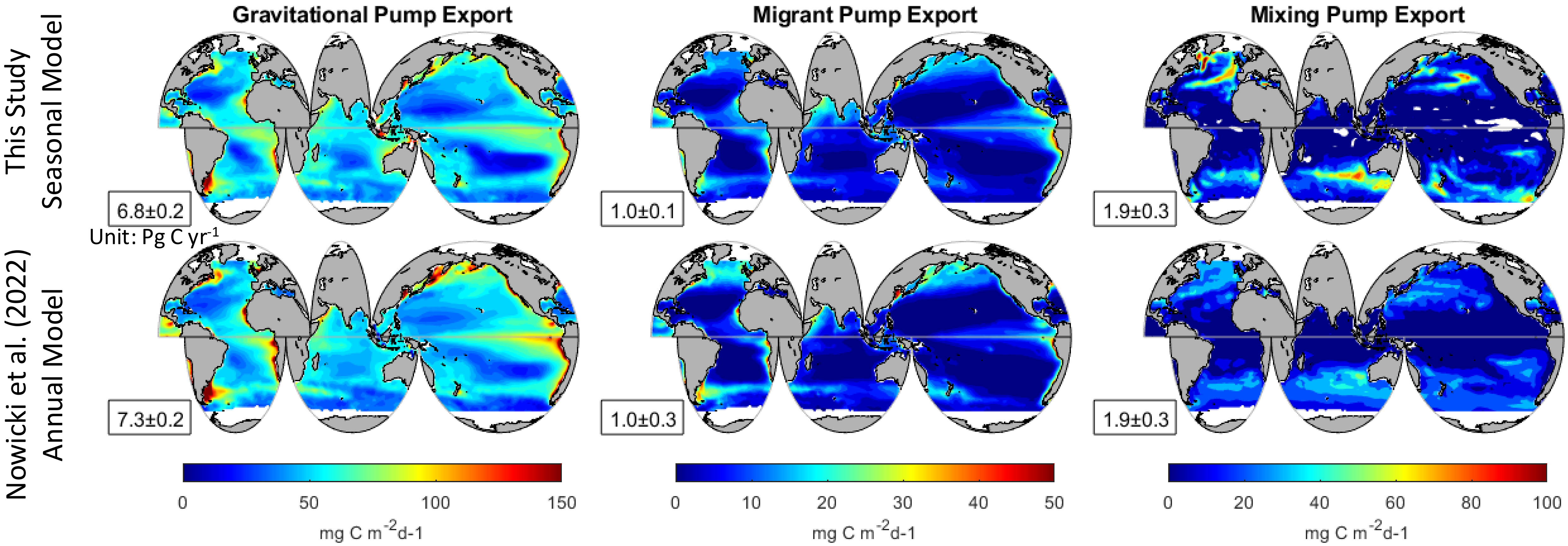
Seasonal Cycles of Carbon Export Pathways



Seasonal Cycles of Carbon Sequestration Pathways

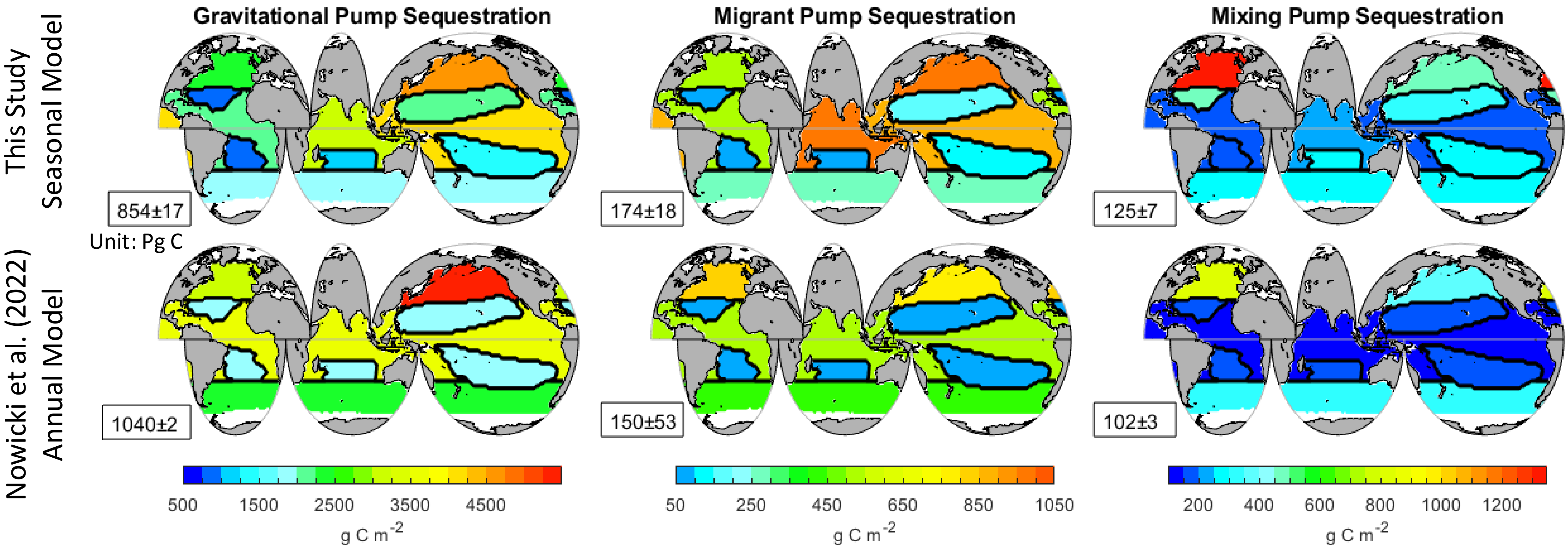


Comparison with Annual-Mean Model



	Seasonal Model	Annual Model
Total Carbon Export ($Pg\ C\ yr^{-1}$)	**9.8±0.5**	**10.2±0.5**

Comparison with Annual-Mean Model

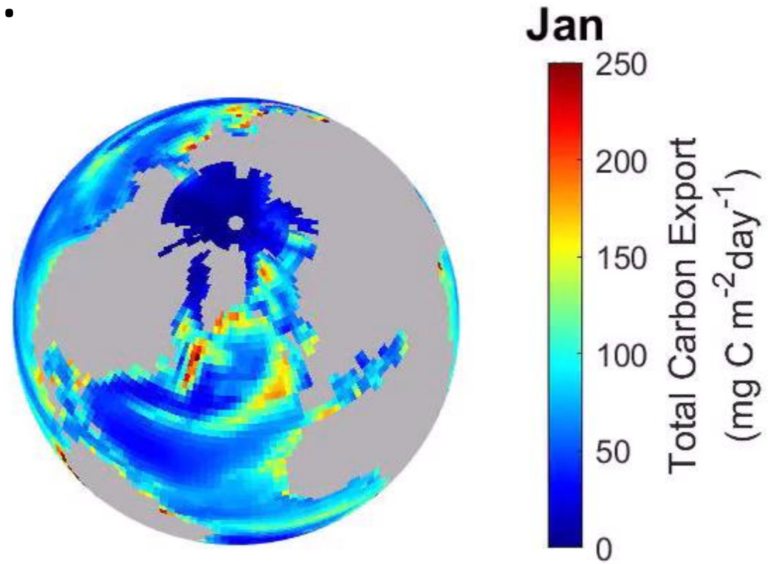


	Seasonal Model	Annual Model	
Total Carbon Export ($Pg\ C\ yr^{-1}$)	**9.8±0.5**	**10.2±0.5**	**4% smaller**
Total Carbon Sequestration (Pg C)	**1152±5**	**1293±11**	**11% smaller**

Take-Home Message

- A new data-assimilated model has been developed to simulate the climatologically monthly biological pump pathways.

- Carbon export and sequestration show strong seasonality in high-latitude regions, driven by seasonal blooms and winter convection.



- Compared with previous annual model, including seasonality of ocean environment leads to similar estimates on global total carbon export and sequestration, with relatively larger influence on sequestration.

The NASA BlueFlux-II campaign: quantifying carbon fluxes along the blue carbon land ocean-aquatic continuum

Ben Poulter
NASA Goddard Space Flight Center
Earth Sciences Division
Biospheric Sciences Lab.

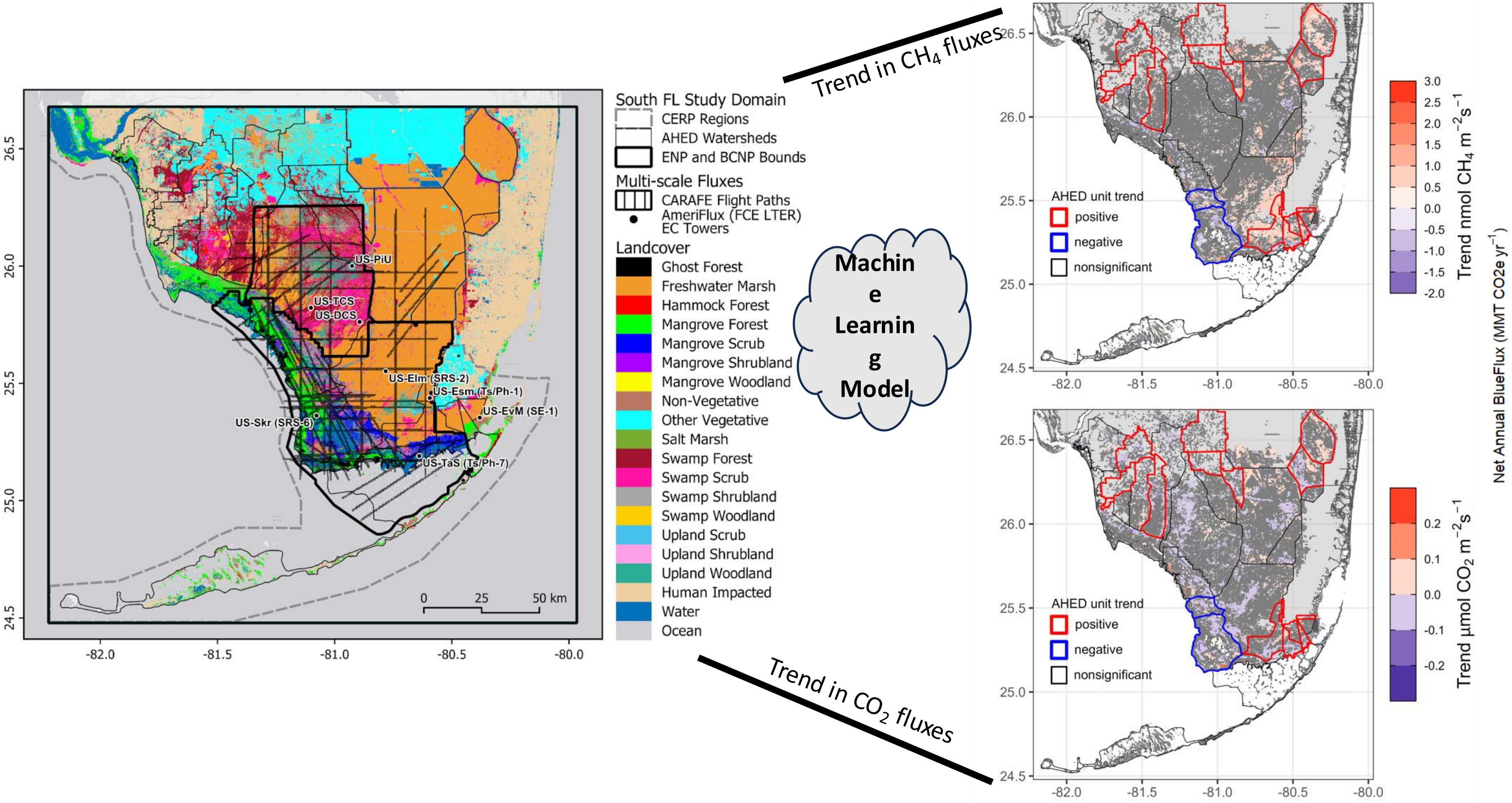
BlueFlux Project Overview

1 NASA, 2 YALE, 3 Boulder, 4 ECU, 5 WAGENINGEN UNIVERSITY & RESEARCH, 6 UNIVERSITY OF PITTSBURGH, 7 FIU FLORIDA INTERNATIONAL UNIVERSITY, 8 Southern Cross University, 9 UNIVERSITY OF MARYLAND

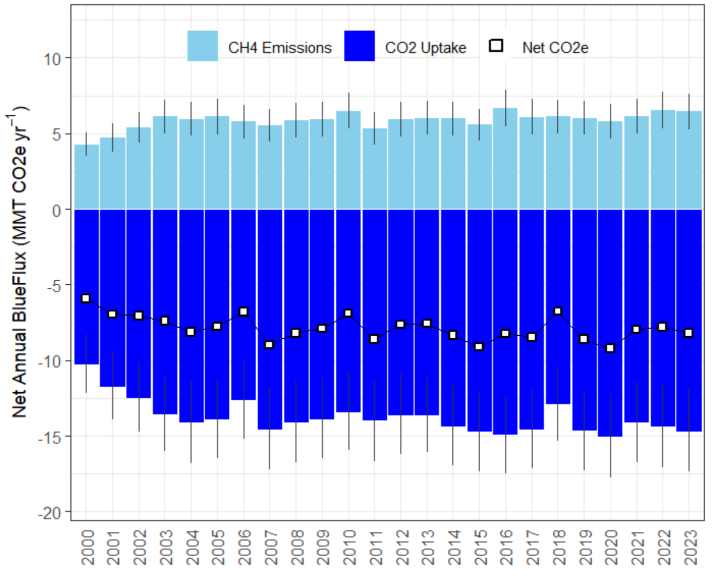
Research Team: Benjamin Poulter[1], Frannie Adams[2], Cibele Amaral[3], Abigail Barenblitt[1], Anthony Campbell[1], Sean P. Charles[4], Rosa Maria Roman-Cuesta[5], Rocco D'Ascanio[2], Erin Delaria[1], Cheryl Doughty[1], Temilola Fatoyinbo[1], Jonathan Gewirtzman[2], Thomas F. Hanisco[1], Moshema Hull[2], S. Randy Kawa[1], Reem Hannun[6], David Lagomasino[4], Leslie Lait[1], Sparkle Malone[7,2], Paul Newman[1], Peter Raymond[2], Judith Rosentreter[2, 9], Nathan Thomas[1], **Glenn M. Wolfe[1]**, Lin Xiong[4], Qing Ying[9], Zhen Zhang[9]

BlueFlux-I key results

- Complex patterns in landscape processes (Coastal Everglades Restoration Plan, sea-level rise, hurricane damage, prescribed fire) impacting trends and inter-annual variability in carbon dioxide and methane emissions
  - MODIS-based reflectance model provides daily, 500-meter perspective on vertical fluxes of GHGs



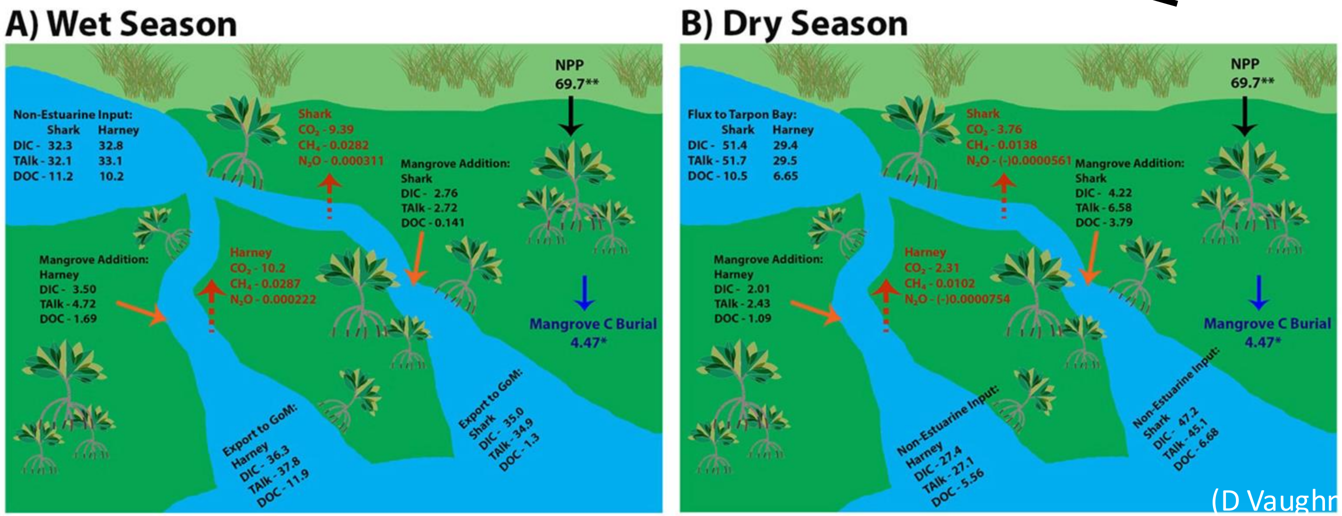
2000-2024 CO_2e fluxes



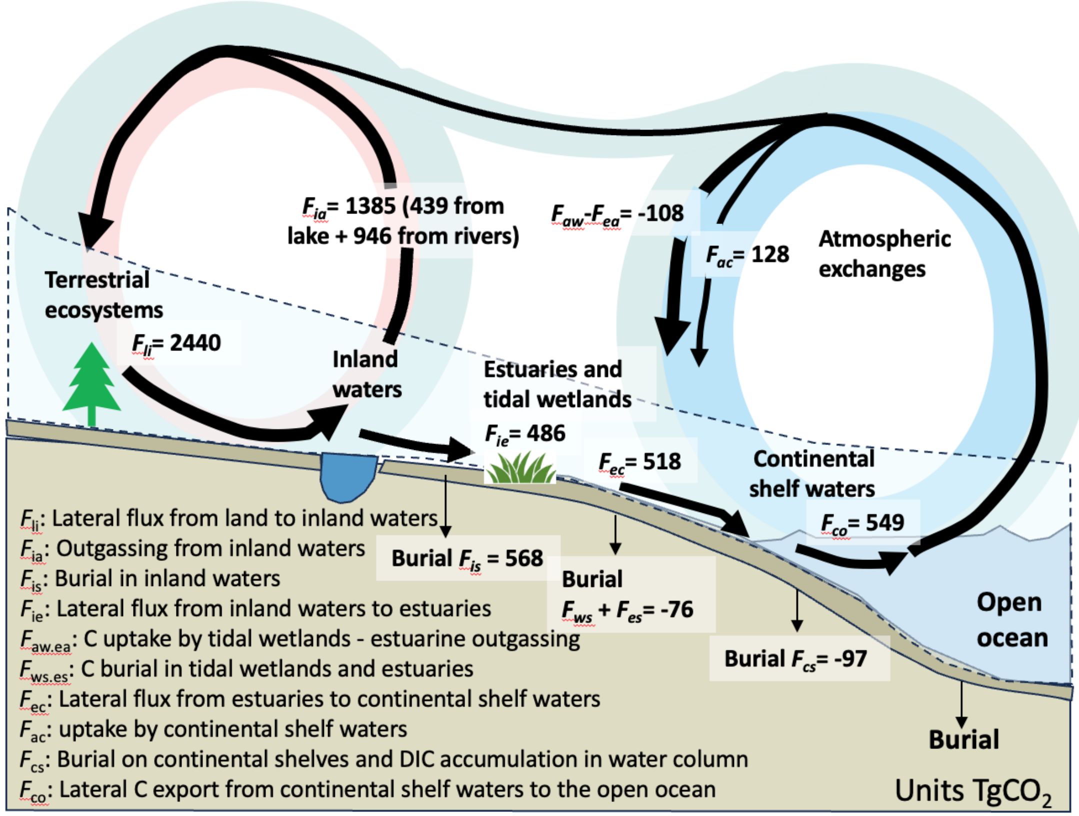
Credit: Cheryl Doughty (NASA GSFC)

BlueFlux-II & the Land Aquatic Ocean Continuum (LOAC)

- Blue carbon refers to long-term carbon burial & sequestration
  - LOAC fluxes removed 9-30% of net ecosystem production measured by aircraft and tower



- BlueFlux-II will refine LOAC fluxes, as well as improve seasonal and land-use representation of GHG fluxes
  - North American LOAC fluxes (2010-2019) quantified as part of the REgional Carbon Cycle Assessment and Processes Study (RECCAP-2)



Poulter, in revision

Stakeholder Engagement & Summary

Stakeholder Engagement

- Stakeholder Workshop (fall 2023, spring 2025)
- Open house (Oct. 2022)
  - Miccosukee high-school students
- Earth Day 2023 (Marathon airport)
  - The Diving Museum
  - Coast Love (mangrove planting)
  - Florida International University
  - Florida Coastal Everglades LTER
- Earth Day 2024
  - Seminole Tribe of Florida (Climate Resilience Team, Summer Reading Prog.)
- NASA ARSET training (Oct. 2024)
  - Conservation International, CU-ESIIL, ELTI
- NASA Earth to Sky 'Florida Squeezed' (Apr. 2024)
  - State agencies, NGO's (National Marine Sanctuary Foundation)
- Other: AGU, radio, documentaries (Shield Documentary, CBC, COP28 plenary), Yale Univ., and NASA EO stories

EARTH TO SKY

Florida SQUEEZED
THE CONVERGENCE OF CLIMATE, COMMUNICATION & COMMUNITY

SHIELD documentary

Publications (data archived on ORNL DAAC search *blueflux*)

- Erin Delaria et al., 2024. Assessment of landscape-scale fluxes of carbon dioxide and methane in subtropical coastal wetlands of South Florida. Journal of Geophysical Research – Biogeosciences.
- Cheryl Doughty et al., in prep.. Historical blue carbon fluxes (2000-2022) for Southern Florida.
- Jon Gewirtzman et al., in prep.. Component-specific mangrove methane fluxes across a gradient of hurricane disturbance and regeneration.
- Ben Poulter et al., 2023, Multi-scale observations of mangrove blue carbon ecosystem fluxes: The NASA Carbon Monitoring System BlueFlux field campaign. Environmental Research Letters.
- Derrick Vaughn et al., in review. Seasonal Dissolved Carbon and Greenhouse Gas Fluxes from Tidal Rivers Draining Mangroves in the Florida Everglades.

Mapping Coastal Wetland Changes from 1985 to 2022 in the US Atlantic & Gulf Coasts and Estimating Lateral Carbon Fluxes

Courtney Di Vittorio, WFU Engineering

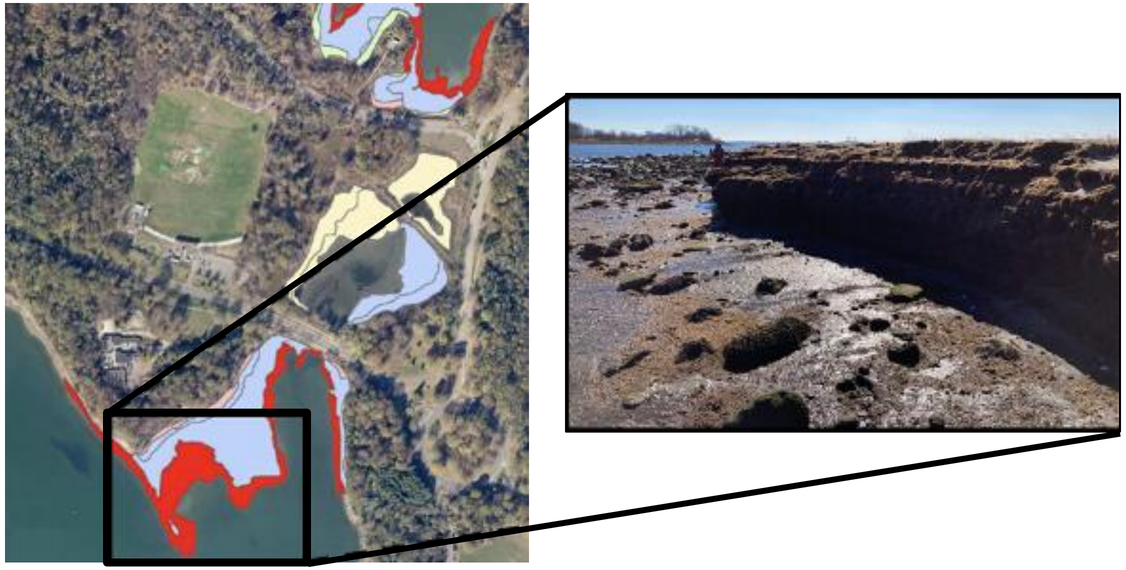
NASA OBB Program Annual Meeting
Dec 3, 2024

NASA OBB
Grant#80NSSC21K1365

WAKE FOREST UNIVERSITY

Project Overview & Motivation

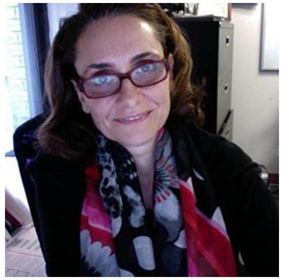
Observations of Marsh Erosion, New York (Dorothy Peteet)



- How much carbon has entered and will enter the ocean?
- How significant is this coastal carbon flux?
- How could we include this in ocean and climate models?

Proposal Team - NASA


Dorothy Peteet


Anastasia Romanou


Christian Braneon

WFU Postdoc, Graduate, and Undergraduate Students


Yasin Rabby


Saeed Movahedi


Melita Wiles


Jacob Louie


Scarlett Johnson


Alex Schluter


Wes Hinchman

How much has eroded and where?

National Wetlands Inventory (NWI)

- Polygon
- Hierarchical Classification Scheme
- Snapshot in Time
- Inconsistent Dates

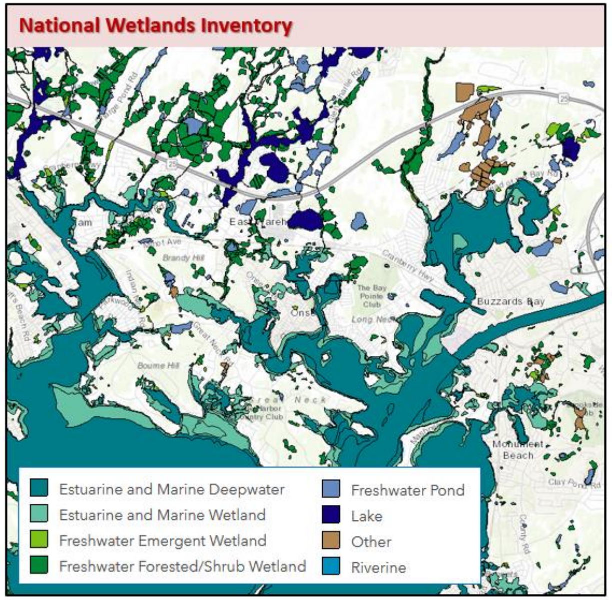


Image Source: Mass.gov

NOAA C-CAP

- Raster (30 meter)
- Aligns with NLCD, but with 10 wetland sub-classes
- 1996, 2001, 2006, 2010, 2016

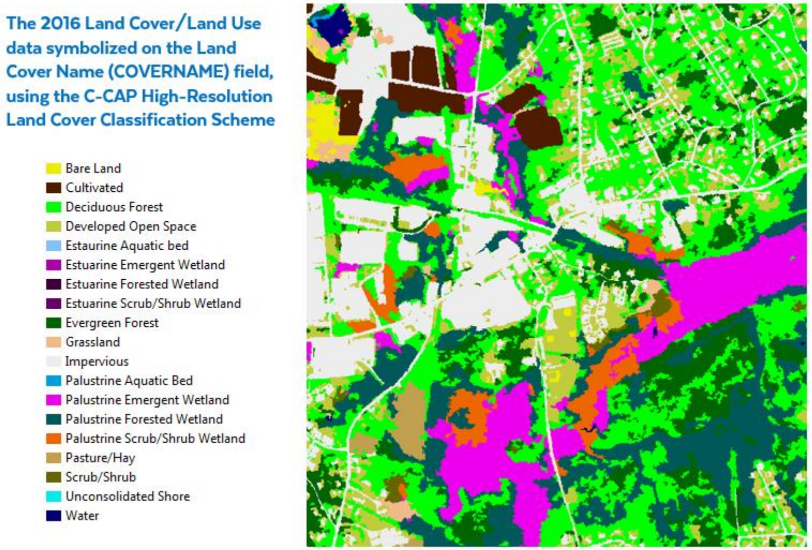
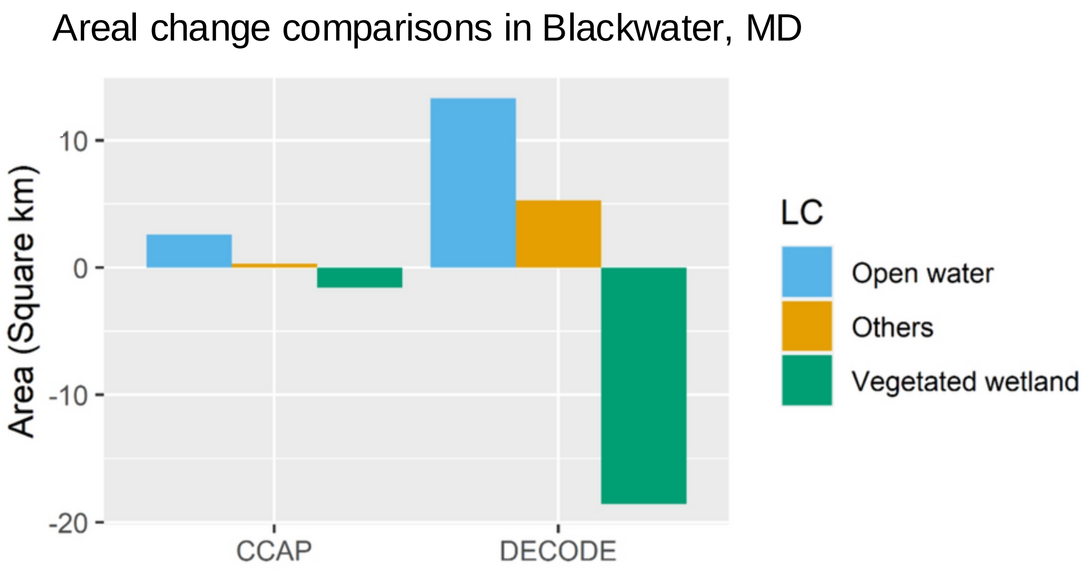


Image Source: Mass.gov

Comparison of coastal wetland inventories and implications for change detection (Rabby & Di Vittorio, 2024)

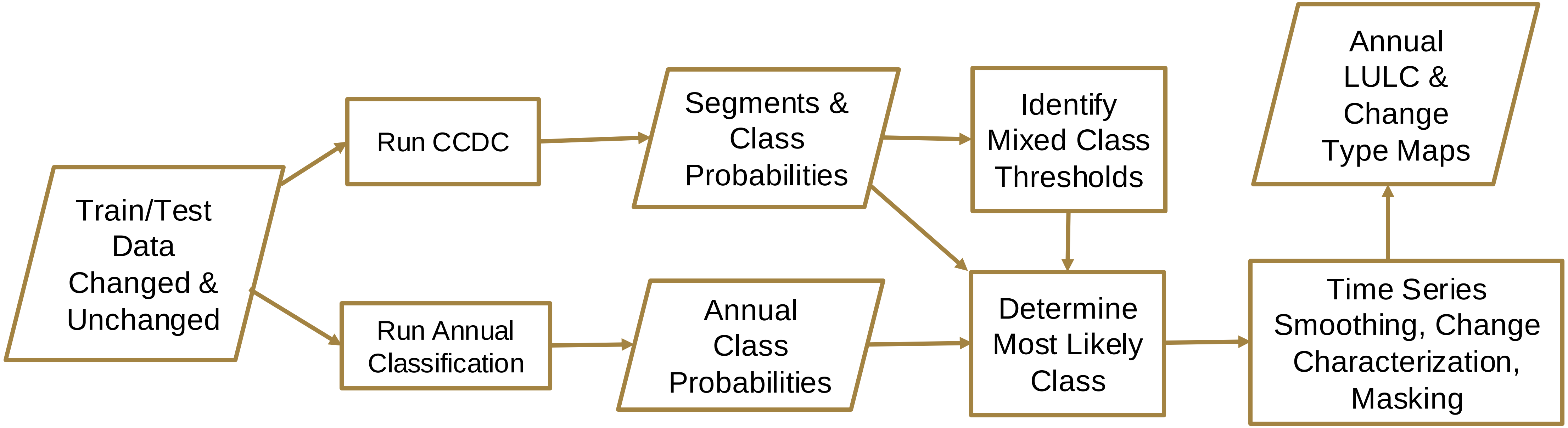
Key Findings

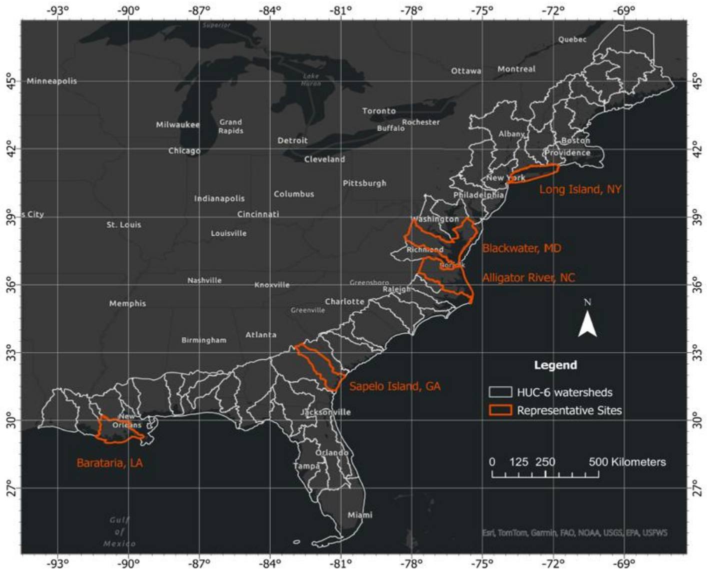
- C-CAP estimates smaller net wetland areas than NWI
- C-CAP estimates larger emergent wetland areas and smaller scrub wetland areas compared to NWI
- DECODE estimates significantly more change than C-CAP



[1]

New Coastal Wetland Change Maps





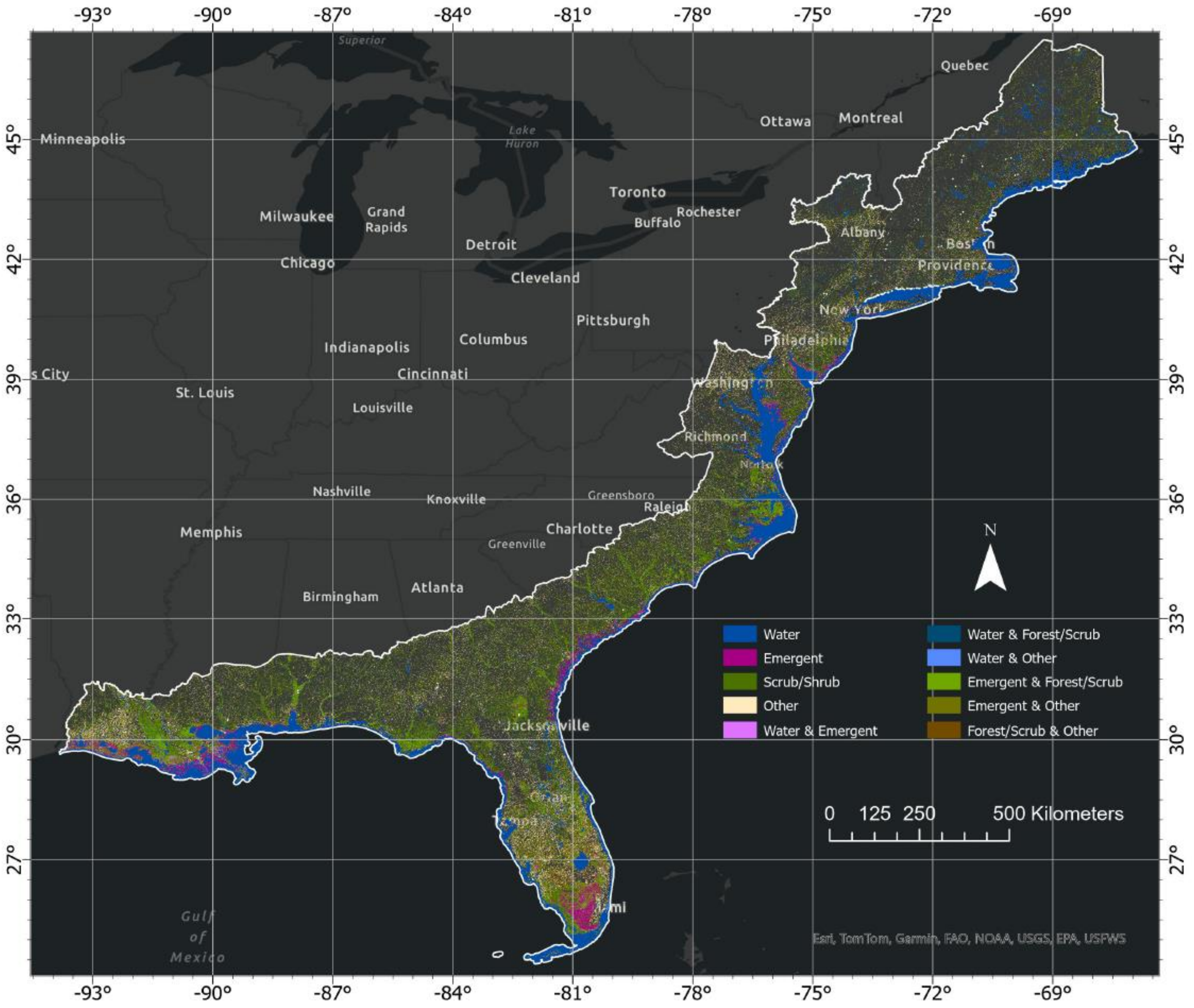
Classes

1 – Water
2 – Emergent
3 – Forest-Scrub
4 – "Other"

11 – Water/Emergent
12 – Water/Forest-Scrub
13 – Water/Other
14 – Emergent/Forest-Scrub
15 – Emergent/Other
16 – Forest-Scrub/Other

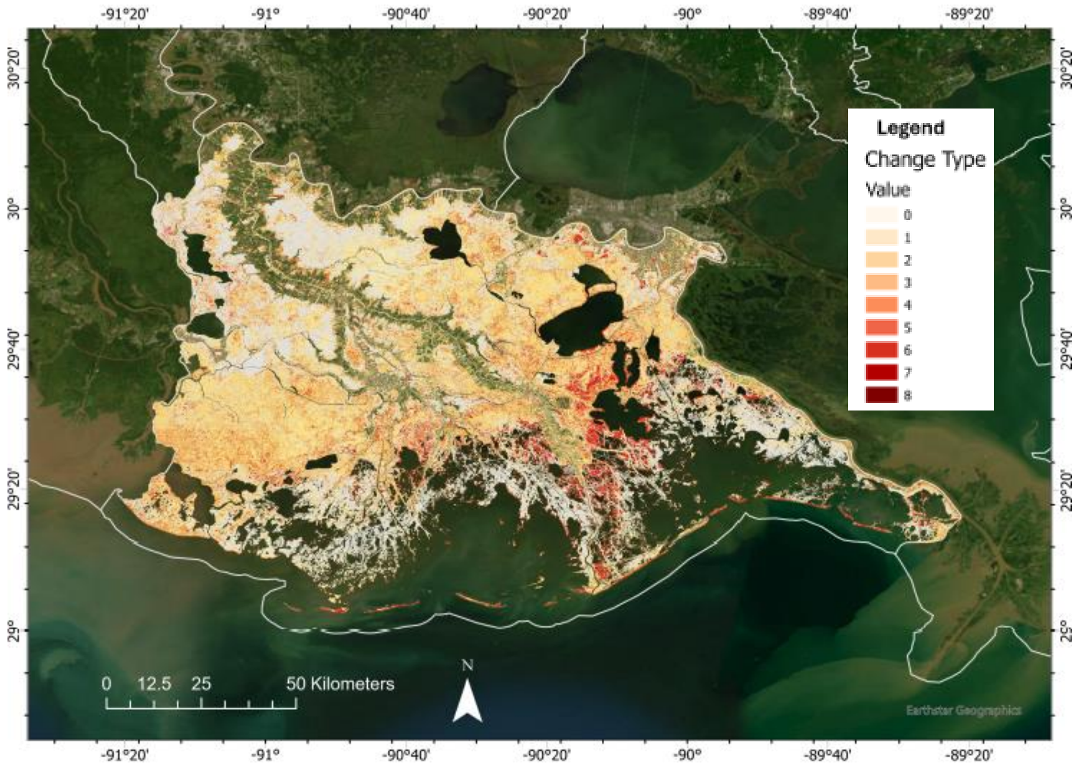
[2] Di Vittorio et al., 2024

Final Product

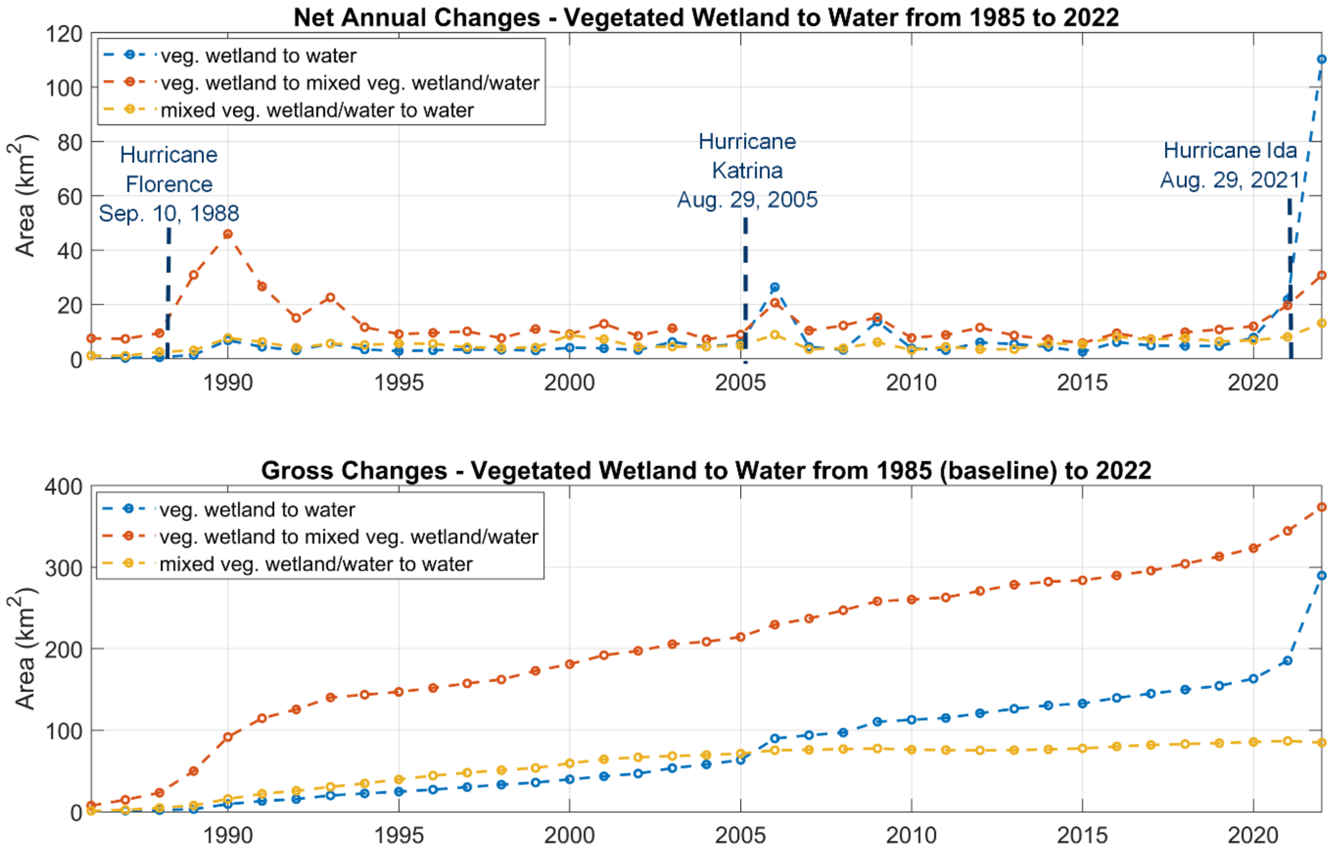


Change Type Map

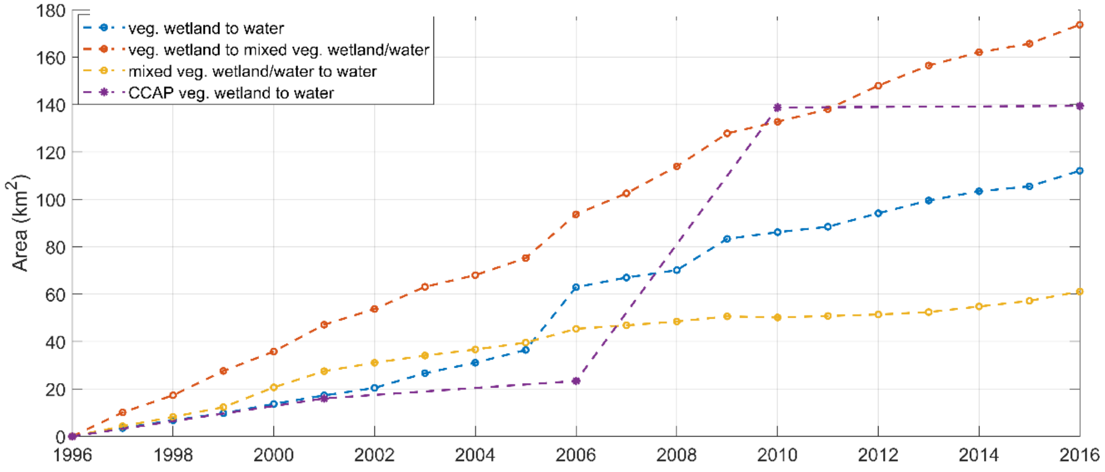
Label	Short Description	Explanation
0	No changes	No transitions in entire time series.
1	Mixed change - temporary	Transition between full and mixed class. Class at the beginning and end match.
2	Mixed change - permanent	Transition between full class and mixed class. Class at the beginning and end are different.
3	Gradual full change - temporary	Full class transition with a mixed class in between. Class at beginning and end match.
4	Gradual full change - permanent	Full class transition with a mixed class in between. Class at beginning and end are different.
5	Abrupt change - temporary	Full class transition with no mixed class in between. Class at beginning and end match.
6	Abrupt change - permanent	Full class transition with no mixed class in between. Class at beginning and end are different.
7	Abrupt and gradual change - temporary	Both gradual and abrupt changes are present. Class at beginning and end match.
8	Abrupt and gradual change - permanent	Both gradual and abrupt changes are present. Class at beginning and end are different.



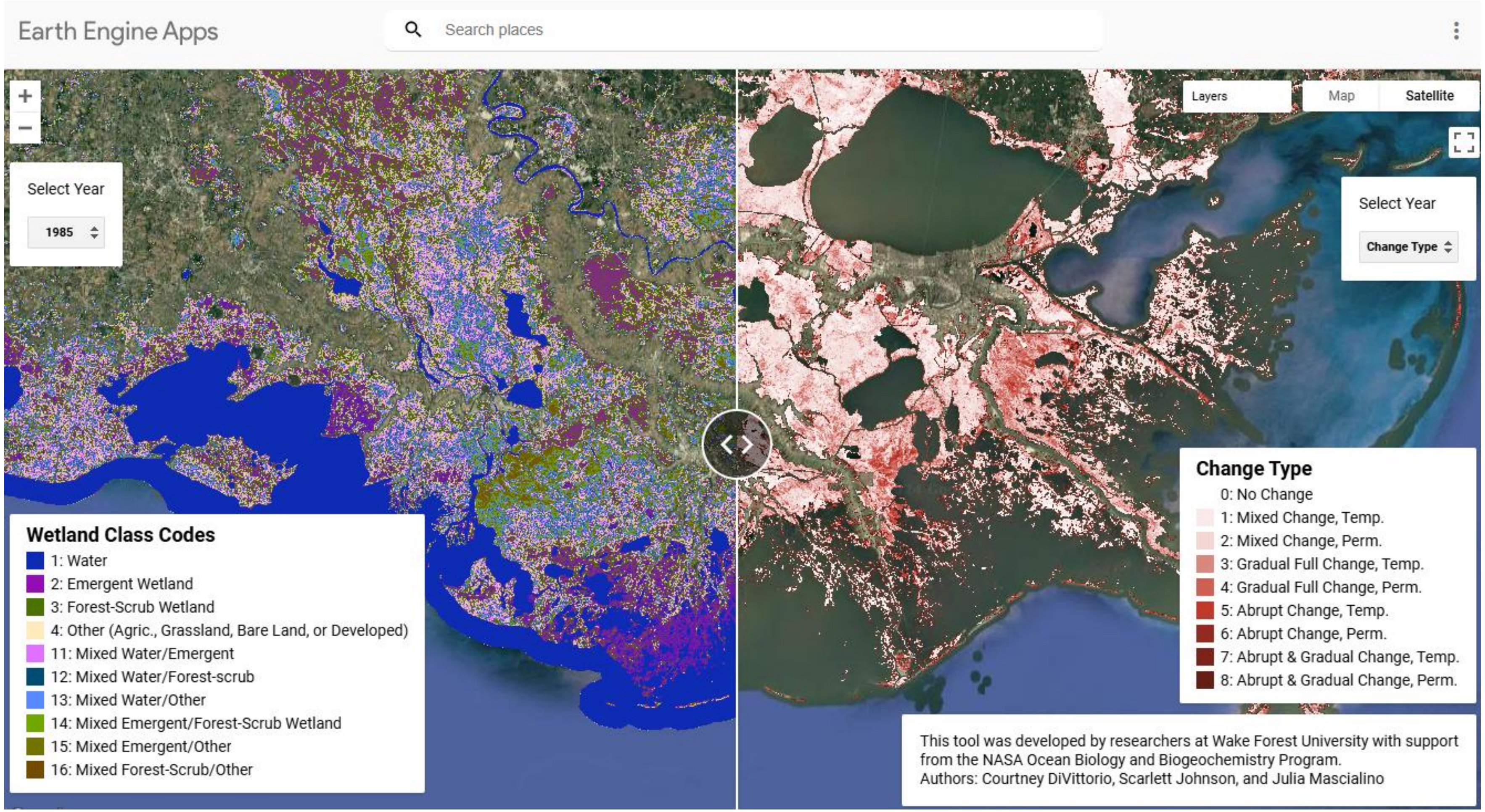
Time Series Change Analysis – Barataria, LA



Comparison with C-CAP



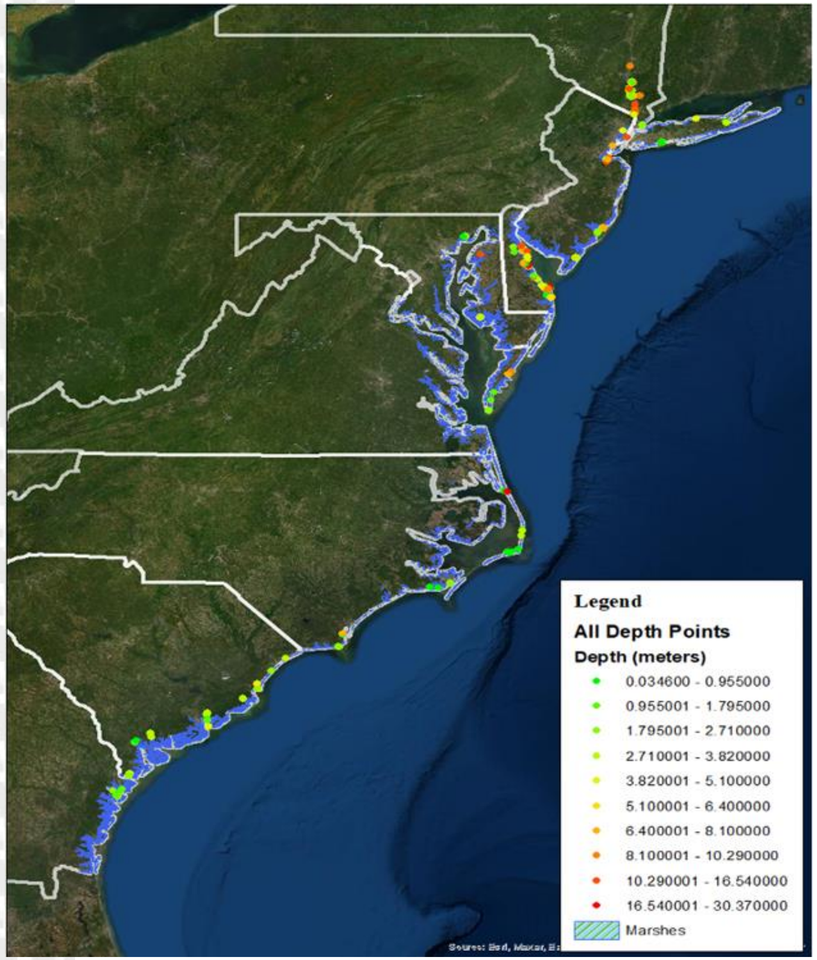
Google Earth Engine App

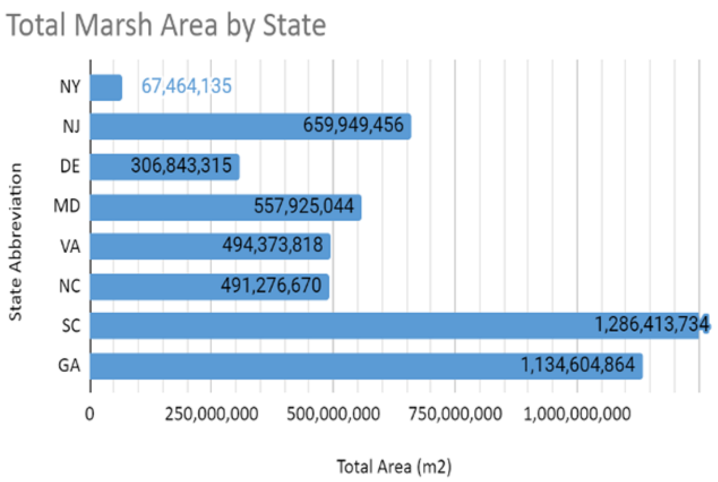


https://ee-cdivittorio-wfu.projects.earthengine.app/view/us-coastal-wetland-land-cover-change-maps-1985-to-2022

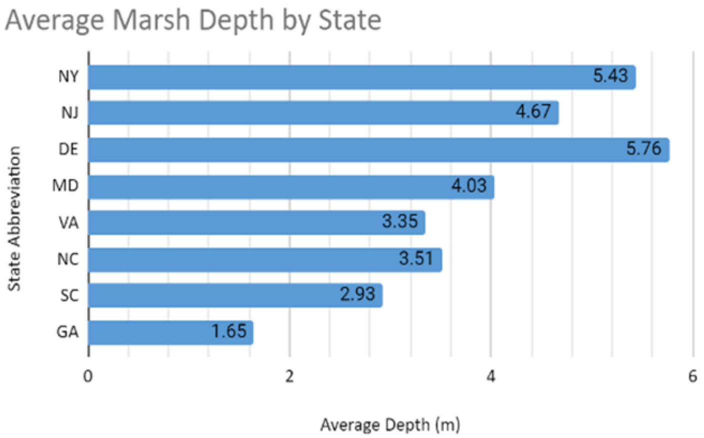
Zenodo: https://doi.org/10.5281/zenodo.13525004

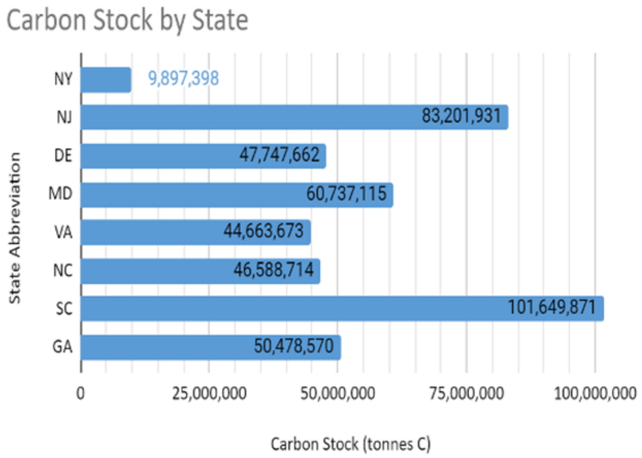
How much carbon is going into the coastal ocean? (Dorothy Peteet)





Carbon Stock = marsh area x depth x 27 Kg C/m^3
(Holmquist et al., 2021) [3]





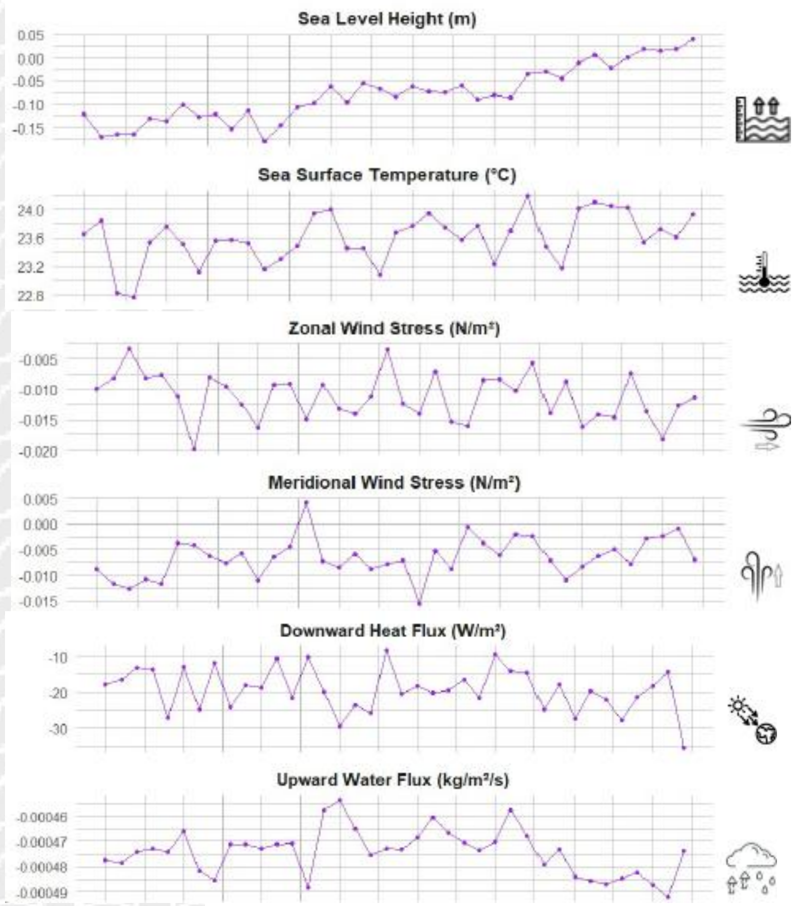
Predictive Models of Marsh Loss

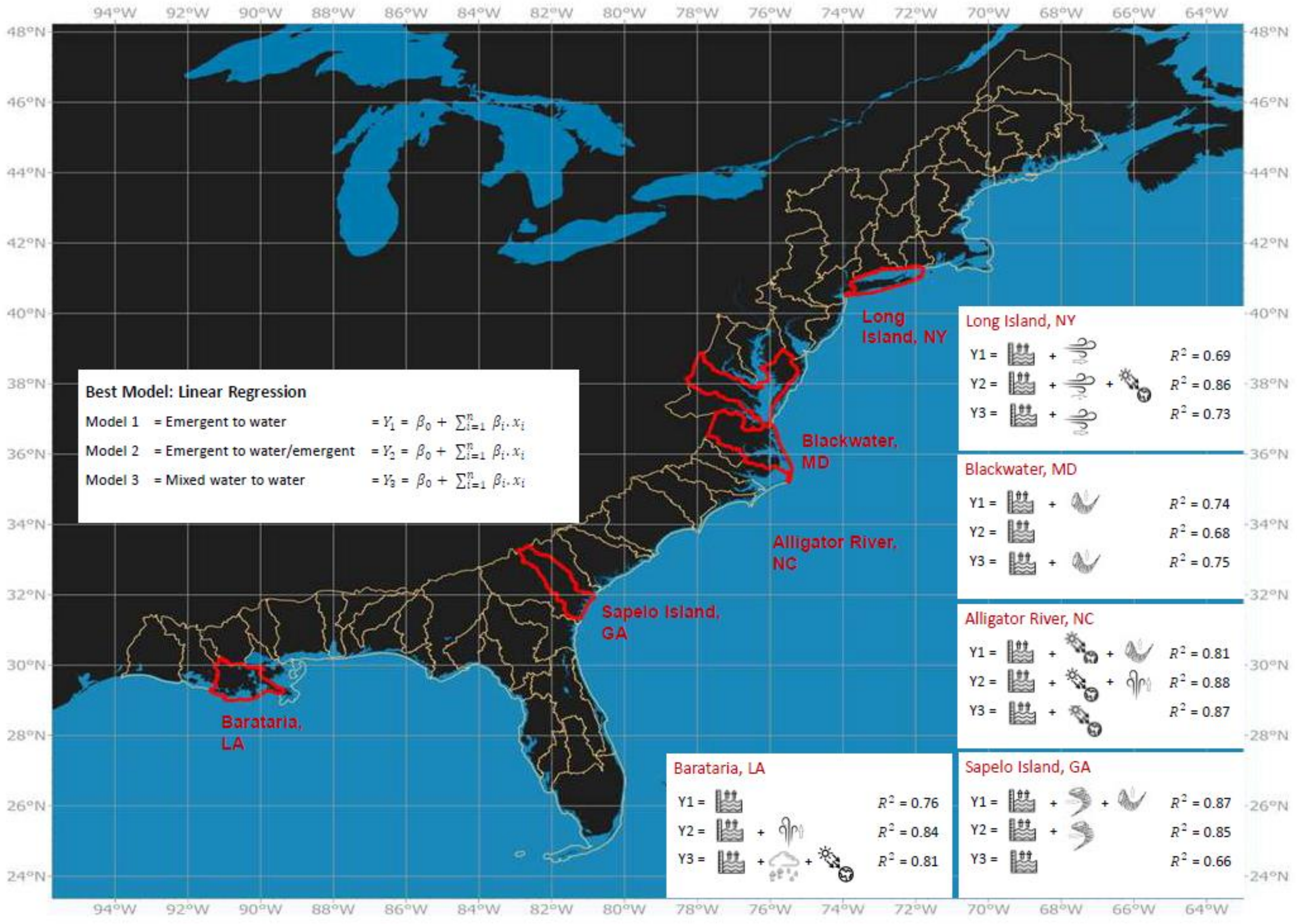
(Saeed Movahedi & Natassa Romanou)

Y: Areal Changes

- Emergent Wetland to Water
- Mixed Wetland/Water to Water
- Wetland to Mixed Wetland/Water

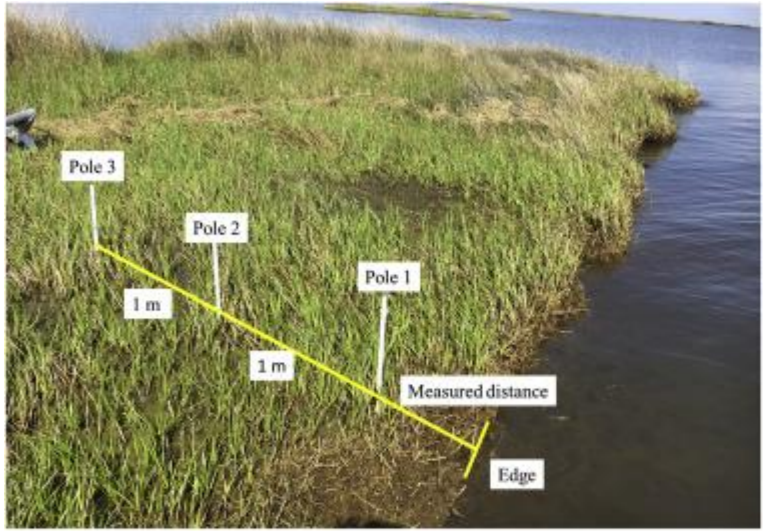
X: Env. Variables from Reanalysis Products

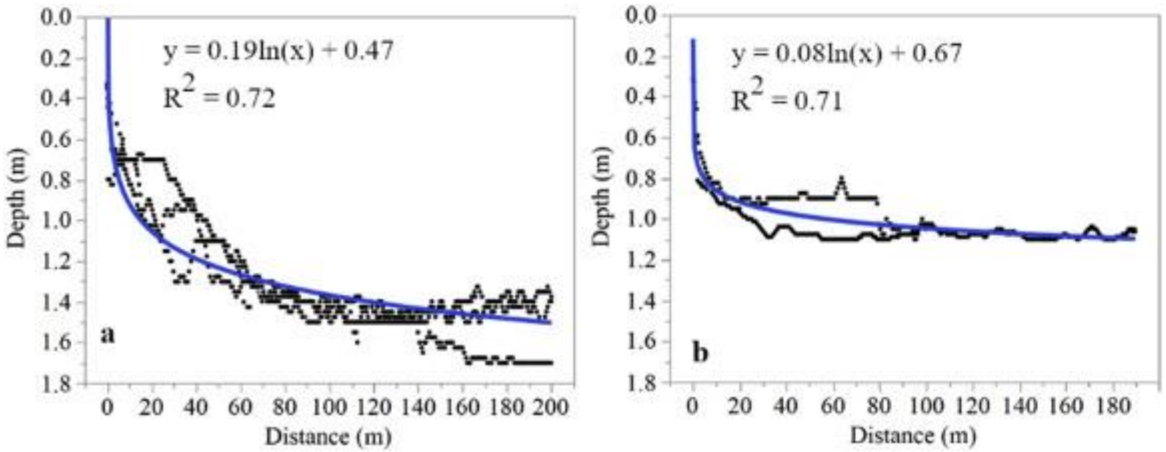




Questions to consider in carbon flux estimates

- What is an acceptable way to estimate marsh depth in areas with sparse data and how should we quantify uncertainty?
- What fraction of the carbon stock enters the coastal ocean when marshes transition to water?
- How should we account for full class changes versus mixed class (transitional) changes in our carbon flux calculations?





[4] Sapkota & White (2019) – 75% of eroded carbon is mineralized

References

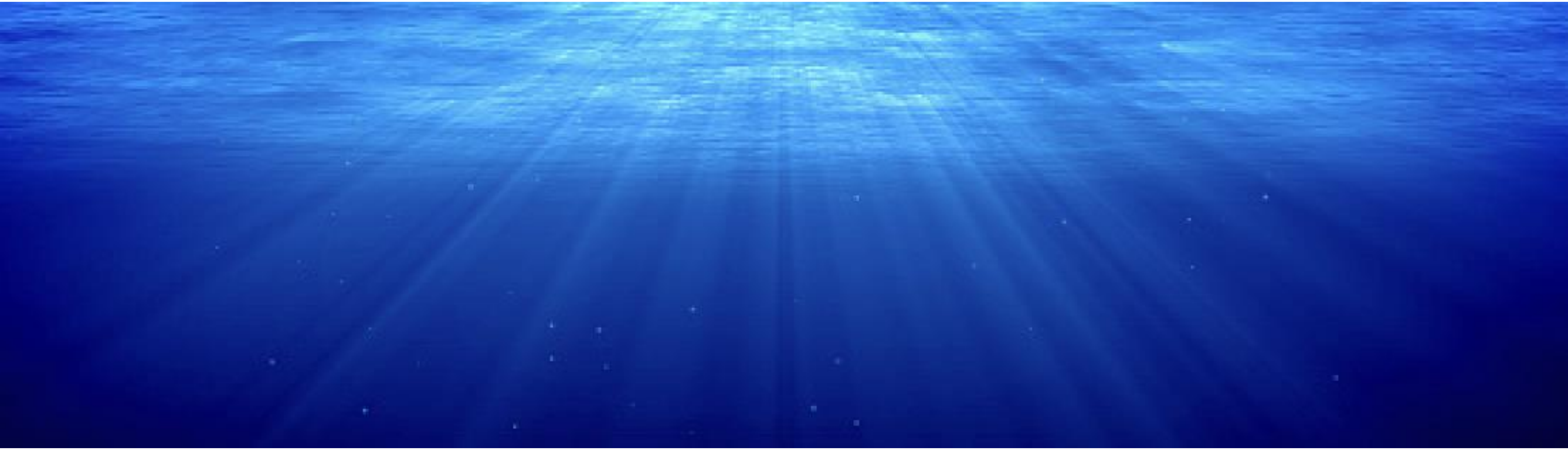
[1] Rabby, Y.W., Di Vittorio, C.A. Comparison of coastal wetland inventories for representative sites in the United States and implications for change detection. *Wetlands Ecol Manage* **32**, 479–507 (2024). https://doi.org/10.1007/s11273-024-09998-9

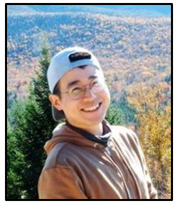
[2] Di Vittorio, Courtney A., et al. "Mapping Coastal Wetland Changes from 1985 to 2022 in the US Atlantic and Gulf Coasts using Landsat Time Series and National Wetland Inventories." Remote Sensing Applications: Society and Environment (2024): https://doi.org/10.1016/j.rsase.2024.101392

[3] Holmquist, J. R., Brown, L. N., & MacDonald, G. M. (2021). Localized scenarios and latitudinal patterns of vertical and lateral resili-ence of tidal marshes to sea-level rise in the contiguous United States. *Earth's Future*, *9*(6), e2020EF001804.

[4] Sapkota, Y., & White, J. R. (2019). Marsh edge erosion and associated carbon dynamics in coastal Louisiana: A proxy for future wetland-dominated coastlines world-wide. Estuarine, Coastal and Shelf Science, 226, 106289. https://doi.org/10.1016/j.ecss.2019.106289

Photobleaching as a major sink of CDOM in the Global Ocean





Xiaohui Zhu and <u>Cédric G. Fichot</u>

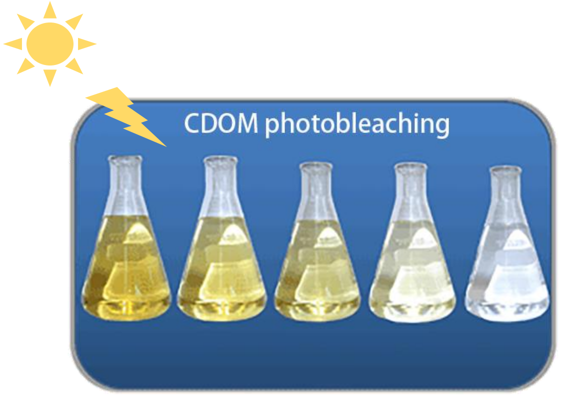
Department of Earth and Environment, Boston University

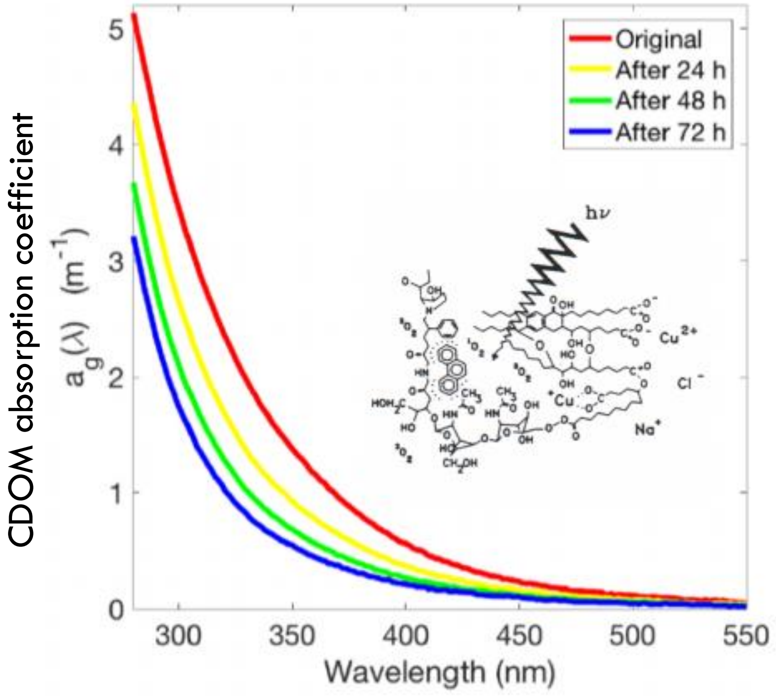
J. Harringmeyer, M. Weiser, K. Kaiser, S. Bélanger, C. Anderson, W. Miller, B. Walker

Remote Sensing of Water Quality

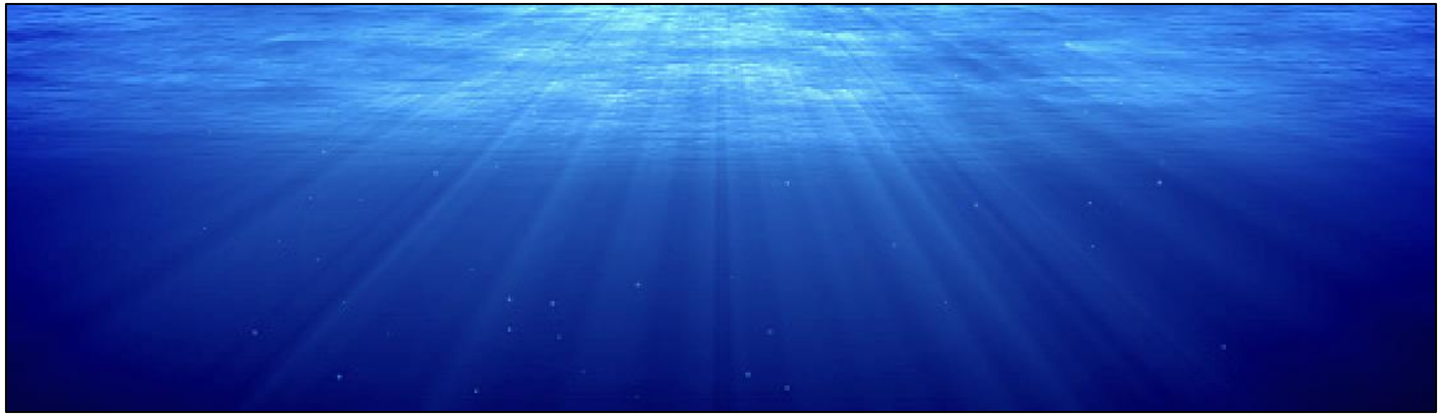
BOSTON UNIVERSITY

Photobleaching of CDOM





- Ubiquitous process that reduces UV & visible light absorption
- Regulates PAR availability and UV exposure in surface waters



- Decouples dynamics of DOC and CDOM in the ocean

How significant is this process globally?

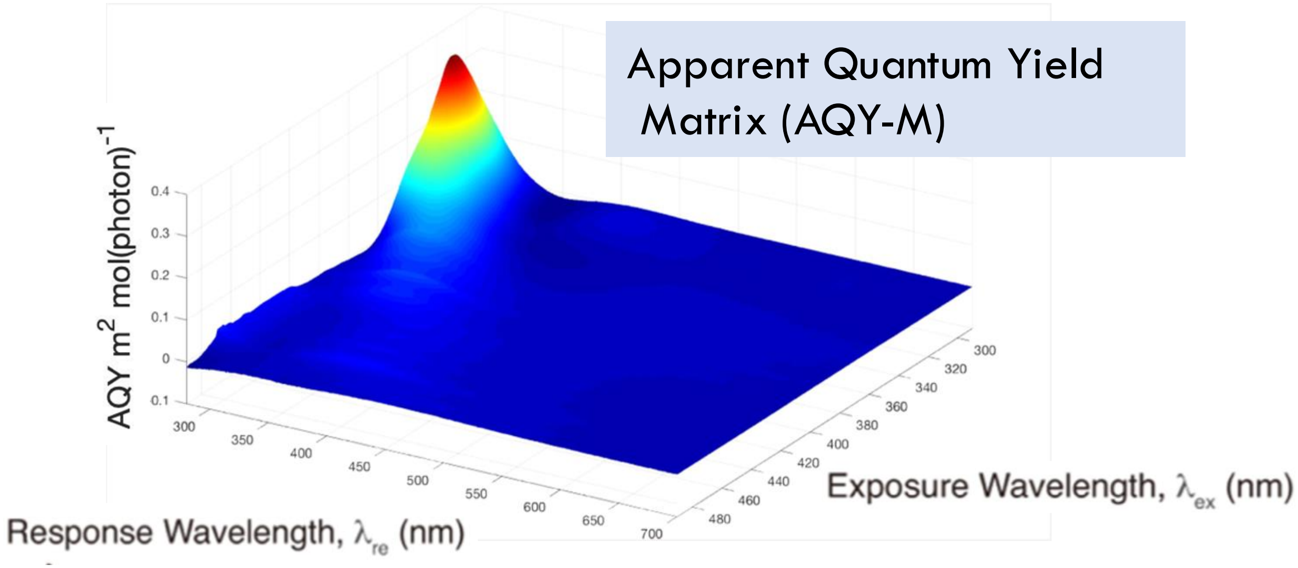
Quantifying photobleaching rates in the ocean has been a challenge

Apparent Quantum Yield (AQY) not well known

- **<u>Difficult to determine</u>**
  Dual spectral dependency (matrix)
  -> exposure λ and response λ

- **<u>What is its variability in the ocean?</u>**

- **<u>Can we constrain this variability?</u>**



Milestones and Objectives

1. Develop a new approach to determine AQY Matrix of natural samples

Zhu et al., *ES&T* (2020)

2. Understand and constrain variability of AQY Matrix in natural waters

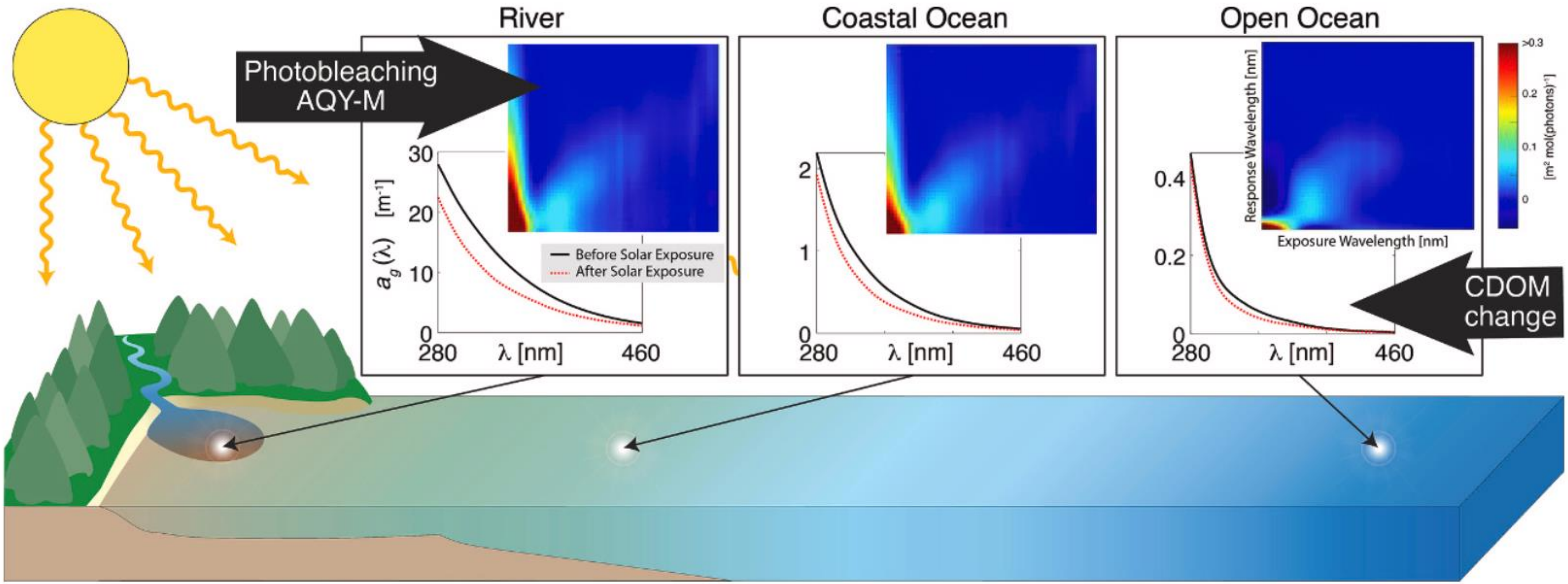
Zhu et al., *STOTEN* (2024)

3. Model photobleaching rates in the global ocean

Zhu and Fichot, *In progress*

Variability of the photobleaching apparent quantum yield matrix (AQY-M)

- CDOM composition/degradation state ($S_{275-295}$)
- Water temperature
- Extent of solar exposure



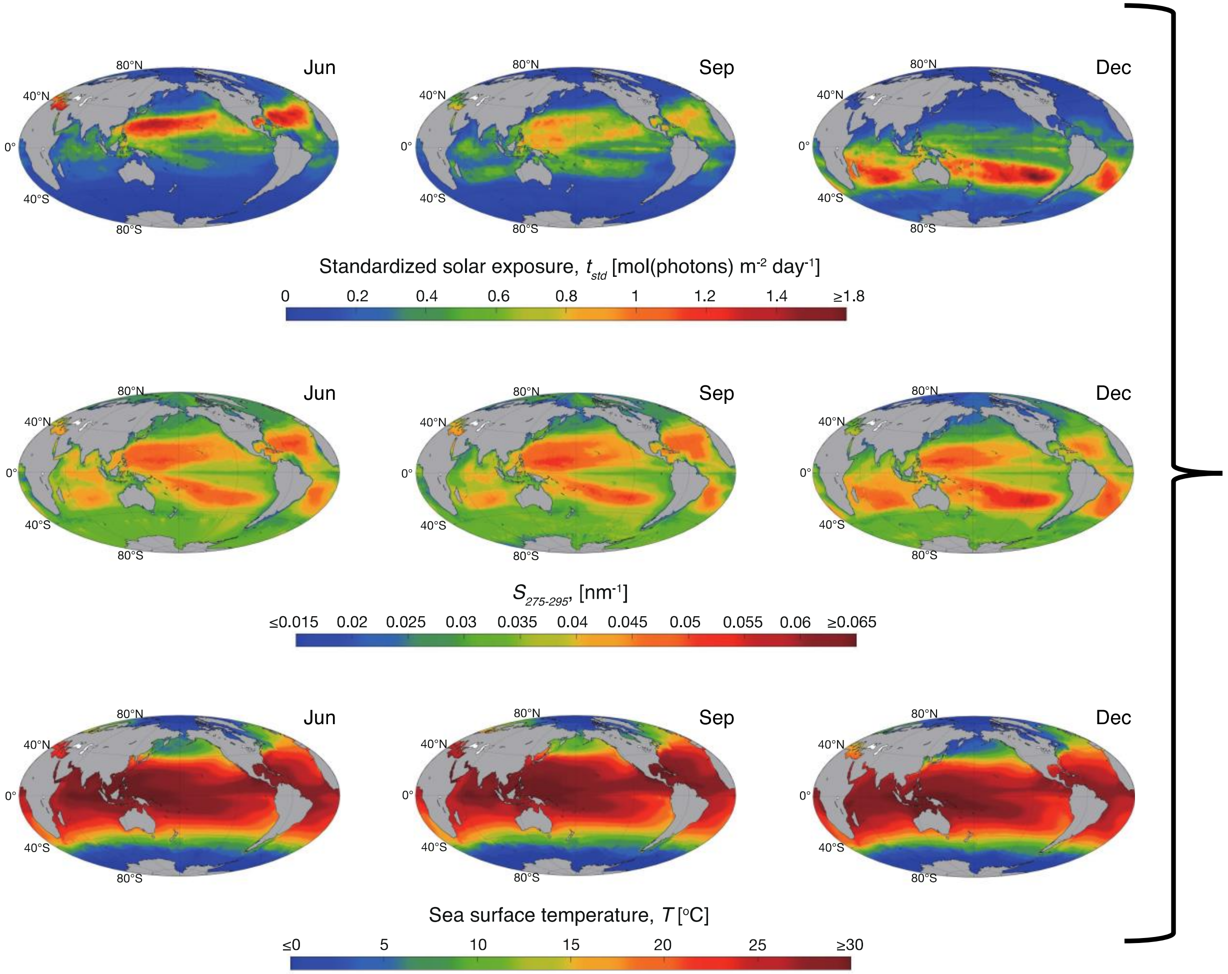
Zhu et al., *STOTEN* (2024)

Implementation on global scales

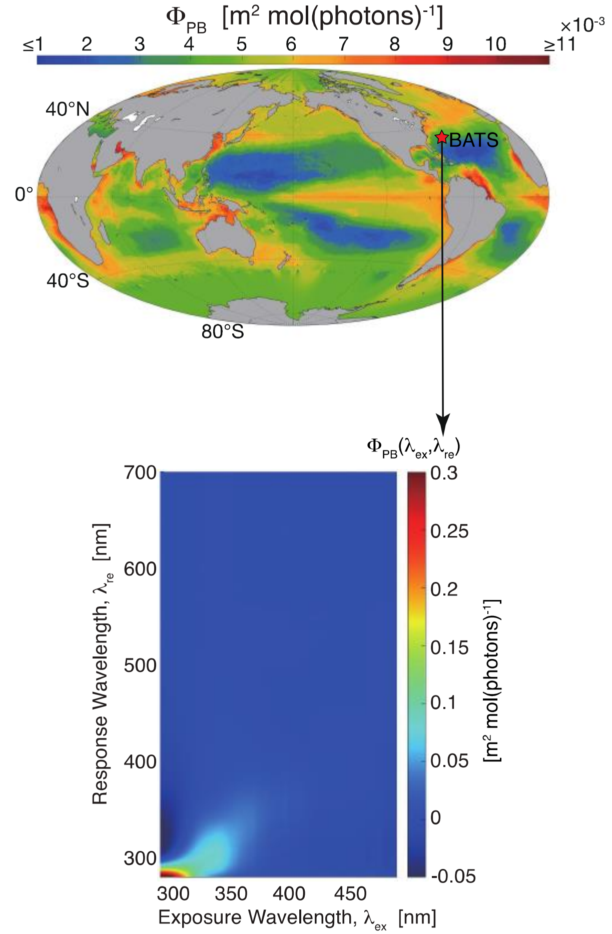
Solar exposure

$S_{275\text{-}295}$

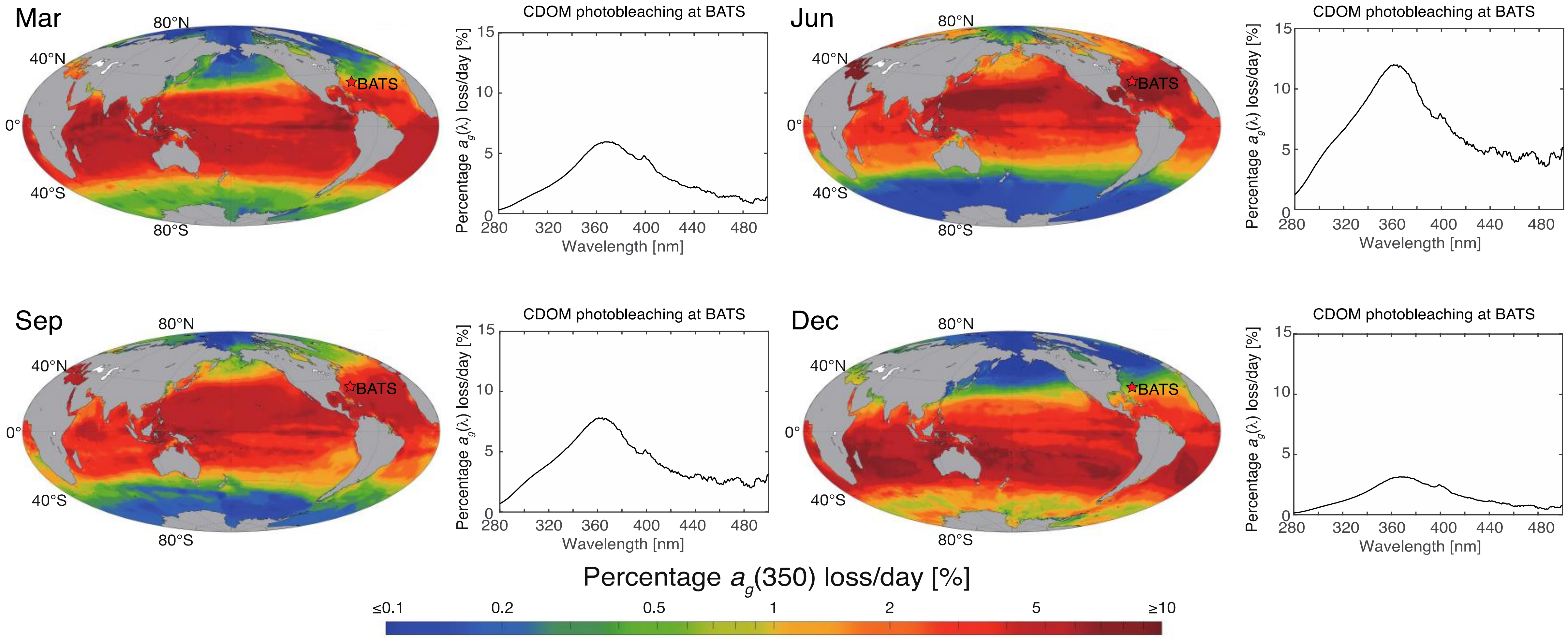
Temperature



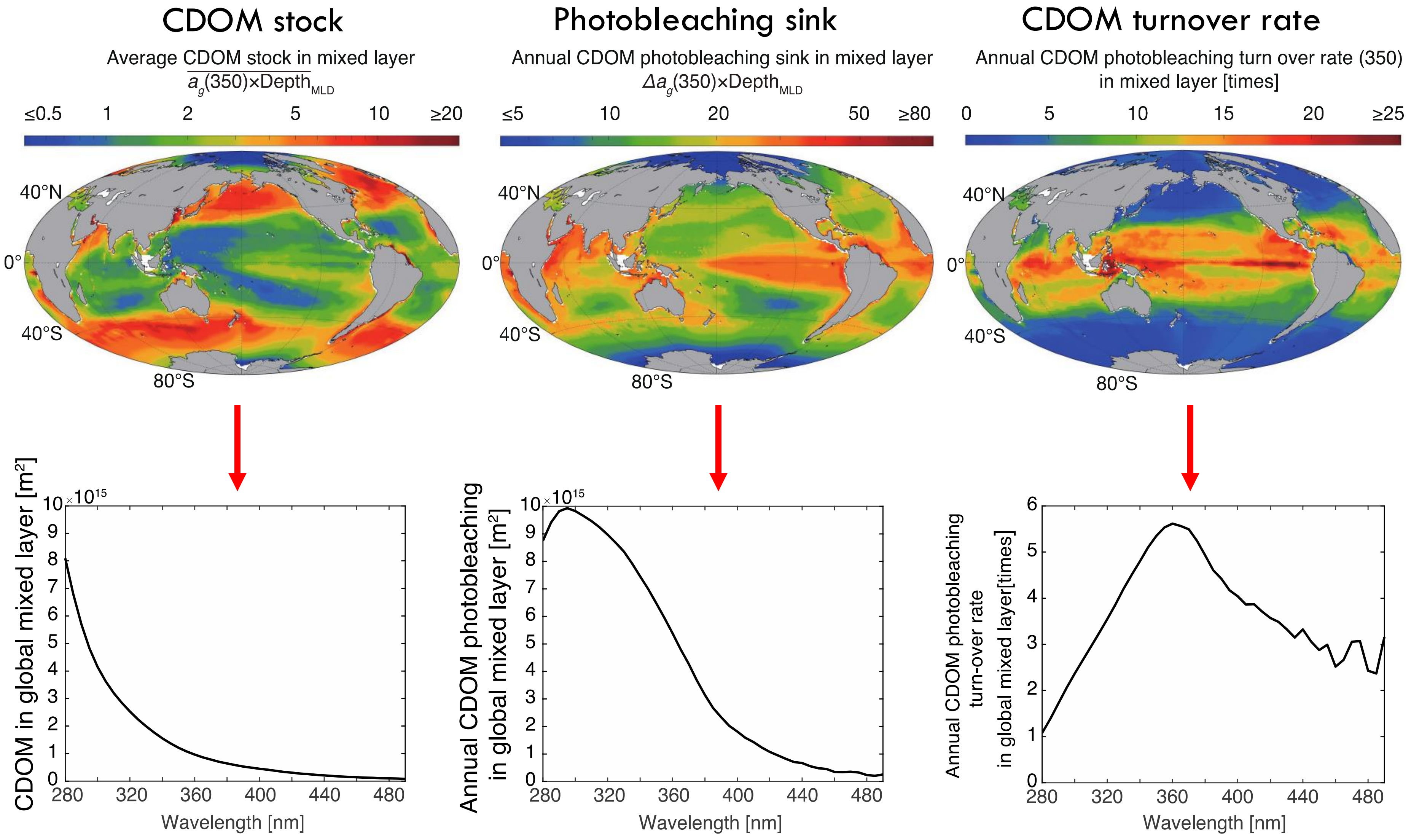
AQY-M



Climatology of photobleaching rates in global mixed layer

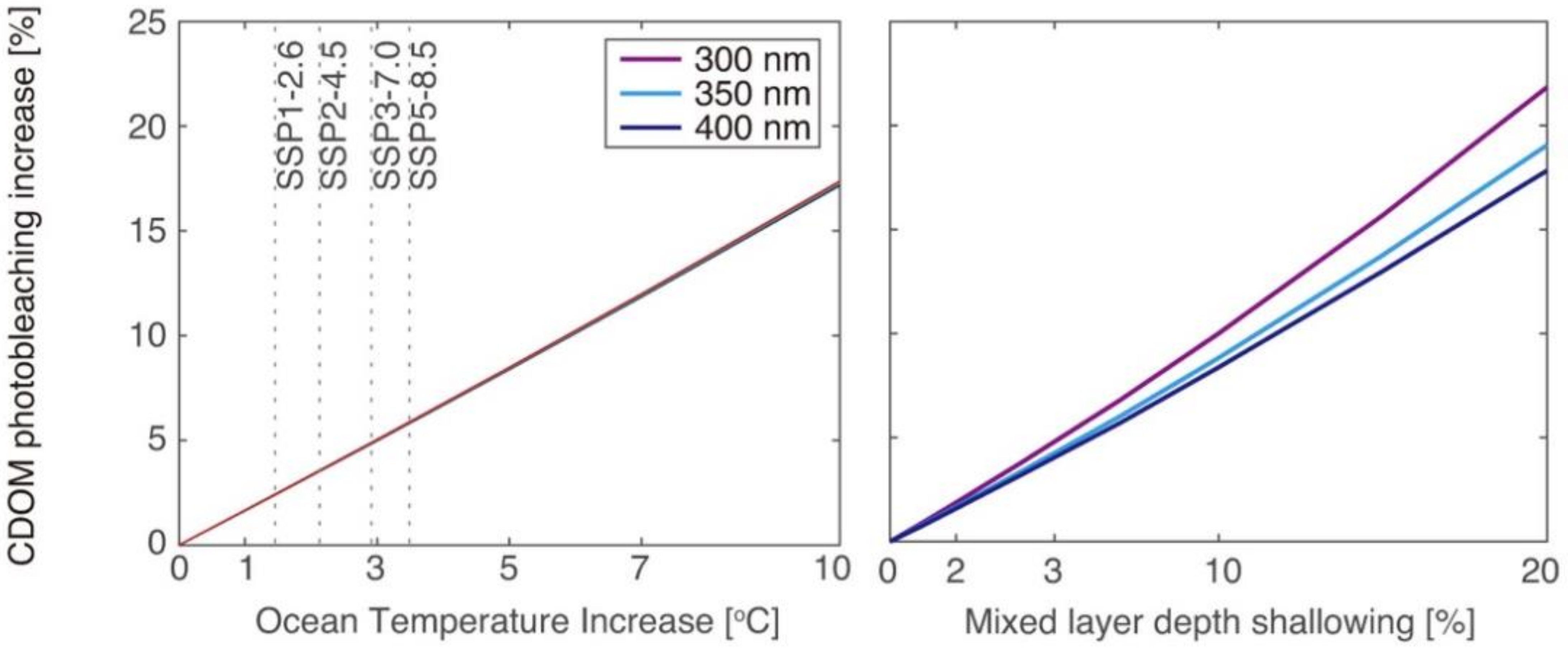


Turnover rate of CDOM by photobleaching in global mixed layer



Photobleaching turns over the CDOM mixed-layer stock 1-to-6 times each year

Sensitivity of photobleaching rates to ocean warming



Conclusions

1. First climatology of spectral photobleaching rates in the global ocean

2. Photobleaching turns over the equivalent of 1-to-6 times the mixed layer CDOM stock each year (1-6% of the global ocean CDOM)

3. Process is sensitive to ocean warming:
   - ⇒ Will it enhance solar exposure in the surface mixed layer in the future?
   - ⇒ What will be the impacts on ecosystems?

Remote Sensing of Water Quality

Thank you

NASA Award #80NSSC2K1655

Tracking Post-Wildfire Sediment Dynamics and Marine Ecosystem Stress: Insights from Legacy and Modern Satellite Missions

Lori Berberian[1,2]
loriberberian@ucla.edu

Kyle C. Kavanaugh[1], Christine M. Lee[2], Erin L. Hestir[3], Mandy Lopez[2,4], Carmen Blackwood[2], Dulcinea Avouris[5]

[1] Department of Geography, University of California, Los Angeles
[2] Jet Propulsion Laboratory, California Institute of Technology
[3] Department of Civil & Environmental Engineering and Sierra Nevada Research Institute, University of California, Merced
[4] Joint Institute for Regional Earth System Science and Engineering, University of California, Los Angeles
[5] US Geological Survey, California Water Science Center, Sacramento California

UCLA

Jet Propulsion Laboratory
California Institute of Technology

UC MERCED

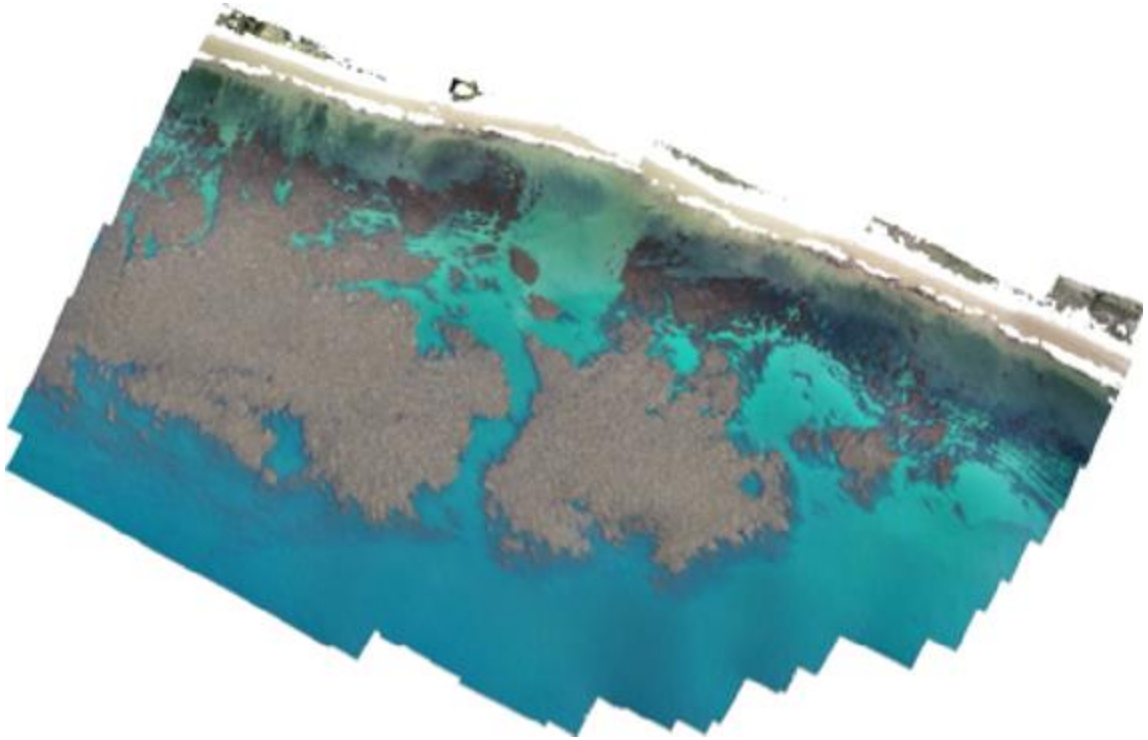
Primary Physical drivers of Kelp Dynamics

Big River Mendocino, CA

Kelp require cool, sunlit, nutrient rich waters to grow.

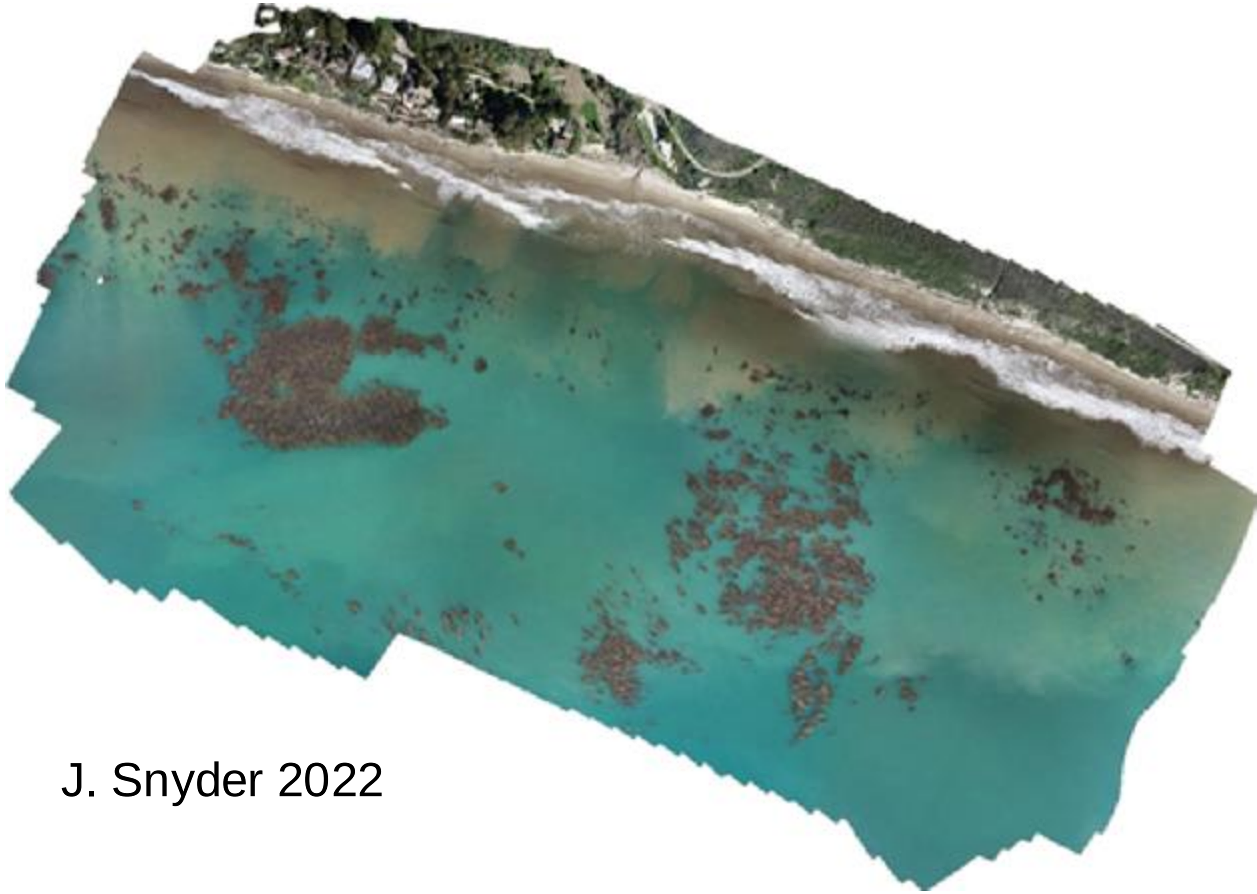
Kelp is Variable!

2018



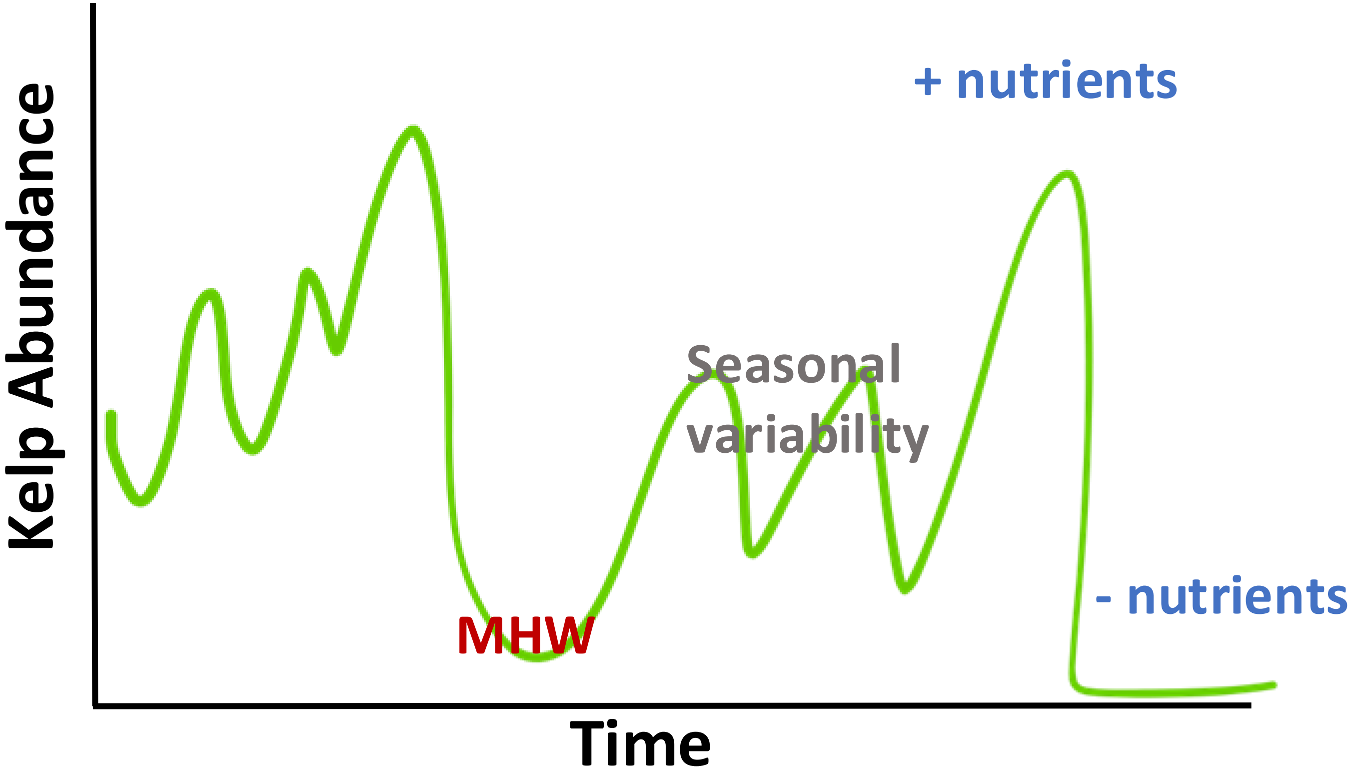
T. Bell 2018

2022



J. Snyder 2022

Understudied Drivers of Kelp Dynamics: Wildfires



Wildfires (?) unexplained variability in this system

Wildfires Can Alter Ocean Water Clarity

Case Study: Woolsey 2018 Fire in Malibu, California

Apr 14, 2018
(pre-fire)

Nov 10, 2018
(fire)

Nov 30, 2018
(post-fire)

Terrigenous Input

- Increased Sediment Runoff
- Total Suspended Matter
- Nutrient Loading (N, P)
- Organic and Chemical Compounds
- Altered Coastal Erosion Patterns

Aerial Input

- Direct Smoke Deposition
- Wind blown ash/debris

Research Question

How did the increase in sedimentation delivery to the coastal ocean after the Woolsey wildfire impact kelp forest in Malibu, CA?

Remotely Sensed Giant Kelp and Ocean Color

Santa Barbara Coastal Long Term Ecological Research

Summary of Products:

- Quarterly Bull kelp and giant kelp canopy area and biomass from Landsat 5,7, 8.
- Area–given by 30 m pixels

European Organization for the Exploitation of Meteorological Satellites

Summary of Products:

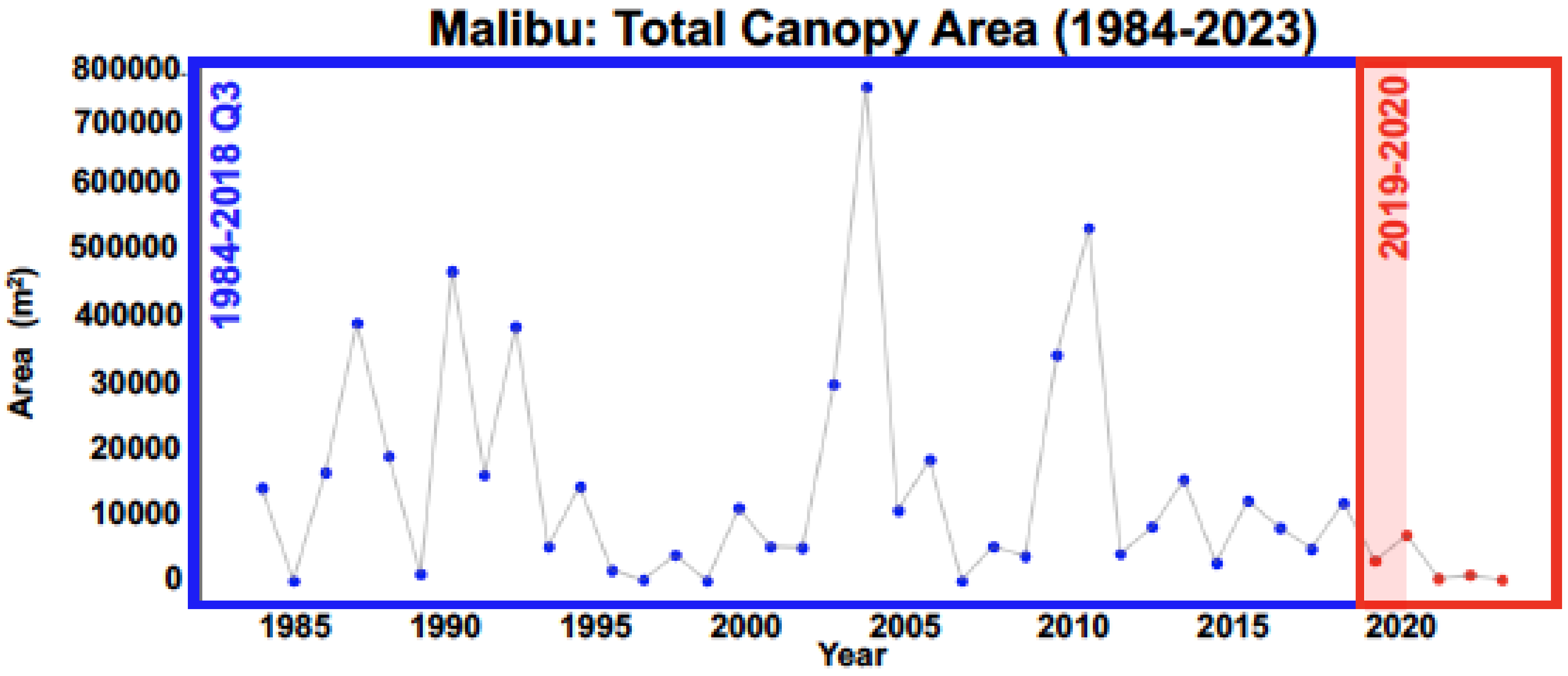
- Total Suspended Matter
- Inherent Optical Properties
- Photosynthetically Available Radiation
- 2 revisit time, 300 m resolution

SCAN ME

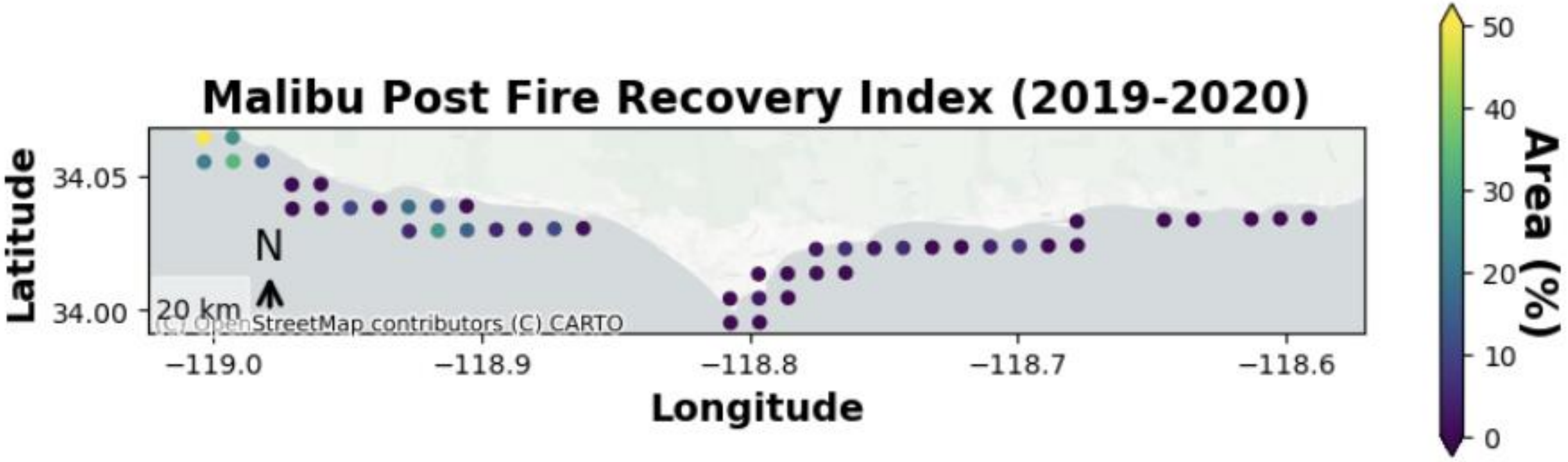
Bell, T., K. Cavanaugh, and D. Siegel. 2024. SBC LTER: Time series of quarterly NetCDF files of kelp biomass in the canopy from Landsat 5, 7 and 8, since 1984 (ongoing) ver 23. Environmental Data Initiative

Malibu’s kelp cover has not recovered Post-Wildfire

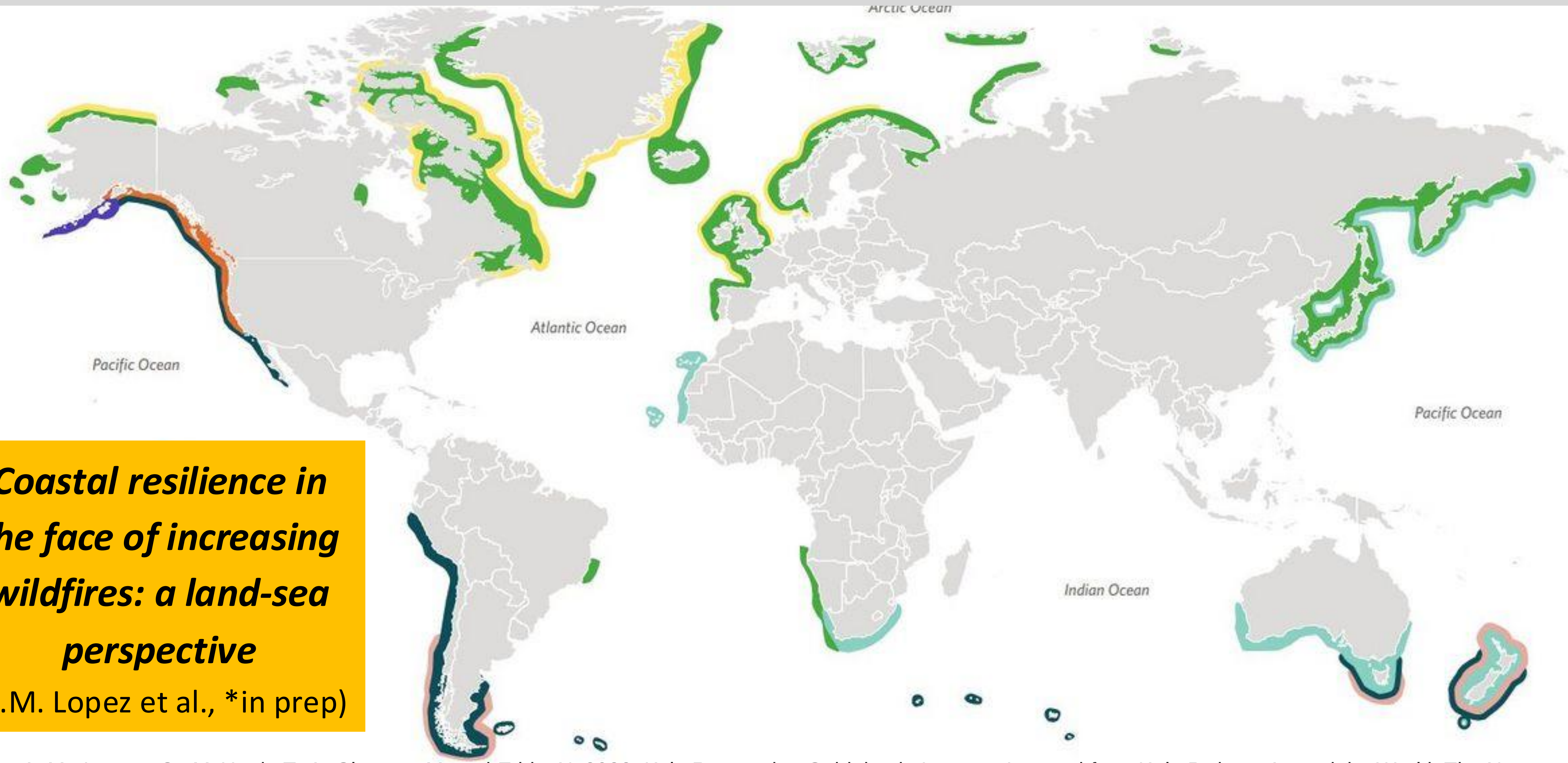
$$\text{Post-Fire Recovery Index (\%)} = \left(\frac{\text{Post-Fire Kelp Canopy } (m^2)}{\text{Historical Average Kelp Canopy} (m^2)} \right) \times 100$$



Post-Fire Recovery Index: Deviation From Historical Average



Global Distribution of Kelp as an Indicator of Marine Coastal Health



Coastal resilience in the face of increasing wildfires: a land-sea perspective

(A.M. Lopez et al., *in prep)

Eger, A. M., Layton, C., McHugh, T. A, Gleason, M. and Eddy, N. 2022. Kelp Restoration Guidebook: Lessons Learned from Kelp Projects Around the World. The Nature Conservancy, Arlington, VA, USA

Conclusion and Future Work

- Implement a **BACI (Before-After-Control-Impact) analysis** with an expanded number of control and test sites

- Model changes in the **light field reaching kelp forests** after wildfire-driven runoff using the **bPAR model**.
    i. Investigate how sedimentation and nutrient influx alter light availability, impacting kelp spatial distribution and growth.

- Provide critical insights into the connections between wildfire events and coastal ecosystem stress and recovery.

Thank you!

Seasonal re-entrainment of respired organic matter decouples surface and annual net community production in the Southern Ocean

Shannon McClish, Seth Bushinsky, Nathan Briggs, Clara Douglas

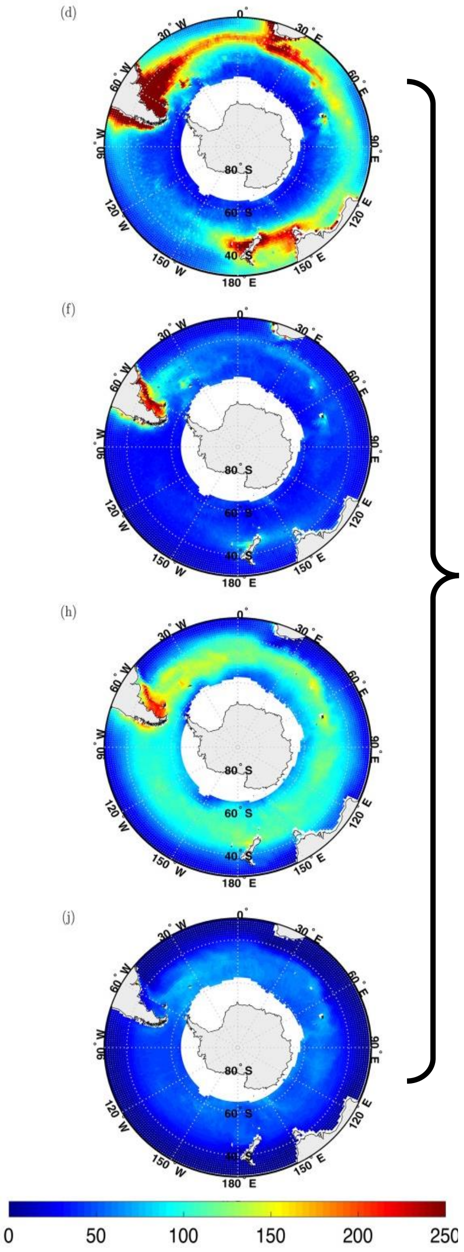
SOCCOM

Unlocking the mysteries of the Southern Ocean

HI-CYCLES GLOBAL OCEAN BIOGEOCHEMISTRY

Arteaga et al, 2018

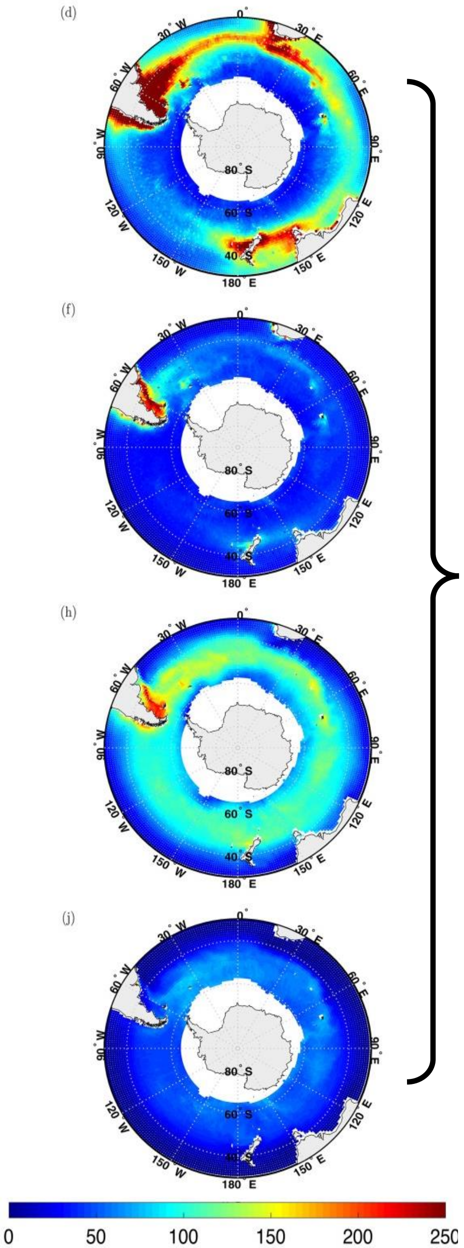
The strength and efficiency of the Southern Ocean biological carbon pump is uncertain



Carbon export (mg C m^{-2} day^{-1}) estimated with 4 different e-ratios (NPP: carbon export)

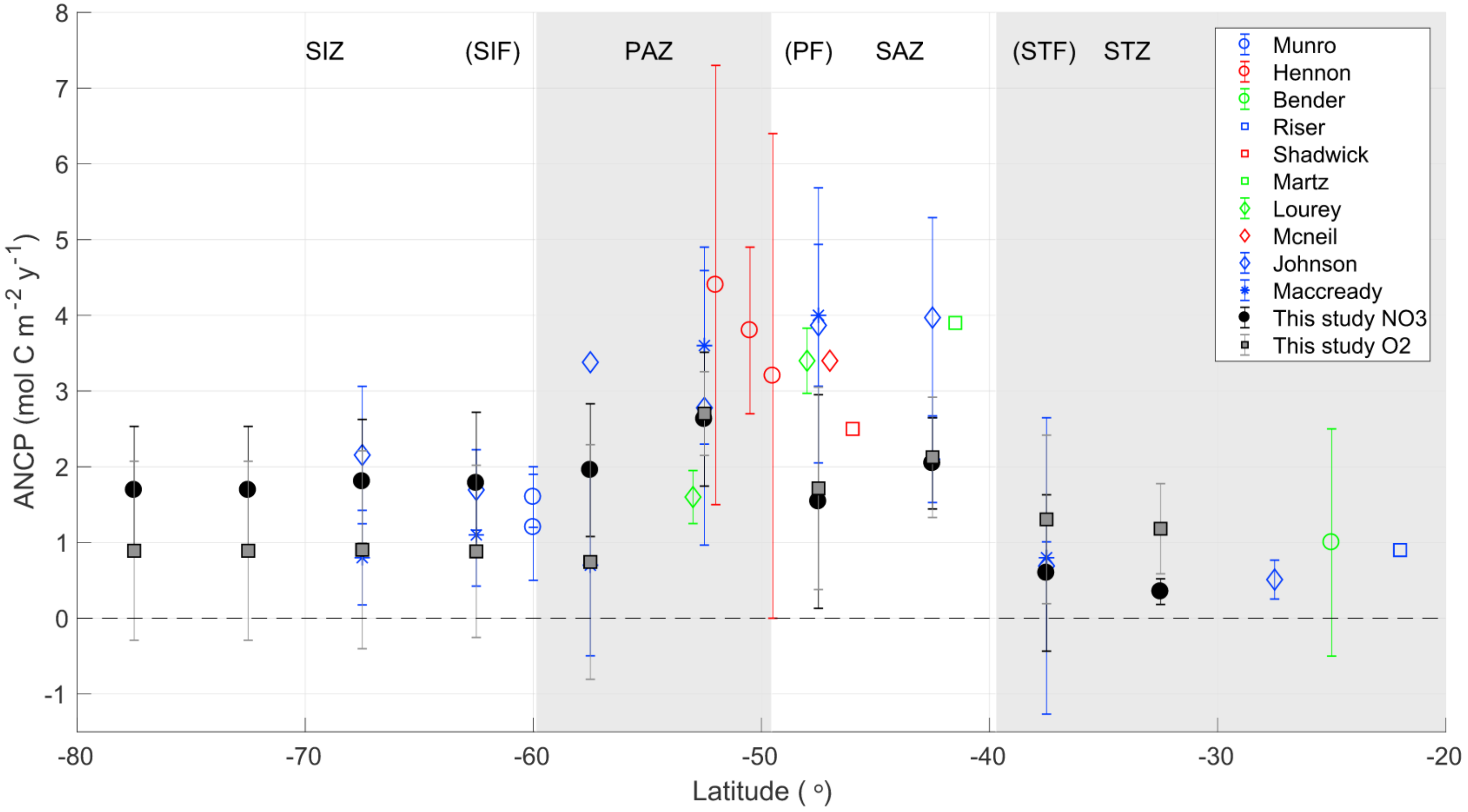
Arteaga et al, 2018

The strength and efficiency of the Southern Ocean biological carbon pump is uncertain.



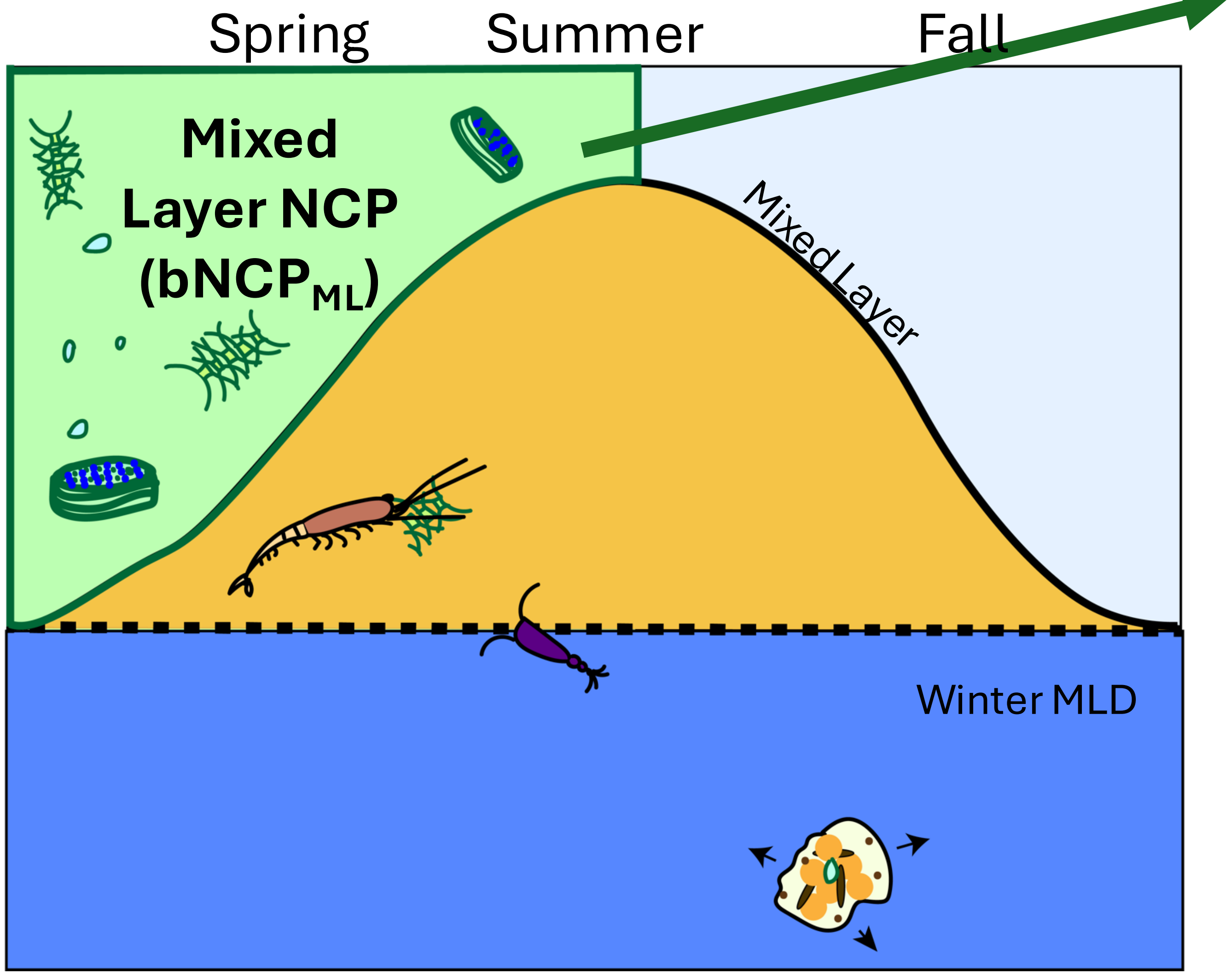
Carbon export (mg C m^{-2} day-1) estimated with 4 different e-ratios (NPP: carbon export)

Arteaga et al, 2019



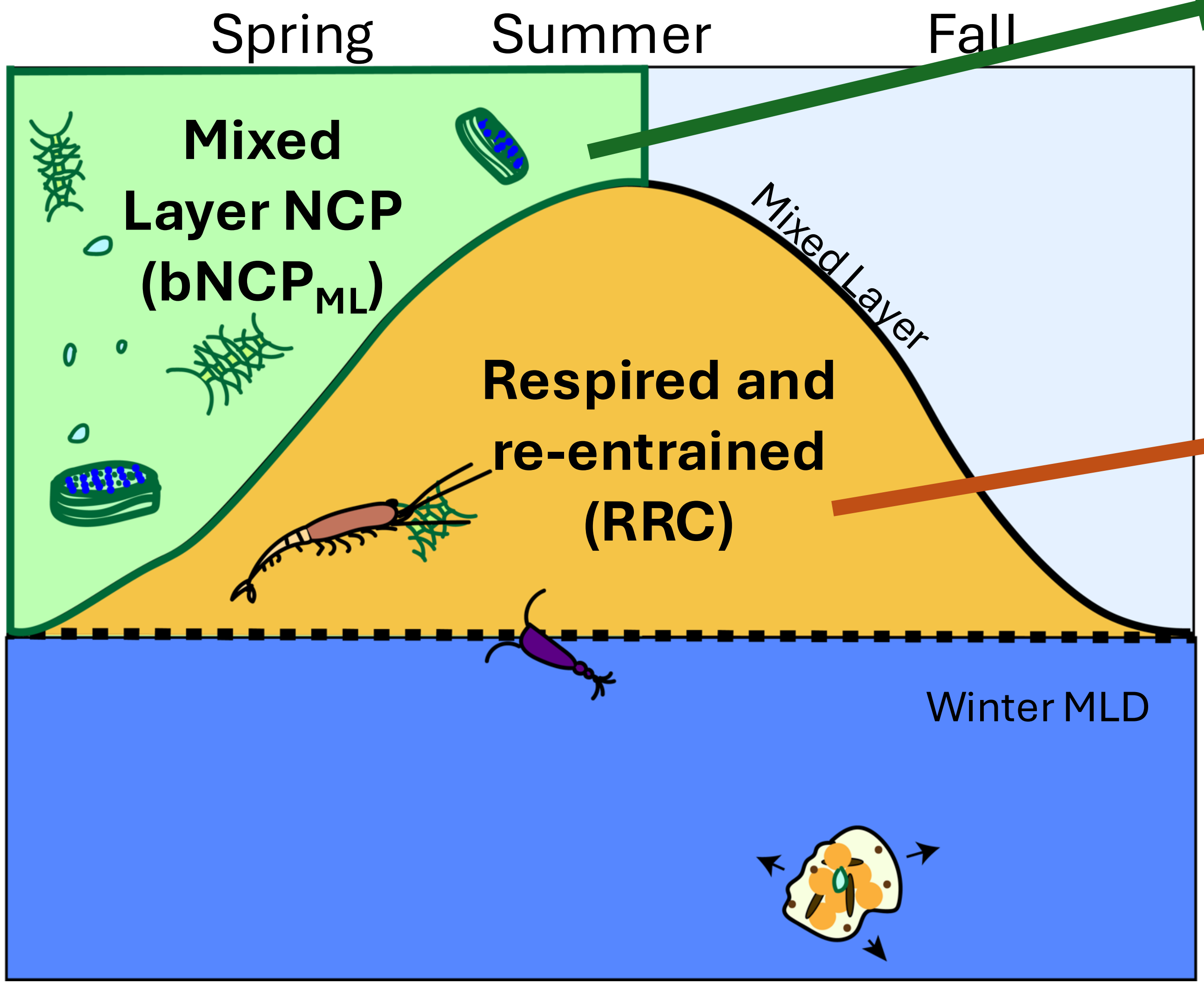
BGC profiling floats have expanded net community production (NCP) estimates, but these estimates are integrated over different times and depth horizons

How is NCP during seasonal blooms ($bNCP_{ML}$) related to annual NCP (ANCP)?



$bNCP_{ML}$: Simple mixed layer nitrate budget during seasonal bloom

How is NCP during seasonal blooms ($bNCP_{ML}$) related to annual NCP (ANCP)?

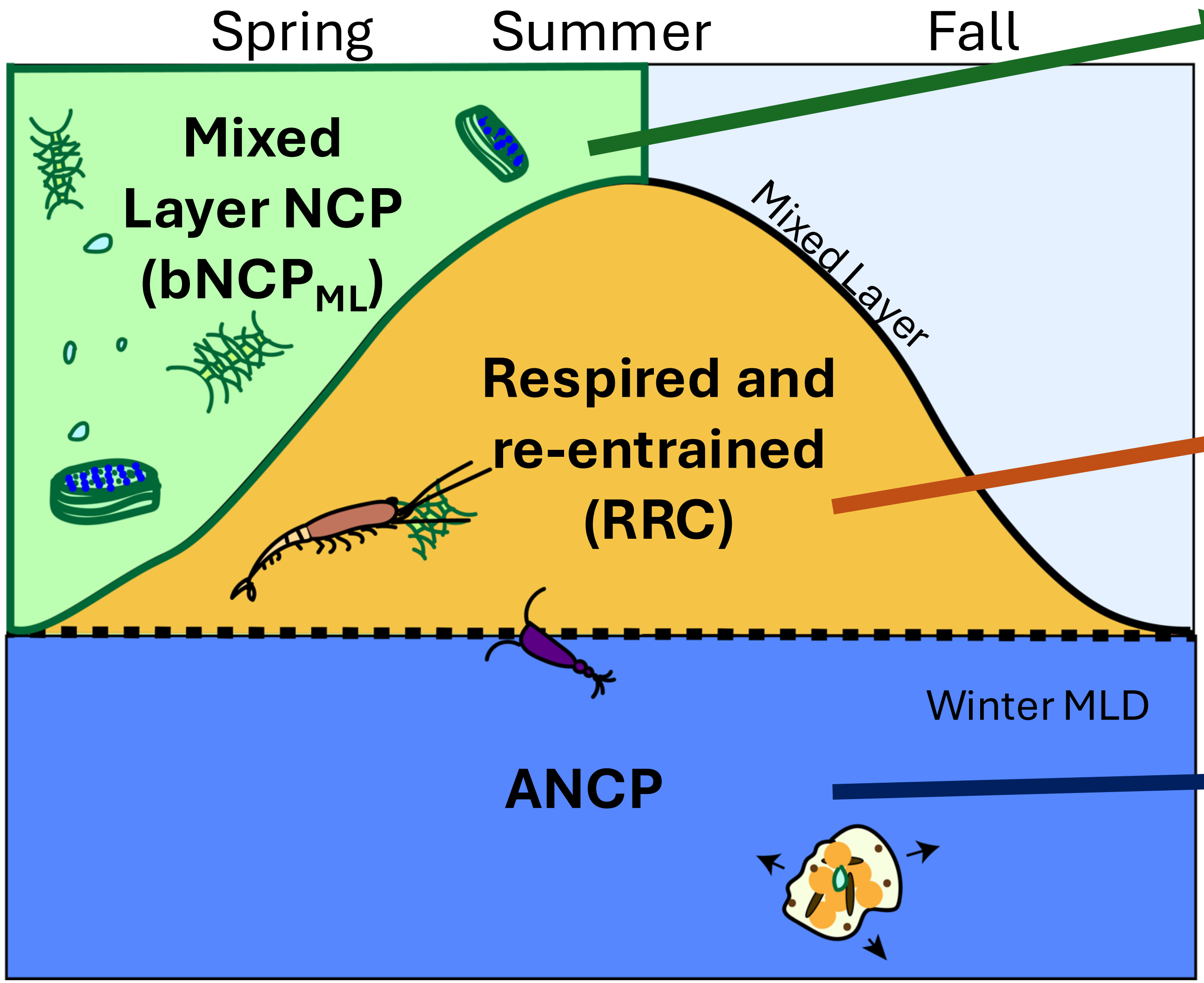


$bNCP_{ML}$: Simple mixed layer nitrate budget during seasonal bloom

Estimate respiration from Oxygen consumption on isopycnals

RRC =carbon respired above winter MLD

How is NCP during seasonal blooms (bNCP$_{ML}$) related to annual NCP (ANCP)?



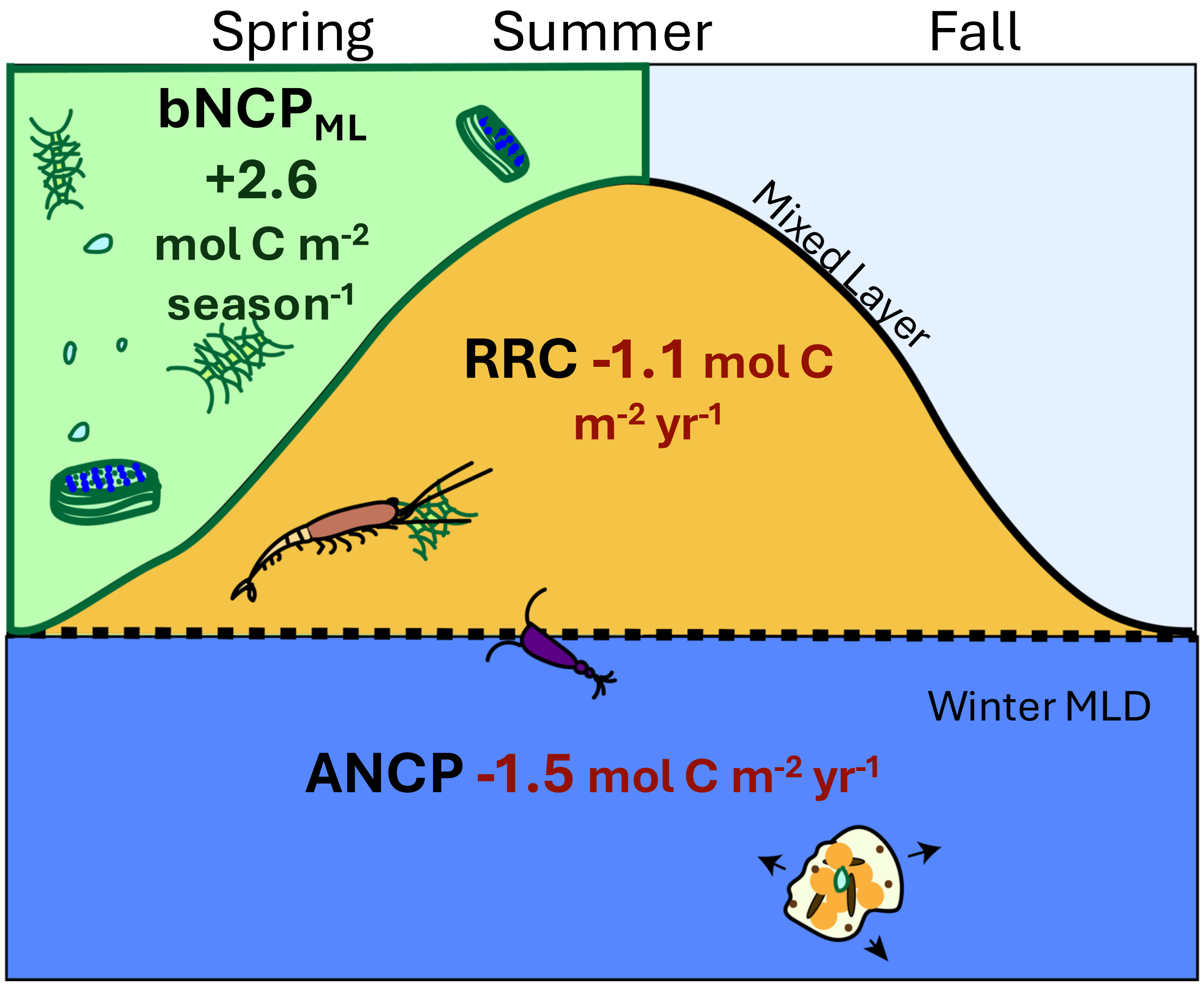
bNCP$_{ML}$: Simple mixed layer nitrate budget during seasonal bloom

Estimate respiration from Oxygen consumption on isopycnals

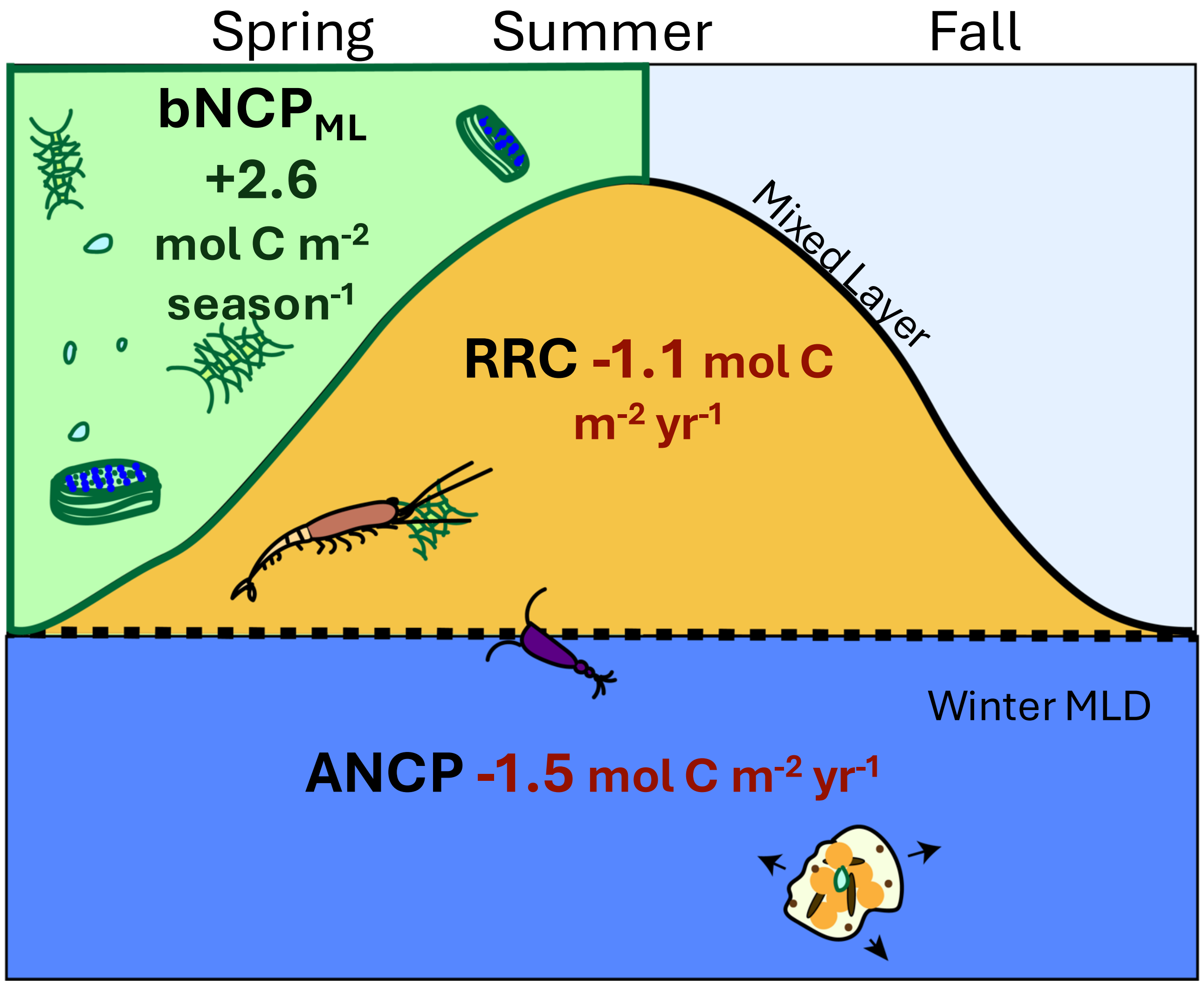
RRC = respired above winter MLD

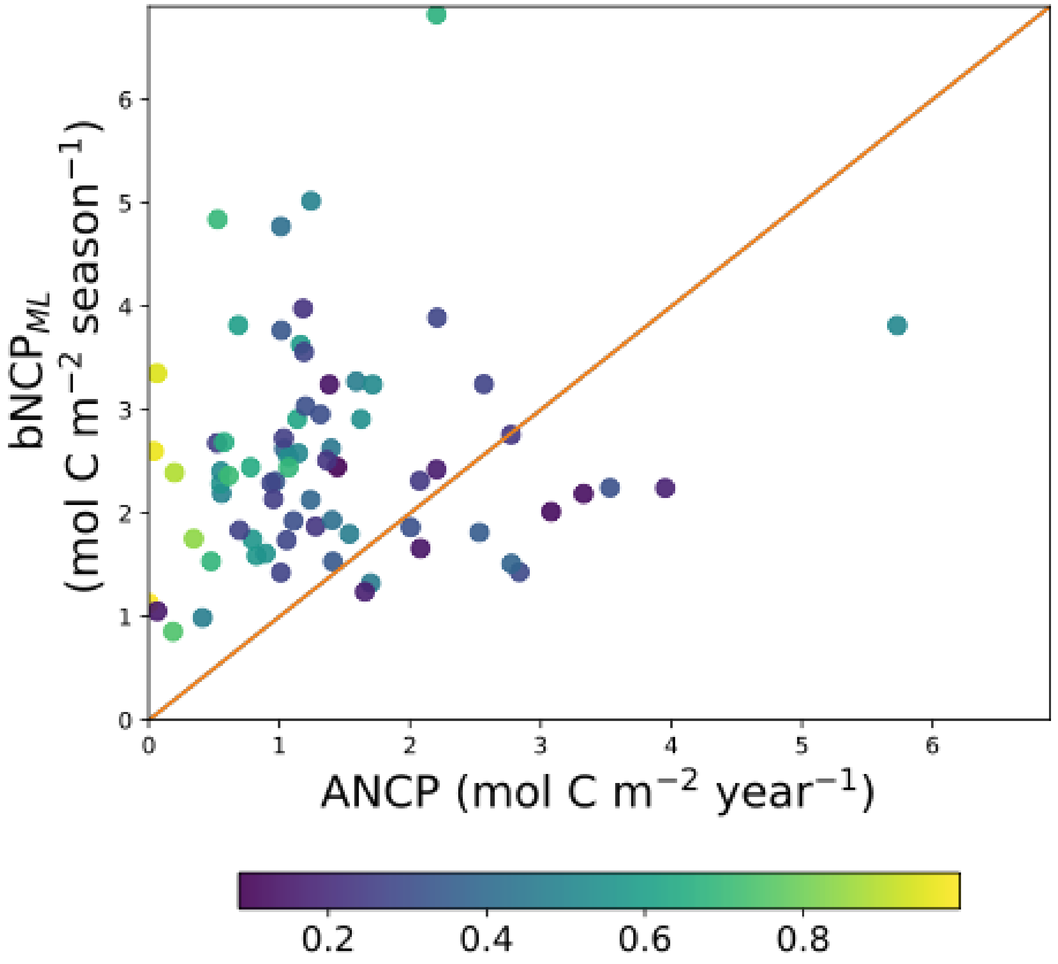
ANCP = carbon respired below winter MLD

On average ~42% of Carbon produced during seasonal blooms is respired and then re-entrained into the mixed layer



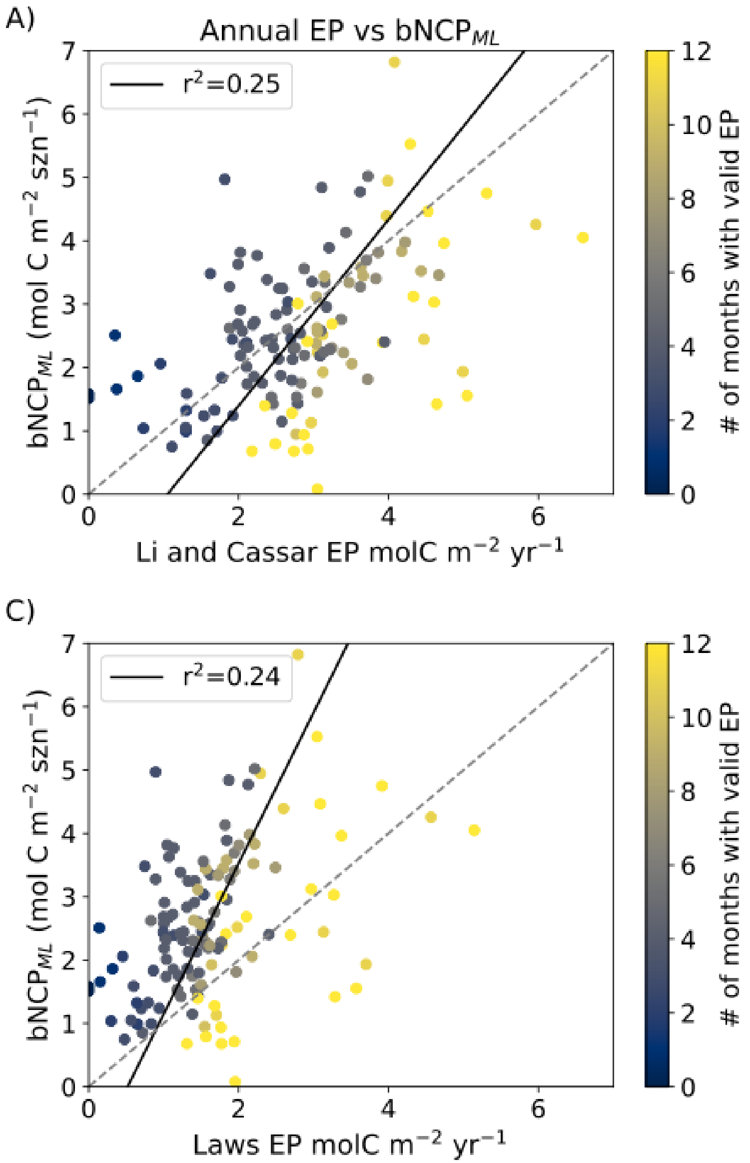
Seasonal re-entrainment of respired carbon decouples bloom NCP ($bNCP_{ML}$) from ANCP





Fraction respired and re-entrained = $\frac{RRC}{(RRC+ANCP)}$

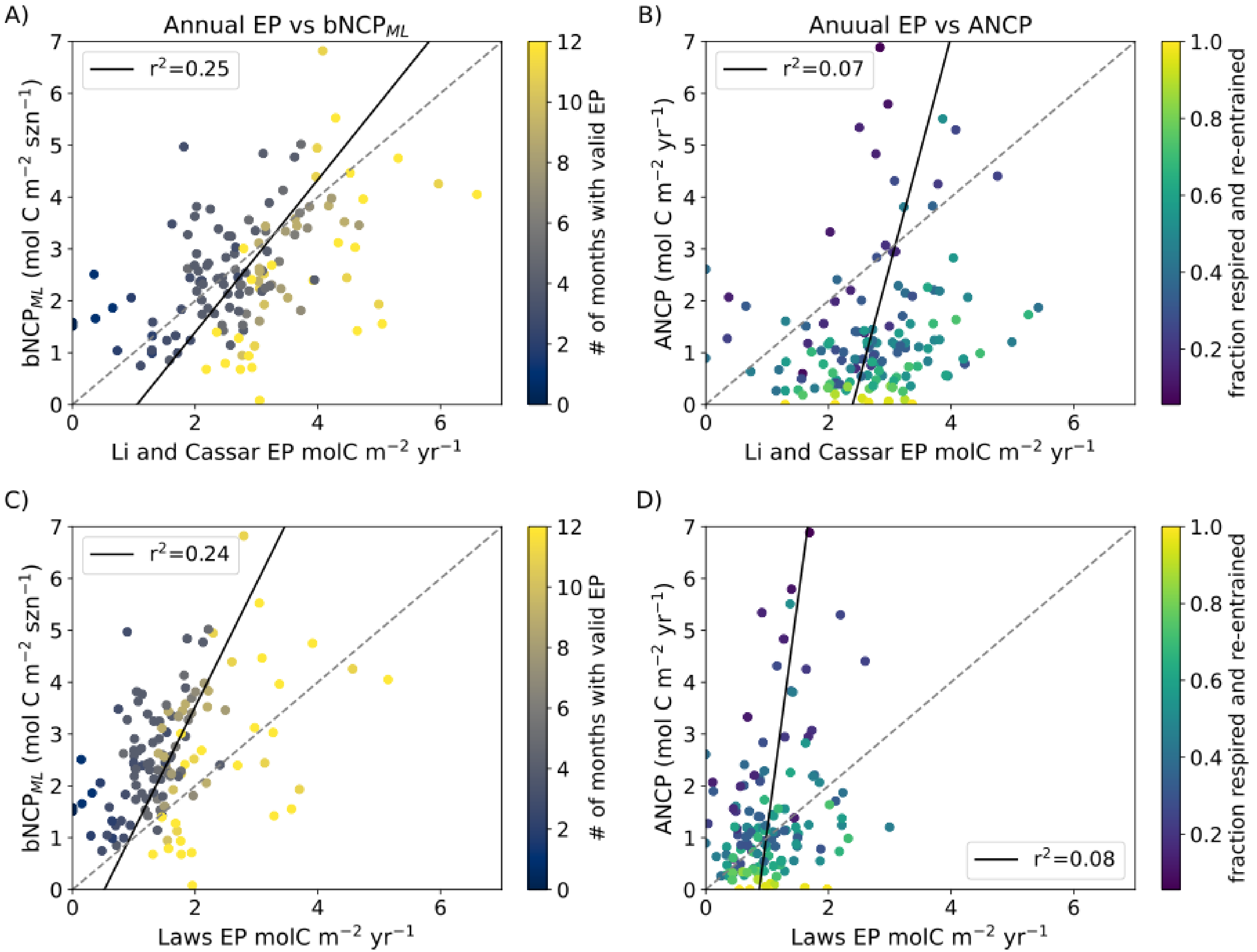
Float-derived bloom NCP ($bNCP_{ML}$) and satellite-derived annual Export Production (EP) are correlated but ANCP and annual EP are not



Annual EP underestimates $bNCP_{ML}$ in polar zones where observations are limited by solar angle and sea ice (A,C)

Annual EP does is not representative of ANCP, in part due to seasonal re-entrainment of respired carbon (B,D)

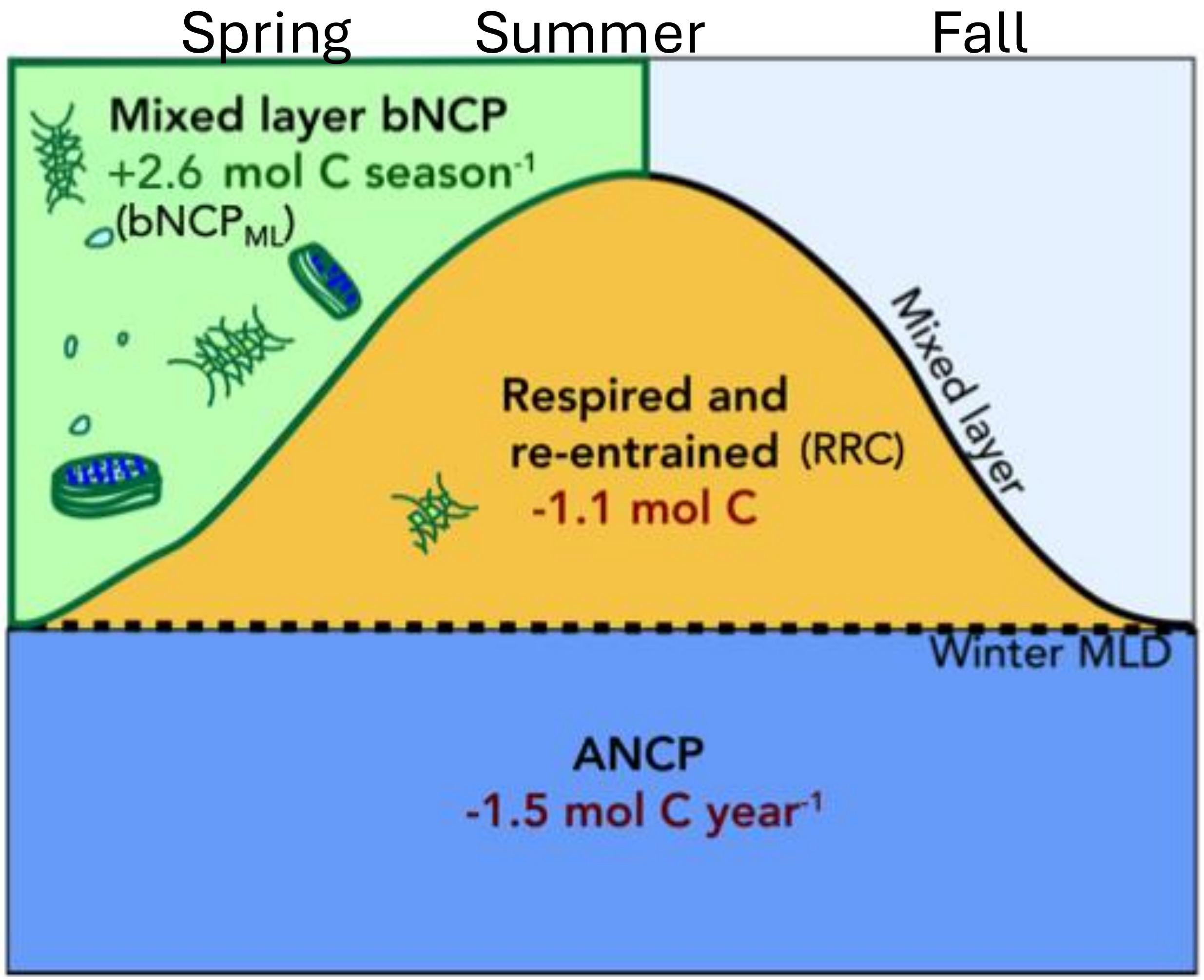
Float-derived bloom NCP ($bNCP_{ML}$) and satellite-derived annual Export Production (EP) are correlated but ANCP and annual EP are not



Annual EP underestimates $bNCP_{ML}$ in polar zones where observations are limited by solar angle and sea ice (A,C)

Annual EP does is not representative of ANCP, in part due to seasonal re-entrainment of respired carbon (B,D)

Conclusions



Currently working to expand this beyond Southern Ocean!

1. 42% ± 22% of organic carbon produced during blooms is respired and re-entrained into the mixed layer in winter.

2. Compensation between respiration and POC loss rates and winter MLD leads to similar fraction of respired and re-entrained carbon throughout Southern Ocean.

3. ANCP estimates using a 100m depth horizon overestimate Southern Ocean ANCP and regional differences.

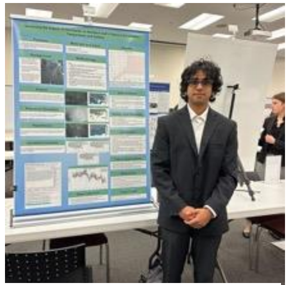
4. Satellite-derived export production is correlated to float $bNCP_{ML}$, but not ANCP, respired and re-entrained carbon is not accounted for in current e-ratios.

Evolution of sediment-derived CDOM upon fluxing to a river-dominated coastal water column

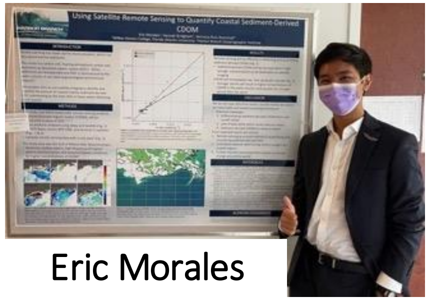
MUREP/OBB

FAU: Jordon Beckler, Hanna Bridgham, Veronica Ruiz-Xomchuk, Owen Silvera, Mason Thackston, Alberto Tonizzo, Tim Moore, Chris Straight, Trevor McKenzie, Mike Twardowski, Gabrielle McHenry

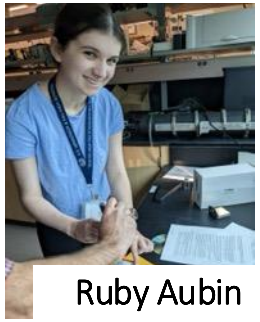
FAU High School & interns: Tricia Meredith (FAU HS Research Coordinator)



Ani Venkat



Eric Morales

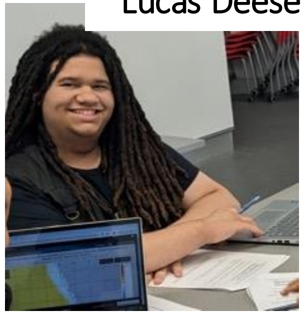


Ruby Aubin

Arman Alexis

Brooke Estevez

Lucas Deese



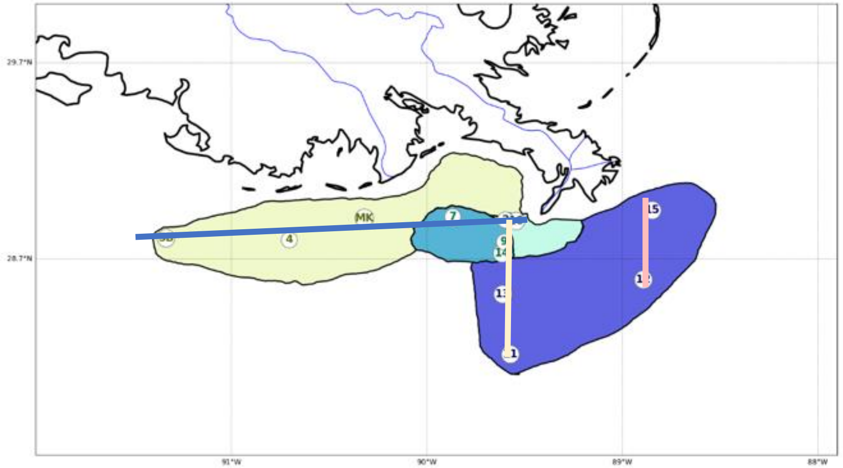
Georgia Tech: Martial Taillefert, Tony Boever, Evan Margette

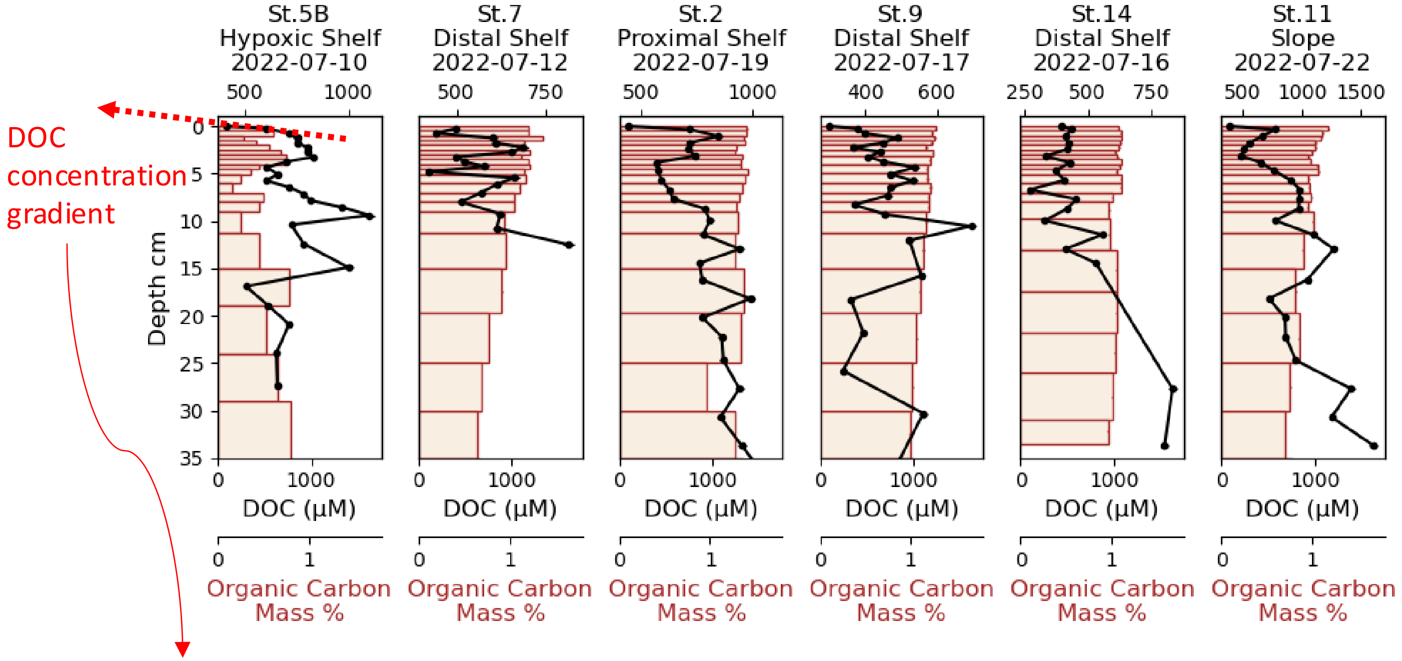
Chemical Oceanography

For 2024 NASA OBB All Hands Meeting
Dec. 3, 2024

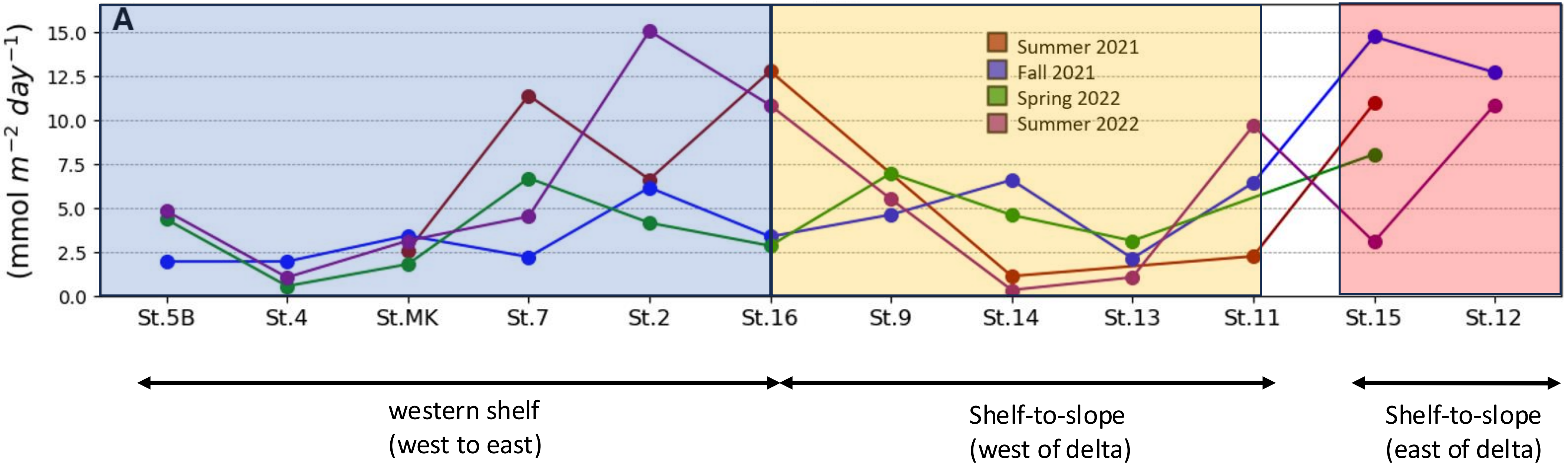
IG: @geochemical.sensing.lab

DOC sediment fluxes



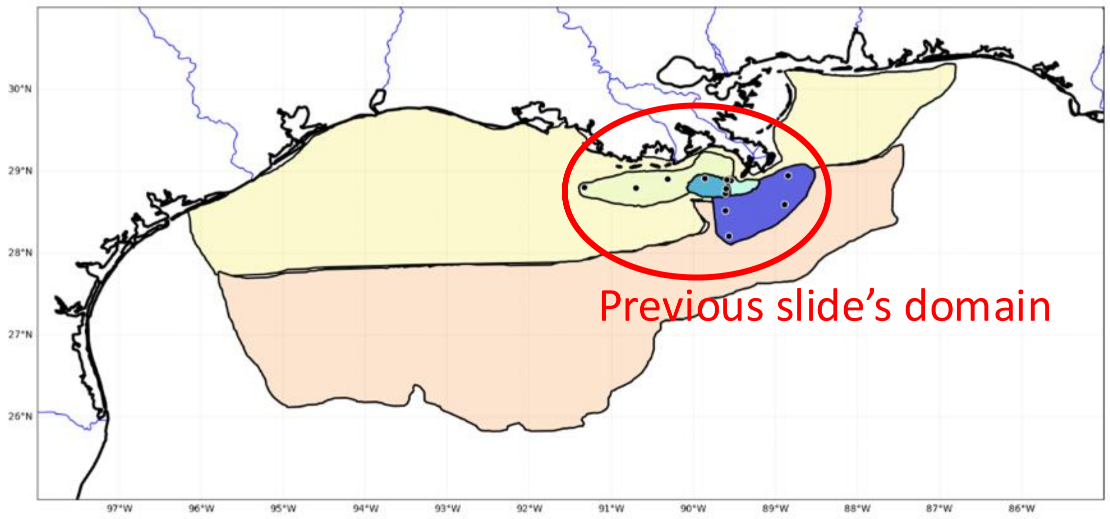


DOC Flux= porosity x diffusion coefficient x DOC concentration gradient @ sediment interface



Brigham et al., in prep for submission to Marine Chemistry

River-dominated coastal sediment-derived DOC can rival fluvial inputs

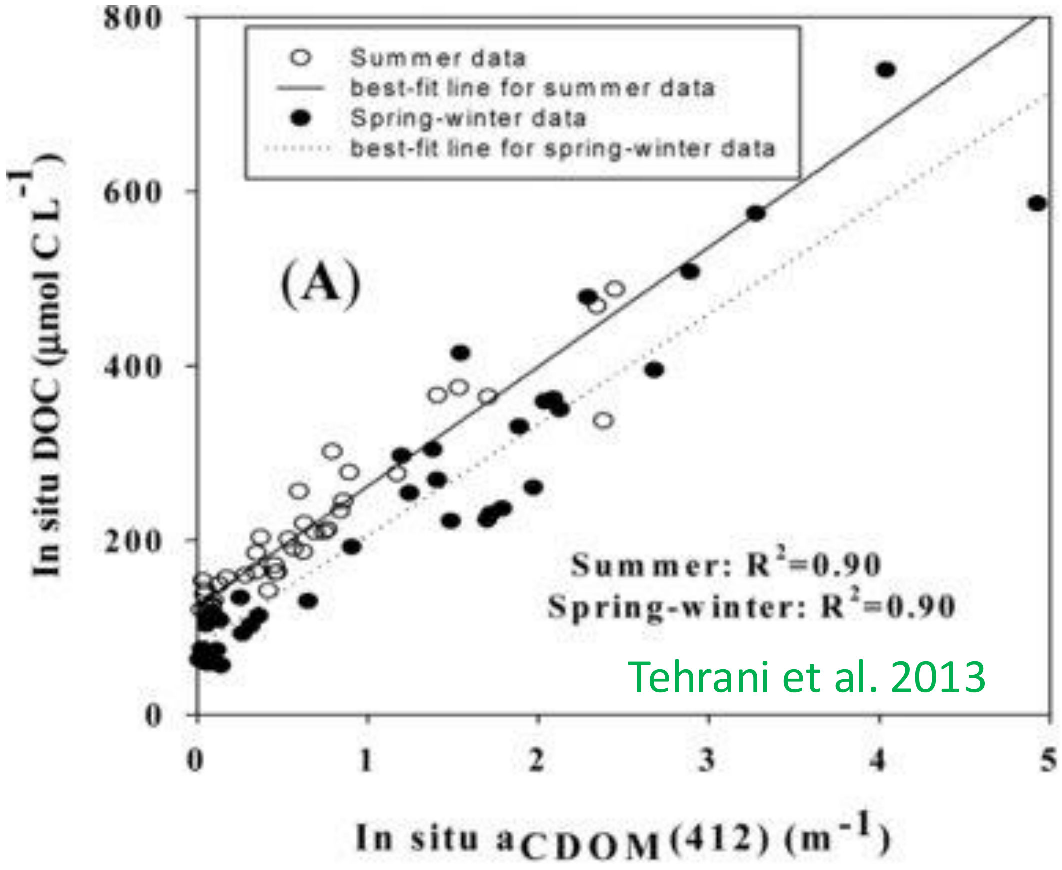


Sediment vs. MS River DOC flux	Area km²	Summer 2021 4 months	Fall 2021 4 months	Spring 2022 4 months	Summer 2022 4 months	Annual
Northern Gulf Shelf: Station 14, 7, 9, MK, 5B, 4 (Tg per season)	123,592	0.91 ± 0.2	0.63 ± 0.22	0.76 ± 0.41	0.59 ± 0.28	2.13 ± 0.87
Northern Gulf Slope: Station 11, 12, 13, 15 (Tg per season)	130,979	1.27 ± 0.47	1.73 ± 0.69	1.07 ± 0.15	1.18 ± 0.9	4.02 ± 1.53
Total Northern Gulf Sediment (Tg area⁻ Season⁻)	254,571	2.18 ± 0.67	2.35 ± 0.91	1.83 ± 0.56	1.77 ± 1.18	**6.16 ± 2.39**
Mississippi River (Tg) (Potter and Xu, 2022).	Discharge 500 $km^3\ yr^{-1}$	Winter 2022 1.56 Tg	Spring 2022 1.31 Tg	Summer 2022 0.91 Tg	Fall 2022 0.75 Tg	Annual 2022 **4.54 Tg**

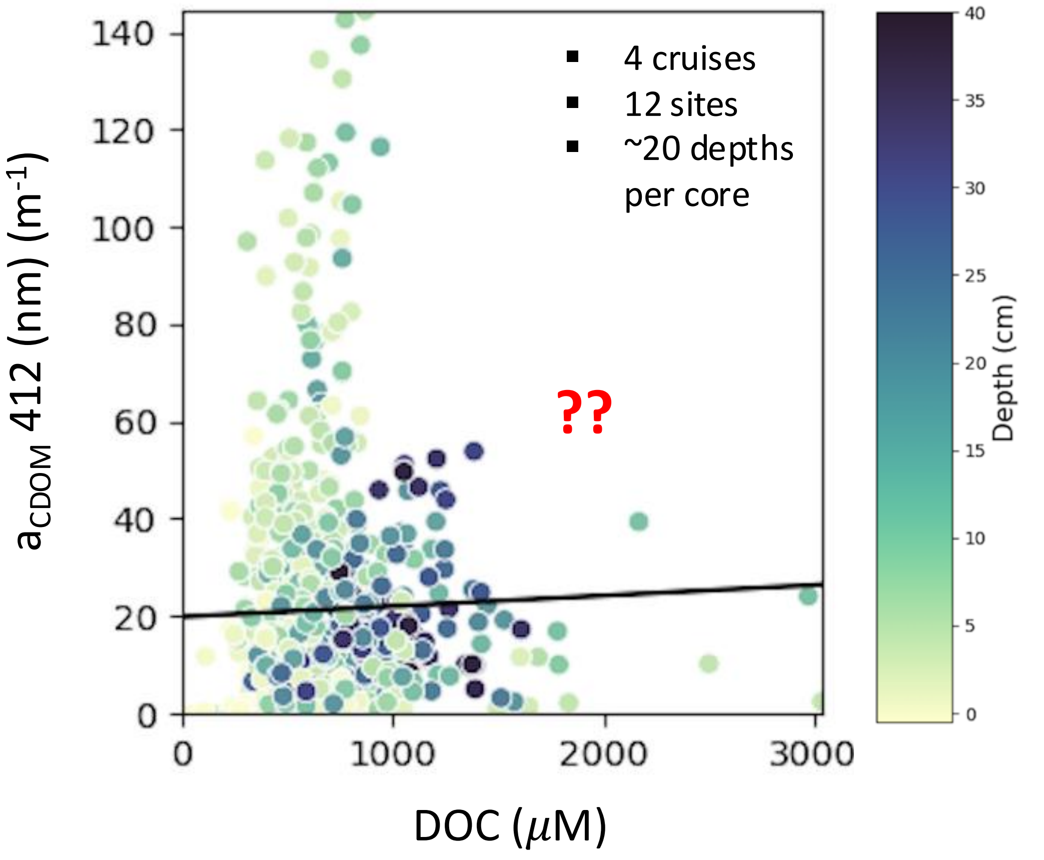
Brigham et al., in prep for submission to Marine Chemistry

Sediments as a major CDOM inventory

Surface waters

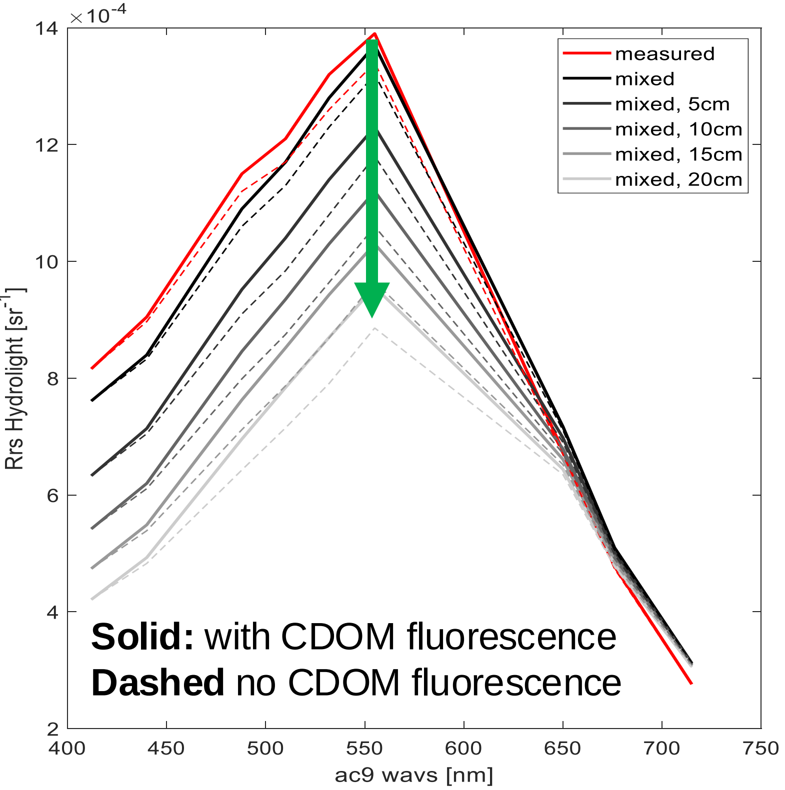


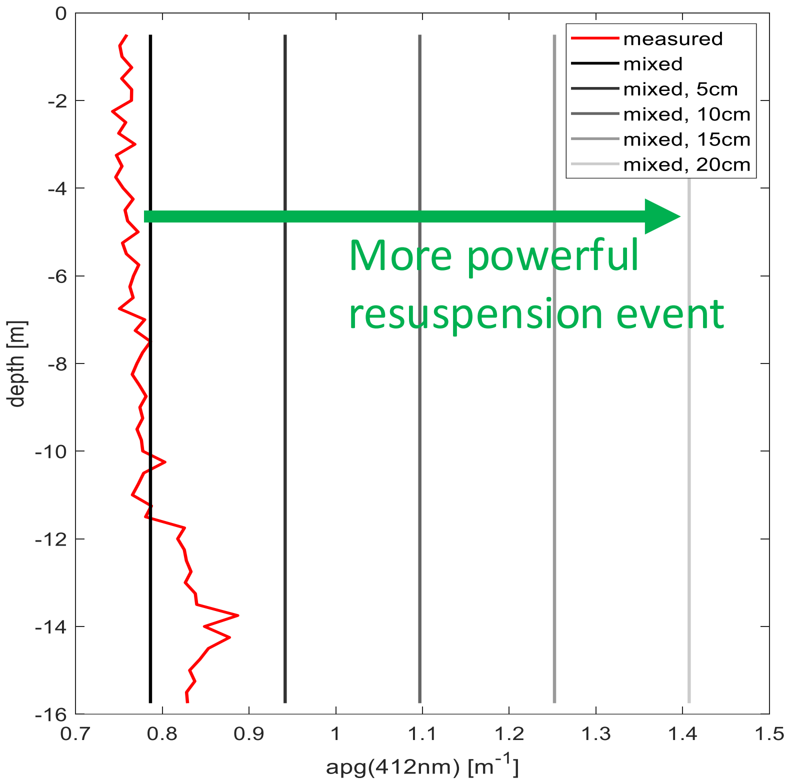
Individual sediment pore water samples

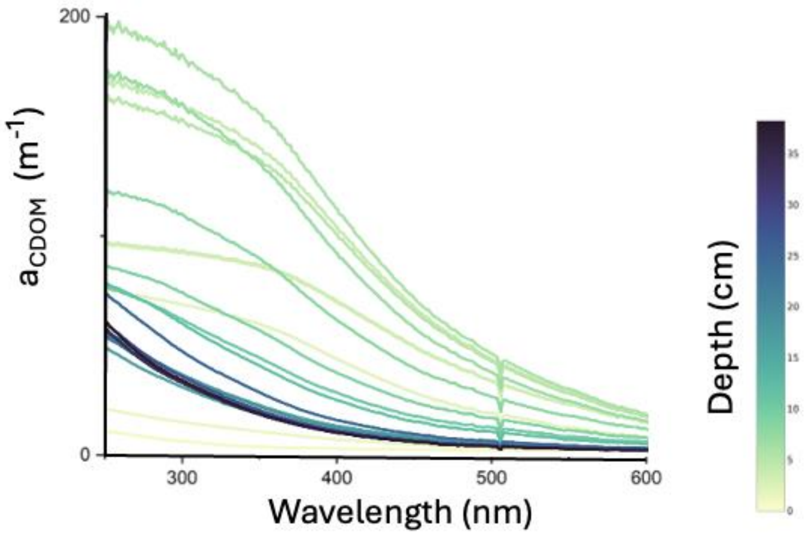


- Pore water [DOC] is ~2-3x river plume DOC… CDOM absorption is 10-100x!
- Sediment CDOM diffusive or erosive (resuspension) fluxes fluxes should be massive?

Forward Rrs modeling of resuspension & conservative mixing of sediment CDOM

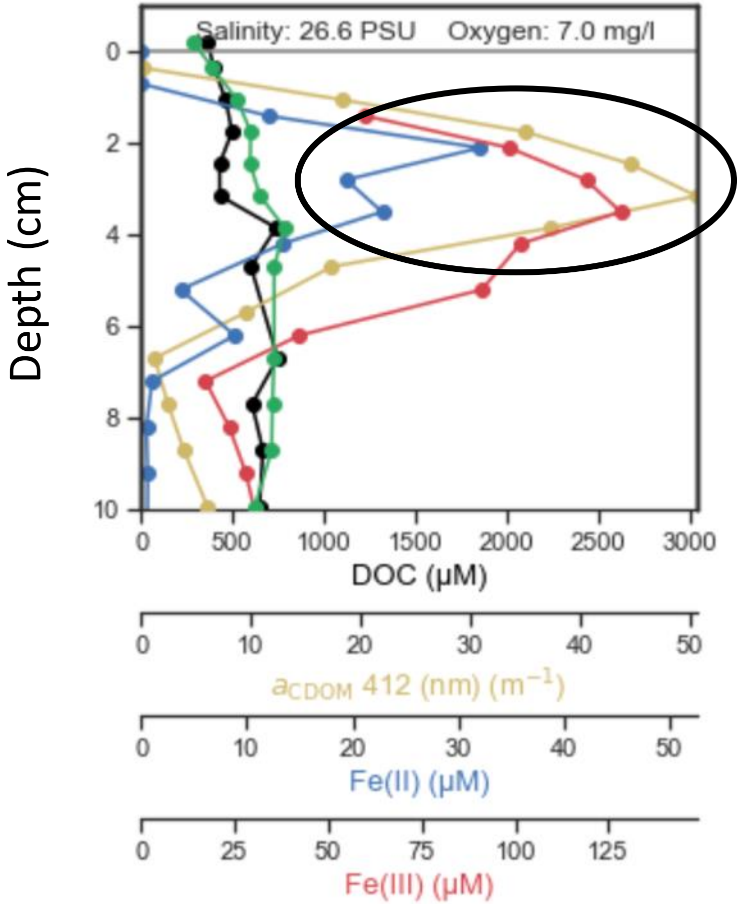




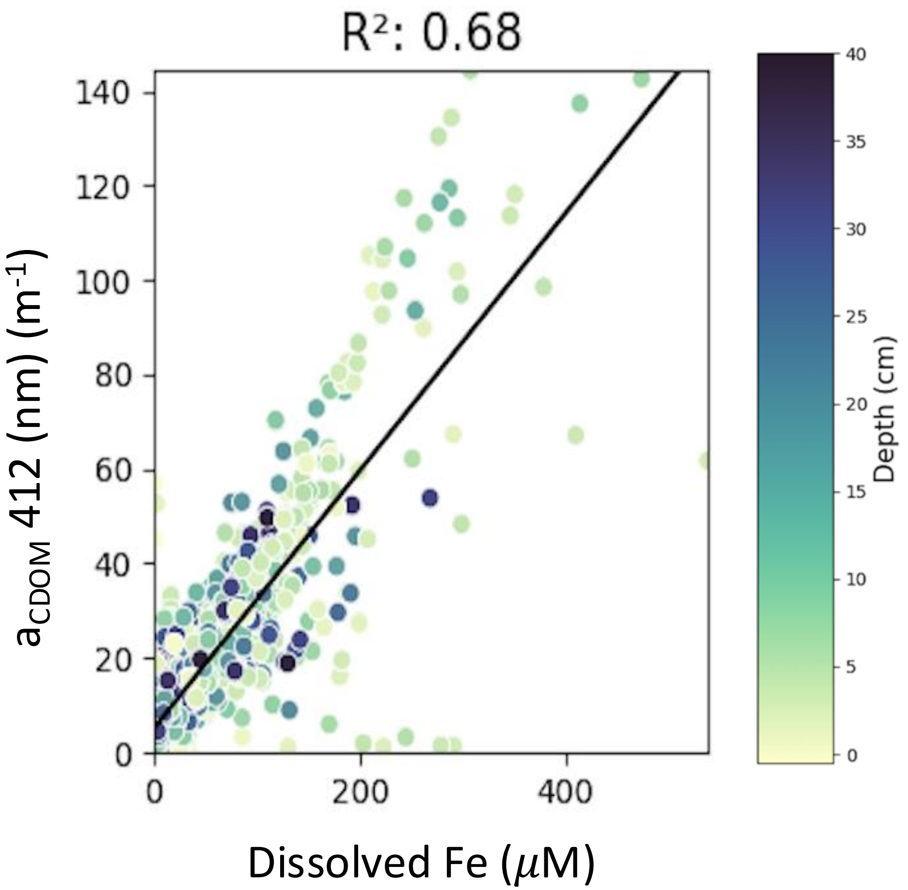


Tonizzo et al., in prep

DOC-Fe(III) complexes regulate CDOM absorption



Mirrored CDOM & dissolved Fe profiles

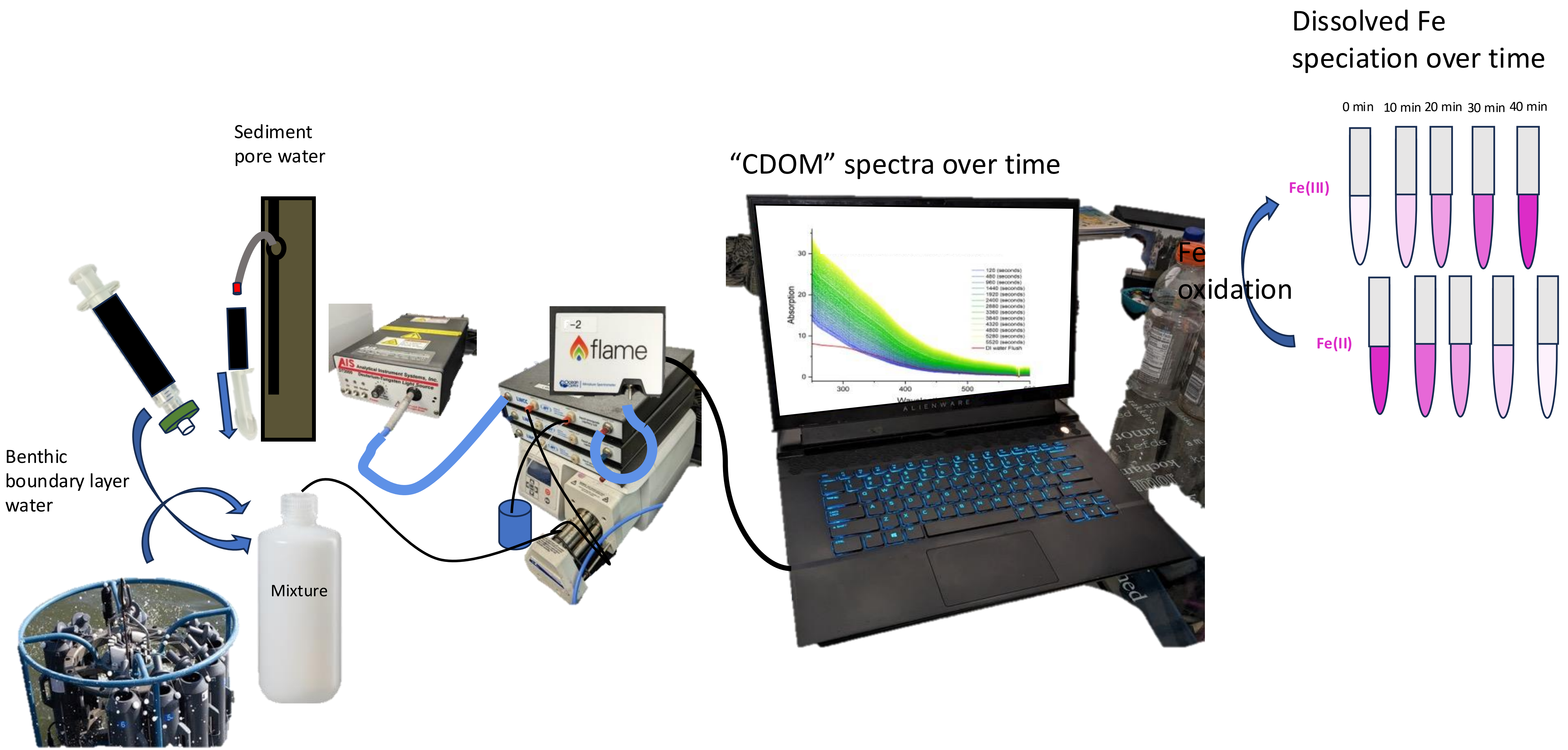


Extreme dissolved Fe concentrations → Must be DOC-Fe complexes

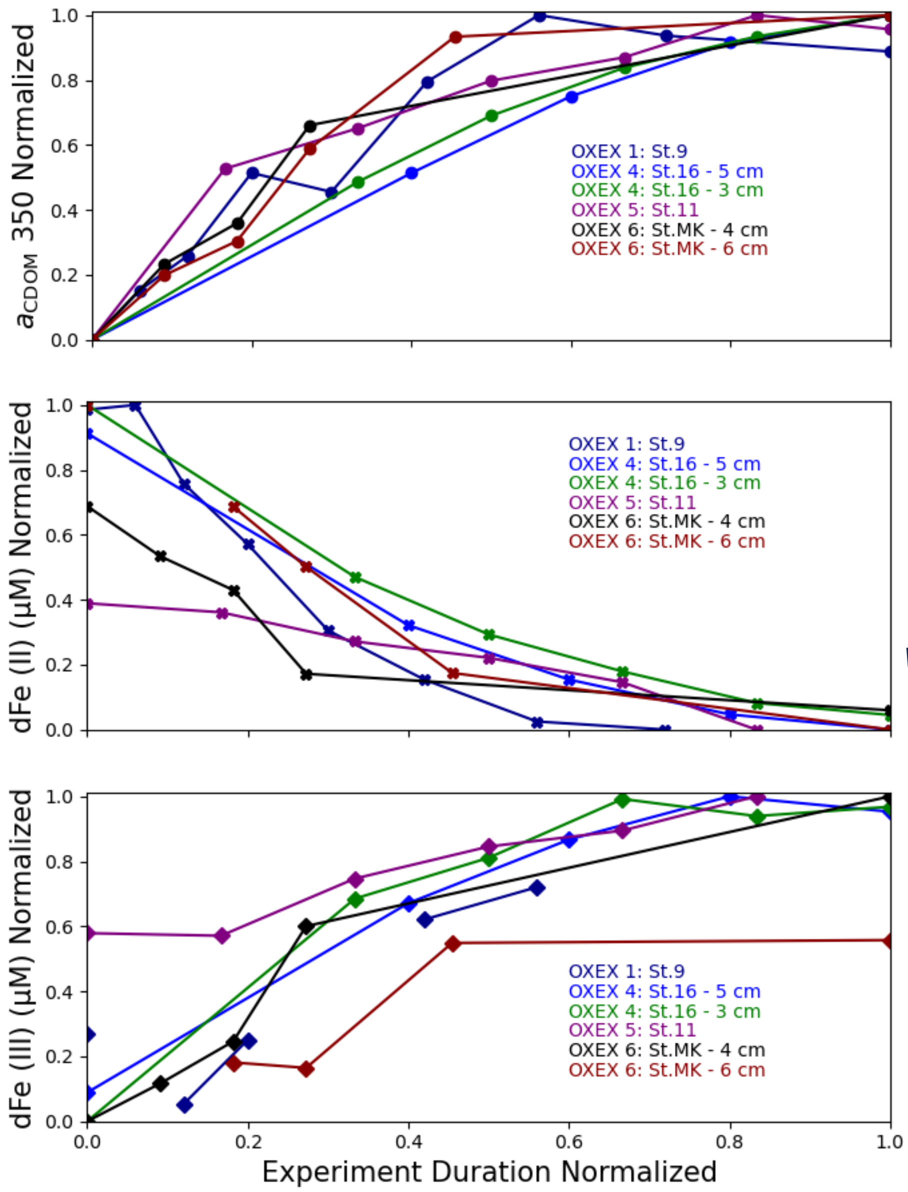
High apparent "CDOM" inventories regulated by dissolved Fe→

Fate during entrainment in oxygenated/turbulent water column?

Simulating entrainment of sediment pore water into BBL

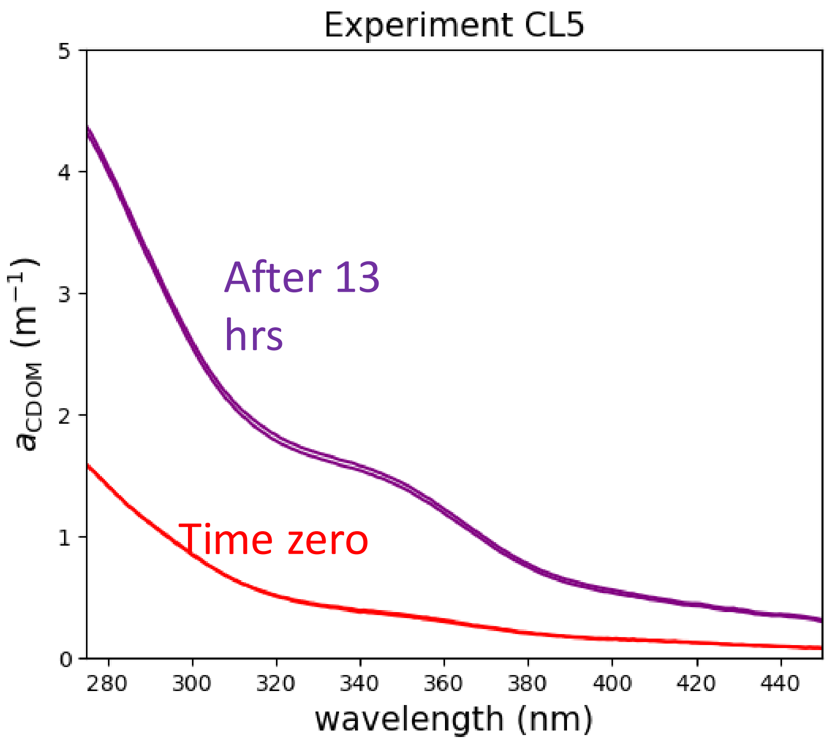


DOC-Fe(II) to DOC-Fe(III) oxidation enhances CDOM absorption



Experiments ranged from ~40-400 min

Fe oxidation



Time	$S_{275\text{-}295}$	$S_{350\text{-}400}$
0 hours	0.0205	0.0196
13 hours	0.00001	0.221

Conclusions

Most comprehensive sediment DOC flux dataset to date (coastal C cycling & reservoirs)

Sediment pore waters display strong absorption, but changes upon WC entrainment

Complex chemistry requires collaboration between optics & geochemistry communities
→implications for any redox-stratified environment

WC impacts likely episodic in nature, persistent observations at depth (AUVs, Argo floats?)

Long term fate of sediment CDOM remain unknown and coupled to Fe chemistry

PACE to be a gold mine for sediment dynamics in particular…
→ towards an iron algorithm?

Lamont-Doherty Earth Observatory
COLUMBIA UNIVERSITY | EARTH INSTITUTE

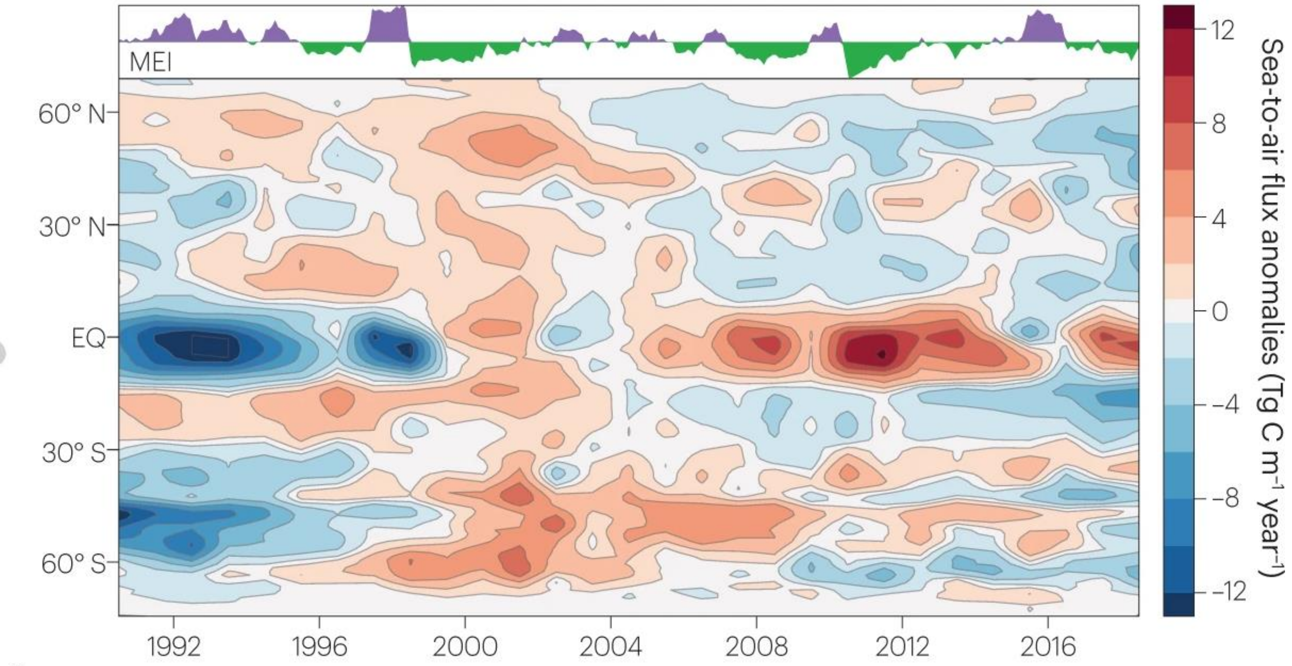
Scale-Dependent Drivers of Air-Sea CO_2 Flux Variability using the ECCO-Darwin Model

Recently published in
Geophysical Research Letters
Poster at AGU, Monday AM

Presenter: Amanda R. Fay

Coauthors: Dustin Carroll, Galen A. McKinley, Dimitris Menemenlis, and Hong Zhang

Motivation



Gruber et al 2023, Nature Review

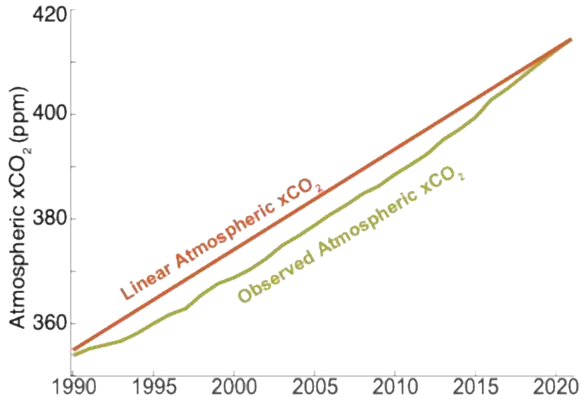
We lack the critical mechanistic understanding of the drivers of variability and change in the ocean carbon sink over recent decades.

Lamont-Doherty Earth Observatory
Columbia University | Earth Institute

Model Experiment

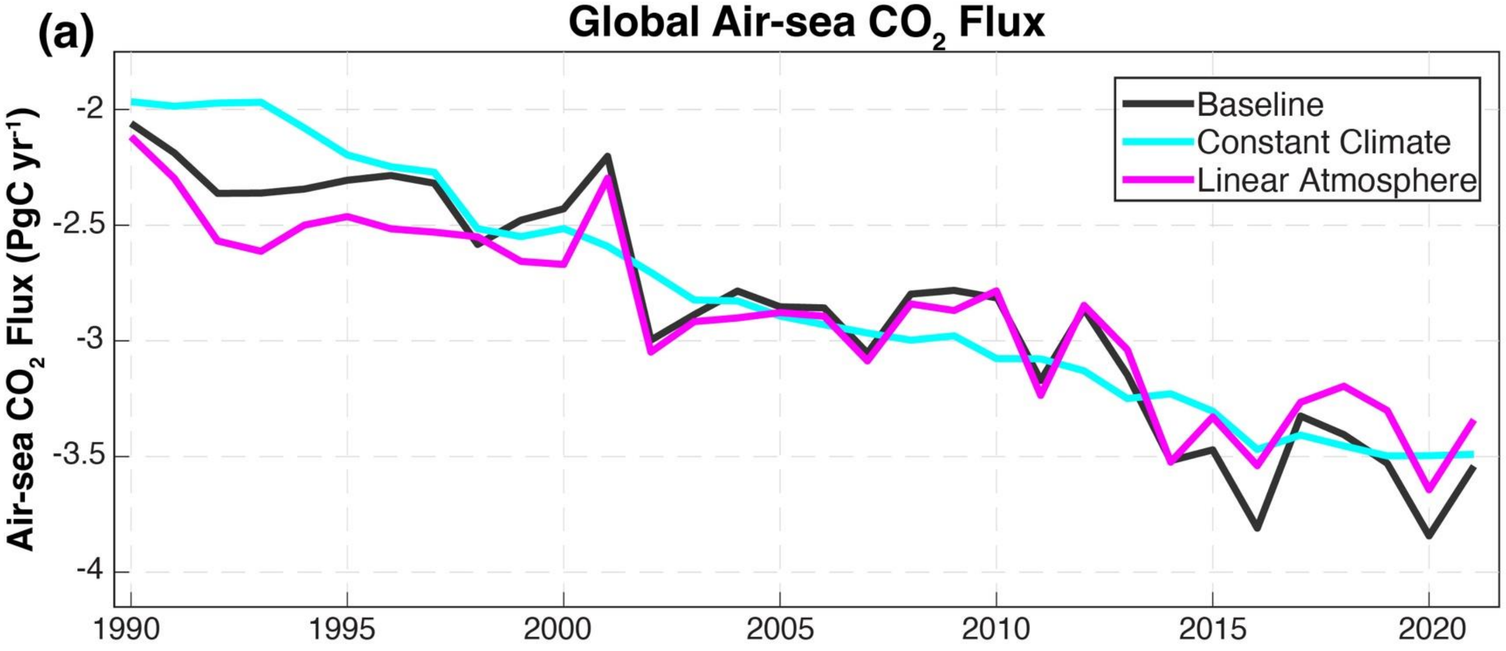
We utilize the ECCO-Darwin ocean biogeochemistry model to run a suite of sensitivity experiments

Simulation	Atmospheric xCO_2	Atmospheric physics
Baseline	Observed atmospheric xCO_2	ECCO LLC270, Extended with ERA5
Linear Atmosphere	Constant 1.92ppm yr^{-1} xCO_2 trend applied	Same as Baseline run
Constant Climate	Observed atmospheric xCO_2	Baseline, with repeating year 1999 forcing



By adjusting forcing fields, we are able to isolate impacts from the variability of the atmospheric CO_2 growth rate and climate.

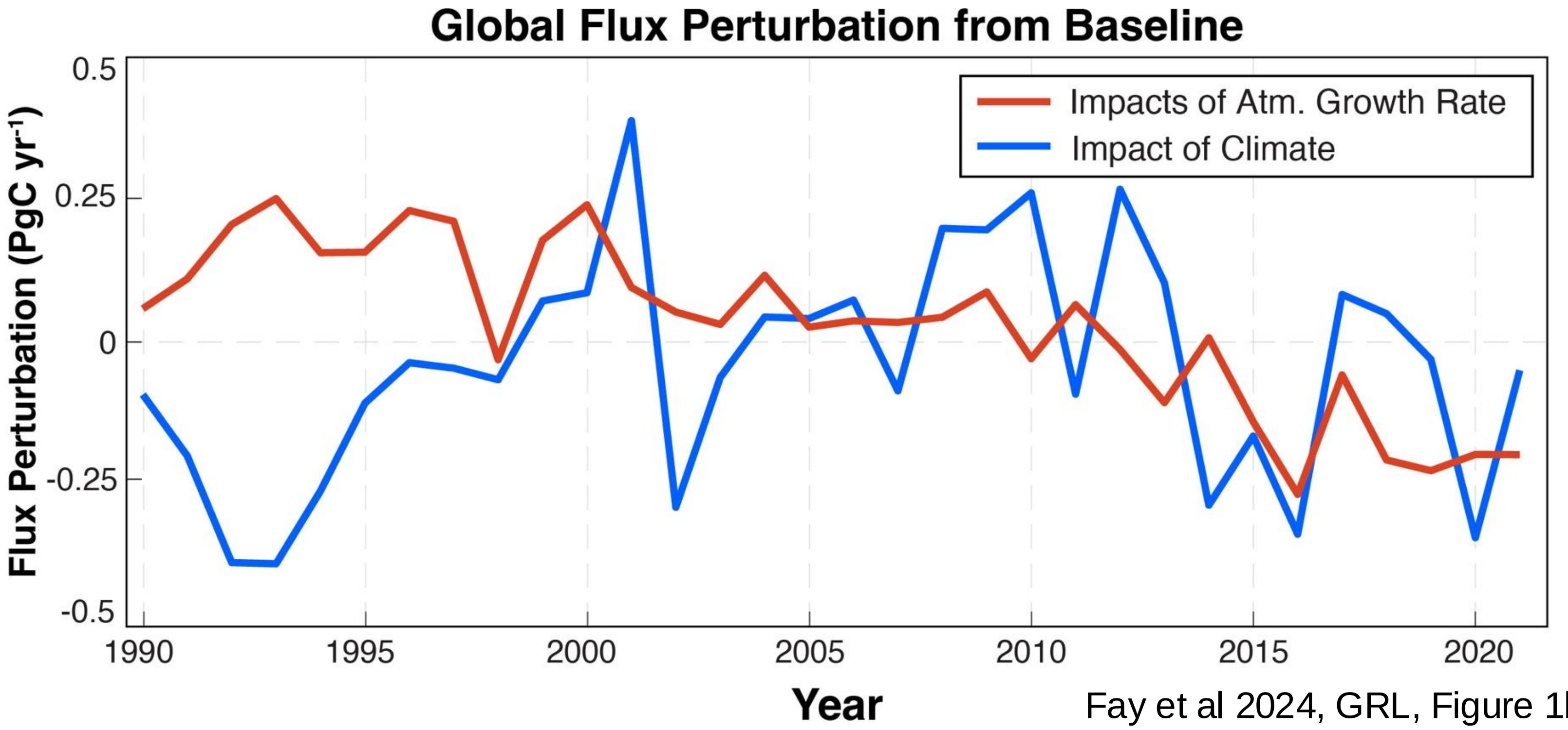
Results: Global Carbon Flux



Fay et al 2024, GRL, Figure 1a

Global annual mean air-sea CO_2 flux results shown for 3 simulations, 1990-2022

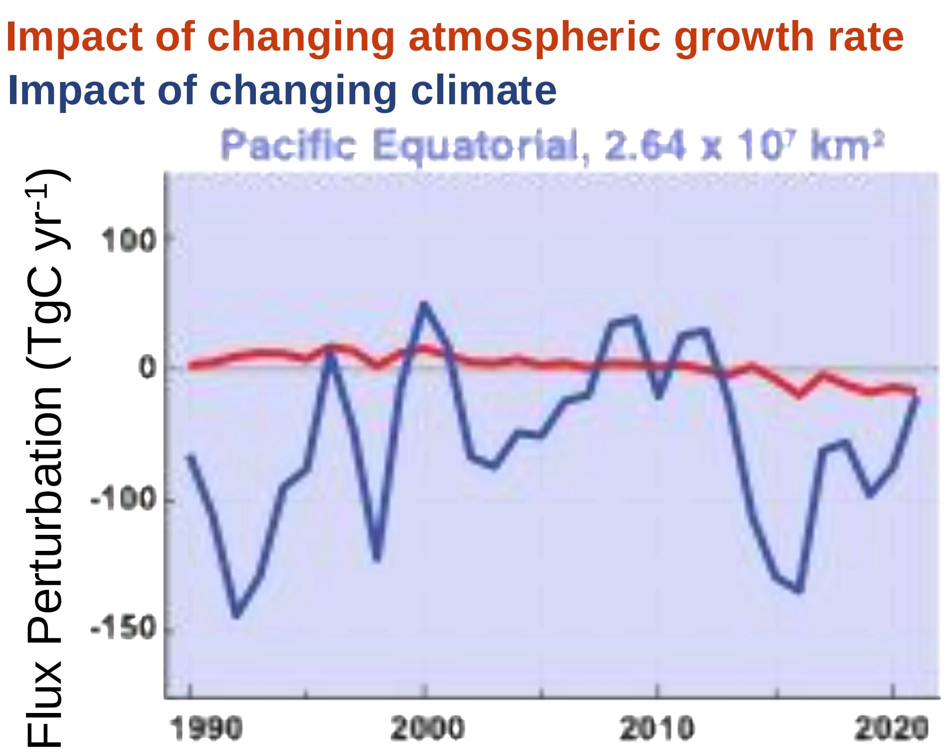
Results: Global Carbon Flux



Fay et al 2024, GRL, Figure 1b

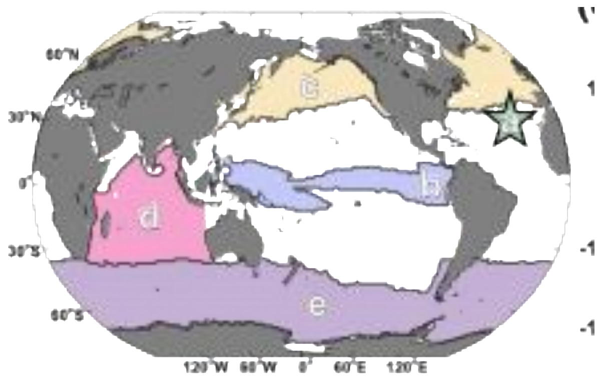
- **Globally, the two forcing types are roughly equal in their magnitude of impact on ocean carbon sink variability.**
- **Considering their variability, the two are comparable, with mean absolute deviation (MAD) values of 0.16 vs 0.11 PgC yr^{-1}**

Results: Regional Carbon Flux



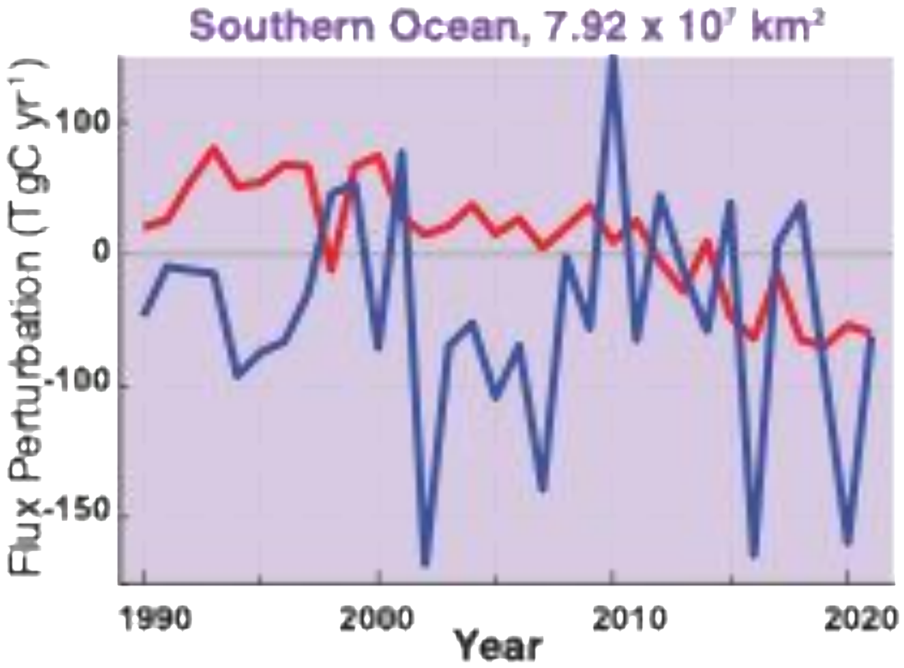
Fay et al 2024, GRL, Figure 2b

Interannual variability in the flux perturbation timeseries is *much larger for the impact of climate* than it is for the impact of changing atmospheric growth rate



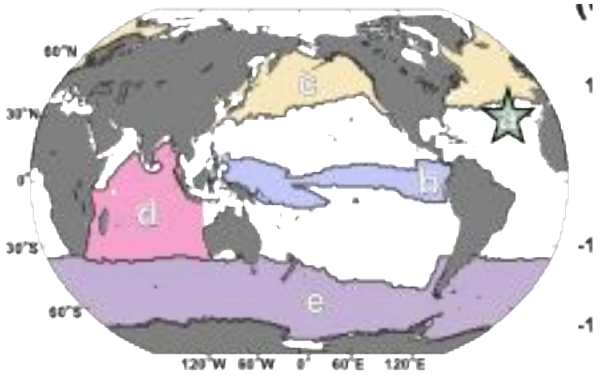
Results: Regional Carbon Flux

Impact of changing atmospheric growth rate
Impact of changing climate



Fay et al 2024, GRL, Figure 2e

As the region of interest gets larger in area, the impact of changing atmospheric growth rate increases.



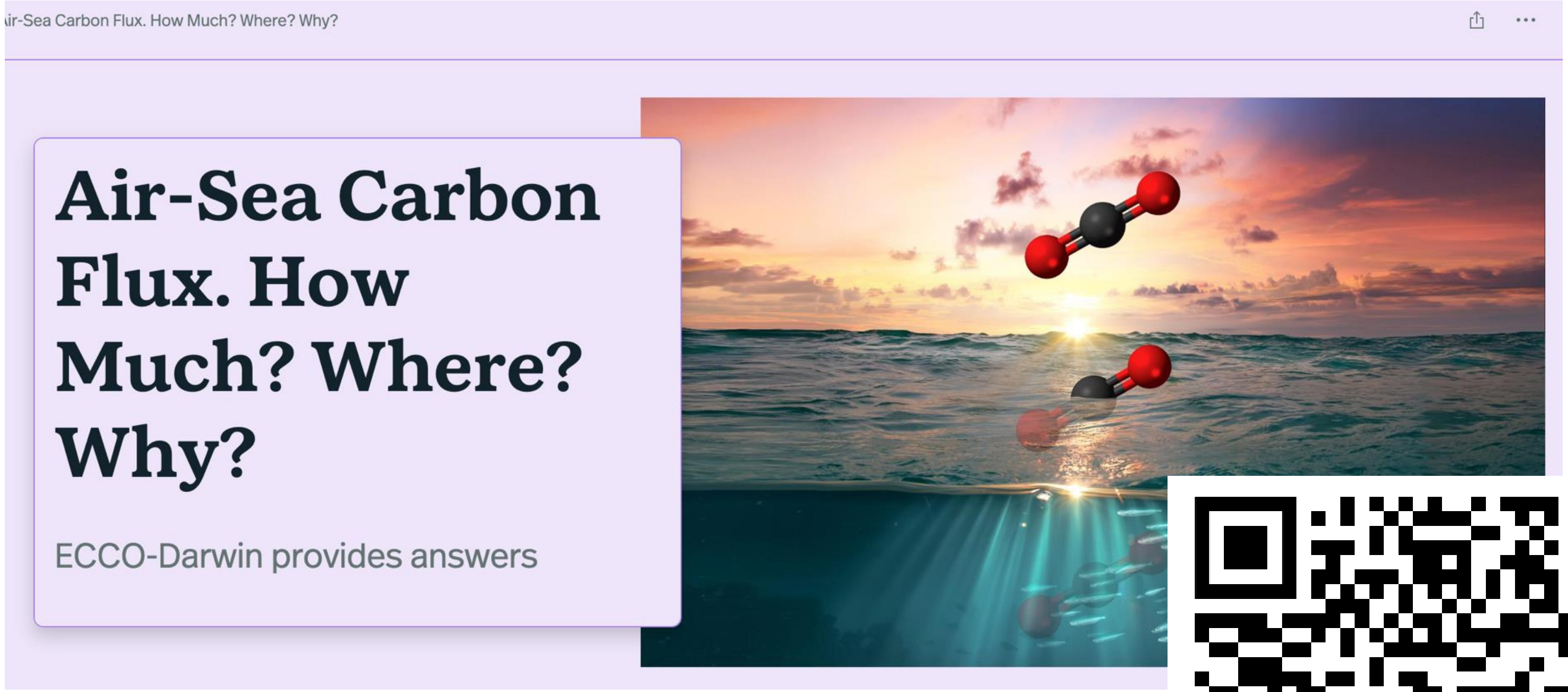
Conclusions

- Variable atmospheric pCO_2 growth rate drives variability in air-sea CO_2 fluxes at all ocean locations, integrating to globally-significant impact
- Climate variability, both internally driven and externally forced, is the dominant driver of variability as spatiotemporal scales become smaller
- Global-mean variability of air-sea CO_2 flux is equally forced by climate and atmospheric growth rate

The implications of our study for real-world ocean observing systems are clear:
in order to detect future changes in the ocean carbon sink due to slowing atmospheric CO_2 growth rates, better observing systems are required.

Check out our arcgis storymap:

NASA storymap available here!



Fish from space: Remote sensing sheds light on the dynamics of mid-trophic levels in the California Current

J. Guiet[1], K. Srinivasan[1], D. Bianchi[1] and C. Wall[2]

[1] University of California Los Angeles

[2] University of Colorado Boulder

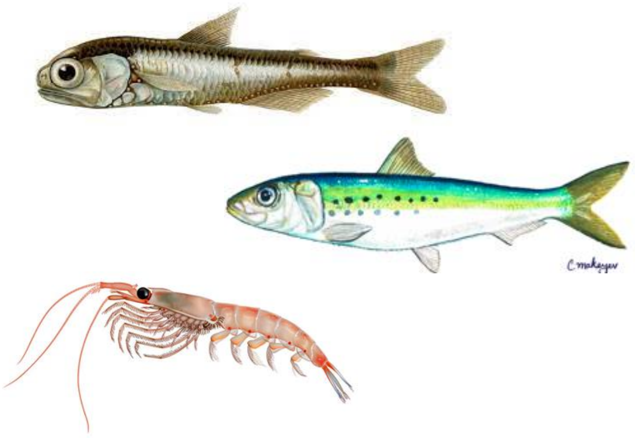
Why mid-trophic levels (MTLs)?

Mid-trophic levels
(MTLs)

- Key component of ecosystems
- Complex dynamics
- Hard to sample

Why mid-trophic levels (MTLs)?

Mid-trophic levels
(MTLs)



- Key component of ecosystems
- Complex dynamics
- Hard to sample

MTLs in EK60
acoustic observation

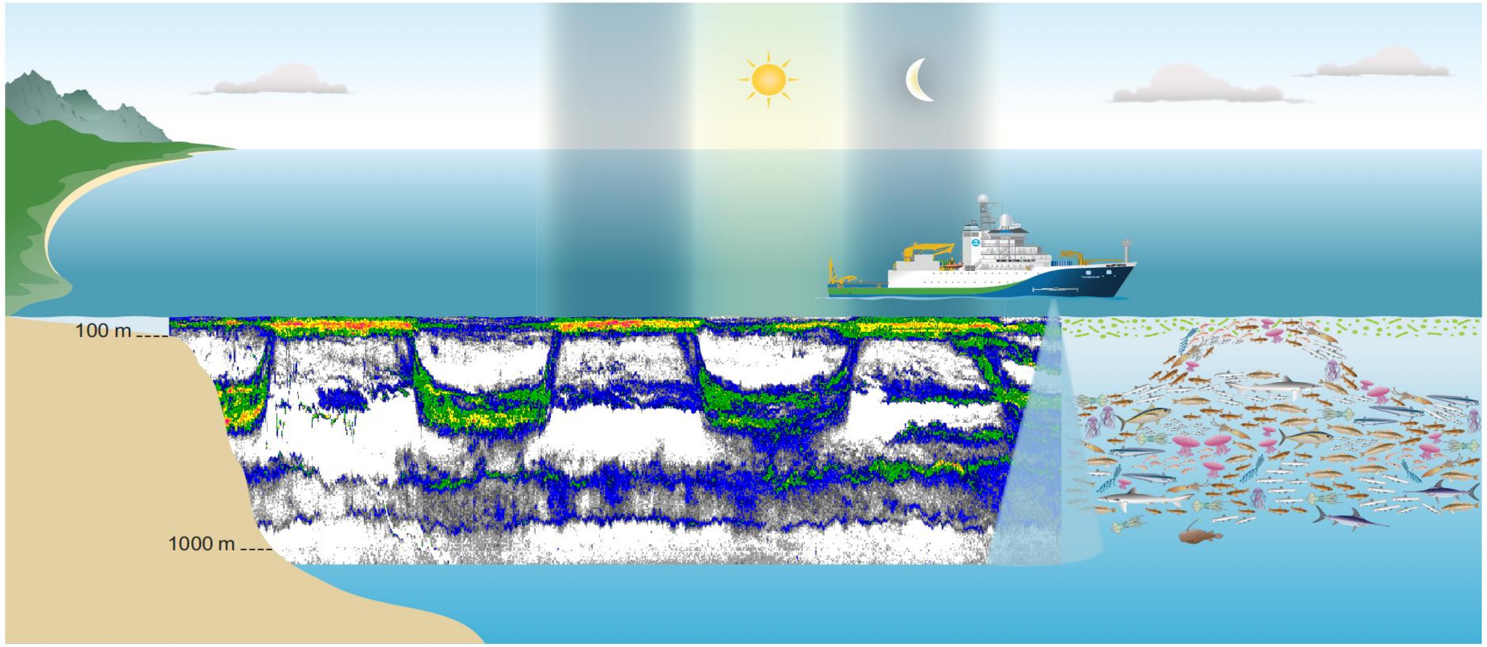
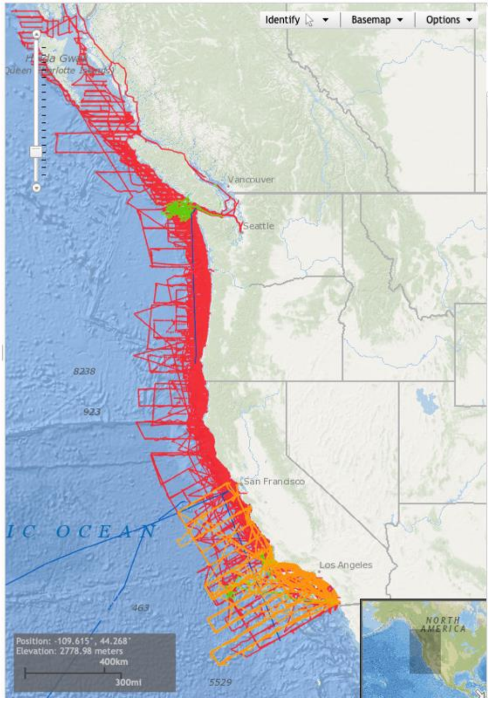


Figure from Haris et al. (2021), *Scientific Data*

How does it relate to remote sensing?

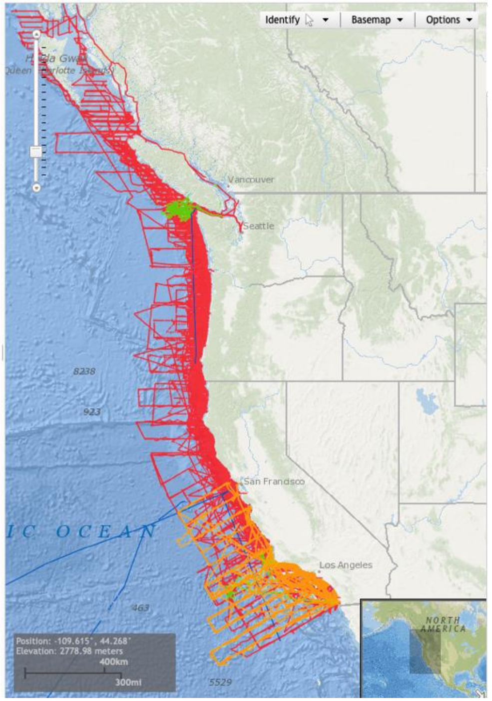
10y of acoustic targets



www.ncei.noaa.gov/maps/water-column-sonar/

How does it relate to remote sensing?

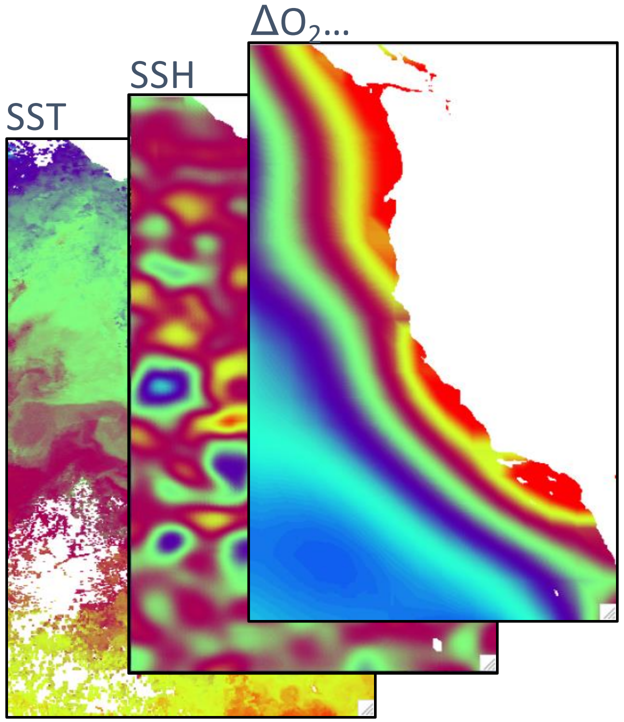
10y of acoustic targets



www.ncei.noaa.gov/maps/water-column-sonar/

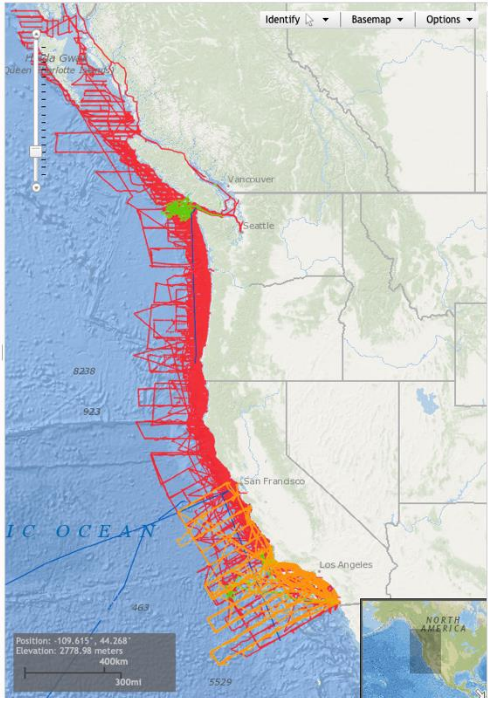
+

Environmental features (17)



How does it relate to remote sensing?

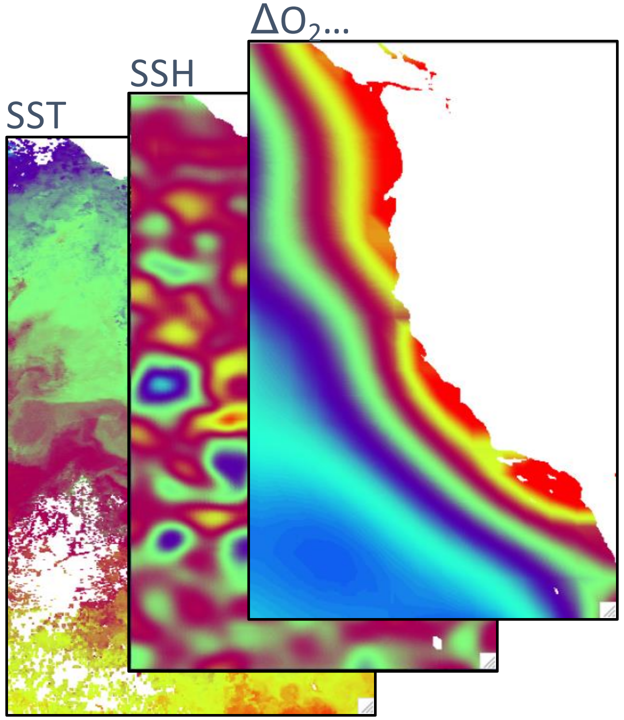
10y of acoustic targets



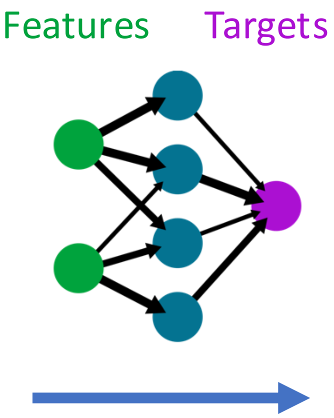
www.ncei.noaa.gov/maps/water-column-sonar/

\+

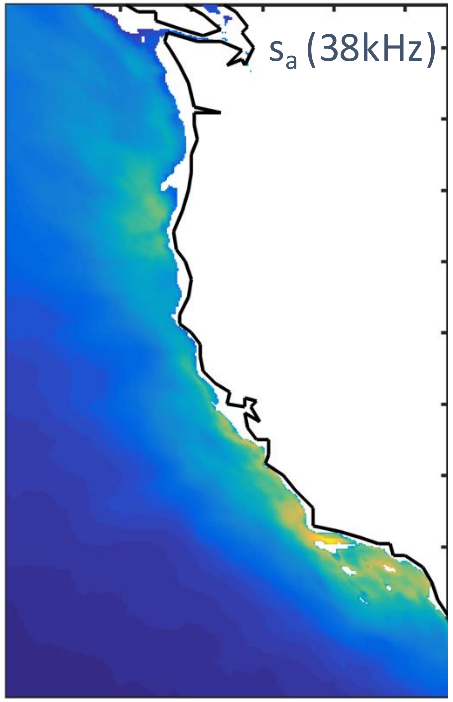
Environmental features (17)



Neural Networks

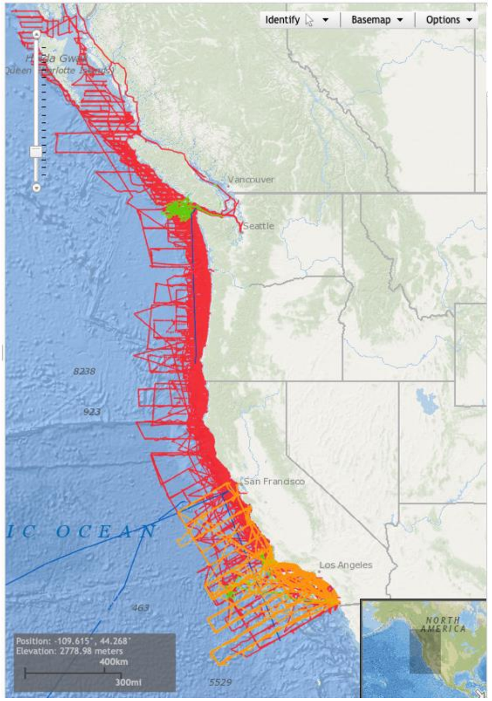


MTLs' dynamics



How does it relate to remote sensing?

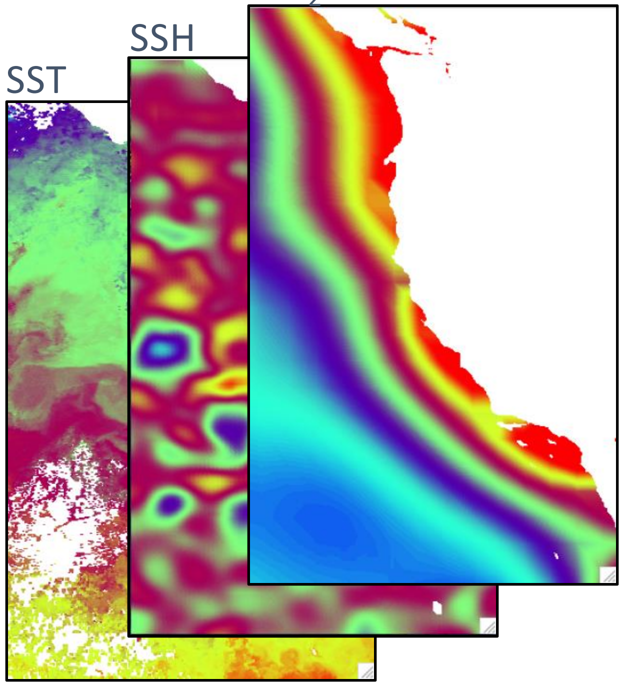
10y of acoustic targets



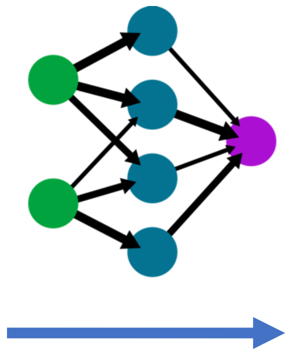
www.ncei.noaa.gov/maps/water-column-sonar/

\+

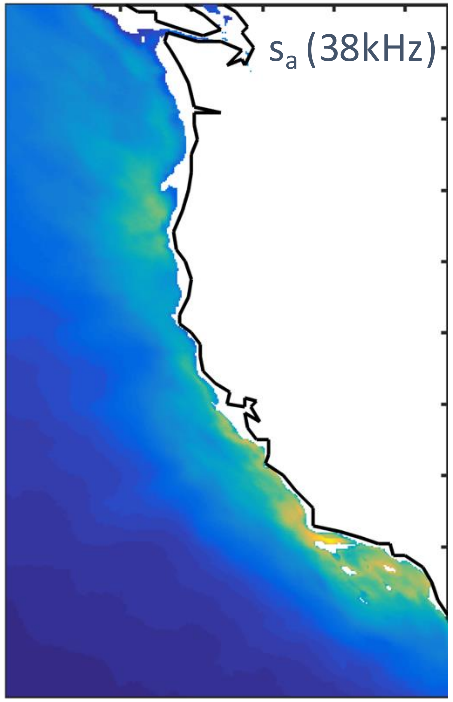
Environmental features (17)



Neural Networks



MTLs’ dynamics



Acoustic and remote sensing data fusion using machine learning can provide new perspectives on the dynamics of MTLs’?

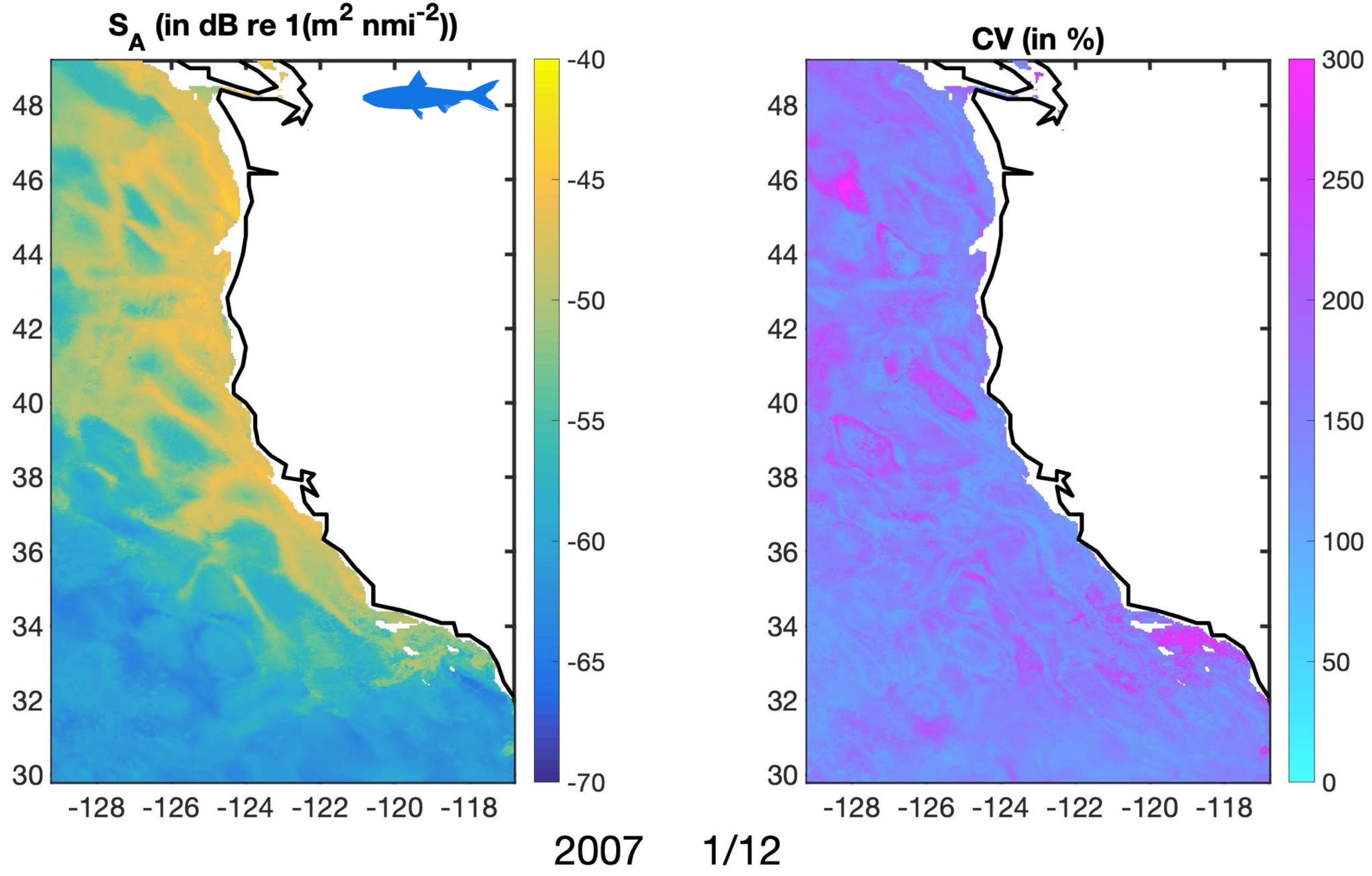
Focus on the California Current Ecosystem (CCE)

10 years of surface acoustic reconstruction in the California Current

Reconstruction from 17 features

+

Matching acoustic observation



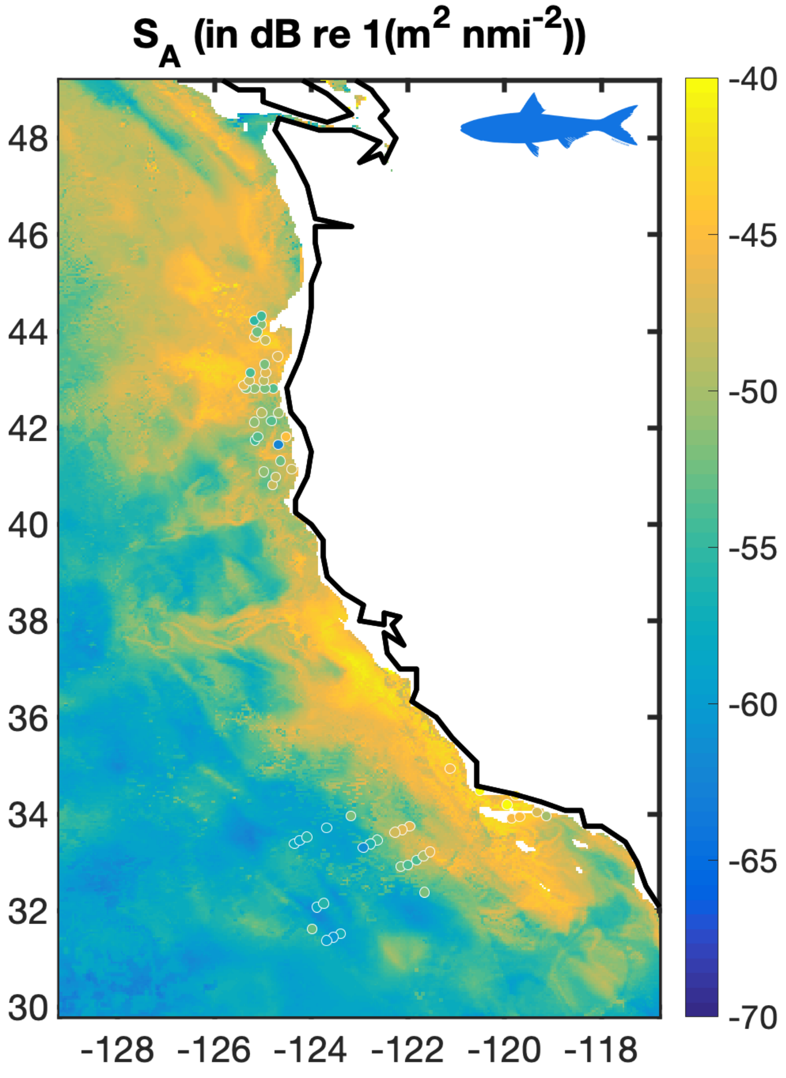
NN models ensemble uncertainty

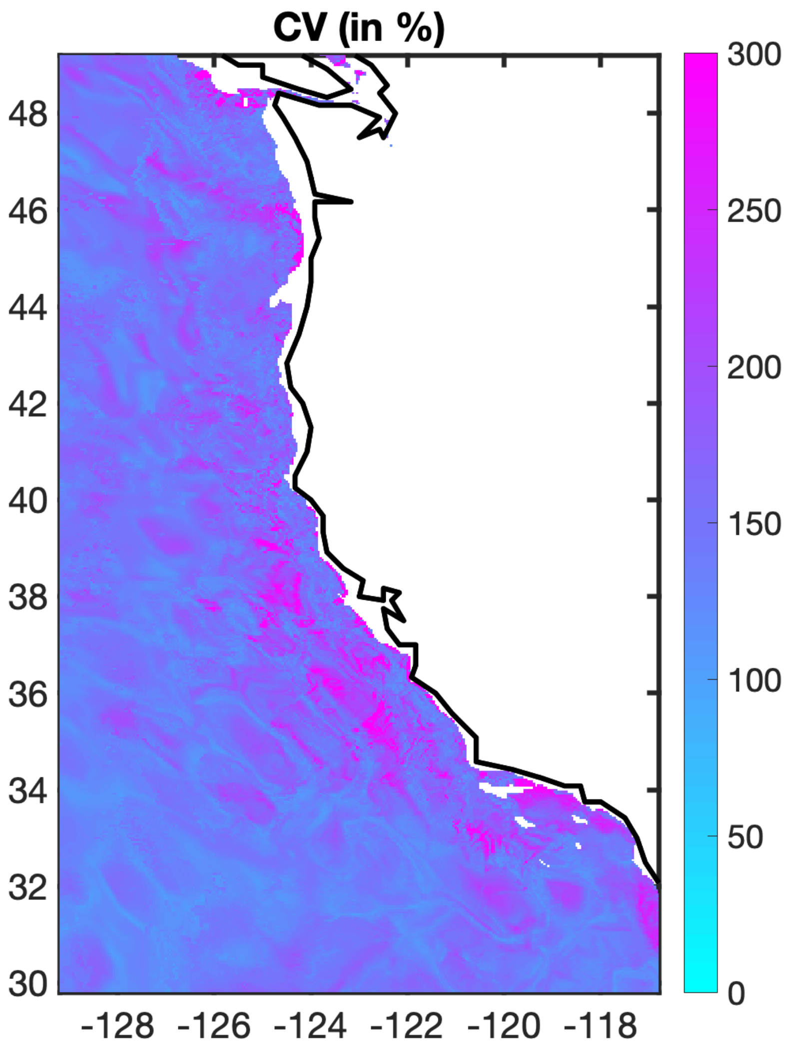
10 years of surface acoustic reconstruction in the California Current

Reconstruction from 17 features

\+

Matching acoustic observation





els

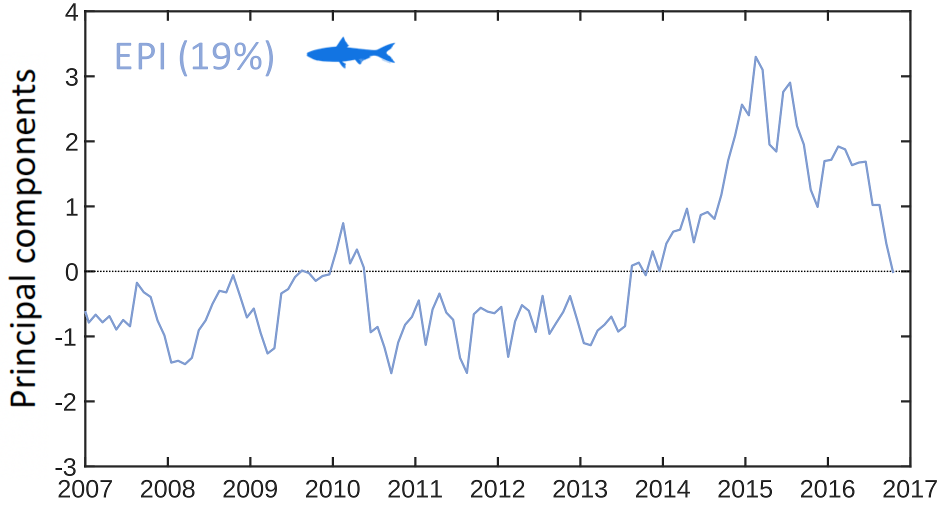
le

nty

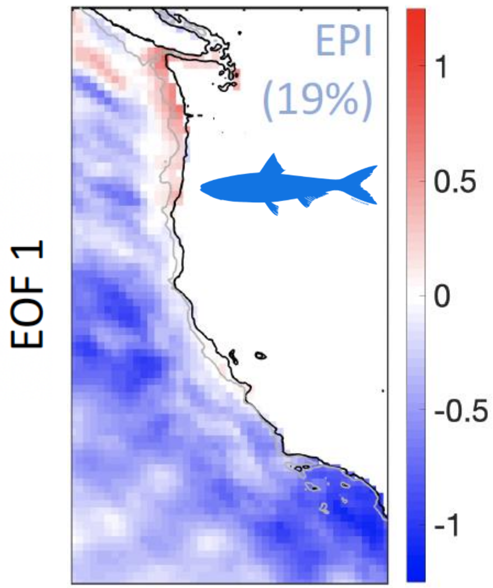
Acoustic reconstruction capture multiple MTLs dynamics, but with extrapolation limitations

Interannual variability of acoustic reconstructions

First principal component



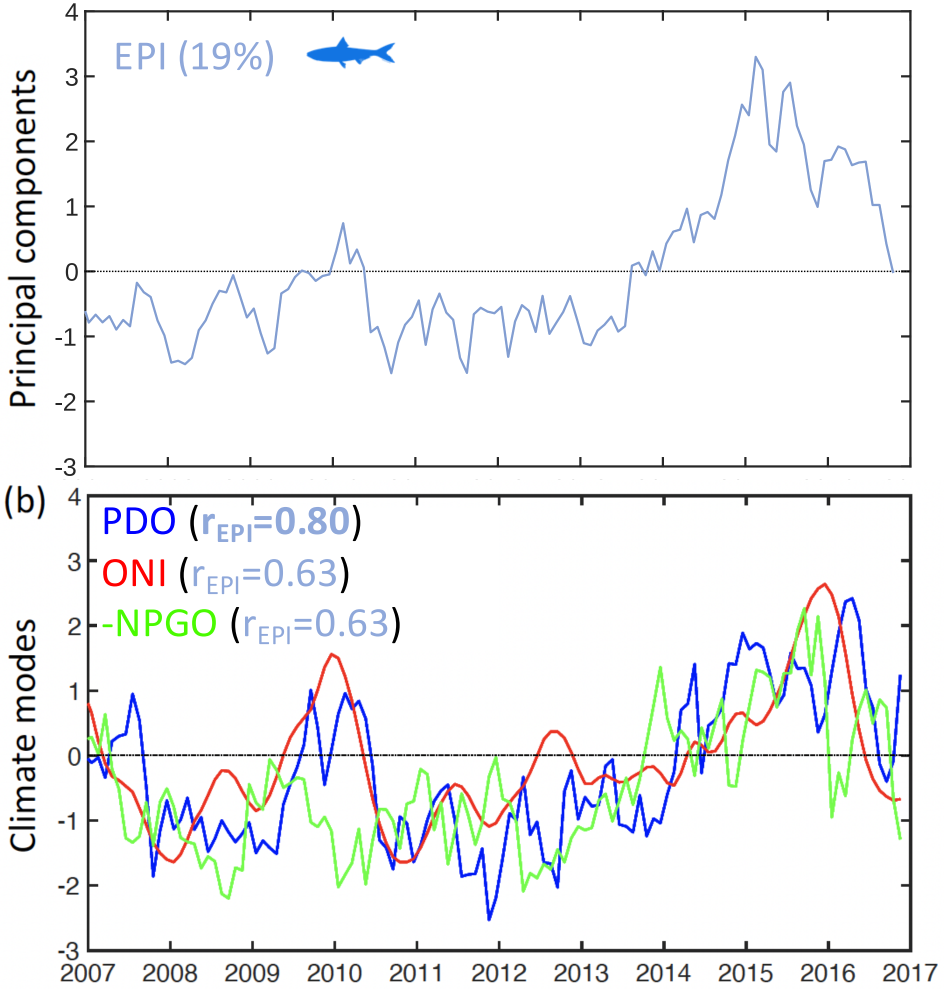
First EOF



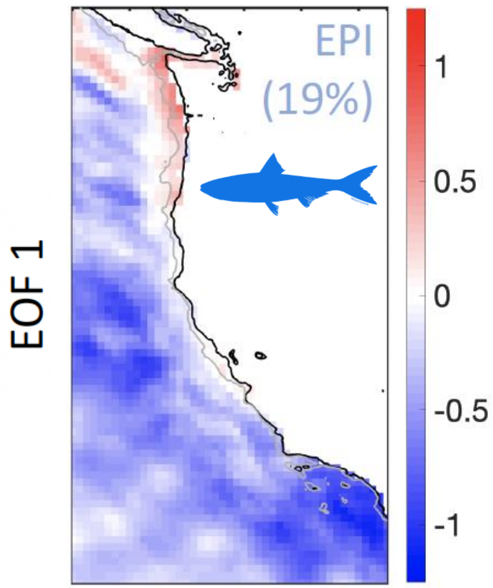
Offshore/southward expansion during negative phases (expected)

Interannual variability of acoustic reconstructions

First principal component vs. climate modes



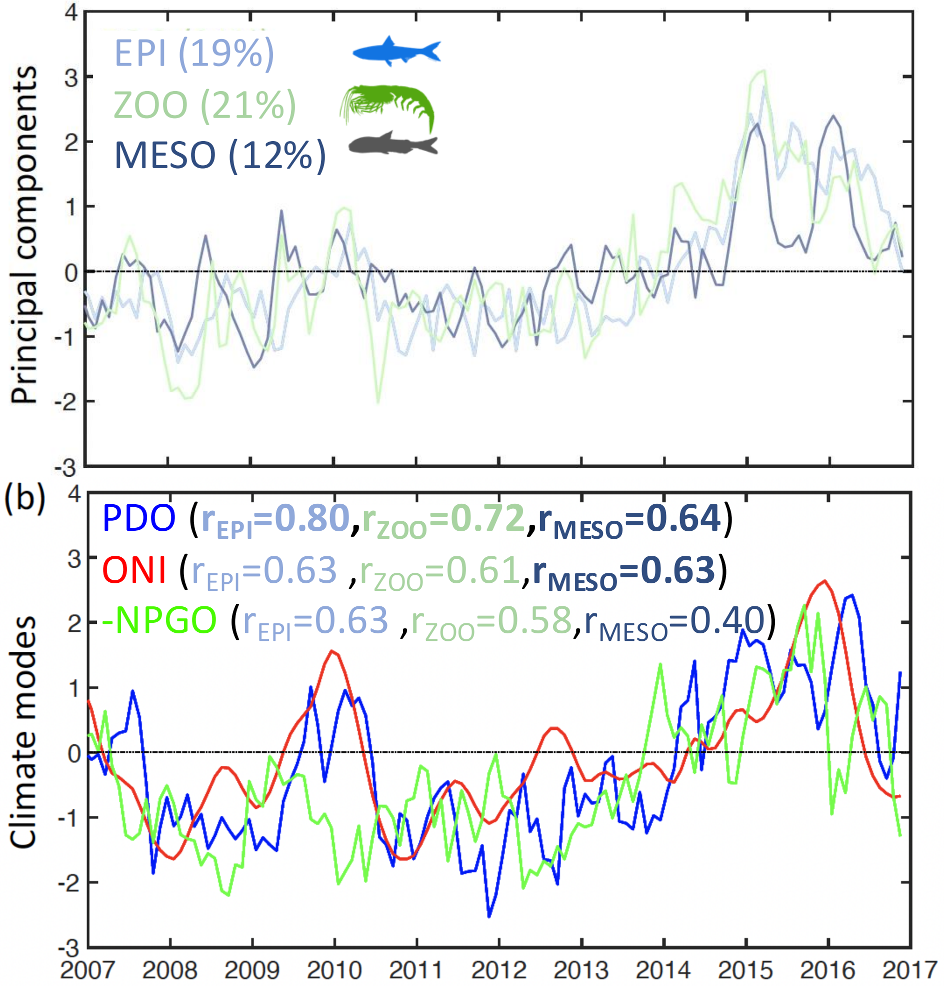
First EOF



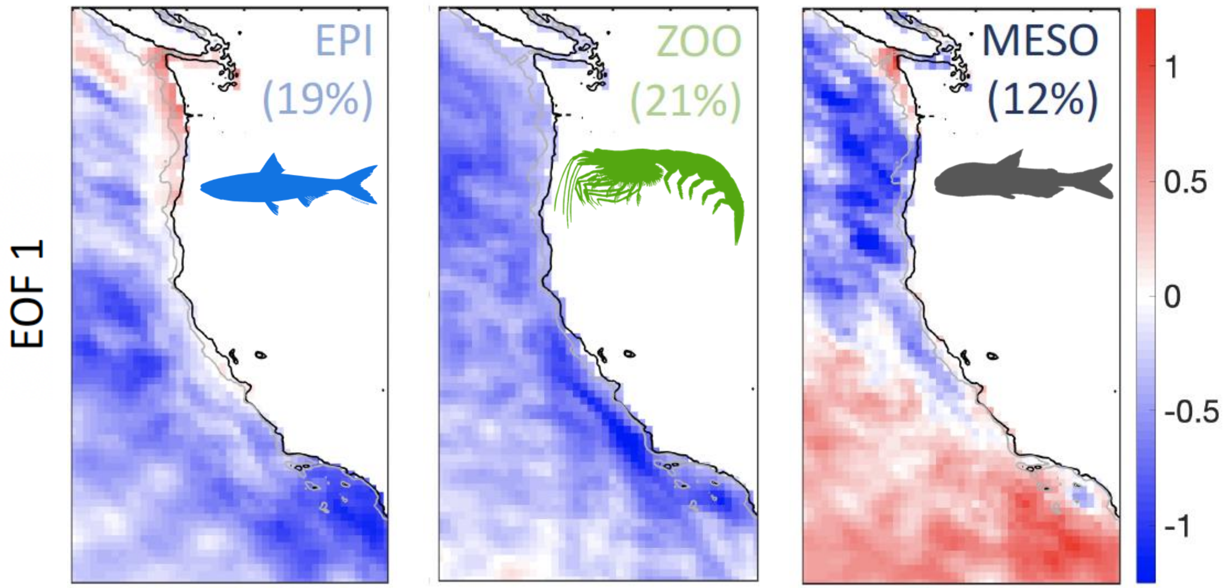
Offshore/southward expansion during negative PDO phases (expected)

Interannual variability of acoustic reconstructions

First principal component vs. climate modes



First EOF



Offshore/southward expansion during negative PDO phases (expected)

Increase in central California during negative PDO phases

North/South shift during negative PDO/ONI phases

Conclusion

Fusion remote sensing acoustic observation allow reconstruction of MTLs' backscatter

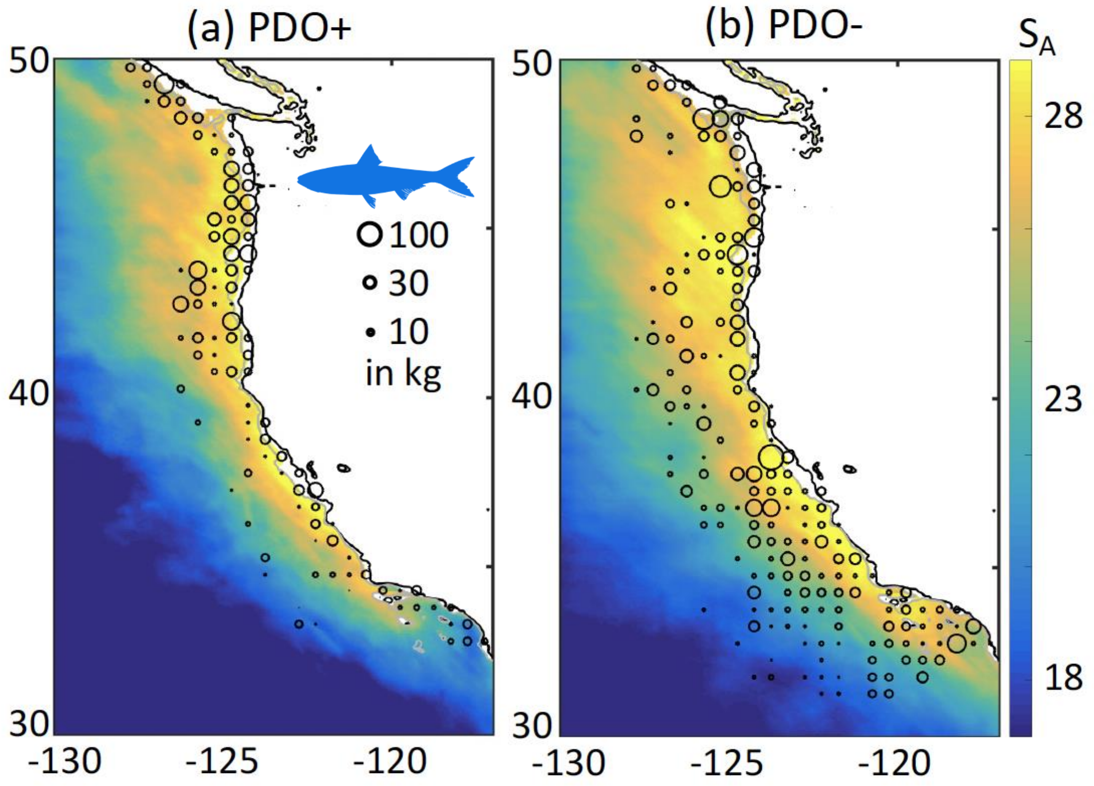
Conclusion

Fusion remote sensing acoustic observation allow reconstruction of MTLs' backscatter

Inter-annual acoustic variability captures expected dynamics of MTLs

- e.g. inter-annual variability of epipelagic fish distribution

Acoustics vs. biomass



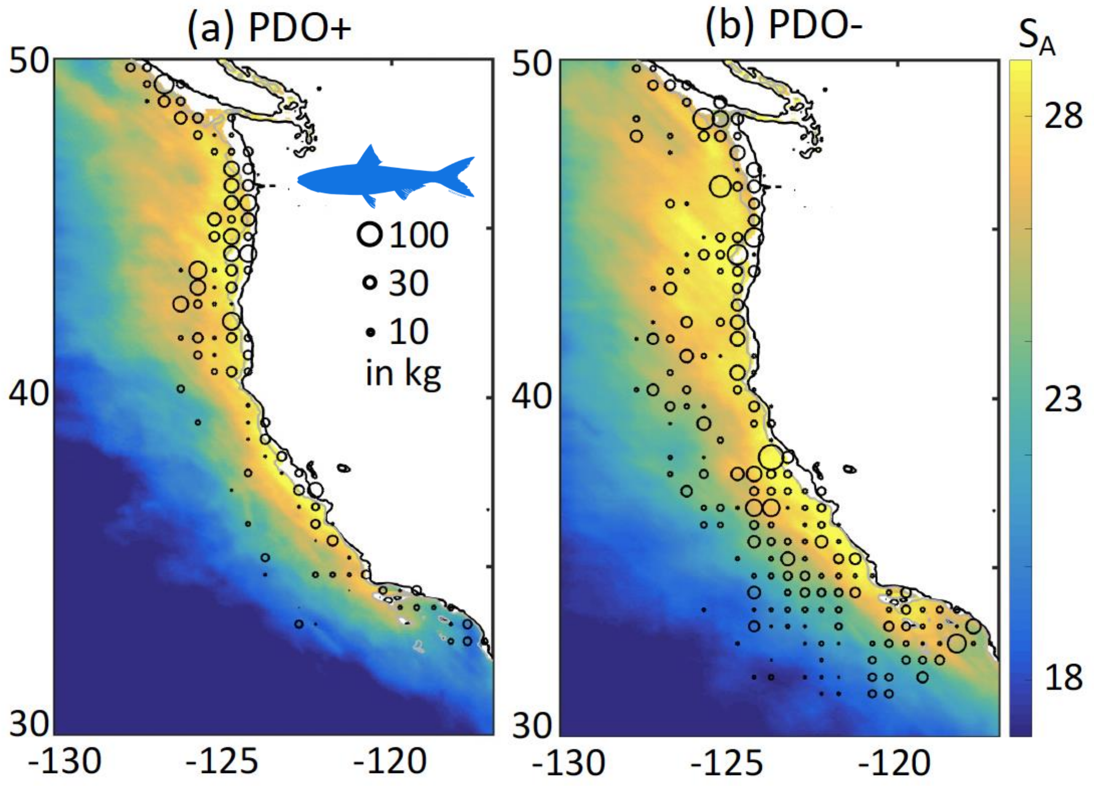
Conclusion

Fusion remote sensing acoustic observation allow reconstruction of MTLs' backscatter

Inter-annual acoustic variability captures expected dynamics of MTLs

- e.g. inter-annual variability of epipelagic fish distribution

Acoustics vs. biomass



Next step: Explore dynamics in other regions (Gulf of Alaska, Central Pacific Ocean), across ocean depth layers, improve connection with MTLs biomass and particle export.

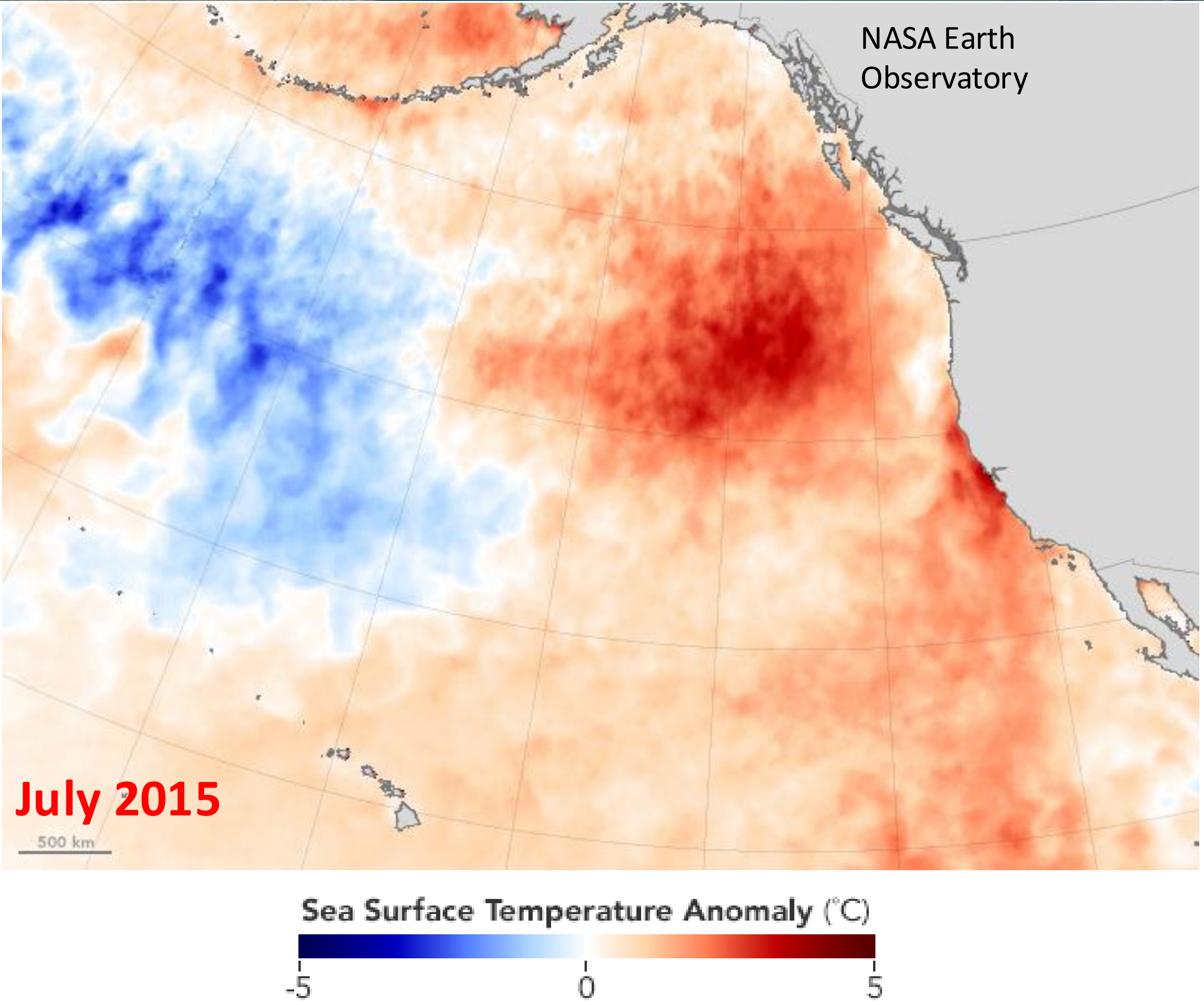
Impact of Pacific Ocean Heatwaves on Phytoplankton Composition and Export Production

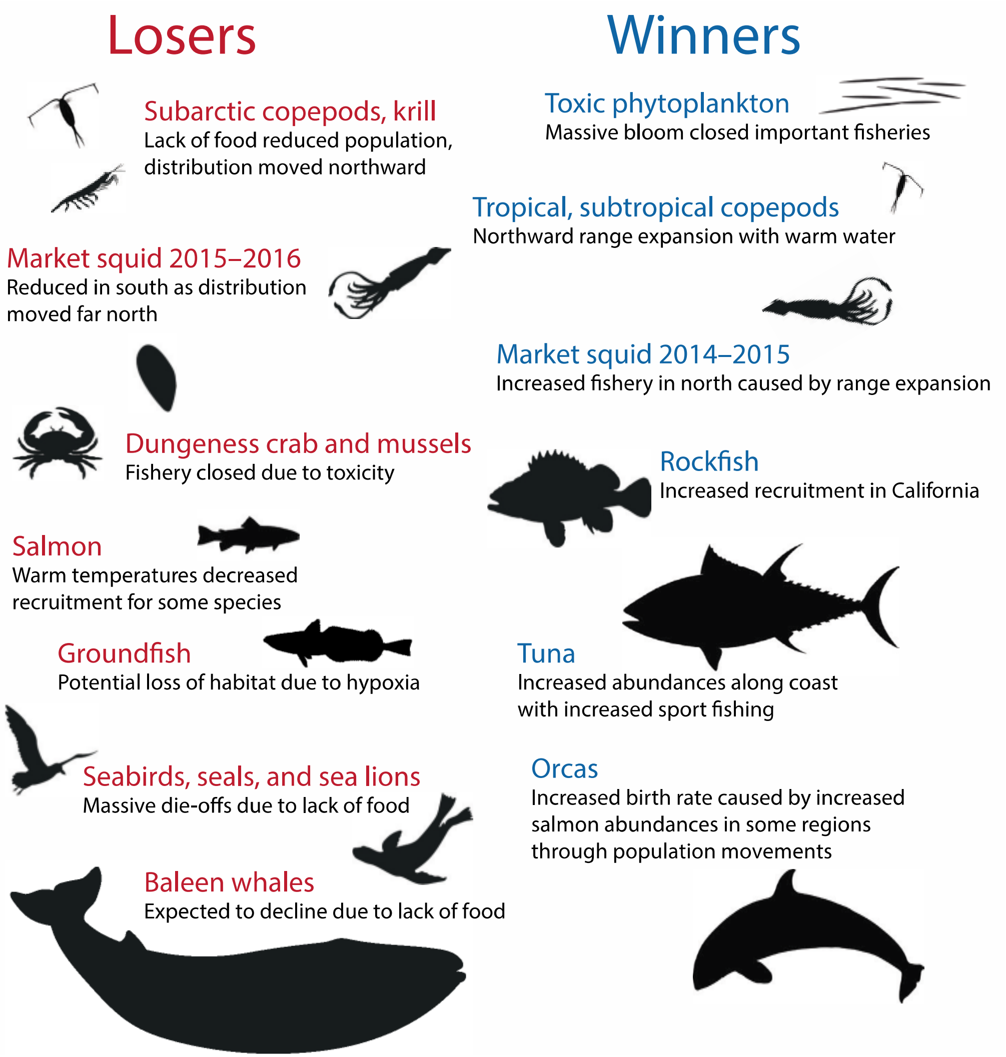
Lionel A. Arteaga

Global Modeling and Assimilation Office (NASA GSFC) / UMBC

Ocean Biology and Biogeochemistry virtual meeting 2024

Ecosystem consequences

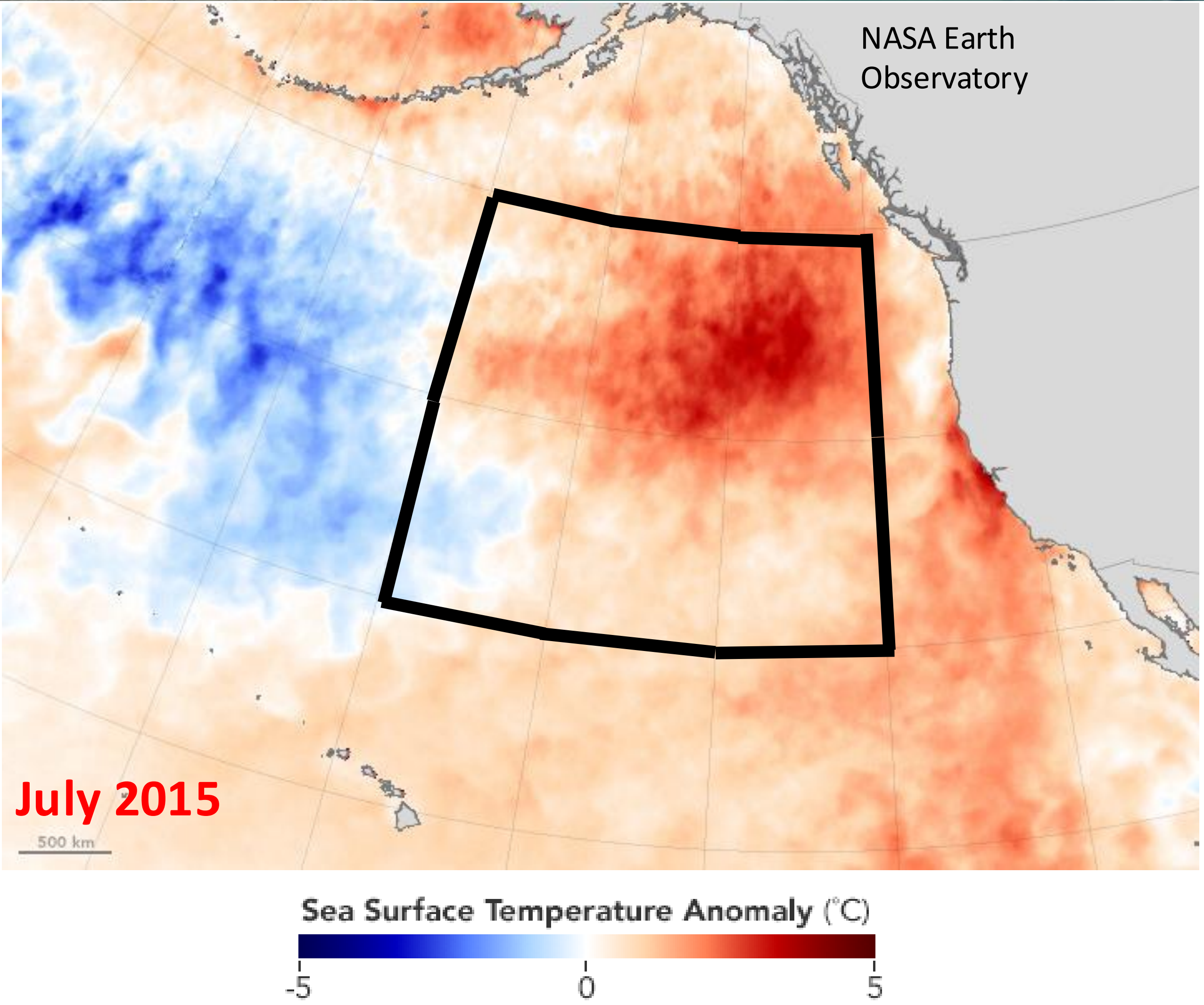


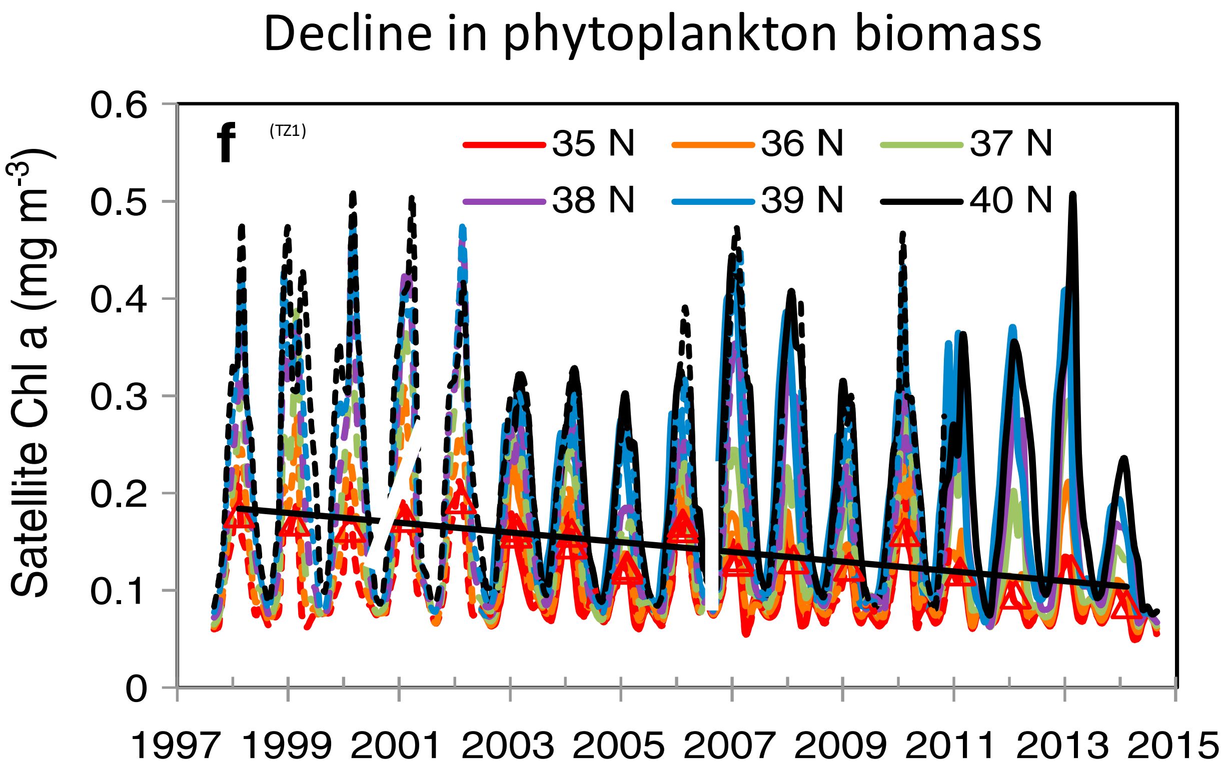


Cavole et al. (2016)

GODDARD EARTH SCIENCES

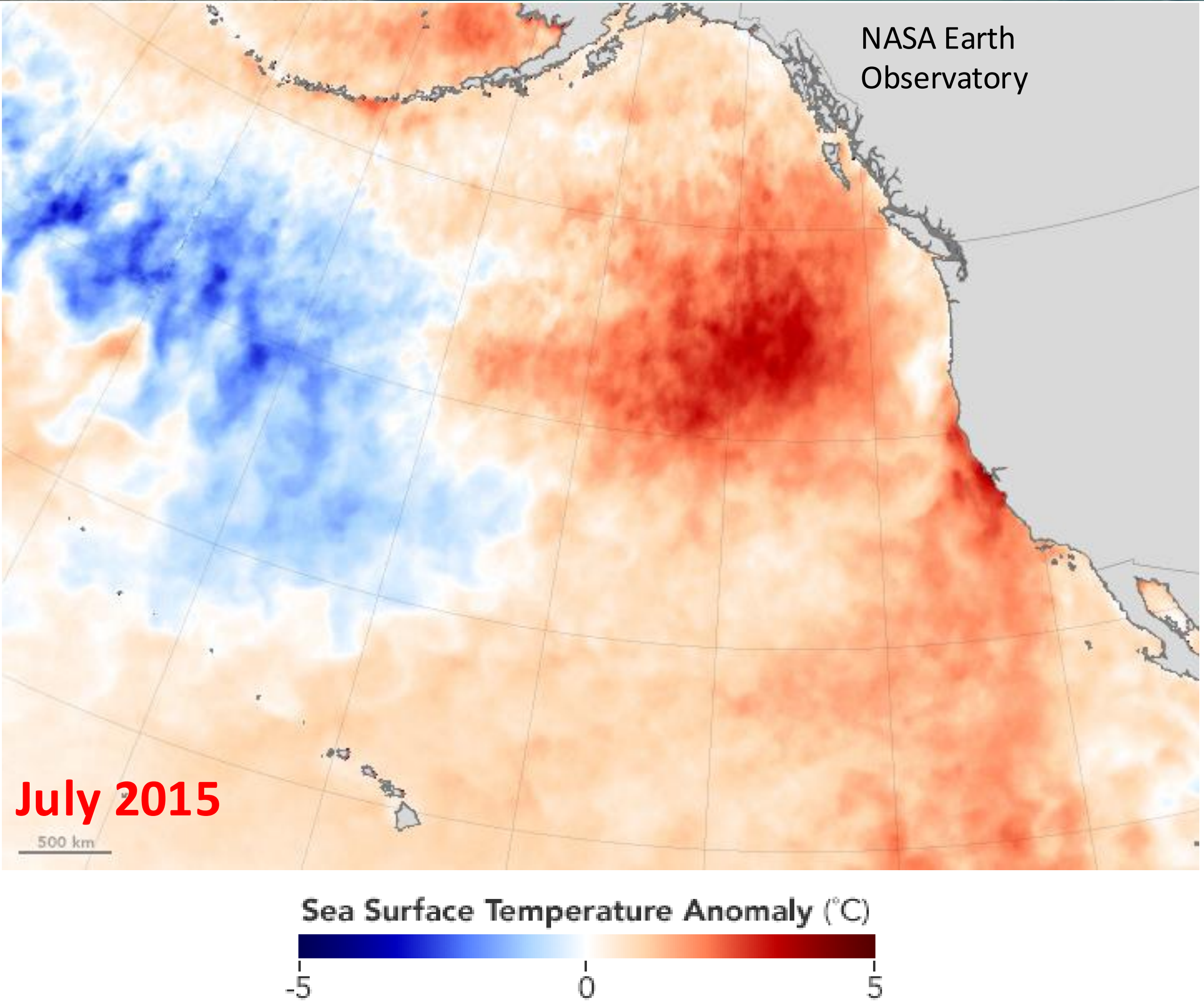
Decline in chlorophyll stock





Whitney (2015)

NASA Ocean Biogeochemical Model (NOBM)



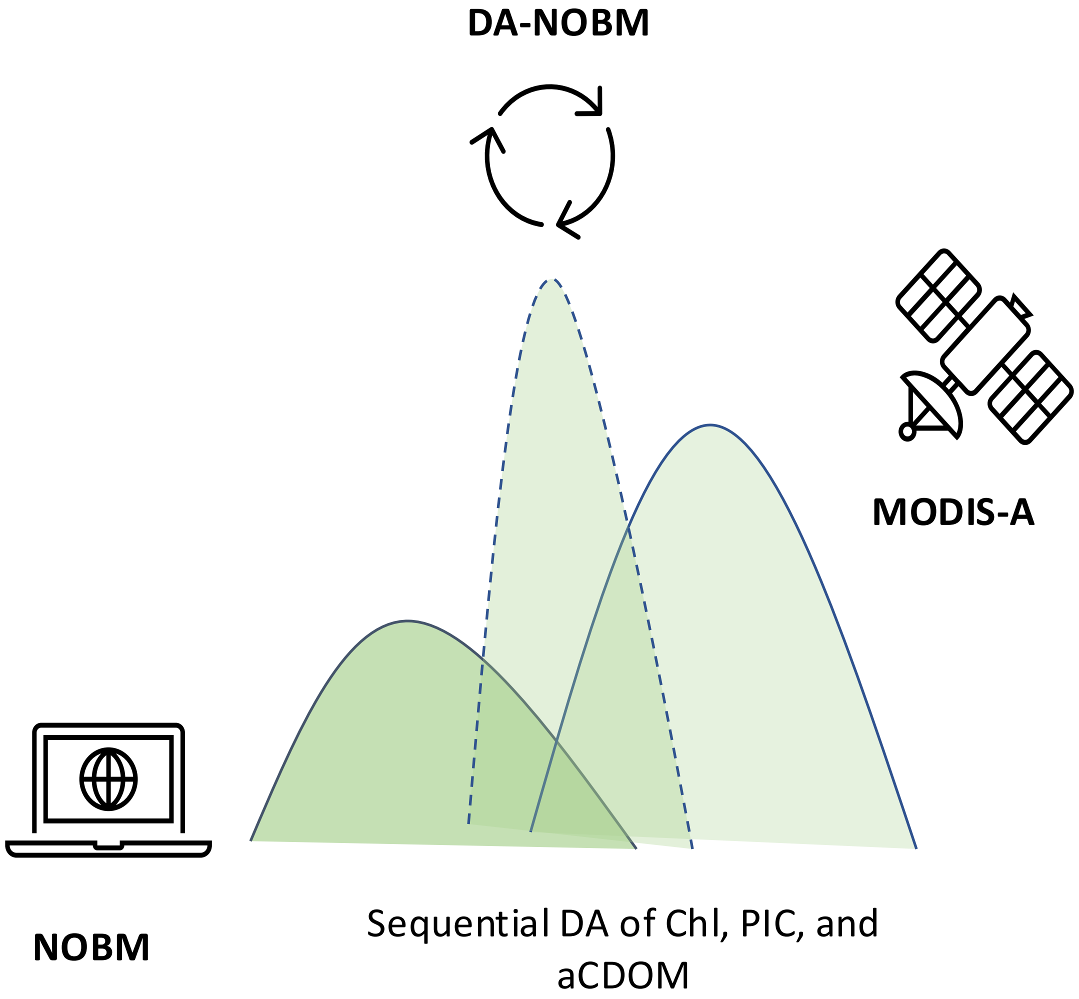
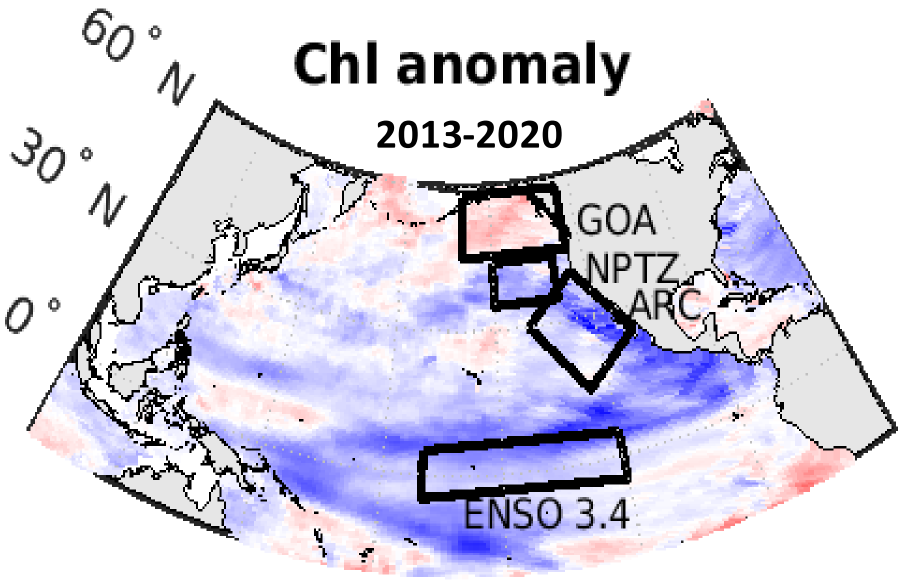


Figure from Arteaga and Rousseaux

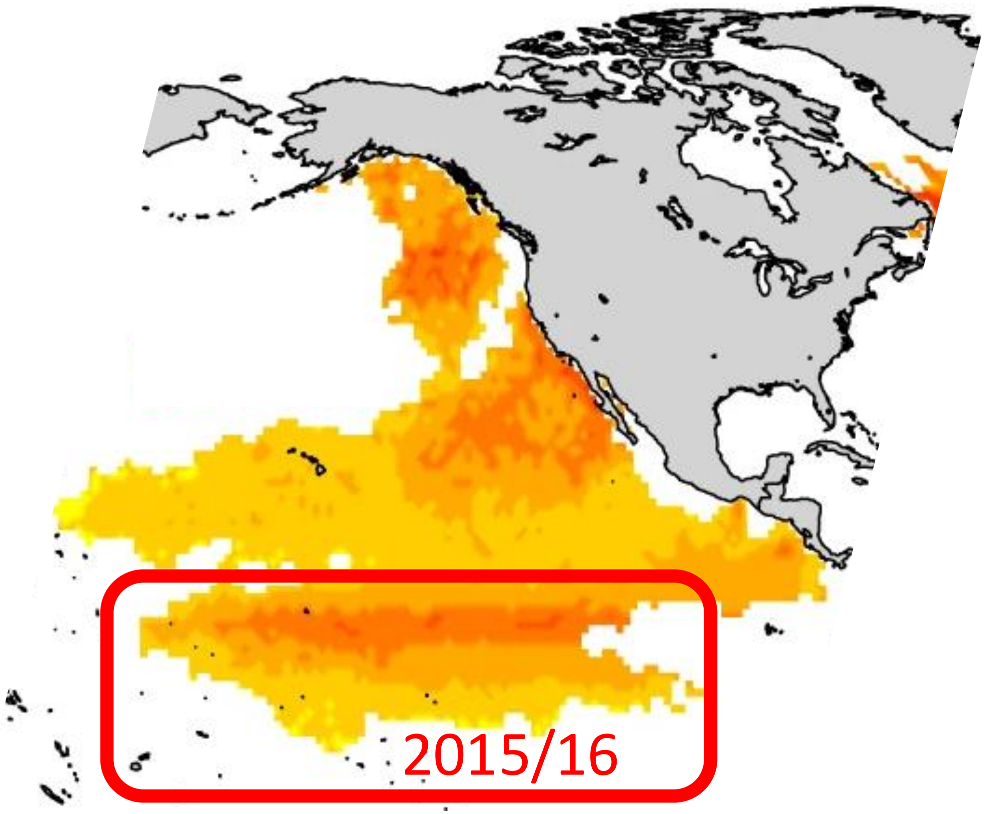
Main findings

Main findings

Original target study areas



Arteaga and Rousseaux (2023)

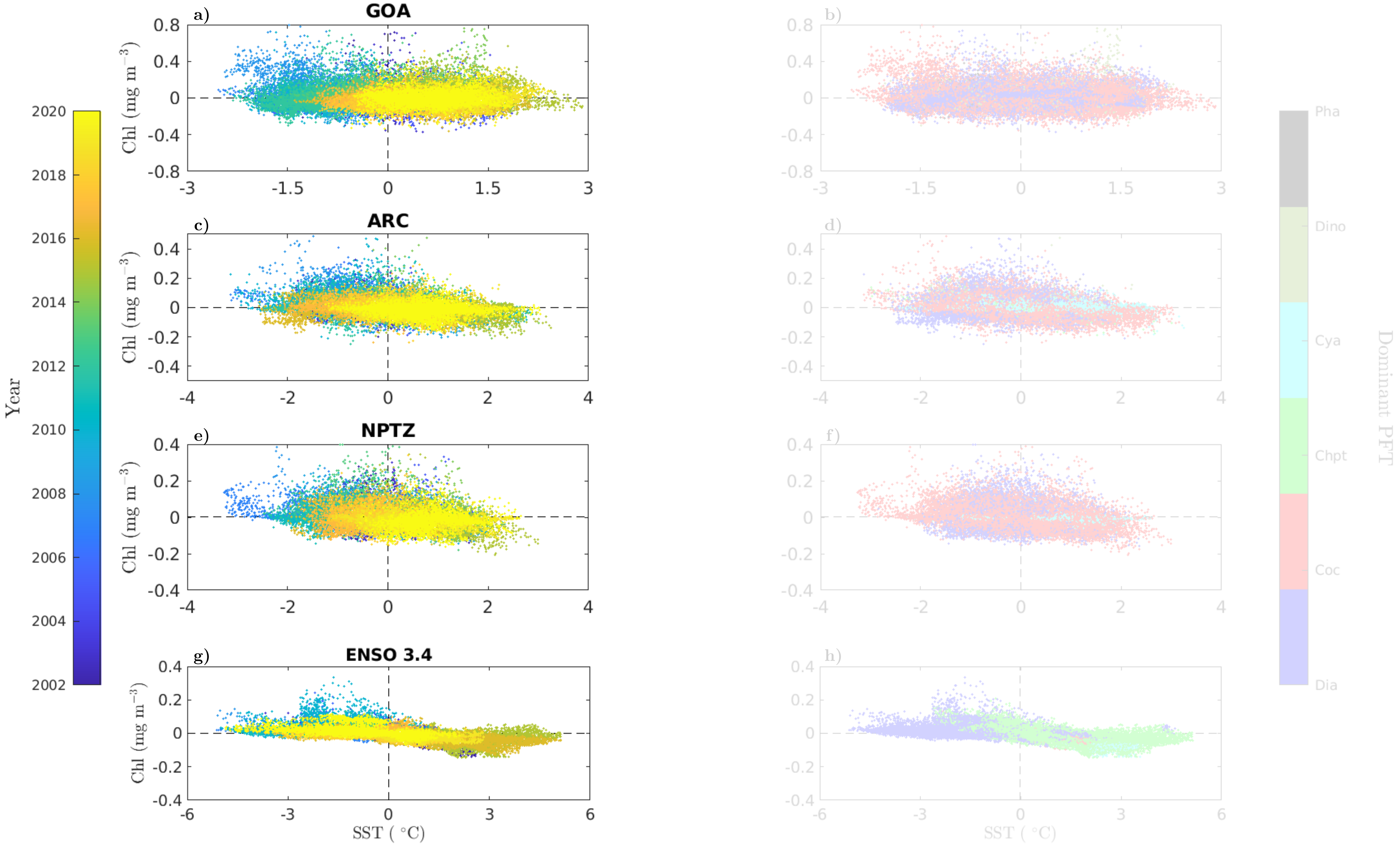


ENSO 3.4: A decline of 40 % in mean surface chlorophyll was associated to a near full collapse in diatoms.

Figure from Laufkötter et al. (2020)

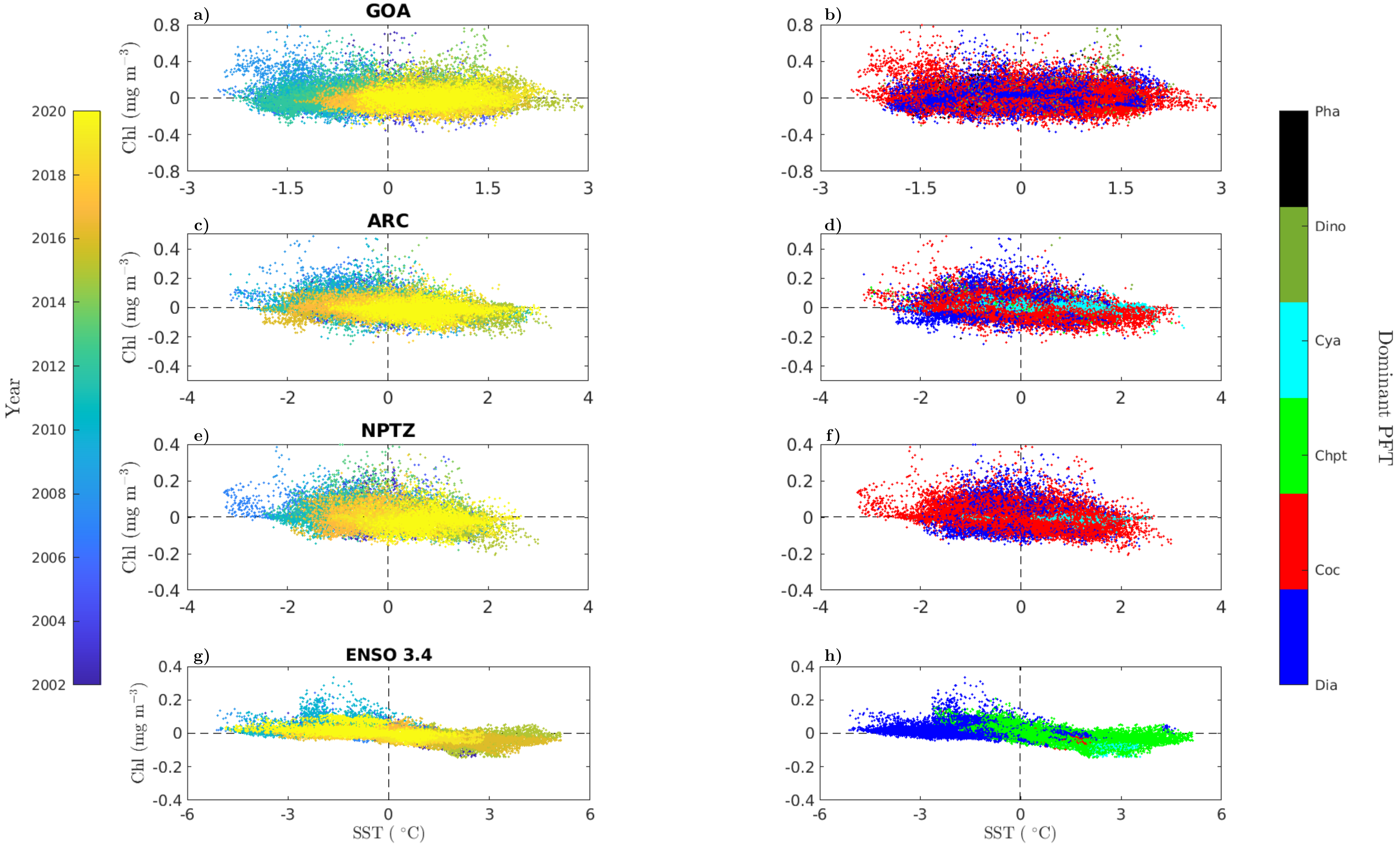
GODDARD EARTH SCIENCES

Changes in phytoplankton community



Arteaga and Rousseaux (2023)

Changes in phytoplankton community



Arteaga and Rousseaux (2023)

Conclusions

Perturbations: Need to be of a greater magnitude than those imposed by the natural climate variability of the seasonal cycle or create a unique imbalance to elicit a clear change in the phytoplankton community composition.

Equatorial Pacific: A decline of 40 % in mean surface chlorophyll was associated to a near full collapse in diatoms. This was driven by strong nutrient limitation as a consequence of low deep water upwelling.

Carbon export: The decline in biomass is mirrored in modeled export and is also observed in independent mapped products of particle backscatter and oxygen utilization derived from BGC-Argo floats. *To be continued*

Postdoc position available to work on heatwaves and carbon export at NASA GSFC

(https://gestar2.umbc.edu/jobs-at-gestar-ii/postdoctoral-research-scientist-position-ocean-biogeochemical-modeling/)

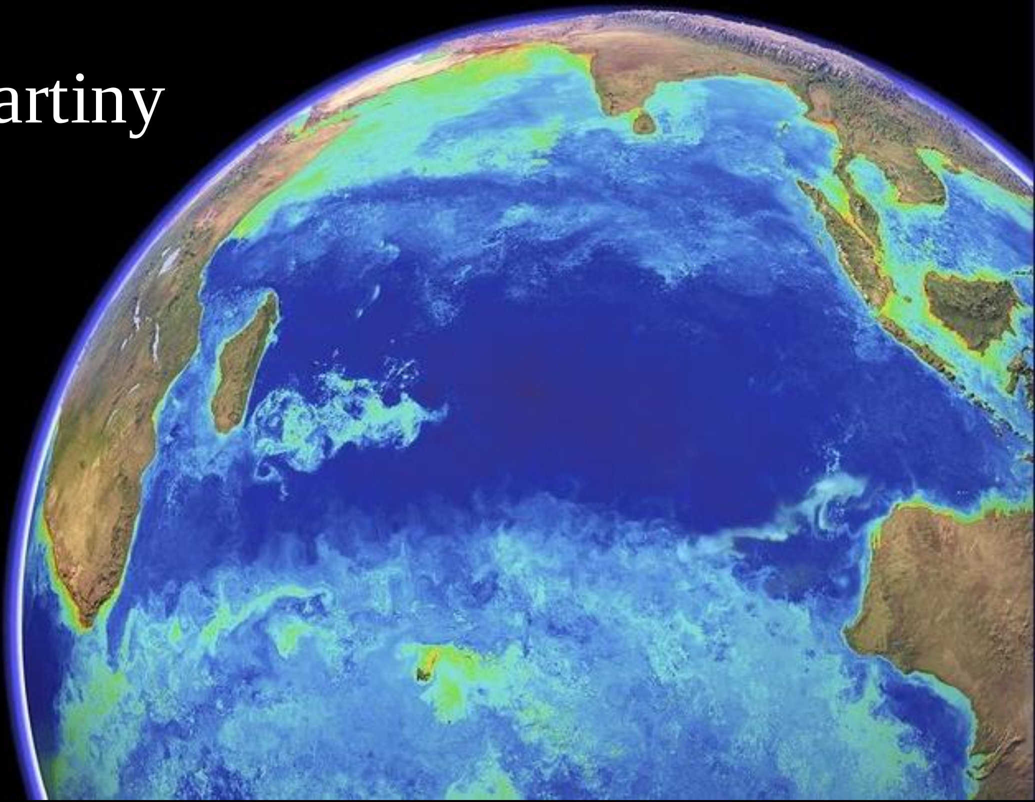
INTEGRATING PHYTOPLANKTON GENOMICS AND REMOTE SENSING TO DETECT IRON STRESS FROM SPACE

Amy Nuno

Advised by: Adam Martiny

UC Irvine

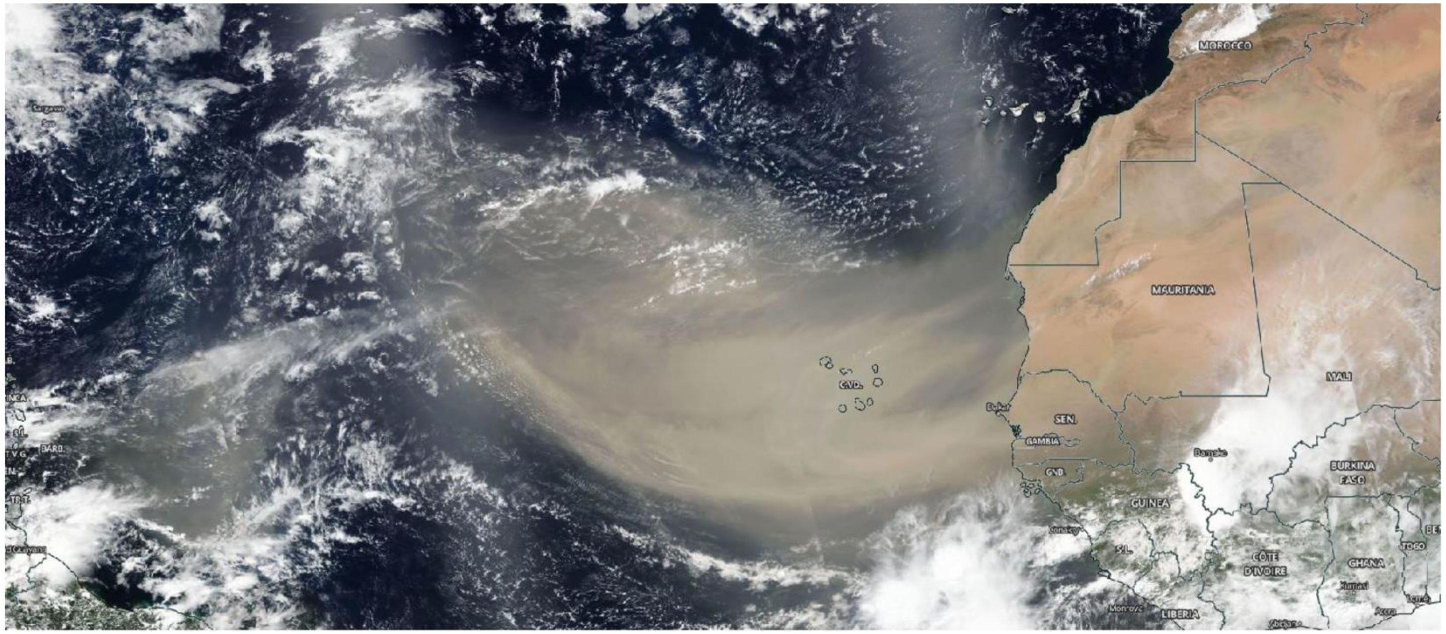
Collaboration with
Toby Westberry and
Mike Behrenfeld
from Oregon State
University



Background

Sources of Iron

- Primary sources of iron
  - Aeolian dust deposition
  - Deep vertical mixing

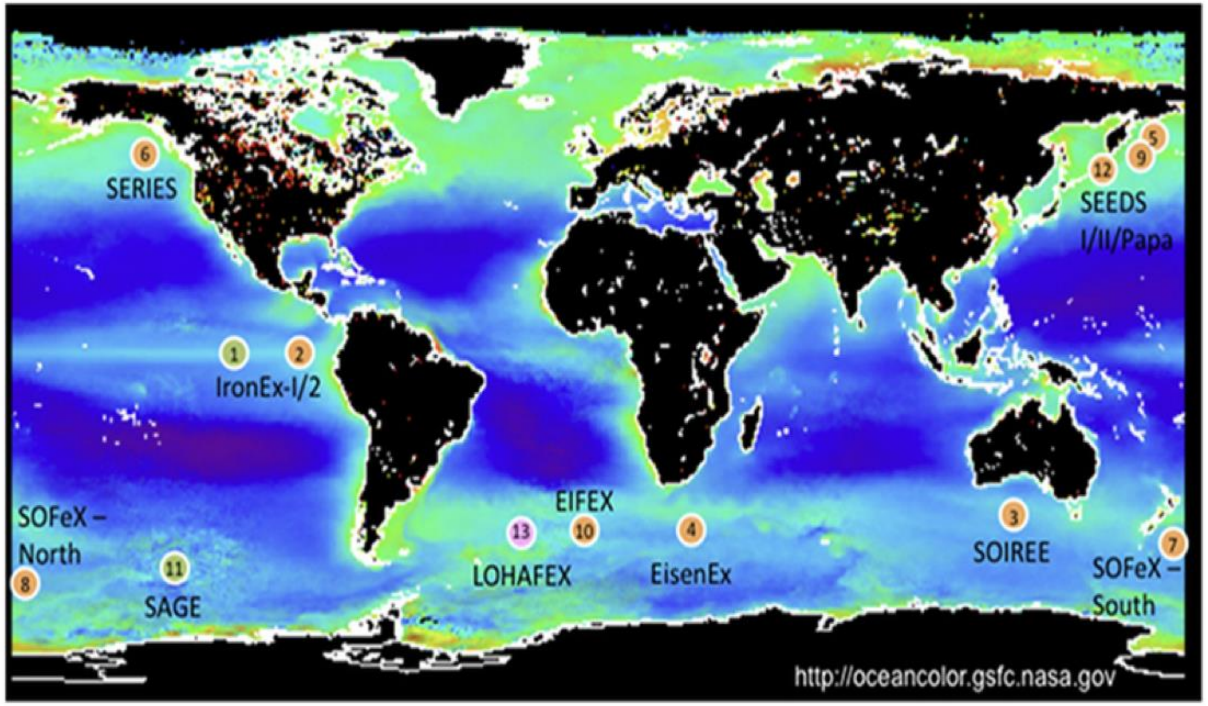


Source: NASA Earth Observatory

Background

Phytoplankton Iron Limitation

- Well-known Iron-limited regions
  - High nutrient, low chlorophyll
  - Validates through *in-situ* iron fertilization experiments
- Seasonally iron-limited regions
- Oligotrophic regions are not well-constrained



Source: https://doi.org/10.4236/ajcc.2019.81002

Background

Phytoplankton Iron Limitation Physiology

- Iron found in both Photosystem I (PSII) and Photosystem II (PSI)
- Under iron limitation, we observe increased fluorescence
  - Increase in the PSII: PSI ratio
  - Disconnected light-harvesting complexes present in HNLC conditions
- Fluorescence can be quantified using the MODIS-Aqua satellite
  - Bands 13 (660 nm), 14 (670 nm), and 15 (750 nm)

Behrenfeld & Milligan, 2013

Methods

Derivation of the Fluorescence Quantum Yield (Φsat)

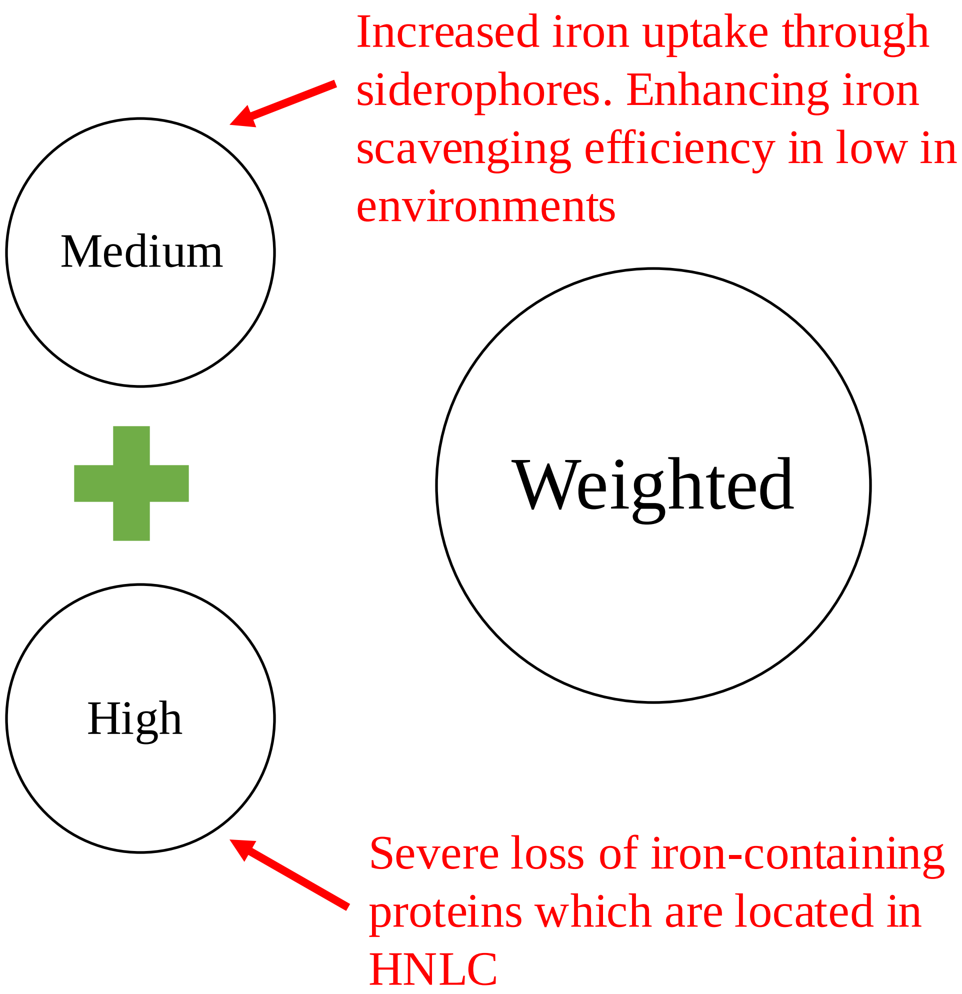
- Isolating signal due to iron limitation in satellite fluorescence
- Three Key Factors Influencing Fluorescence:
  1. **Chlorophyll concentrations**
  2. **Pigment packaging effects on light absorption**
  3. **Non-photochemical quenching**
- Fluorescence Quantum Yield (Φsat):
  - Likelihood that absorbed light energy is emitted as fluorescence rather than used in photochemistry or lost as heat.
  - Formula:
    - $$\Phi sat = \frac{\text{Fluorescence photons}}{\text{Absorbed photons}}$$

- Data Sources
  - MODIS nFLH, Chlorophyll-a, and iPAR
- Methodology
  - Follow Behrenfeld et al., 2009 to calculate Φsat.
  - Apply additional corrections

Methods

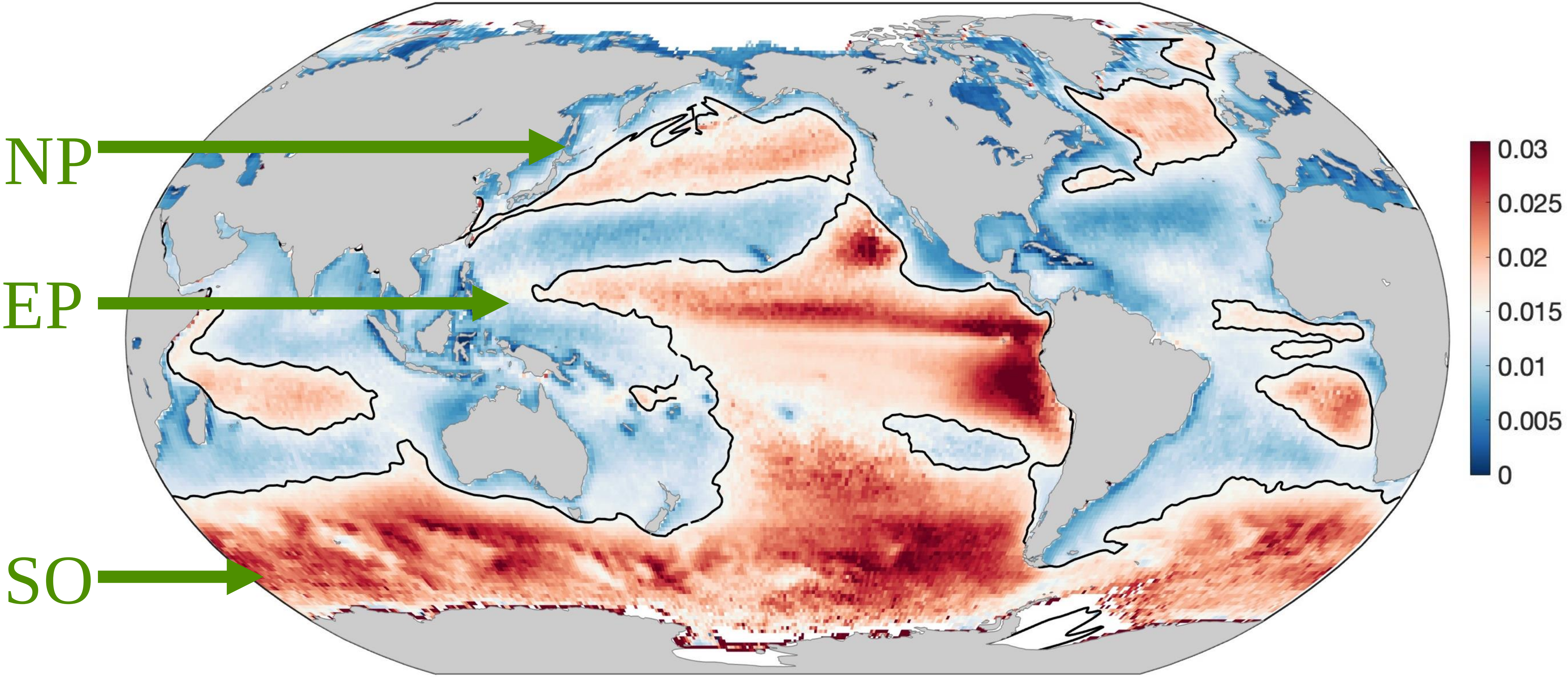
Validation of Φsat with Genomic Iron Stress Biomarkers

- Validate Φsat with
    1. *In-situ* genomics
    2. Bottle experiments
    3. *In-situ* nutrient concentrations
    4. Iron stress models
- Genomics and Φsat were matched spatially and temporally



Results

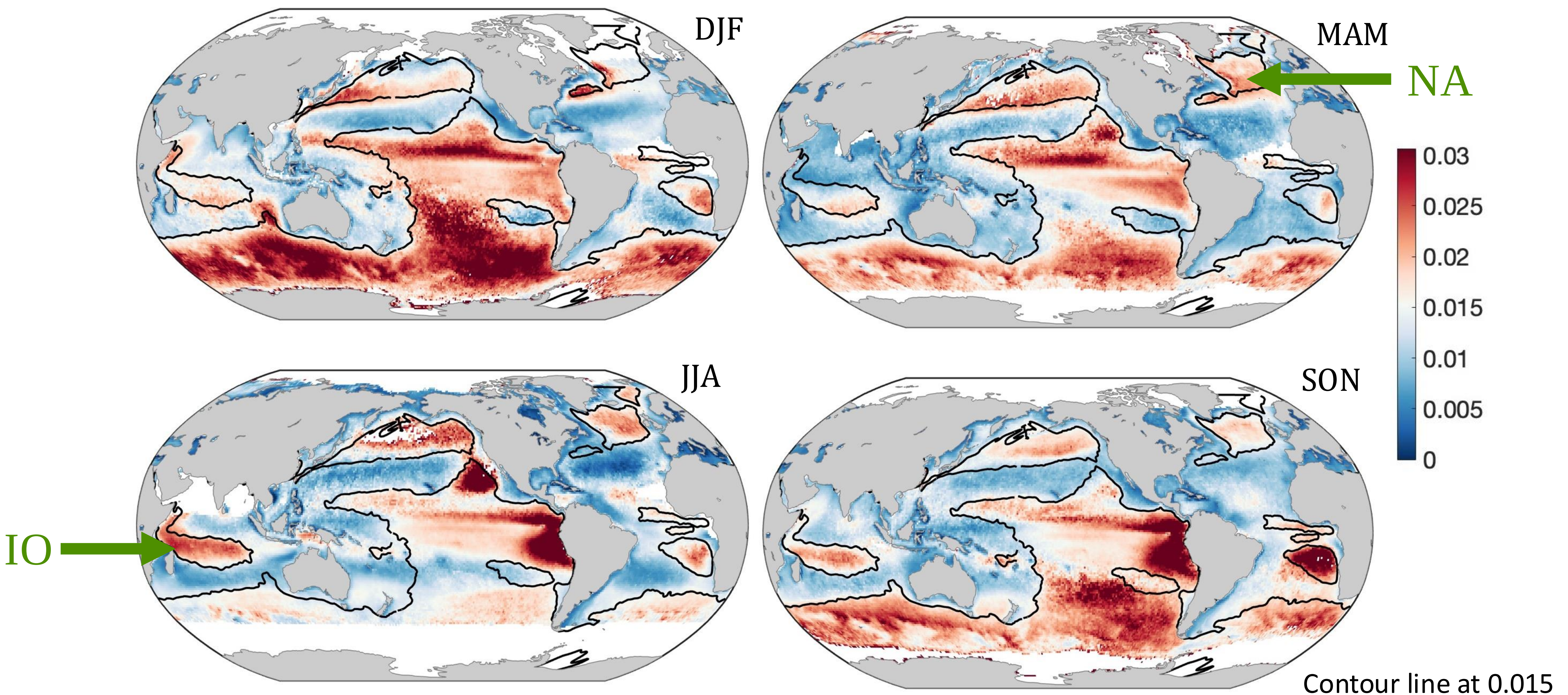
Climatological Mean ϕ_{sat}



Contour line at 0.015

Results

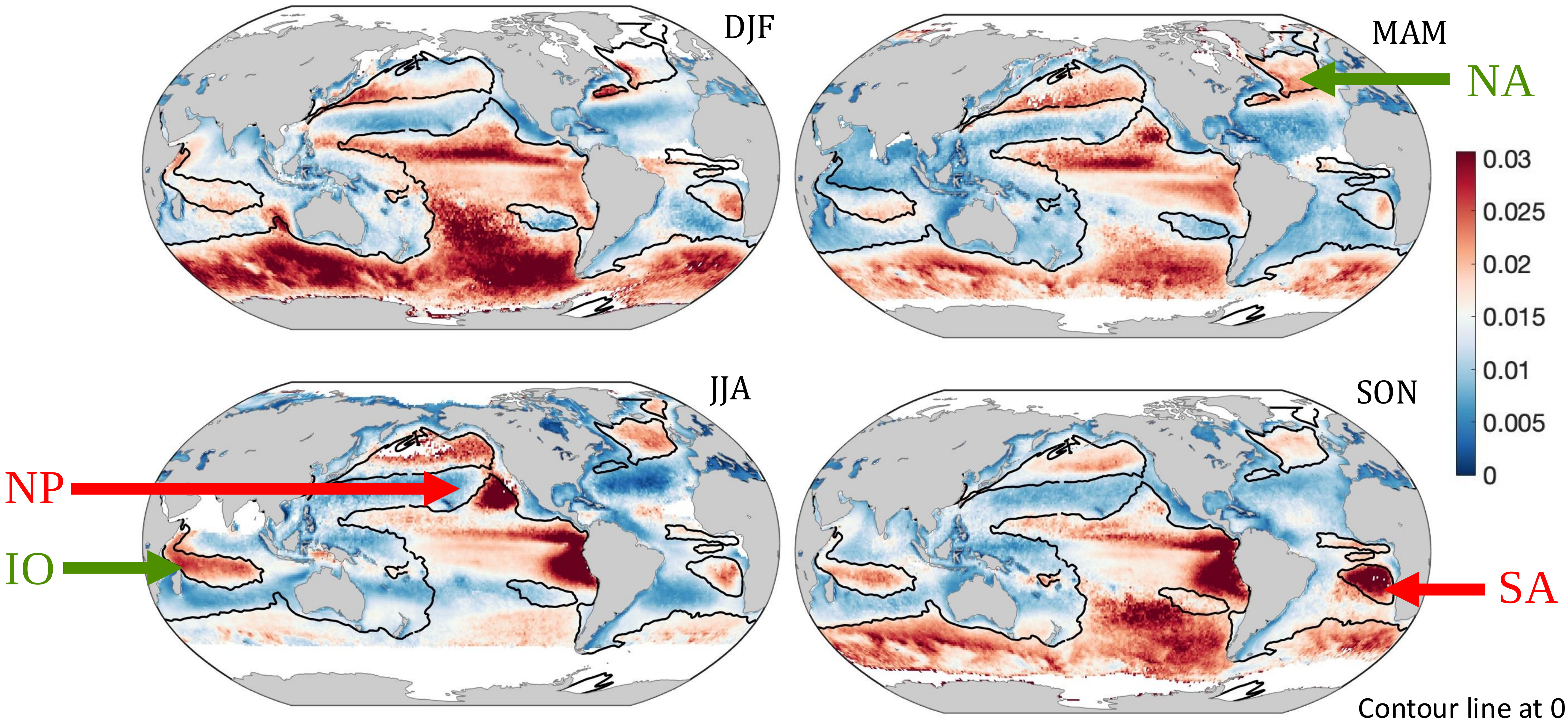
Seasonal Climatology ϕ_{sat}



Contour line at 0.015

Results

Seasonal Climatology ϕ_{sat}

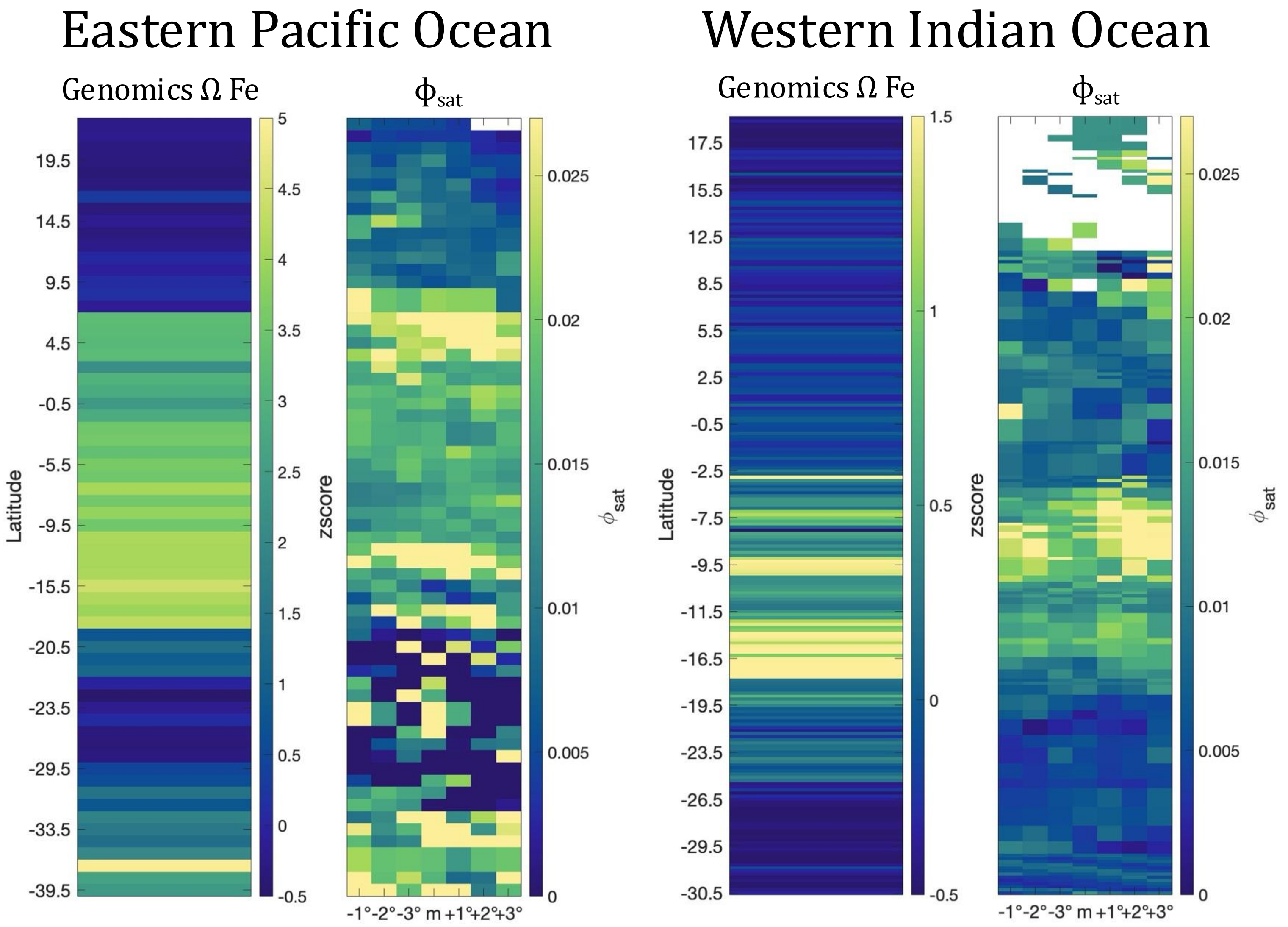


Contour line at 0.015

Results

Spatial Patterns of Iron Stress Genomics and ϕ_{sat}

- Pacific Ocean transect
  - ϕ_{sat} captures the HNLC dynamics
  - ϕ_{sat} in the gyre is more dynamic
- Indian Ocean Transect
  - ϕsat captures the seasonal elevated values



Conclusion

1. In-situ genomics iron stress biomarkers and other data datasets support ϕ_{sat} as an iron stress proxy.
2. Iron stress occurs when macronutrient levels are elevated.
3. Iron stress regions are dynamic.

Ocean Biology and Biogeochemistry: Our Science II

Understanding the Drivers of Global Kelp Forest Dynamics

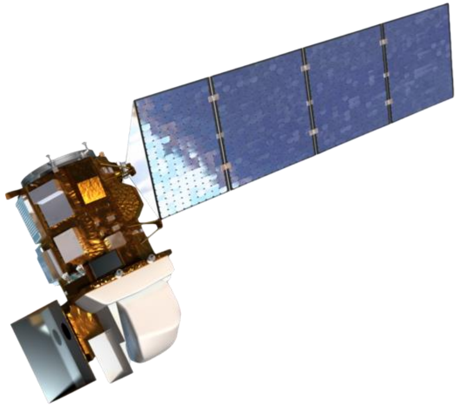
PIs: Tom Bell (WHOI), Kyle Cavanaugh (UCLA), Jarrett Byrnes (UMass Boston)

Postdocs: Henry Houskeeper (WHOI), Julieta Kaminsky (Fulbright – Argentina)

Graduate Students: Katherine Cavanaugh (UCLA), Ashland Aguilar (WHOI), Jessica Smith (WHOI)

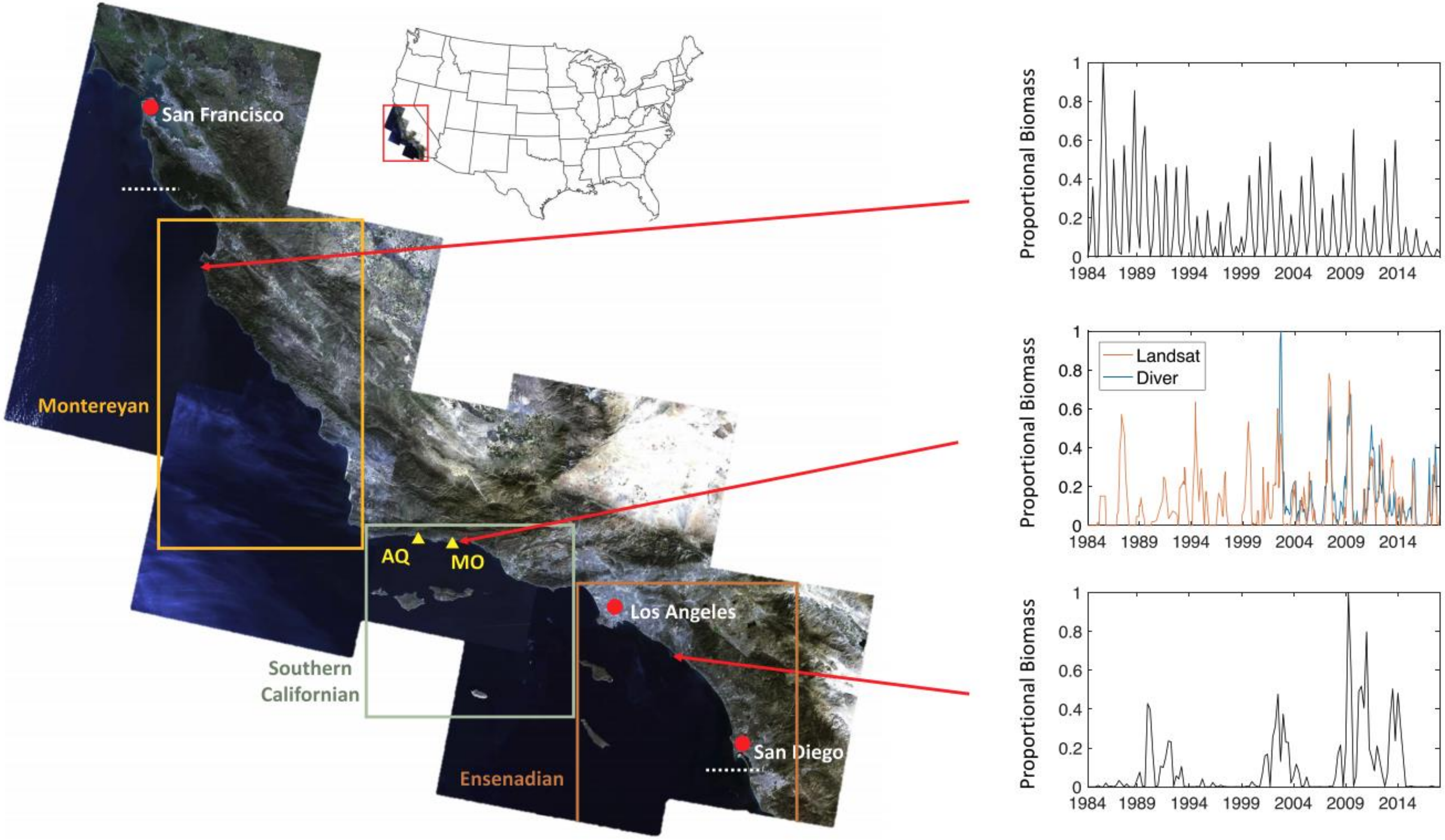
Collabs: Caro Pantano (Argentina), Nur Arafeh Dalmau (Mexico), AJ Smit (South Africa), Luba Reshitnyk (Canada), Mike Stekoll (AK), Heidi Pearson (AK), and many more

Long-term, large spatial extent monitoring of kelp canopy dynamics from the Landsat satellites



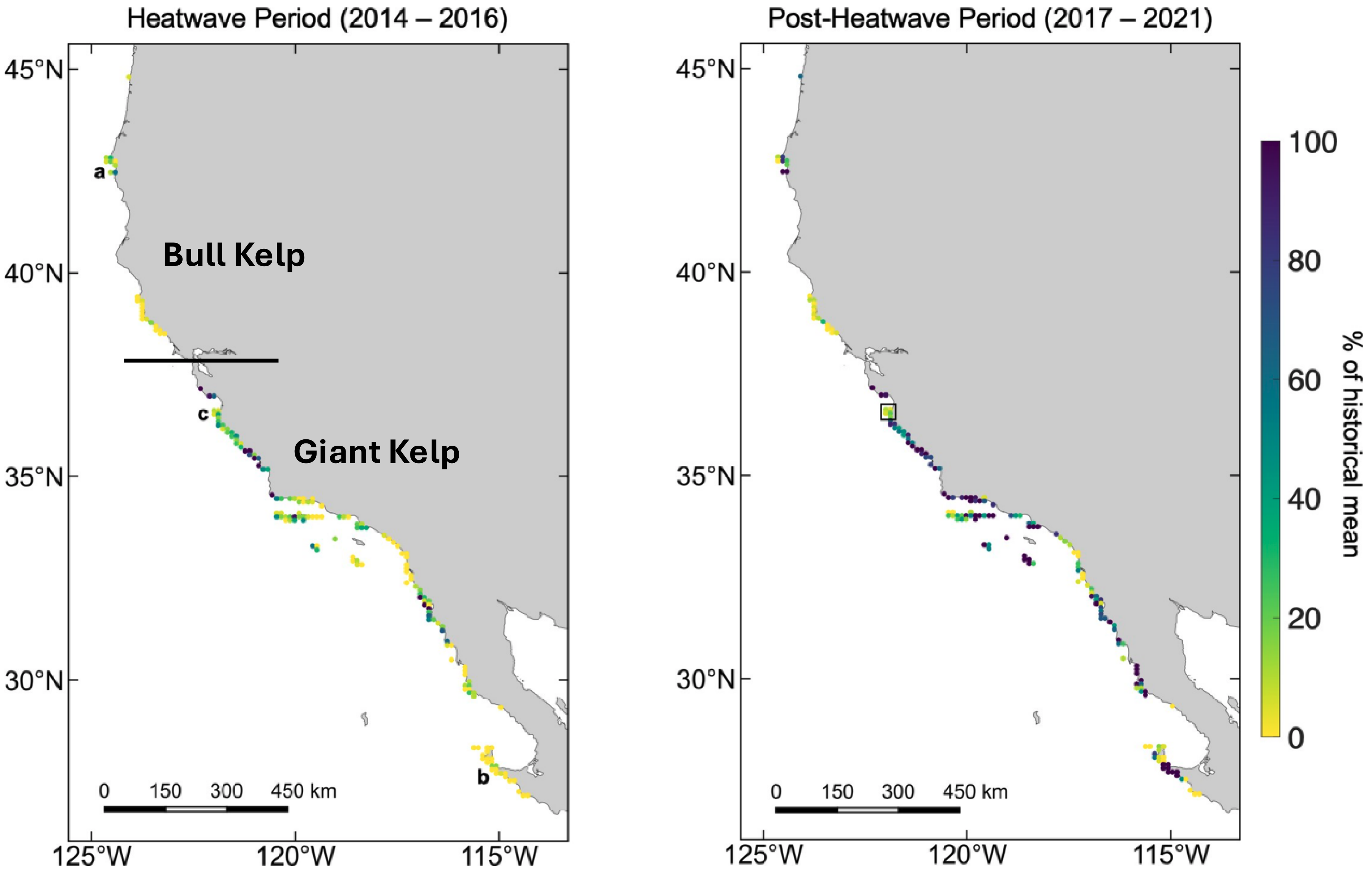
Temporal Coverage
1984 – *present*
8 – 16 day repeat

Spatial Resolution
30m pixel res.



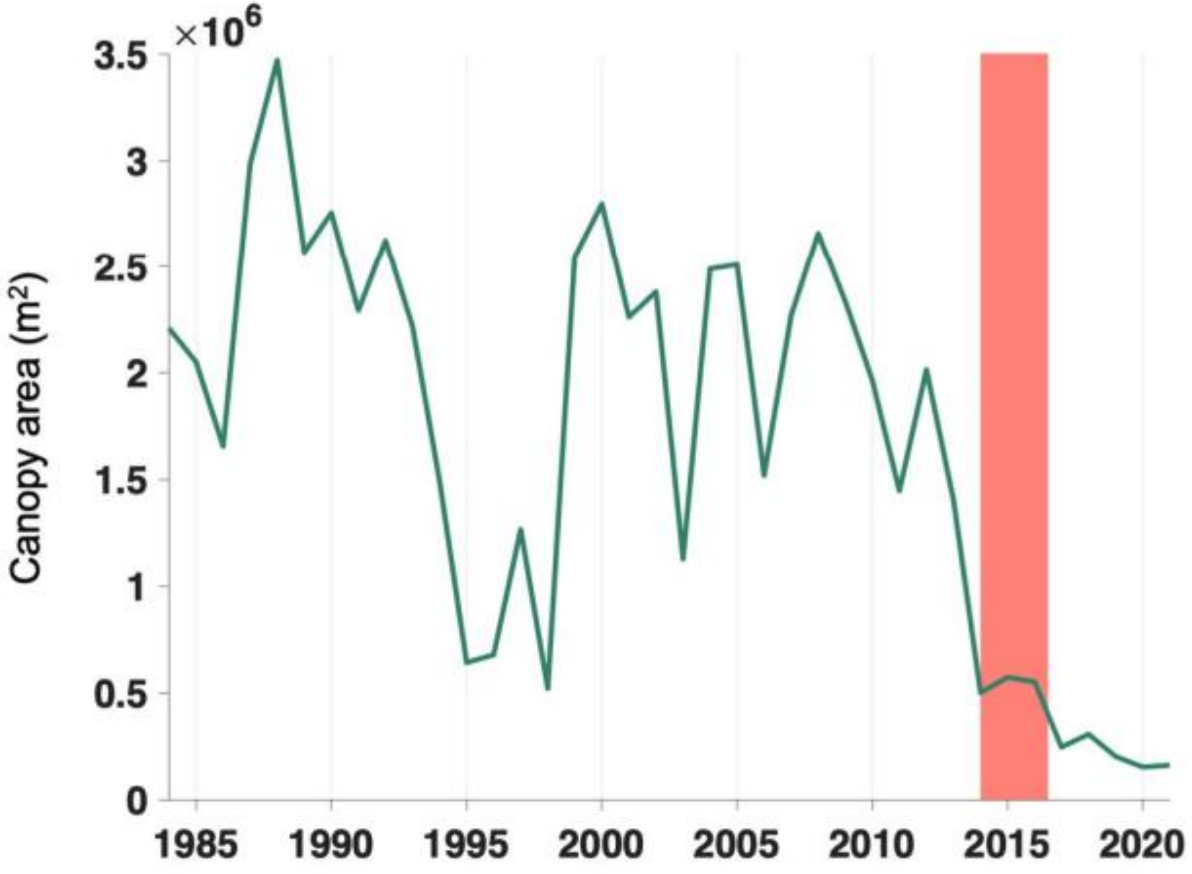
Bell et al. 2020

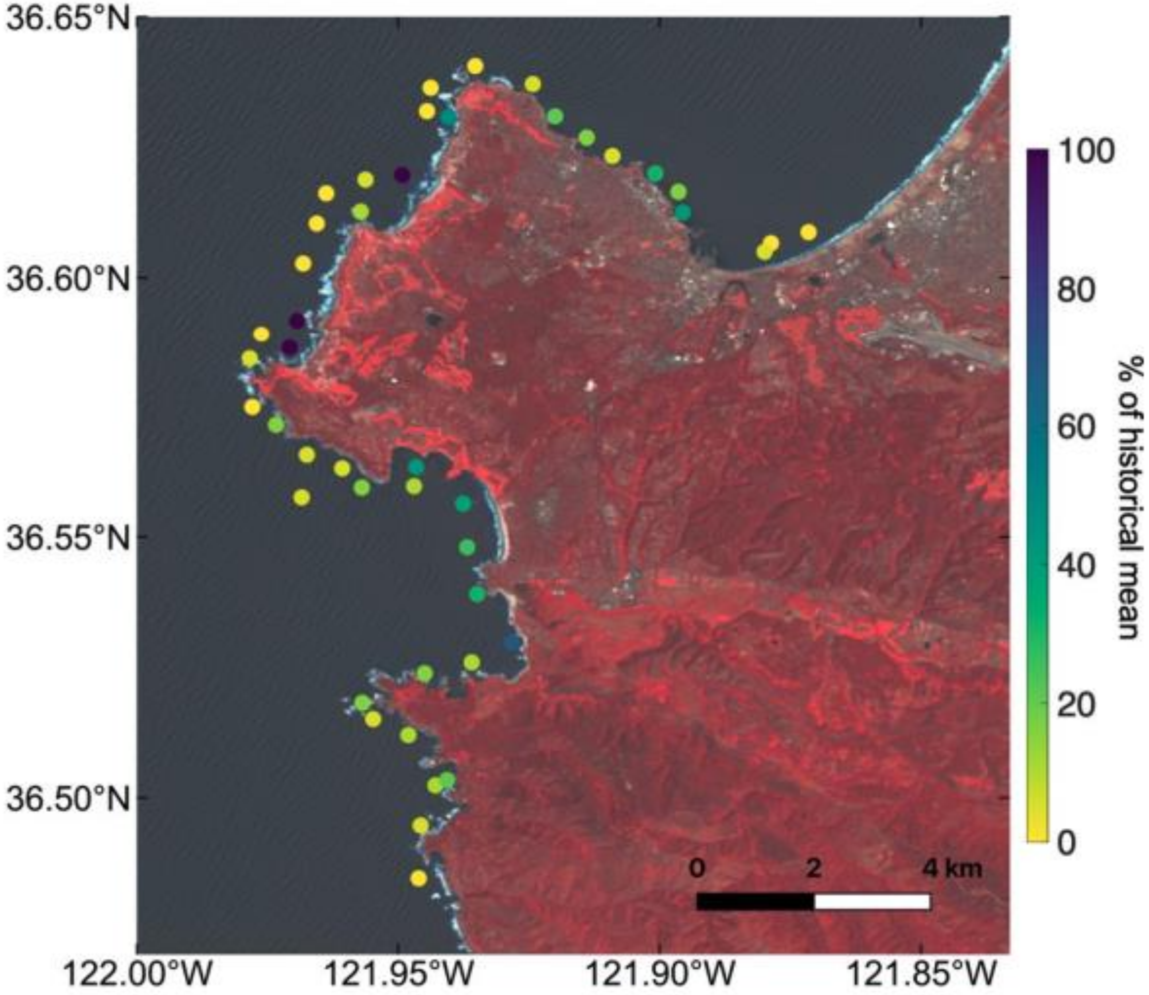
Resistance and Resilience of Kelp to Marine Heat Waves



Bell et al. 2023 PLOS One

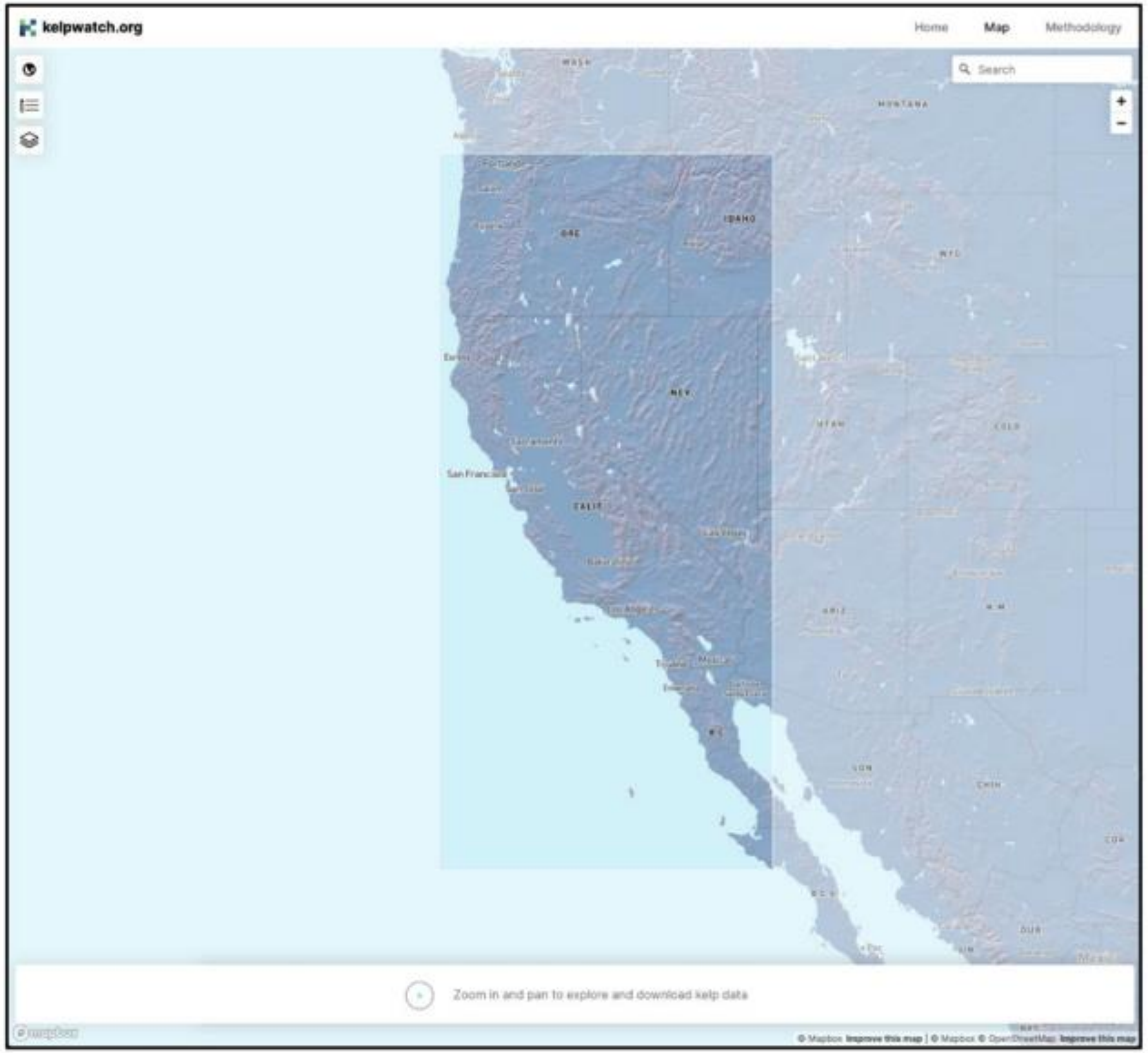
Kelp on the Monterey Peninsula has collapsed...

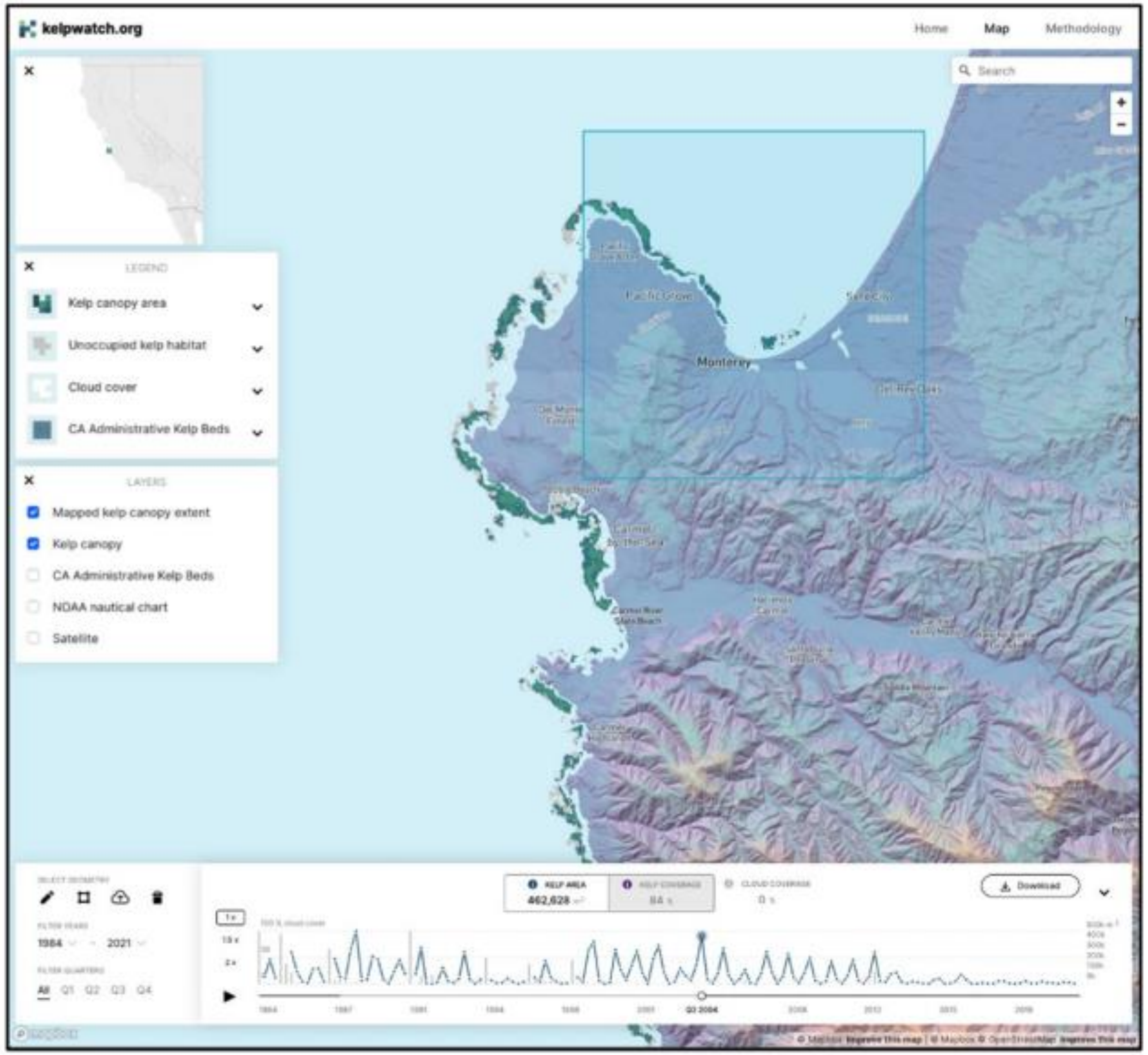




Bell et al. 2023 PLOS One

Kelpwatch.org: Data visualization and Access





Bell et al. 2023 PLOS One

kelpwatch.org

Home Map Methodology Kelp Report Cards

Location

Select, draw or upload a shape to get data for your area of interest

Select

Mapped Areas

Draw | Upload

Clear Selected Location

Learn more about supported files

Filters

Explore emergent kelp area and coverage changes through time.

Period

Start Year 1984 to **End Year** 2024

Time Variable

Calendar Year (All Quarters)

Learn more about Time Variable

Layers

- [x] Kelp canopy (Landsat)
- [x] Satellite

Map Legend

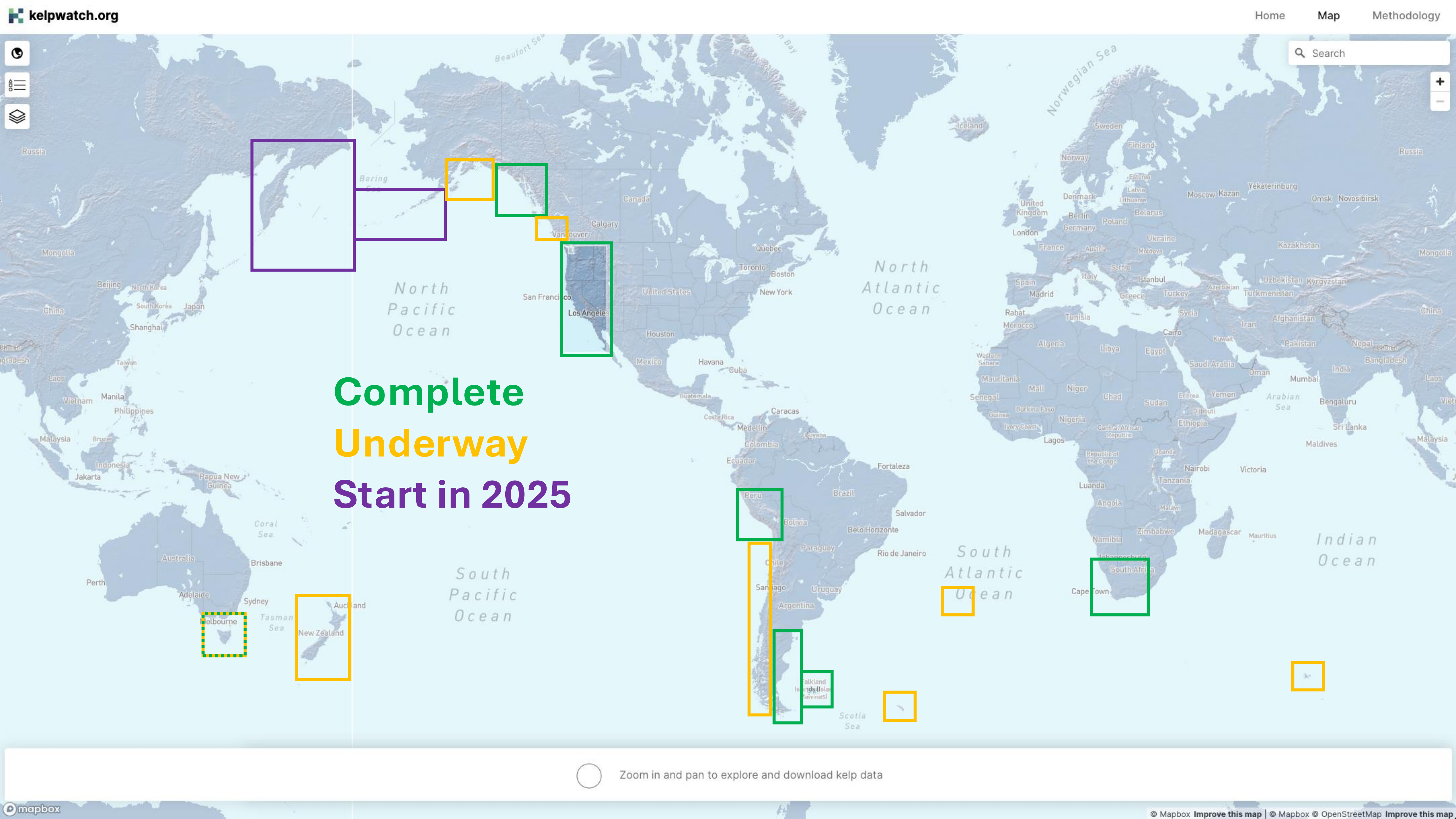
Search

11.1

Drawn Area

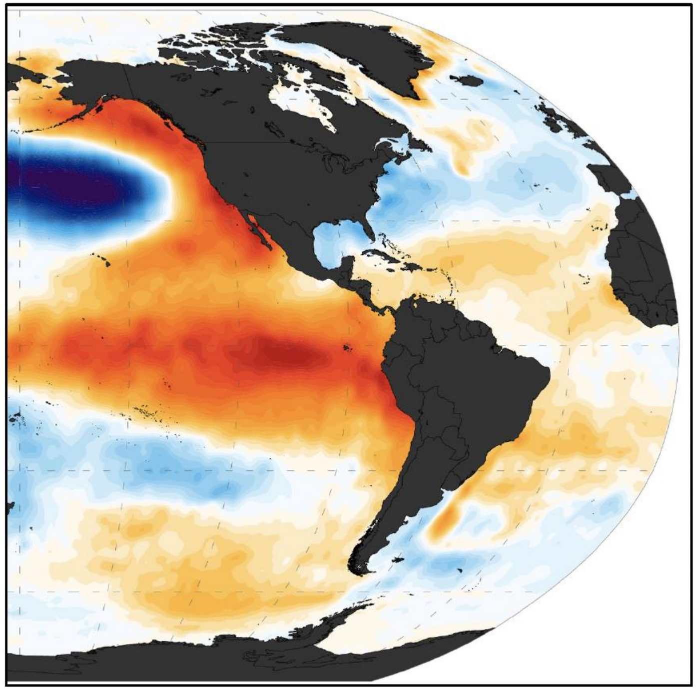
Landsat | 1984-2024 | Calendar Year (All Quarters) | Emergent Kelp Area

Kelp Area: 9,176,301 m^2 | Kelp Coverage: 63 % | Cloud Coverage: 0 %

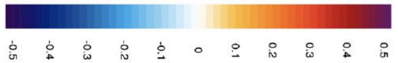


kelpwatch.org
Home
Map
Methodology
Search
Complete
Underway
Start in 2025
North Pacific Ocean
South Pacific Ocean
North Atlantic Ocean
South Atlantic Ocean
Indian Ocean
Zoom in and pan to explore and download kelp data
© Mapbox Improve this map | © Mapbox © OpenStreetMap Improve this map

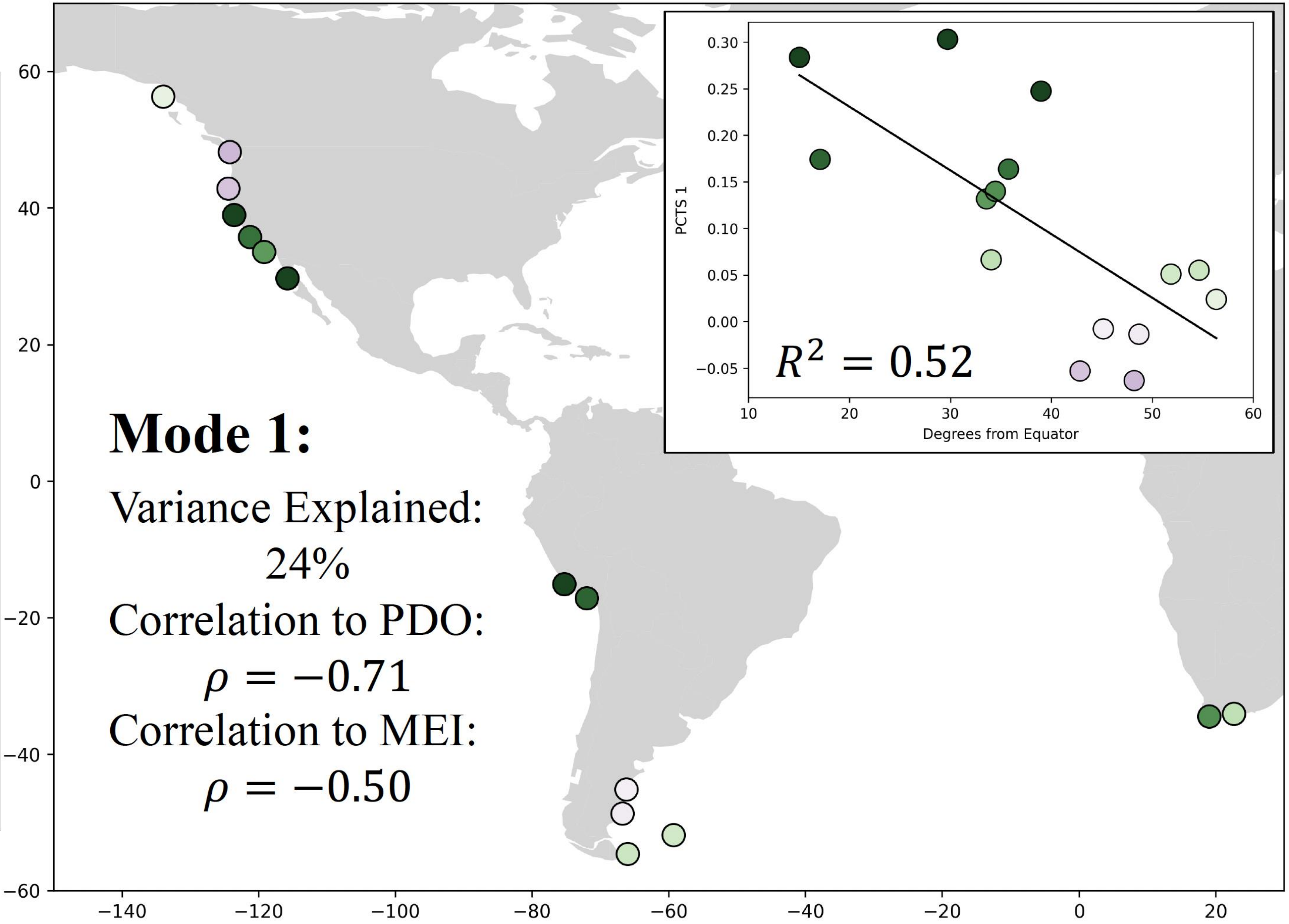
Warm Phase of PDO



SST Anomalies (ºC sd^{-1})



http://www.metoffice.gov.uk/hadobs/hadisst/data/download.html



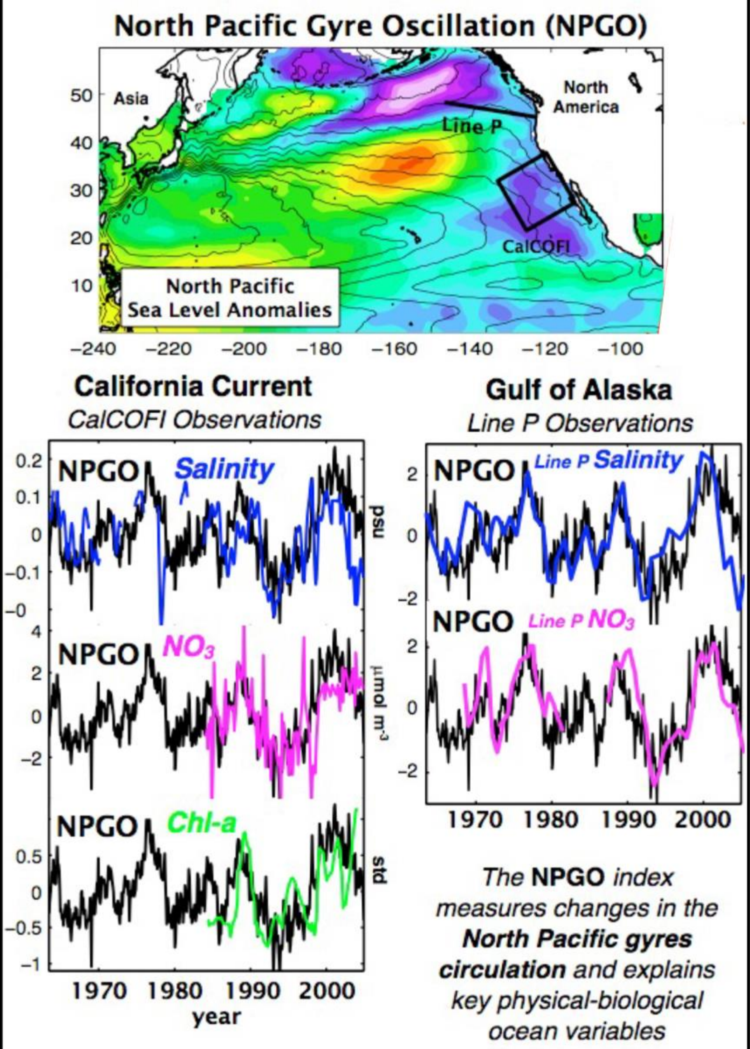
Mode 1:

Variance Explained: 24%

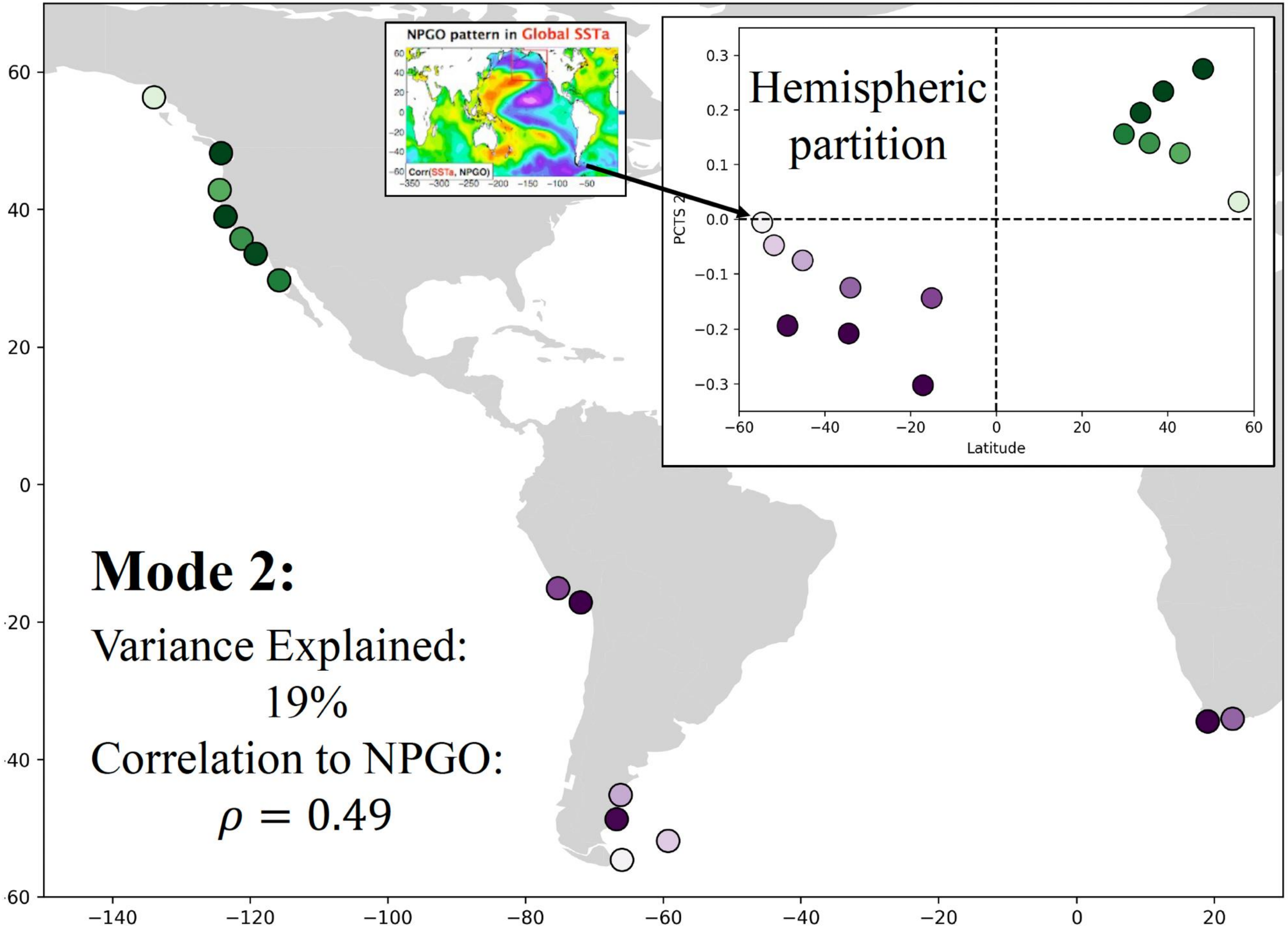
Correlation to PDO: $\rho = -0.71$

Correlation to MEI: $\rho = -0.50$

Houskeeper et al. *in prep*



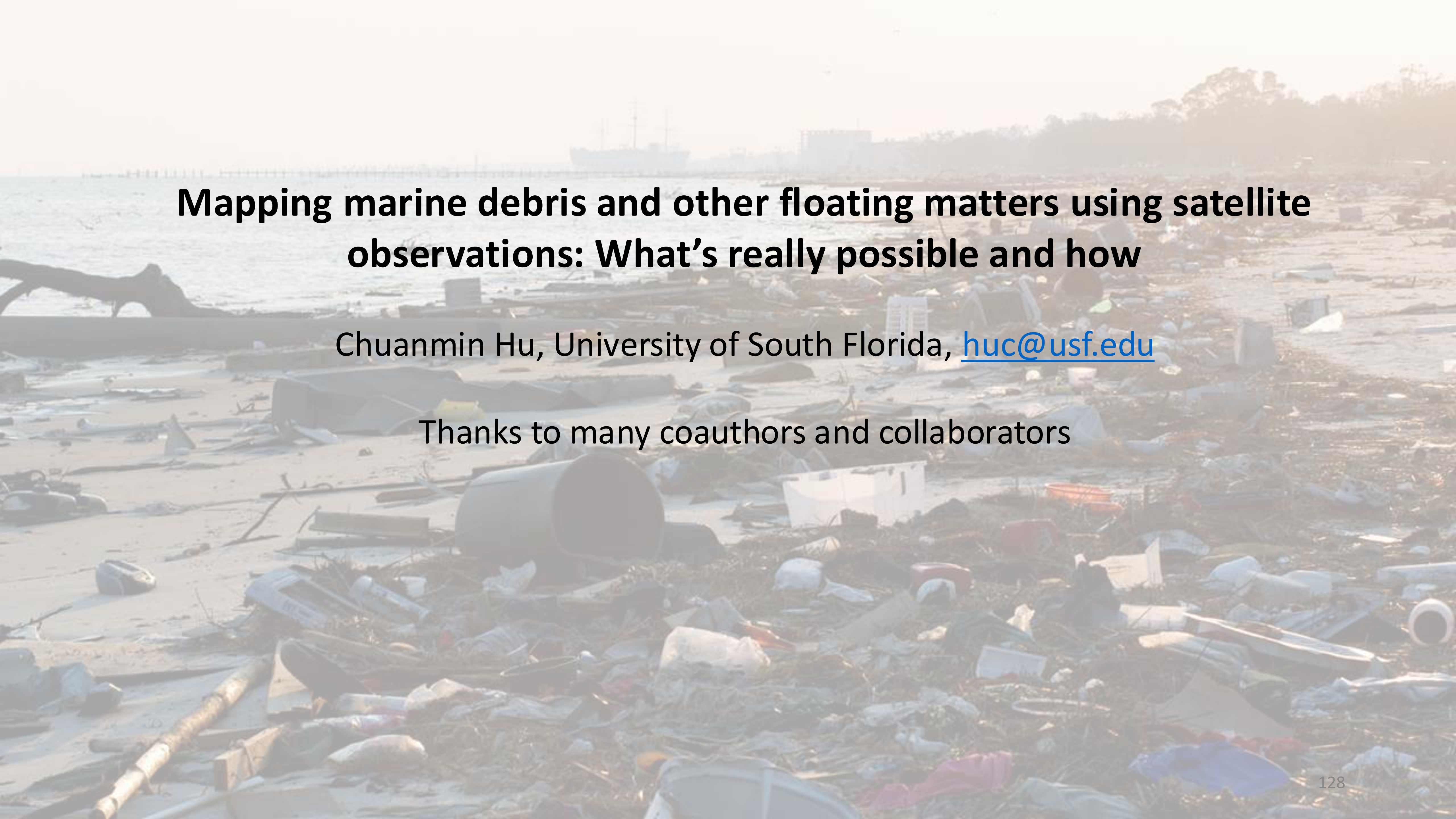
Di Lorenzo, et al. (2008).
http://www.o3d.org/npgo/



Houskeeper et al. *in prep*

Thank you!

tbell@whoi.edu



Mapping marine debris and other floating matters using satellite observations: What's really possible and how

Chuanmin Hu, University of South Florida, huc@usf.edu

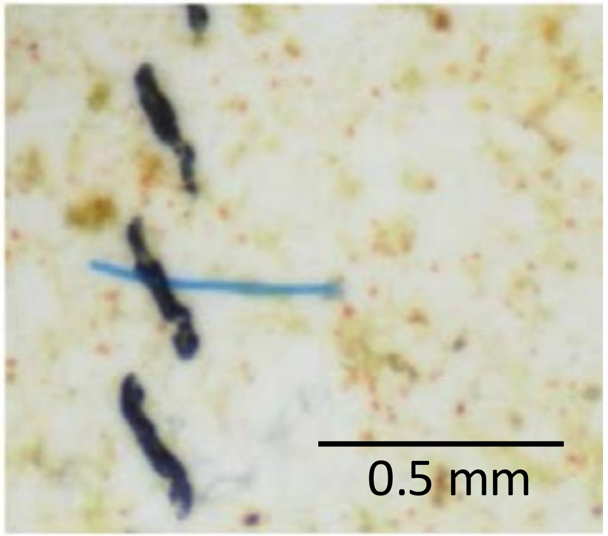
Thanks to many coauthors and collaborators

What are we talking about?
The many types of marine debris (a.k.a. marine litter)

Marine debris: Solid materials released to the marine environment from natural disasters or human activities: Microplastic particles, plastic bags, plastic bottles, fishing gear, tree branches/leaves, driftwood…

Microplastic particles

Microfibers (> 91%), mostly < 1 mm



Barrrows et al. (2018)

Larger particles (< 5 mm)

Garaba & Dierssen (2018)

Macroplastics

& other debris

Web source

Mixture

of everything

Web source

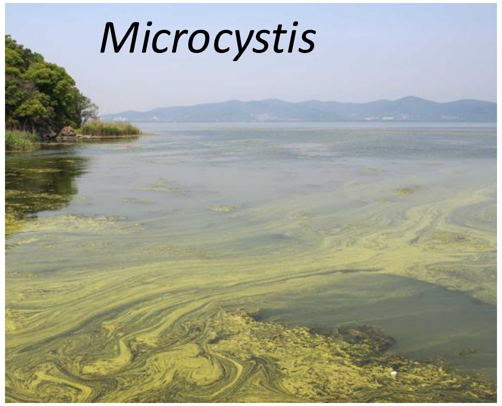
What are we talking about?
The many types of floating matters


Marine debris


Sargasssum fluitains/natans

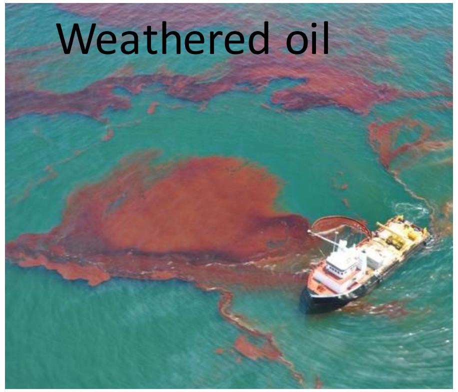
Sargasssum horneri

Ulva prolifera

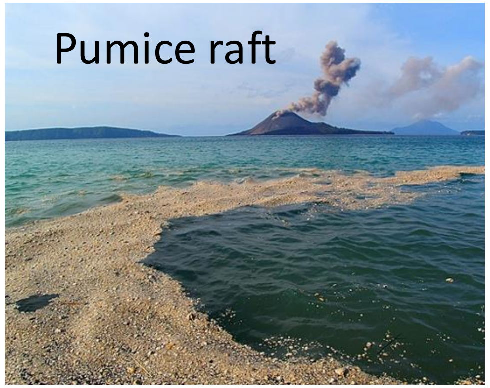

Microcystis

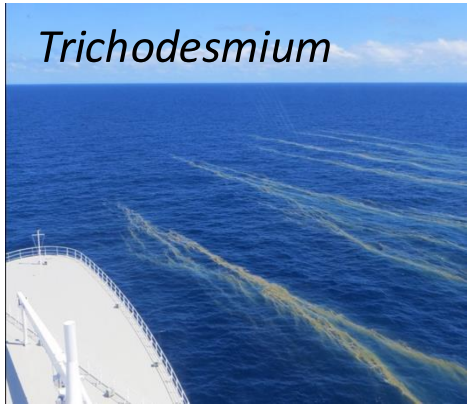

Green *Noctiluca*


Red *Noctiluca*


Weathered oil


Sea snot


Pumice raft


Trichodesmium


Shrimp eggs


Dead seagrass


Dead fish

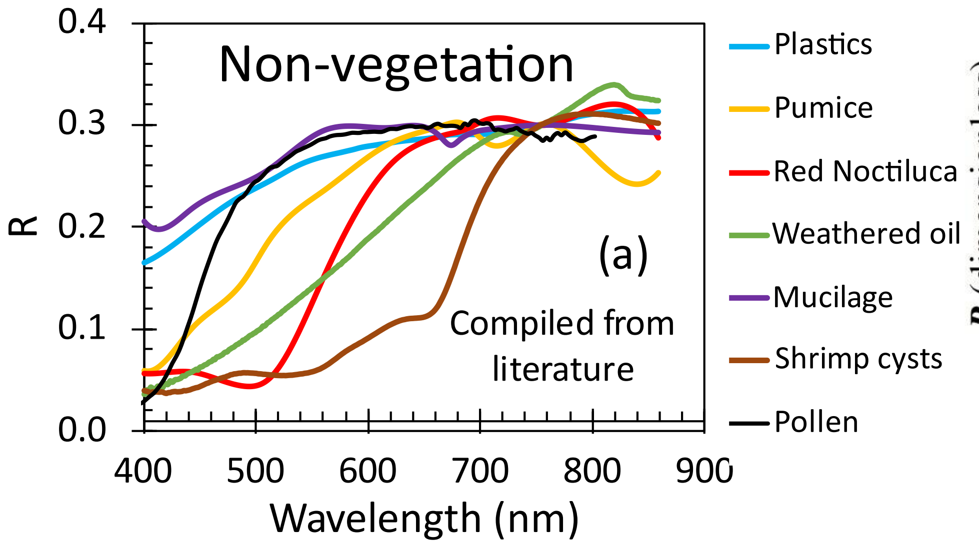

Pollen

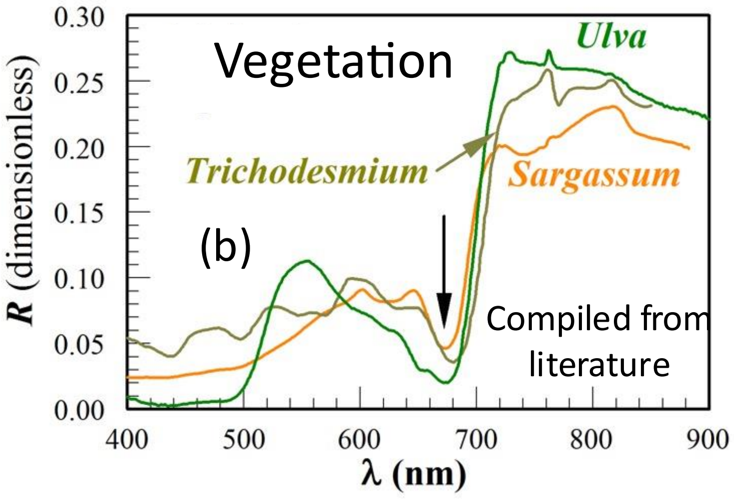
What's really possible?

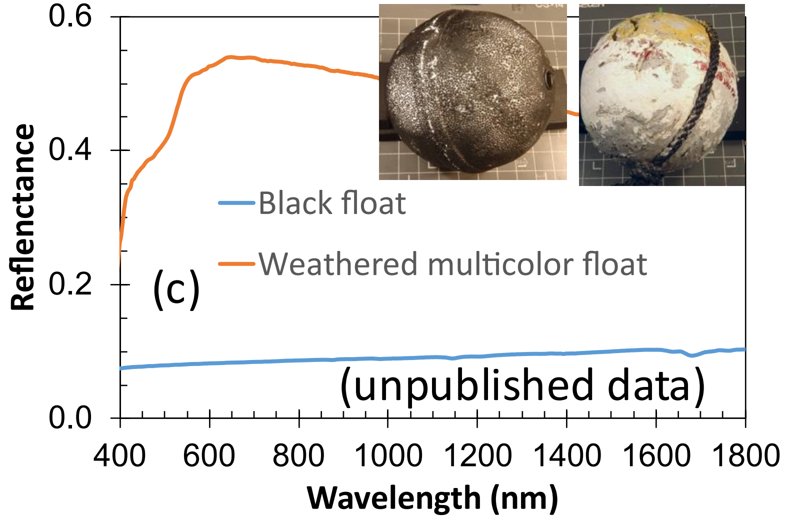
- LIDAR – still in laboratory and conceptual phase
- SAR – very limited use, for both microplastics and others
- Passive optics – most often used, possible but still difficult

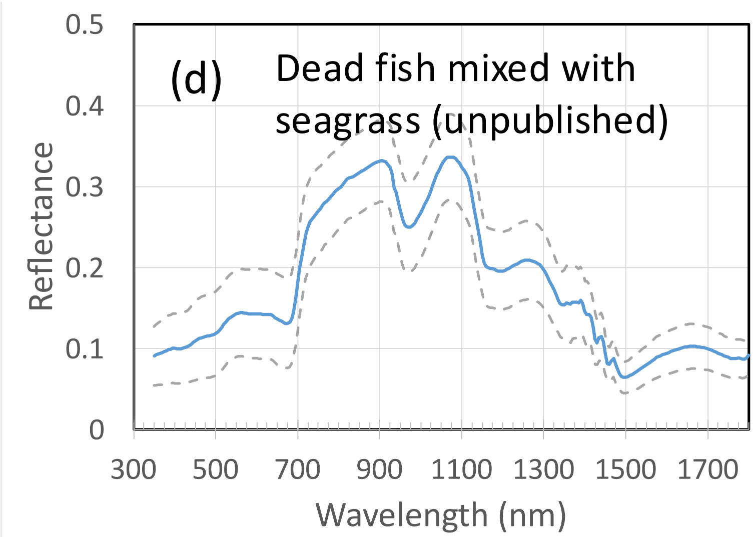
Why is it so difficult?

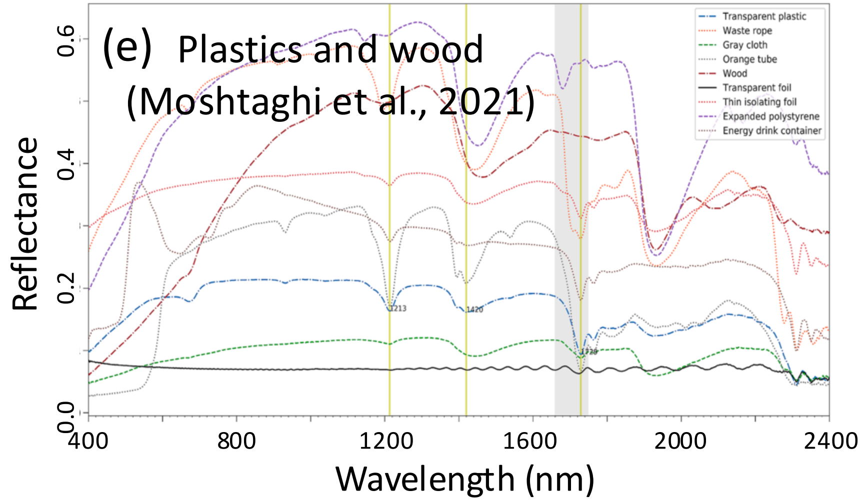
1) Too small – often < 1% of a pixel size; 2) Spectral similarity

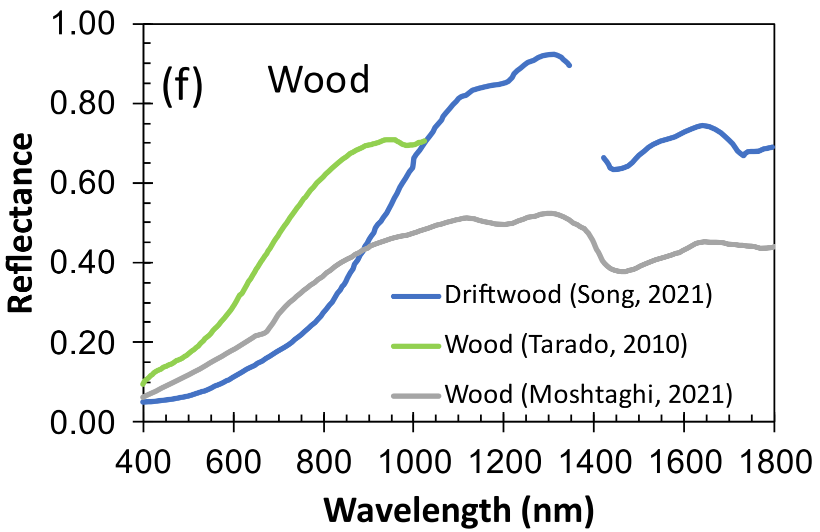




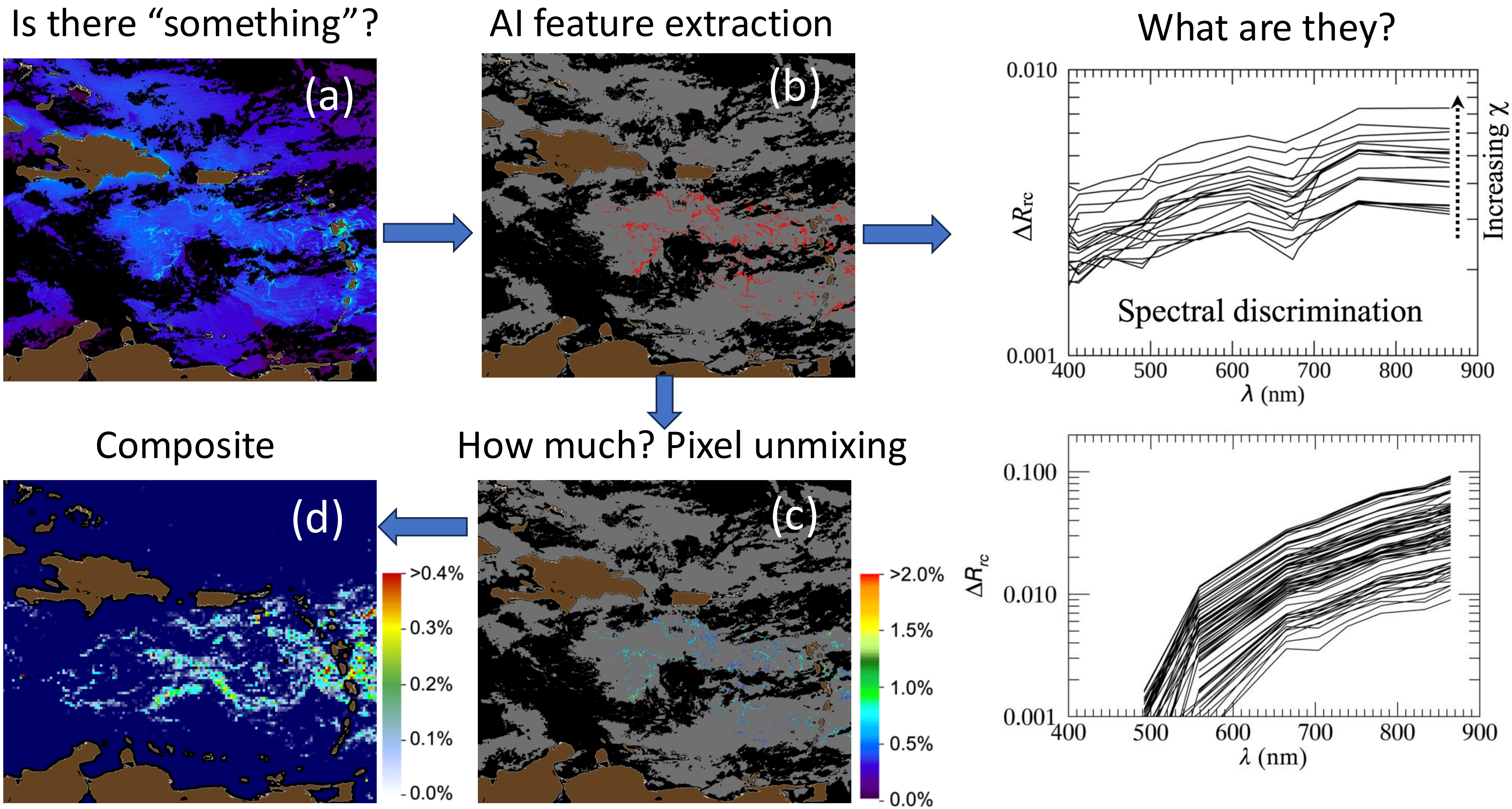




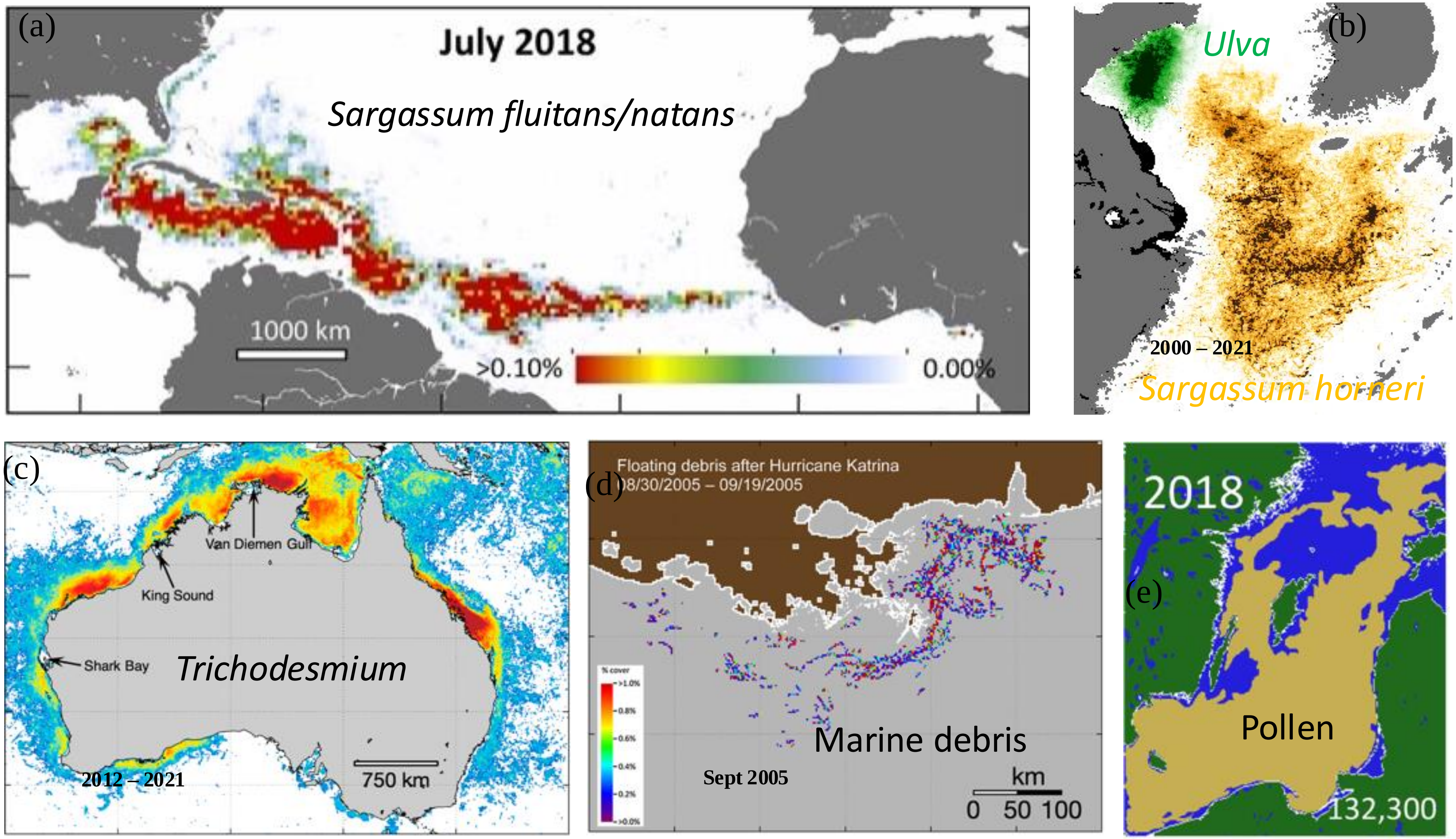




Conceptually and in practice – how?

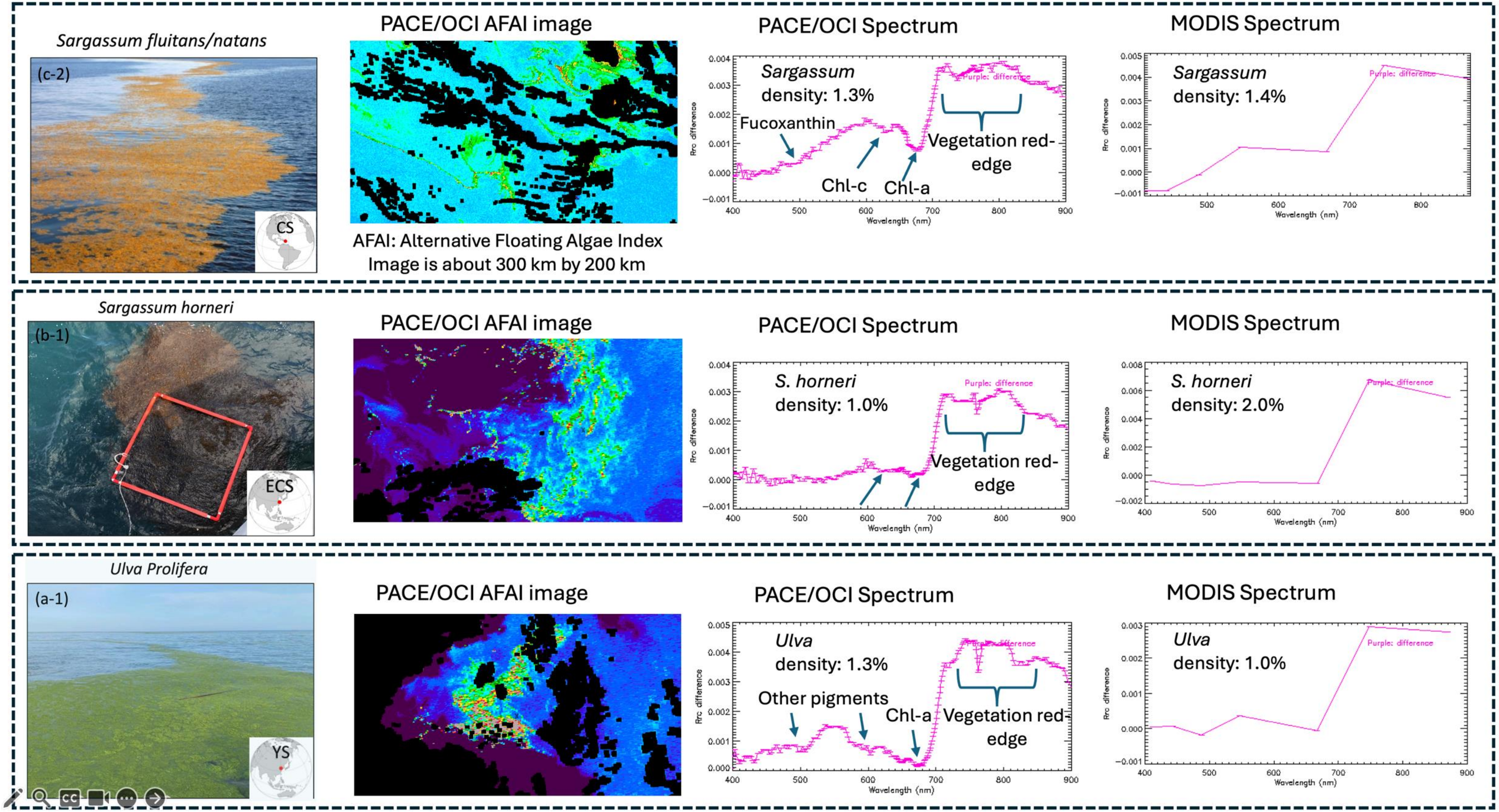


How – examples



What’s next?

PACE/OCI shows the capacity of imaging spectroscopy over floating algae; MODIS does not



Summary

- Remote detection of marine debris and other floating matters is technically challenging, but still possible with passive optics
- Conceptual design to detect, discriminate, and quantify them
- Some successes have been achieved, but much remains to be done

What's next

- Improve algorithms and reduce uncertainties – complete the spectral library, and take advantage of hyperspectral and high-resolution sensors (e.g., Cubesats)
- Global mapping – where and how much are marine debris and other types of floating matters?

Linking Chemical Composition of Untreated Wastewater with Laboratory, In Situ, and EMIT Spaceborne Spectroscopy

Eva Scrivner[1,2],

Natalie Mladenov[3], Trent Biggs[1], Alex Grant[3], Elise Piazza[1], Stephany Garcia[1], Christine Lee[4], Christiana Ade[4], Ileana Callejas[4], Benjamin Holt[4], Daniel Sousa[1]

[1]*Department of Geography, San Diego State University, San Diego, CA, USA*

[2]*Department of Marine Sciences, University of Connecticut, Groton, CT, USA*

[3]*Department of Civil, Construction, and Environmental Engineering, San Diego State University, San Diego, CA, USA*

[4]*Jet Propulsion Laboratory, California Institute of Technology, Pasadena, CA, USA*

NASA Remote Sensing of Water Quality Program Grant #80NSSC22K0907

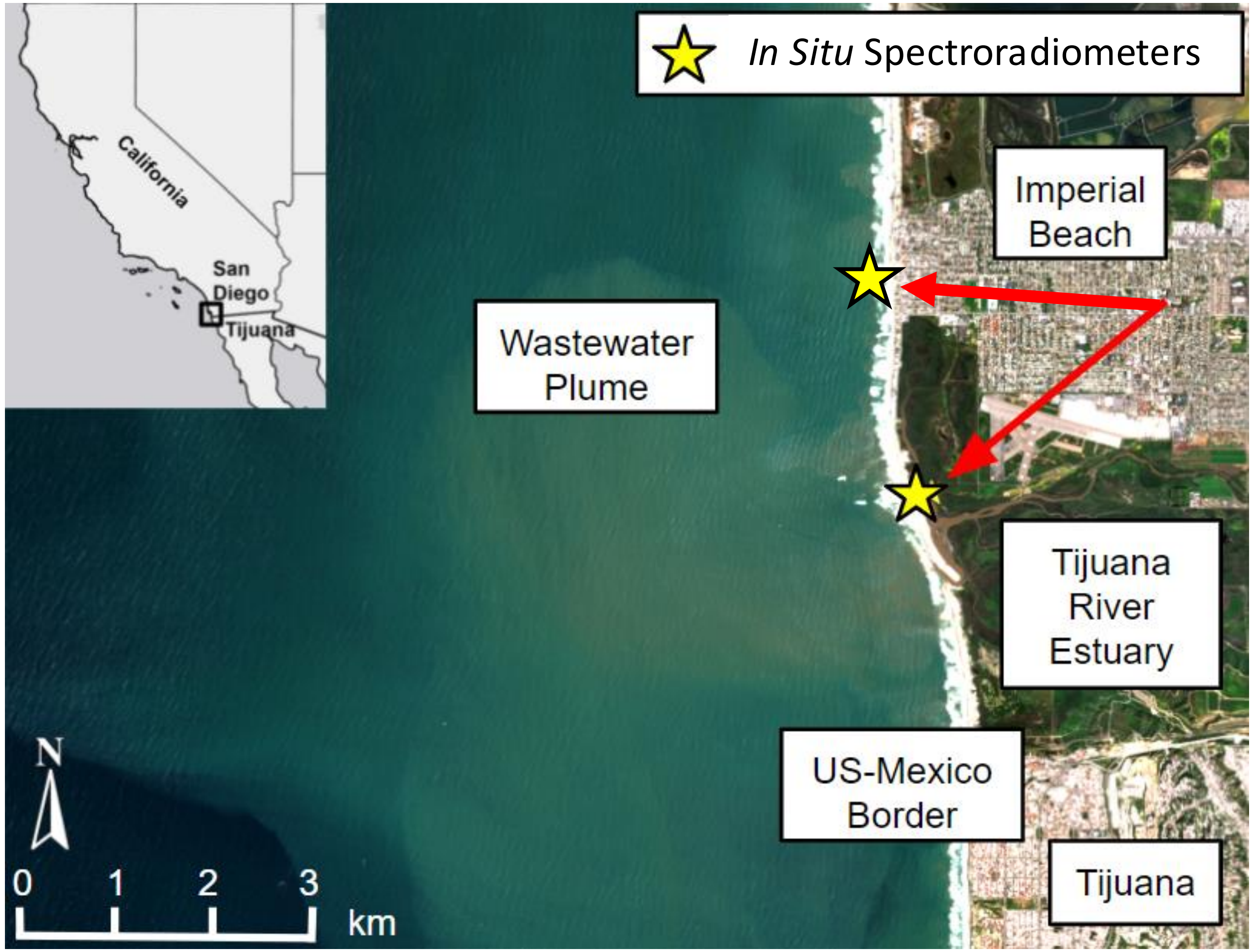
& NASA Applications-Oriented Augmentations for Research and Analysis Program #80NSSC23K1460

SDSU

Jet Propulsion Laboratory

Wastewater Discharge in the Tijuana River

- Hundreds of millions of liters of wastewater are expelled into the Tijuana River annually.
- Carries harmful pollutants through two major cities (> 3 million residents) and a protected estuary.



Research Objectives

1) What spectral features exist in pure and mixed Tijuana River wastewater?

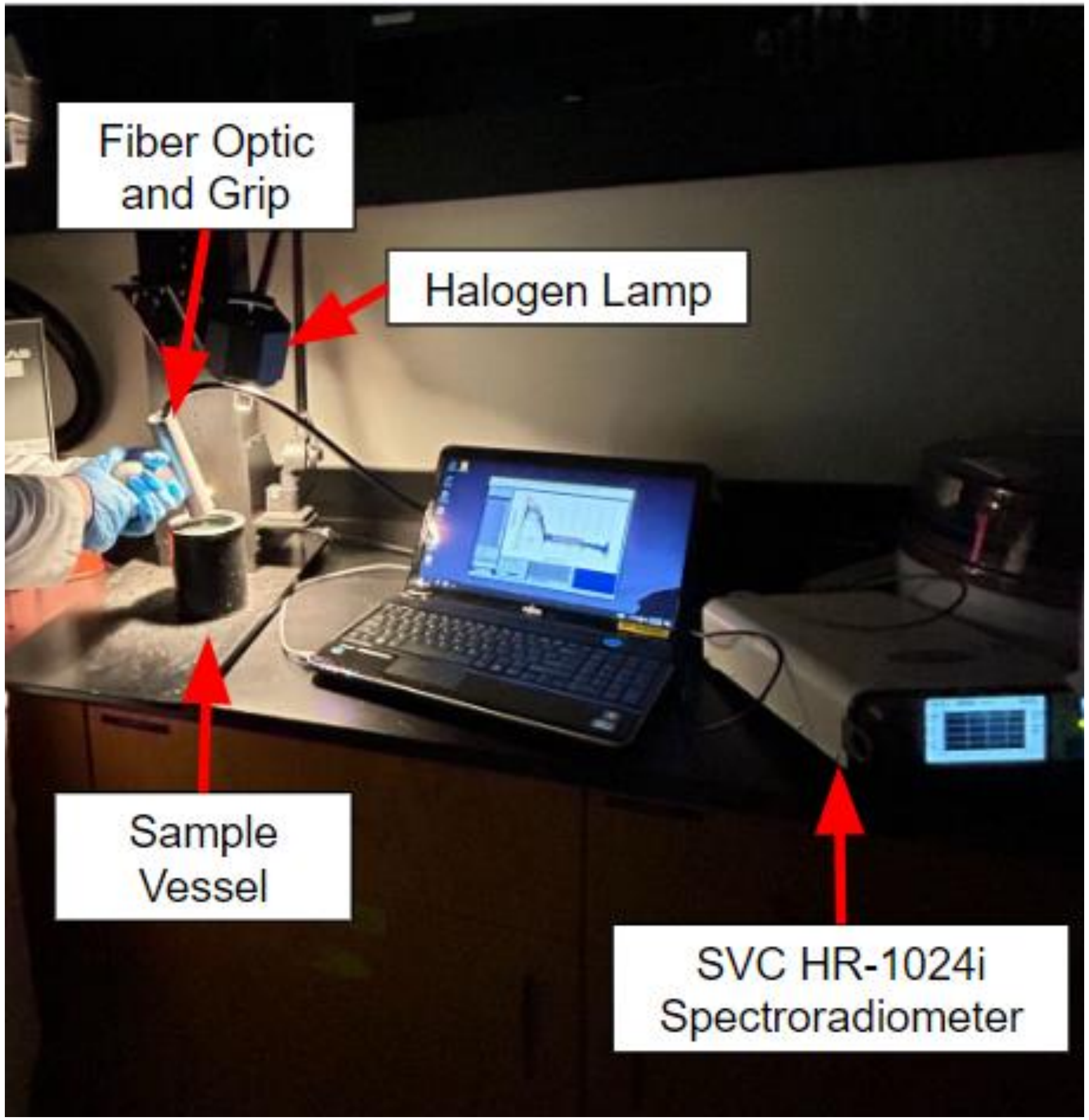
2) With what strength do these features correlate with paired water quality measurements?

3) Are these features present *in situ* or in satellite imagery?

Methods

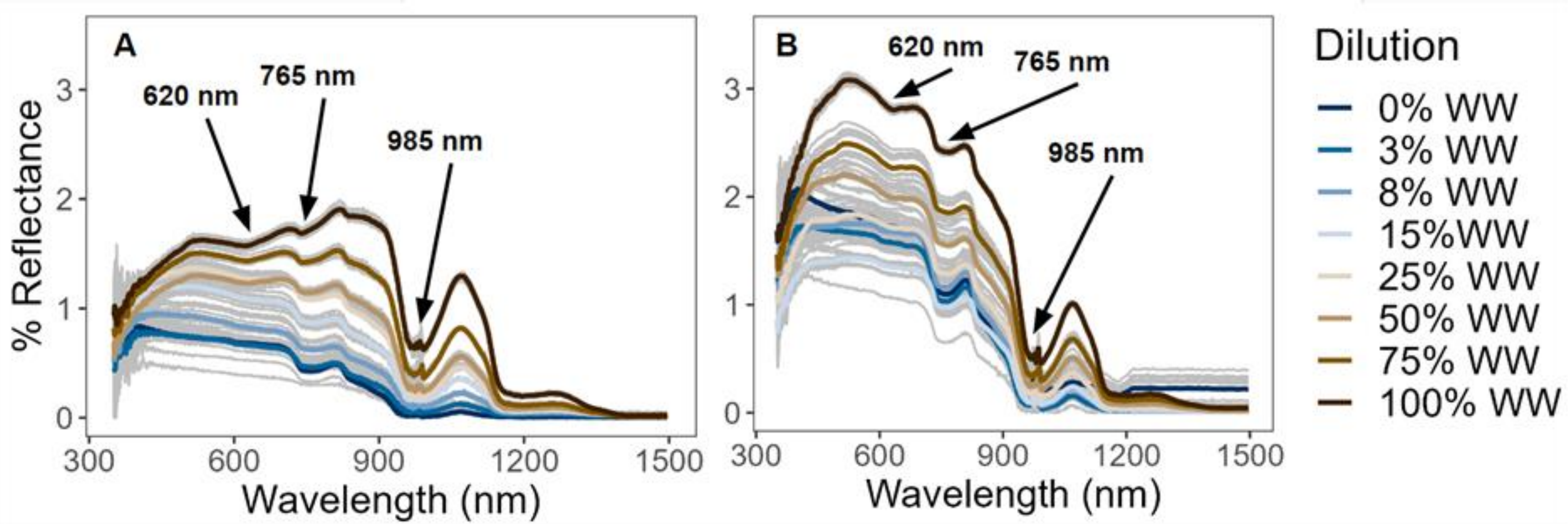
Experimental Design

- Varying dilutions of WW-SW were prepared.
- Reflectance measurements made using Spectra Vista Corporation™ (SVC) HR-1024i spectroradiometer.
- Concurrent water quality measurements made with a HORIBA Aqualog® benchtop fluorometer.
- Challenging laboratory constraints due to hazardous nature of untreated wastewater and limited sample volume.

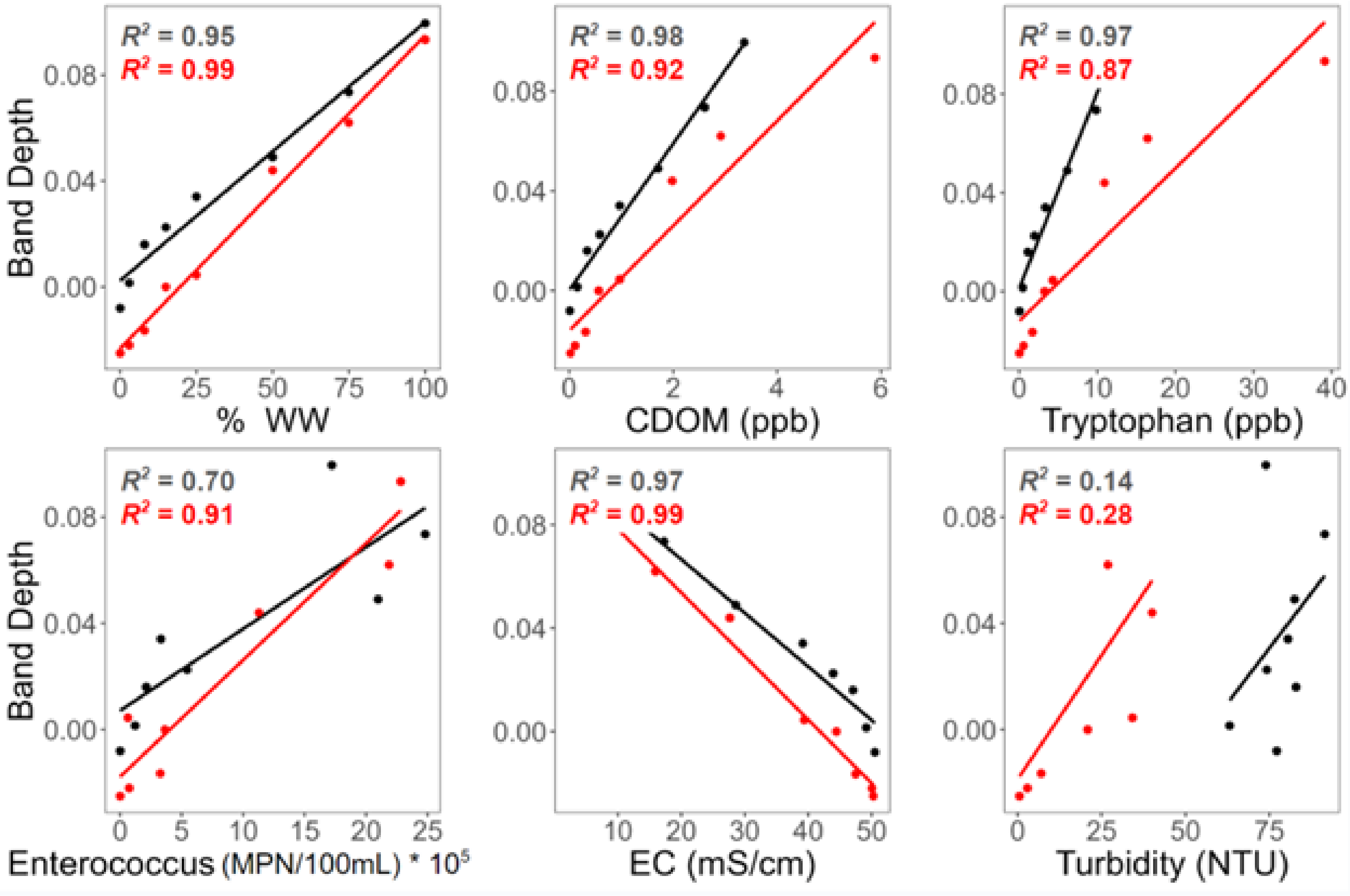


Results

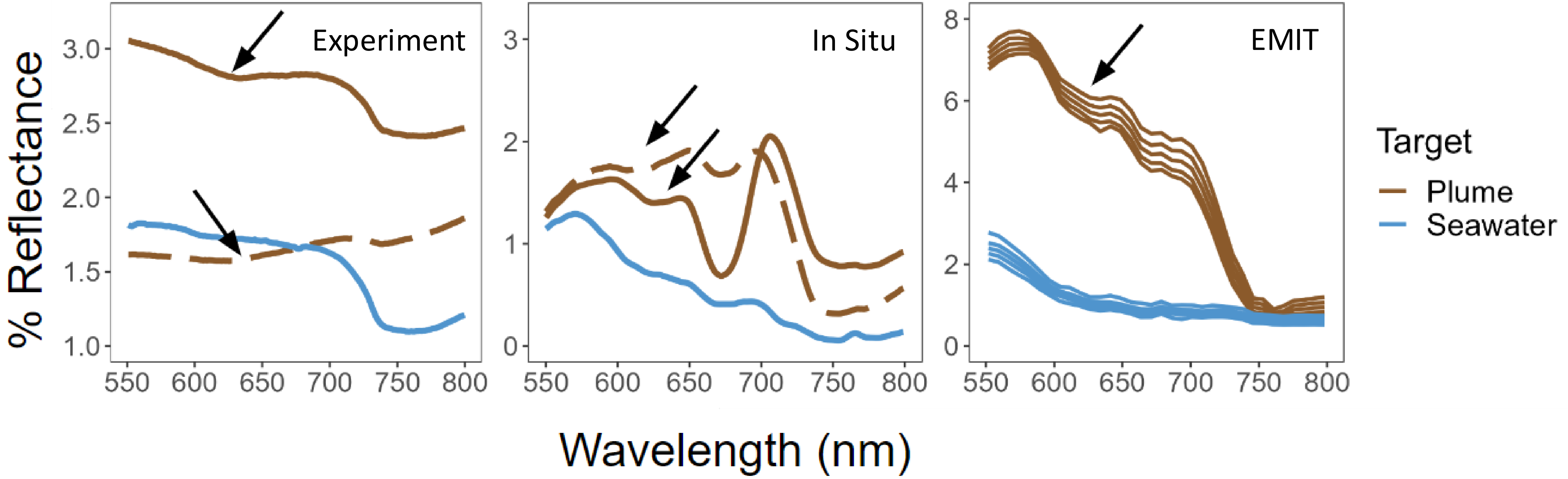
As % WW increases, 620 nm absorption increases



Water quality parameters were highly correlated with 620 nm depth.

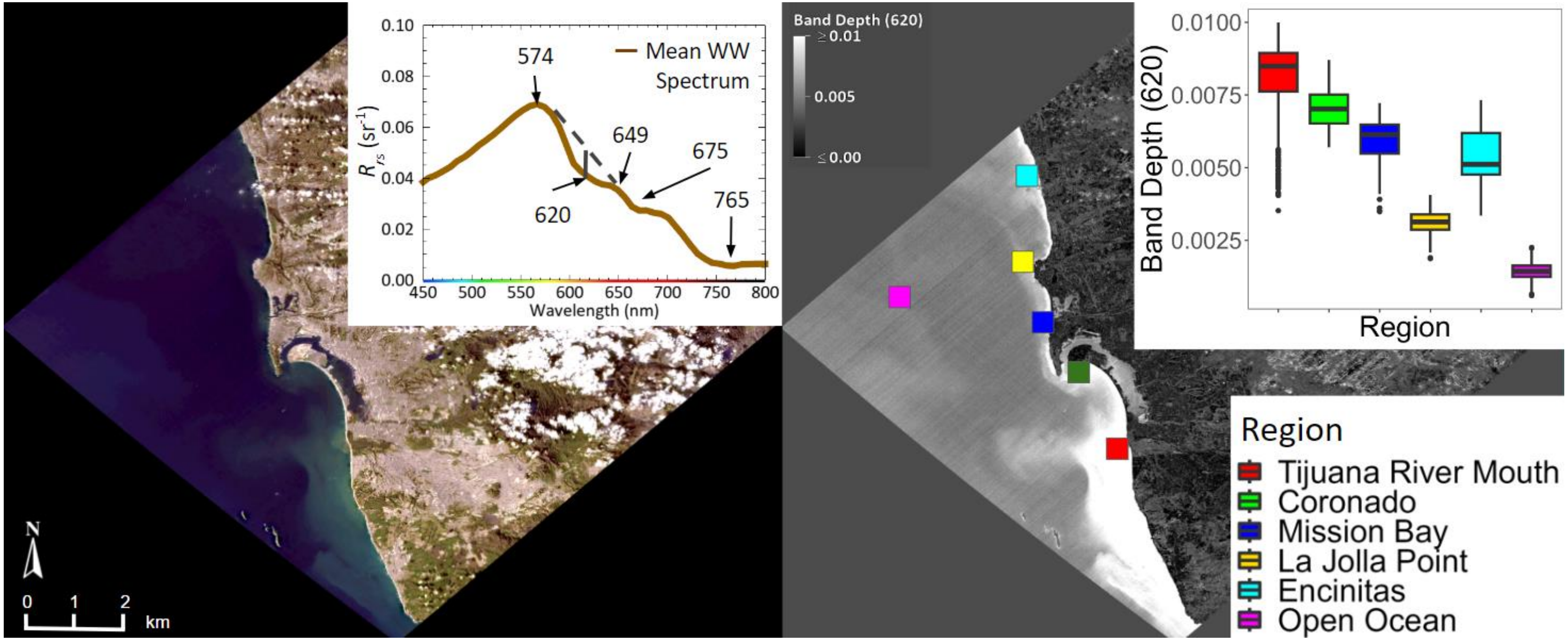


620 nm absorption present *in situ* and in EMIT imagery



(A) 100% WW laboratory reflectance spectra from October (dashed) and February (solid) experiments.
(B) Spectra from a field-deployed spectroradiometer of a known wastewater plume (25 March 2023).
(C) Spectra from an EMIT hyperspectral satellite image over a known wastewater plume (25 March 2023) and open ocean.

Band Depths Trace Wastewater Plume in EMIT Imagery



Discussion

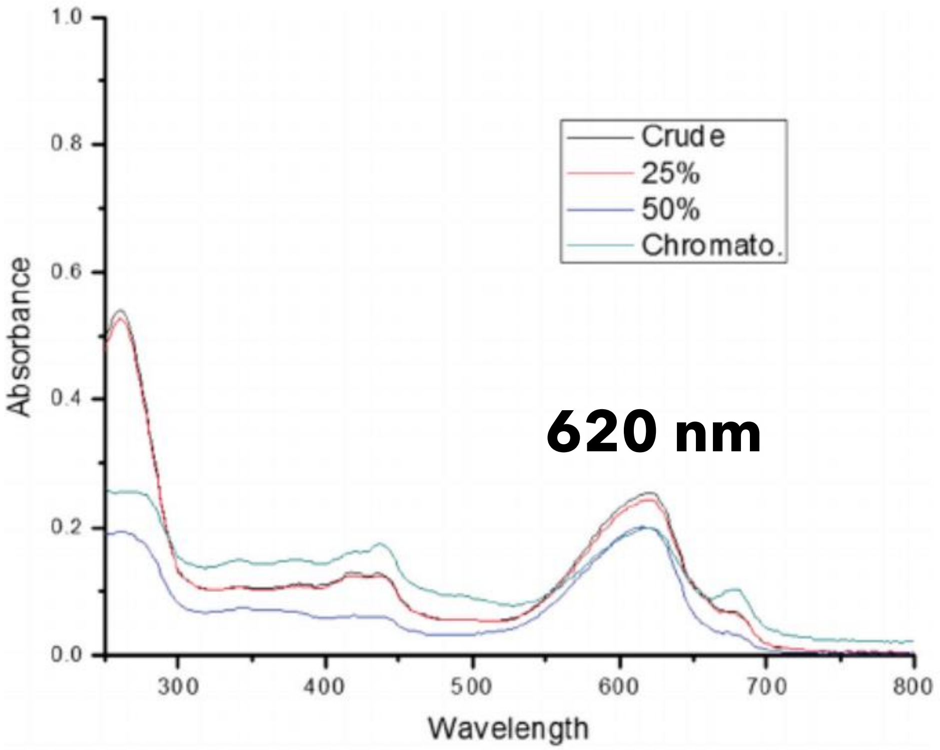
Results Summary

620 nm absorption:

1) increases under high wastewater conditions,
2) has high correlation with water quality parameters,
3) present *in situ* and in hyperspectral imagery

Phycocyanin

- Phycocyanin characteristically absorbs at 620 nm.
- Accessory pigment in cyanobacteria.
- Commonly found or even employed in secondary wastewater management.



Absorption spectra of purified phycocyanin.
Figure credit: *Paswan et al., 2015*

Future Applications

- Continue ongoing sampling to characterize change in wastewater composition
  - Major recent policy change (September, 2024) resulted in near-complete redirection of discharge from Tijuana River Estuary to Punta Bandera outfall in Mexico
- Operationalize algorithms to map this feature in the Tijuana River Estuary and San Diego / Tijuana coastal ocean.
- Results are encouraging for use of EMIT and other hyperspectral satellite sensors in water quality applications.
- Ongoing work integrating hyperspectral signatures with multispectral (Planet, Landsat, and Sentinel-2), SAR (Sentinel-1) & thermal (ECOSTRESS)
  - Erin Reilly, Master's Thesis (SAR) ; Lily Winesett, Undergraduate Honors Thesis (multispectral)

Acknowledgments

- **We would like to thank the large group of collaborators and students who make our field and laboratory sampling efforts possible, including but not limited to:** Lily Winesett, Erin Reilly, Callie Summerlin, David Penn, Mia Pollasky, Julian Gutierrez, Scotty Dingwall, Blanca Heredia, Trinity Weary, Tate Mckay, and Yzatis Silva.

Thanks! Questions?

Photo Credit: Sippakorn Yamkasikorn

Coastal Vulnerability in the Face of Increasing Wildfires:

A Land-sea Perspective Integrating Physical, Biological, and Socioeconomic Factors

Mandy Lopez[1,2]
amanda.m.lopez@jpl.nasa.gov

Christine M. Lee[1], Erin L. Hestir[3], Lori A. Berberian[4], Carmen Blackwood[1], Michelle Gierach[1]

[1] Jet Propulsion Laboratory, California Institute of Technology

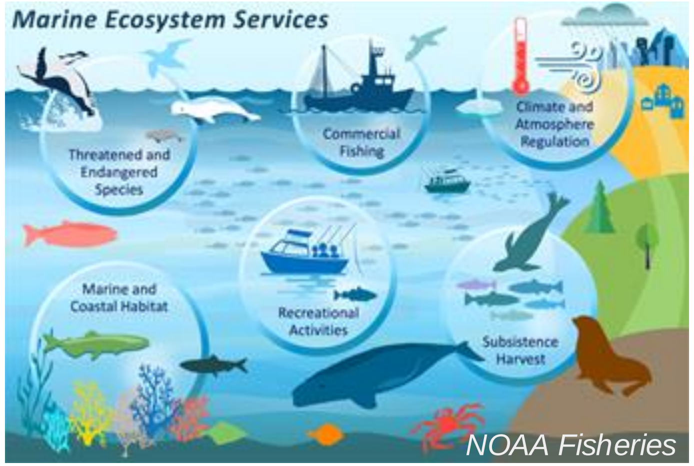
[2] Joint Institute for Regional Earth System Science and Engineering, University of California, Los Angeles

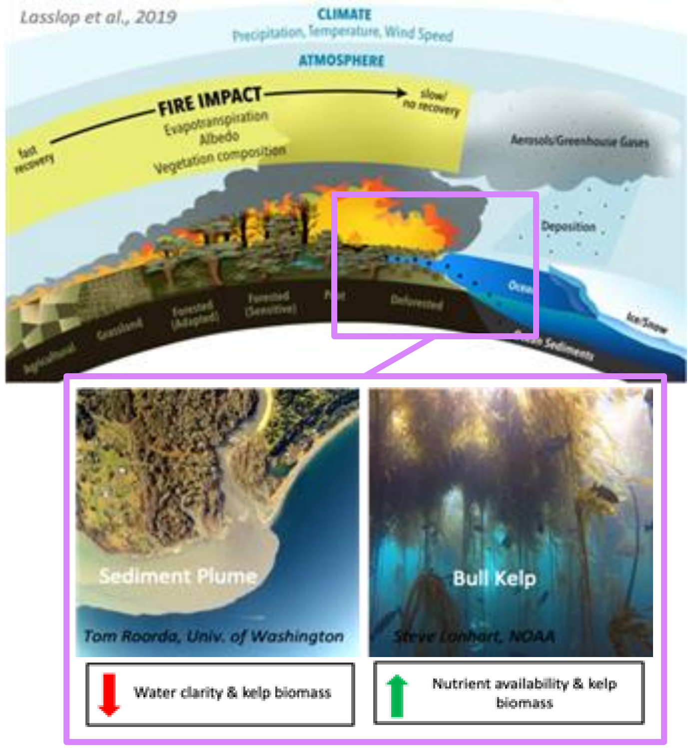
[3] Department of Civil & Environmental Engineering and Sierra Nevada Research Institute, University of California, Merced

[4] Department of Geography, University of California, Los Angeles

Climate change, wildfires, and the land-ocean continuum

- Coasts are biodiversity hotspots providing key ecosystem services (e.g., habitat, carbon cycling, fisheries, recreation)
  - ~4 billion people live near or depend on coasts
- Wildfires increasing in frequency and severity due to changing climate and human activities
- Major implications of wildfires for humans and the environment
  - 15% of terrestrial and freshwater species higher extinction risks due to fire
  - 2001-2019 fires caused >110 M ha of global forest loss
  - 2020 California fires cost $149 B across economic, health, and environmental sectors
- Fires reduce vegetation cover/infiltration and increase erosion
  - Coastal watersheds link land to sea – increased runoff changing exports of sediment, nutrients, carbon, pollutants
  - Coastal vulnerability and resilience overlook wildfire influence on marine ecosystems and the humans dependent on them





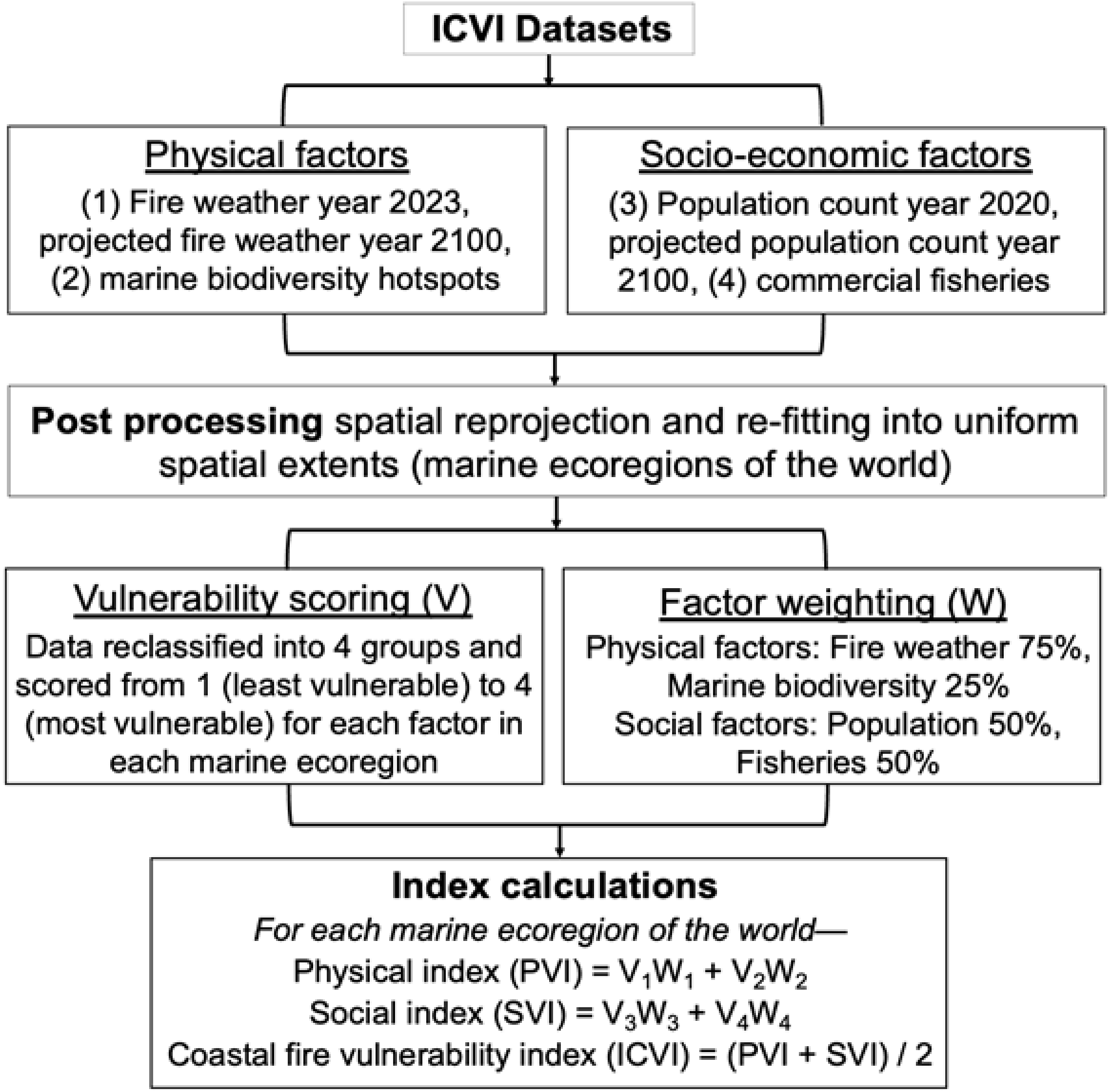
Global coastal wildfire vulnerability index

- Coastal vulnerability indices traditionally reflect physical factors like coastal slope, sea level rise, etc.
- Wildfire vulnerability indices assess socioeconomic-ecological vulnerability in inland systems *overlooking the coastal domain*
- **Knowledge gap: coastal vulnerability to wildfire!**

1. Integrated coastal wildfire vulnerability index (ICVI) combining physical and socioeconomic factors

1. Coastal indigenous seafood consumption and marine protected areas (MPA) data overlaid with ICVI results to further assess coastal vulnerability to fire

1. Identify priority areas for coastal wildfire resilience efforts and opportunities for space-based observations to improve understanding



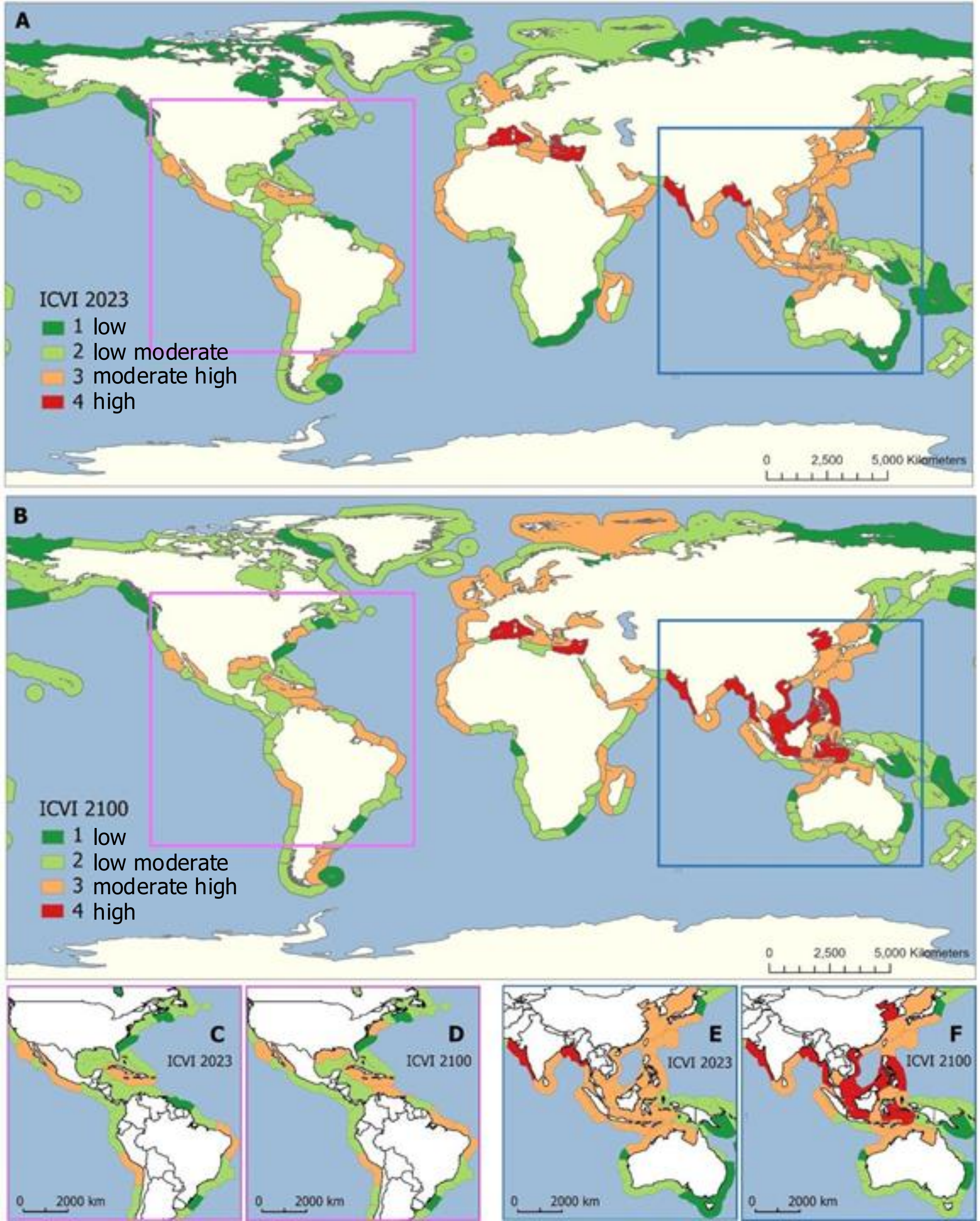
Coasts most vulnerable to wildfire

- Highest vulnerability in North Africa-South Europe and South-Southeast Asia currently, and expands into South-Southeast-East Asia by 2100

- Moderate to high vulnerability in most of Asia and select areas in Europe, Africa, Central-South America, by 2100 this expands in the Americas, Europe, Africa

- Offers first look at potential coastal vulnerability to wildfire, how does it compare with MPA and coastal indigenous seafood consumption? (next slide)

- Future work could benefit from additional data including sea level rise, blue carbon inventories (kelp, corals, seagrasses, indigenous coastal resource use (i.e., subsistence, ceremonial), etc.



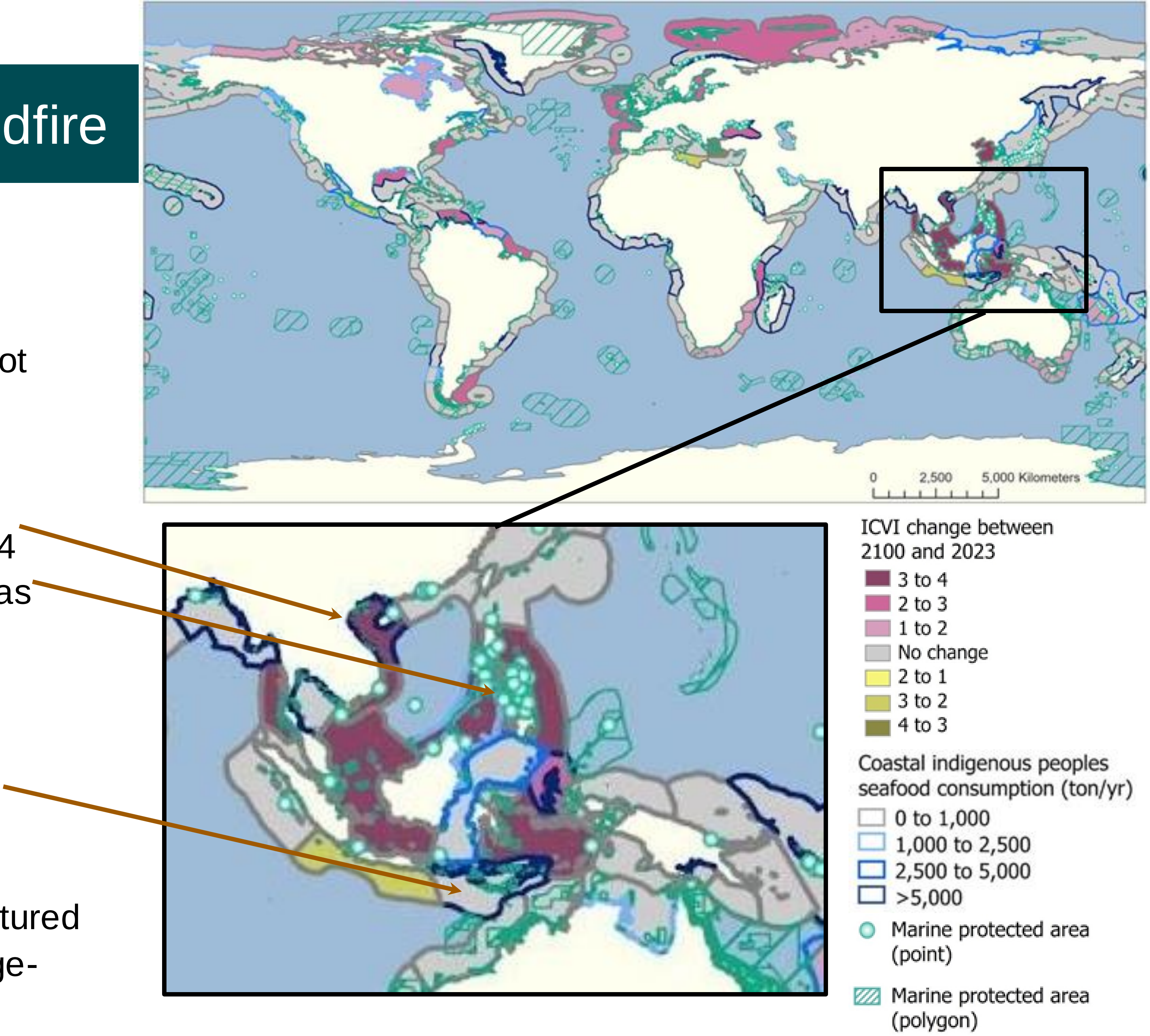
Coasts most vulnerable to wildfire

- MPA presence and high amounts of indigenous seafood consumption further emphasize vulnerable regions in South America, Southeast Asia, and Oceania not fully captured by ICVI

- Both Vietnam and The Philippines highly vulnerable with ICVI increases from 3 to 4 between 2023 and 2100, only Vietnam has high indigenous seafood consumption

- Lesser Sunda Islands, Indonesia no ICVI change between 2023 and 2100 yet high indigenous seafood reliance and MPAs

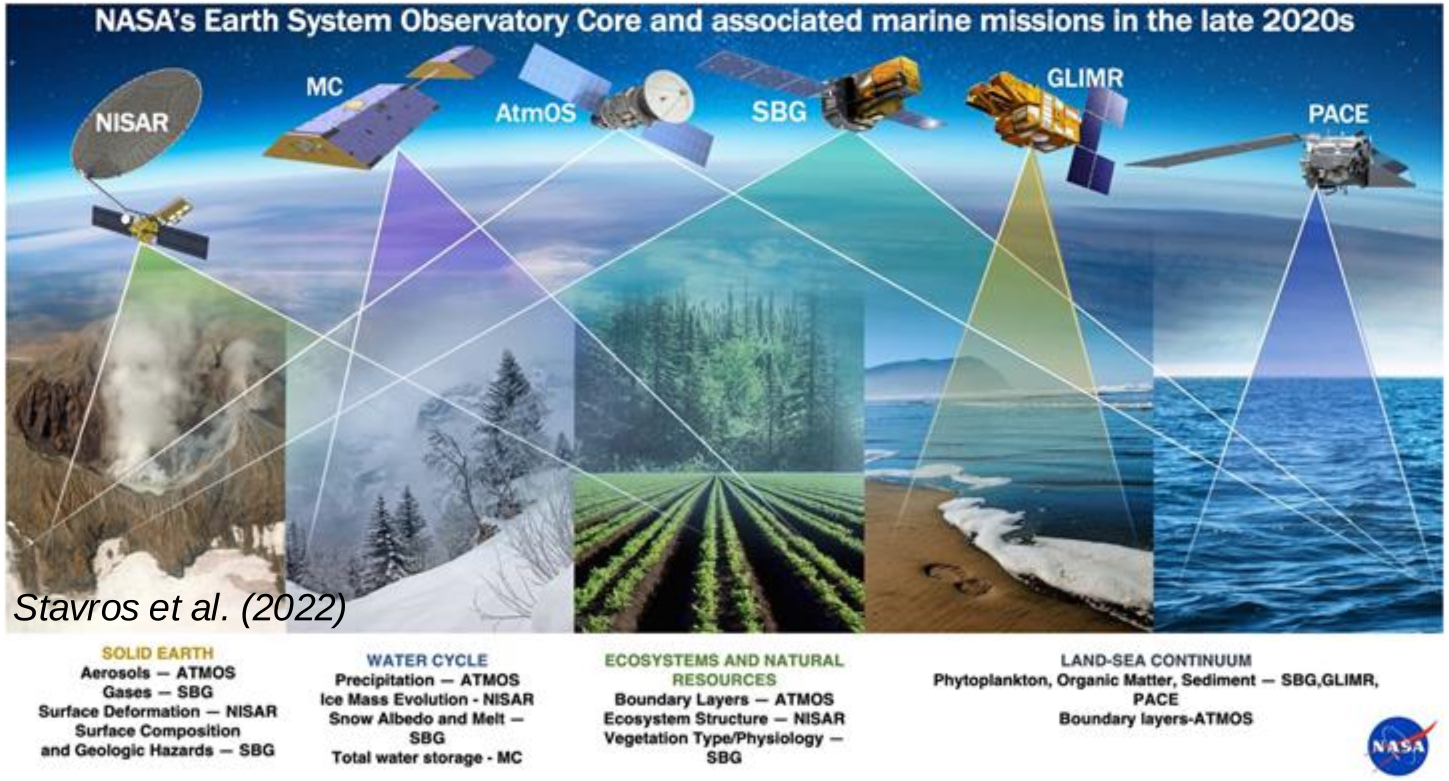
- Indigenous perspectives are not well captured by this ICVI, need for more inclusive, large-scale data



Remote sensing as a tool for understanding coastal wildfire vulnerability

- Robust and integrated social, economic, <u>environmental</u> data at local to global levels are critical
  - Current and future MPA management
  - Equitable inclusion of communities (especially indigenous)

- In situ data limitations: satellite remote sensing can provide global coverage datasets at varying spatial and temporal scales to understand complex land-sea dynamics



Stavros et al. (2022)

Synergy example: Depending on spatial resolution and temporal revisits PACE or SBG could capture wildfire event and potentially post-fire coastal impacts, while GLIMR's sub-daily observations are well-suited to record ephemeral coastal processes like post-fire turbidity plumes and phytoplankton blooms

Thank you!

amanda.m.lopez@jpl.nasa.gov

Woolsey Fire near Malibu, California November 2018
Photo Credit: U.S. Forest Service

USF COOL
College of Marine Science
Optical Oceanography Lab

NASA

How have Florida's red tides changed over the past 40 years? Bridging CZCS to MODIS observations

Yao Yao [a], Chuanmin Hu [a], Brian Barnes [a], Katherine Hubbard [b], Cheng Xue [a], Jennifer Cannizzaro [a]

[a] University of South Florida, College of Marine Science, St. Petersburg, Florida, United States of America
[b] Florida Fish and Wildlife Conservation Commission, St. Petersburg, Florida, United States of America

NASA OBB annual meeting, Dec 3 & 5, 2024

How have Florida’s red tides changed over the past 40 years?

Why is it so difficult to address?

Field sampling

limited in both space and time, and often from event response. Difficult to make statistical assessment

Remote sensing

limited in accuracy due to many factors

So what?

To date, there is still dispute on whether red tides have increased in the past 40-50 years.

Our approach

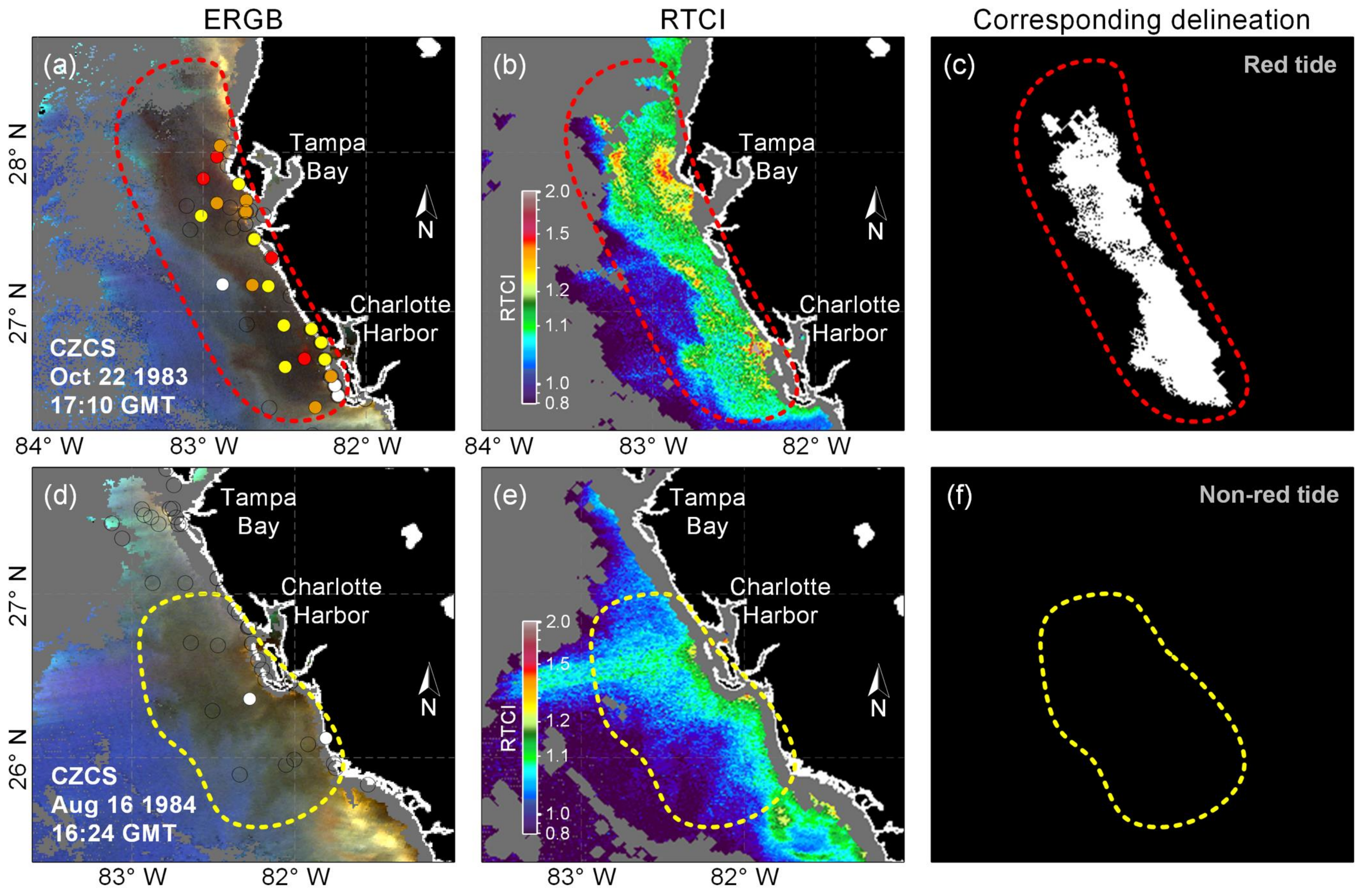
1. Combine the strengths of field sampling and remote sensing to make integrated red tide data products

2. Bring in CZCS (1978-1986) to the picture, together with MODIS/A (2003 -)

3. Difficulty: comparing CZCS with MODIS is apples-to-oranges, so we have to change it to apples-to-apples.

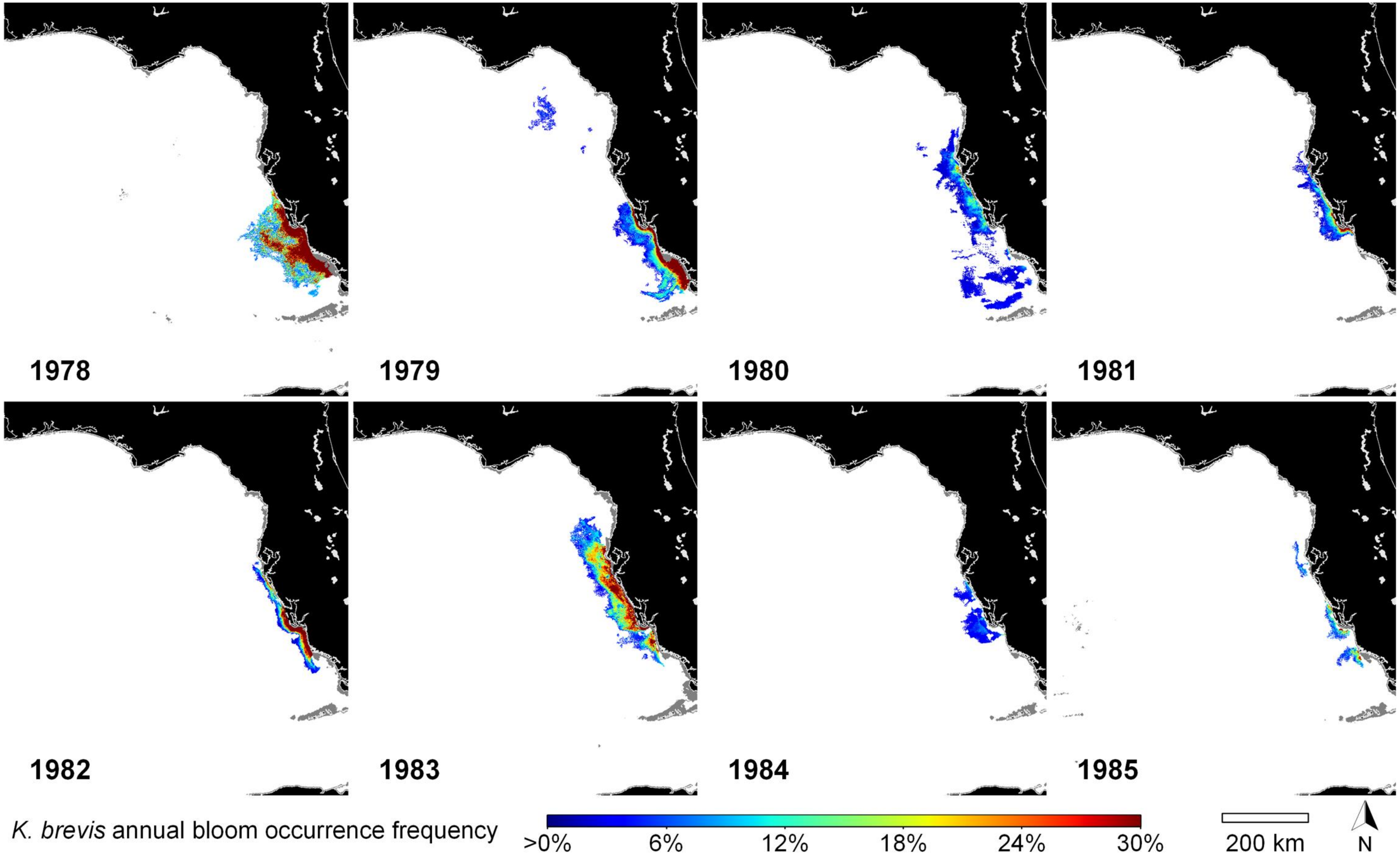
1. Combine the strengths of field sampling and remote sensing => red tide maps

(1) darkish, reddish patches on ERGB images;
(2) high in situ cell abundance (>100,000 cells/L) in or near patches;
(3) high RTCI



Karenia brevis
cell abundance (cells L^{-1})
± 7days
0 – 1,000
1,001 – 10,000
10,001 – 100,000
100,001 – 1,000,000
Above 1,000,000

1. Combine the strengths of field sampling and remote sensing => annual bloom frequency



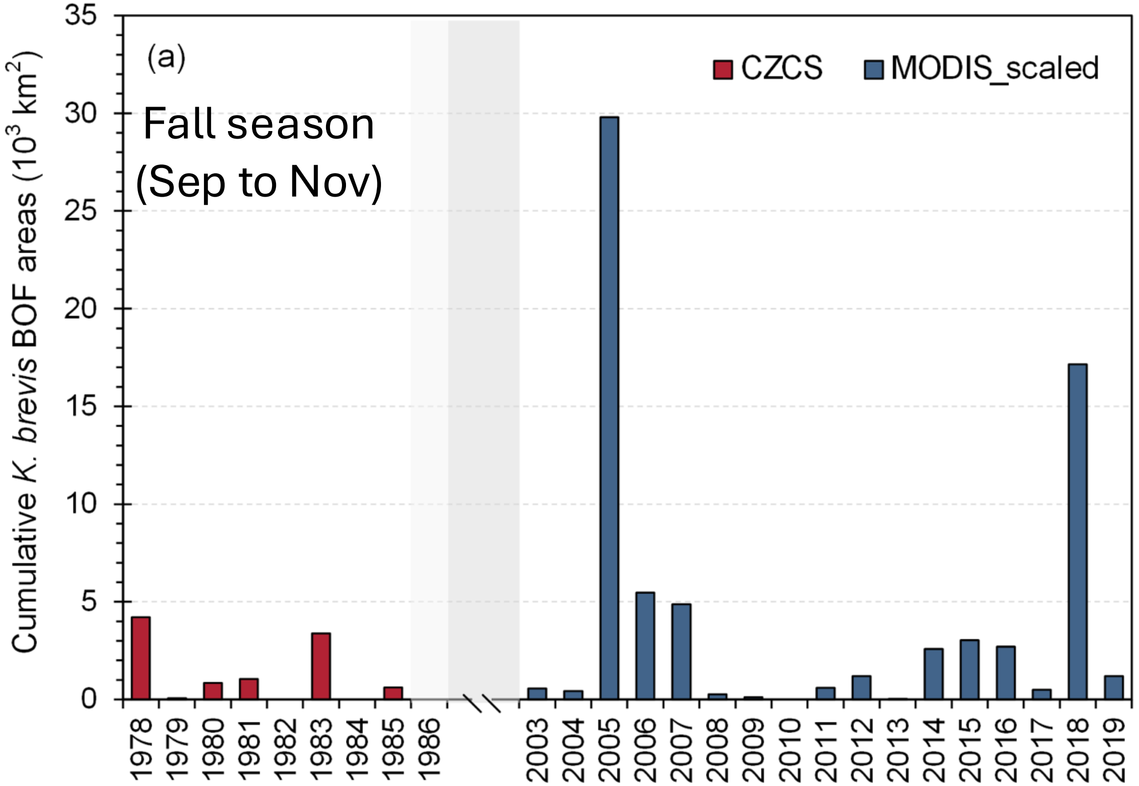
2. Make apples-to-apples comparison between CZCS and MODIS

How? Downgrade MODIS to CZCS

- Reduce MODIS data to 8 bits to match CZCS SNRs
- Reduce MODIS bands to CZCS bands
- Reduce MODIS revisit frequency to CZCS revisit frequency

Then, we have a new CZCS mission after 2003 to compare with the 1978-1986 CZCS mission

3. Do we see any changes in this apples-to-apples comparison?



	1978 - 1985	2003 - 2019
Annual bloom probability	75.0%	87.5% – 100% for any 8-year period
Mean bloom area (km^2)	1,270	80% chance of > 1,270
Mean duration (months)	2.8	4.1 – 5.8 for any 8-year period

Summary

- Integration of field and satellite data results in red tide maps
- Downgrading MODIS and combining with CZCS lead to a long-term red tide data record
- What have not changed? seasonality and general locations of red tides
- What have changed:

    Longer durations of blooms,

    Higher annual occurrence frequency,

    Most likely (80% chance) bloom size

Observed anthropogenic carbon changes in Subantarctic Mode Water: From formation regions to interior pathways

Daniela König[1], Seth Bushinsky[1], Mathilde Jutras[1] & Ivana Cerovečki[2]

[1]Department of Oceanography, University of Hawai‘i at Mānoa, Honolulu, HI, USA

[2]Scripps Institution of Oceanography, University of California San Diego, La Jolla, CA, USA

Motivation: Ocean carbon uptake variability & uncertainty

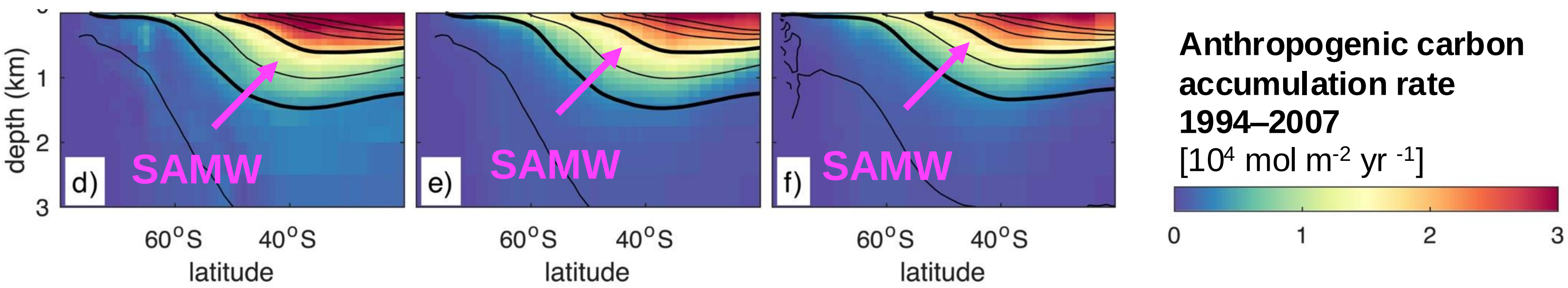
Hauck, et al. 2023

Anthropogenic carbon* accumulation in the ocean interior:

eMLR(C*) *observation-based*

OCIM *inverse model*

GOBMs *Global ocean biogeochemical models*



Anthropogenic carbon accumulation rate 1994–2007 [10^4 mol m^{-2} yr^{-1}]

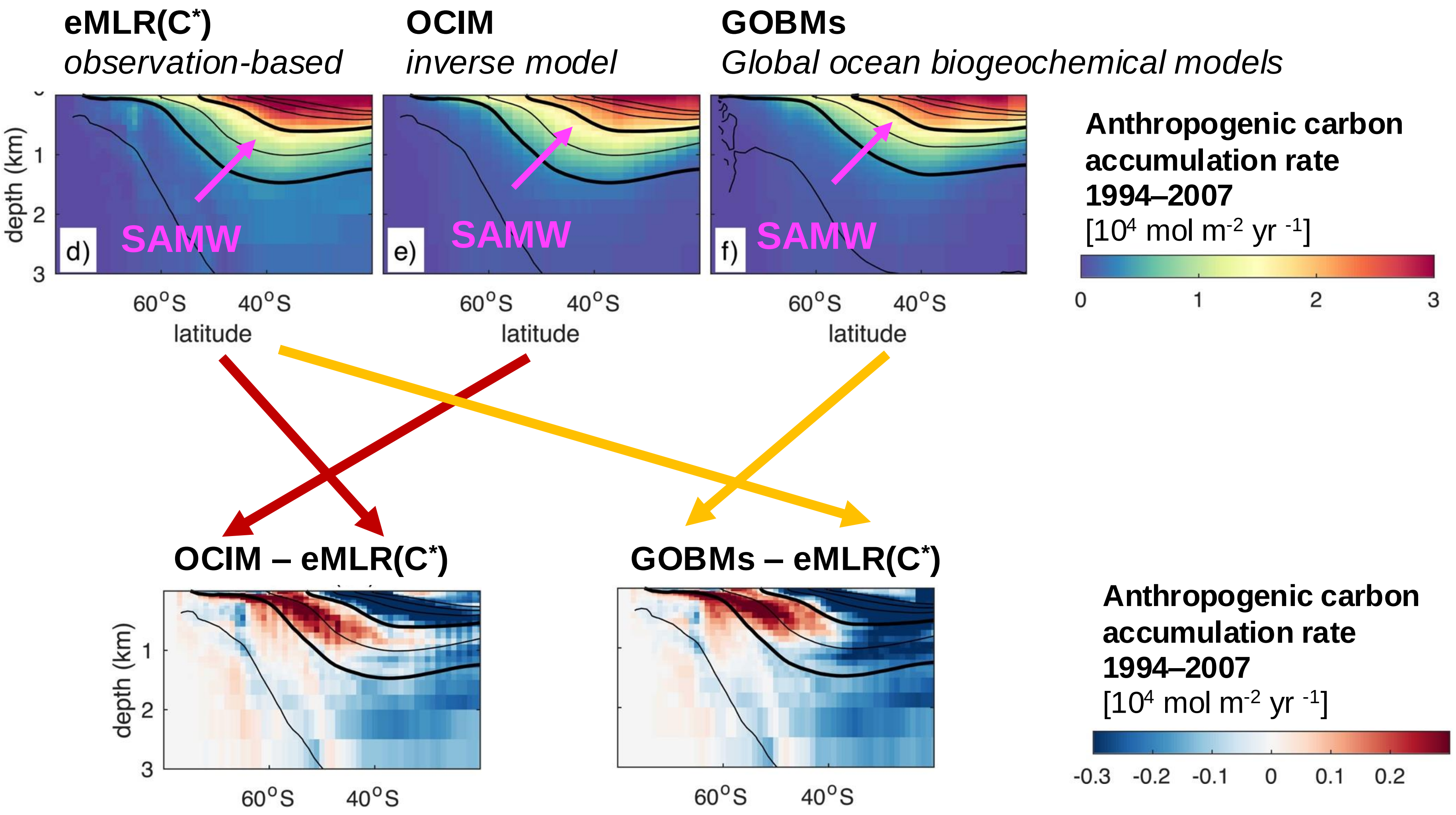
**zonally integrated*

Motivation: Ocean carbon uptake variability & uncertainty

Hauck, et al. 2023

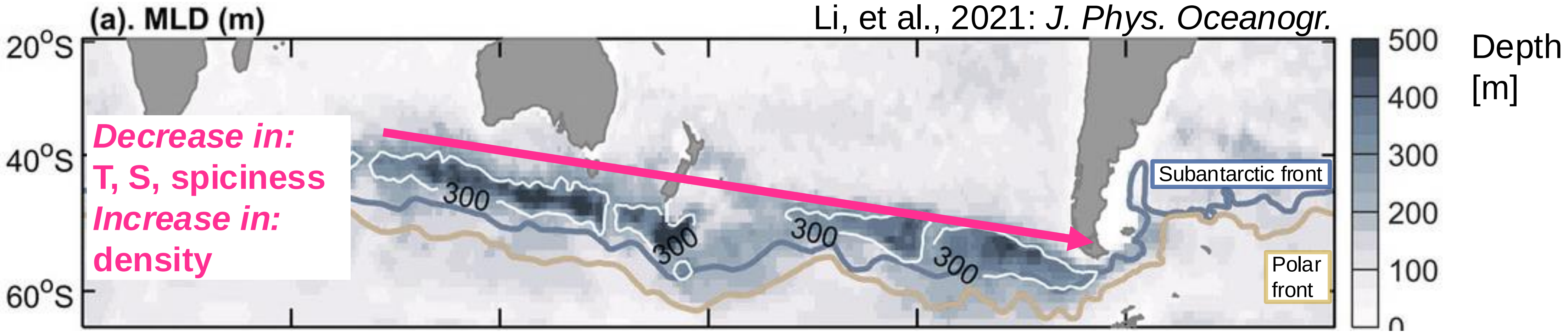
Anthropogenic carbon* accumulation in the ocean interior:

**zonally integrated*



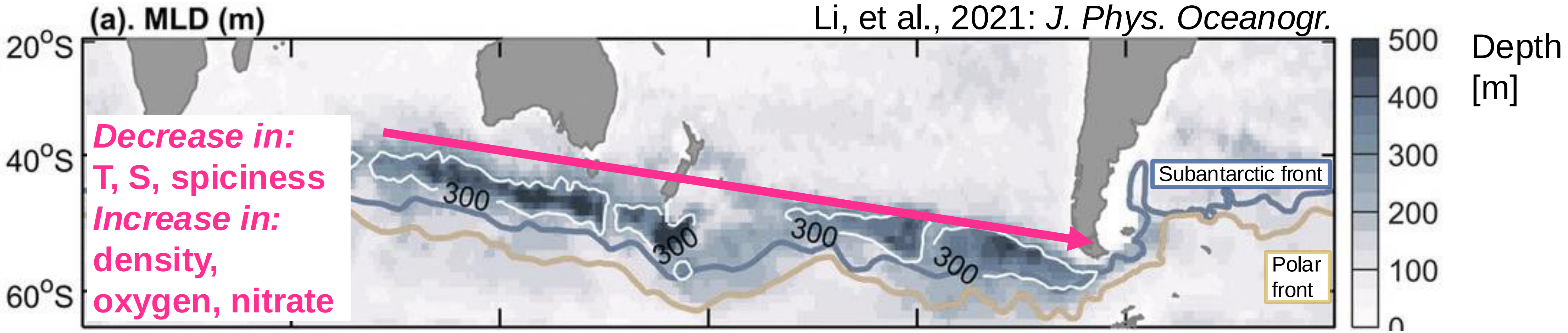
Subantarctic mode water: formation & physical properties

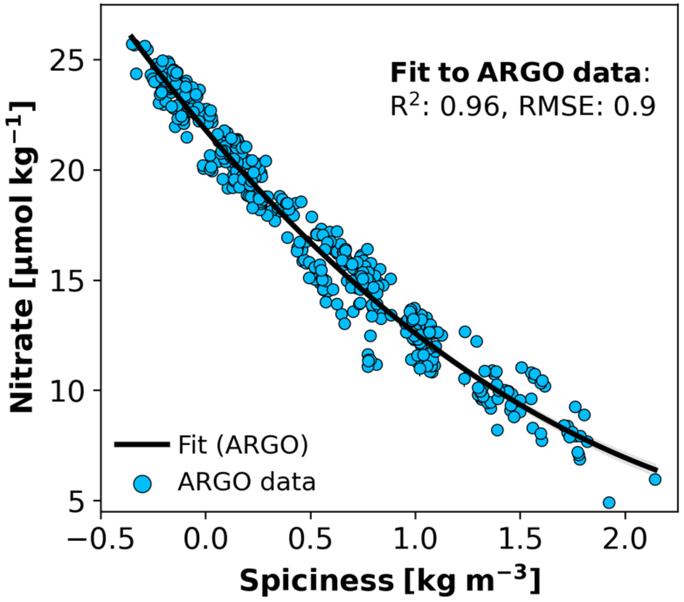
Li, et al., 2021: *J. Phys. Oceanogr.*

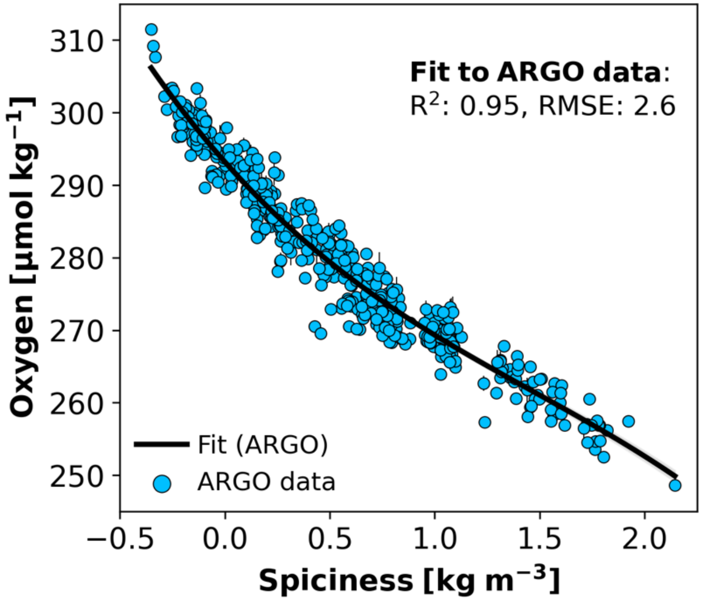


Biogeochemistry of SAMW at formation

Li, et al., 2021: *J. Phys. Oceanogr.*



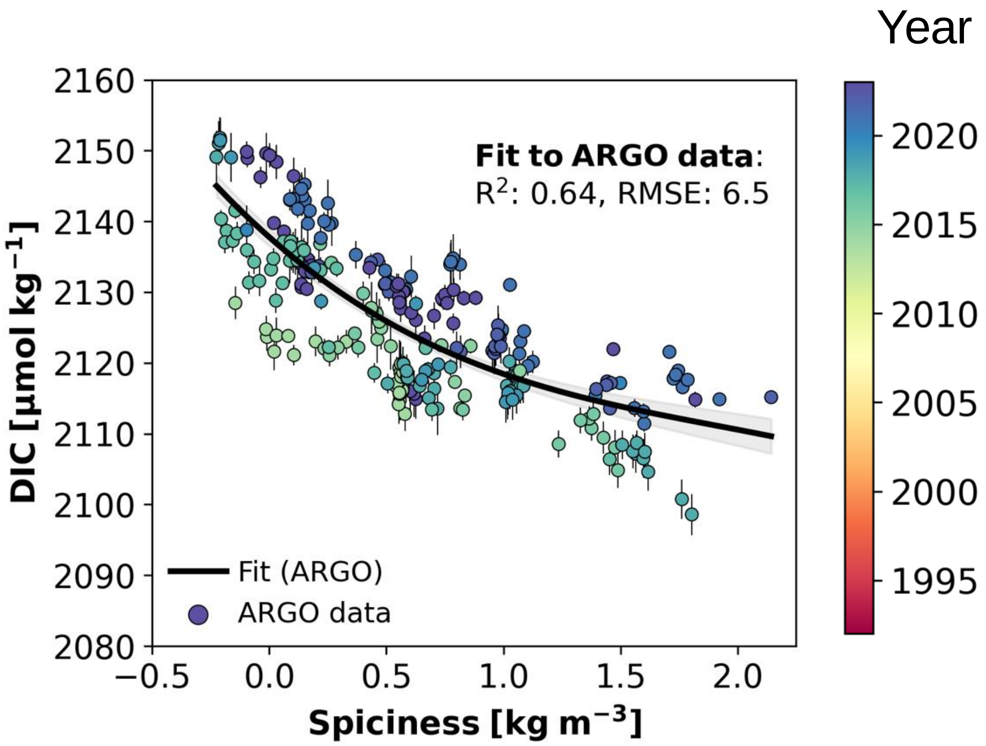


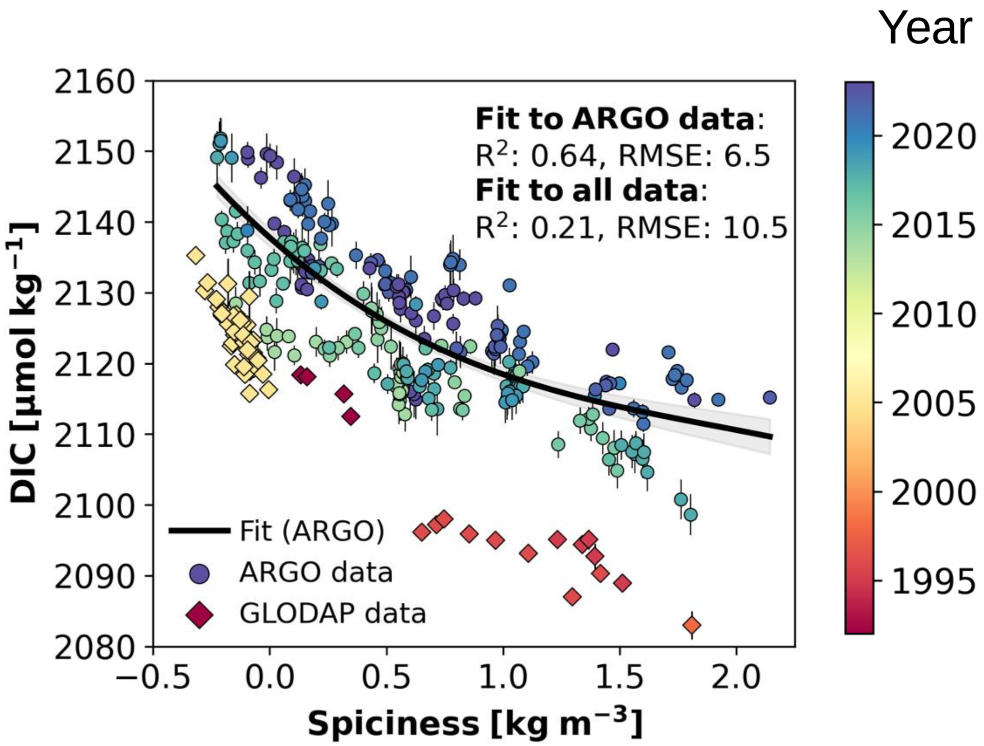


Strong correlation between deep winter mixed layer spiciness and nitrate & oxygen

Data from ARGO floats with >200m mixed layer depth

DIC accumulation in SAMW formation regions

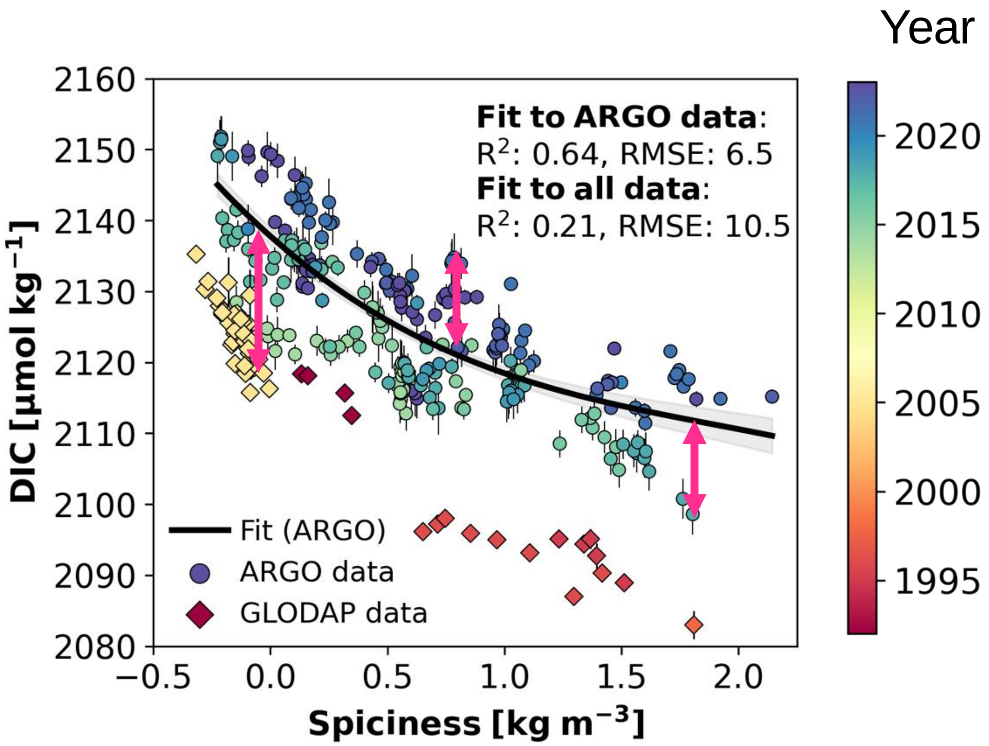


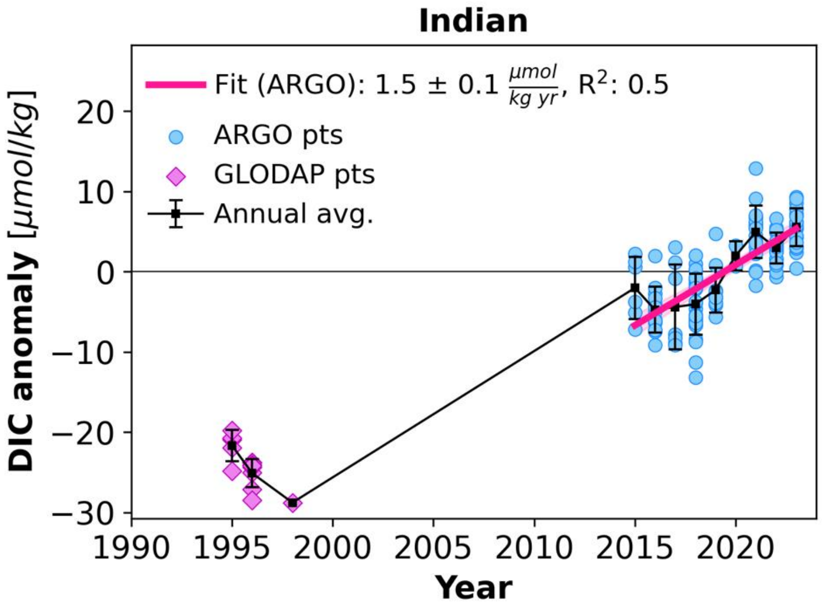


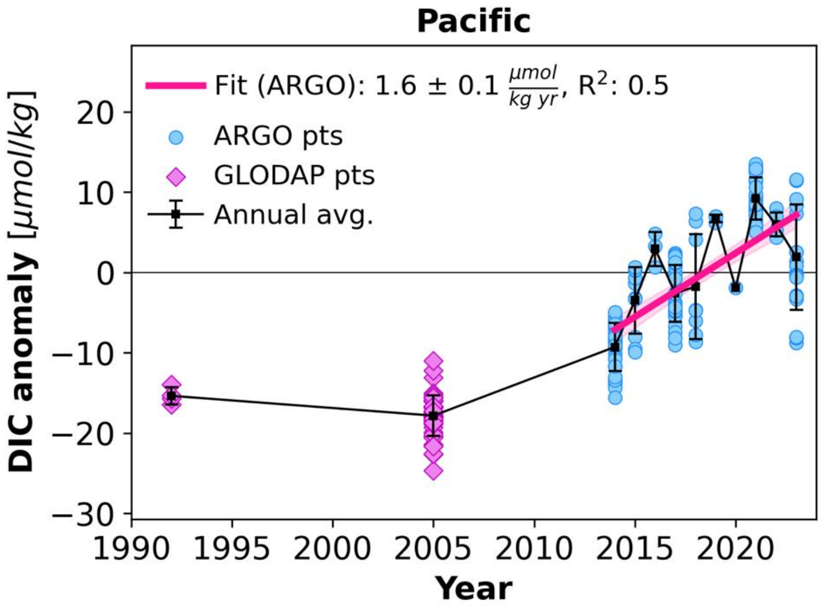
Correlation does not work as well for DIC due to increasing atmospheric CO_2

Especially obvious for older shipboard data (from GLODAP)

DIC accumulation in SAMW formation regions

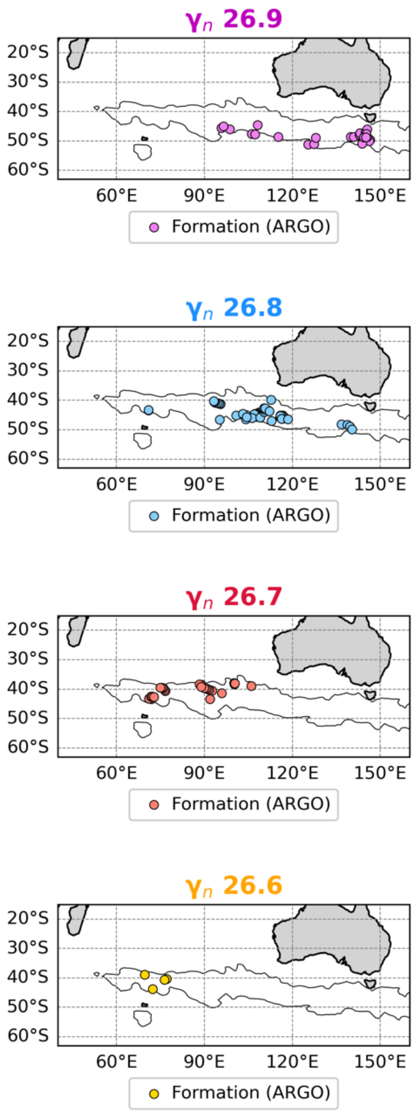


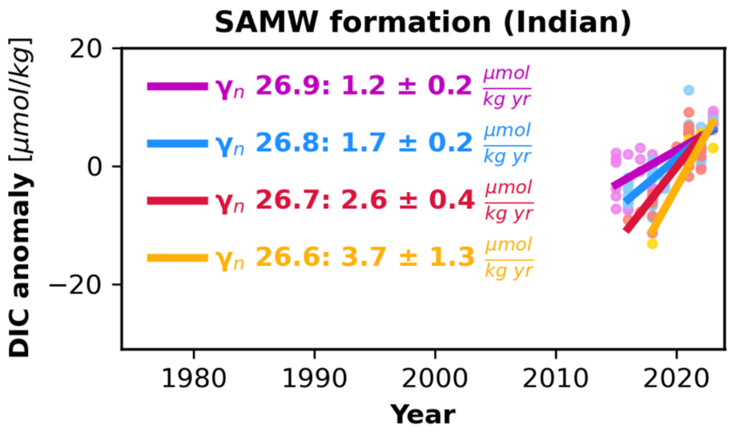


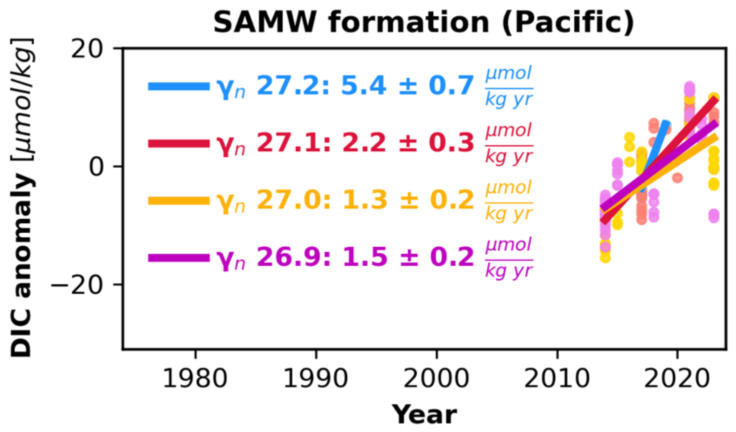


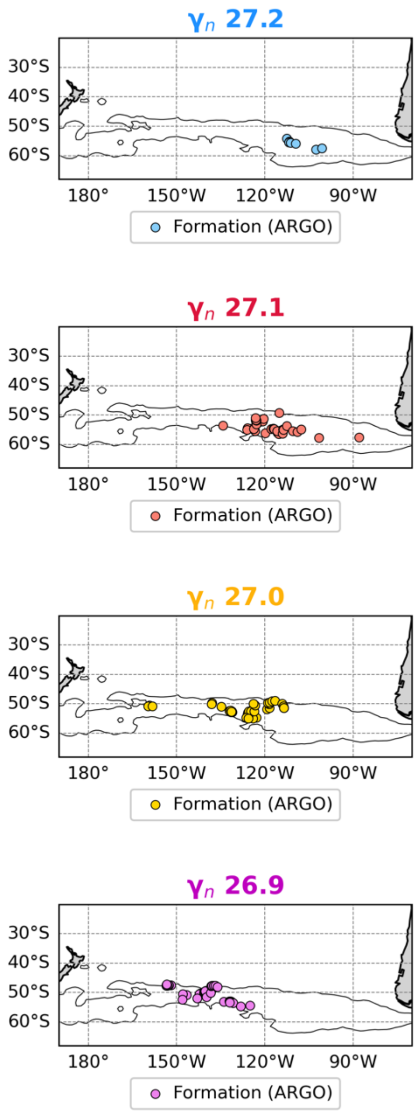
Can use anomalies from (cubic) regression through ARGO data to estimate DIC increase

DIC accumulation in different density layers

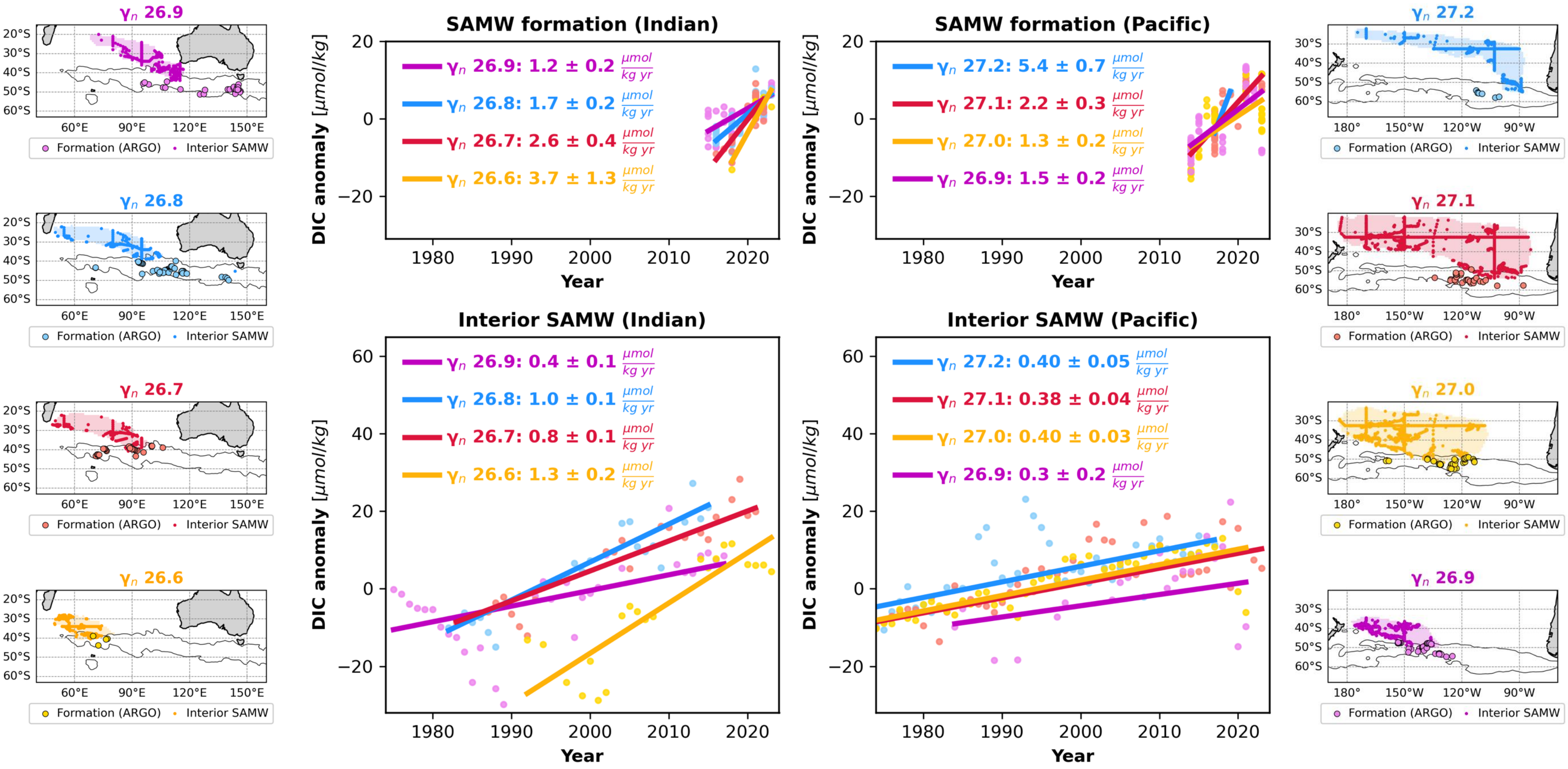




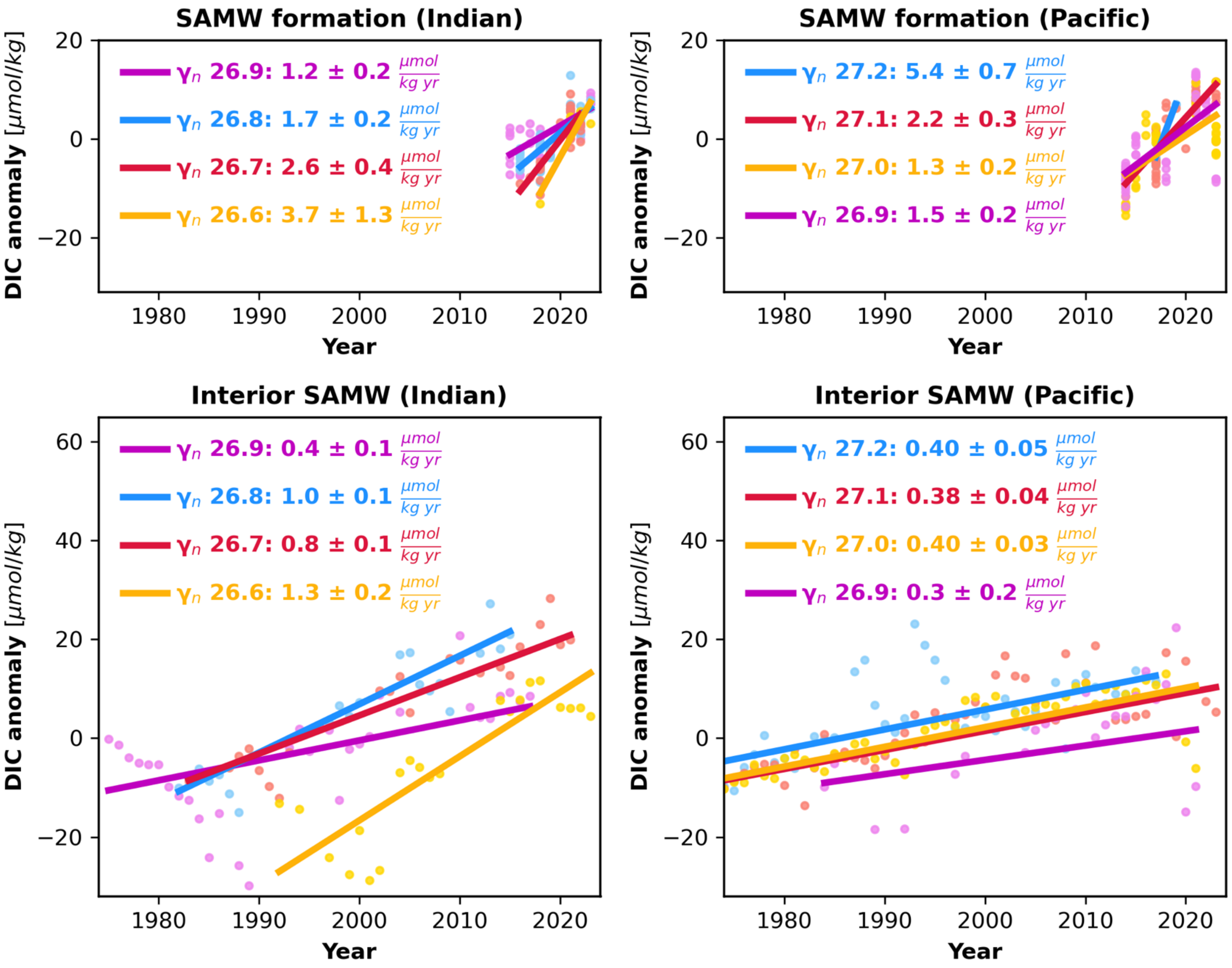




DIC accumulation in different density layers



DIC accumulation in different density layers



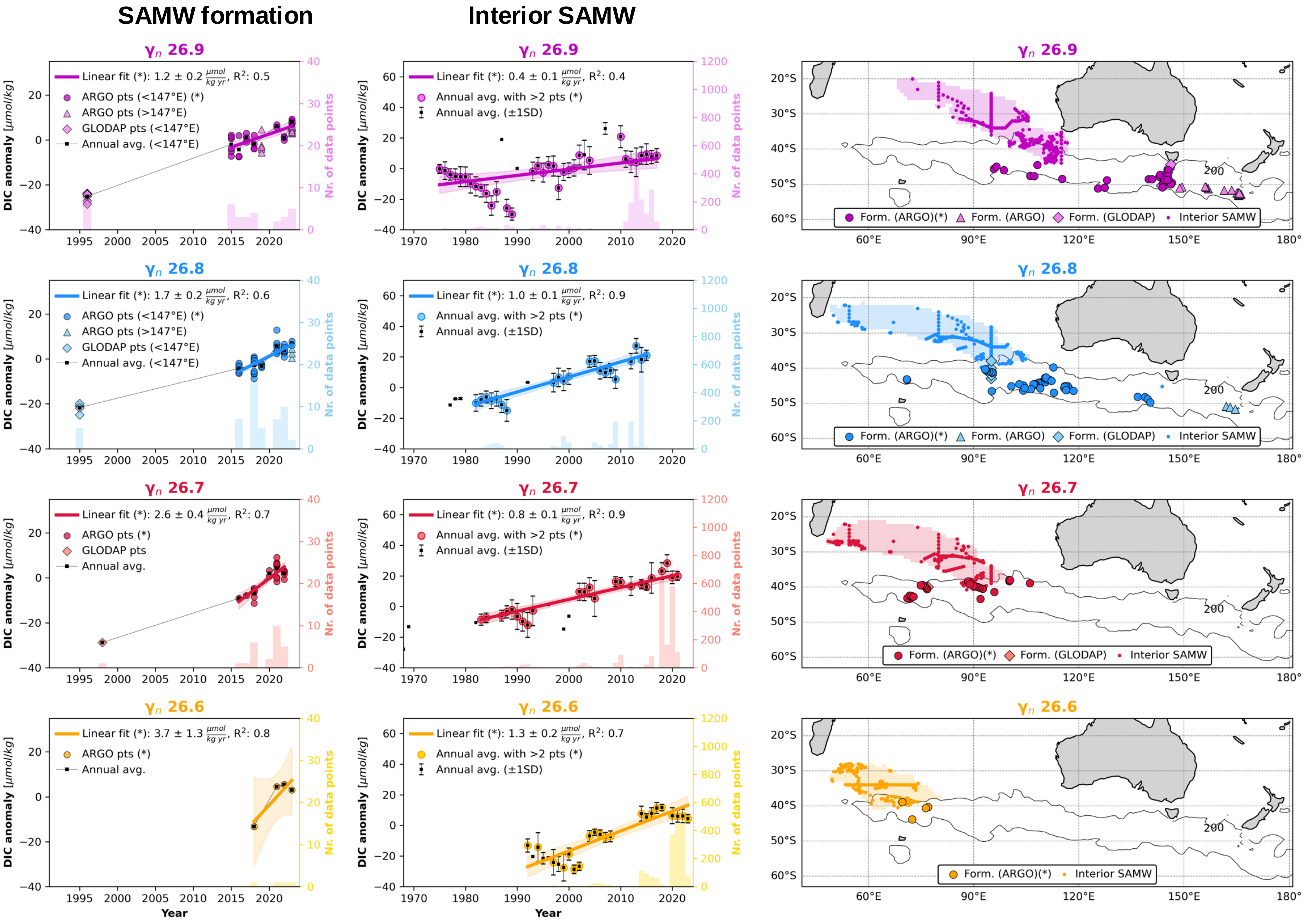
Stronger carbon accumulation in lighter layers (more or less)

Stronger carbon accumulation in denser layers

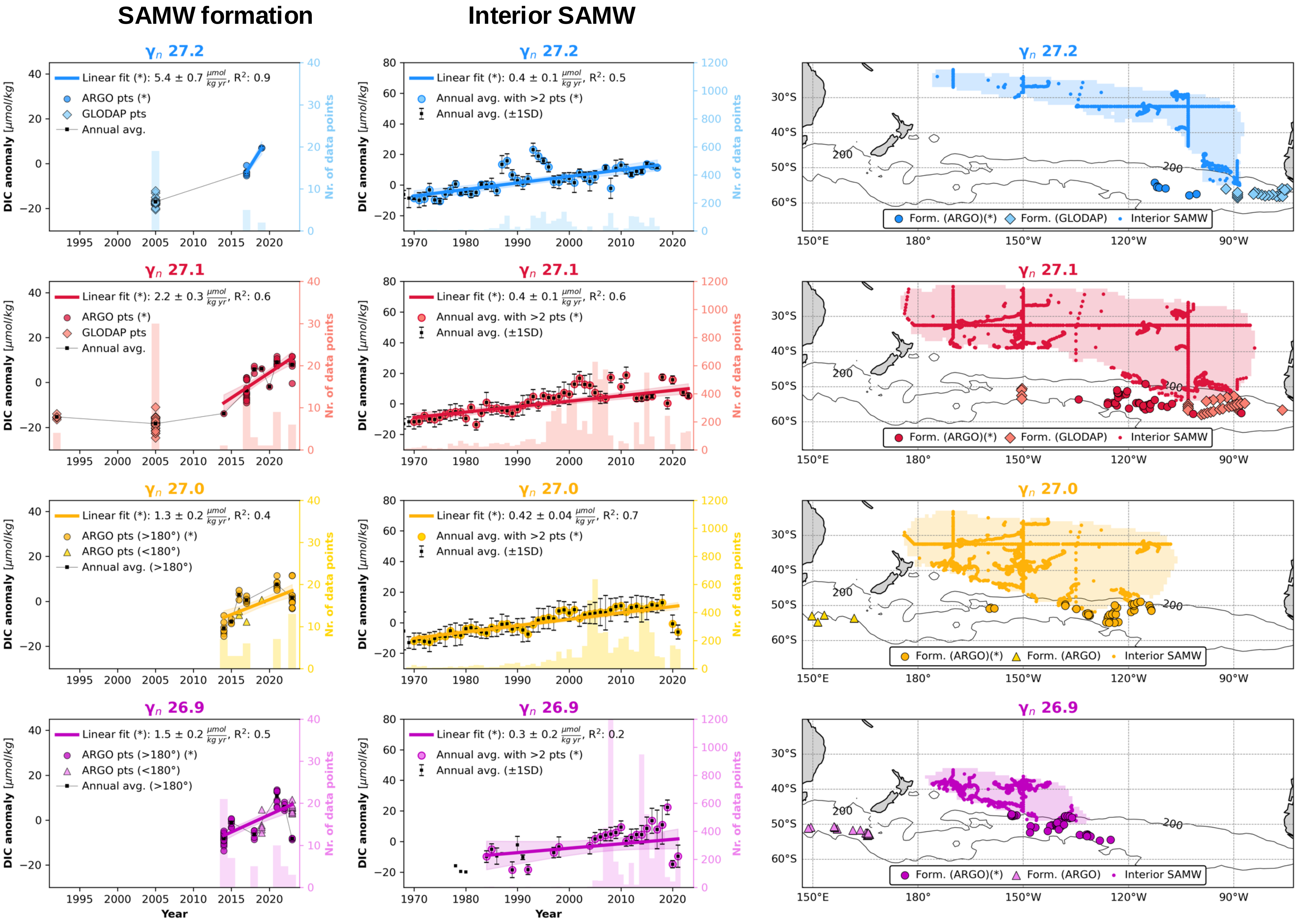
Similar carbon accumulation in all layers

Bonus slides

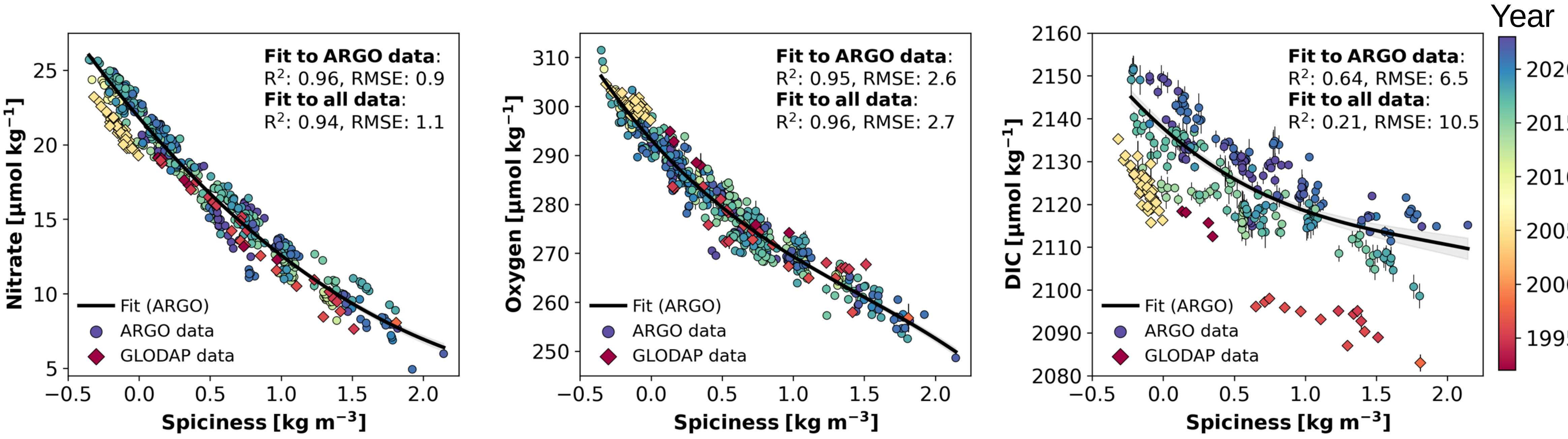
Indian Ocean

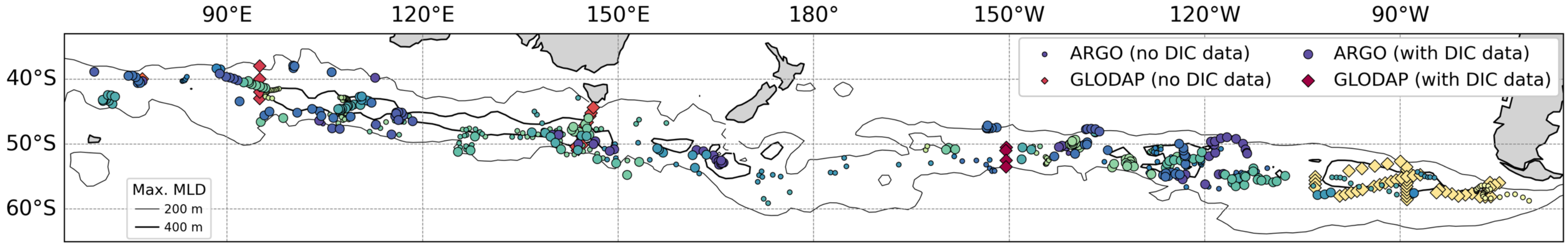


Pacific Ocean

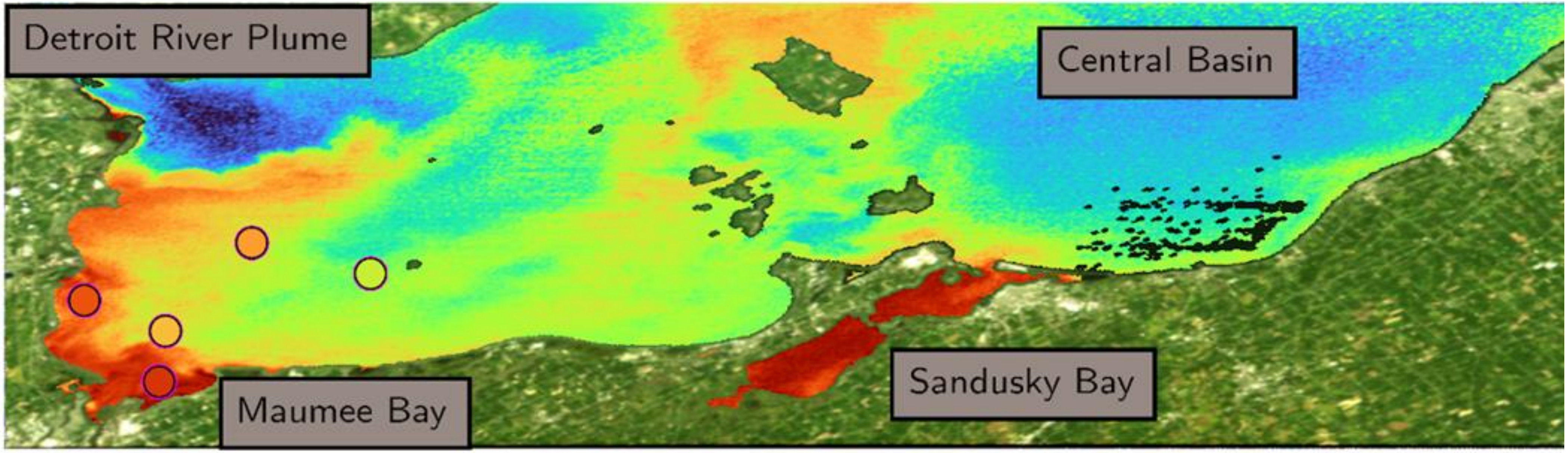


Biogeochemistry of deep winter mixed layers





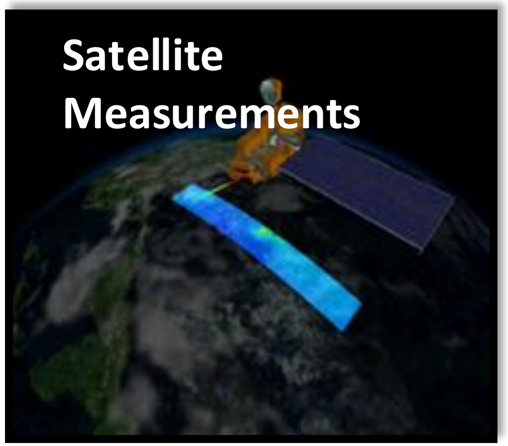
Aquaverse: An Aquatic Inversion Scheme for Remote Sensing of Fresh and Coastal Waters



Ryan E. O'Shea[1,2] (ryan.e.o'shea@nasa.gov); Arun M. Saranathan[1,2]; Akash Ashapure[1,2]; Will Wainwright[1,2]; Brandon Smith[1,2]

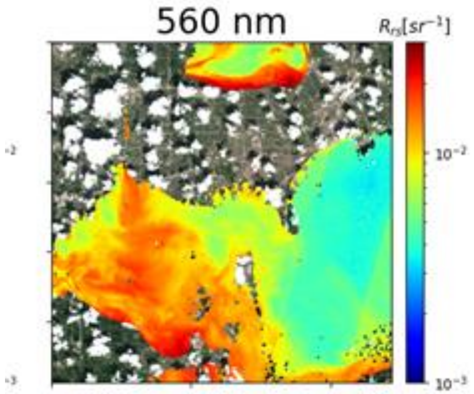
[1]Science Systems and Applications Inc., Lanham, MD, U.S.
[2]NASA Goddard Space Flight Center, Greenbelt, MD, U.S.

Aquaverse: An Aquatic Inversion Scheme for Remote Sensing of Fresh and Coastal Waters



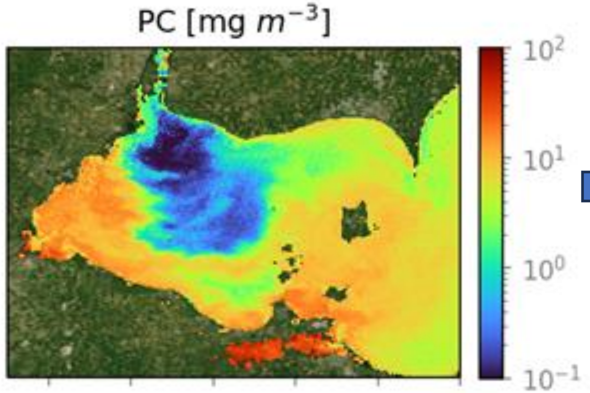
TOA radiance

Atmospheric Correction



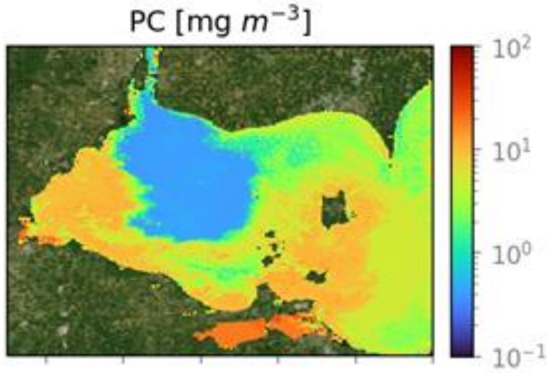
TOA → Rrs

Inverse Modeling



Rrs → IOPs and BPs

Uncertainty Products

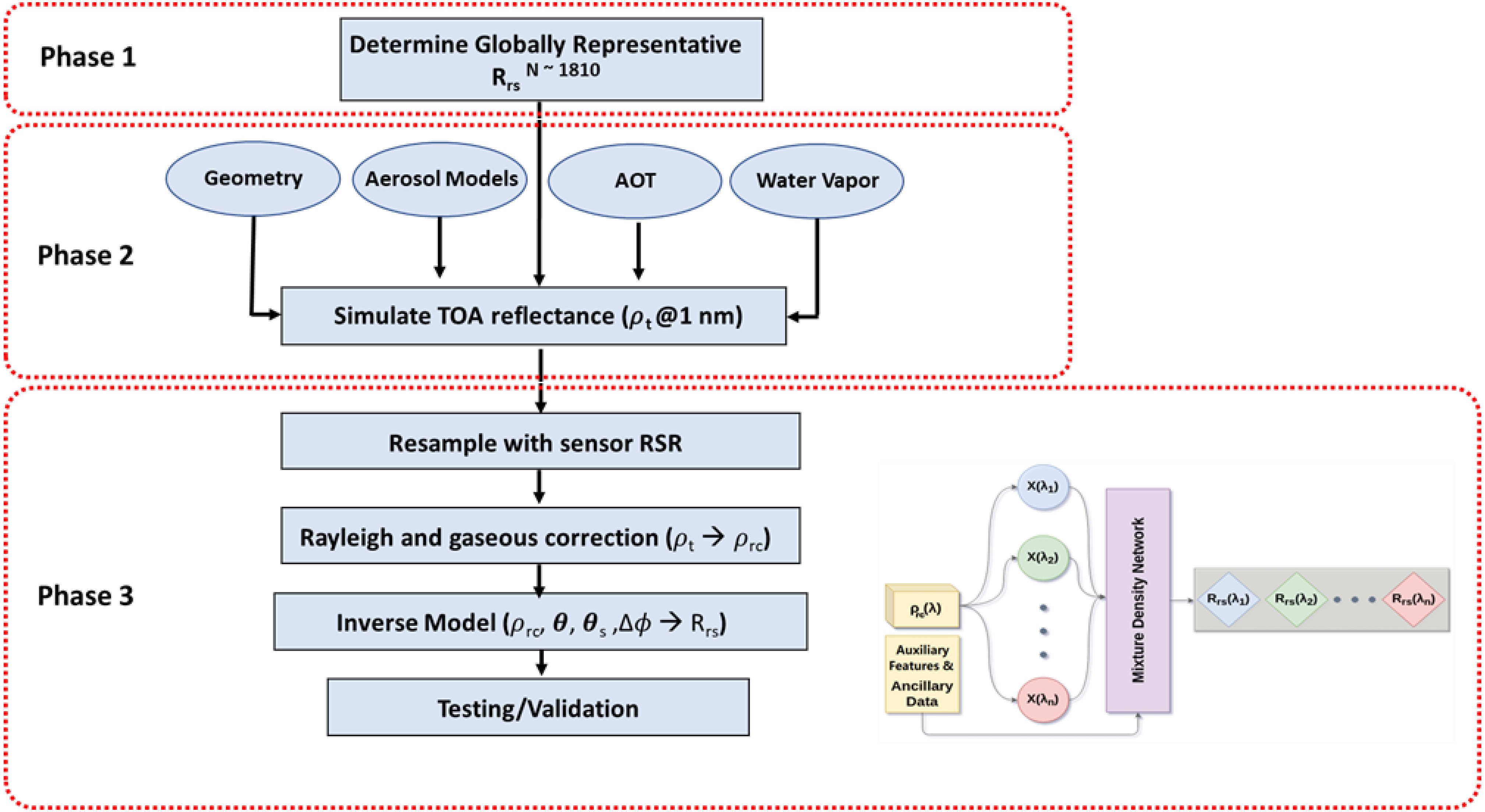


Rrs, BPs, IOPs → Uncertainty

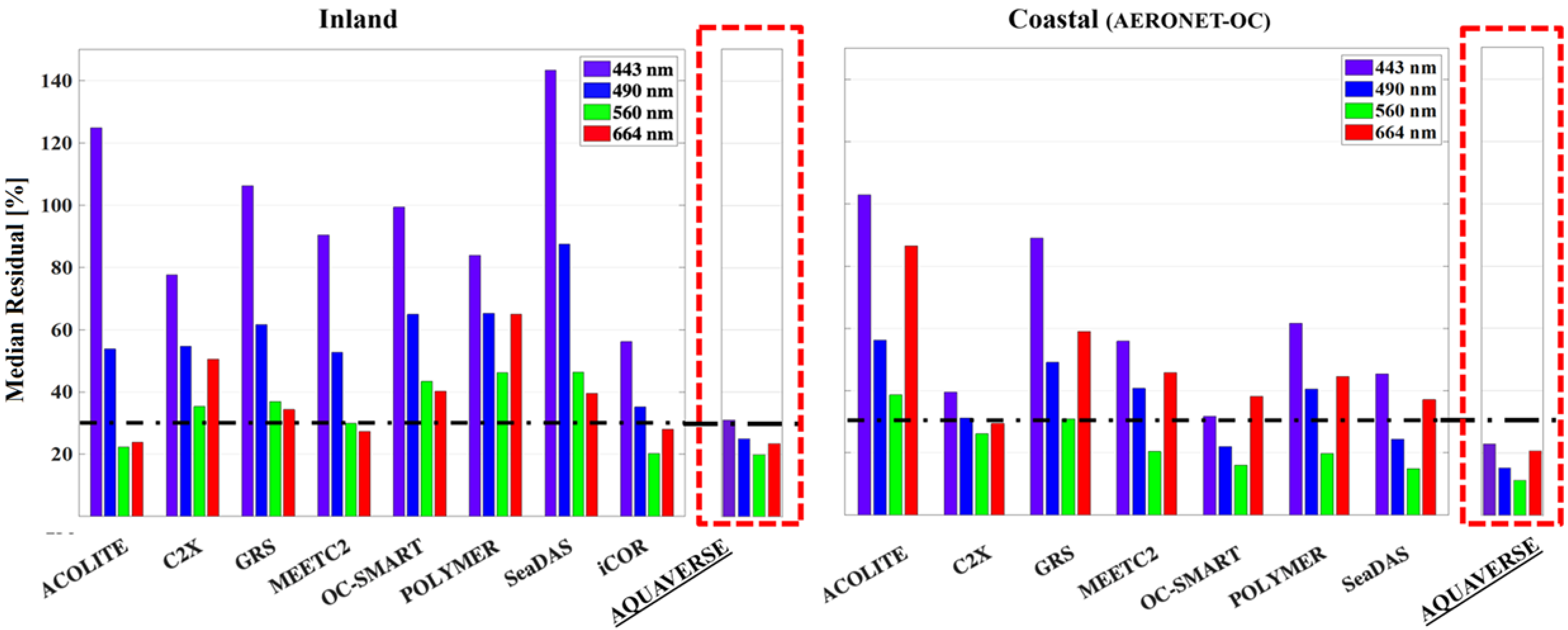
STREAM: Stakeholder Access

Atmospheric Correction Model Development

Goal: Develop an atmospheric correction processor that outperforms the state-of-the-art for inland & coastal waters.
Target missions: Landsat-8/OLI & Sentinel-2/MSI



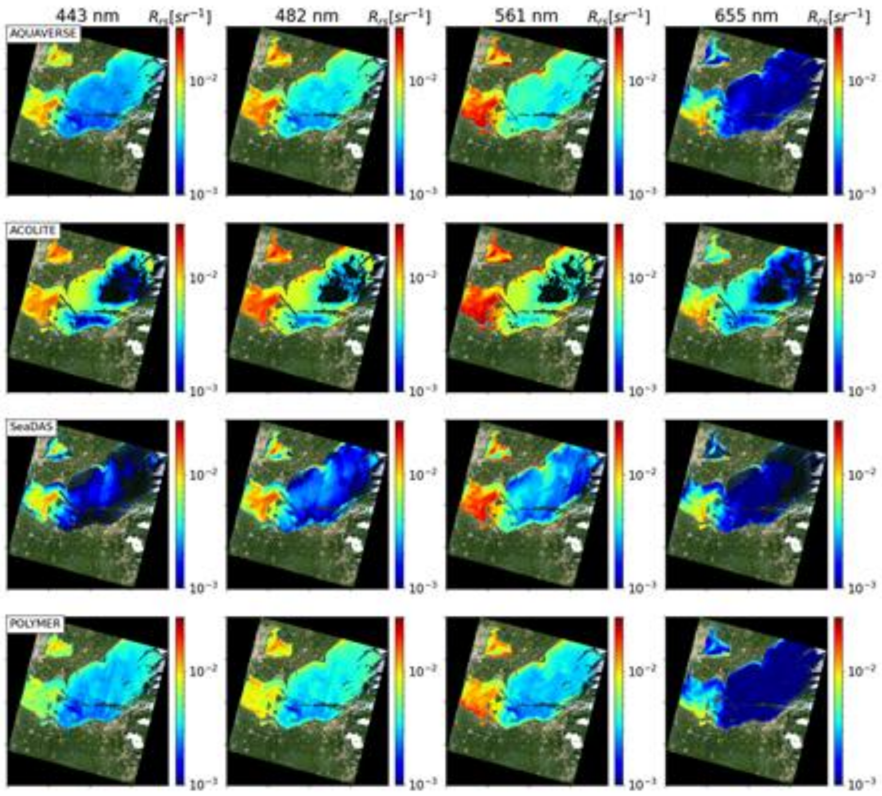
Performance Assessment



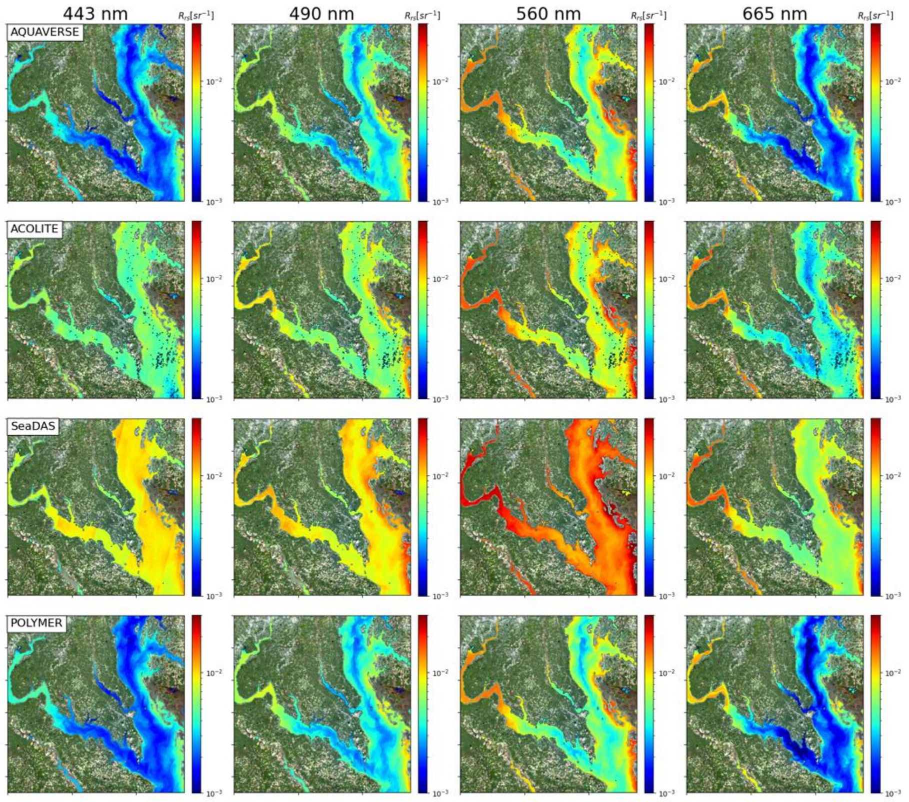
Pahlevan et al. 2021. ACIX-Aqua: A global assessment of atmospheric correction methods for Landsat-8 and Sentinel-2 over lakes, rivers, and coastal waters. Remote Sensing of Environment, 258, 112366

Visual Performance Assessment

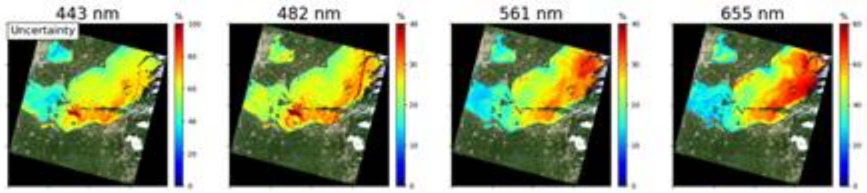
Landsat-8/OLI on August 19, 2023



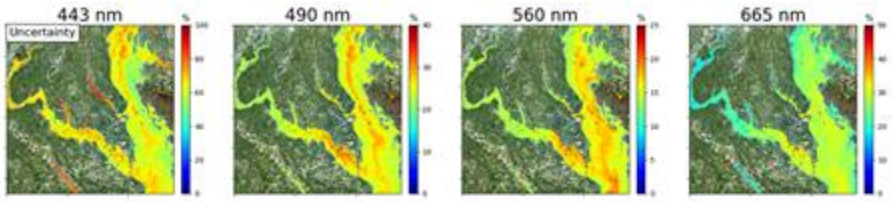
Sentinel-2/MSI on October 17, 2020



Aquaverse Uncertainty



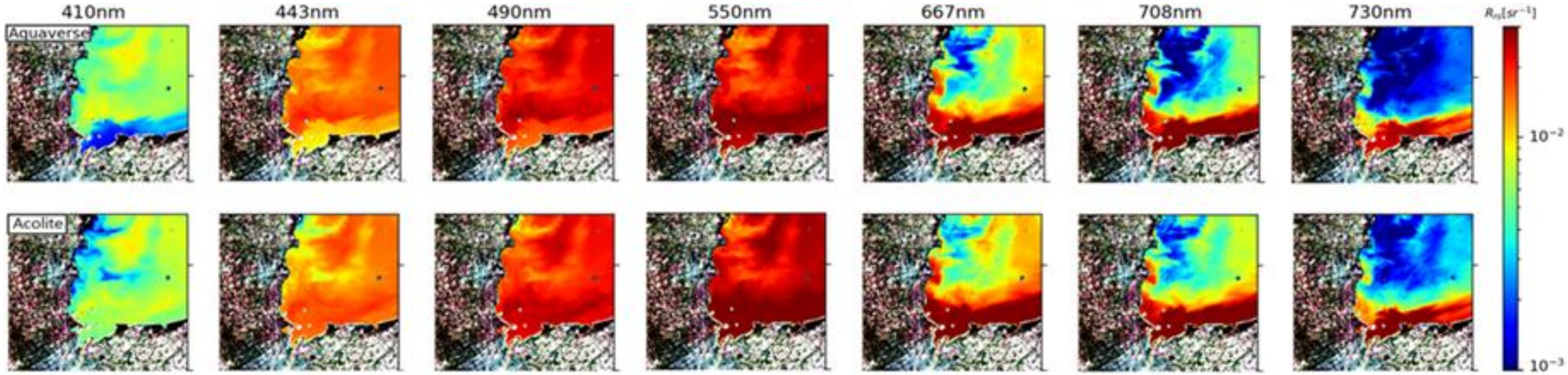
Aquaverse Uncertainty

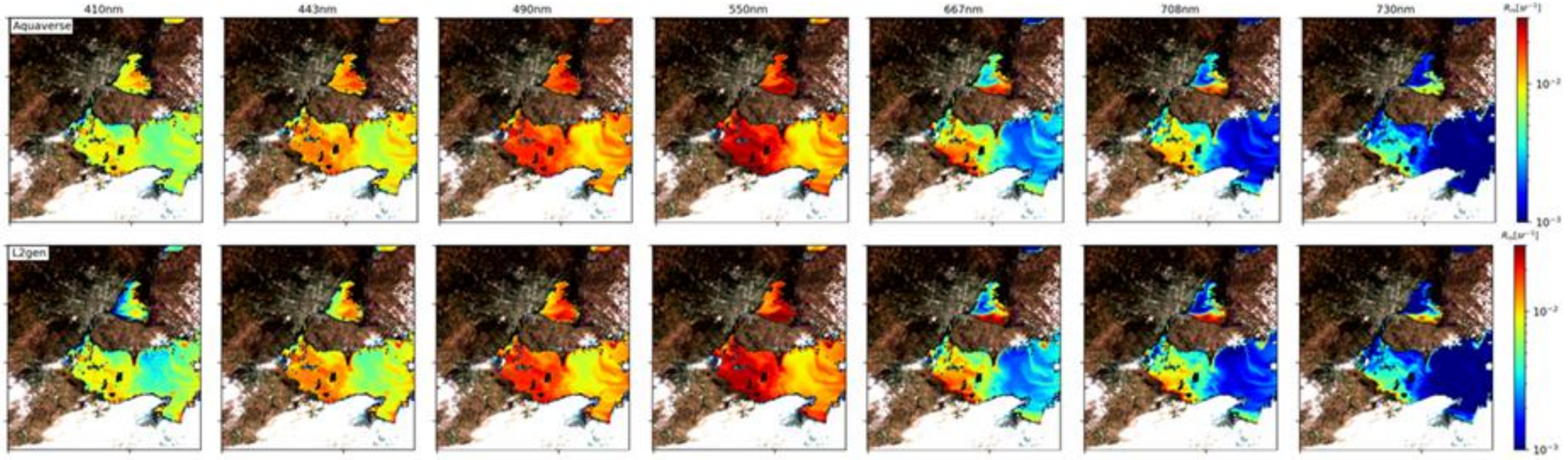


Preliminary Hyperspectral AC Results

Lake Erie: Near simultaneous retrieval of Aquaverse generated Rrs from EMIT and PACE

EMIT (4/19/2024)





PACE (4/19/2024)

<u>Aquaverse inverse modeling</u>: A universal algorithm for water quality and HAB monitoring

- *Objective*
  - Enable generating globally ***consistent***, ***reliable***, *and* ***advanced*** products from **a universal algorithm** for water quality and HAB monitoring in **inland and coastal waters**

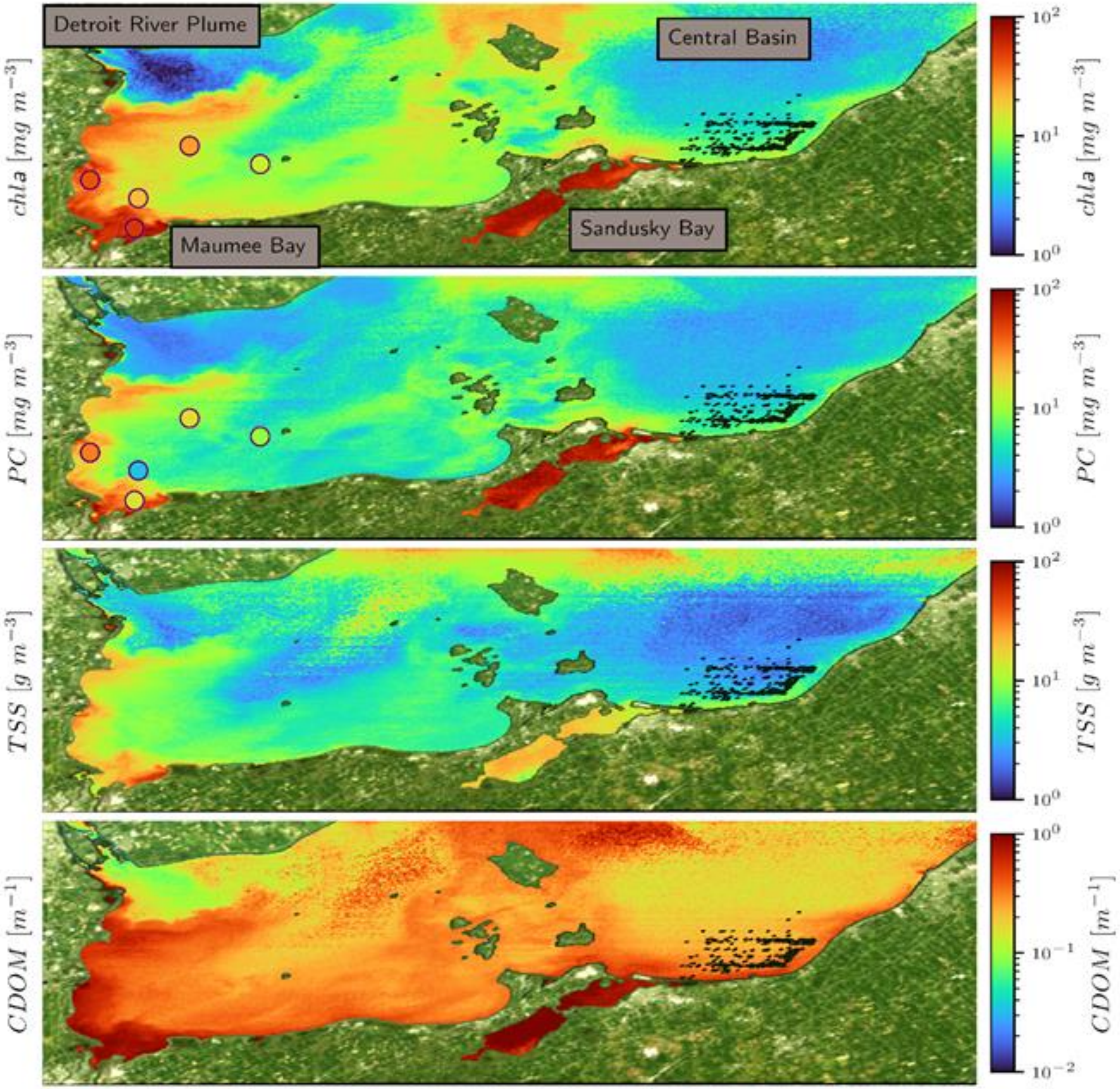
- *Products*
  - Chlorophyll-a (Chla)
  - Phycocyanin (PC)
  - Total Suspended Solids (TSS)
  - Secchi Disk Depth (Zsd)
  - Inherent optical properties (absorption by CDOM, algal, and non-algal particles)

- *Satellite Missions*
  - Multispectral data: **Sentinel-3 /OLCI, Sentinel-2/MSI, & L8/OLI**
    - **MODIS & VIIRS** coming soon, **Planet** to follow
  - Hyperspectral data: **HICO, PRISMA, & PACE**
    - **EMIT** coming soon

- *Validation sites*
  - Lake Erie
  - Chesapeake Bay
  - Utah Lake

Lake Erie
HICO: Oct 30th 2013

Qualitative Validation of BP & IOP Retrieval in Inland & Coastal Waters



Lake Erie (09/08/2014)

HICO

***In situ* concentration**

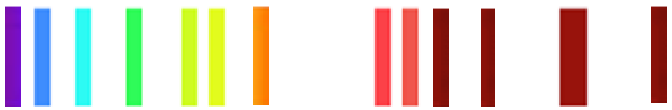
DRP + CB are oligotrophic

SB + MB are eutrophic – HABs

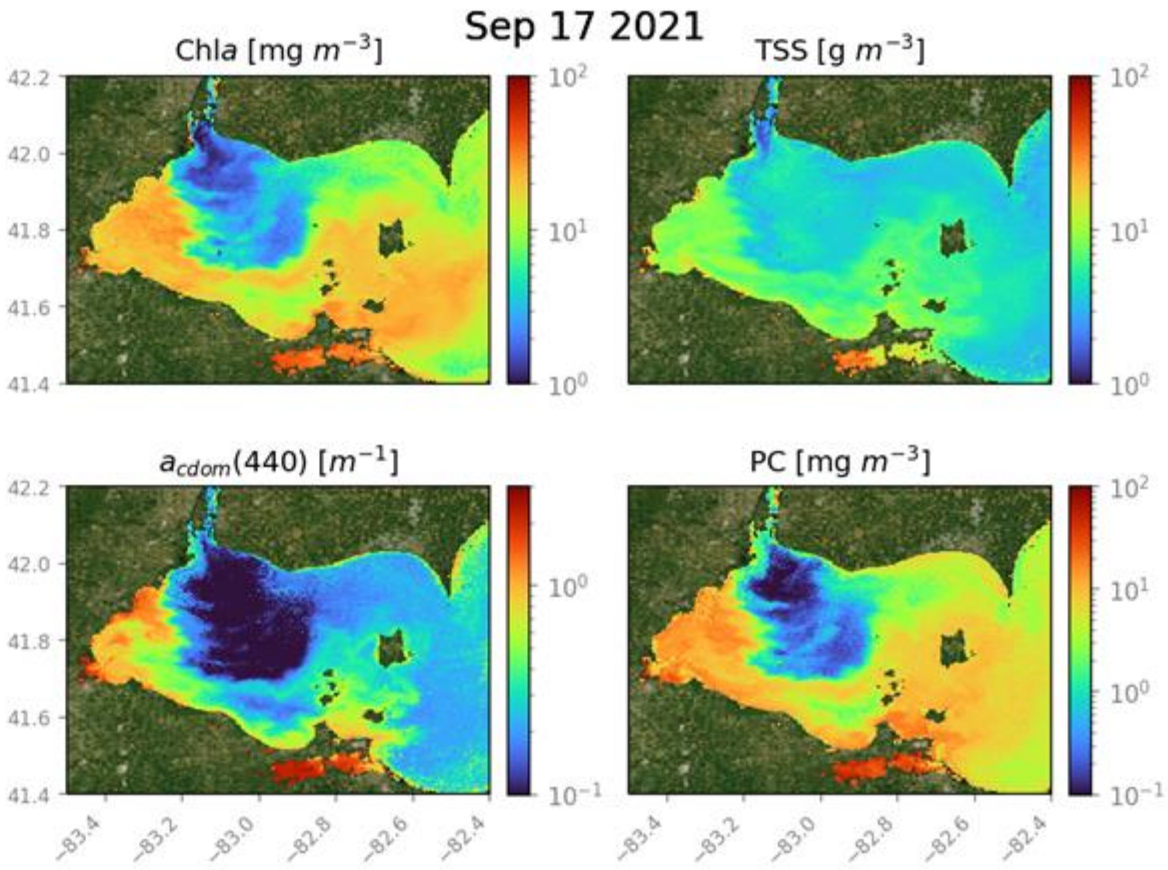
AQV matches complex spatial distribution in Maumee Bay confirmed via *in situ* measurements

Moore et al. 2017
Binding et al. 2019
O'Shea et al. 2023

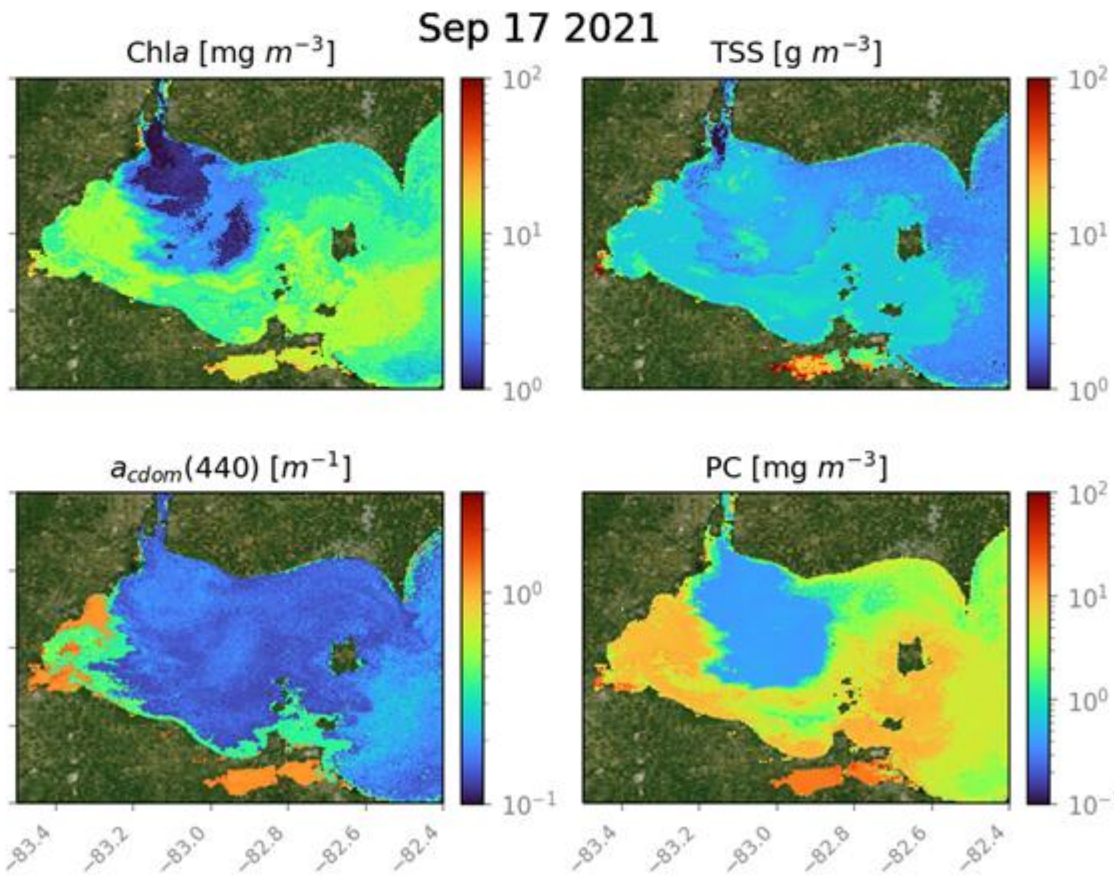
Examples from OLCI: products & **uncertainties**

OLCI 

Estimates

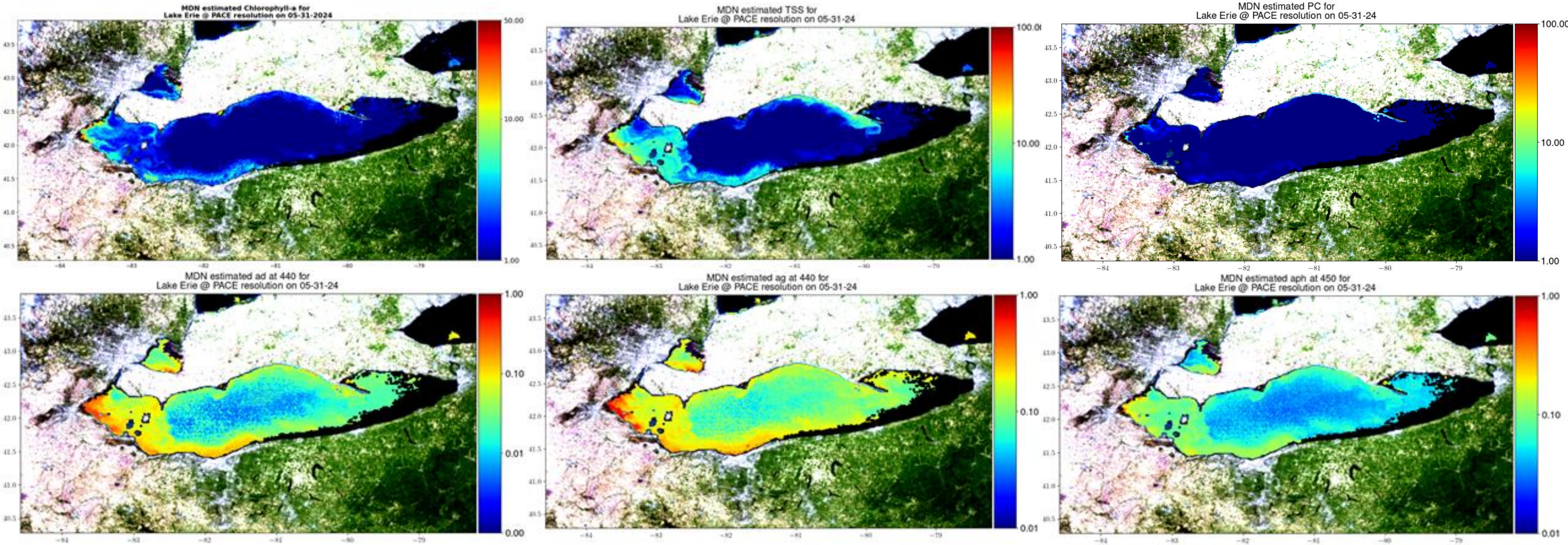


Uncertainties



SeaDAS-processed imagery

Aquaverse Preliminary PACE Inversion results

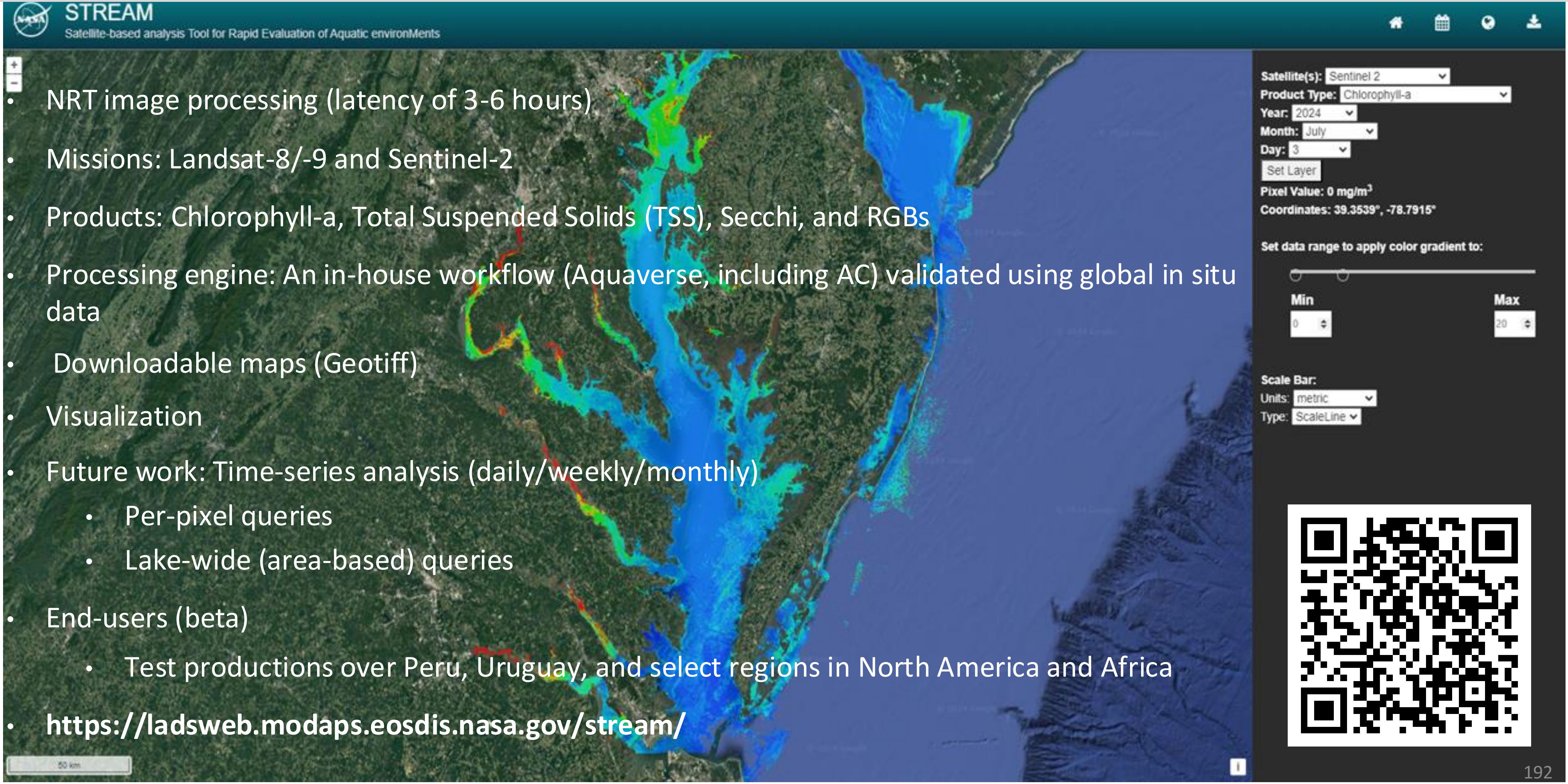


Future work for PACE:

1. Atmospheric correction for inland/coastal waters
2. Zsd & b_{bp} retrieval
3. Total uncertainty
4. PCC retrieval

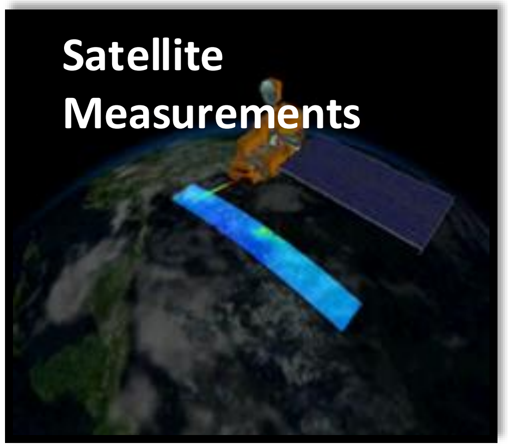
Inverse modeling & uncertainty tutorials

STREAM: Online GUI for OLI/MSI Chl/TSS/Zsd Products via AQV AC



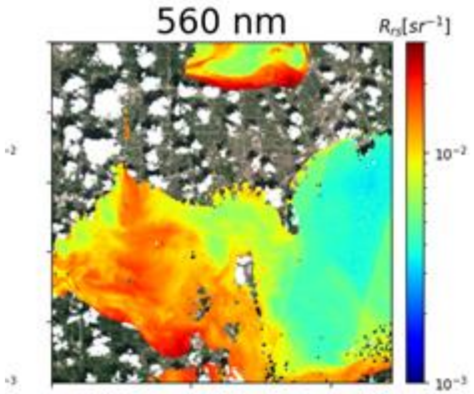
- NRT image processing (latency of 3-6 hours)
- Missions: Landsat-8/-9 and Sentinel-2
- Products: Chlorophyll-a, Total Suspended Solids (TSS), Secchi, and RGBs
- Processing engine: An in-house workflow (Aquaverse, including AC) validated using global in situ data
- Downloadable maps (Geotiff)
- Visualization
- Future work: Time-series analysis (daily/weekly/monthly)
    - Per-pixel queries
    - Lake-wide (area-based) queries
- End-users (beta)
    - Test productions over Peru, Uruguay, and select regions in North America and Africa
- **https://ladsweb.modaps.eosdis.nasa.gov/stream/**

Aquaverse: An Aquatic Inversion Scheme for Remote Sensing of Fresh and Coastal Waters



TOA radiance

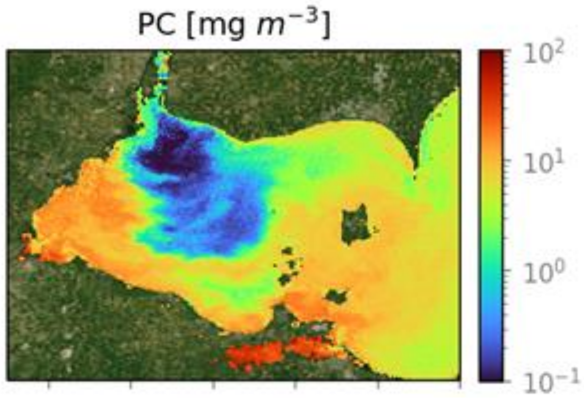
Atmospheric Correction



TOA → Rrs

STREAM

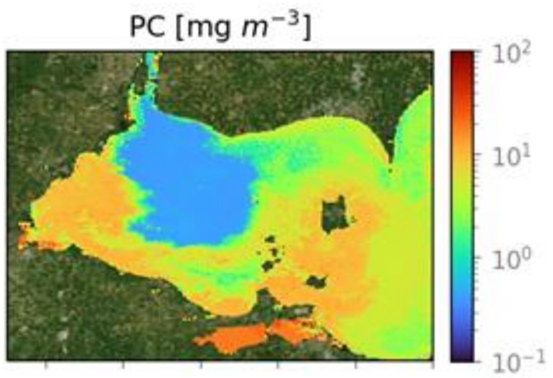
Inverse Modeling



Rrs → IOPs and BPs

STREAM: Stakeholder Access

Uncertainty Products



Rrs, BPs, IOPs → Uncertainty

Inverse modeling & uncertainty tutorials

Acknowledgements

- **Funding sources:**
- OBB, RSWQ, EMIT, PACE
- NASA PACE Science and Applications Team
- NASA EMIT Science and Applications Team
- Landsat Science Team

STREAM

AGU sessions

Ryan O’Shea : Mon. 9 Dec. B11K, Poster #1459
Ryan O’Shea : Tues. 10 Dec. GC21W, Poster #0161
Will Wainwright : Tues. 10 Dec. H22D-05 11:05-11:15
Arun Saranathan: Tues. 10 Dec. H23F, Poster #1070
Akash Ashapure : Wed. 11 Dec. IN31B Poster #2011
Akash Ashapure : Wed. 11 Dec. GC32A-02 10:30-10:40

Inverse modeling & uncertainty tutorials

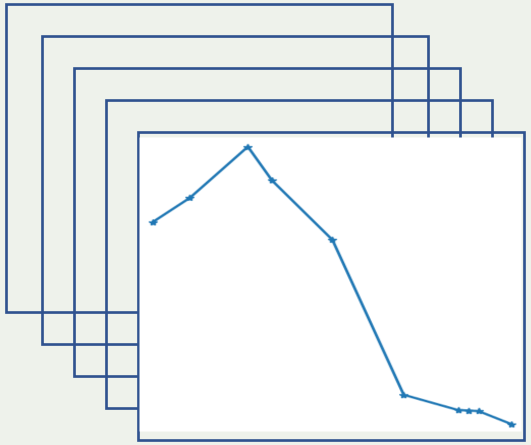
Using domain adaptation to improve Chlorophyll-a predictions from optical remote sensing data

Arun M. Saranathan[1,2], Mortimer Werther[3], Ryan E. O'Shea[1,2], and Akash Ashapure[1,2]

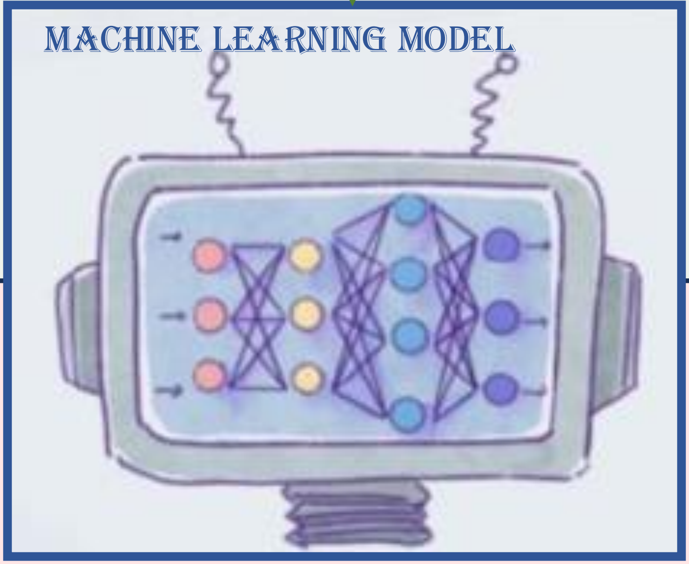
[1]GSFC-619.0, NASA Goddard Space Flight Center. [2]Freshwater Sensing Program, SSAI. [3]Swiss Federal Institute of Aquatic Science and Technology

MODEL TRAINING AND VALIDATION

IN SITU OPTICAL MEASUREMENTS



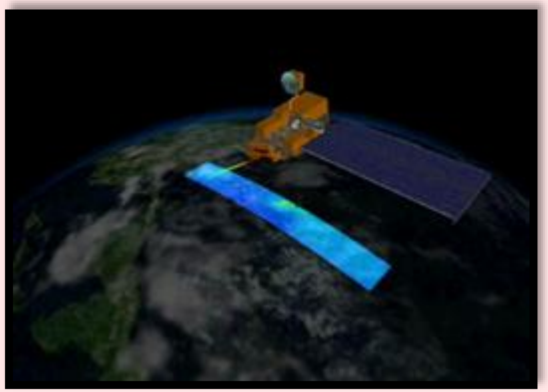
Training based on *in situ* prediction error

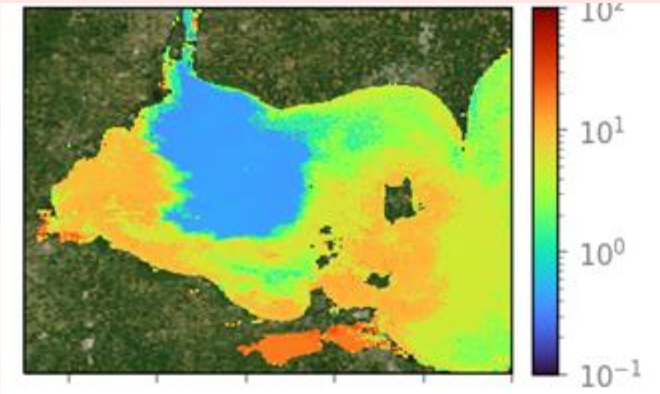


Chl*a*

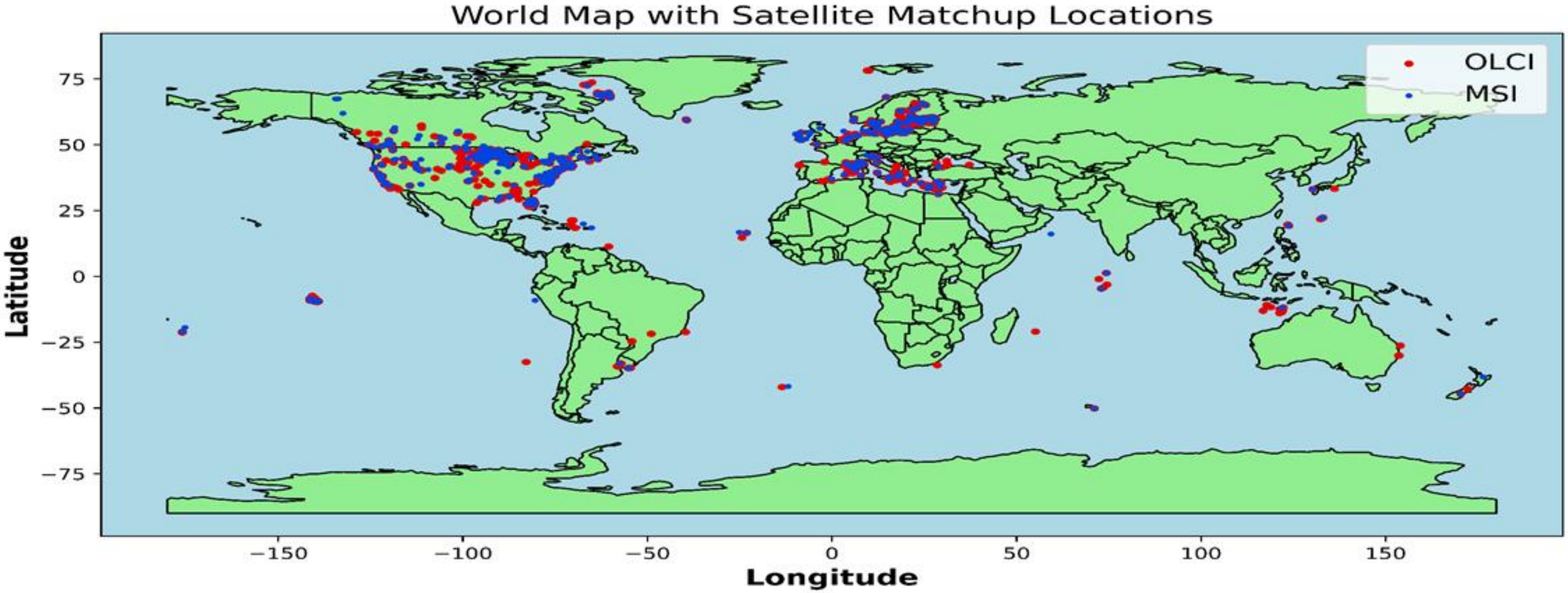
MODEL APPLICATION

SATELLITE OPTICAL MEASUREMENTS





Satellite matchup datasets

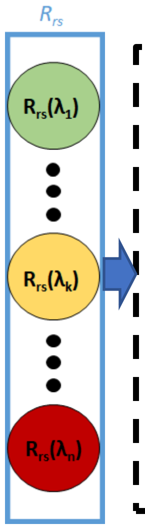


Satellite matchup data: Collocated pair of satellite measured Rrs and near concurrent *in situ* chlorophyll-a measurements (~ +/- 4 hours).

- OLCI: 3101 matchup examples (AC methods: L2GEN)
- MSI: 2692 matchup examples (AC methods: Aquaverse)

Localized dataset, with slight differences in location, measurement time, acquisition conditions of the different data-streams.

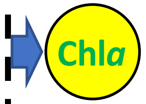
Machine Learning Based Inversion Framework

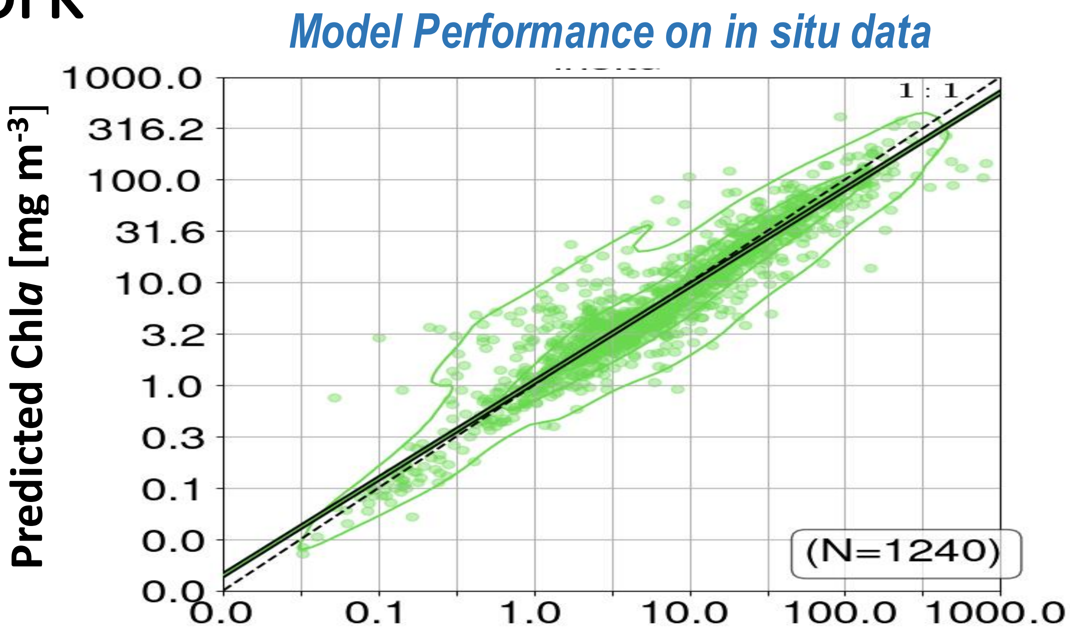


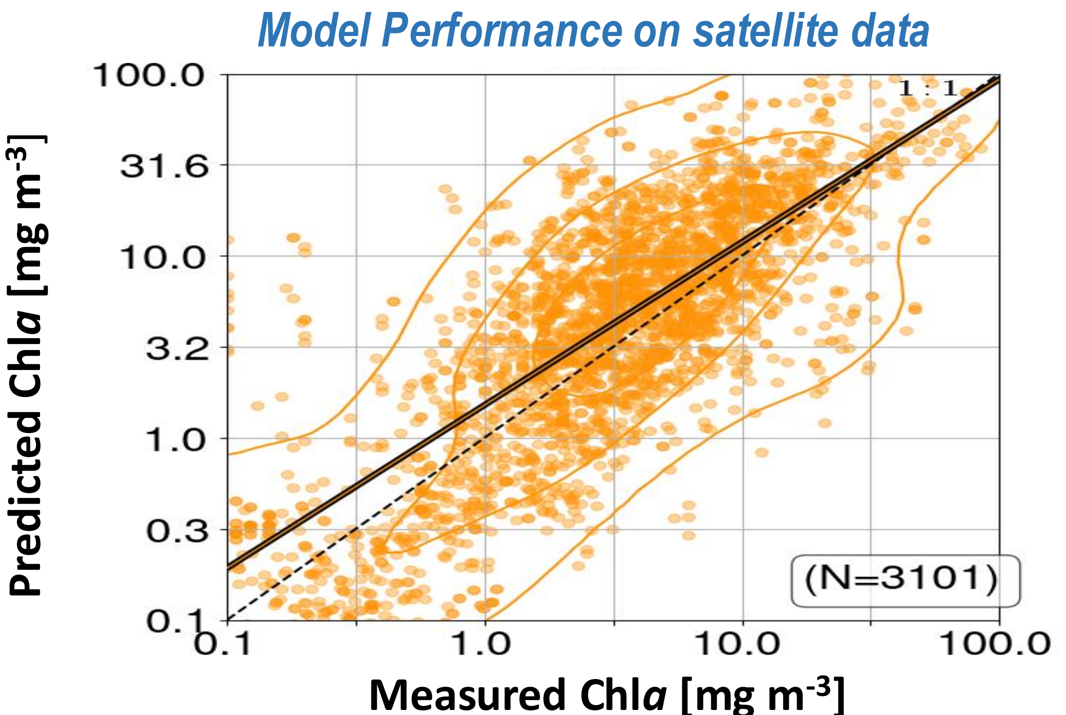
MACHINE LEARNING MODEL

Machine Learning (ML) tools commonly use remote sensing reflectance (R_{rs}) as input and learn the mapping from this input to Chlorophyll-a (Chl*a*) .

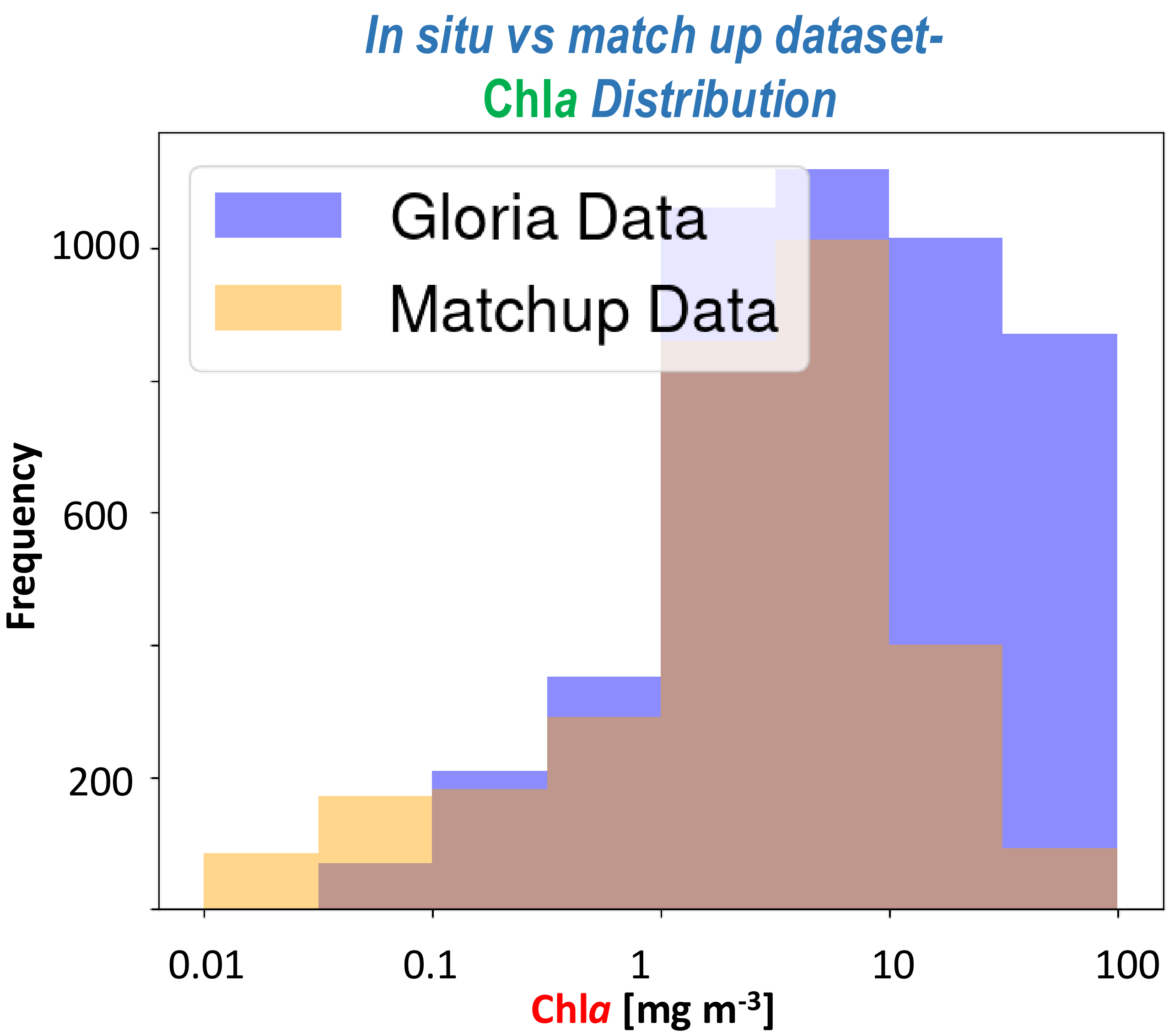
ML approaches show excellent Chl*a* estimation on *in situ* labeled datasets.

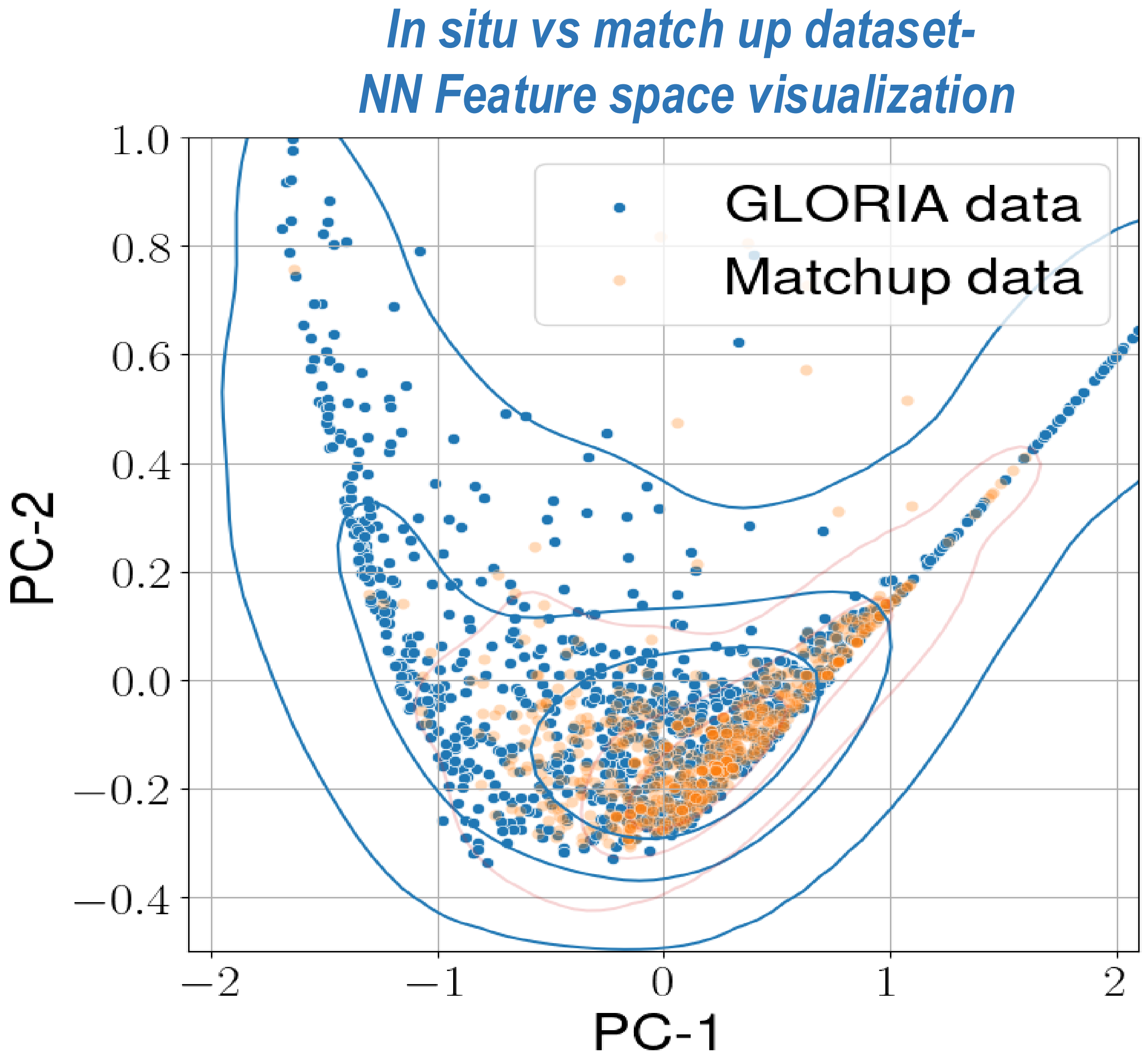




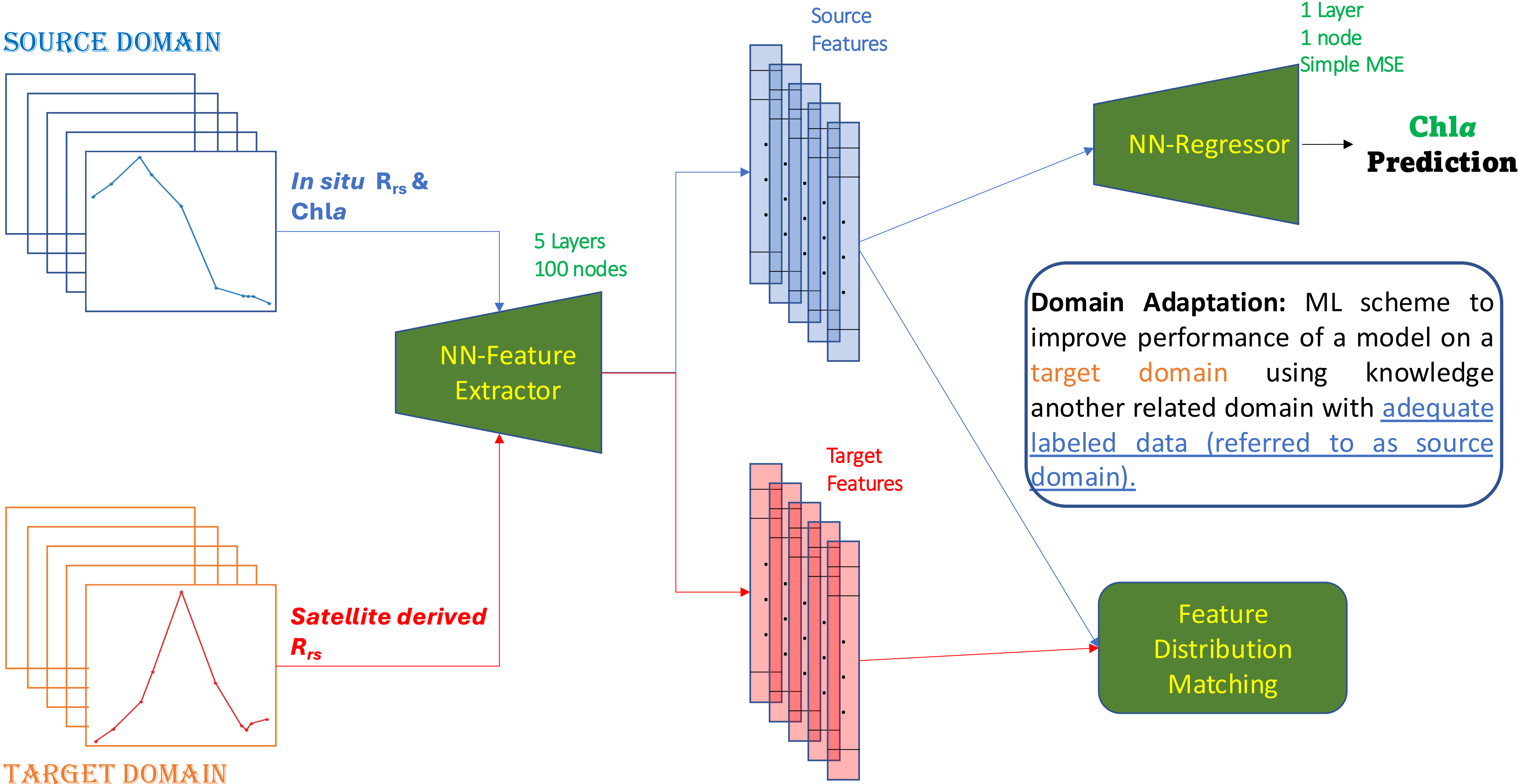


In situ vs Matchup data differences



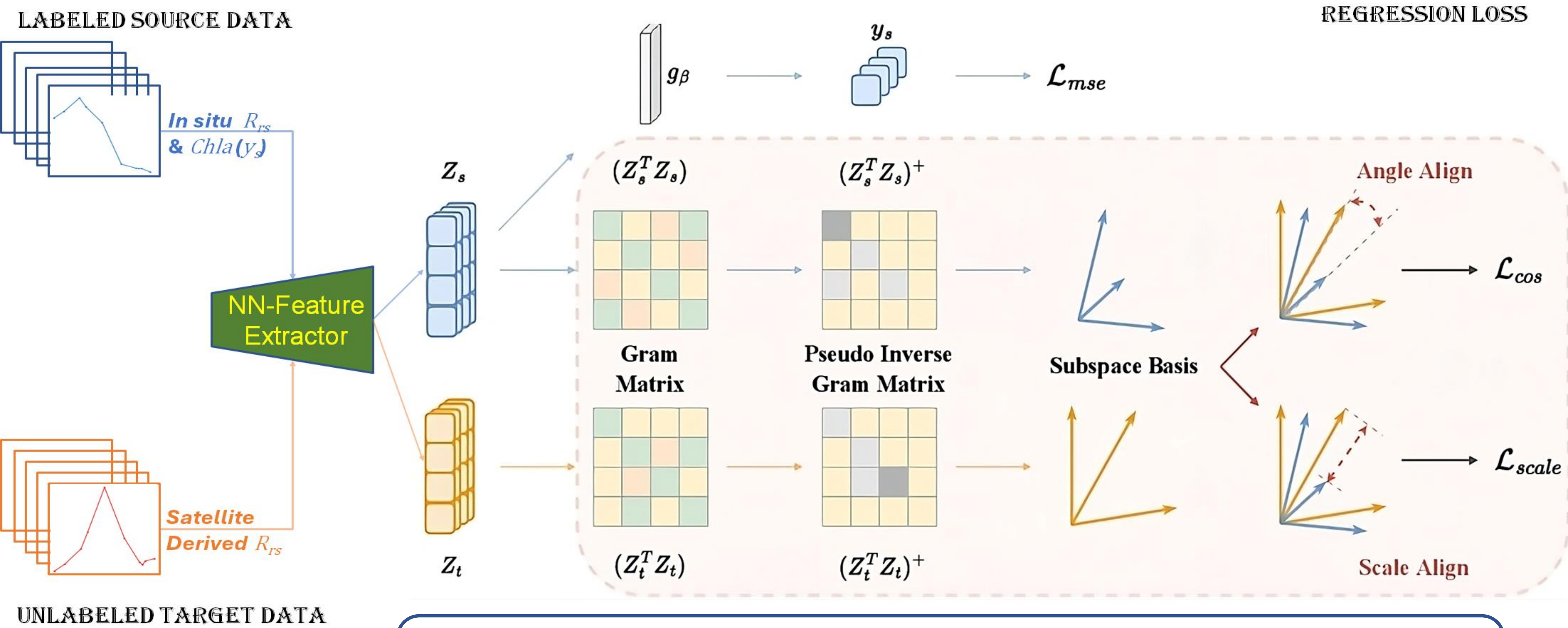


Domain Adaptation



Domain Adaptation: ML scheme to improve performance of a model on a target domain using knowledge another related domain with adequate labeled data (referred to as source domain).

Domain Adaptation Regression by Aligning Inverse Gram Matrices (DARE-GRAM) [Nejjar et al. 2023]



Implementation Details

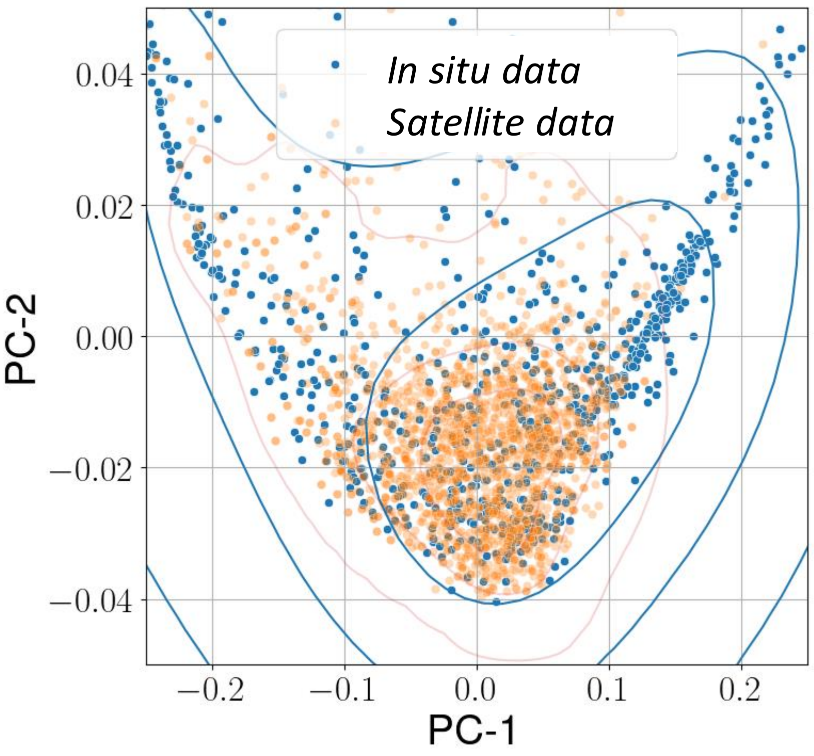
- Python(PyTorch)
- ReLU activations
- Source Rrs & Chla (M=6197)
- Target Rrs (~250K)
- Hidden Layers/Nodes= 5/100
- Optimizer: Adam

Results

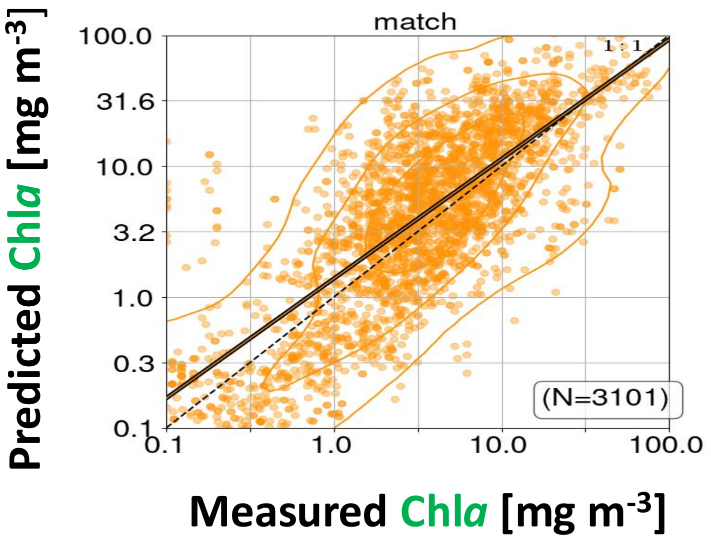
Comparison of mean residuals (MAE) in Chlorophyll-a prediction

Sensor	MDN (Basic NN)	DARE-GRAM (Domain Adaptation)	% Gain
OLCI (N=3101)	12.426	4.923	**60.38%**
MSI (N=2692)	14.171	5.648	**60.14%**

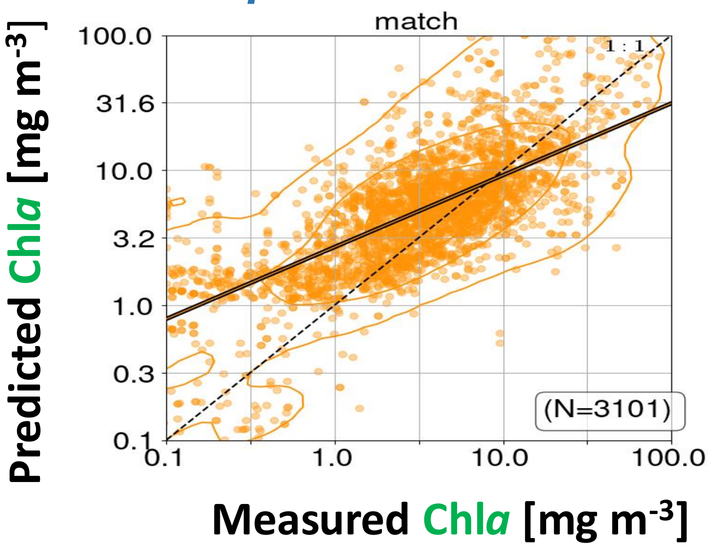
Model features visualization



Basic Neural Network- MDN



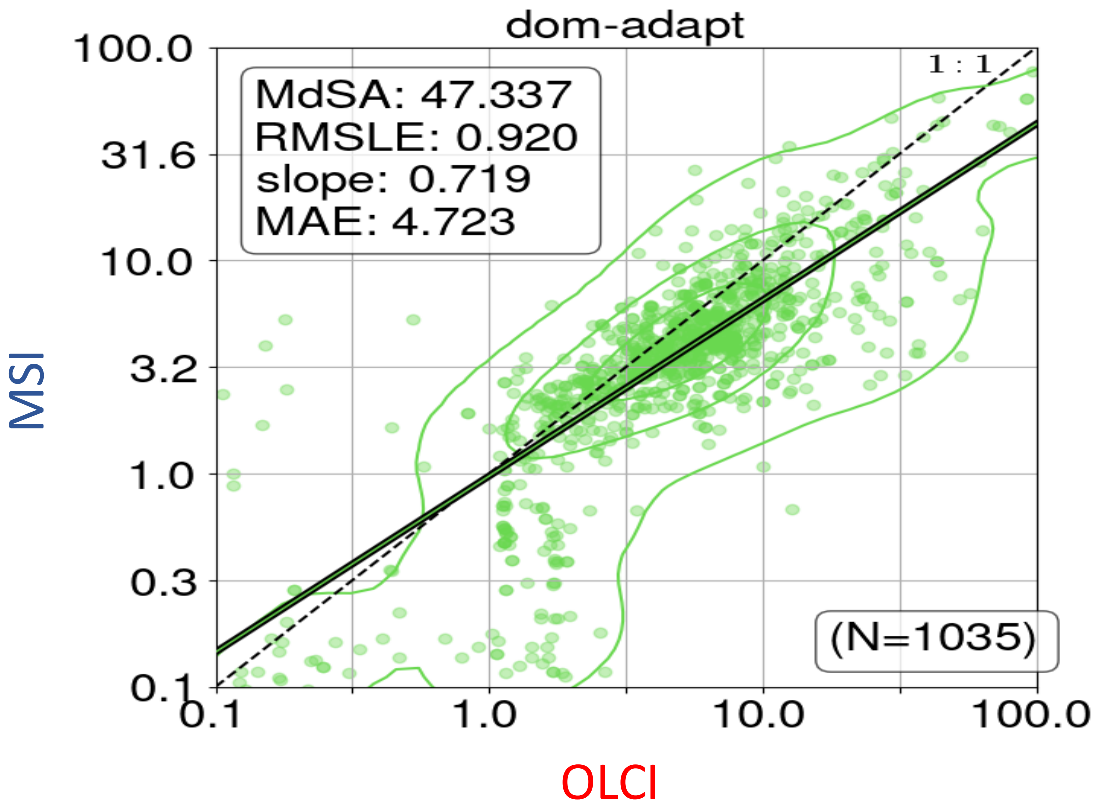
Domain Adaptation: DARE-GRAM

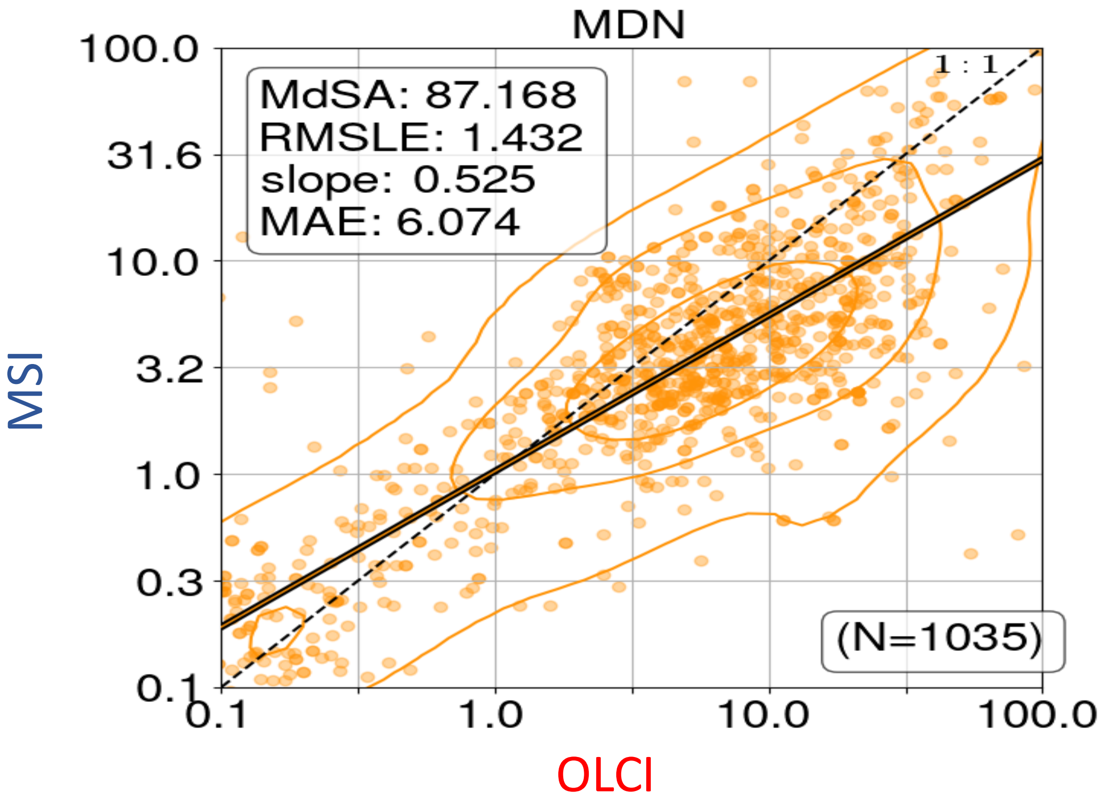


Results

- DARE-GRAM predictions exhibit a significant improvement in *Chla* estimation- across metrics.
- Investigate and address the bias present in the DARE-GRAM results.

Harmonization via Domain adaptation





- **Creating a concurrent Matchup dataset:** Scanned the OLCI and MSI matchup datasets to identify concurrent samples from the two. Based on this analysis identified 1035 common samples.
  - Samples have both OLCI and MSI Rrs, with corresponding *in situ* Chla.
  - Spatial Difference between OLCI and MSI Rrs pixels: < 200m.
  - Temporal difference between the OLCI, MSI and *in situ* measurements: <1 day (same date).

- Both the domain adapted models include “explicit domain matching” with the *in situ* (gloria) datasets leading to more harmonized results.

Conclusions

- By leveraging unlabeled satellite Rrs pixels in the training phase, domain adaptation-based methods appears to learn features that are less affected by the various distortion processes in satellite Rrs, leading to improved Chl*a* estimation.
- The satellite Rrs feature distribution better matches the in situ Rrs feature distribution indicating more similarity between source and target features.

Future Works

1. Generate and compare spatial Chl*a* from DARE-GRAM with corresponding MDN Chl*a* maps.
2. Investigate the effect of the atmospheric correction on the performance of the domain adaptation algorithms.
3. Investigate the source of the bias present in the DARE-GRAM predictions. If not possible to eliminate correct by using model calibration approaches.

Acknowledgements

Funding sources:

- OBB, RSWQ
- NASA PACE Science and Applications Team
- NASA EMIT Science and Applications Team
- Landsat Science Team

Help and suggestions

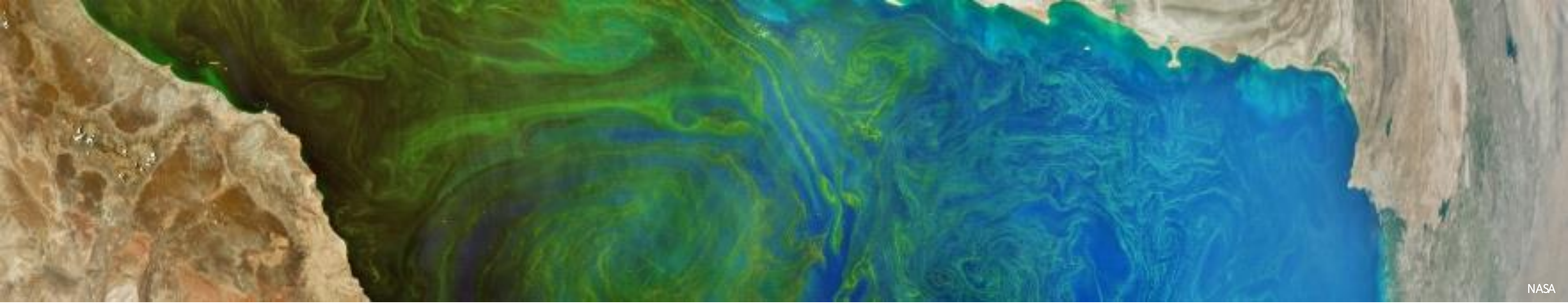
- Dr. Nima Pahlevan
- Mr. Brandon Smith
- Dr. Sundarabalan V.B.

STREAM

AGU sessions

Ryan O'Shea	: Mon.	9 Dec.	B11K,	Poster #1459
Ryan O'Shea	: Tues.	10 Dec.	GC21W,	Poster #0161
Will Wainwright	: Tues.	10 Dec.	H22D-05	11:05-11:15
Arun M. Saranathan:	**Tues.**	**10 Dec.**	**H23F,**	**Poster #1070**
Akash Ashapure	: Wed.	11 Dec.	IN31B	Poster #2011
Akash Ashapure	: Wed.	11 Dec.	GC32A-02	10:30-10:40

Inverse modeling & uncertainty tutorials



Phytoplankton communities quantified from hyperspectral ocean reflectance correspond to pigment-based communities

Sasha J. Kramer, Stéphane Maritorena, Ivona Cetinić, Jeremy Werdell, and David Siegel

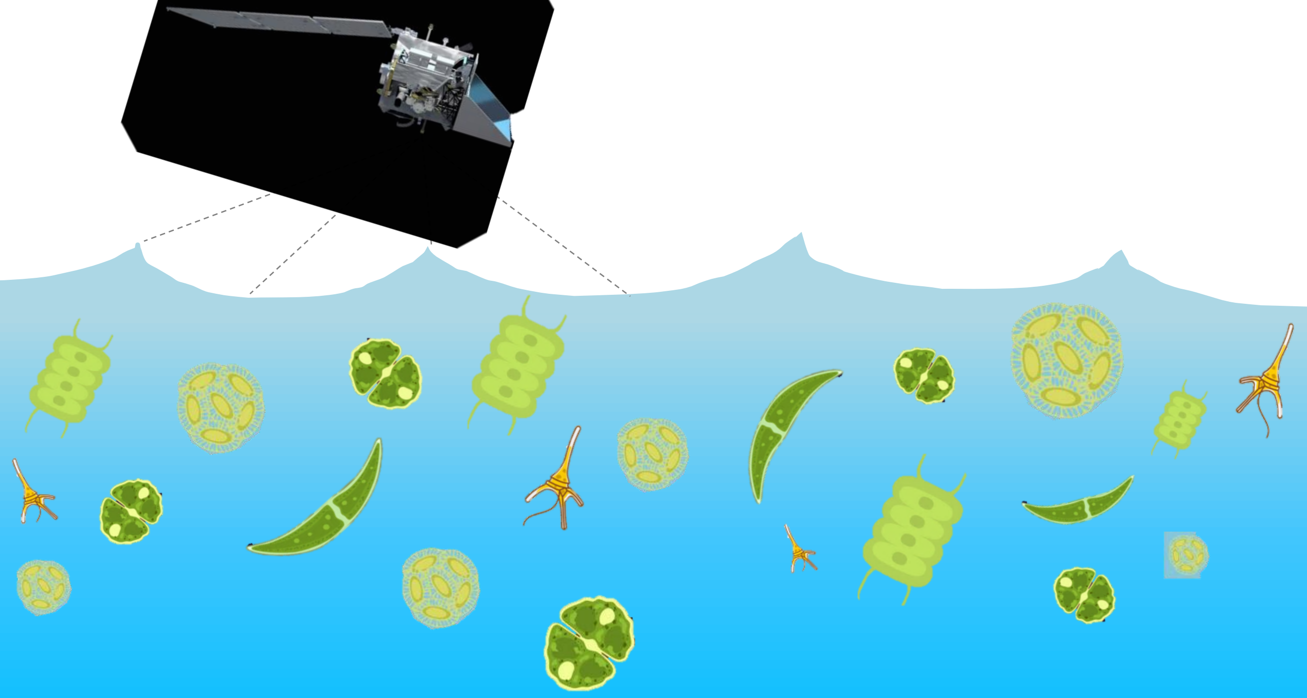
skramer@mbari.org

SIMONS FOUNDATION PACE NASA

DECEMBER 2024

the David & Lucile Packard FOUNDATION MBARI

Goal for today



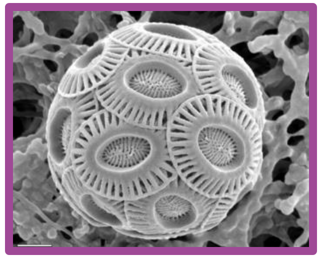
Compare the composition and distribution of phytoplankton communities derived from

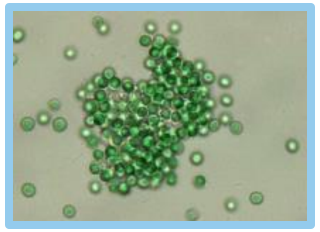
1) HPLC pigments and

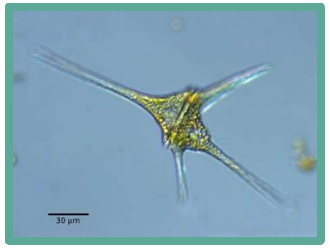
2) hyperspectral $R_{rs}(\lambda)$

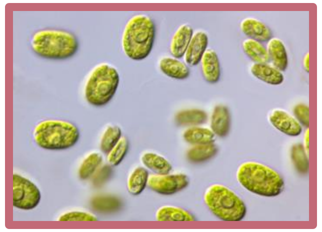
High Performance Liquid Chromatography pigments

Phytoplankton have different pigments; some can be used as biomarkers to separate certain groups.



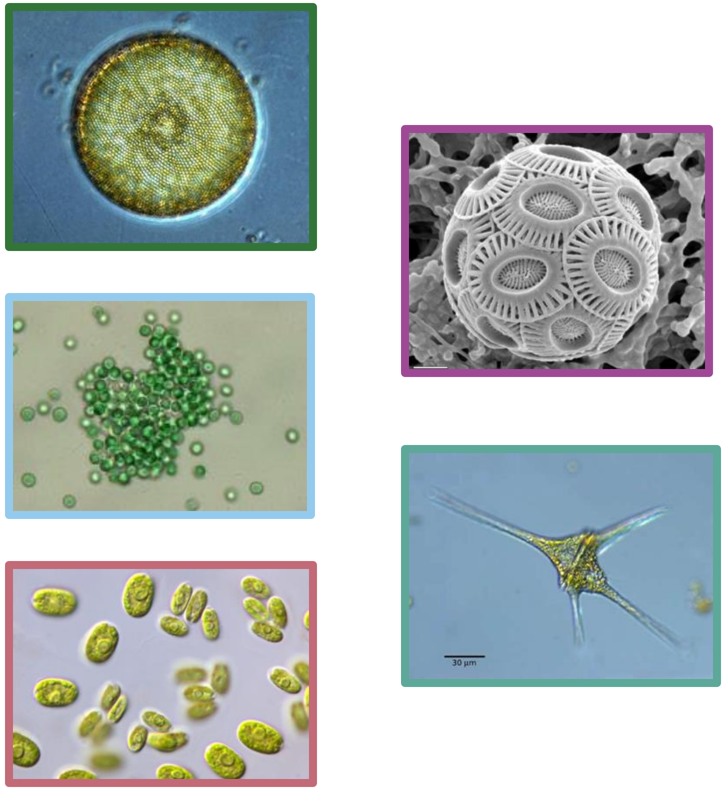


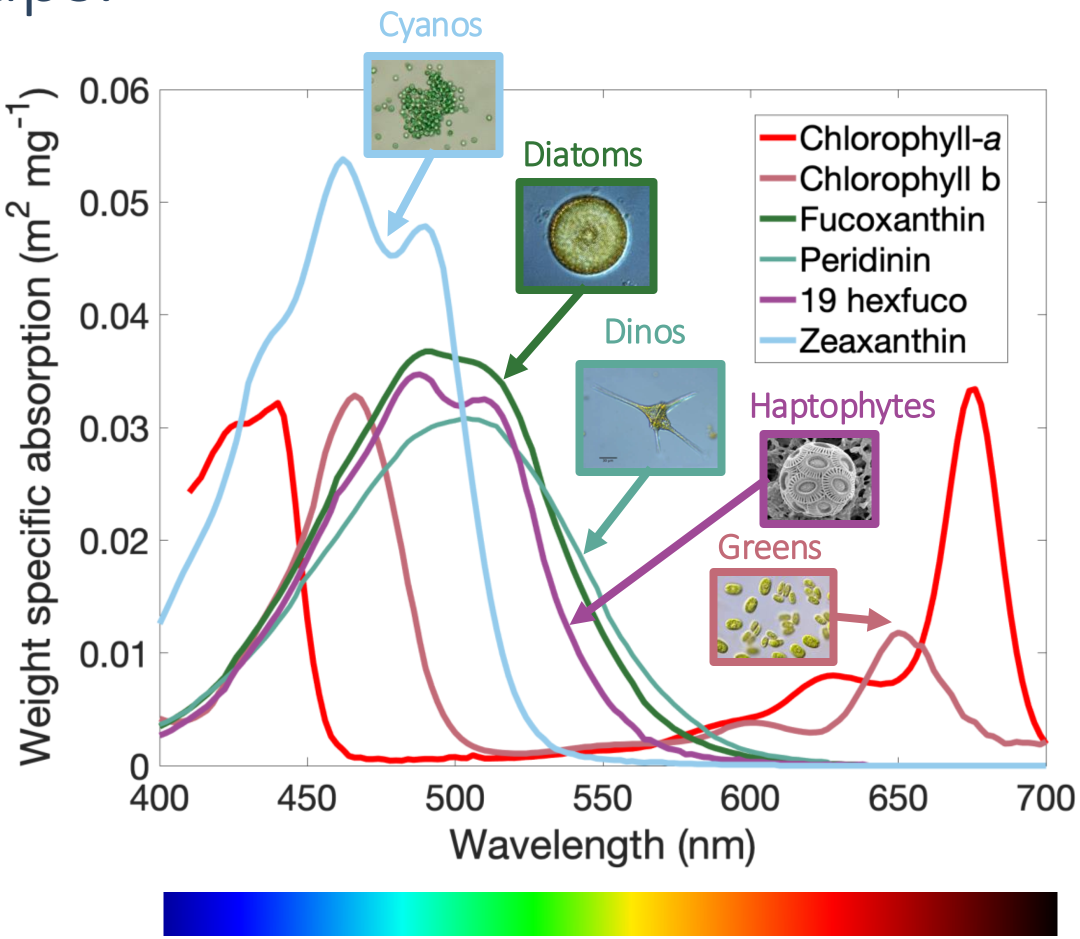




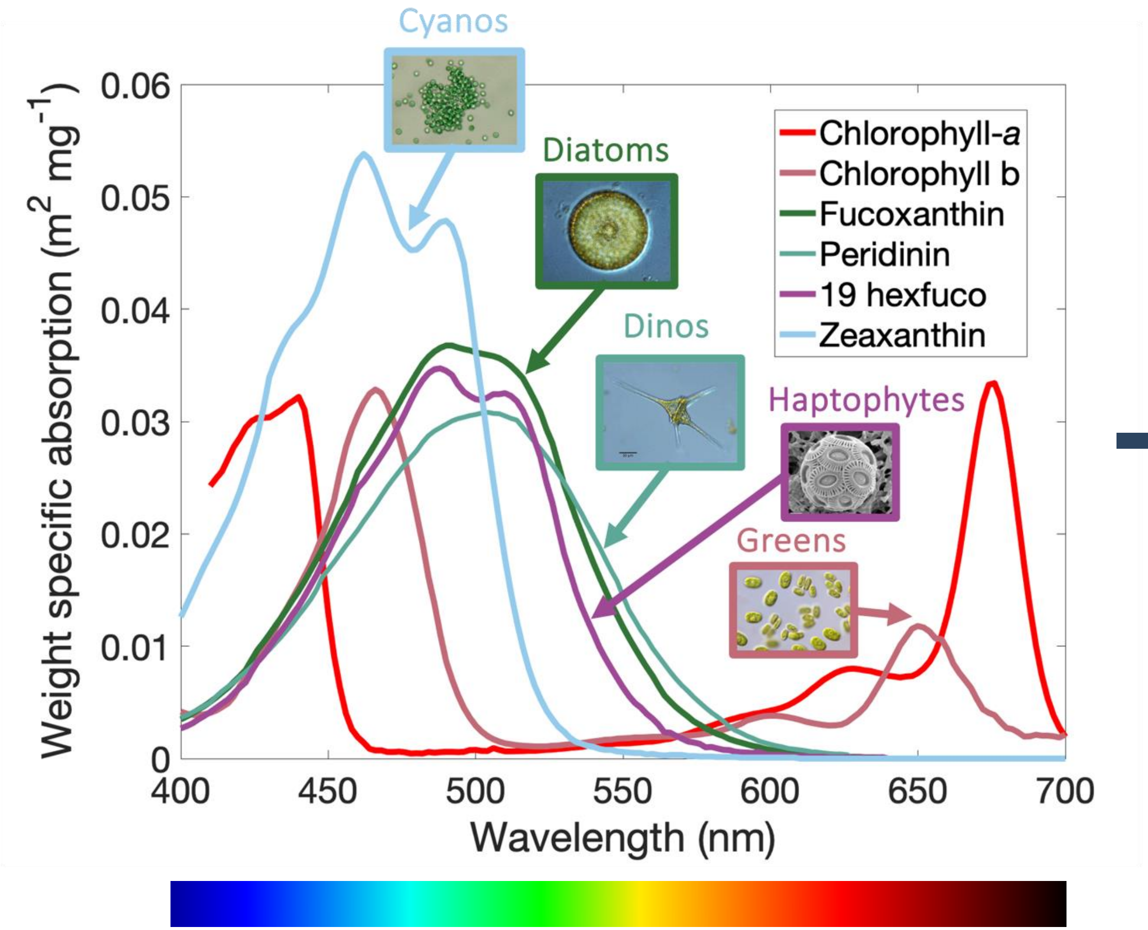
Phytoplankton pigments affect absorption

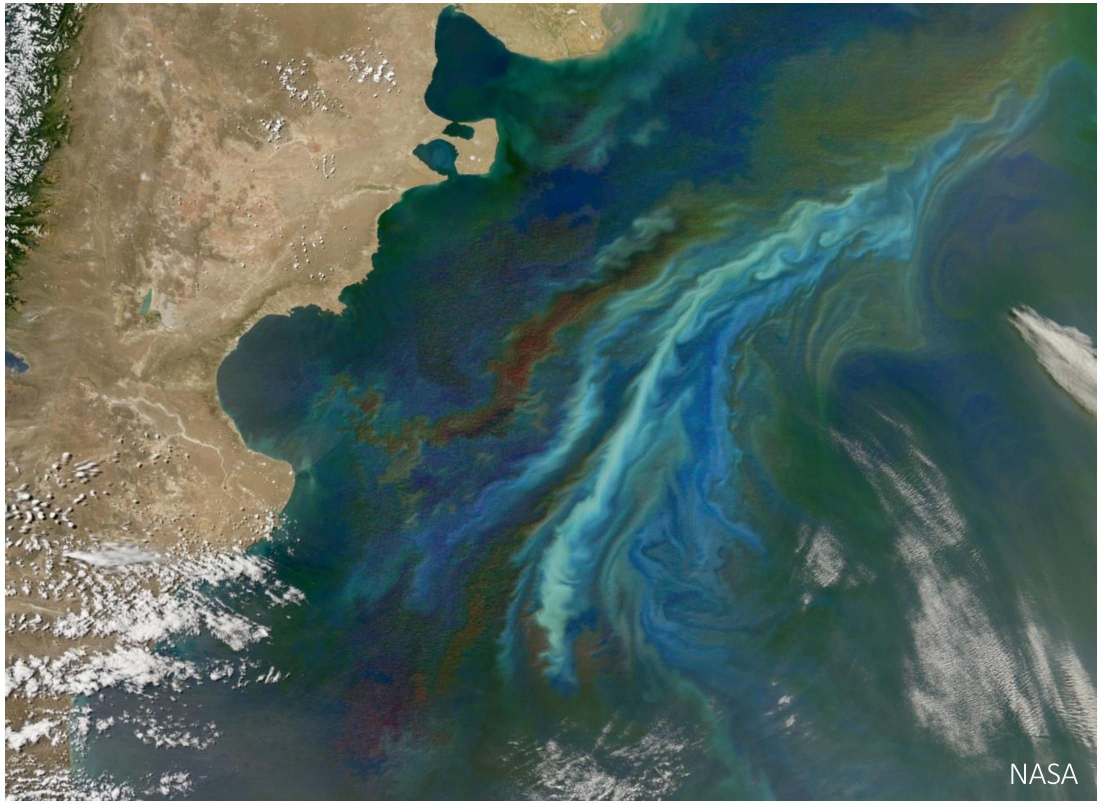
Phytoplankton have different pigments; some can be used as biomarkers to separate certain groups.



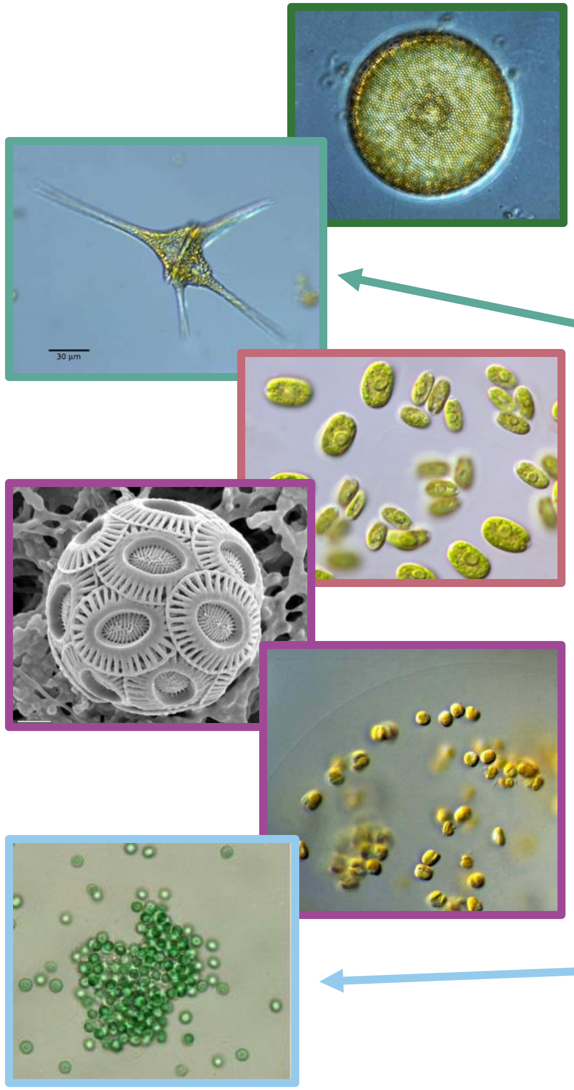


Pigments link phytoplankton and ocean color

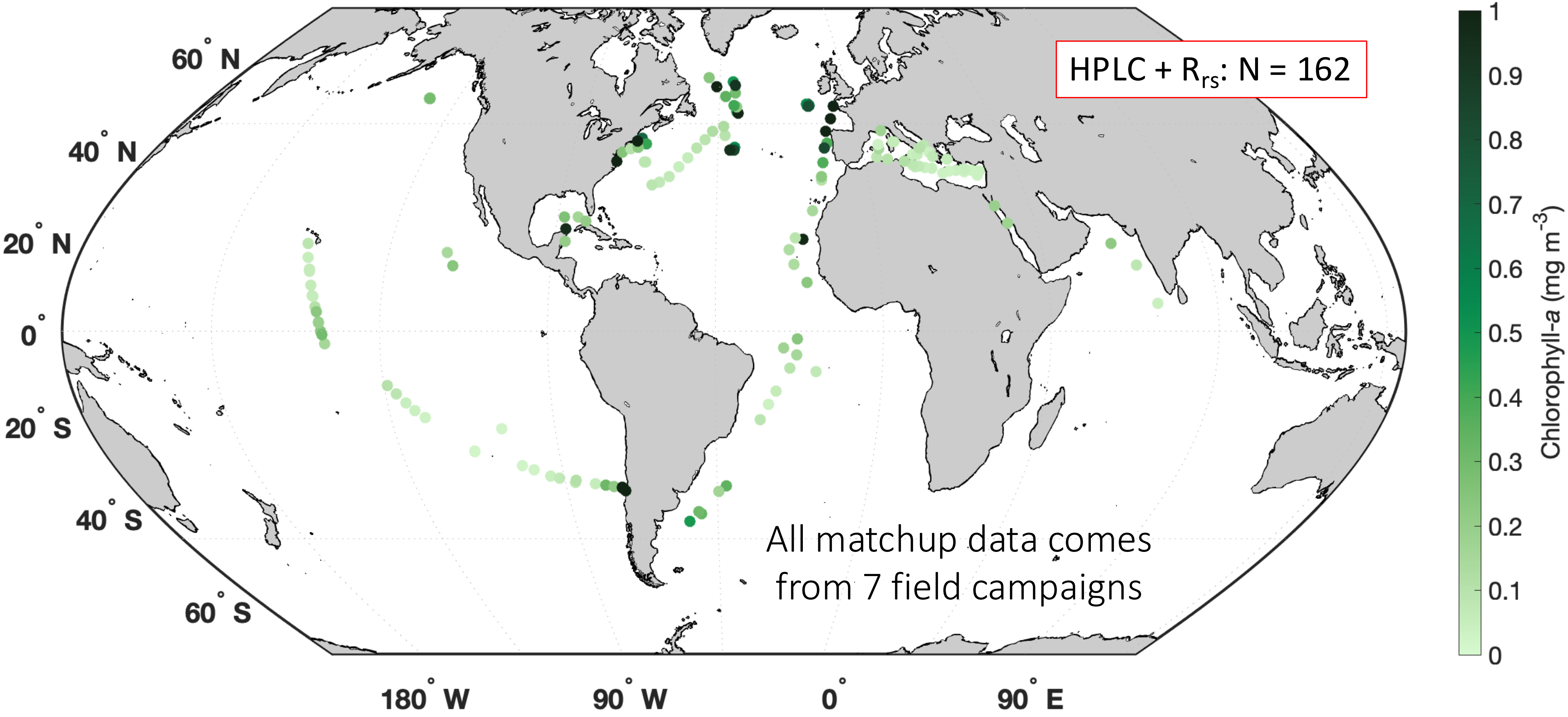




Phytoplankton pigments and taxonomy



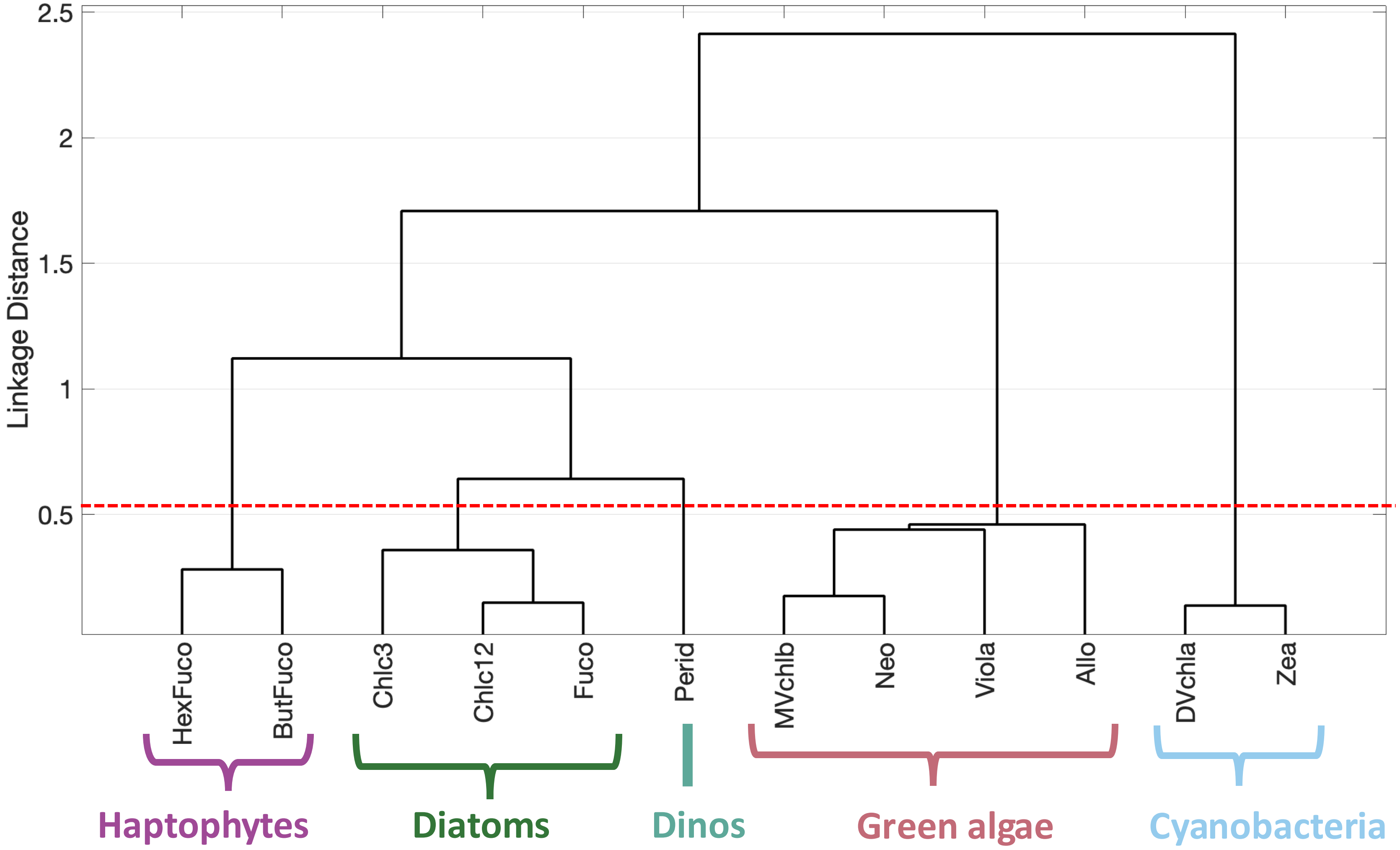
Phytoplankton group	Associated marker pigment(s)
Diatoms	Fucoxanthin
Dinoflagellates	Peridinin
Green algae	MV chlorophyll b
Haptophytes	19’-hexanoyloxyfucoxanthin
Cyanobacteria	Zeaxanthin, DV chlorophyll-*a*



Adapted from Kramer et al., 2022 *Remote Sensing of Environment*

Max five pigment-based groups separate in this dataset

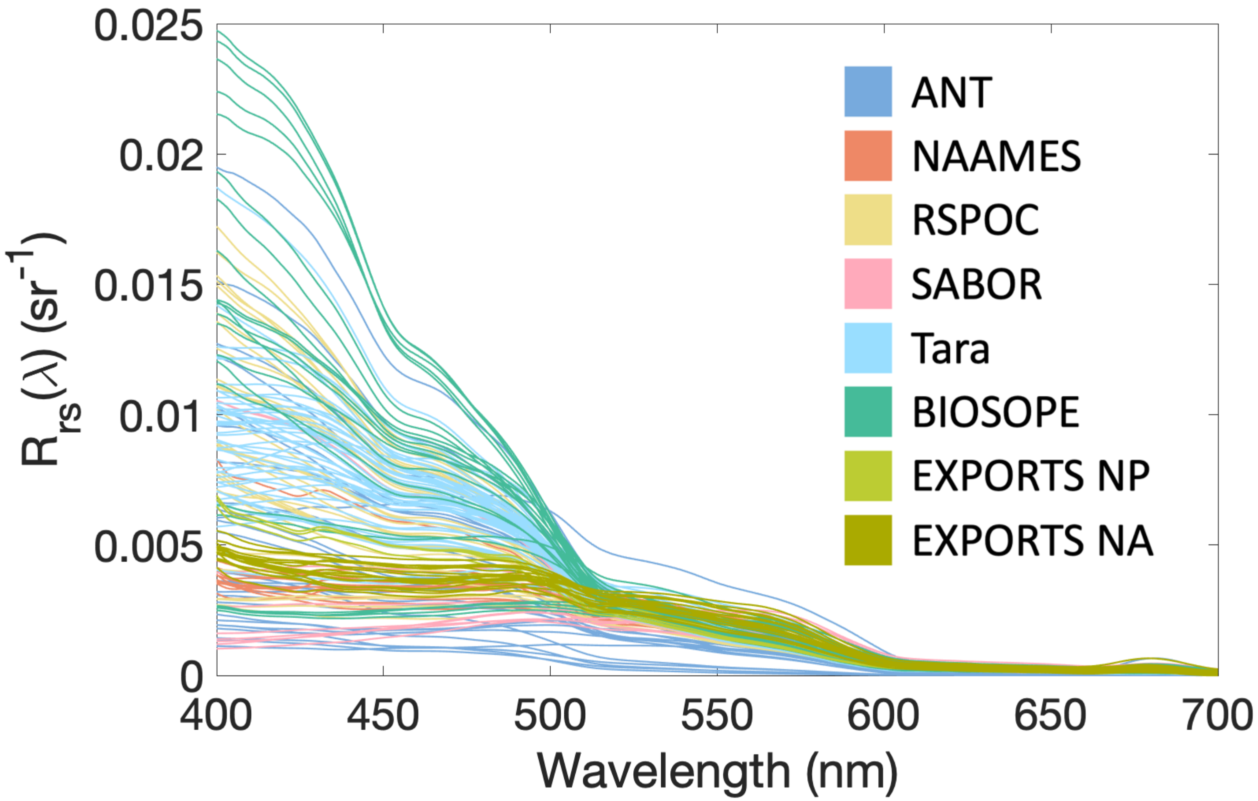
Paired global dataset of hyperspectral $R_{rs}(\lambda)$ and HPLC pigments can be used to separate **at most** these five phytoplankton groups.



Kramer et al., 2024 *Optics Express*

Maximizing hyperspectral R_{rs} information content

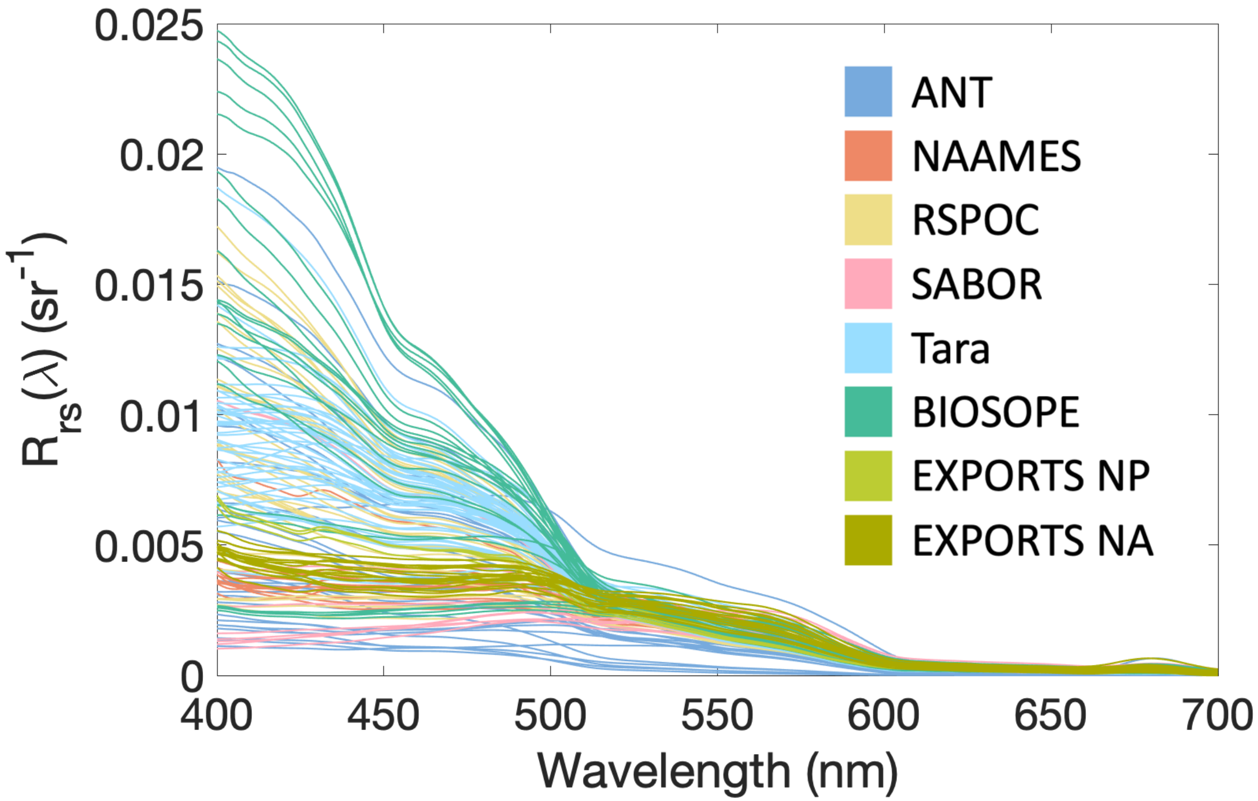
Measured spectra



Adapted from Kramer et al., 2022 *Remote Sensing of Environment*

Maximizing hyperspectral R_{rs} information content

Measured spectra



Construct a generic hyperspectral model to reconstruct remote sensing reflectance:

$R_{rs,mod}(\lambda) = f(a, b_b)$ where

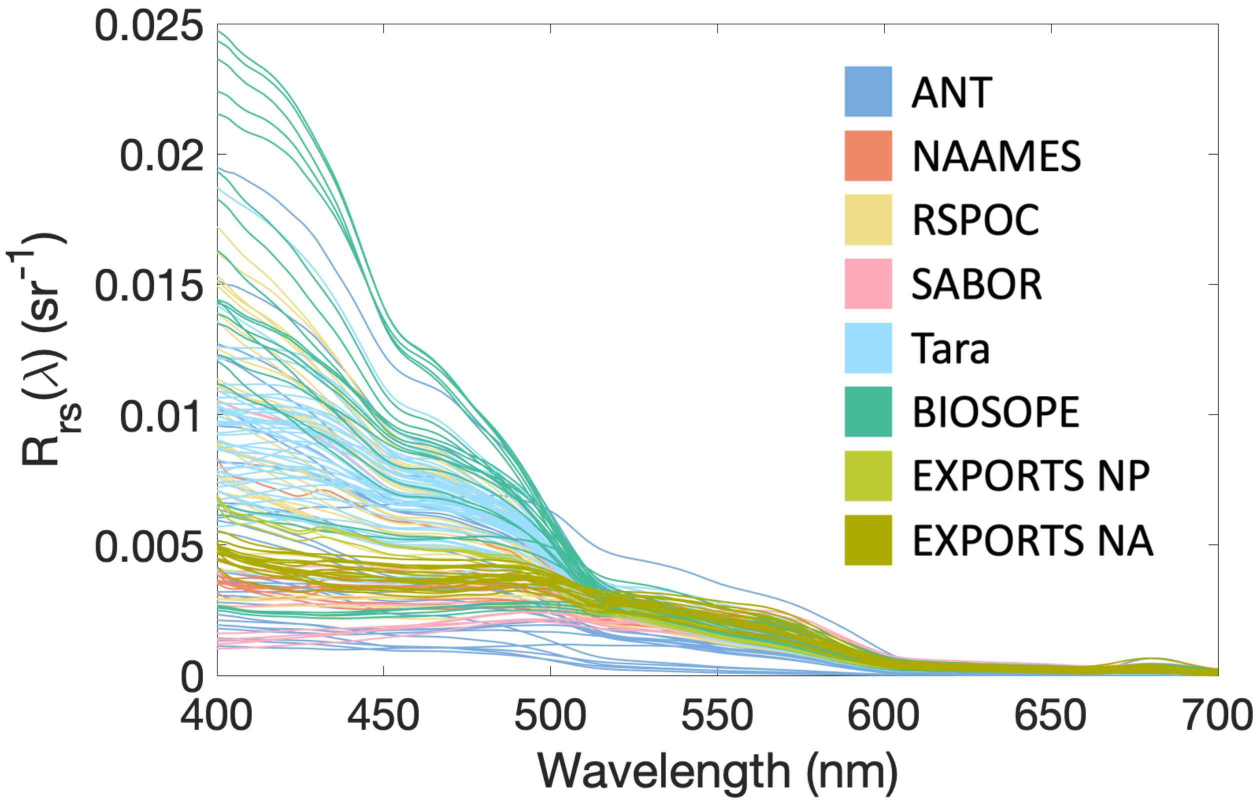
$a = a_{ph} + a_{dg} + a_{water}$ and

$b = b_{bp} + b_{bwater}$

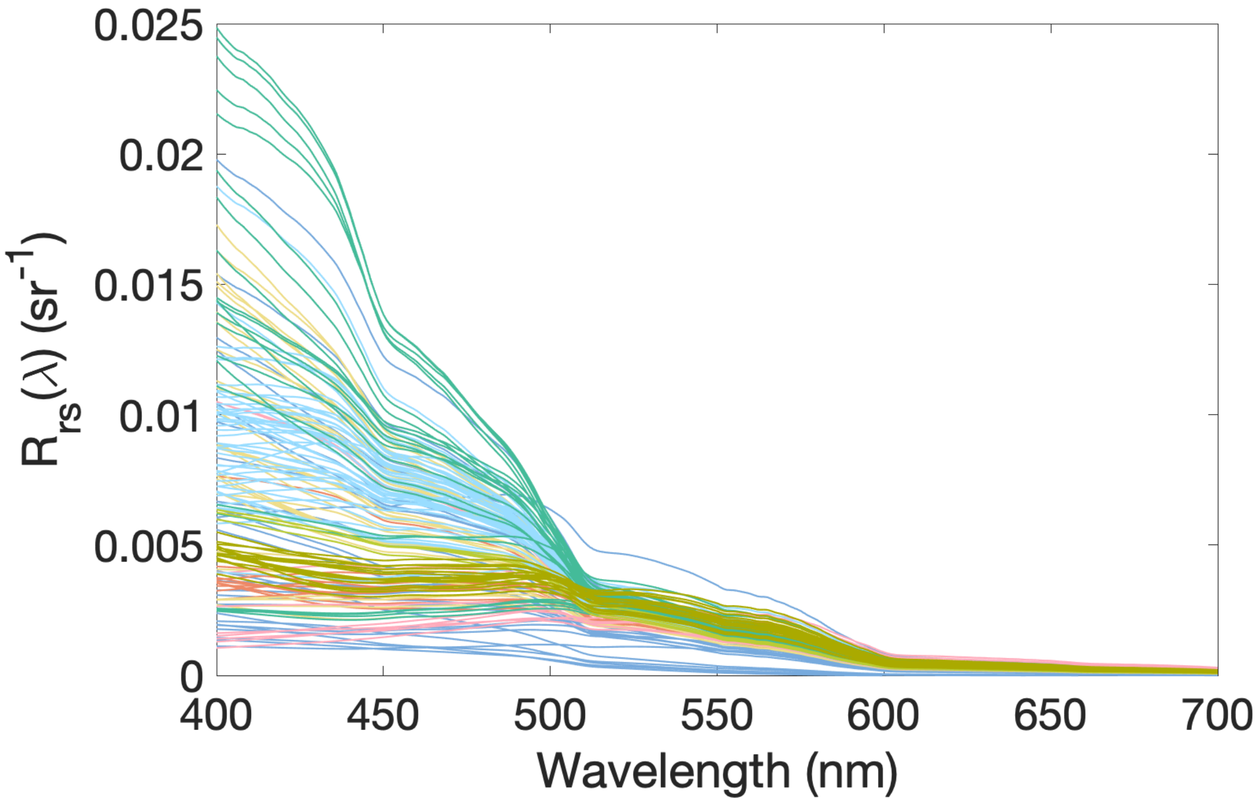
Adapted from Kramer et al., 2022 *Remote Sensing of Environment*

Maximizing hyperspectral R_{rs} information content

Measured spectra



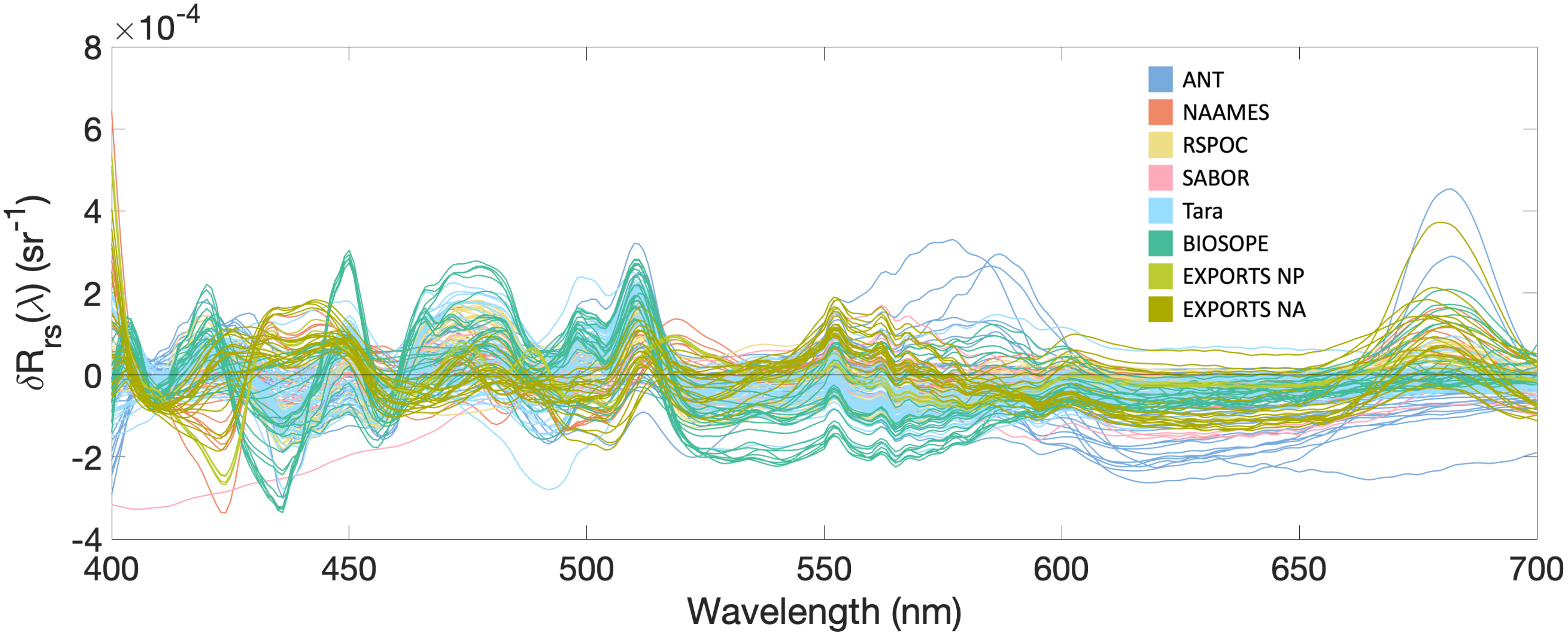
Modeled spectra



They should look identical if our assumptions were correct

Adapted from Kramer et al., 2022 *Remote Sensing of Environment*

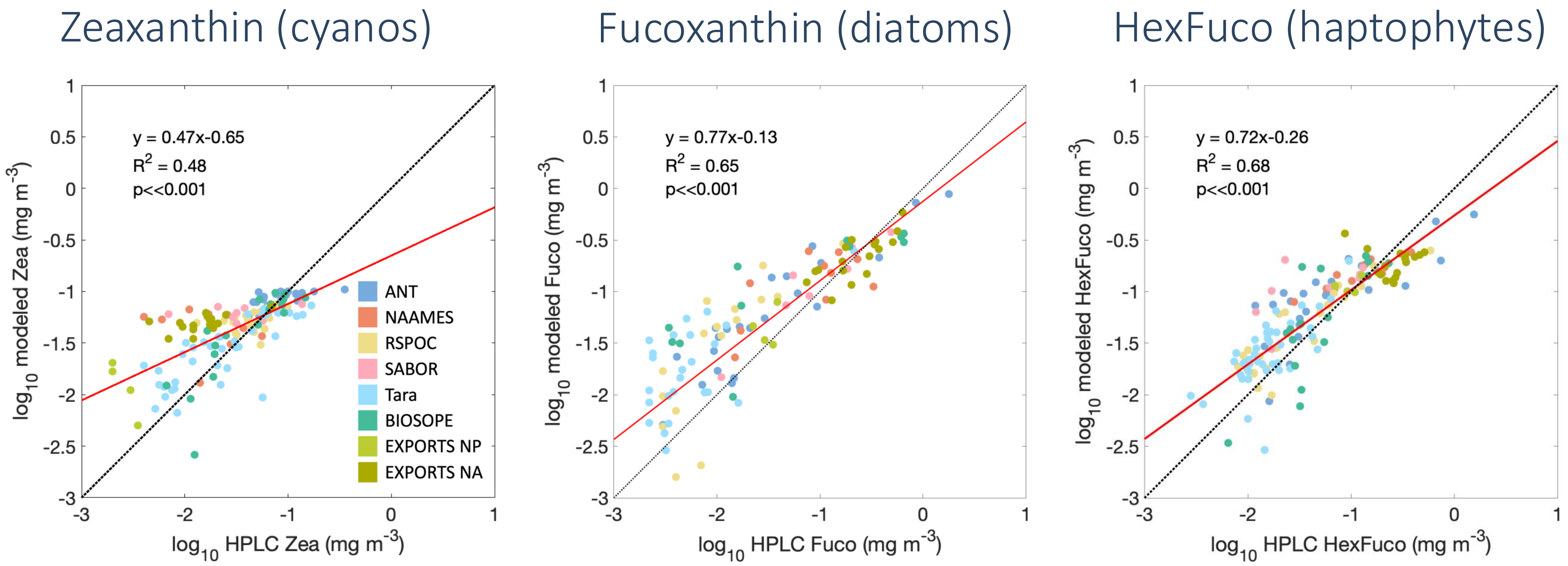
R_{rs} residual $(\delta R_{rs}) = R_{rs,meas}(\lambda) - R_{rs,mod}(\lambda)$



Use the reflectance residual (δR_{rs}) for further modeling…

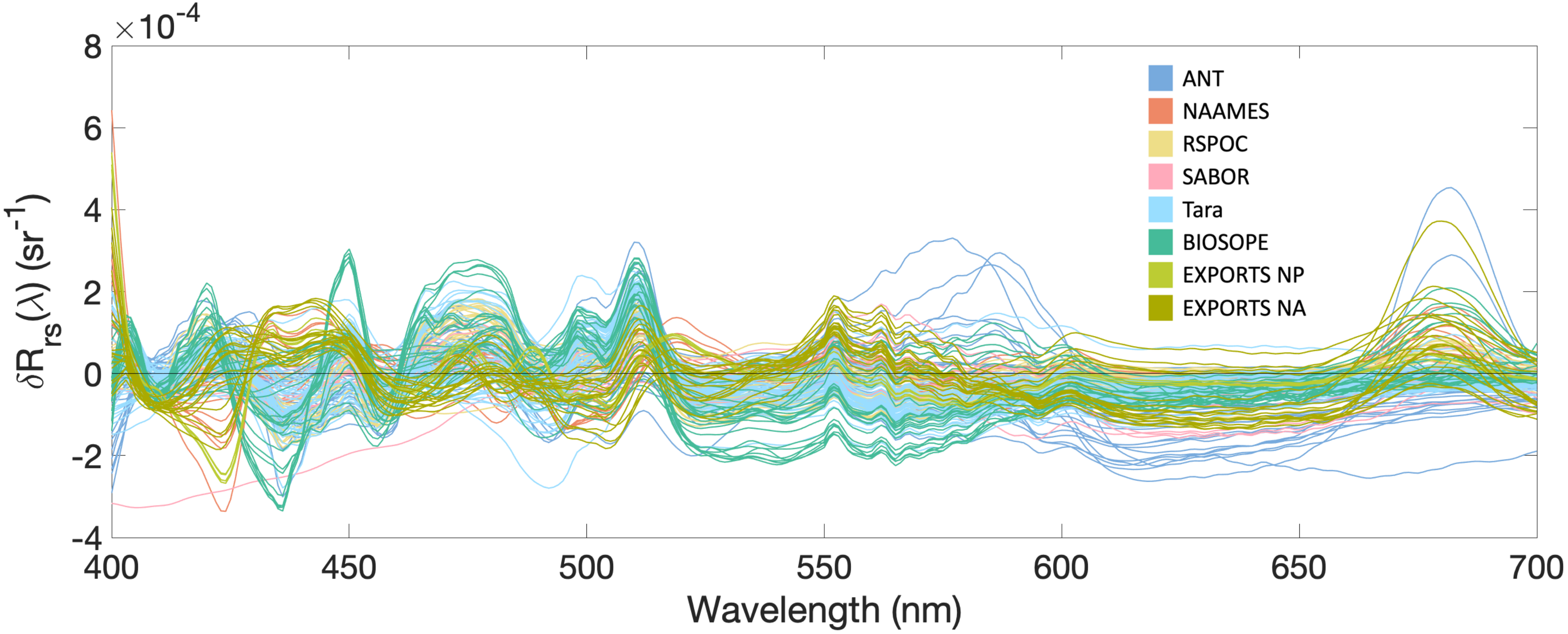
Adapted from Kramer et al., 2022 *Remote Sensing of Environment*

Modeled SDP pigments vs. measured pigments



Adapted from Kramer et al., 2022 *Remote Sensing of Environment*
with new data included in Kramer et al., 2024 *Optics Express*

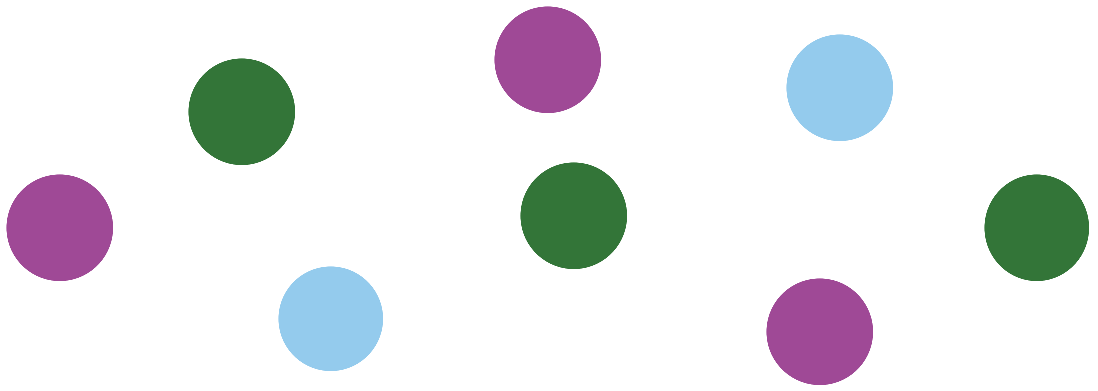
What else can we do with the R_{rs} residual (δR_{rs})?



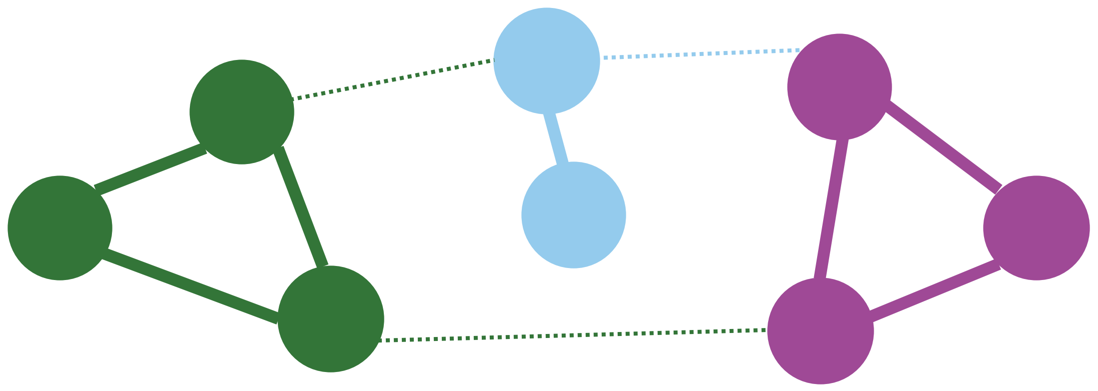
Adapted from Kramer et al., 2022 *Remote Sensing of Environment*

Network-based community detection analysis

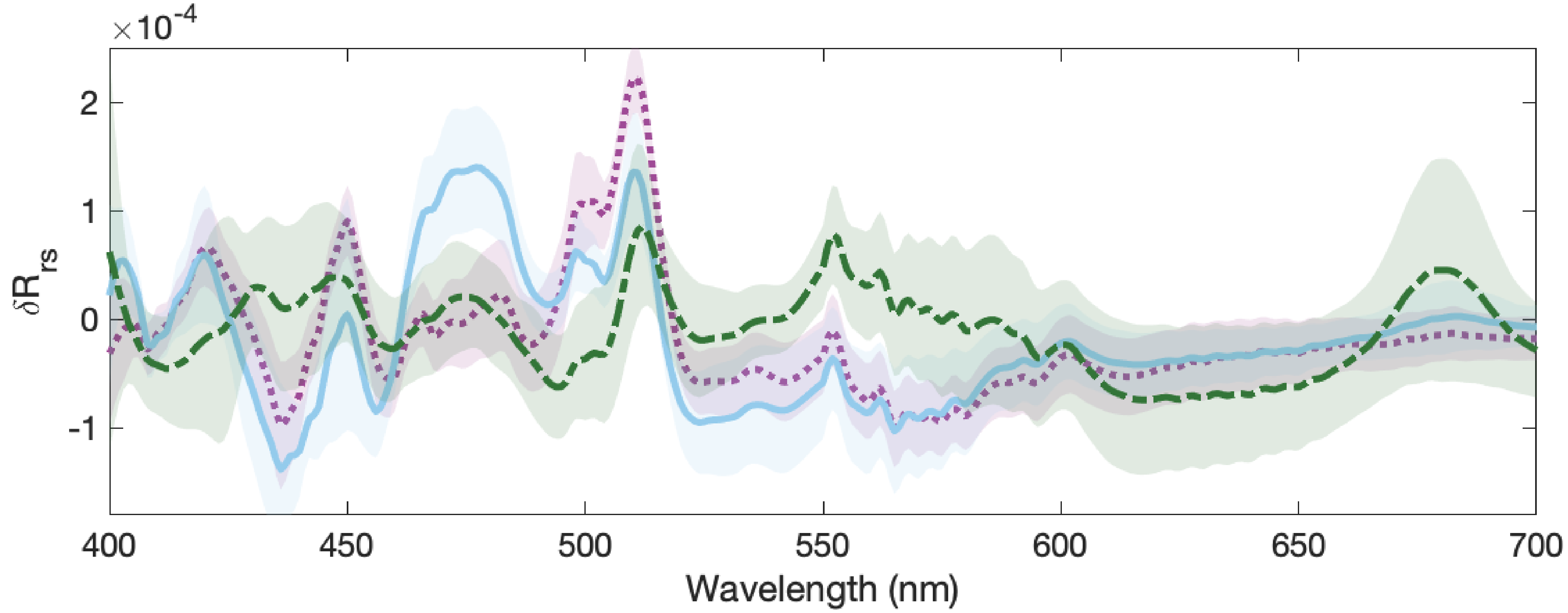
Assign each sample to a community based on its associated characteristics.



Form communities that maximize within-group connections and weaken between-group connections.

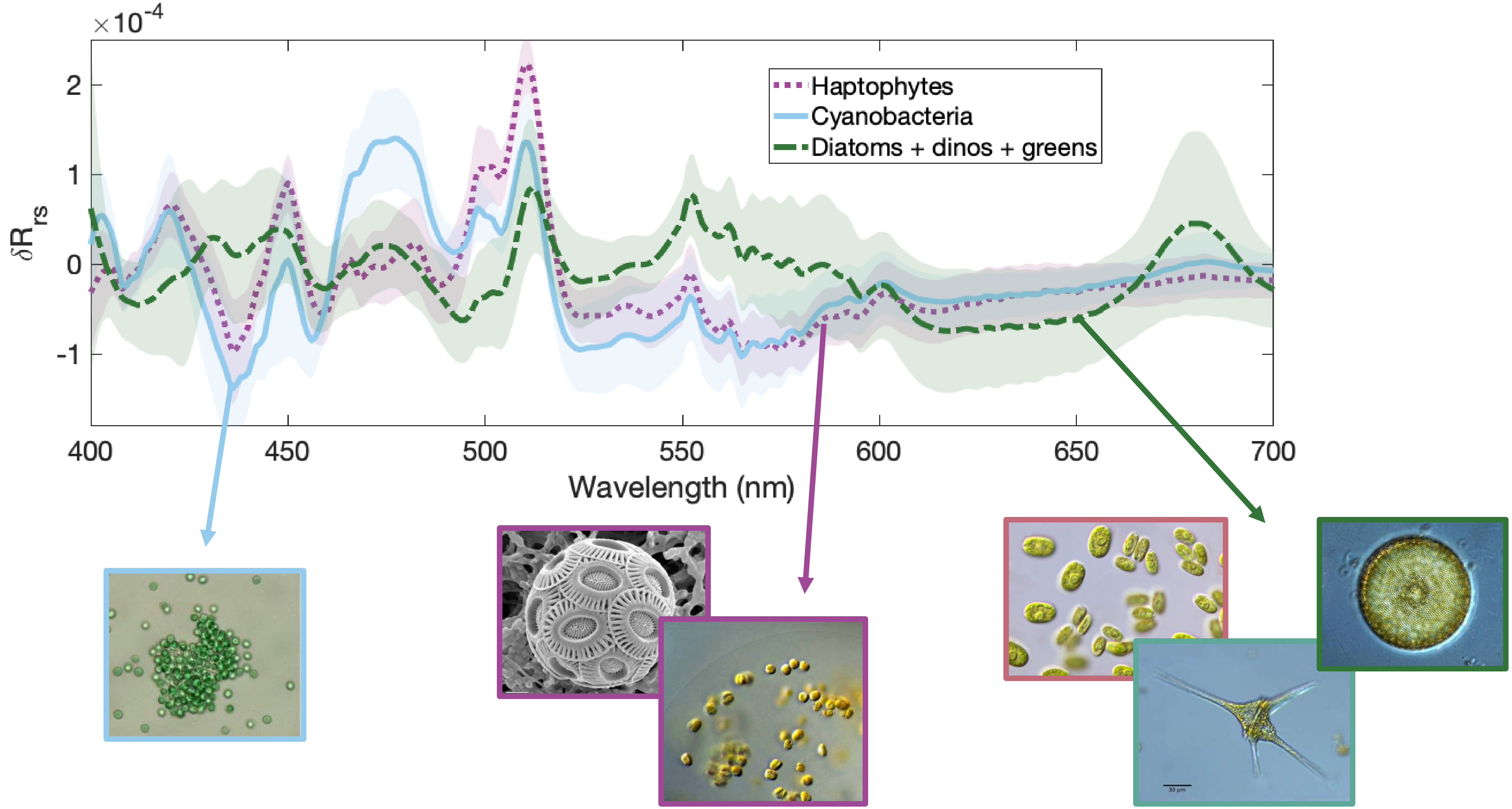


Community detection analysis: 3 δR_{rs} communities



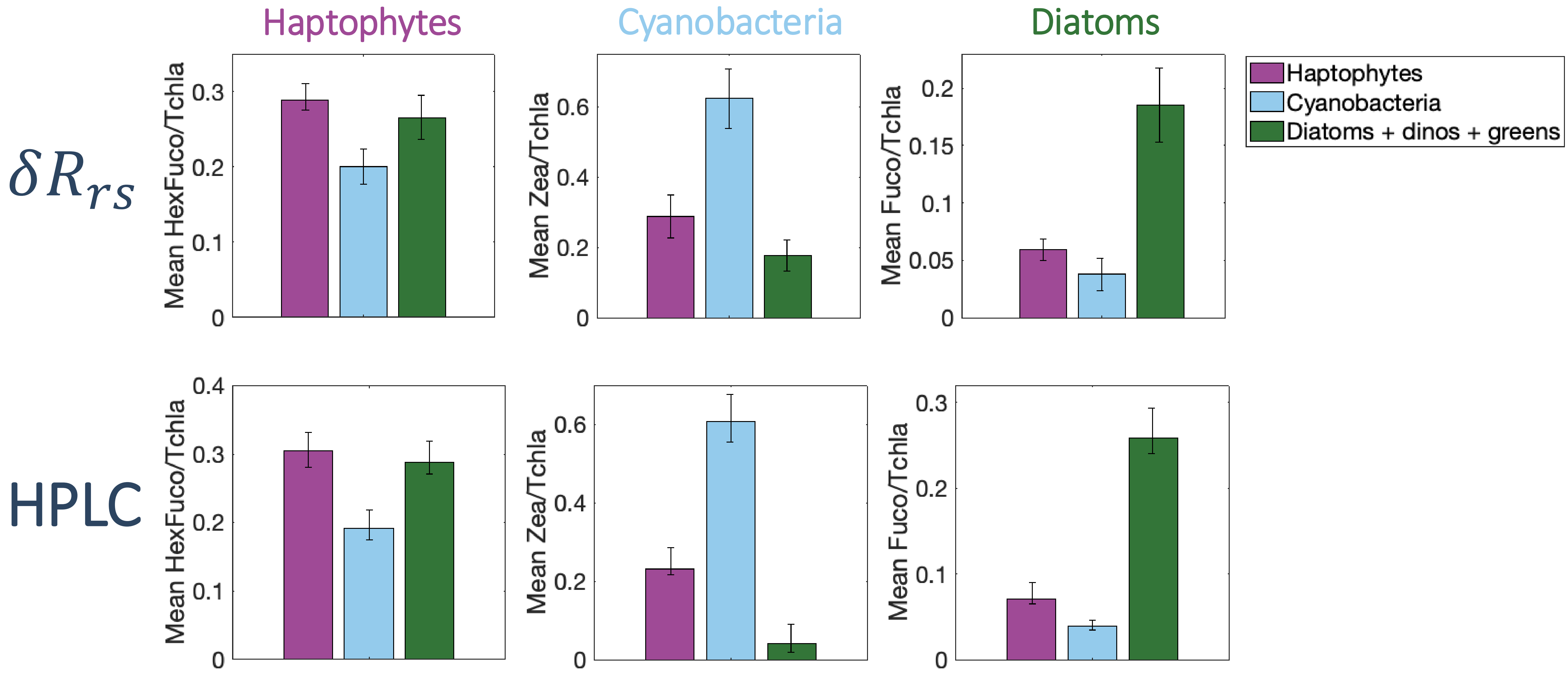
Kramer et al., 2024 *Optics Express*

Community detection analysis: 3 δR_{rs} communities



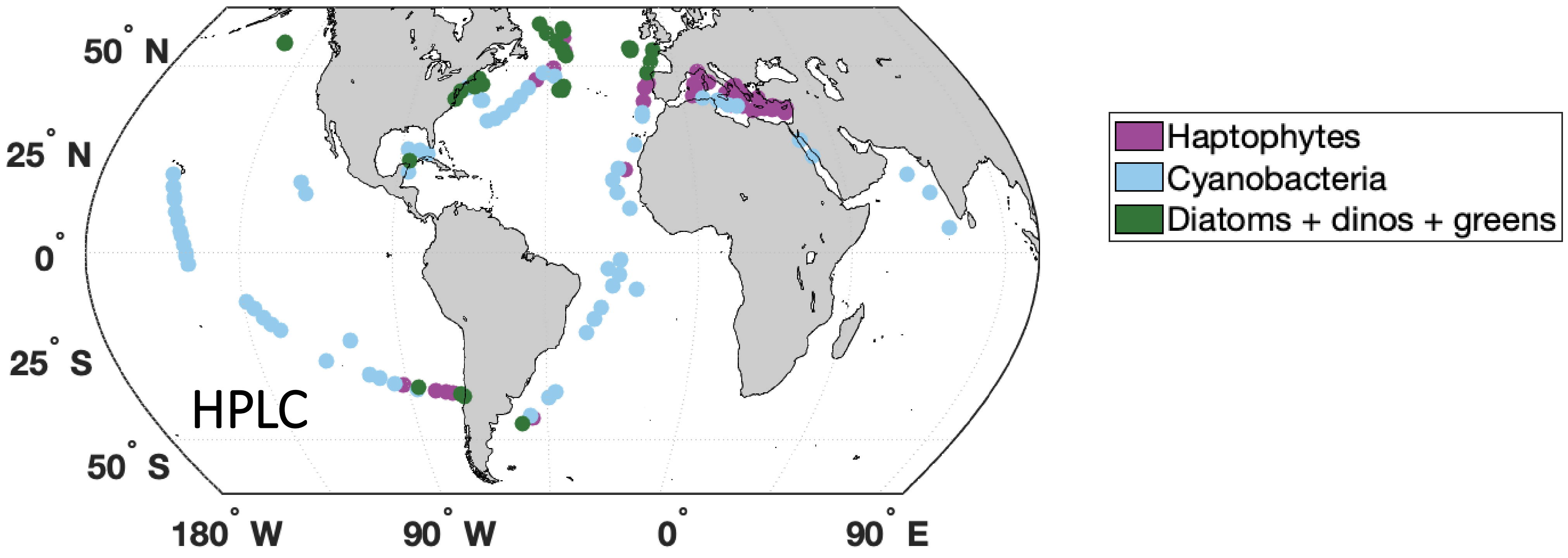
Kramer et al., 2024 *Optics Express*

Three communities also separate from HPLC pigments



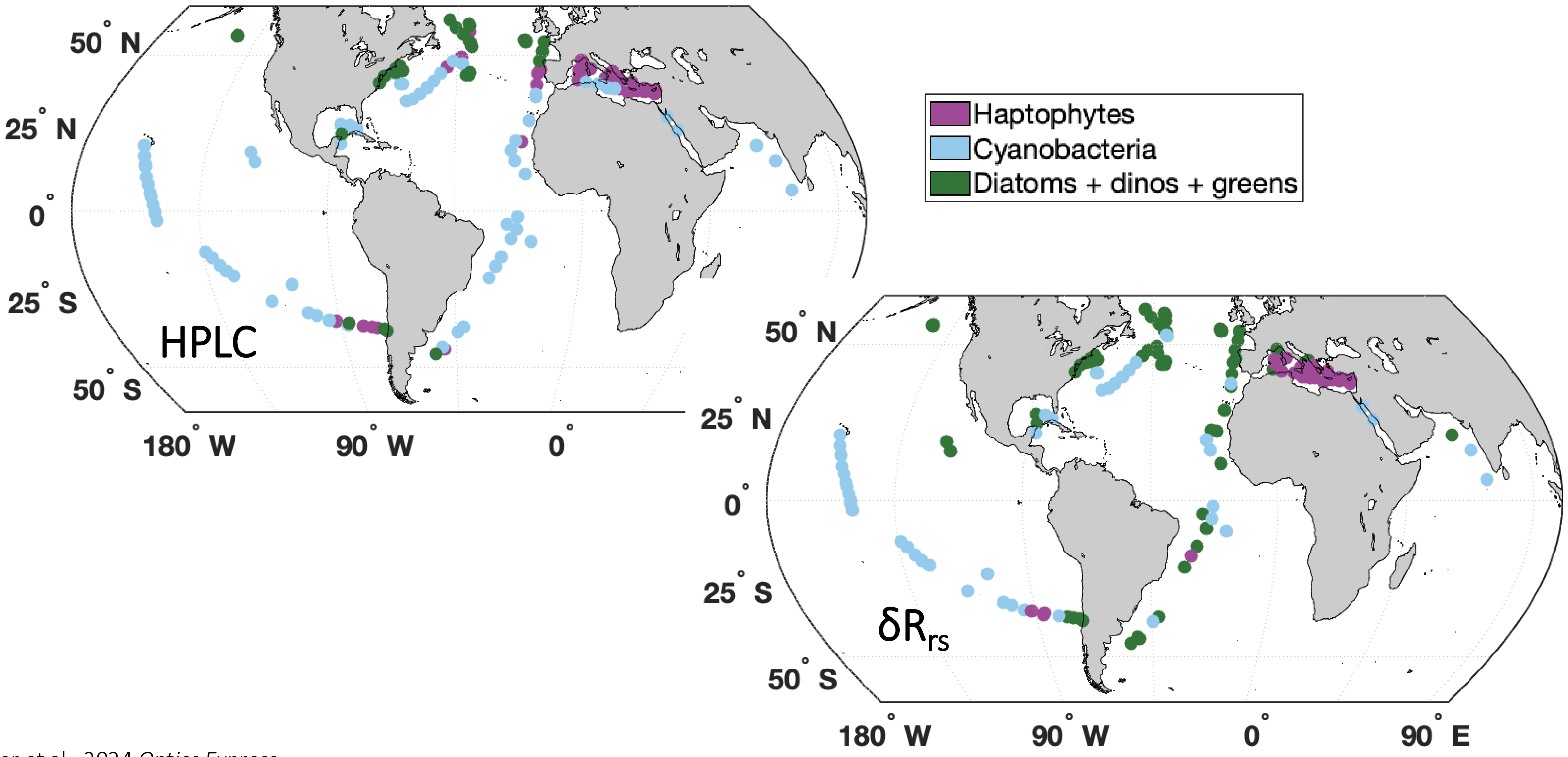
Kramer et al., 2024 *Optics Express*

Global distribution of the three communities



Kramer et al., 2024 *Optics Express*

Global distribution of the three communities

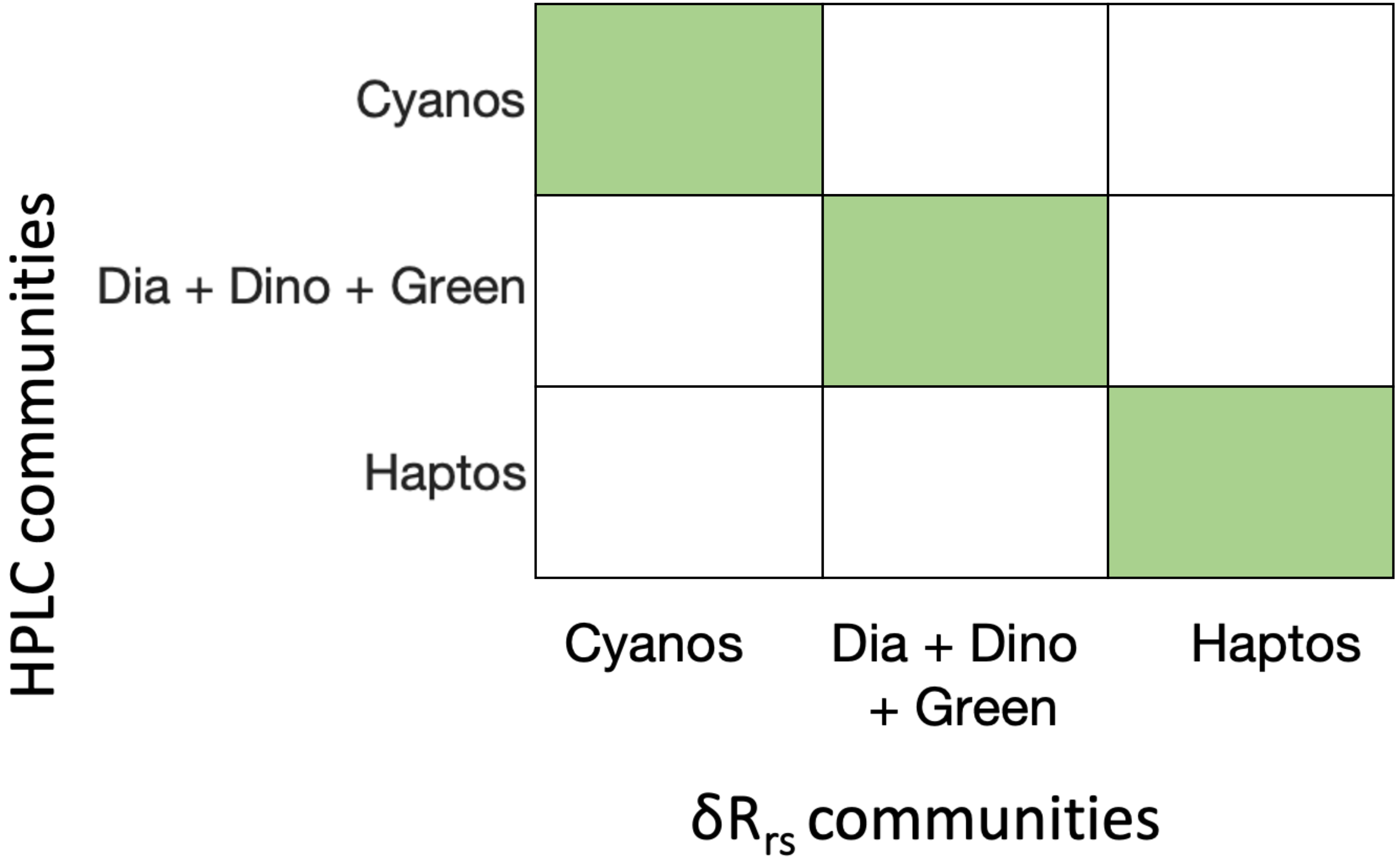


Kramer et al., 2024 *Optics Express*

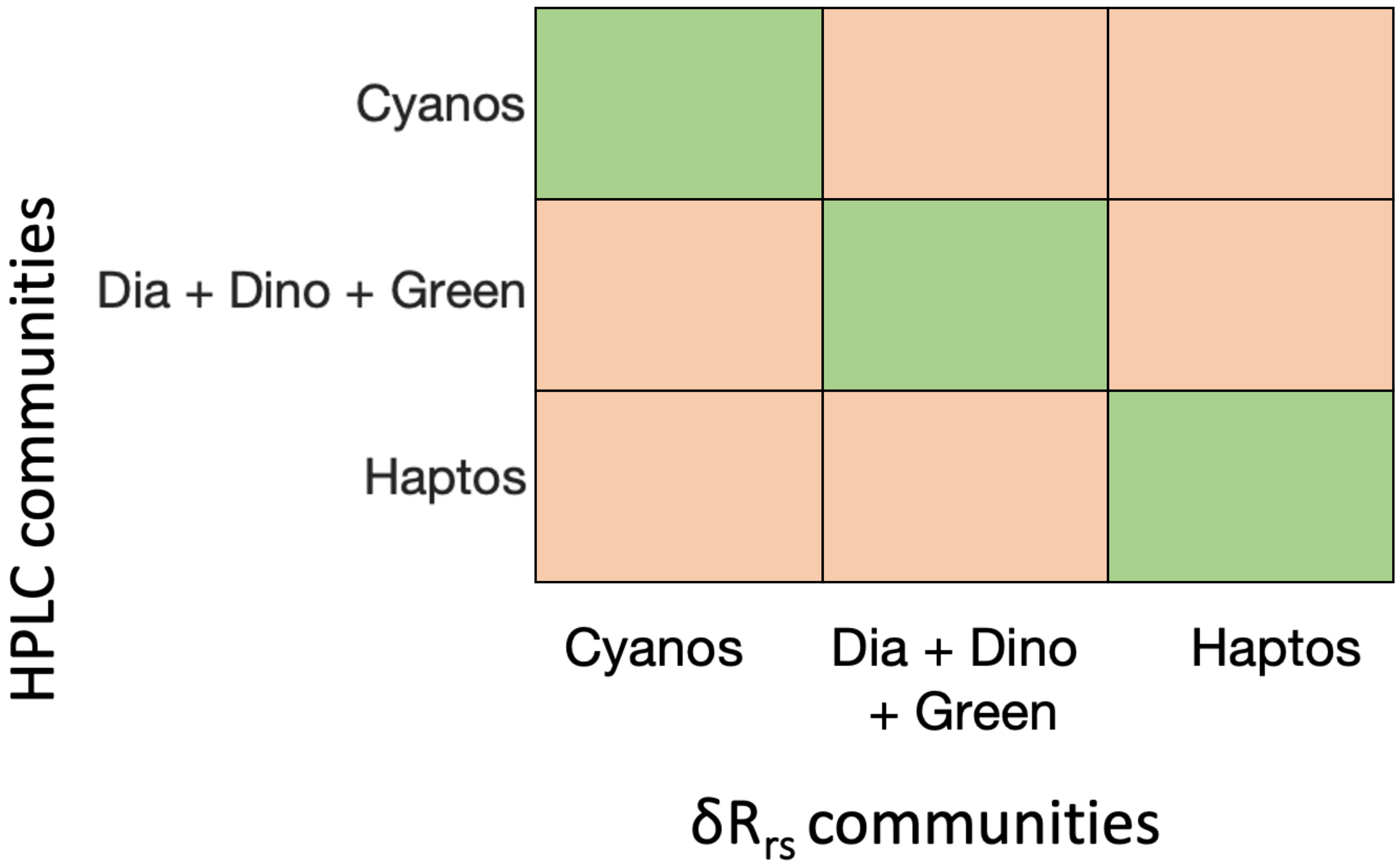
How well do δR_{rs} communities match HPLC communities?

HPLC communities \ δR_{rs} communities	Cyanos	Dia + Dino + Green	Haptos
Cyanos			
Dia + Dino + Green			
Haptos			

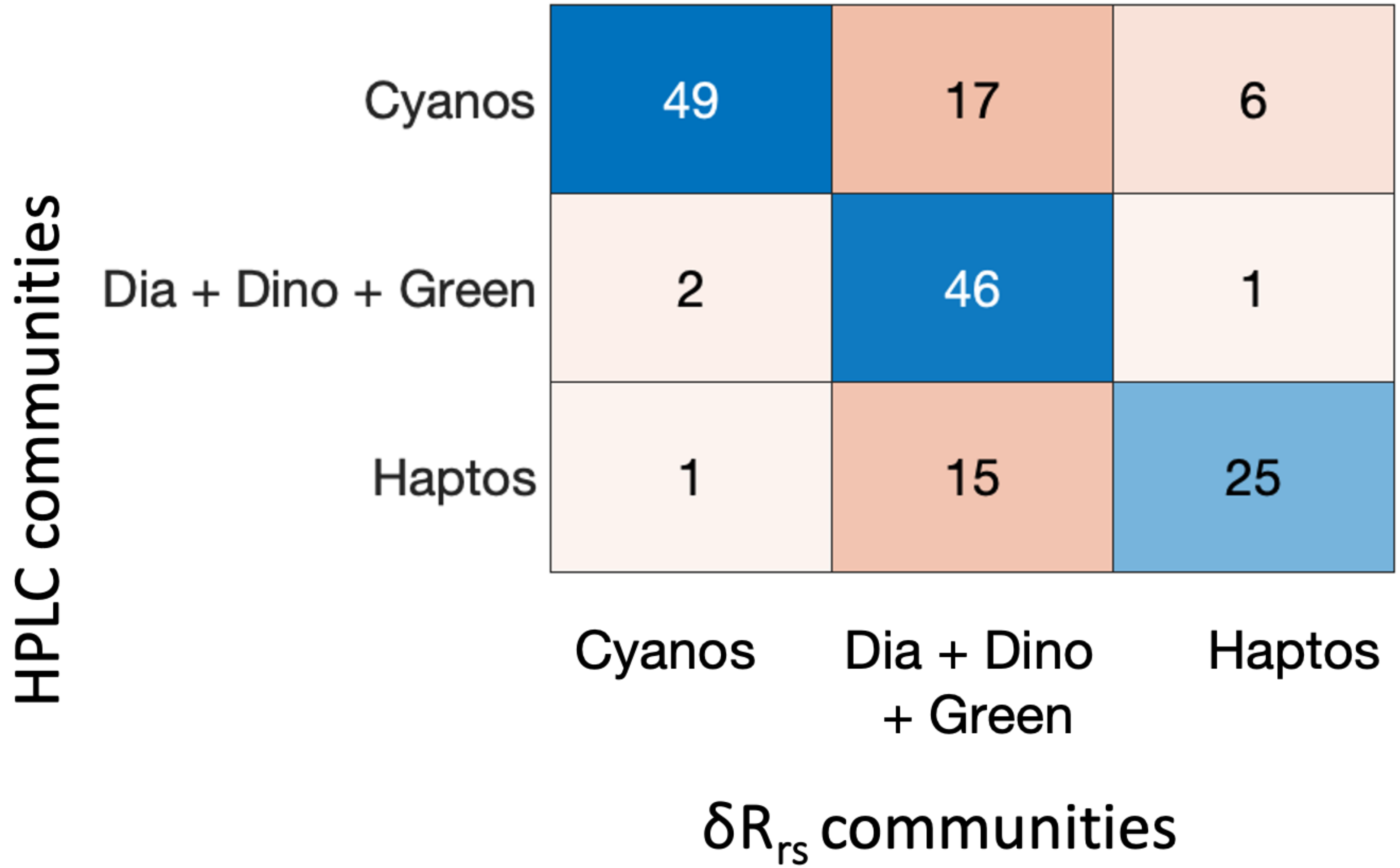
How well do δR_{rs} communities match HPLC communities?



How well do δR_{rs} communities match HPLC communities?

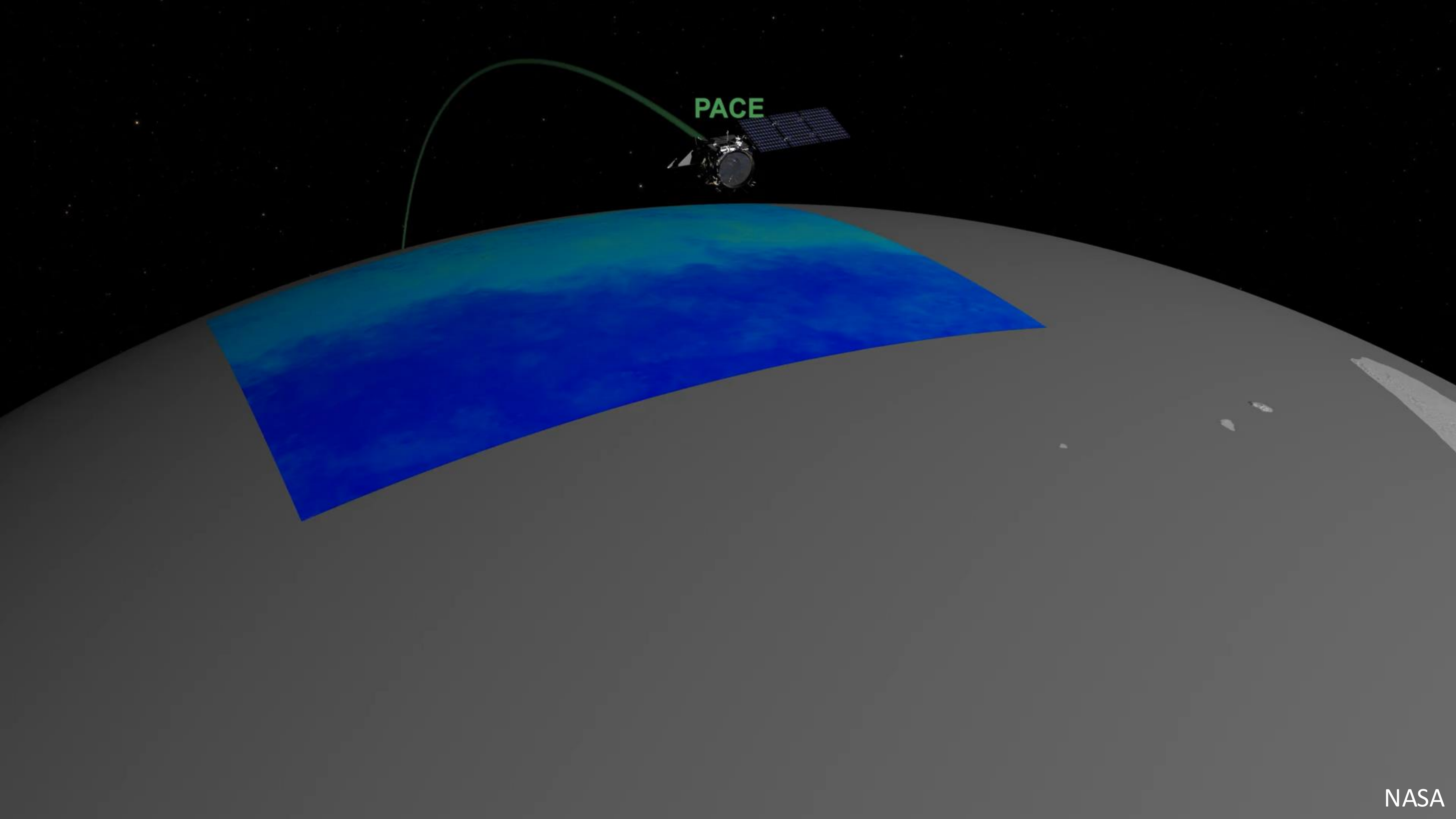


How well do δR_{rs} communities match HPLC communities?

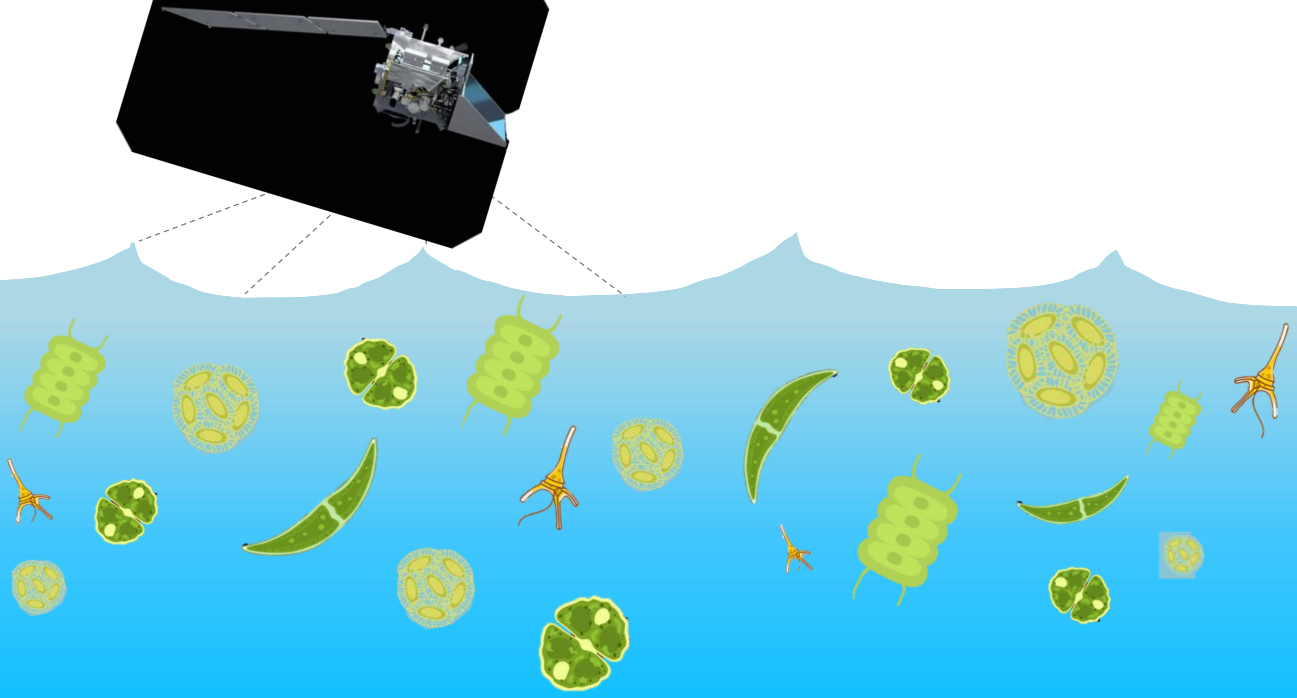


74% of samples correctly assigned (120 of 162)

Kramer et al., 2024 *Optics Express*


PACE
NASA

Next steps



1) SDP model is currently being implemented for PACE to model phytoplankton pigments

2) $\delta R_{rs}(\lambda)$ spectra will be available as a product from SDP and PACE: compare variability in space and time, compare communities from PVST HPLC.

Thanks and acknowledgements

Kramer et al., 2024
Optics Express

All researchers, technicians, captains, and crew who contributed to data collection, preparation, analysis, and submission (particular thanks to Ali Chase, Emmanuel Boss, Nils Haëntjens, Jason Graff, Brian VerWey, Collin Roesler, Heidi Sosik, Taylor Crockford, and Sue Drapeau).

Thank you to Dylan Catlett for SDP model development support.

Thanks to the EXPORTS, NAAMES, and PACE science teams, and to Colleen Durkin & the Carbon Flux Ecology lab at MBARI.

EXPORTS
EXport Processes in the Ocean from RemoTe Sensing

PACE
Plankton, Aerosol, Cloud, ocean Ecosystem

Funding sources for work shown here: NDSEG Fellowship, NASA Ocean Biology and Biogeochemistry, Simons Foundation Postdoctoral Fellowship in Marine Microbial Ecology, David and Lucile Packard Foundation.

SIMONS FOUNDATION

the David & Lucile Packard FOUNDATION

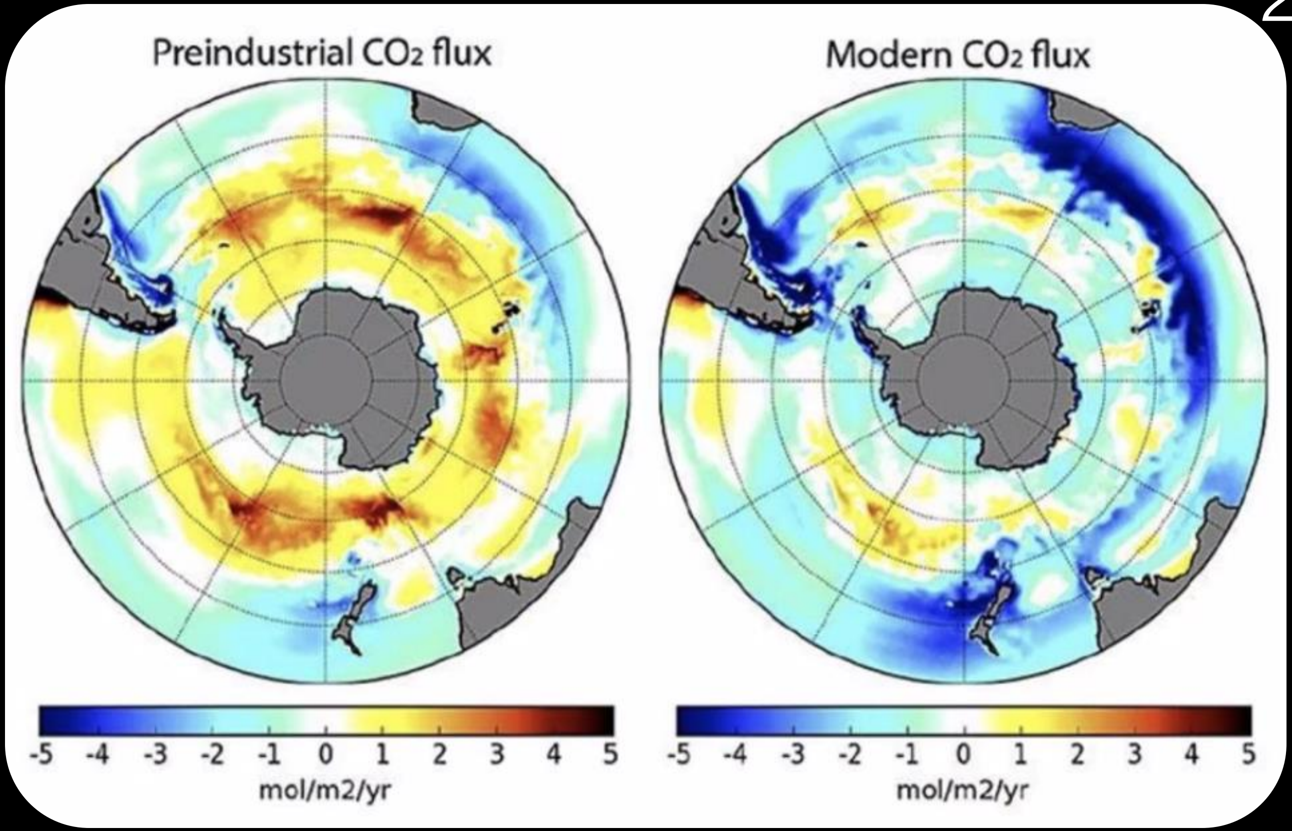
NASA

Seasonal variability of surface ocean carbon uptake and chlorophyll-a concentration in the West Antarctic Peninsula

Jessie Turner, UConn ➡ ODU (Jan 2025)
Co-Authors: Heidi Dierssen, Dave Munro, Amanda Fay, Sharon Stammerjohn, Heather Kim

Lightning Talk for NASA OBB Virtual Meeting, December 5, 2024

Is the Southern Ocean a CO_2 Sink?

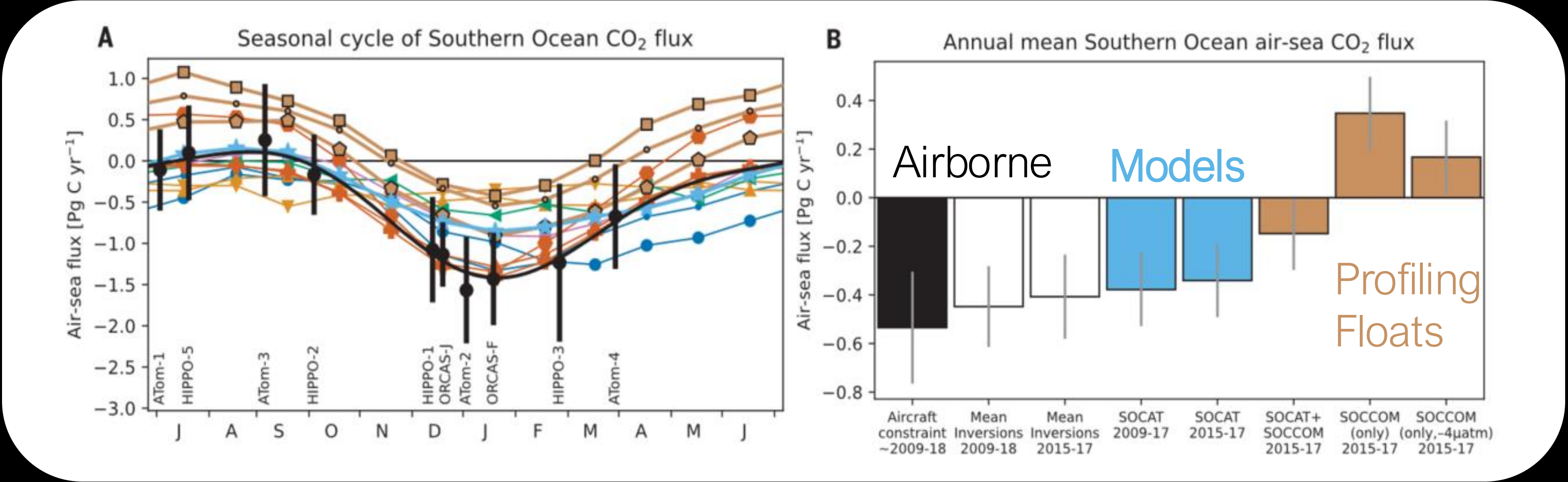


13th Carbon Mitigation Initiative Annnual Report
https://cmi.princeton.edu/annual-meetings/annual-reports/year-2013/quantifying-the-ocean-carbon-sink/

Southern Ocean thought to be one of the largest sinks of anthropogenic CO_2 in the global ocean…

Is the Southern Ocean a CO_2 Sink?

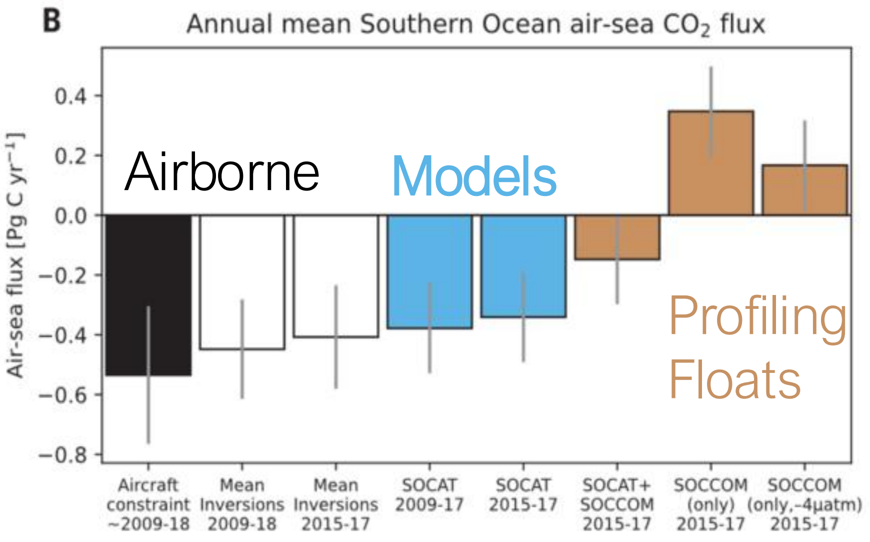
- How much CO_2 does the Southern Ocean really take up?
- Even the ***sign*** is uncertain:



(Long et al. 2021, Science)

Is the Southern Ocean a CO_2 Sink?

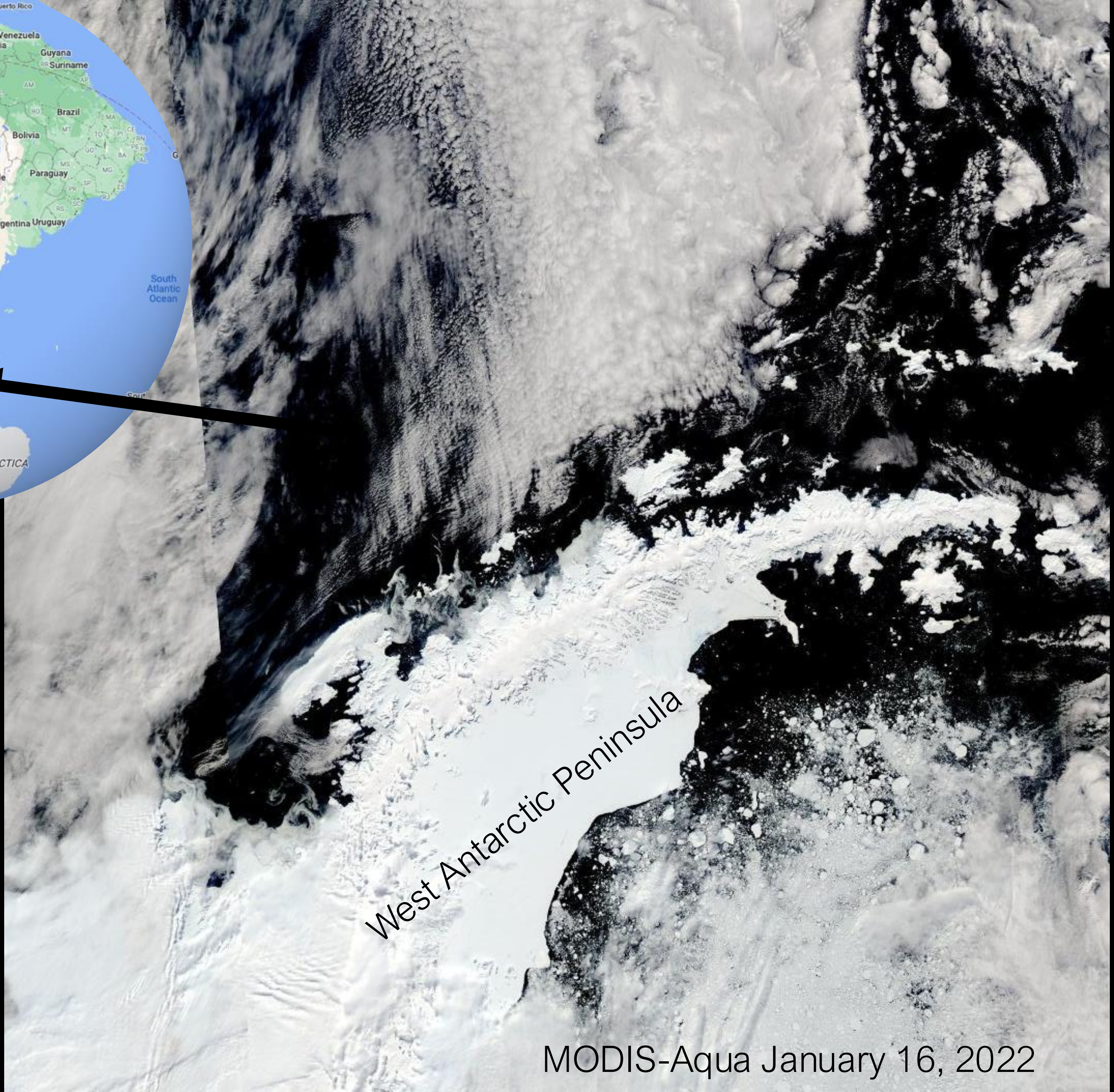
- How much CO_2 does the Southern Ocean really take up?
- Even the ***sign*** is uncertain:



(Long et al. 2021, Science)

- What about specific regions?
- How does it vary with latitude?
- Can ocean color help us?

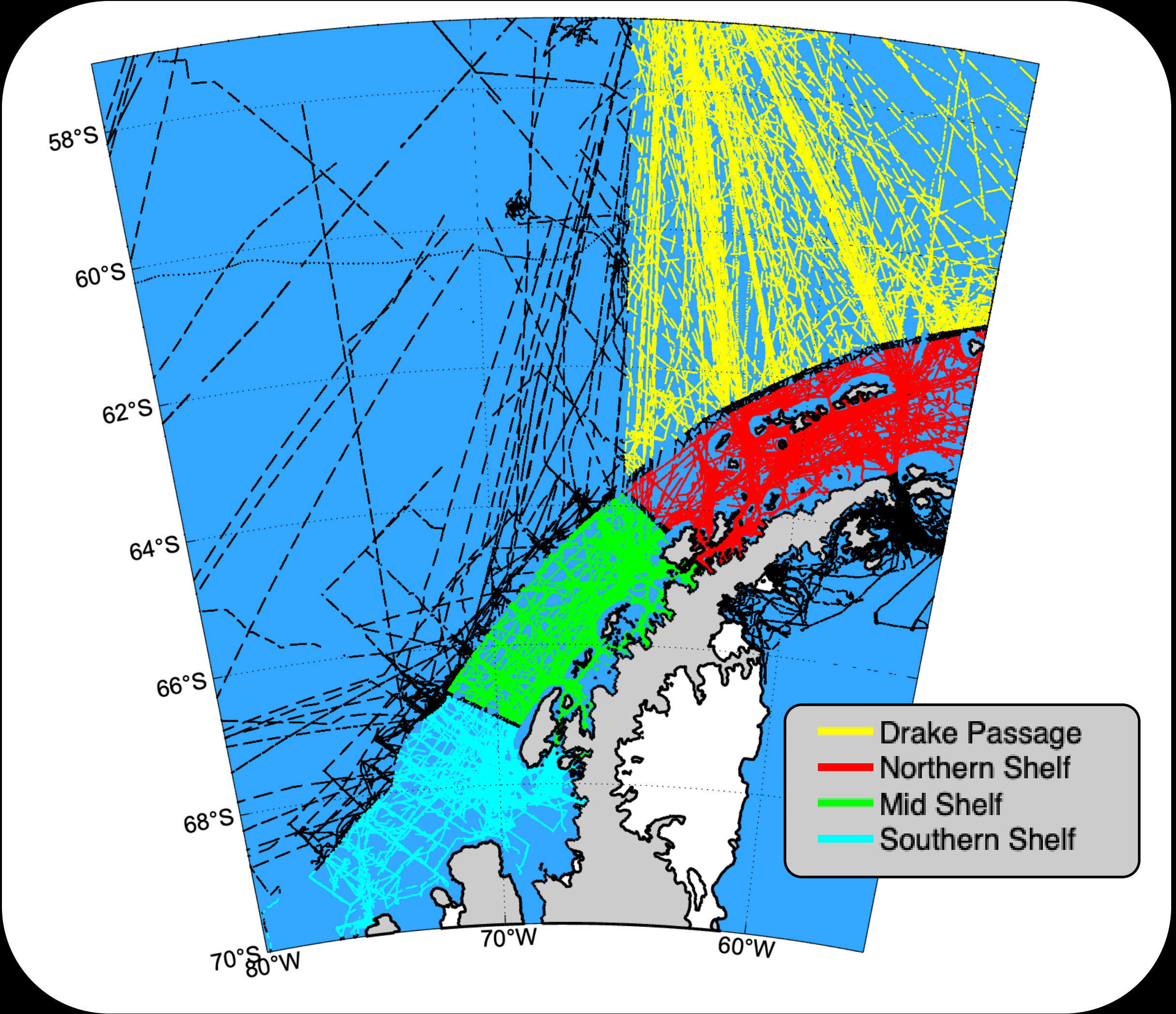
Regional case study: West Antarctic Peninsula



Regional case study: West Antarctic Peninsula

- Legacy of in situ observations LTER 1990-2024
- Rapidly warming
- Sea ice decline
- Glacial retreat
- Collaboration to incorporate ocean optics

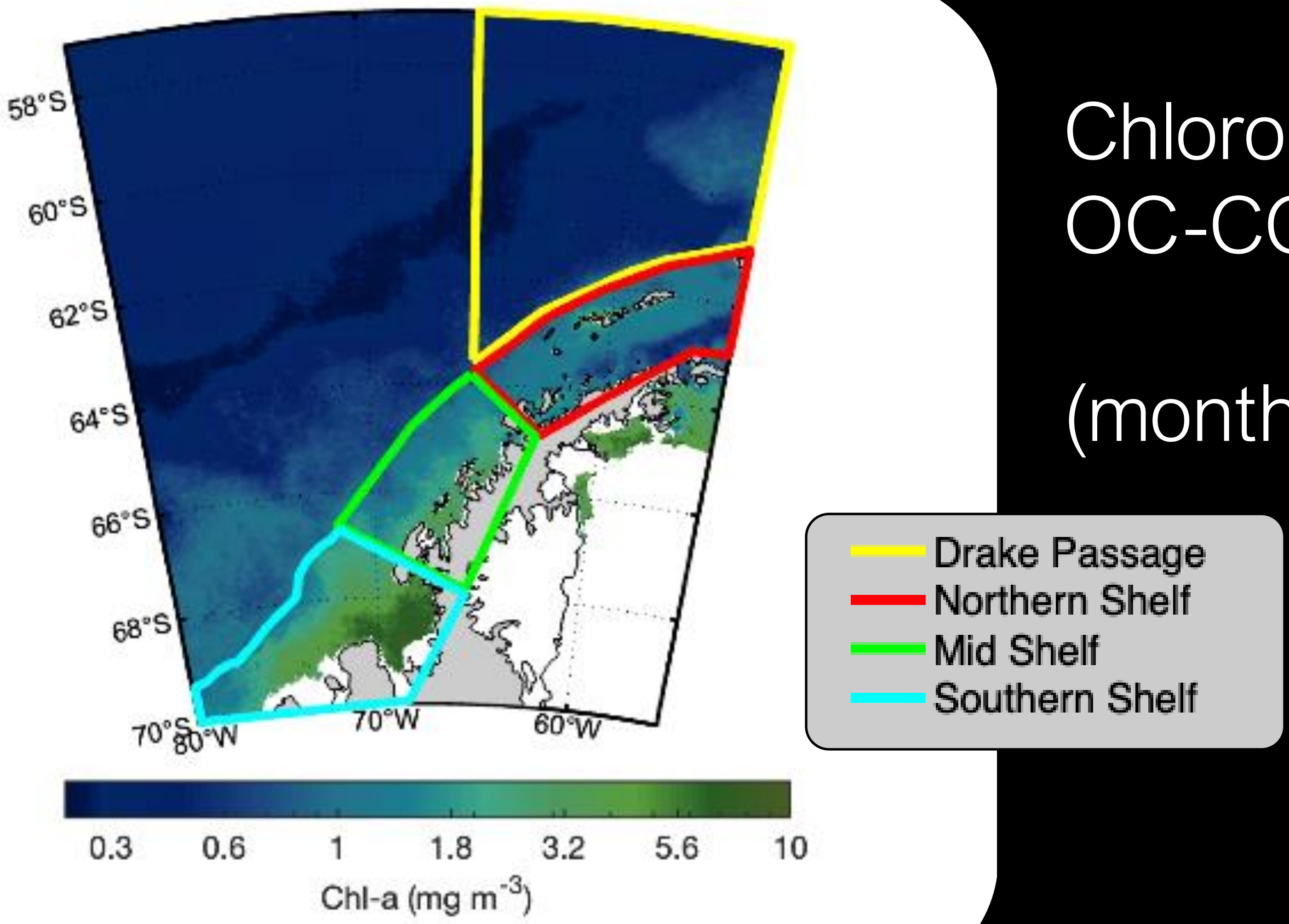
Methods



20 years of ship-track in situ pCO_2 data

(2000-2020, binned to monthly data)

Methods

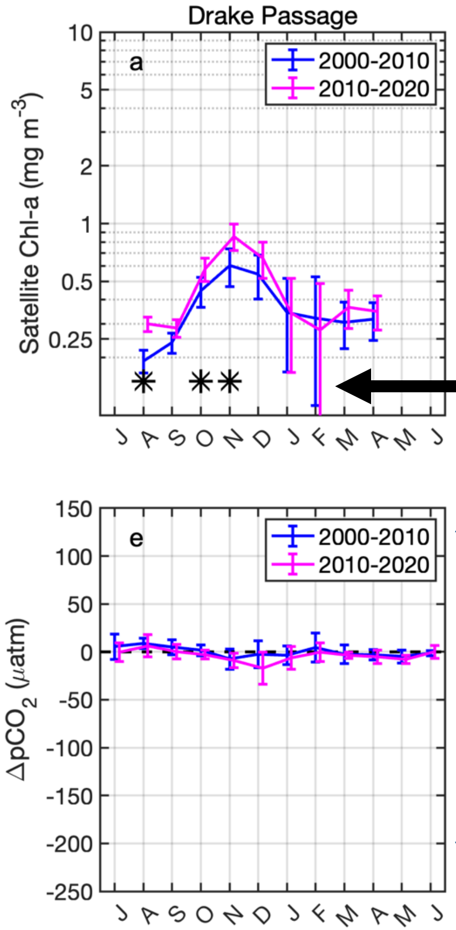


Long-term mean 1997-2022

Chlorophyll-a from OC-CCI

(monthly data)

Results



Chlorophyll-a from OC-CCI

* Decades significantly different for that month

Outgassing - positive

Delta pCO_2 (uptake or outgassing)

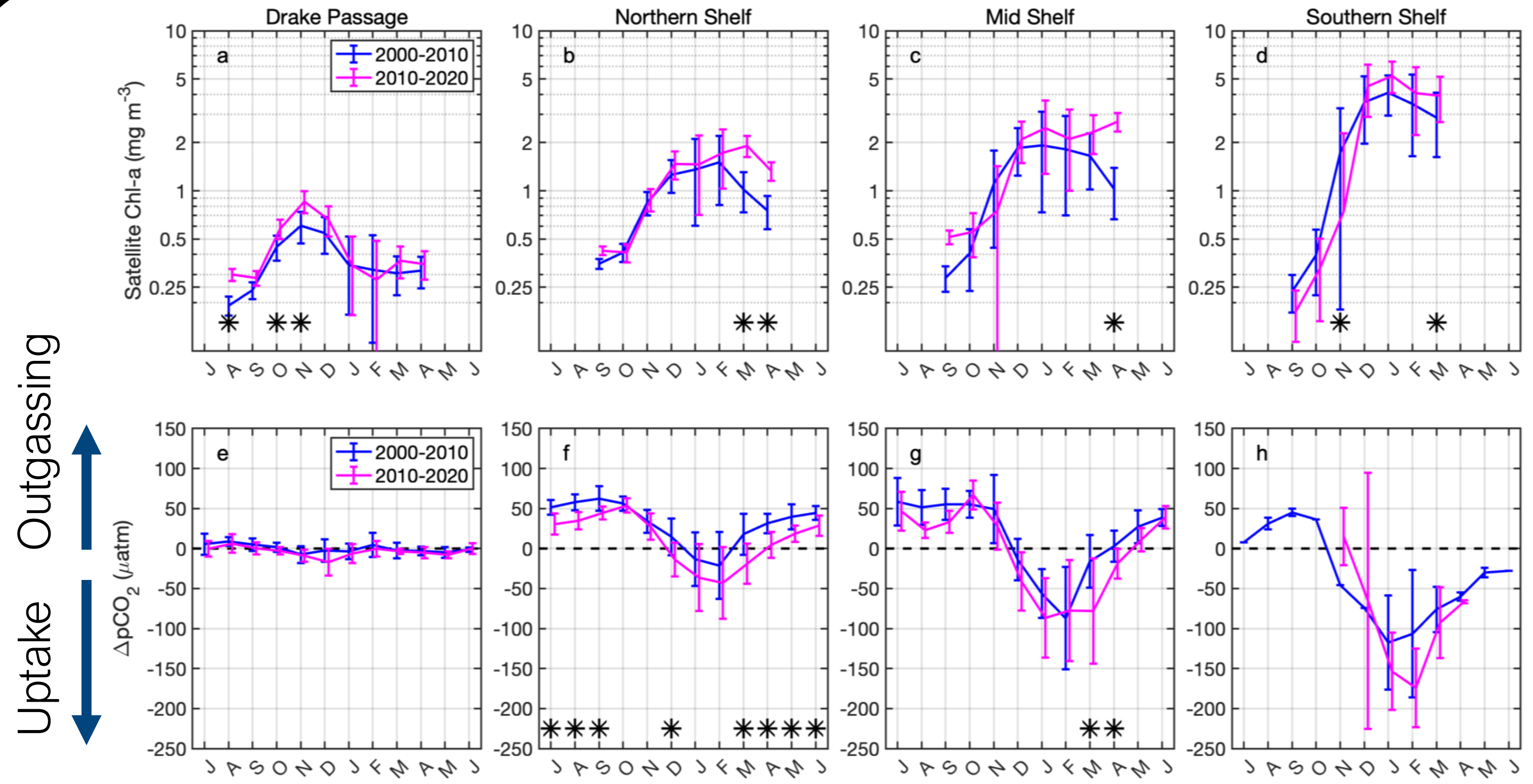
Uptake - negative

Seasonal cycle

Spring – Summer – Fall

Turner et al. GRL (In Revision)

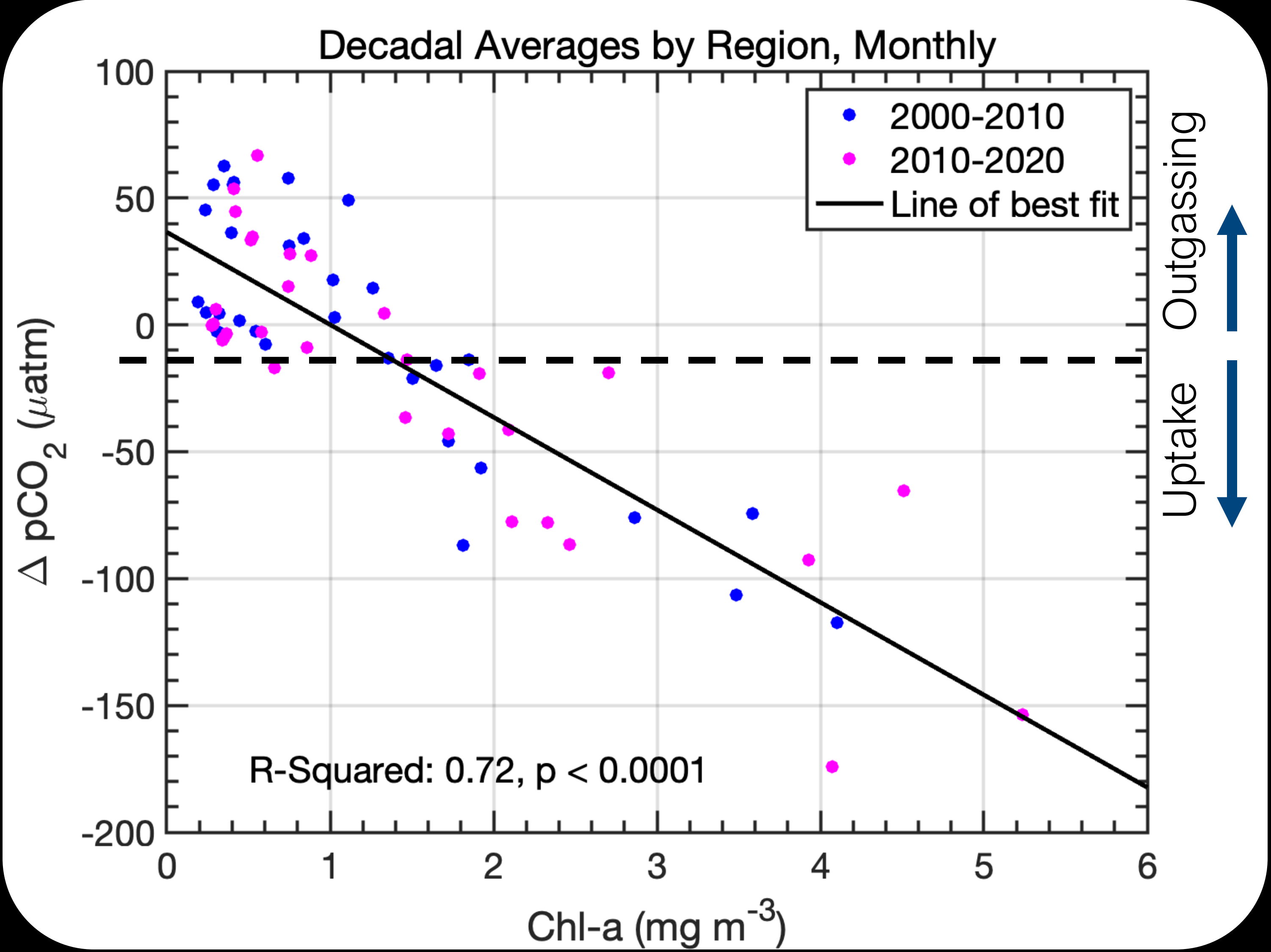
Tightly coupled biology and CO_2 uptake



	Drake Passage	Northern Shelf	Mid Shelf	Southern Shelf
2000s:	R = -0.73, p = 0.026	R = -0.97, p < 0.001	R = -0.86, p = 0.006	R = -0.97, p < 0.001
2010s:	R = -0.67, p = 0.050	R = -0.92, p = 0.050	R = -0.86, p = 0.006	R = -0.81, p = 0.099

Turner et al. GRL (In Revision)

Tightly coupled biology and CO_2 uptake



Turner et al. GRL (In Revision)

I am actively recruiting students for Fall 2025 and 2026 at Old Dominion University in Norfolk, Virginia

Contact: jturners@odu.edu

Home / College of Sciences / Ocean & Earth Sciences

Ocean & Earth Sciences

The Department of Ocean & Earth Sciences acquires and disseminates knowledge of the earth system, including the relationships among the biological, chemical, geological and physical components of our planet. It is critical that we understand both natural and human-induced processes that change this system so we are prepared to meet present and future challenges.

Acknowledgements

Postdoc mentor: Heidi Dierssen, UConn

Collaborators on Antarctica work:
- Michael Cappola, UDel
- Sharon Stammerjohn, CU Boulder
- Oscar Schofield, Rutgers
- Dave Munro, CU Boulder
- Heather Kim, WHOI
- Maria Kavanaugh, OSU
- Hilde Oliver, WHOI
- Amanda Fay, Columbia/Lamont-Doherty

Western Antarctic Peninsula and South Shetland Islands, September 16, 2021 (HawkEye)

Questions?

Contact: jturners@odu.edu