Beyond total biomass: Progress towards detecting phytoplankton communities from space

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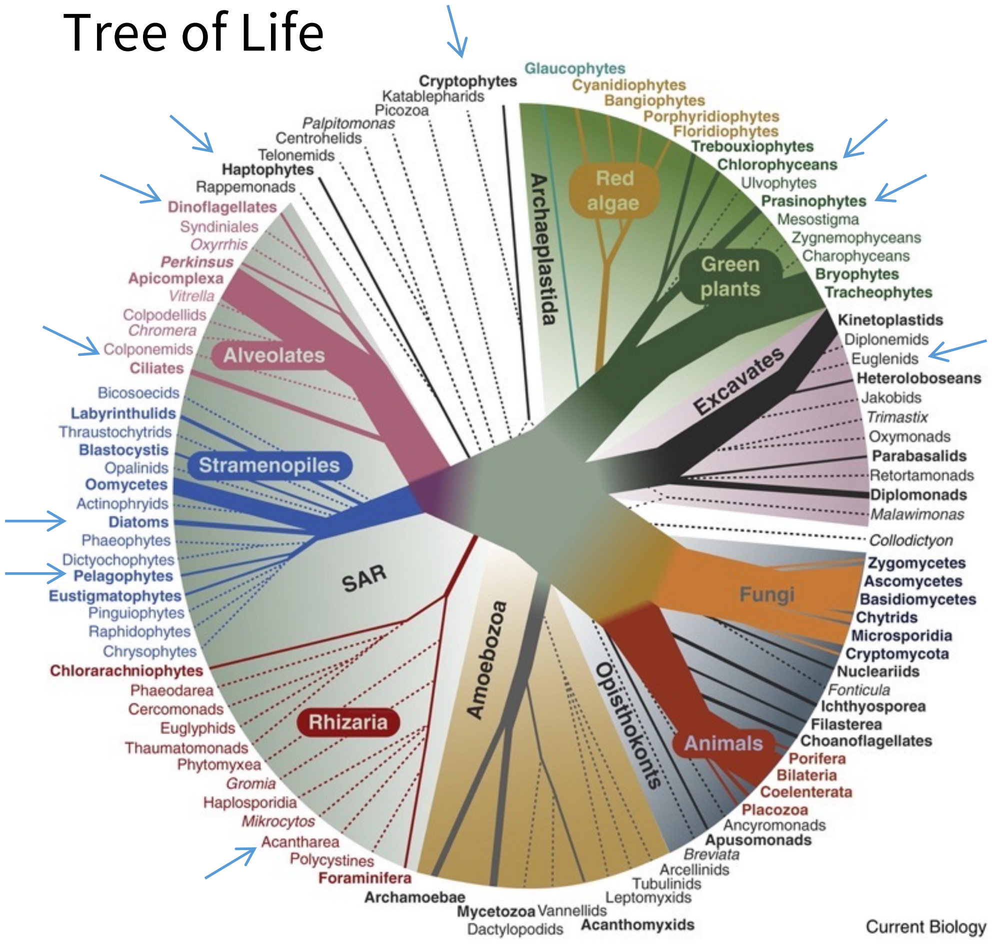
Why Phytoplankton Community Composition?

- **Global change**
  - latitudinal distributional shifts
  - phenology shifts
  - bloom dynamics
- **Biogeochemical modeling**
  - phytoplankton community composition
  - nutrient cycling
  - export of particles
- **Ecological processes**
  - rates of primary production
  - nitrogen fixers, DMS producers, silicifiers, calcifiers
  - trophic dynamics & food web efficiency
- **Ecological indicators**
  - hypoxia
  - eutrophication
  - informed monitoring and assessment
- **Environmental reporting**
  - meeting thresholds
  - species composition
  - detecting anomalies
- **Hazard Monitoring**
  - detection and tracking of harmful algal blooms
  - assessing storm impacts
  - monitoring oil spill extent and cleanup
- **Food Security**
  - finding pelagic and benthic habitats for fisheries
  - locations/monitoring for aquaculture
  - food safety & toxin production

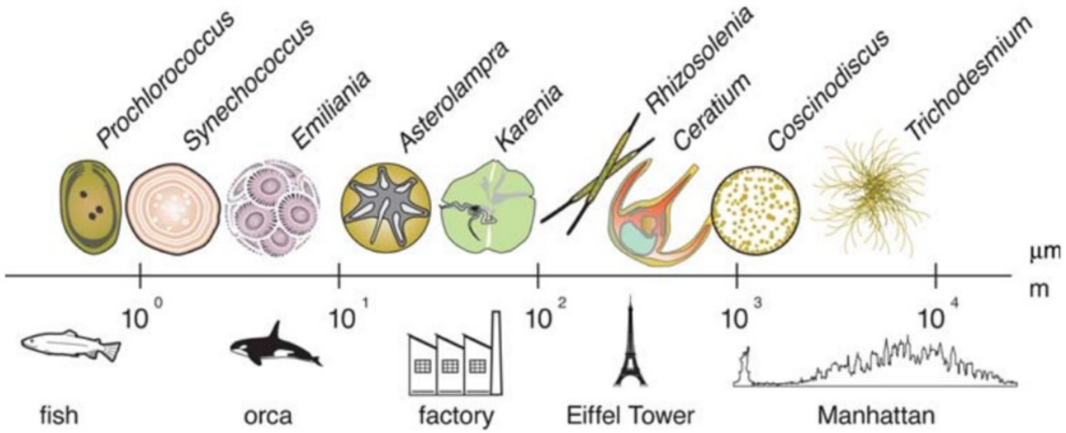
Dierssen et al., 2021

Phytoplankton are taxonomically and functionally diverse

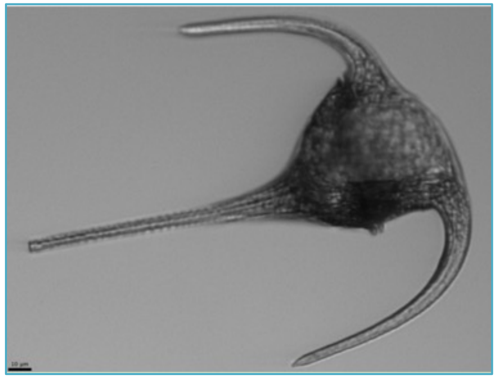
Tree of Life

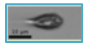


Burki and Keeling, 2014

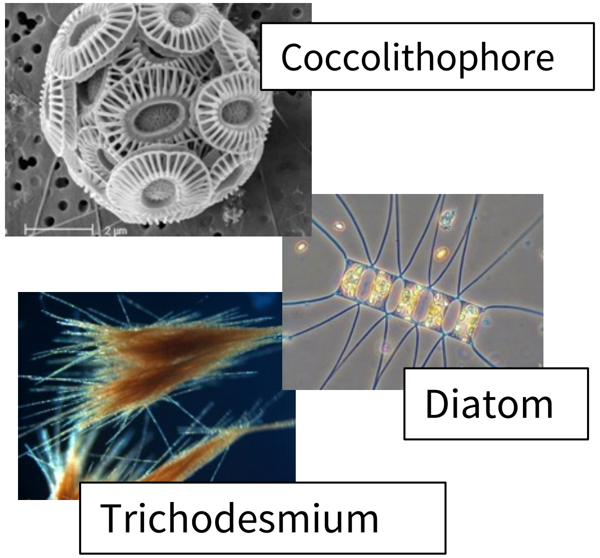


Finkel et al., 2010





Phytoplankton imaged with an Imaging FlowCytobot, shown at the same scale



Background & Motivation

Our ocean **teems with life**, supporting many of Earth's **economies.**

PACE will reveal the diversity of organisms fueling marine food webs and how ecosystems respond to environmental change.

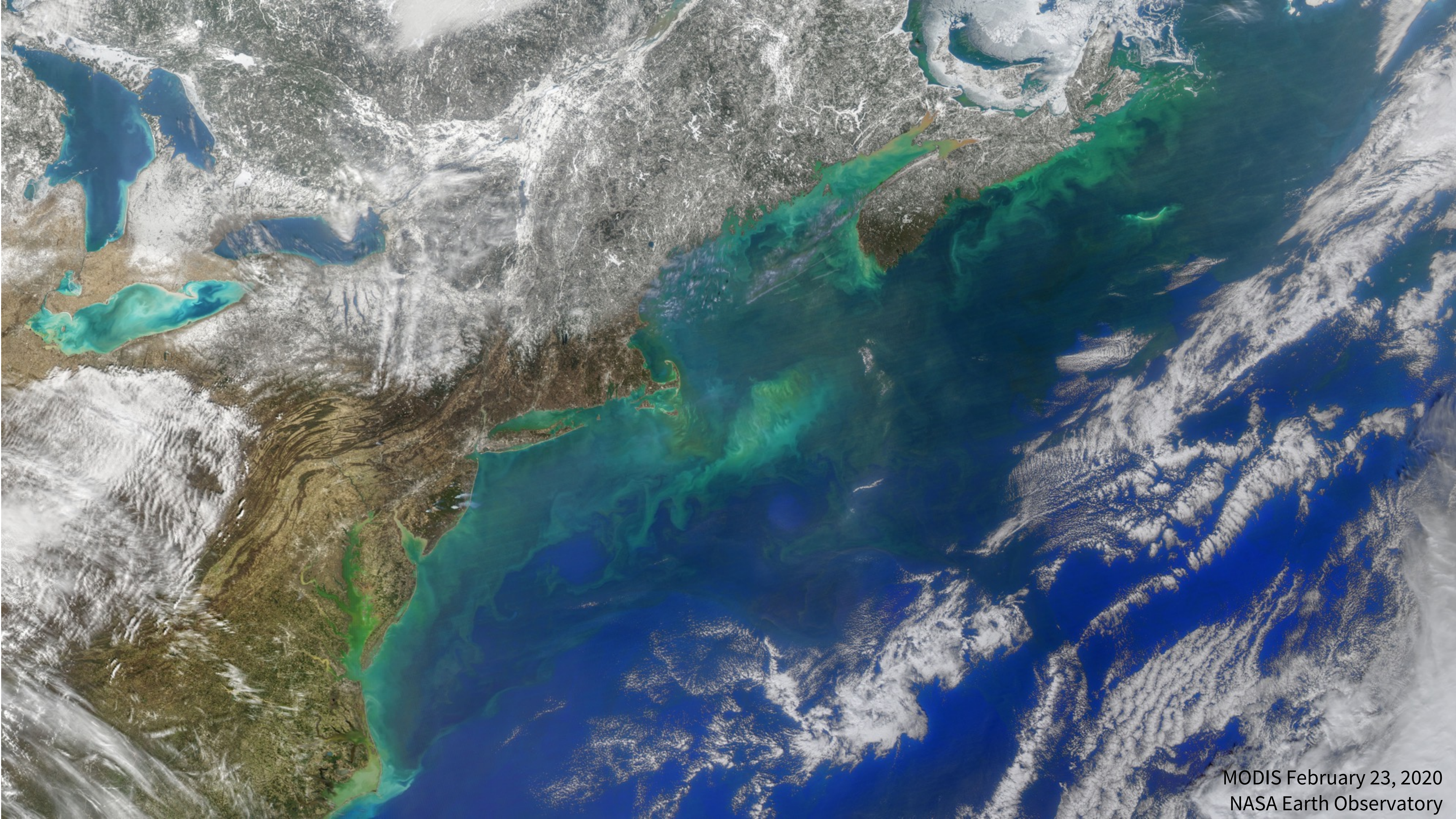
https://pace.gsfc.nasa.gov/

Background & Motivation

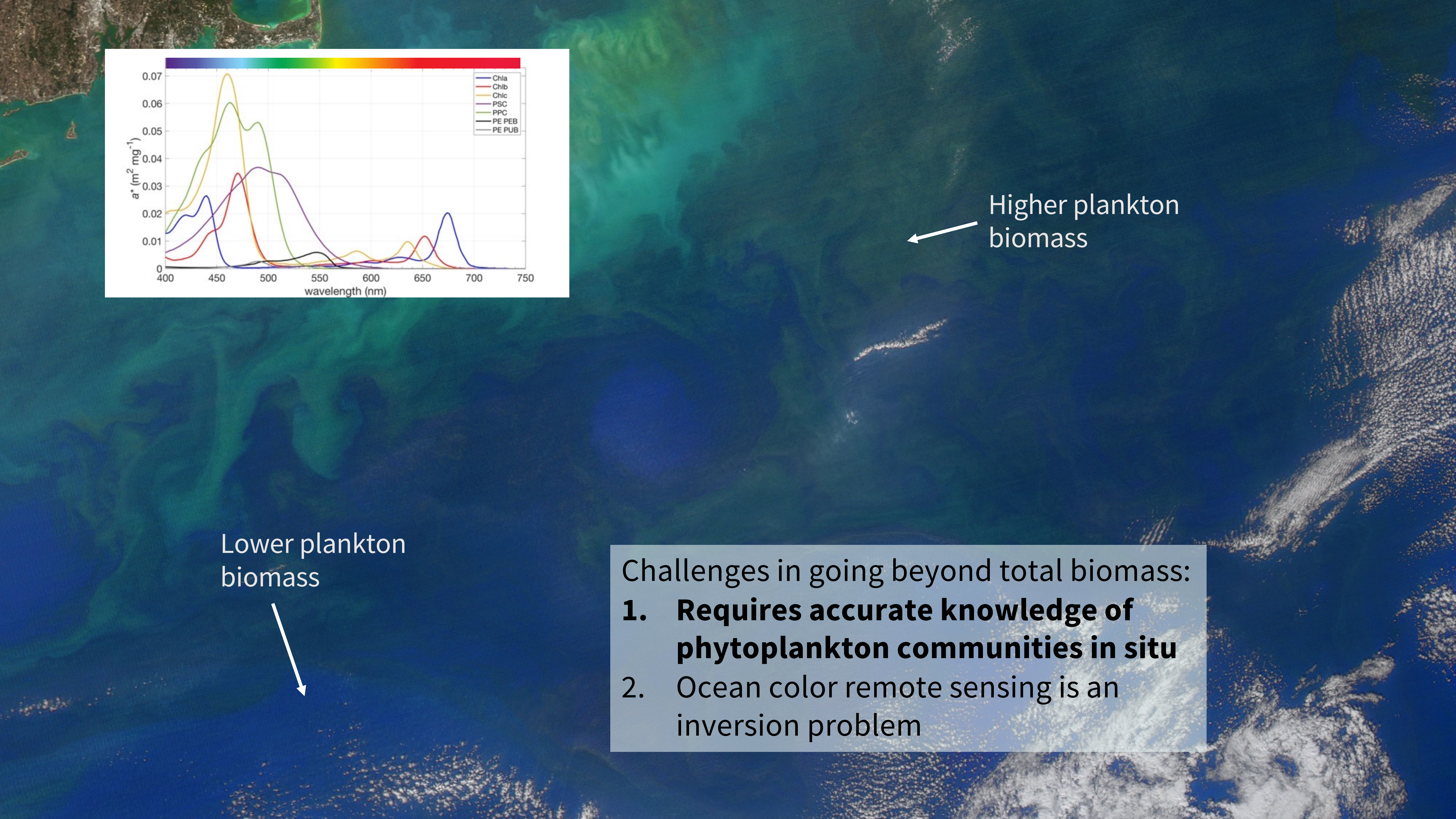
→ How can we move beyond Chl *a*-based estimates of phytoplankton communities from space?

→ Can we estimate PCC at finer spatial scales (pixel level?) with the added information from PACE (hyperspectral OC and polarization; improved uncertainty calculations)?

→ What types/how much data are needed to build robust predictive algorithms?



MODIS February 23, 2020
NASA Earth Observatory



Challenges in going beyond total biomass:

1. **Requires accurate knowledge of phytoplankton communities in situ**
2. Ocean color remote sensing is an inversion problem

Globally Consistent Quantitative Observations of Planktonic Ecosystems

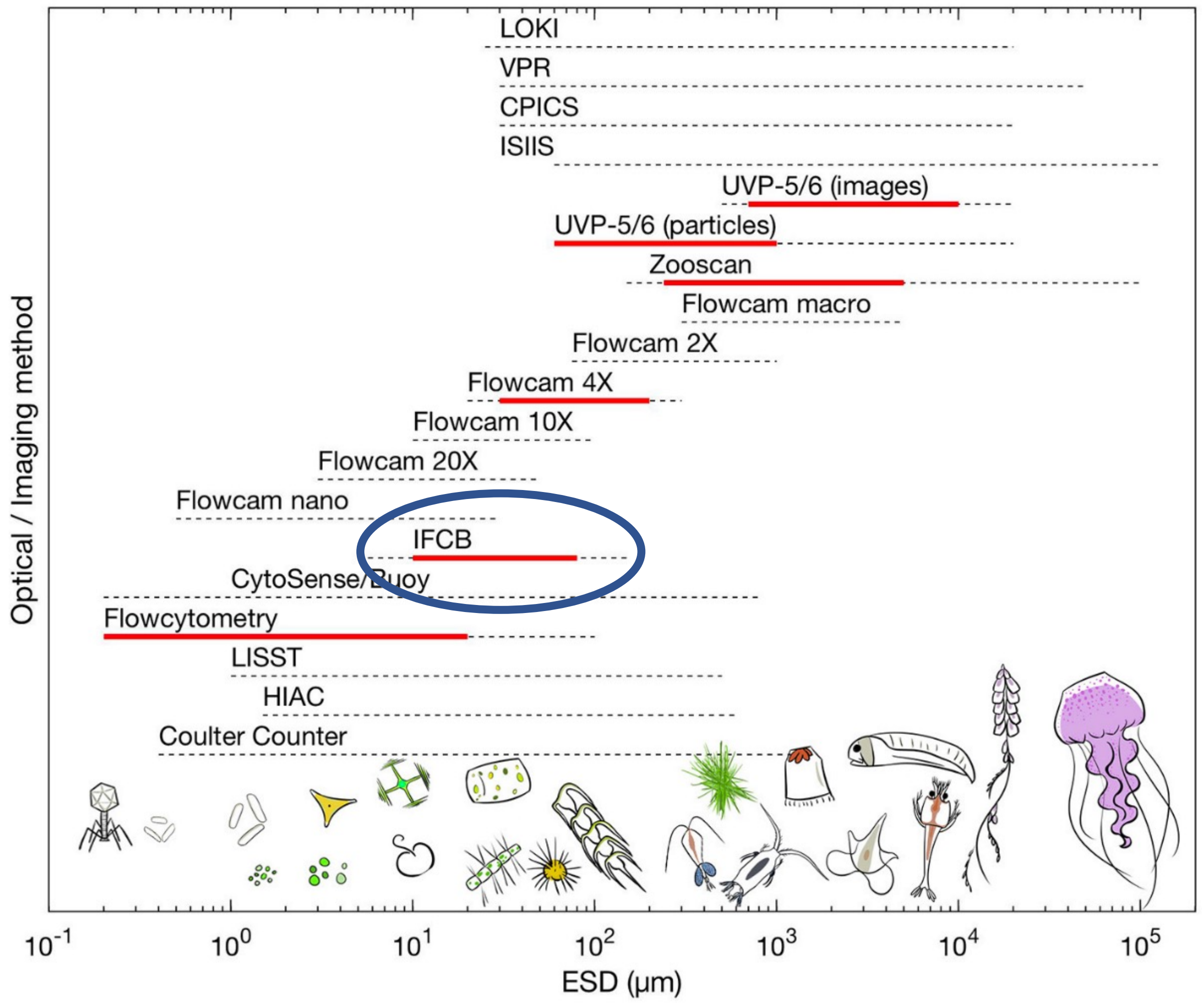
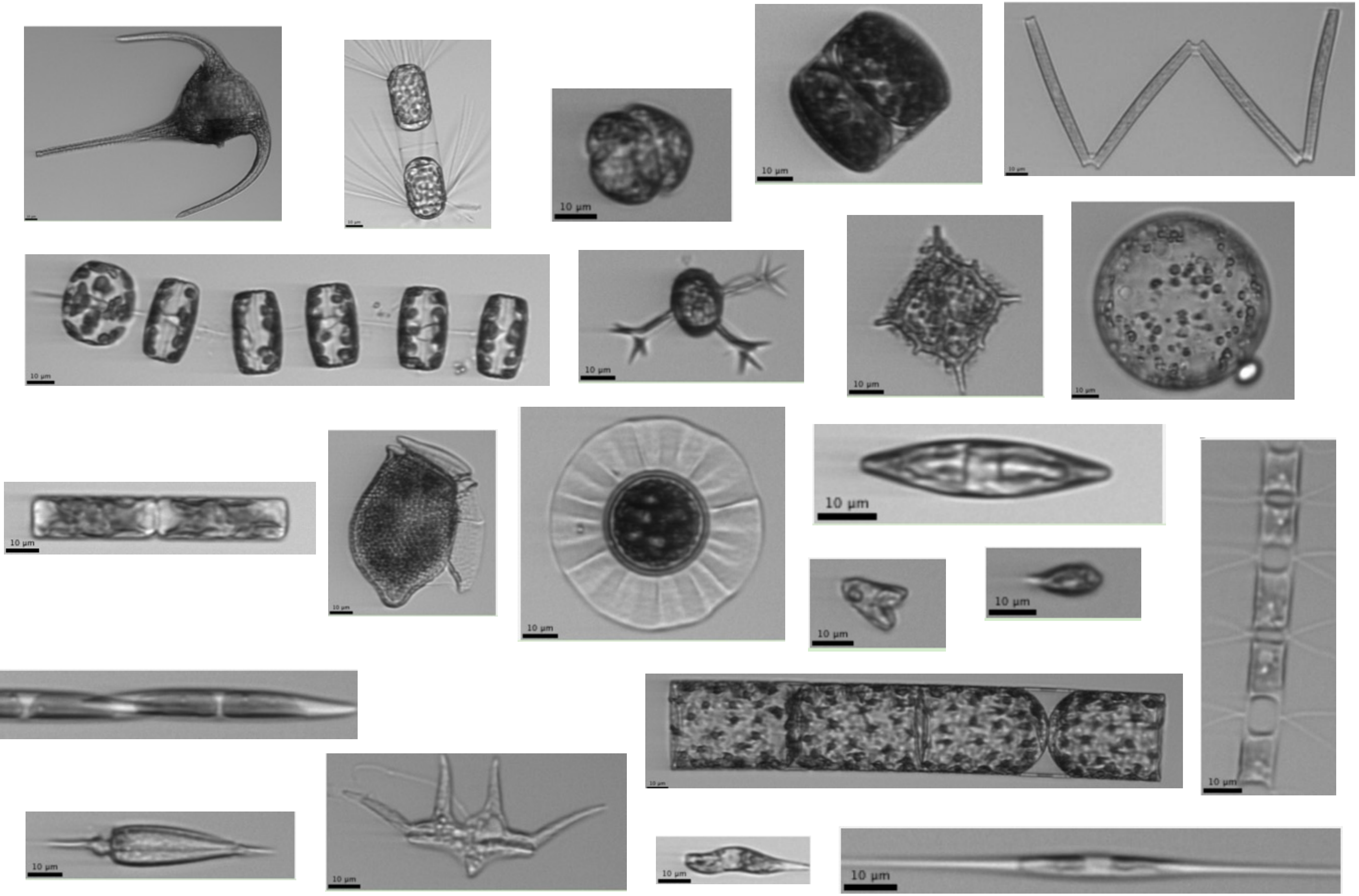


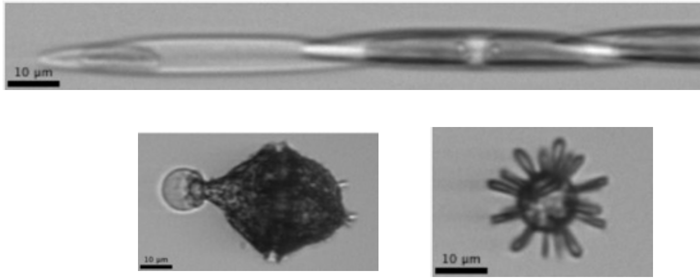
FIGURE 1 | Comparison of the total size range of plankton (in equivalent spherical diameter; ESD) that available optical and imaging methods can sample. Dashed lines represent the total operational size range from commercial information while the red line represent the practical size range which is efficient to obtain quantitative information, for an example see **Figure 2**. Drawings by Justine Courboules.

Lombard et al., 2019

Plankton imagery used to determine community composition of cells ~7-150 µm

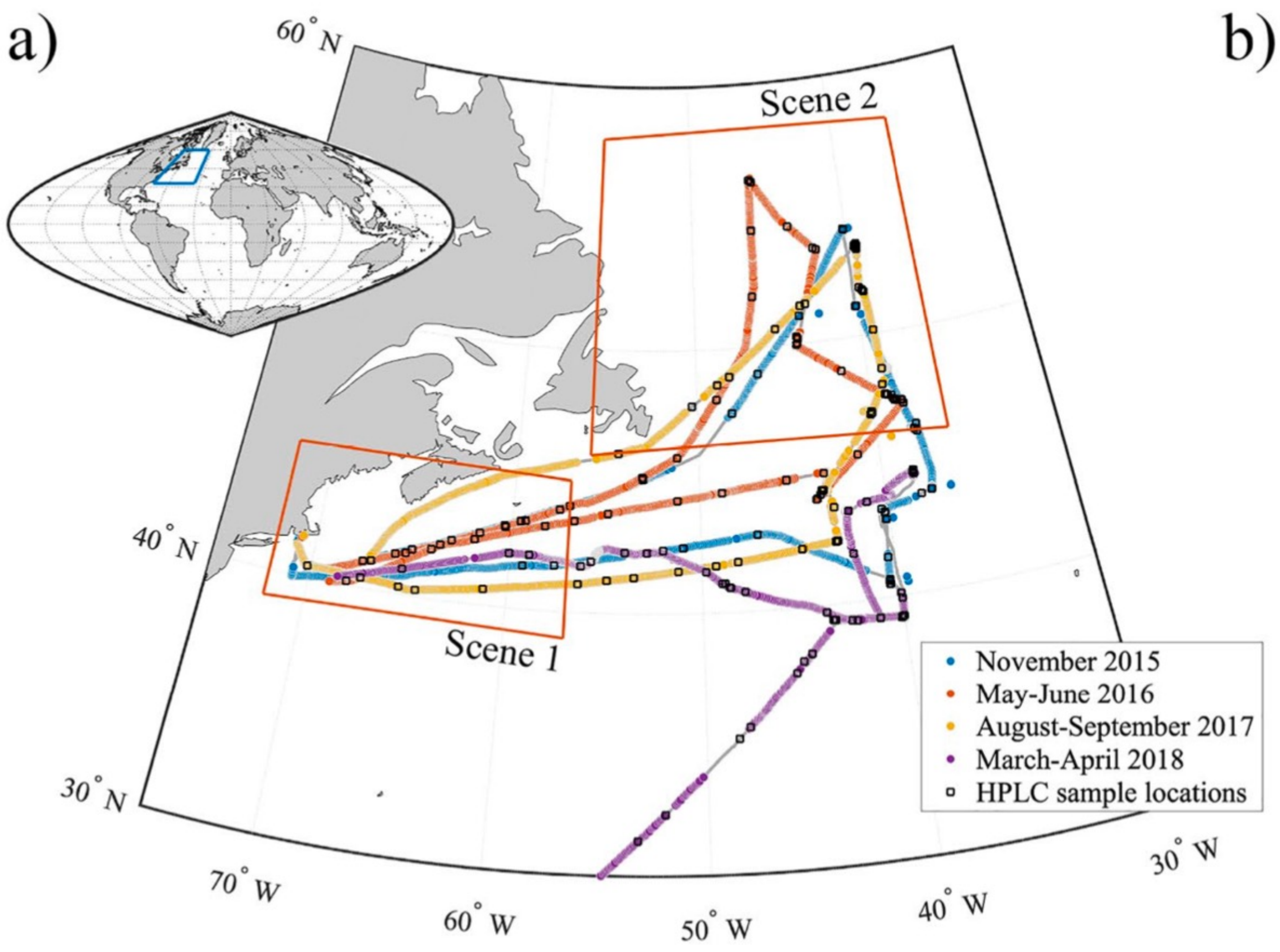
Imaging FlowCytobot (IFCB)

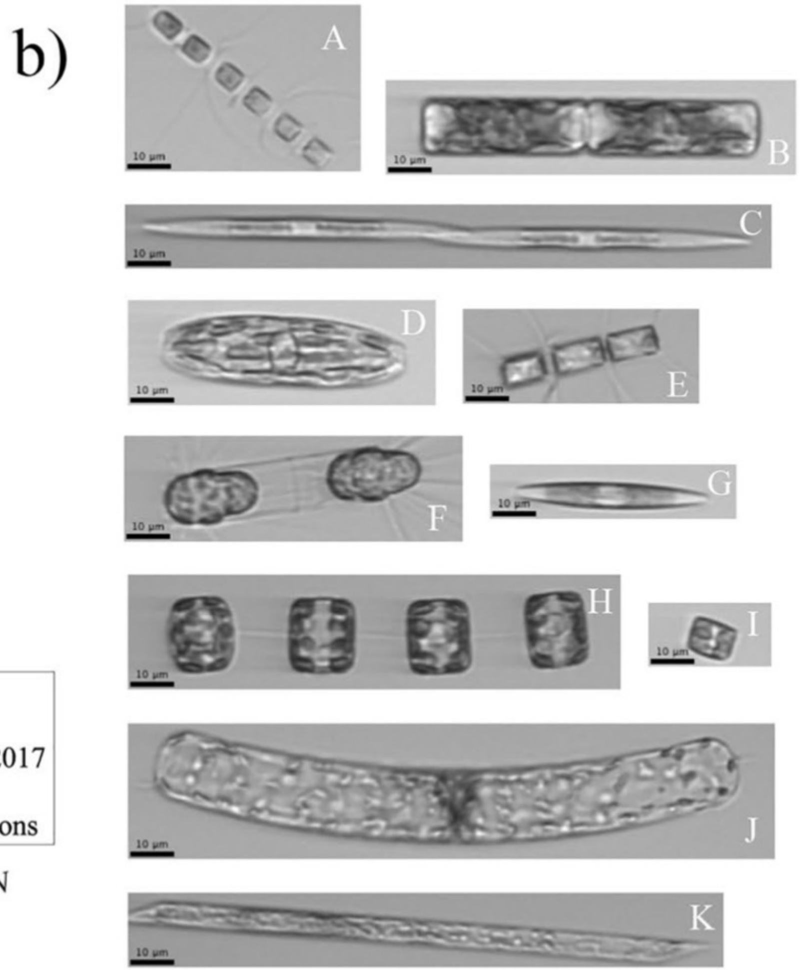




~5 million IFCB images spanning four seasons

Diatoms

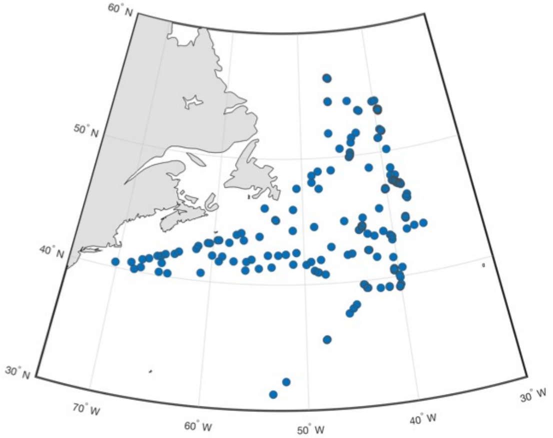




Chase et al., 2022

Multiple approaches used to classify diatom images

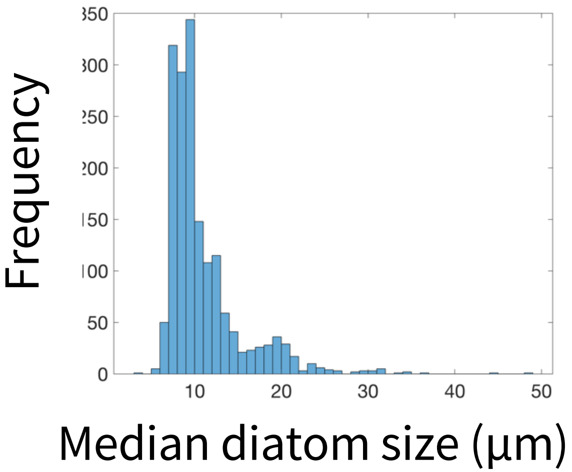
1) 2.2 million images manually validated over two years



EcoTaxa 2.5

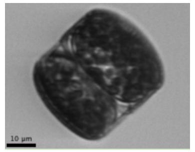
ecotaxa.obs-vlfr.fr

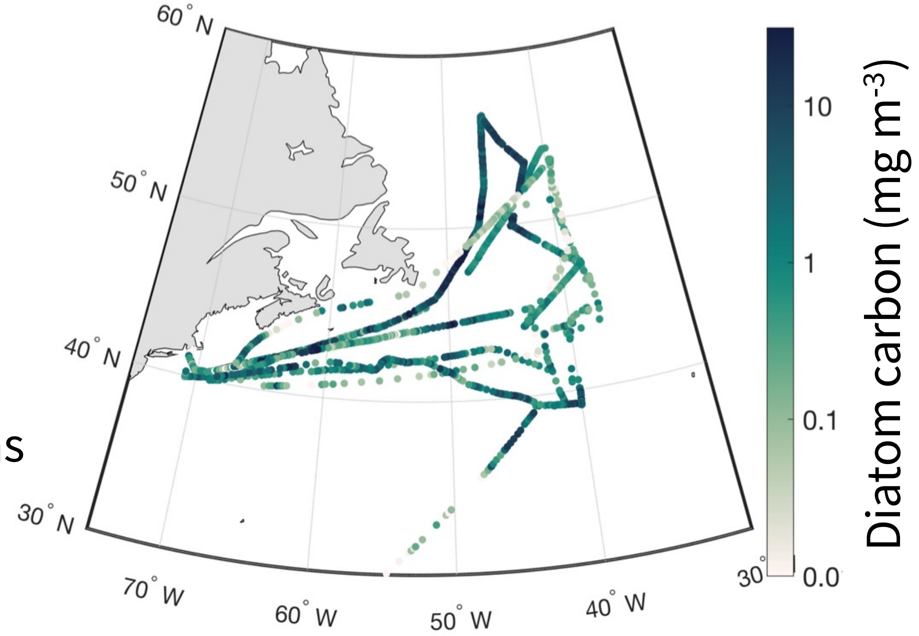
2) > 300,000 images of diatoms, labeled with a deep learning classification network



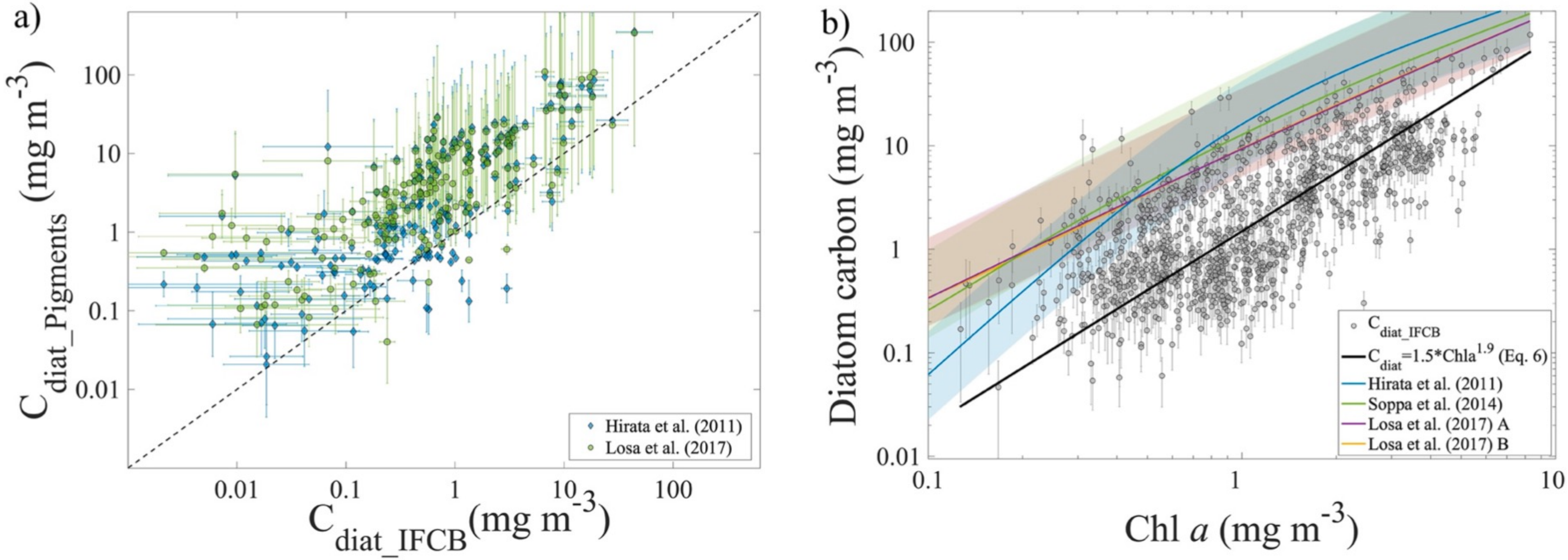
Emmett Culhane

Cell biovolume → carbon via established conversions



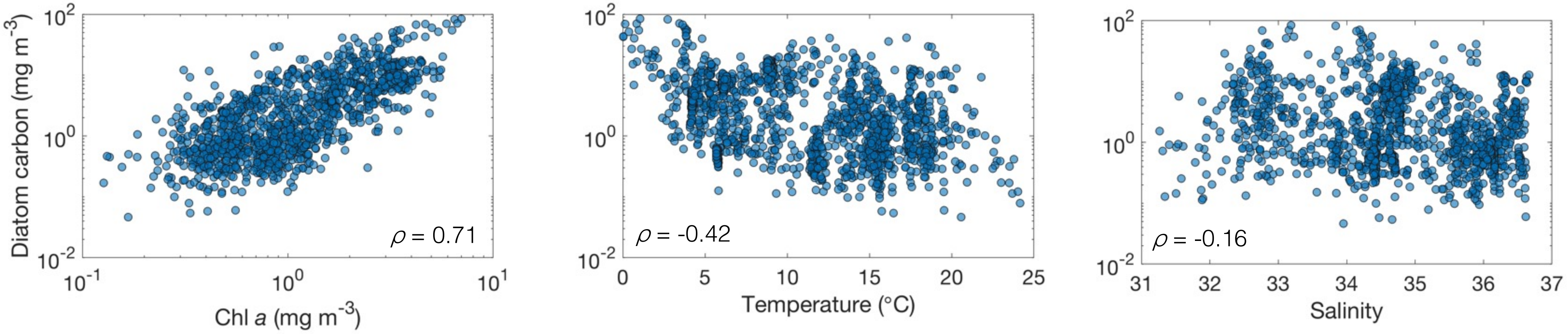


Algorithms based on pigment proxies show higher diatom carbon estimates relative to IFCB-based estimates

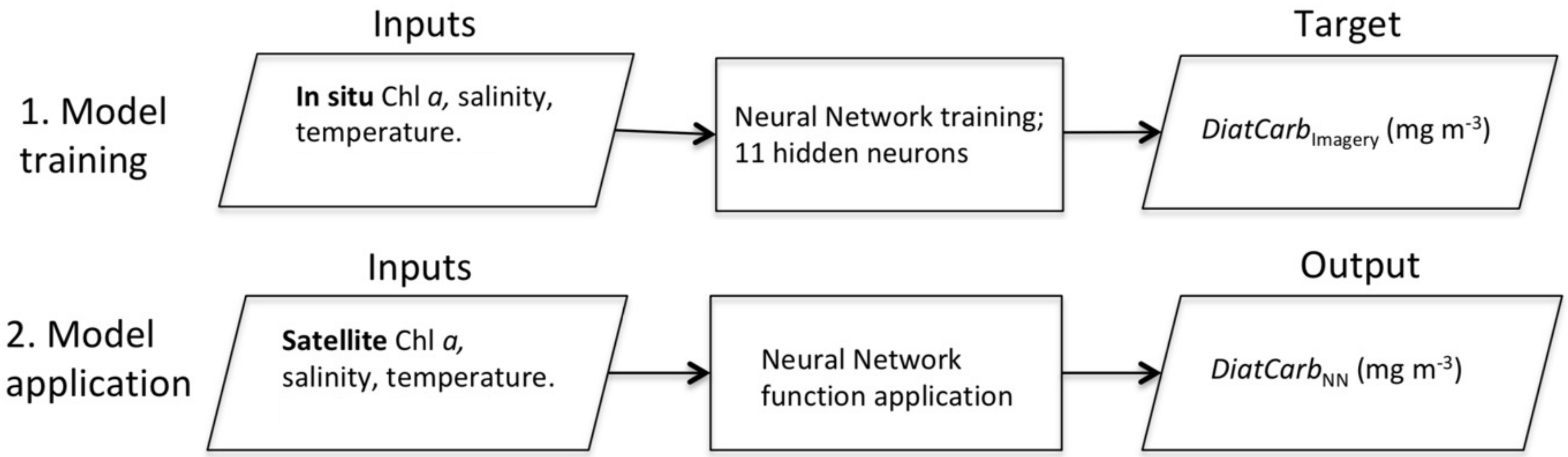


Chase et al., 2022

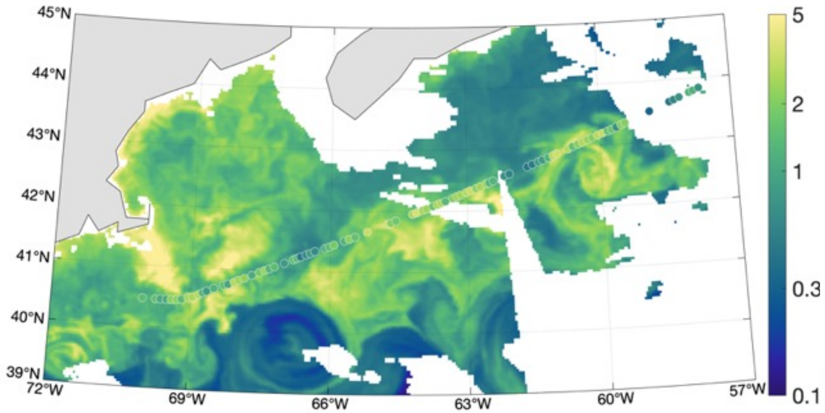
Shallow neural networks trained using plankton imagery data



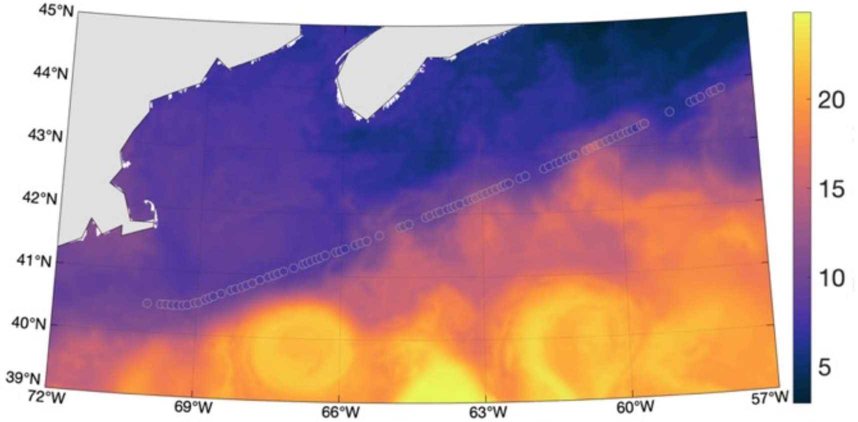
→ Diatom carbon and environmental variables are correlated but with high variability



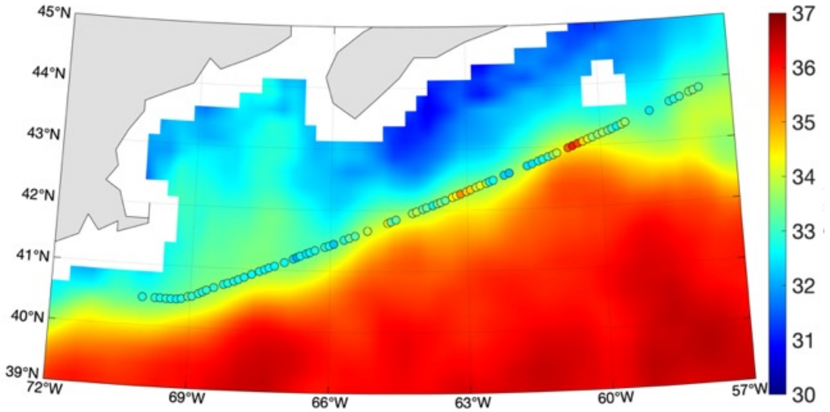
Merging satellite products from multiple platforms



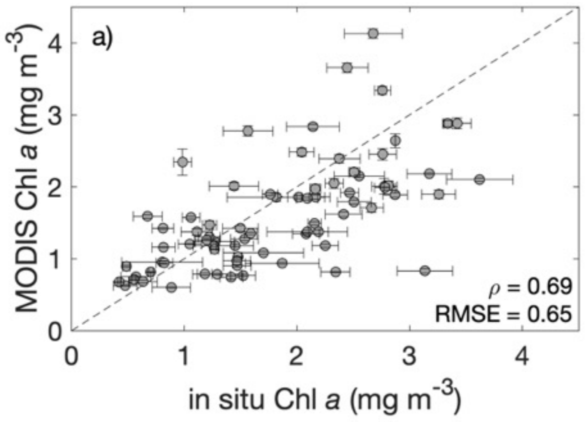
Daily MODIS Aqua Chl *a*

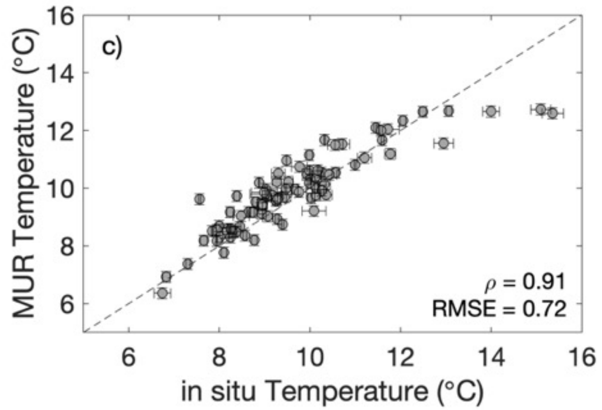


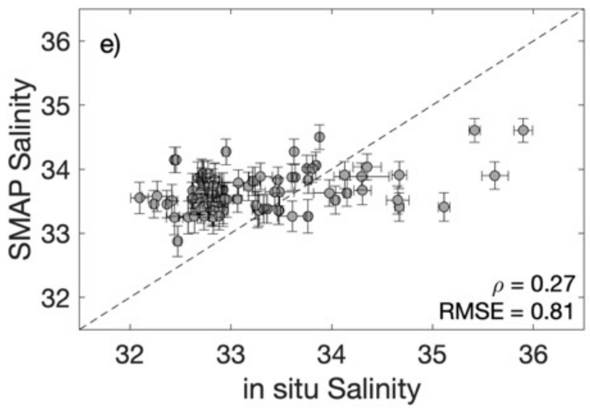
Daily MUR SST product



Monthly SMAP SSS



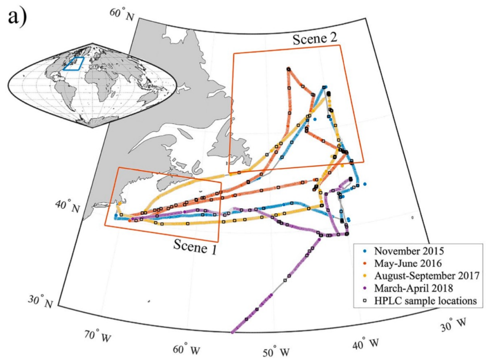


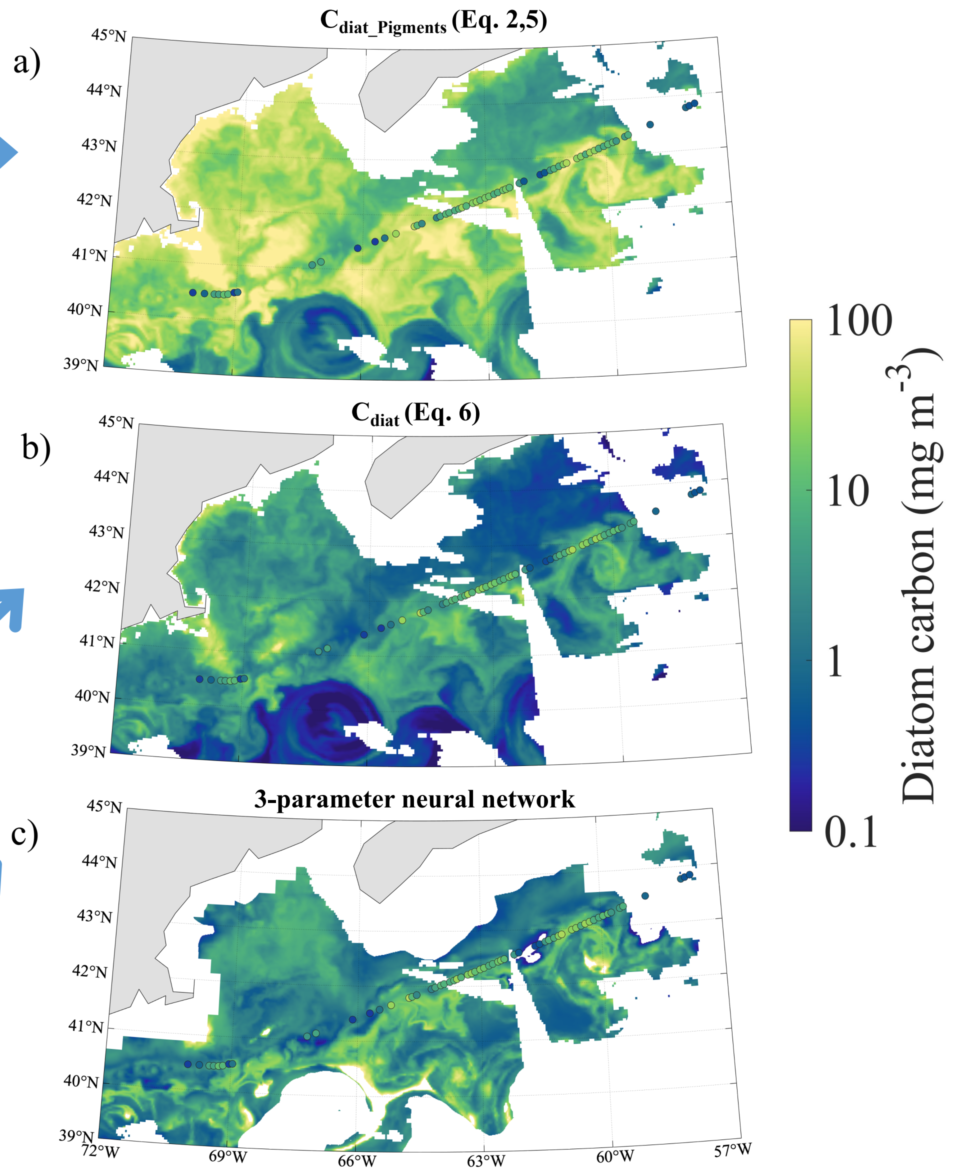


Plankton imagery data enable improved satellite-based diatom carbon estimates

Diatoms defined by pigment proxy

Diatoms defined by plankton imagery





Previous Chl a-based method (Hirata et al., 2011)

Updated Chl a-based method

Neural network-based method

Chase et al., 2022

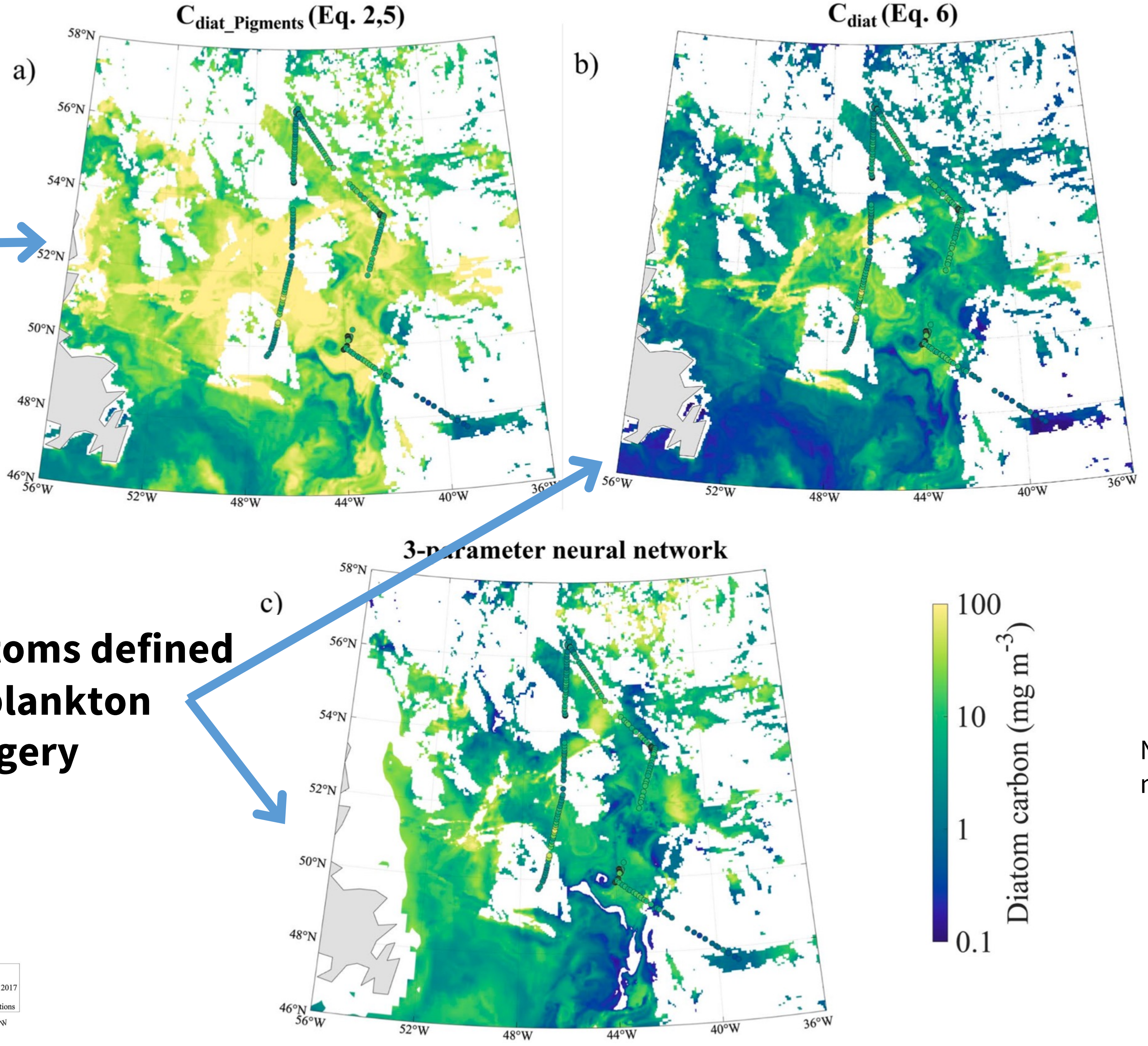
Diatoms defined by pigment proxy

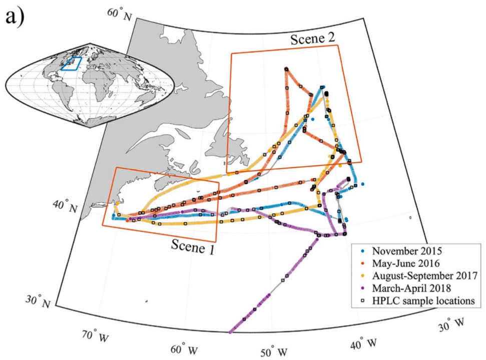
Previous Chl a-based method (Hirata et al., 2011)

Updated Chl a-based method

Diatoms defined by plankton imagery

Neural network-based method





Chase et al., 2022

Uncertainty calculations

Cell biovolume estimate

Diatom ID accuracy

$$\mathbf{Unc_{data}} = \sqrt{\mathbf{0.17^2 + 0.18^2 + 0.1^2 + 0.29^2}} = \mathbf{0.39},$$

Statistical counting error

Chl *a* uncertainty

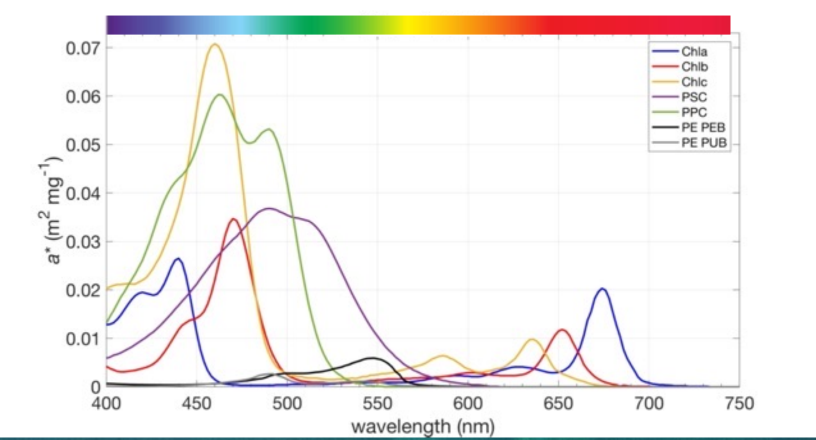
$\mathbf{Unc_{data}}$

Neural network uncertainty

$$\mathbf{Unc_{NN}} = \sqrt{\mathbf{0.39^2 + 0.52^2}} = \mathbf{0.65},$$

At low estimated diatom carbon values, the absolute error dominates over the relative error, and thus $Unc_{NN} = max(1.05\ mg\ m^{-3}, 65\%)$

Is it good enough???



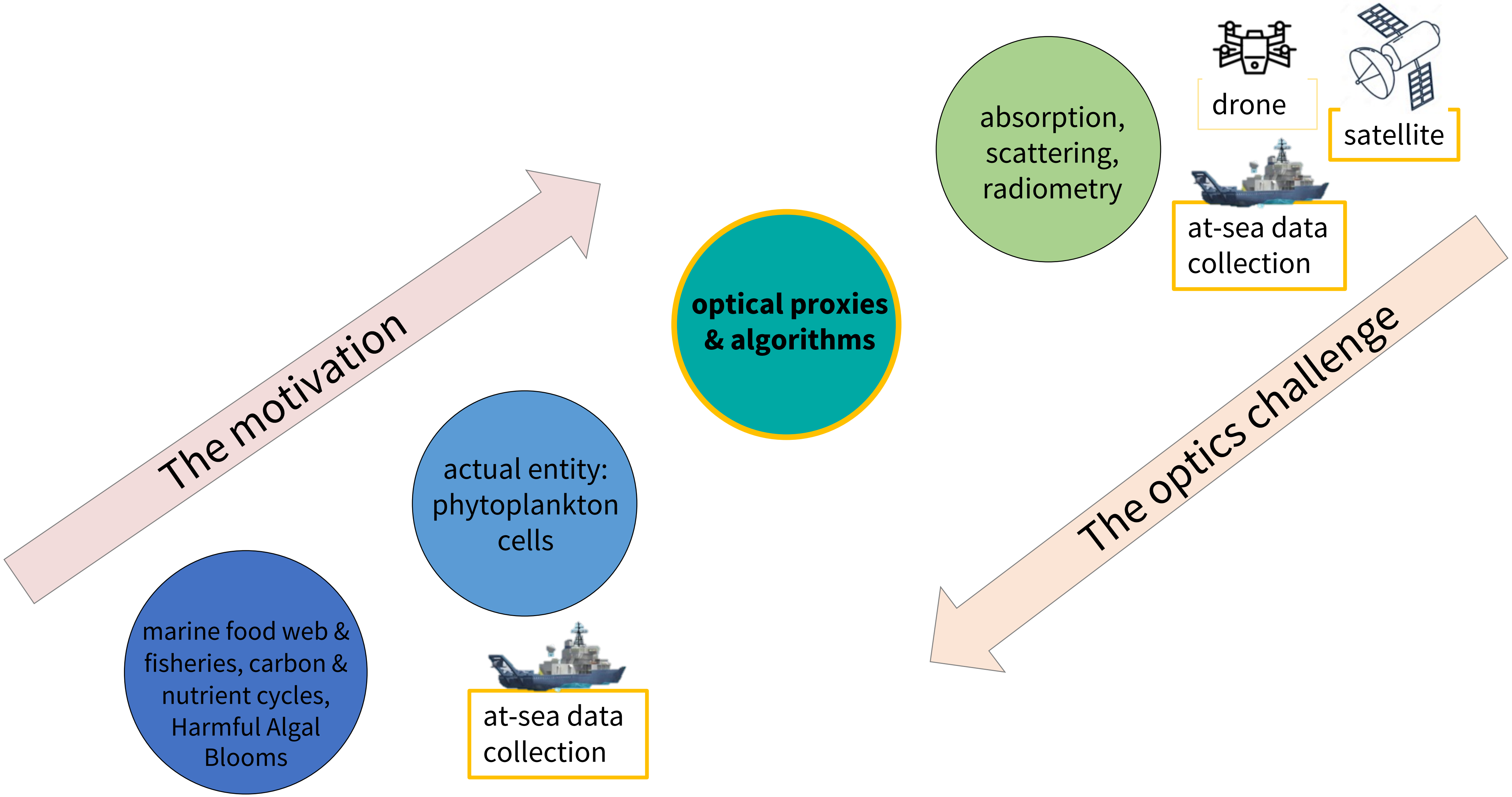
Higher plankton biomass

Lower plankton biomass

Challenges in going beyond total biomass:

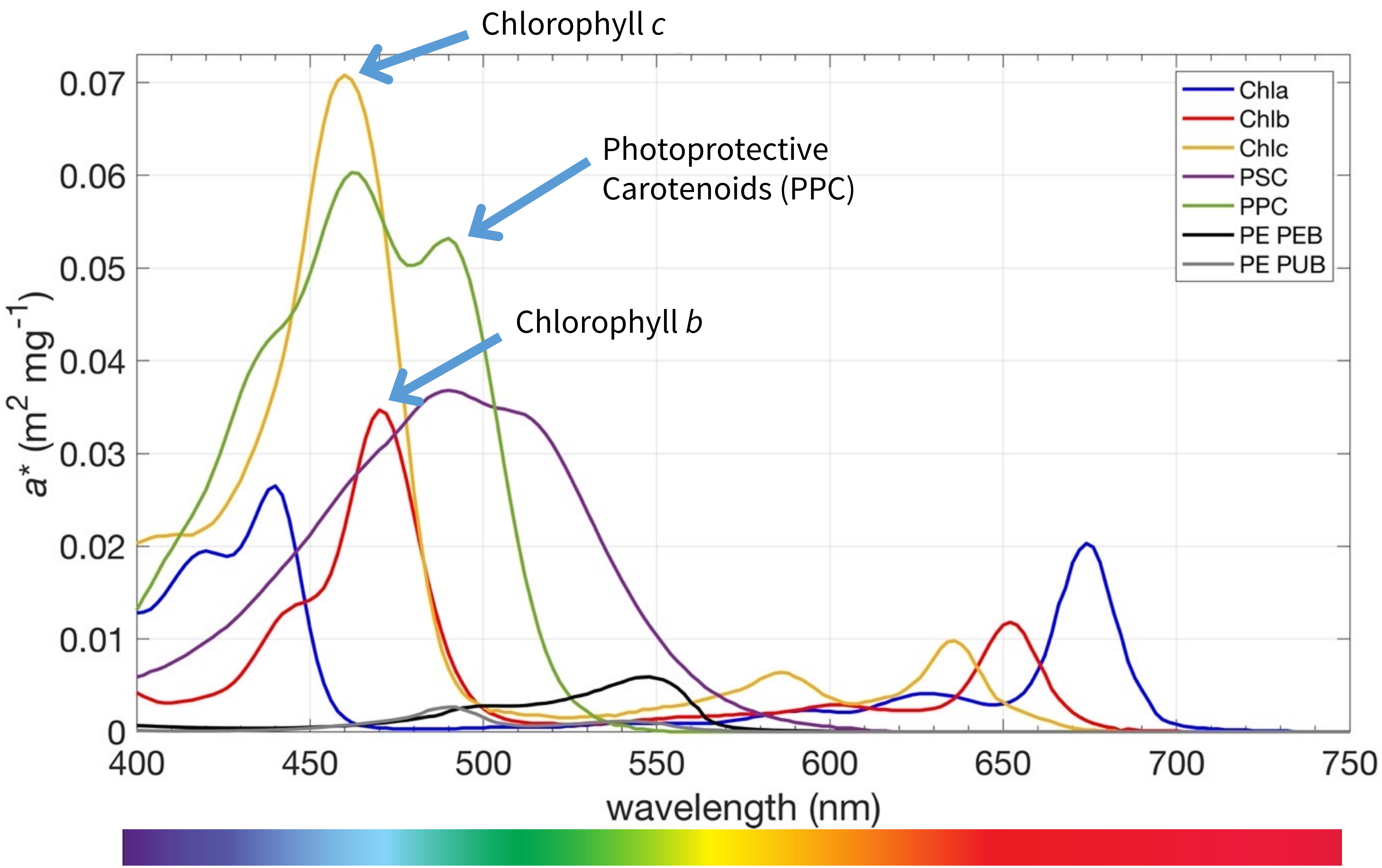
1. Requires accurate knowledge of phytoplankton communities in situ
2. **Ocean color remote sensing is an inversion problem**

Analytically, ocean color remote sensing is an inversion problem



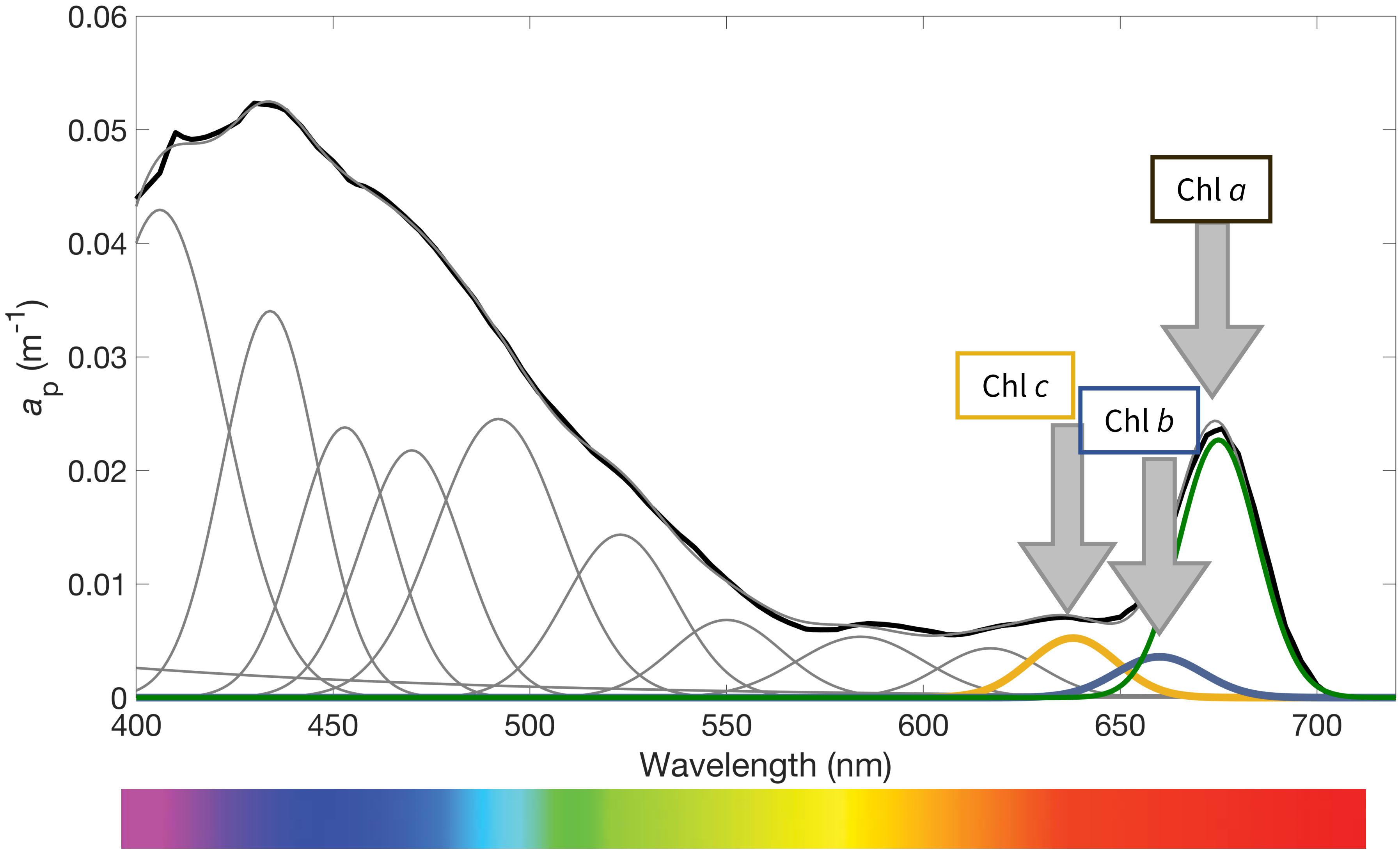
Adapted from M. J. Perry

Phytoplankton pigments drive spectral absorption features



data from Bidigare et al. 1990

Phytoplankton pigments estimated from absorption spectra

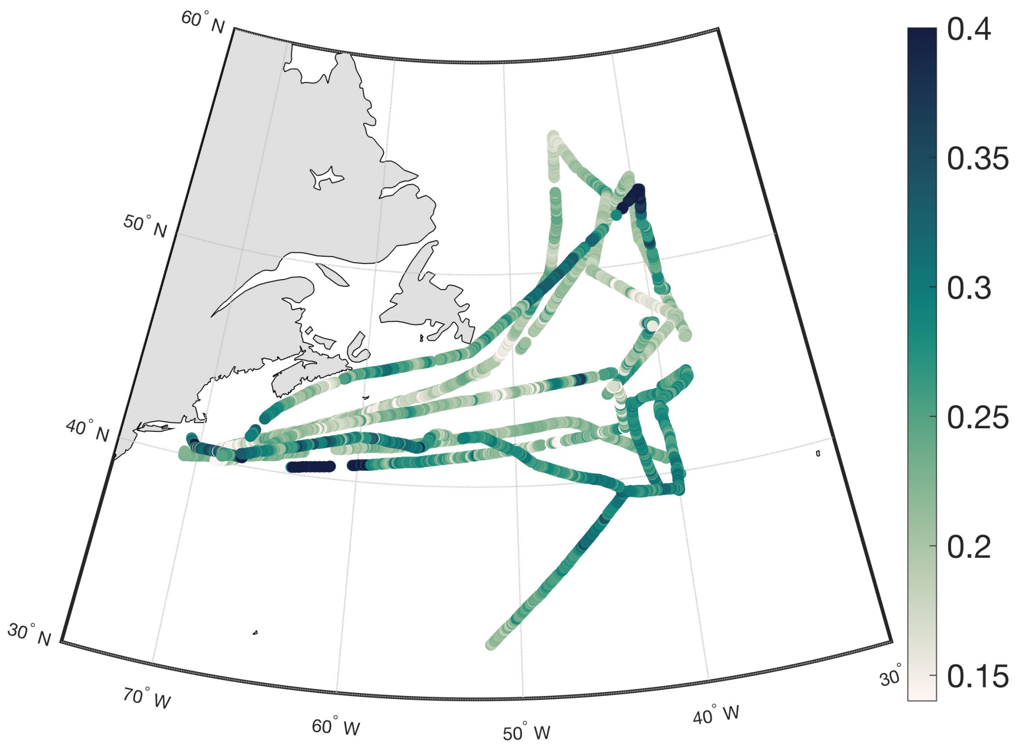


ac-s instrument

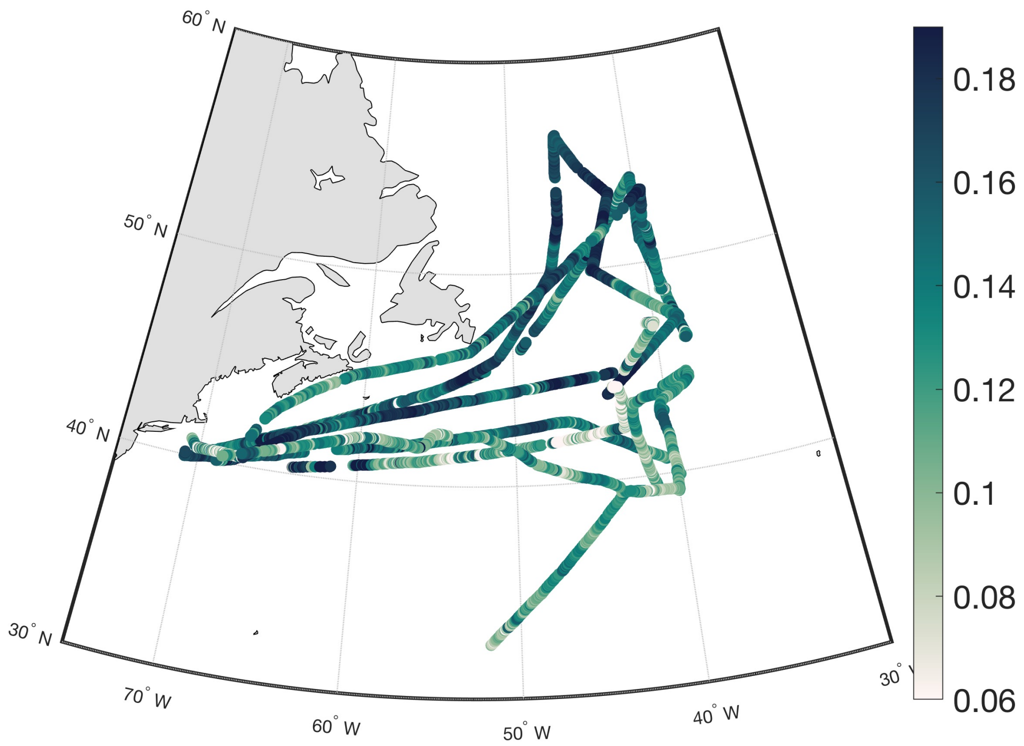
Chase et al., 2013

Relative pigment values vary spatially, and differently from [Chl *a*]

Chlorophyll b : Chlorophyll a

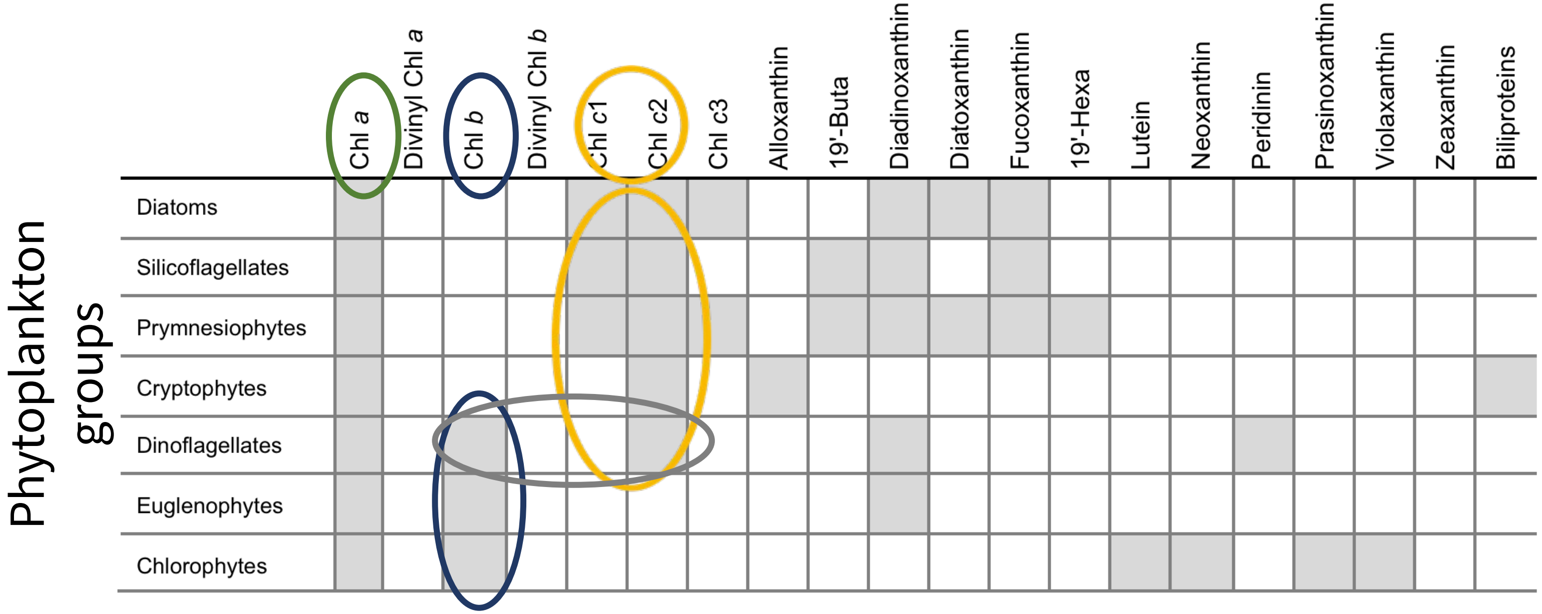


Chlorophyll c : Chlorophyll a



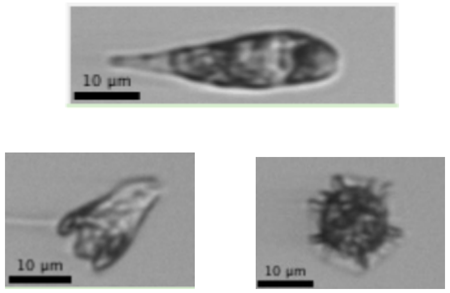
Phytoplankton pigments can help differentiate groups

Pigments from discrete water samples (HPLC)



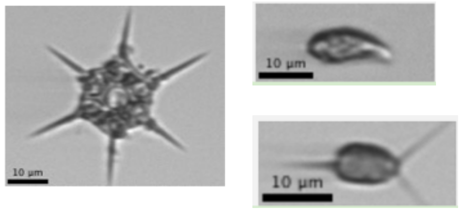
Chlorophyll *b*

Chlorophytes, Euglenoids

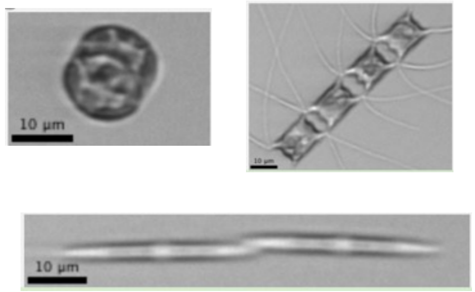


Chlorophyll *c*

Silicoflagellates
Prymnesiophytes
Cryptophytes

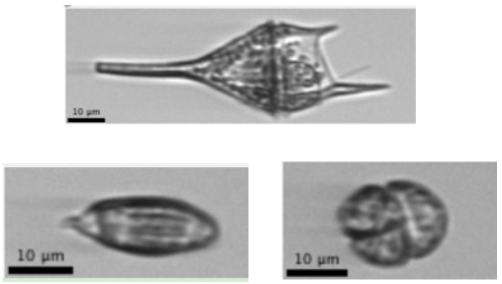


Diatoms



Chlorophylls *b* & *c*

Dinoflagellates

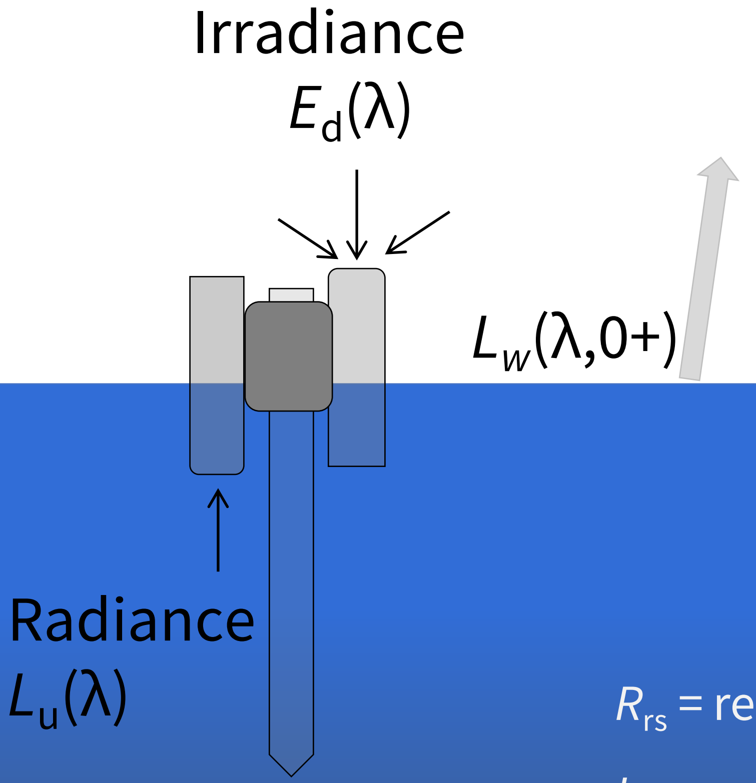


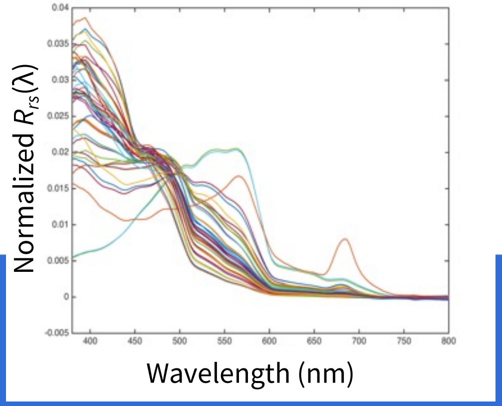
Hyperspectral $R_{rs}(\lambda)$ measured in situ enables method development

$$R_{rs}(\lambda) = \frac{L_w(\lambda,0+)}{E_d(\lambda)}$$

South Atlantic Ocean

Amazon River Plume





R_{rs} = remote-sensing reflectance

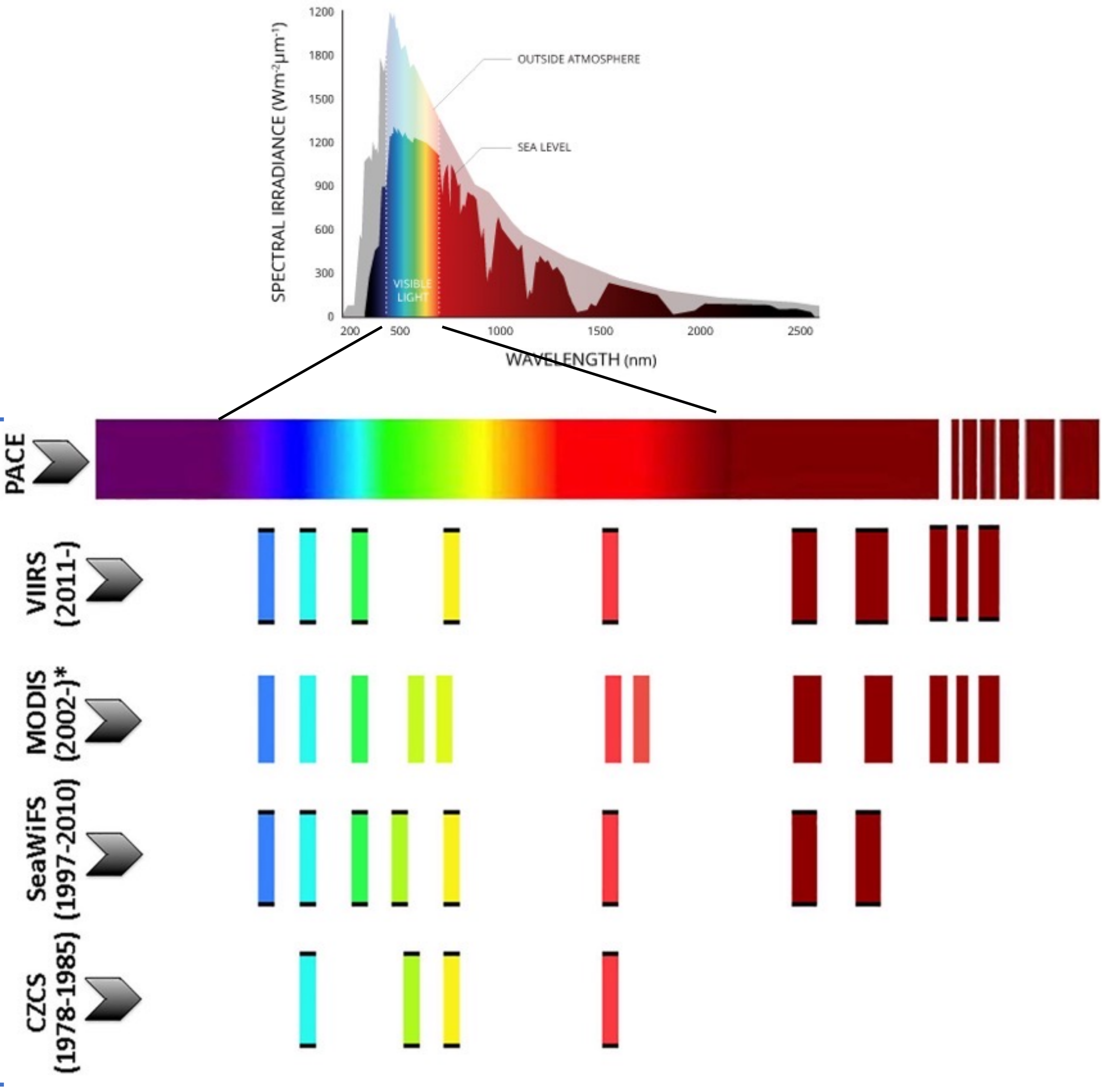
L_w = water-leaving radiance

L_u = upwelling radiance

E_d = downwelling irradiance

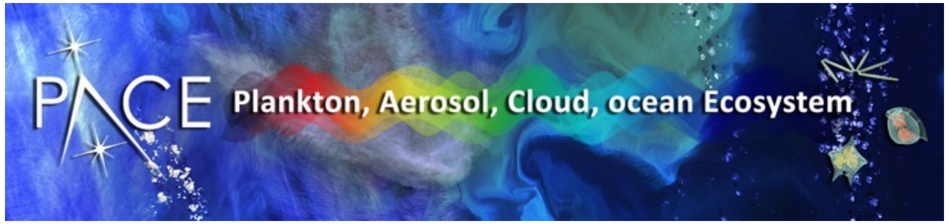
Pigments from hyperspectral $R_{rs}(\lambda)$: Chase et al., 2017; Kramer et al., 2022

Near-future hyperspectral satellite measurements



Satellite ocean color missions

PACE simulation https://pace.gsfc.nasa.gov/



→ Anticipated launch date early 2024

→ Hyperspectral ocean color measurements provide more information across the visible wavelengths compared to multispectral ocean color data

Ongoing & future research

- Include data from other ocean basins in diatom carbon neural network model
- Define the spatial scale limitations for predictive models of diatom carbon
- Incorporate a size metric for diatoms (e.g., large and small types) into the algorithm
- Consider how to best define other groups that may not be imaged comprehensively by the IFCB
- **UTOPIA project for plankton image analysis**

UTOPIA: User-friendly Tools for Oceanic Plankton Image Analysis

- Designed as an evolving community space for IFCB data analysis resources
- Open-source code, examples and user guide for deep learning approaches to classifying plankton and particle images
- Future goal: a "live pipeline" that supports the re-training of deep learning networks following the contribution of new IFCB data

Dr. Valentina Staneva
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Hisham Bhatti
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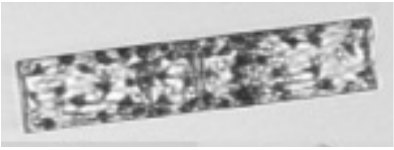
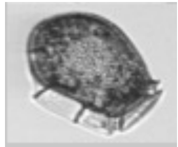
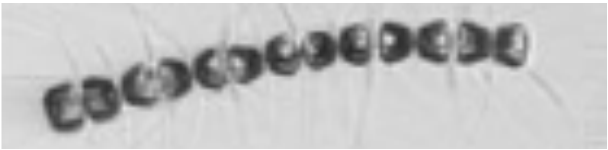

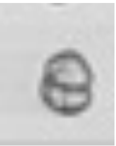
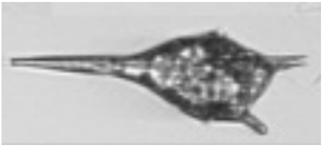

Please visit https://github.com/ifcb-utopia and/or contact alichase@uw.edu to be involved

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ifcbUTOPIA
User-friendly Tools for Oceanic Plankton Image Analysis (UTOPIA) is for use with data from the Imaging FlowCytobot (IFCB)

Take-home messages

1. Plankton cell imagery or combined methodologies to define the phytoplankton community greatly enhance algorithm development

2. Hyperspectral data is anticipated to further improve phytoplankton community composition algorithms, but robust algorithms will still rely on (1)

Thank you!

Washington Research
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NASA

PACE
Plankton, Aerosol, Cloud, ocean Ecosystem
Advanced Measurements of Sea & Sky
NASA • Goddard Space Flight Center

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