Biodiversity and biogeochemistry applications of bio-optical data in the Northern California Current: Marine Biodiversity Observation Network

MBON Marine Biodiversity Observation Network

OSU Oregon State University College of Earth, Ocean, and Atmospheric Sciences

OOI Bio-optics Course: July 18, 2023

Maria Kavanaugh, Oregon State U.

OSU: Robert Cowen, Mo Schmid, Su Sponaugle, Laurie Juranek, Miguel Goni

USF: Enrique Montes

NOAA NWFSC: Jennifer Fisher, Kym Jacobsen, Nicolaus Adams, Stephanie Moore, A. Fischer

OCNMS: Jenny Waddell

NANOOS: Jan Newton

NOAA National Oceanic and Atmospheric Administration U.S. Department of Commerce

National Marine Sanctuaries

IOOS Integrated Ocean Observing System

NANOOS

Office of Naval Research Science & Technology ONR

BOEM Bureau of Ocean Energy Management

CIMRS

CoastWatch

NASA

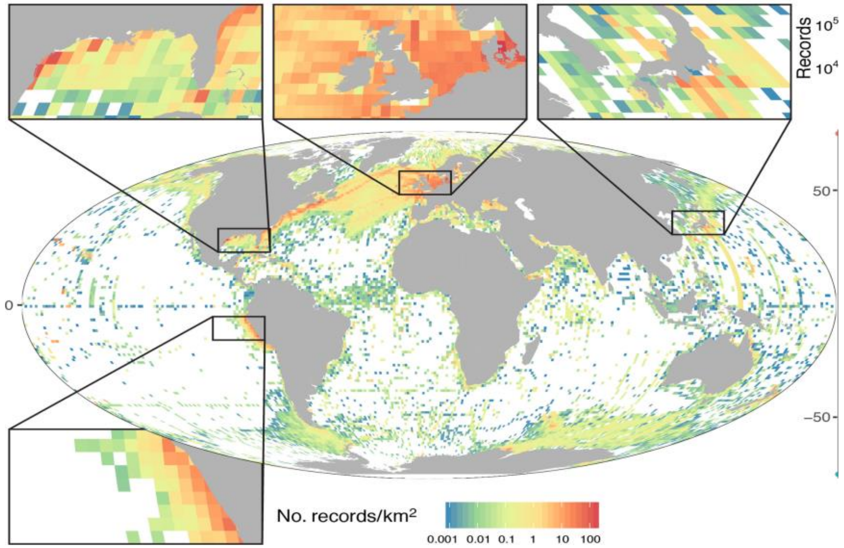
Maria Kavanaugh
Office : Burt 204
maria.Kavanaugh@oregonstate.edu
BS/MS Zoology (Marine Ecology)
PhD Biological Oceanography: OSU

Seascape ecologist, biological oceanographer

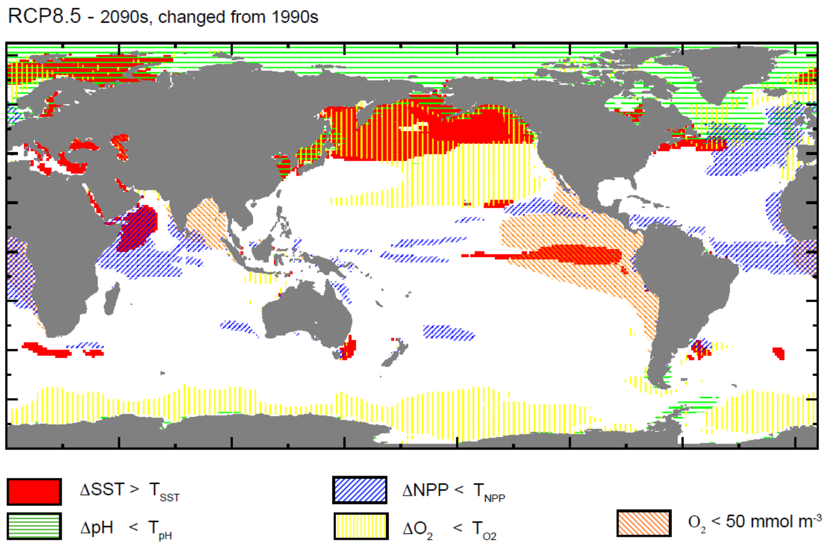
Plankton biodiversity, biogeography
Satellite remote sensing, machine learning

A grand challenge

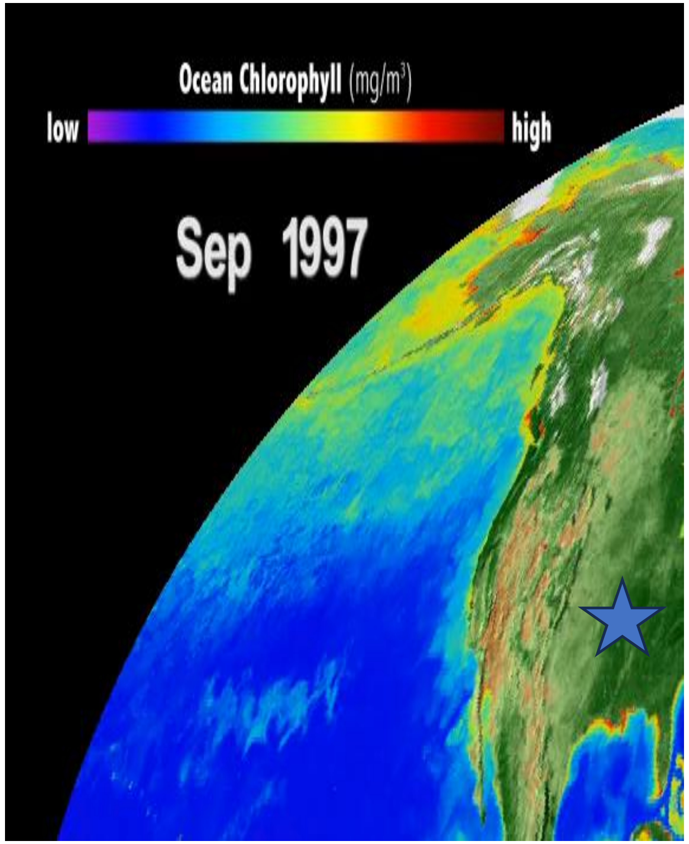
- Biodiversity is a key indicator of ocean health and provides insight to food abundance, quality, and safety. But baselines are sparse.
- As climate changes, how systems and communities will respond/reorganize to multiple, overlapping stressors is unknown.
- The ocean moves and species responses to environmental changes are complex and non-constant.
- Coastal conditions exacerbate these challenges (space/time, remote sensing, regional inputs).
- *OOI assets monitor these shifts and assist with validation and scaling*



Muller Karger et al., 2017



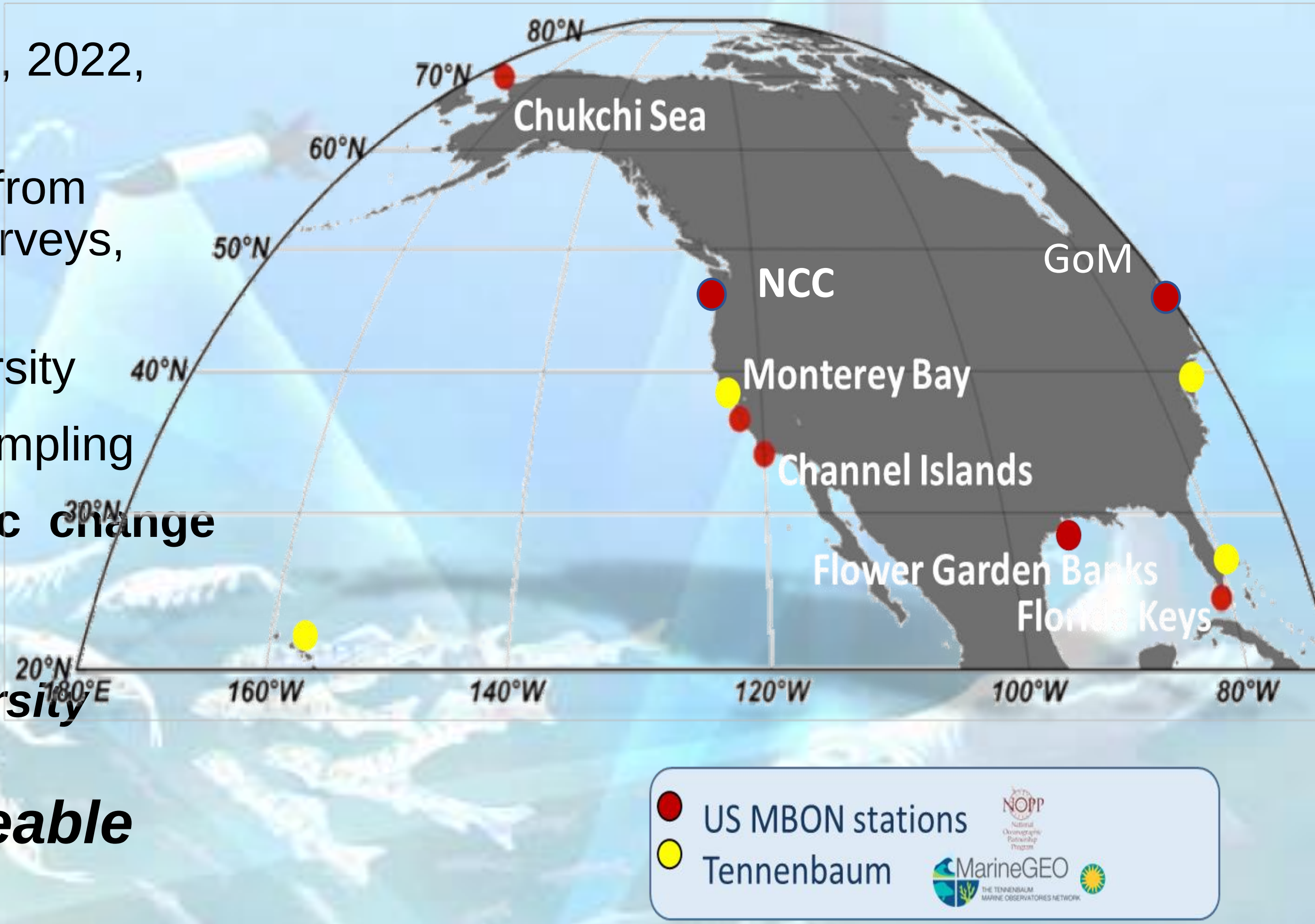
Bopp et al., 2013



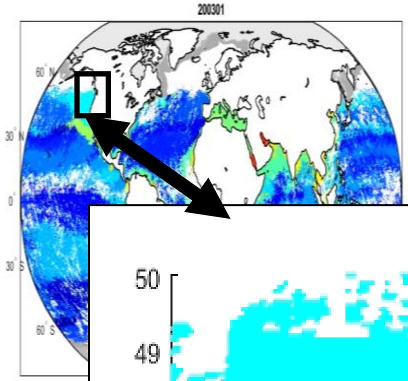
Marine Biodiversity Observation Network

National Ocean Partnership funded: 2014, 2019, 2022, 2024

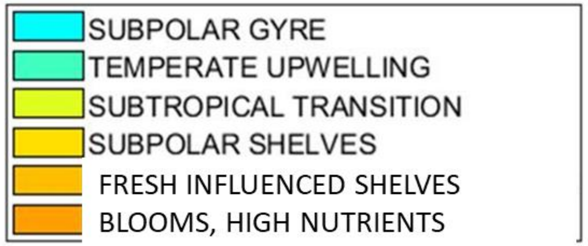
- Integrate and synthesize existing information from monitoring programs: IOOS, OOI, fisheries surveys, LTER, Sanctuaries
- Define minimum criteria for observing biodiversity
- Develop/Apply technology for autonomous sampling
- **Detect and track biophysical/biogeographic change through advanced remote sensing**
- **Embed organismal information into ocean observatories through *meaningful biodiversity indicators***
  - ***Informative, mechanistic, scaleable***

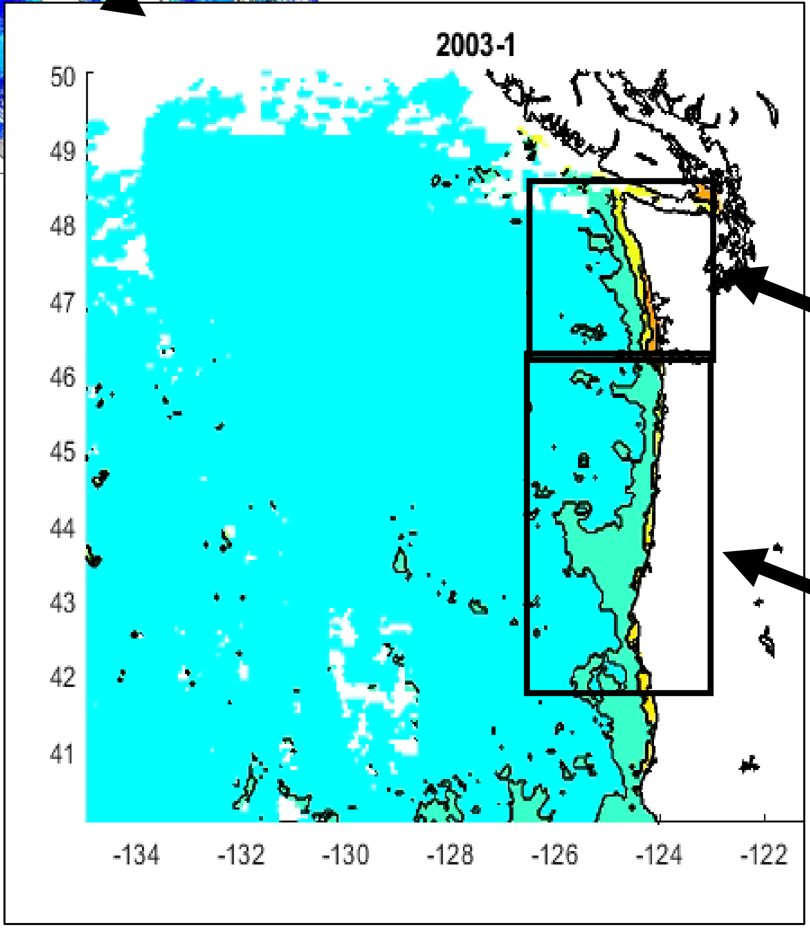


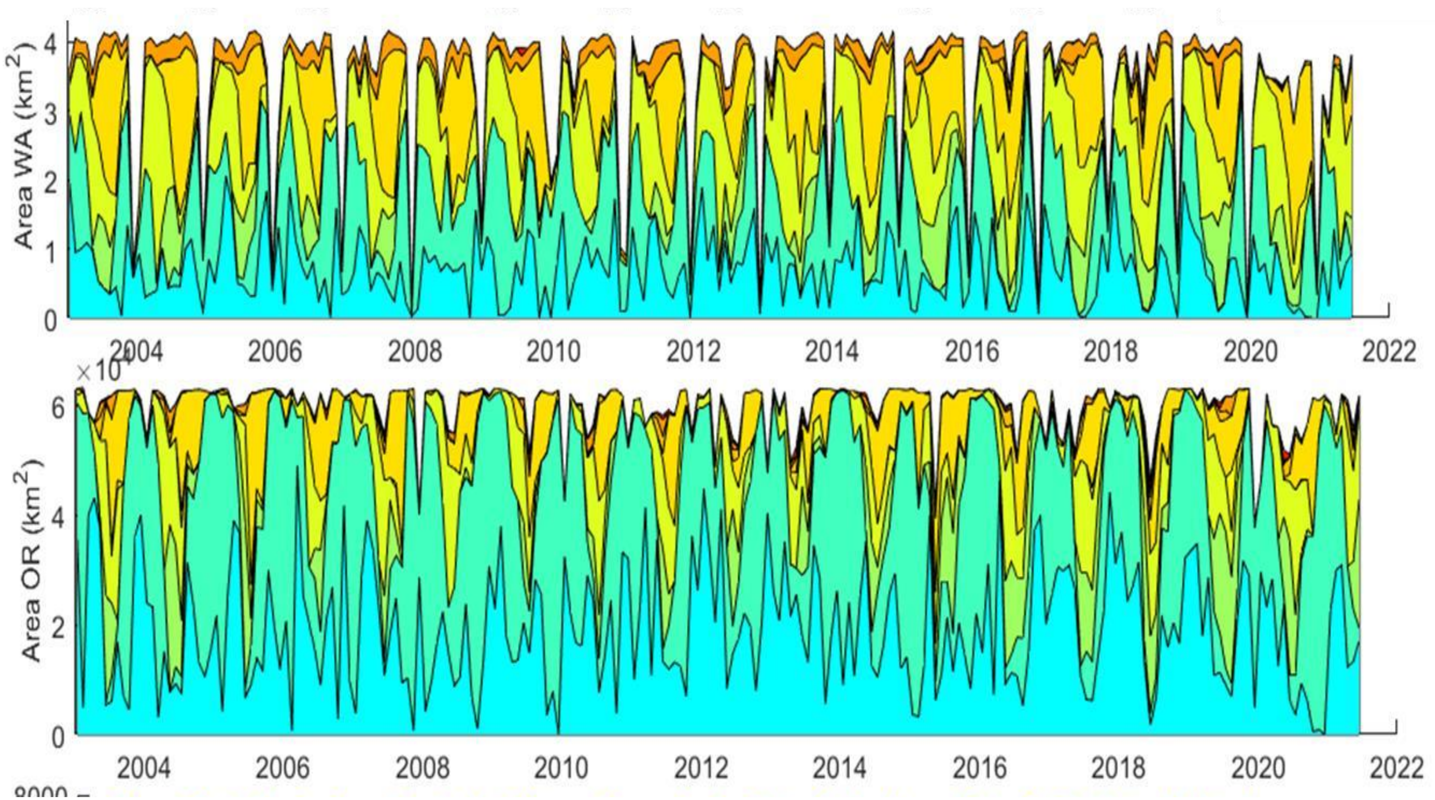
Context and biogeographic change: distributions and patterns across seascape habitat patches that scale up



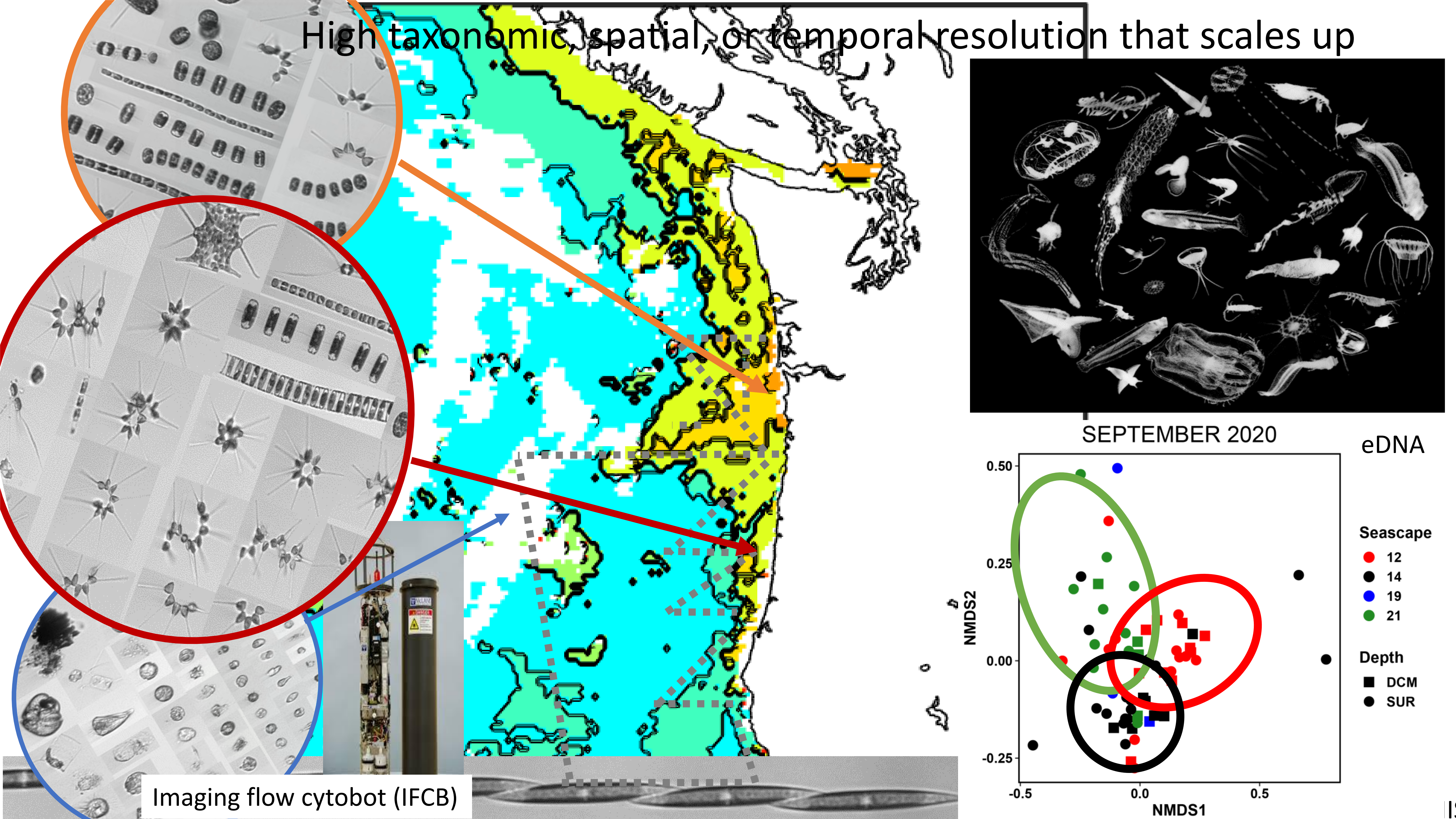
Seascapes are a dynamic classification of water mass/pelagic habitat.
Temperature, salinity, dynamic topography, sea-ice;
Chlorophyll, CDOM, normalized fluorescence





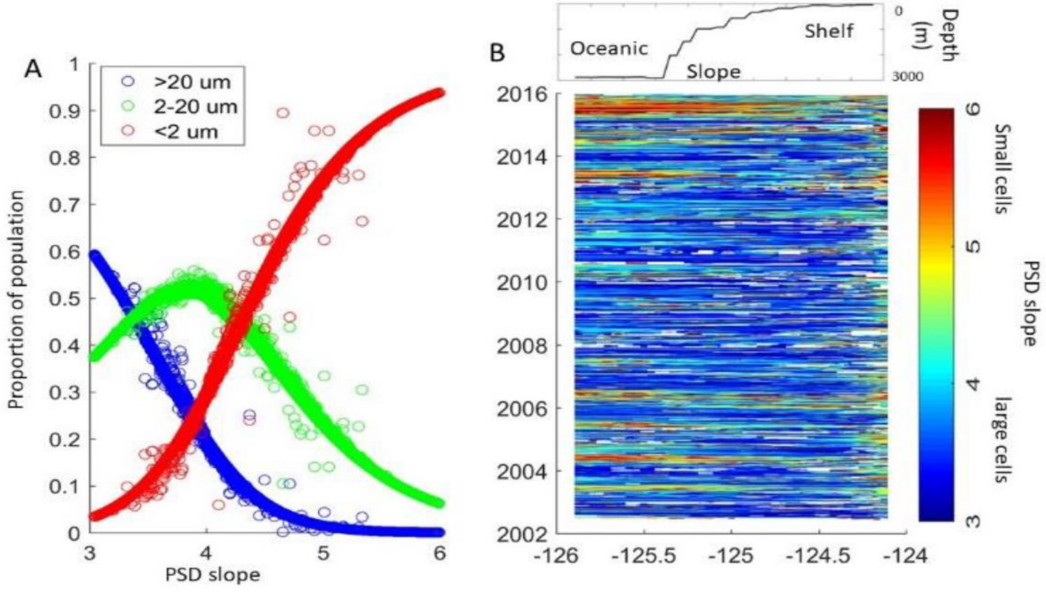


Seascape extent (km^2) in the NCC

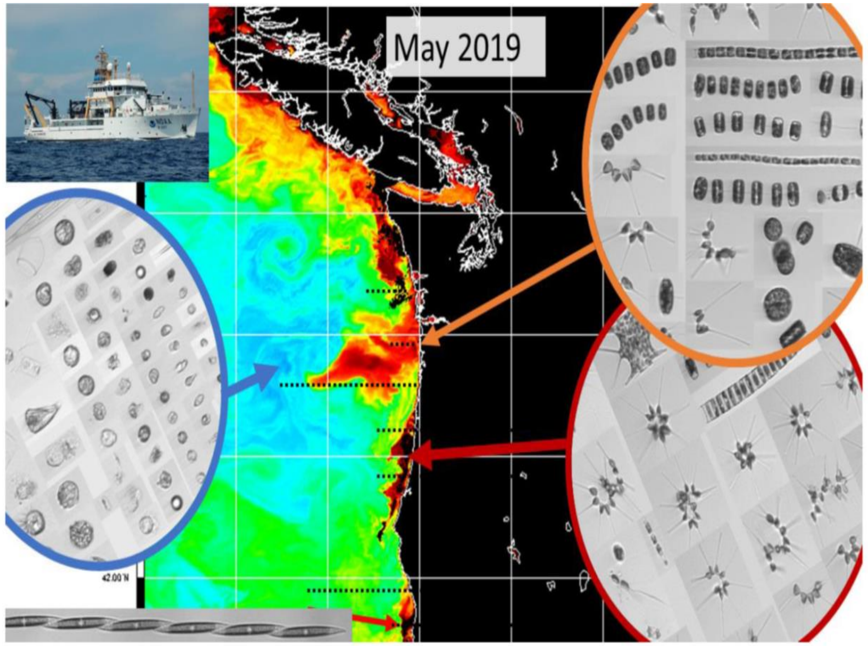

High taxonomic, spatial, or temporal resolution that scales up
Imaging flow cytobot (IFCB)
SEPTEMBER 2020
eDNA
NMDS2
NMDS1
0.50
0.25
0.00
-0.25
-0.5
0.0
0.5
Seascape
12
14
19
21
Depth
DCM
SUR

Regionally-tuned plankton community composition contribute to MBON and PACE Applications

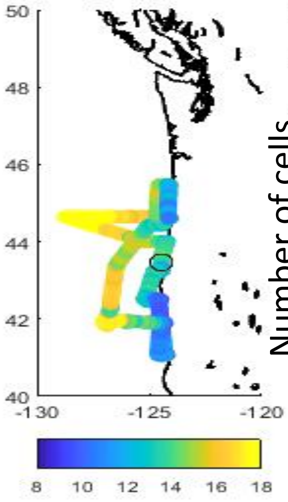
1. Size, dominance, and community composition
2. IOPs (ac-s, Hyper-bb) and imaging underway
3. Future: link OOI data (see also Ian's work!)



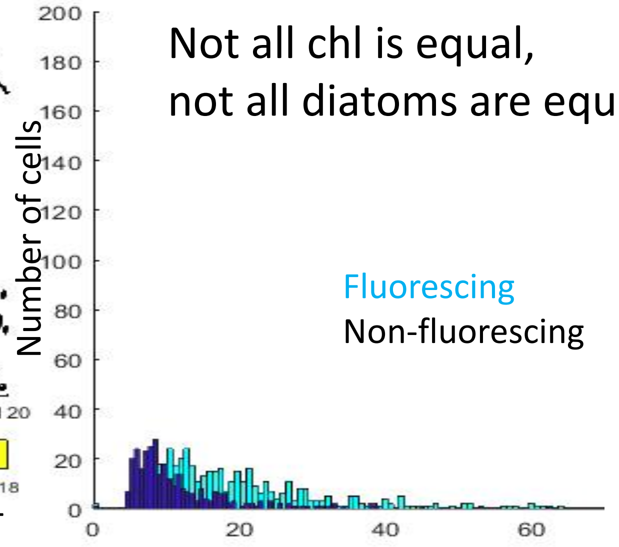
Particle size distribution model from Rrs (Kostadinov et al. 2009)
evaluated for Newport Hydrographic Line 2002-2016



Example dominant species from imaging flow cytometry



Cruise track SST

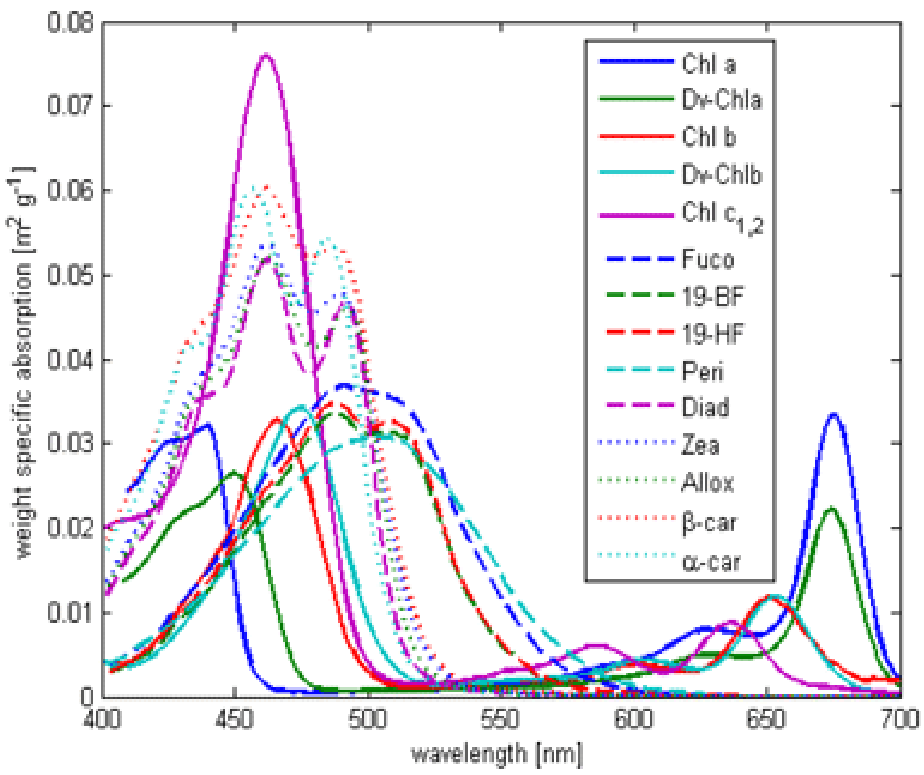


Not all chl is equal,
not all diatoms are equal!

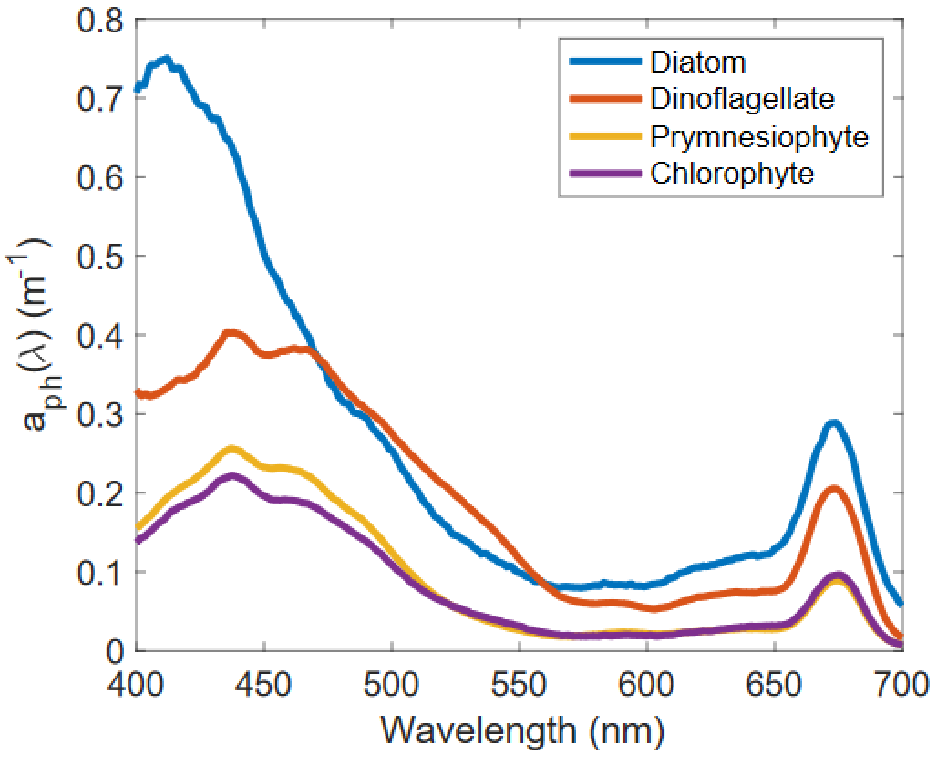
Size distribution of phyto vs. microheterotrophs-detritus

Ac-s: phytoplankton absorption

- *Different phytoplankton have different ecological and biogeochemical roles/functions. Important for fisheries, tracking carbon, predicting harmful algal blooms.*



Phytoplankton taxa have evolved different accessory pigments that absorb and scatter light in different wavelengths (Bricaud et al., 2002).

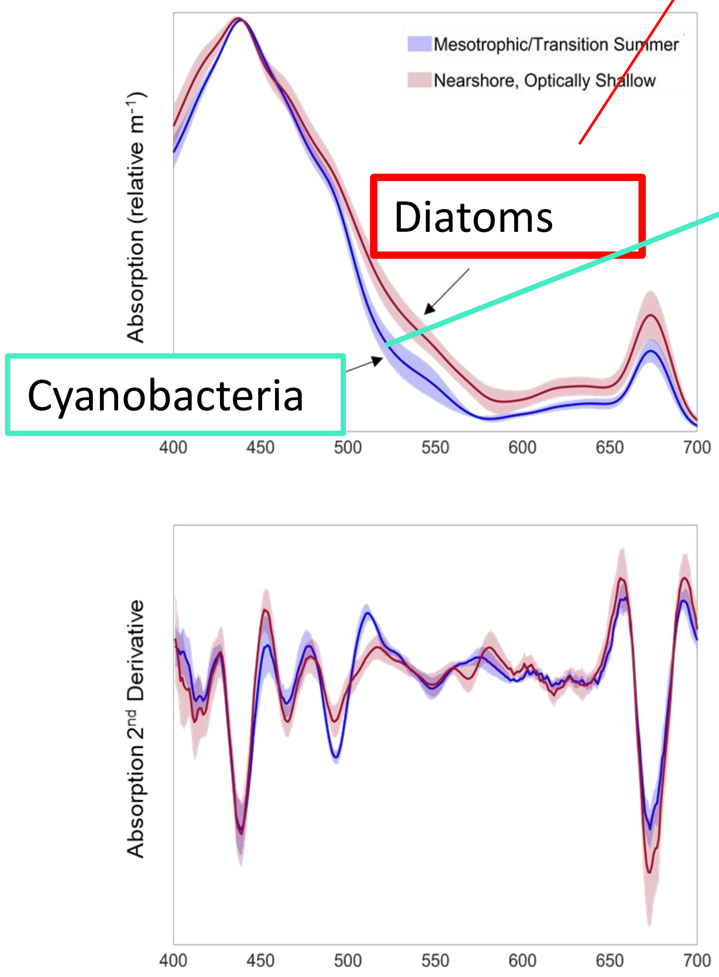


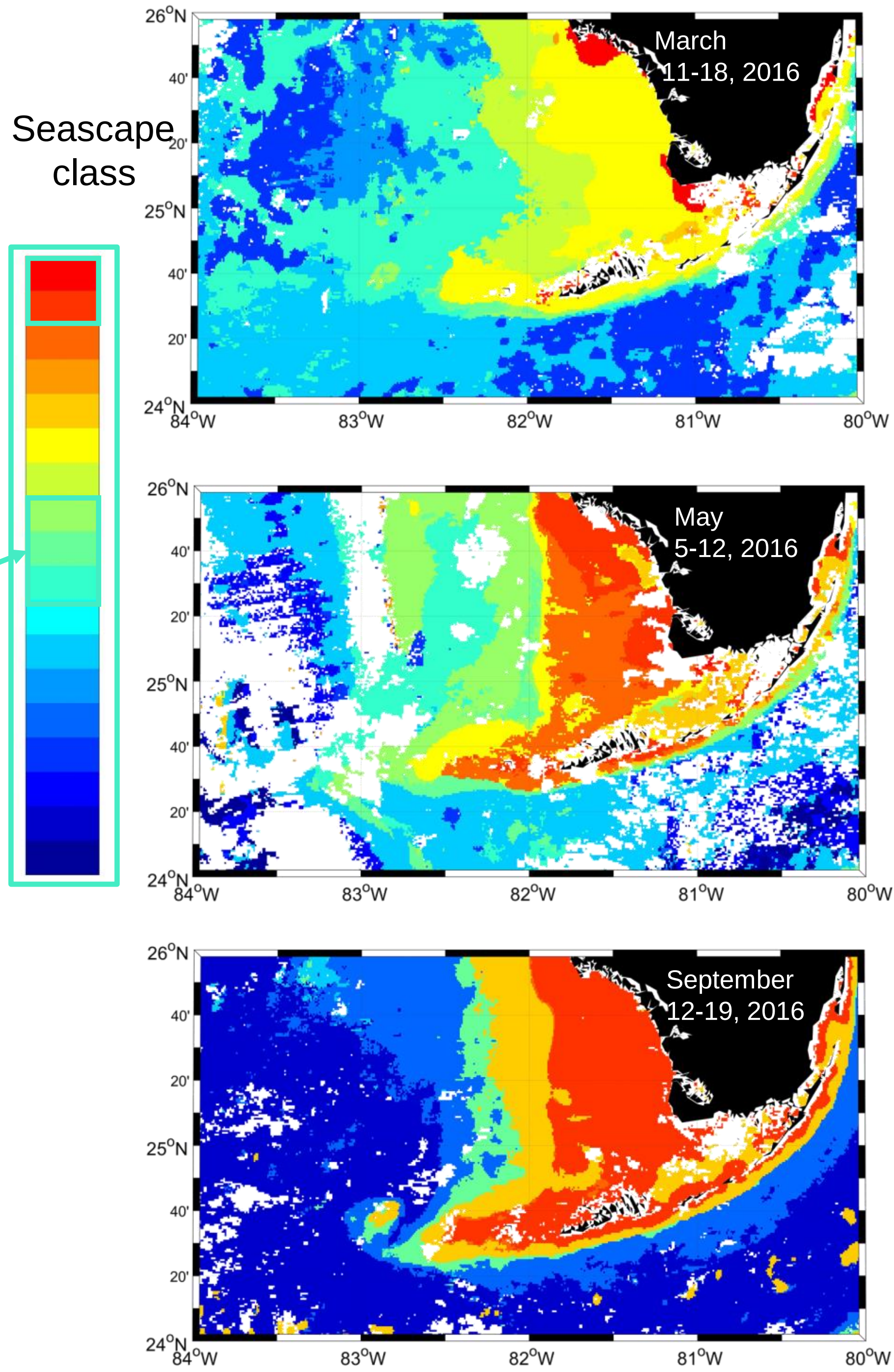
Blooms of dominated by different phytoplankton groups have different spectra (from Catlett and Siegel, 2018)

Seascapes have different (**phyto)plankton** communities and other optical constituents: **improve algorithms** in complex coastal zones

Seascapes have different average spectra and are dominated by different phytoplankton (diatoms vs cyanobacteria).

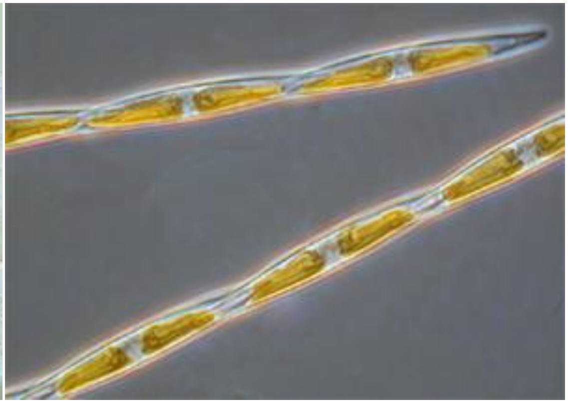
Microscopy and pigments confirm different communities across seascapes. (Montes et al. 2020; Kavanaugh et al. 2014)

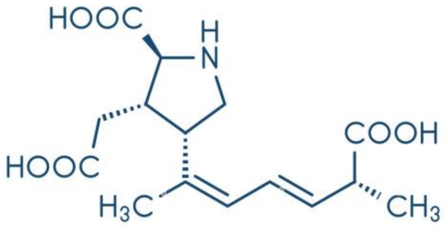




Particles abundance, size, shape, and chemical makeup affect several important processes:

- Food availability for higher trophic levels (fish, us)-- abundance
- Sinking rates and food chain transfer efficiency– size
- Growth rates, grazing rates and sinking rates—shape
- Primary production rates, nutrient cycling, toxicity -- chemical makeup

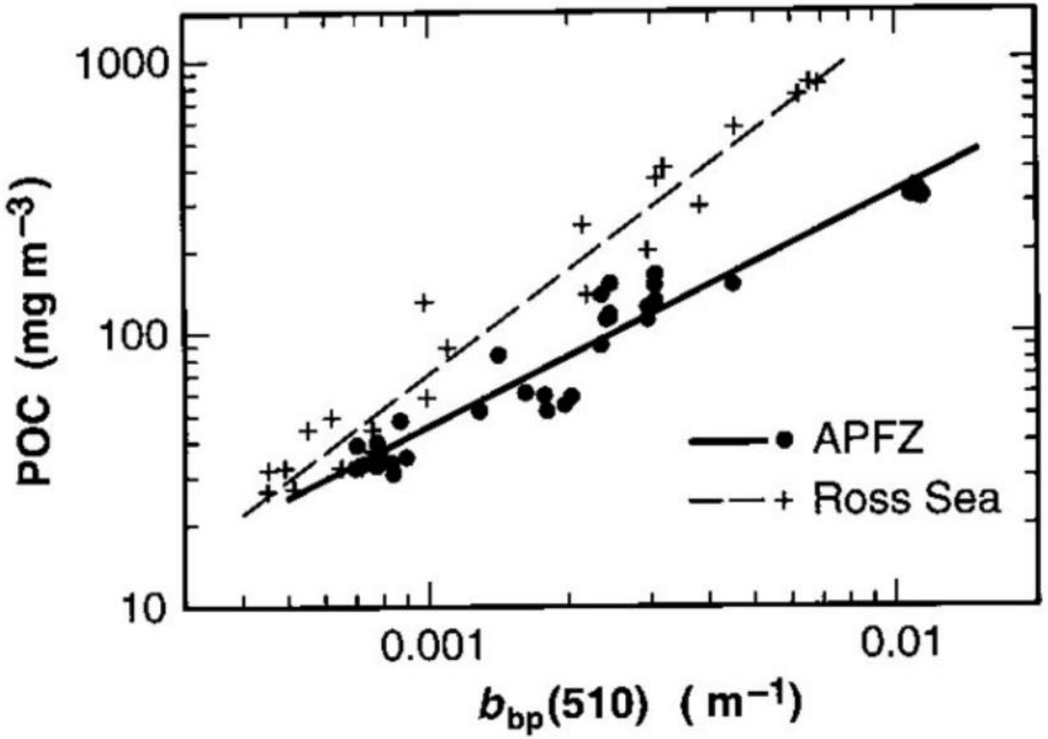


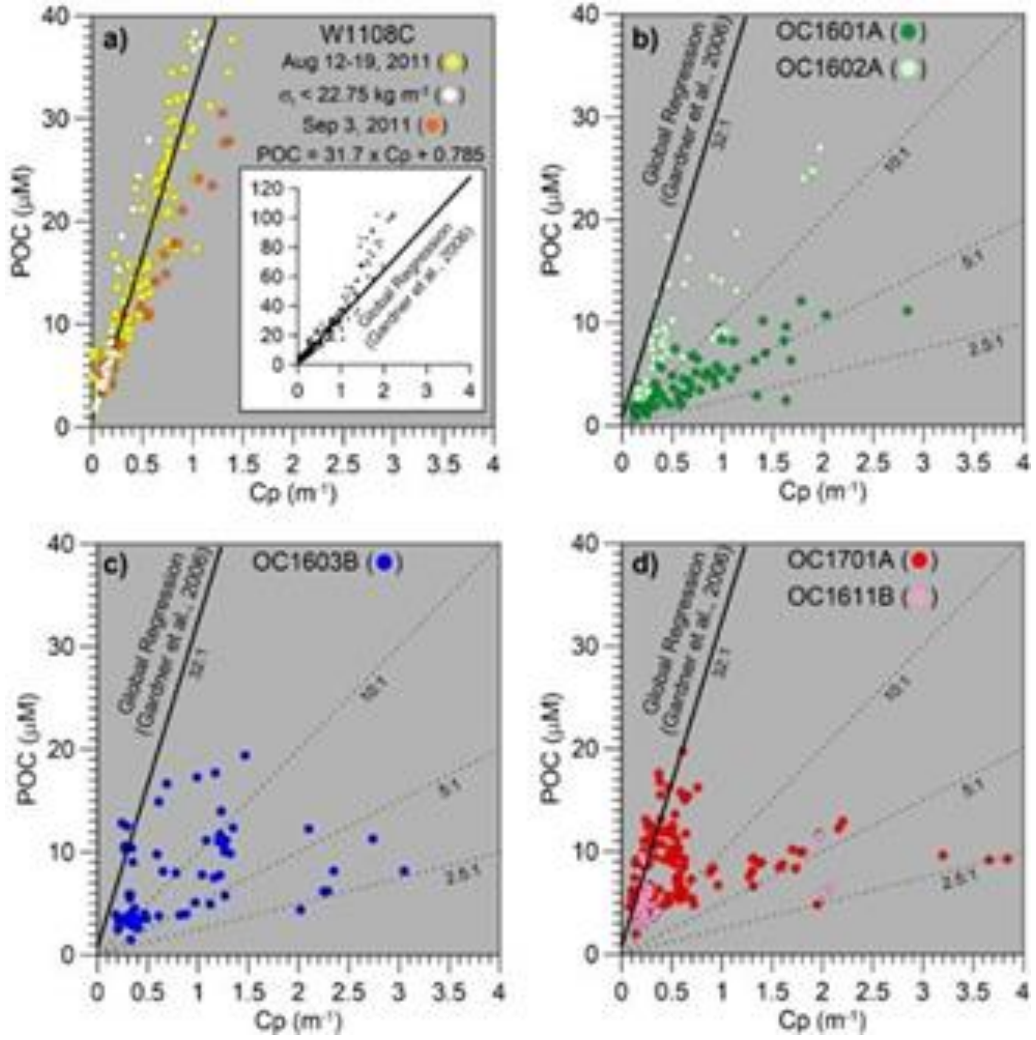


domoic acid

Total attenuation and Backscattering: POC

Particulate organic carbon can be derived from backscattering and attenuation.
Lots of regional variability

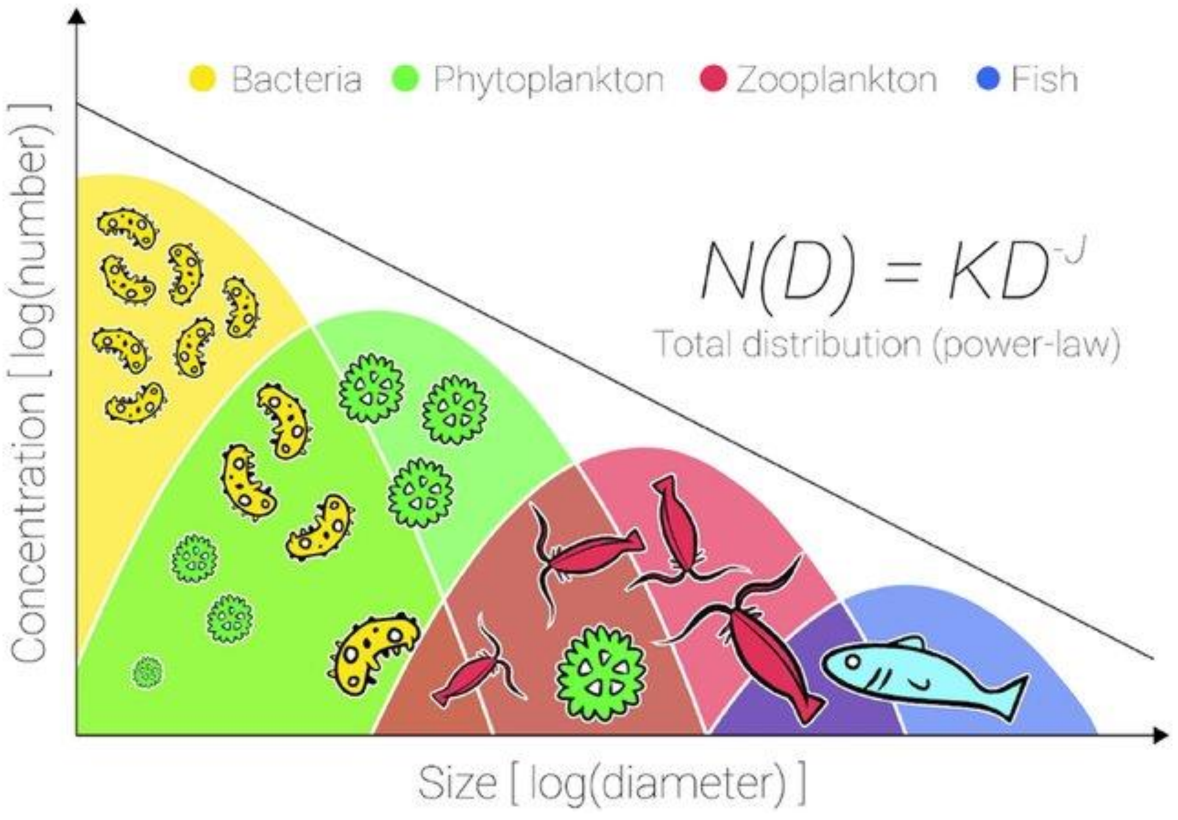




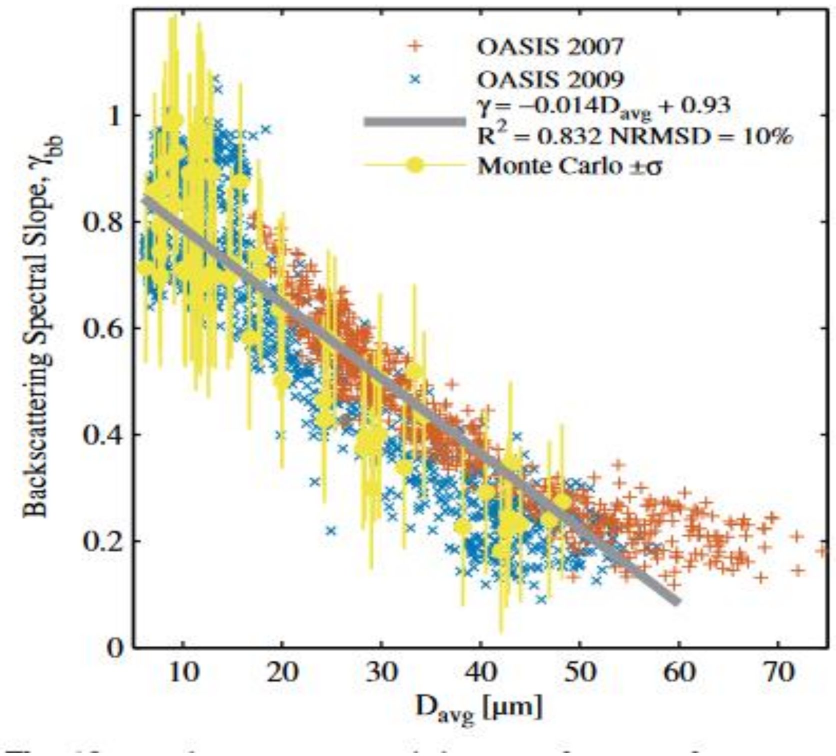
From Stramski et al., 1999
From Goni et al., 2022

Particle abundance and size

- Size structure can indicate trophic state, sinking rates.
- Particle size slope important parameter



From Davies et al., 2021, Scientific Reports



From Slade et al., 2015. Applied Optics
Lots of efforts to calculate spectral slopes and ratios from back scatter, total scatter, and total attenuation.
Challenge: algorithms assume spherical shapes

Particles can range in size and function from microbes to fish: In-situ Ichthyoplankton Imaging System (ISIIS)

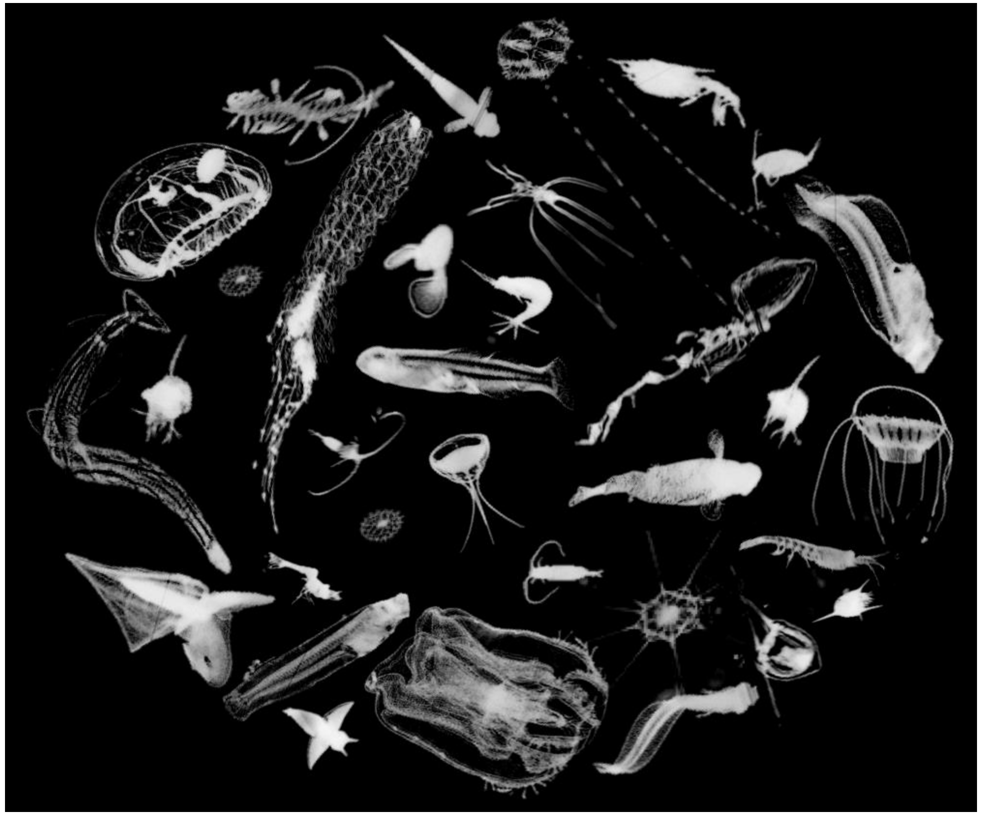


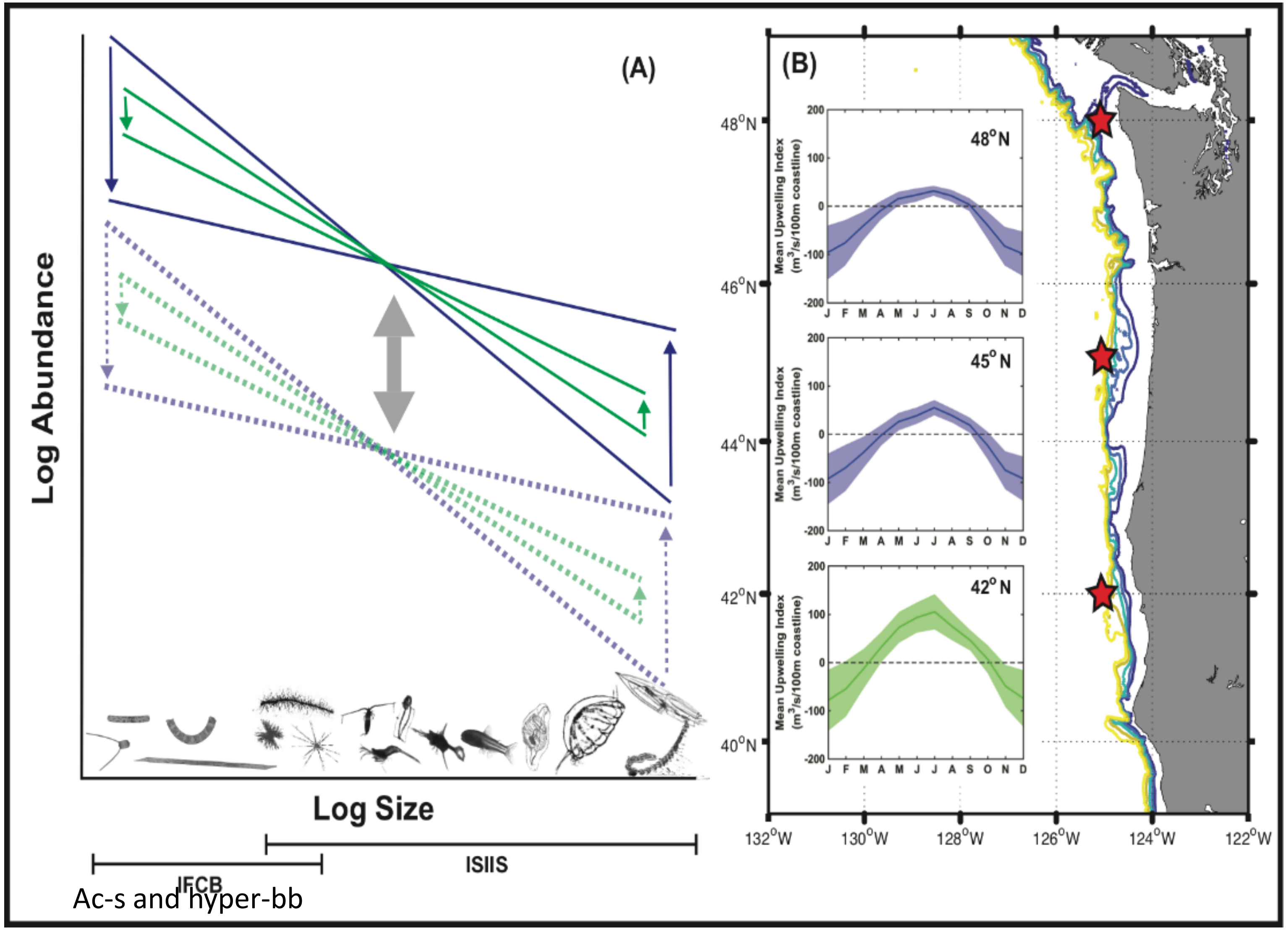
Fig. 1. Example images of plankton taken by ISIIS. Imaged taxa range from larger protists & phytoplankton to larval fish & gelatinous zooplankton.

Fig. 2. ISIIS being prepared for deployment on NOAA Ship *Shimada* as part of NCC MBON sampling.

Bio-optical measurements across trophic levels enable testing ecological hypotheses:

Does lower trophic level slope correlate to fish?

Does multitrophic level size structure (diversity, and abundance) vary as a function of upwelling regime and interannual variability?



Christian Briseno-Avena & Moritz Schmid

Bio-optical data can inform fisheries management!

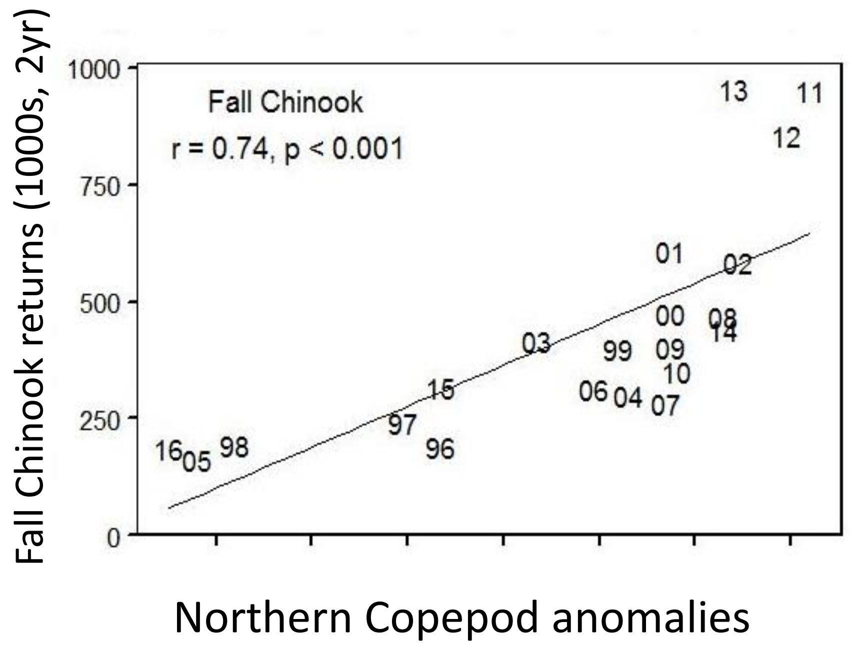


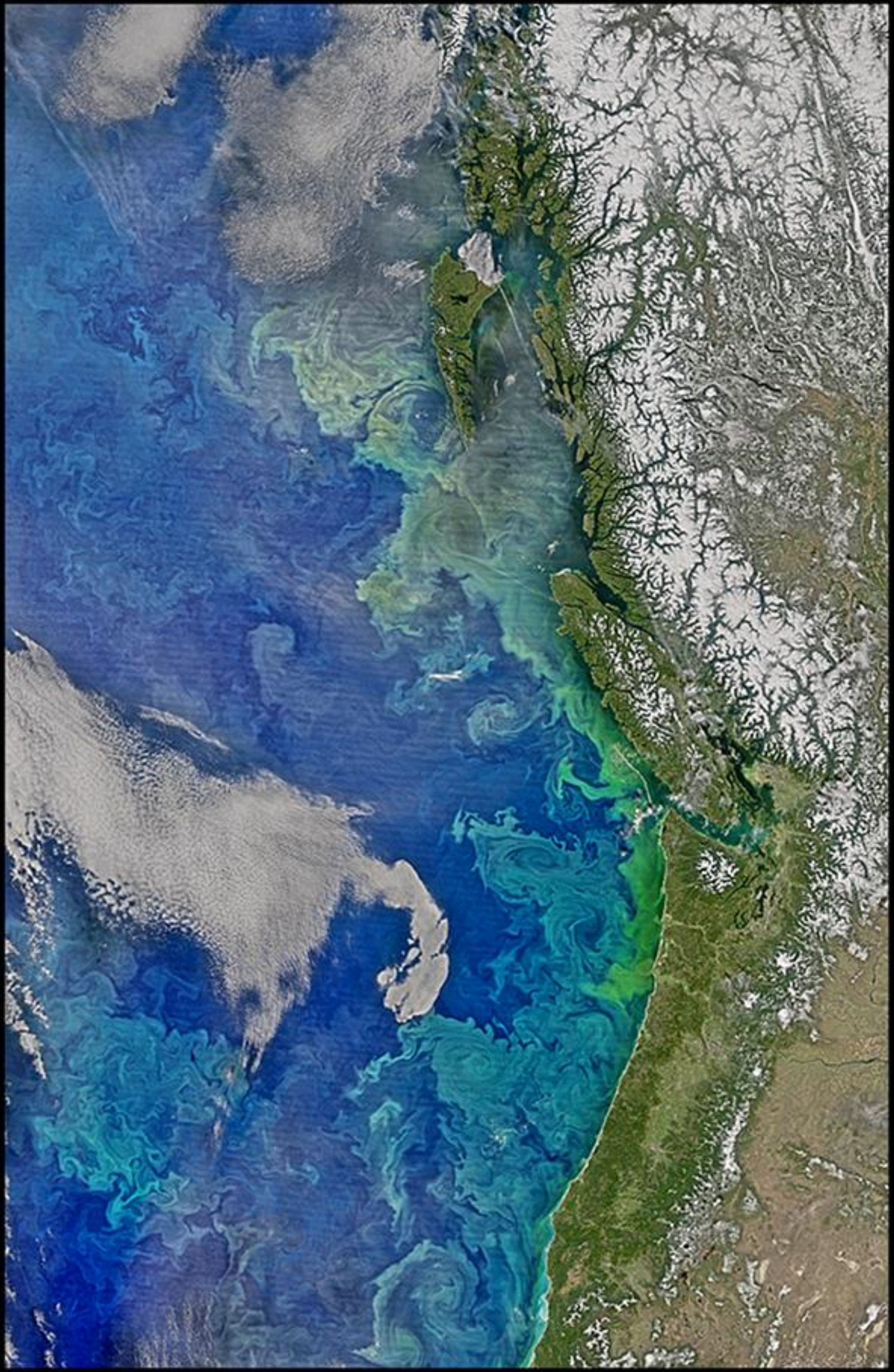
Table SF-01. Ocean ecosystem indicators of the Northern California Current. Colored squares indicate positive (green), neutral (yellow), or negative (red) conditions for salmon entering the ocean each year. In the two columns to the far right, colored dots indicate the outlooks for adult returns based on ocean conditions in 2018 (coho salmon) and 2017 (Chinook salmon).

	Juvenile Migration Year				Adult Return Outlook	
	2015	2016	2017	2018	coho 2019	Chinook 2019
Large– scale ocean and atmospheric indicators						
PDO (May - Sept)	red	red	red	yellow	yellow	red
ONI (Jan - Jun)	red	red	yellow	green	green	yellow
Local and regional physical indicators						
Sea surface temperature	red	red	green	red	red	green
Deep water temperature	red	yellow	red	red	red	red
Deep water salinity	red	yellow	green	green	green	green
Local biological indicators						
Copepod biodiversity	red	red	red	yellow	yellow	red
Northern copepod anomalies	red	red	red	green	green	red
Biological spring transition	red	red	red	red	red	red
Winter ichthyoplankton biomass	green	green	green	green	green	green
Winter ichthyoplankton community	red	red	red	red	red	red
Juvenile Chinook salmon catch – June	yellow	red	red	yellow	yellow	red
Juvenile coho salmon catch – June	yellow	yellow	red	green	green	red

Proposed through MBON:

PSD (within and across trophic levels)

Diatoms: Dinoflagellate (ac-s absorption, IFCB)



Summary

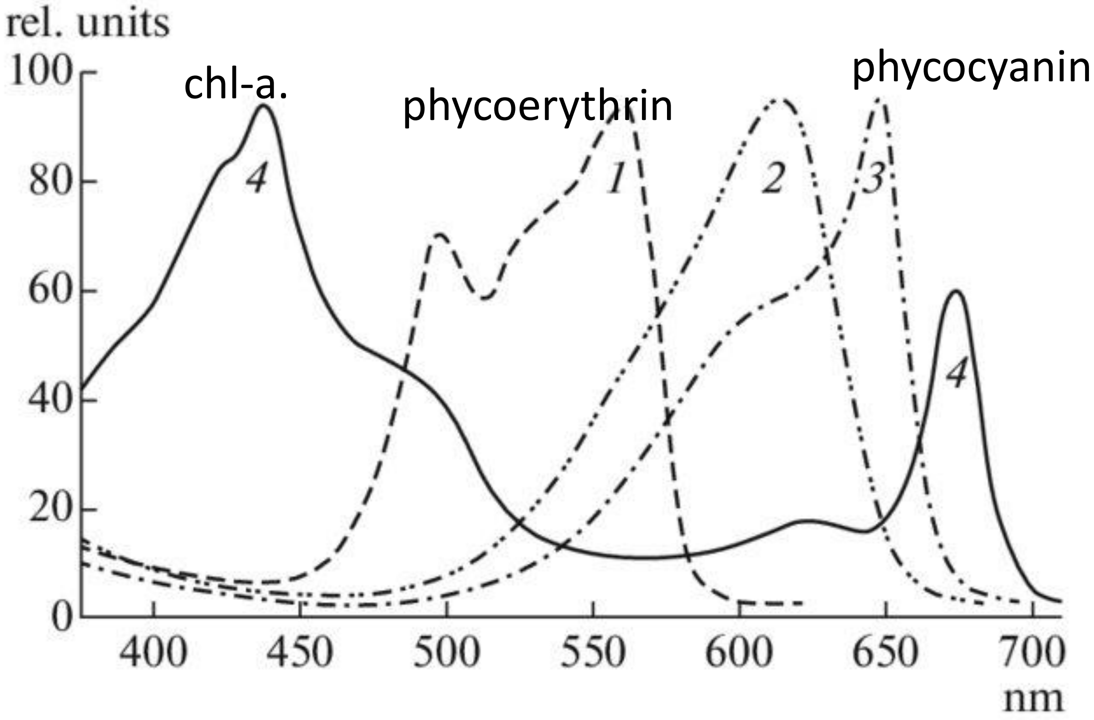
- Bio-optical observations provide insight: planktonic diversity to ecosystem functioning
- Ideal observations are high resolution (space, time, taxa) that scale up
- Ideal platforms allow for concurrent physical, chemical, and rate measurements
- Support ecosystem science AND the development of multi-scale, synoptic indicators to inform Ecosystem-based management

Thank you!

maria.kavanaugh@oregonstate.edu

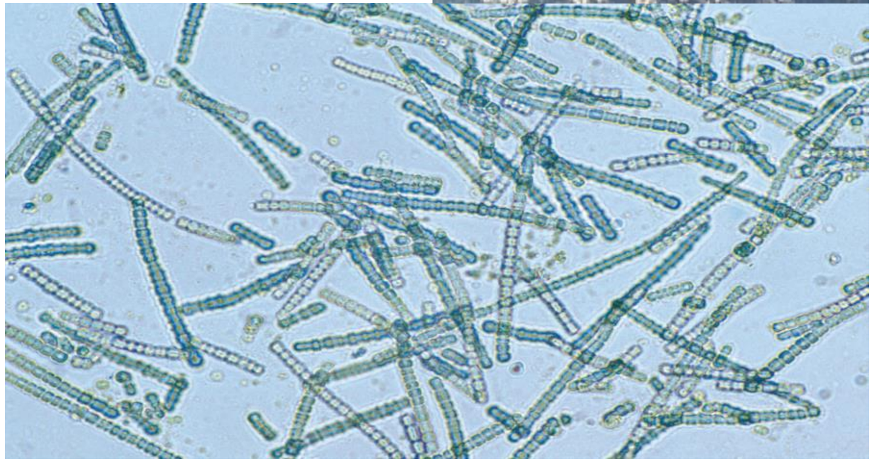
Chl-a, PE, PC fluorescence

Accessory pigments can perform both photosynthesis and photoprotective duties.



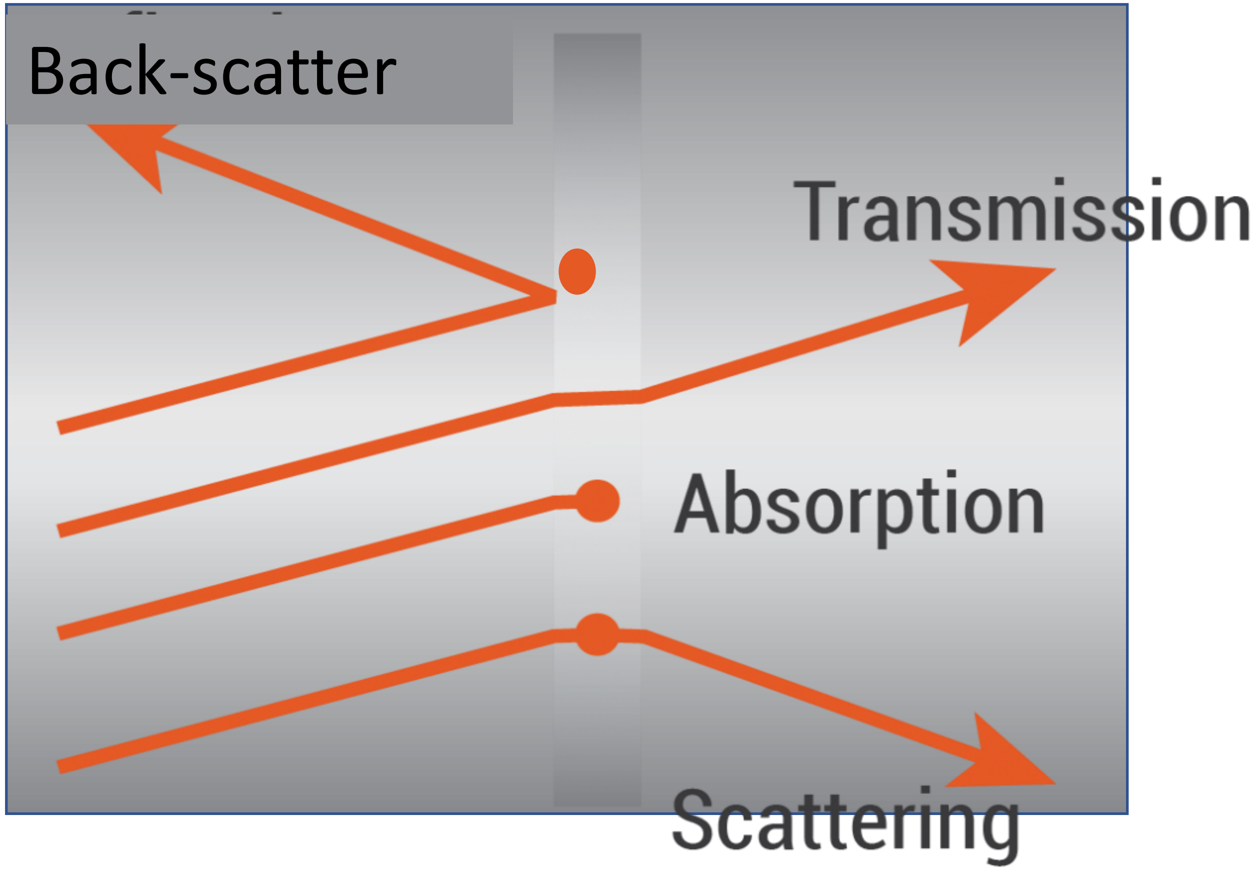
Measurement acceptance angle of 140°. Chl-a ex= 470nm em=695nm, phycoerythrin ex= 520nm , em 595nm, and phycocyanin ex =630nm em=680nm. All raw counts are converted into corresponding units using the scale factor derived during calibration (µg Chl/L for CHL and ppb for PE and PC).

Cyanobacteria are important phytoplankton in some ecosystems: nitrogen fixation, primary production



The interaction of light and stuff in the water can tell us a lot about the stuff

- **Attenuation** is the loss of light along a path. Related to transmission.
- Light is attenuated by stuff in the water that **absorbs** light or **scatters** it off the path
- Backscatter is equivalent to reflectance (but doesn't require a surface).
- **Fluorescence** is the emission of absorbed light (comes with energy change).



Attenuation(c)= absorption (a) + scattering (b)

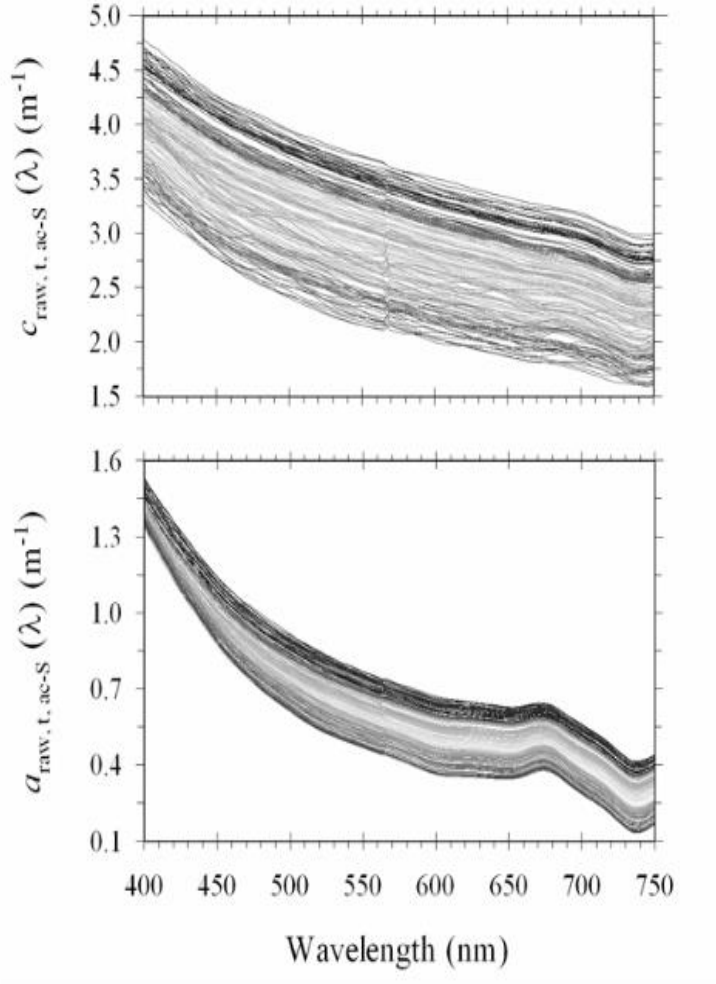
Particles will scatter light based on their abundance, size, shape, and chemical makeup

- We all have practical first-hand experience of the first two.
- Rain (large drops in thunderstorm >1000μm) vs fog (small drops, 10s μm)

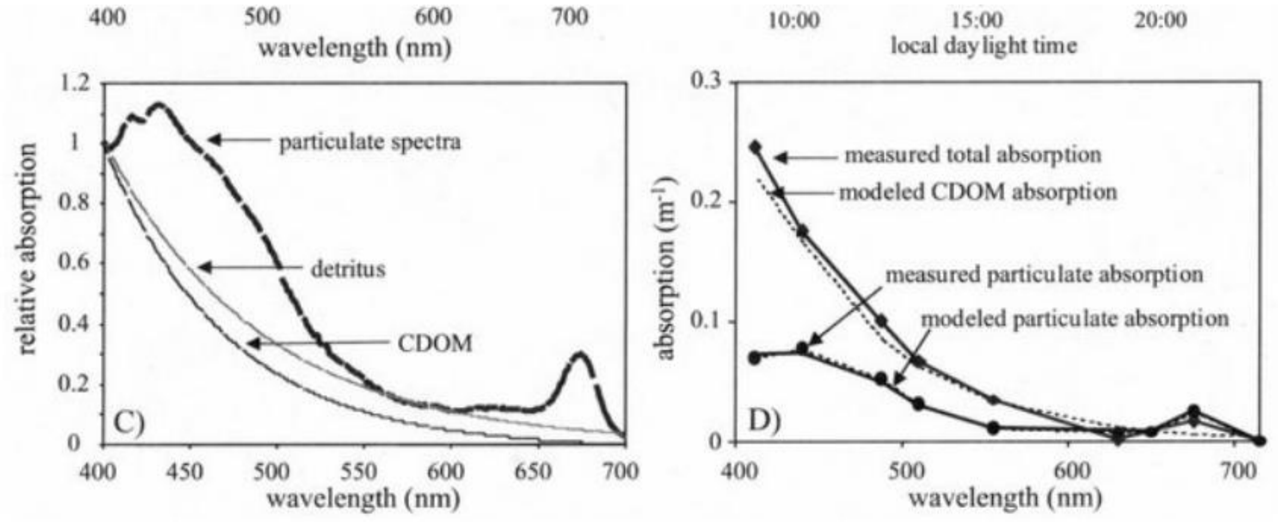


AC-S Absorption and attenuation.

ROT: C ~ 3xA

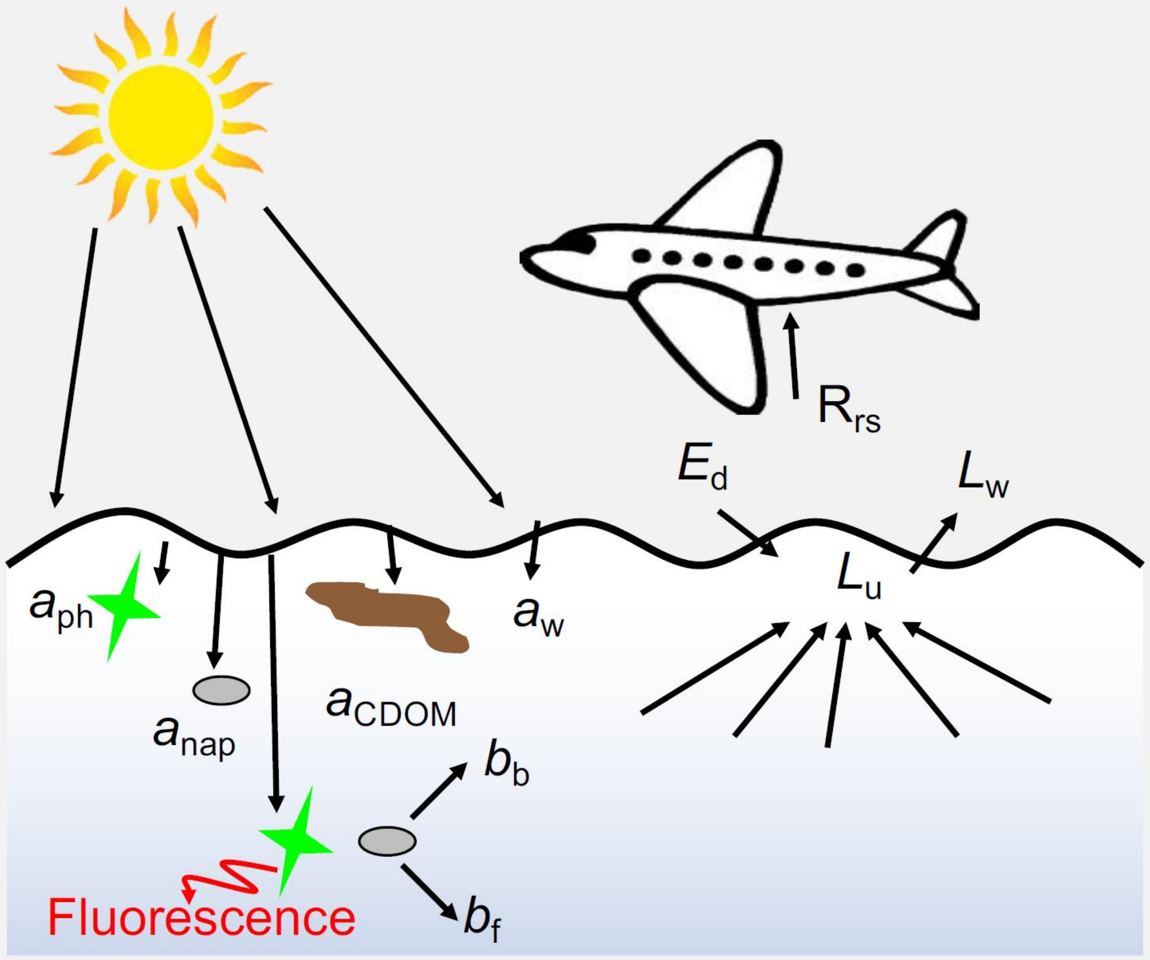


Multiple spectra (~120) for each tube
Collected in slow descent through depth
(Flow through would be similar through time).



Spectra are time-binned and an appropriate dissolved blank is subtracted.
Automatic filtration 10 min every hour
Linear interpolation between blanks?

Ocean color satellites measure reflectances at multiple wavelengths to infer in water properties



$$\mathrm{Rrs}\left(\lambda,0^+\right)\cong C\,\frac{b_b(\lambda)}{a(\lambda)+b_b(\lambda)}=\frac{L_w(\lambda)}{E_d\left(\lambda,0^+\right)}$$

Inherent Optical Properties
a = absorption
b = scattering

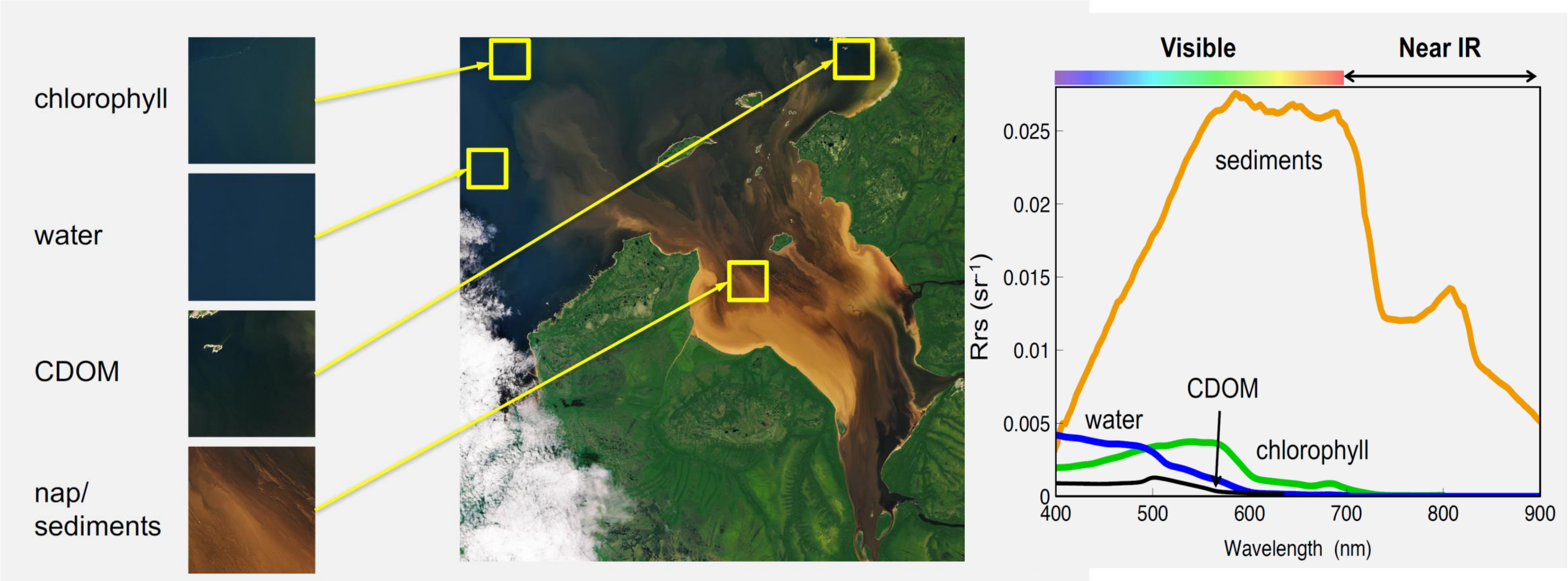
Affected by amount/quality of stuff

Apparent Optical Properties
L_w = water leaving radiance
L_u = upwelling radiance
E_d = downwelling irradiance
R_{rs} = remote sensing (rs) reflectance

Affected by angle, sea state, quality/quantity of light

Optical oceanographers calculate IOPs from AOPs and visa versa using radiative transfer theory and algebra (inversions)

Algorithms continue to improve to separate various optically active constituents

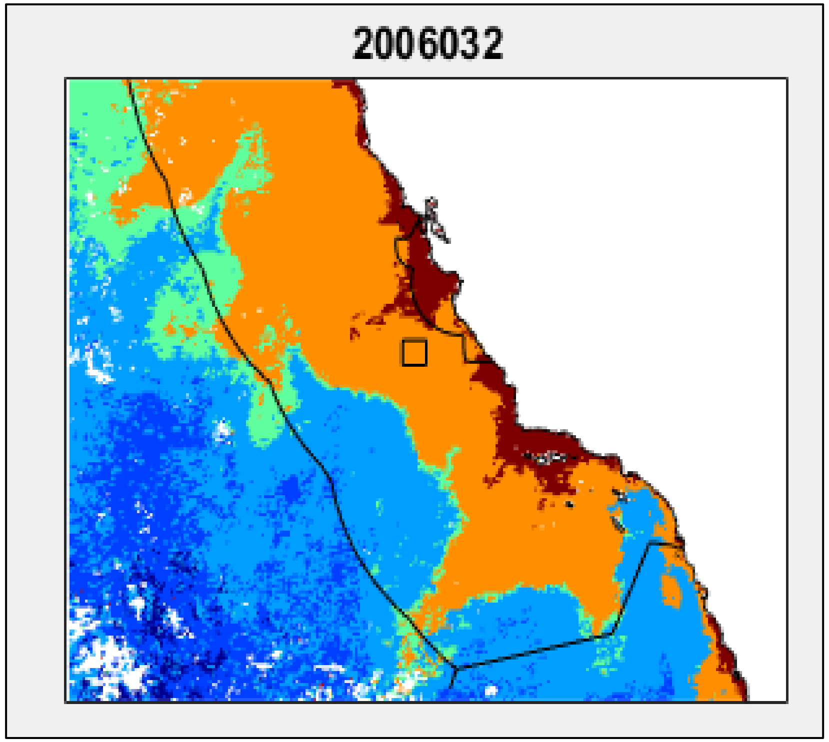


QUESTION: What happens to data quality as the sensor moves from land to water?

Sherry Palacios: NASA ARSET and BAERI

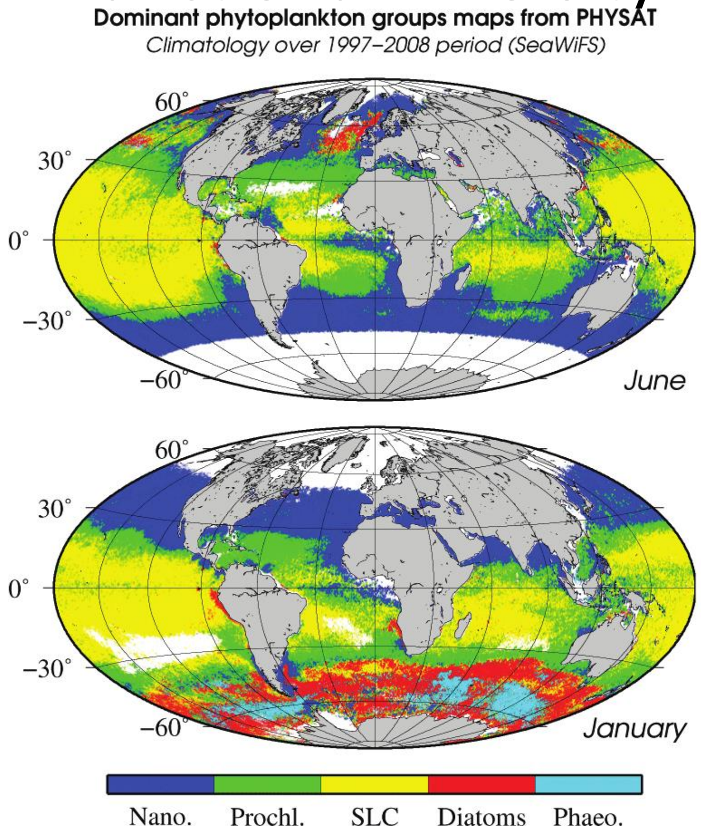
Biodiversity from space?

Habitat Diversity



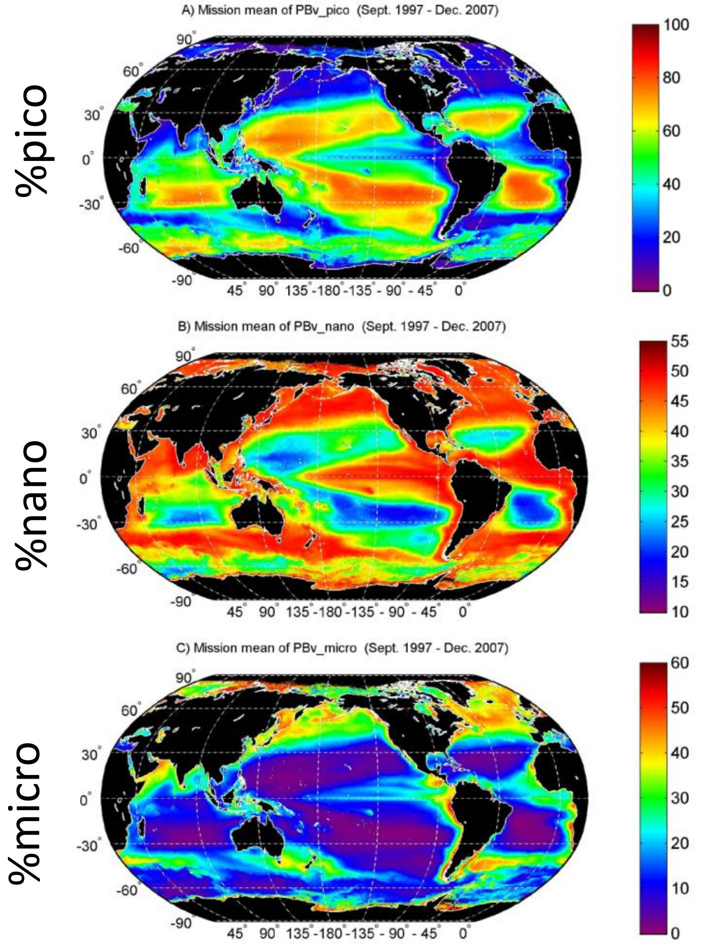
Habitats can represent unique assemblages

Phytoplankton Functional Diversity



Accessory pigments of different functional types have different absorption/reflection spectra

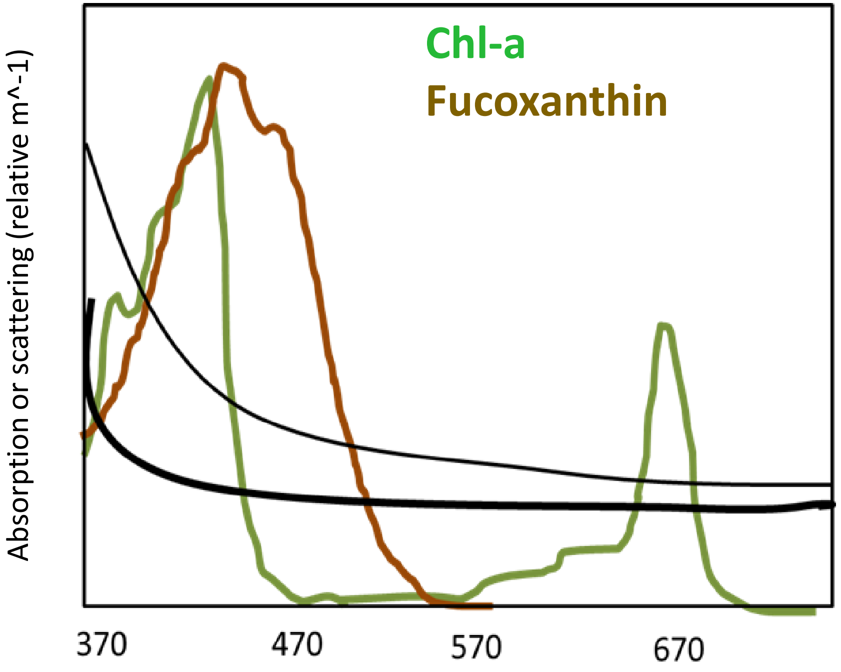
Size Structure

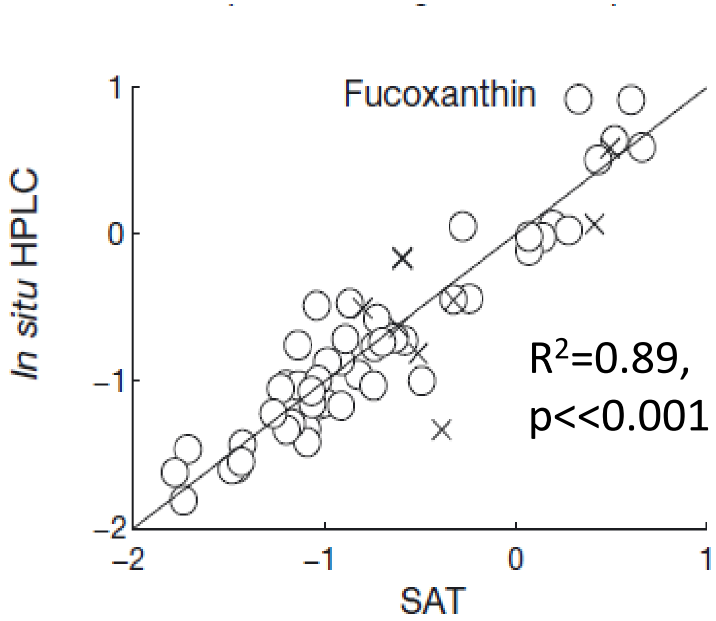


Kostadinov et al., 2010

Scattering (b- slide 25) varies by size of particle (cell)

How do phytoplankton functional type algorithms work?
Single species case: diatoms in Antarctica





Small cells scatter more

Large cells scatter less

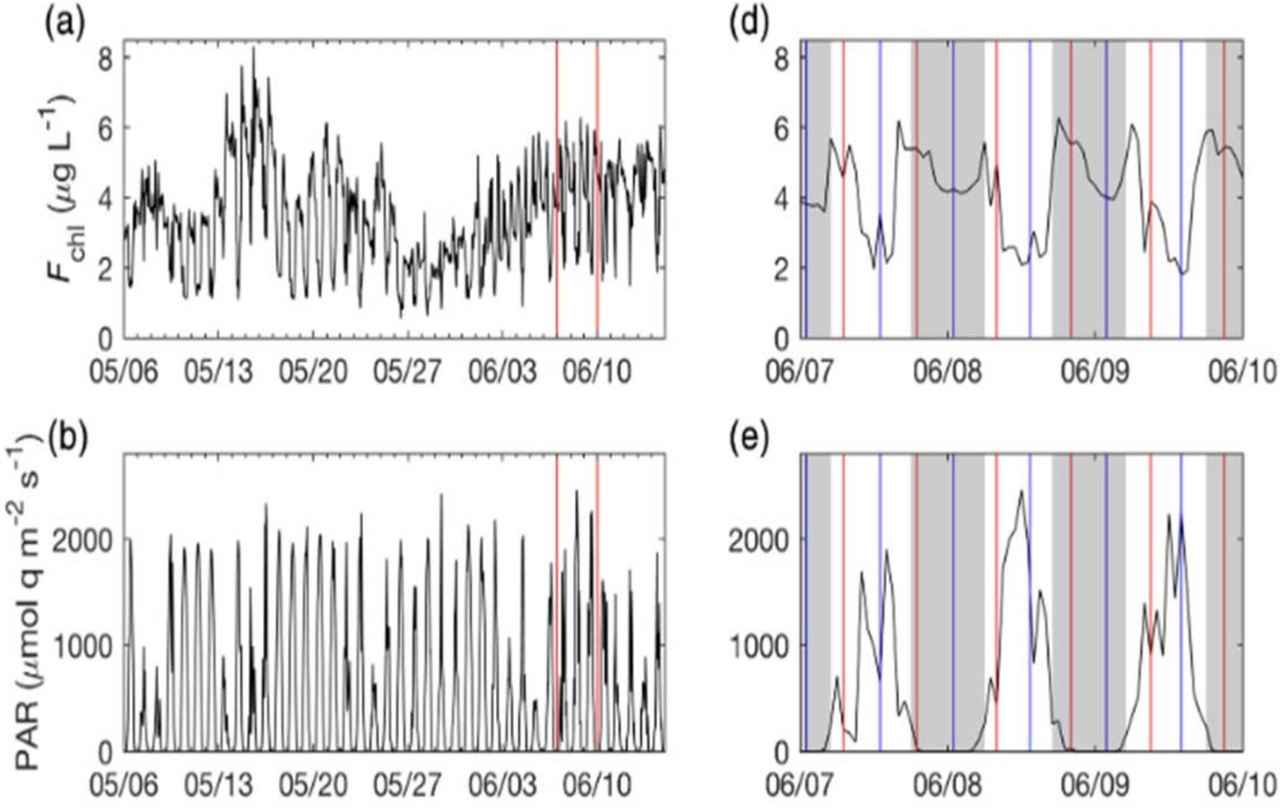
Log_{10} [fuco]= 1.49- 0.67 R_{412} + 1.98 R_{443} – 2.33 R_{488}

Where R= Rrs_{λ}/ Rrs_{555}

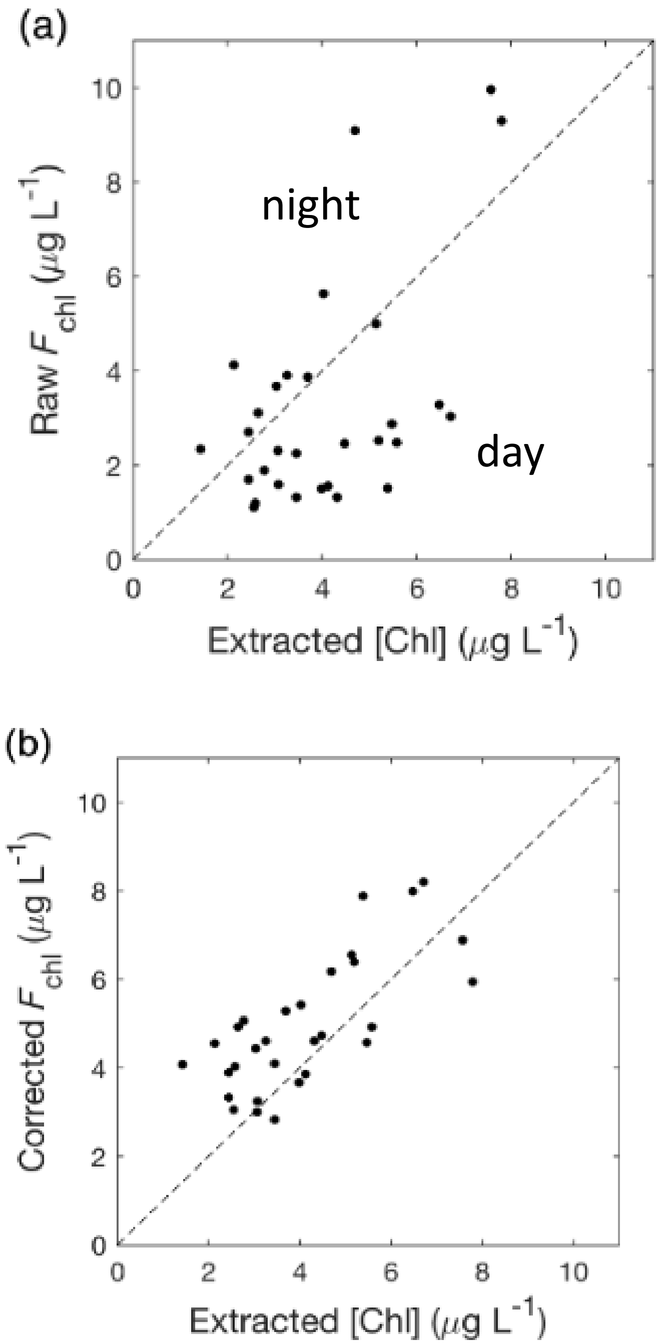
Diurnal cycles in fluorescence can lead to error (~2 fold).

Cells will shunt more photons to heat dissipation to protect cell from damage under sustained high light (e.g. noonday sun).

Helpful to know, and to compare to values based on other properties (e.g. absorption). See ac-s.



From Carberry et al., 2021



ACS-Optical Absorption (A) /Beam Attenuation (C)

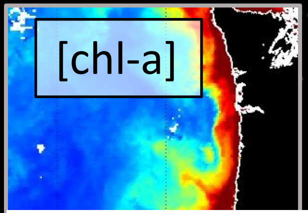
- Units of 1/m.
- Describe the optical characteristics of particles in the water.
- Can be used as proxies for other data products (sanity checks for fluorometric chl-a, e.g.)

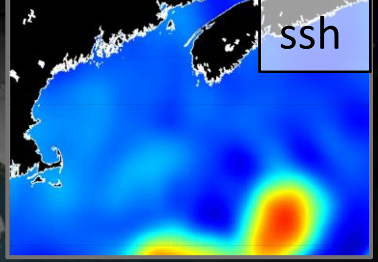
Chlorophyll-a
Roesler and Barnard 2013

$$CHL_{ALH} = \frac{A676 - \frac{A715 - A650}{715 - 650} * (676 - 650) + A650}{0.0104}$$

Particulate Organic Carbon
Gardner et al, 2006

$$POC = C660 \ * 380$$



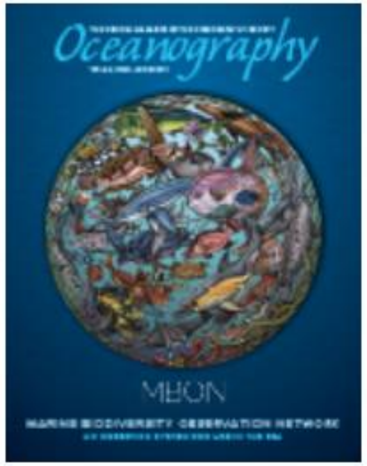


MBON utilizes multiple platforms at multiple scales, advances B/E remote sensing in four ways:

OPEN ACCESS

Satellite Remote Sensing and the Marine Biodiversity Observation Network: Current Science and Future Steps

Maria T. Kavanaugh, Tom Bell, Dylan Catlett, Megan A. Cimino, Scott C. Doney, Willem Klajbor, Monique Messié, Enrique Montes, Frank E. Muller-Karger, Daniel Otis, Jarrod A. Santora, Isaac D. Schroeder, Joaquin Triñanes, David A. Siegel



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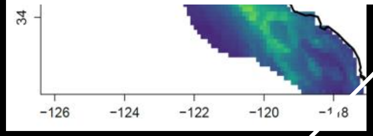
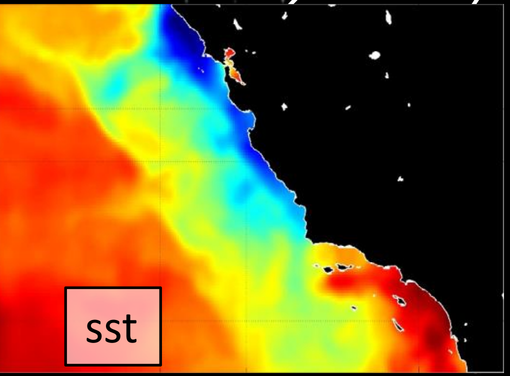
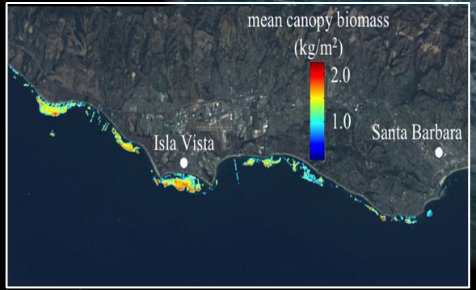
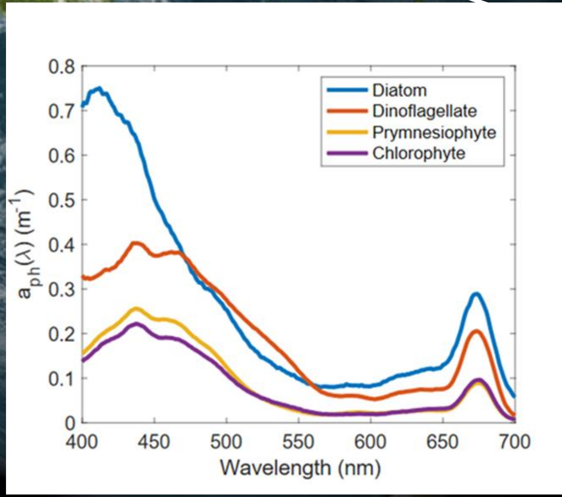
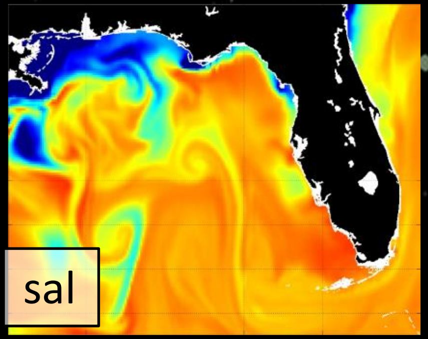








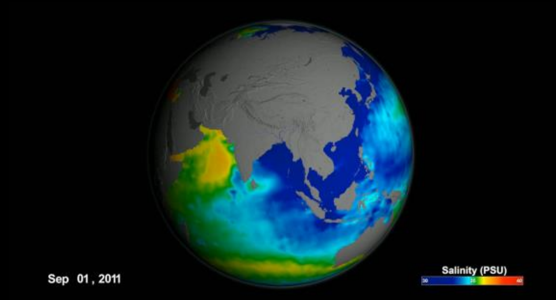


Pelagic seascape ecology : framework to relate organisms to dynamic habitat for global marine biodiversity observing network

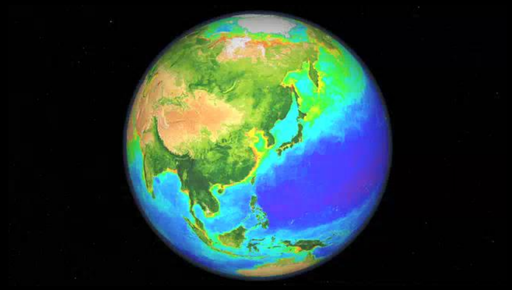
GEO BON

Multiplatform Integration Machine Learning:

Satellite remote sensing, ecosystem models



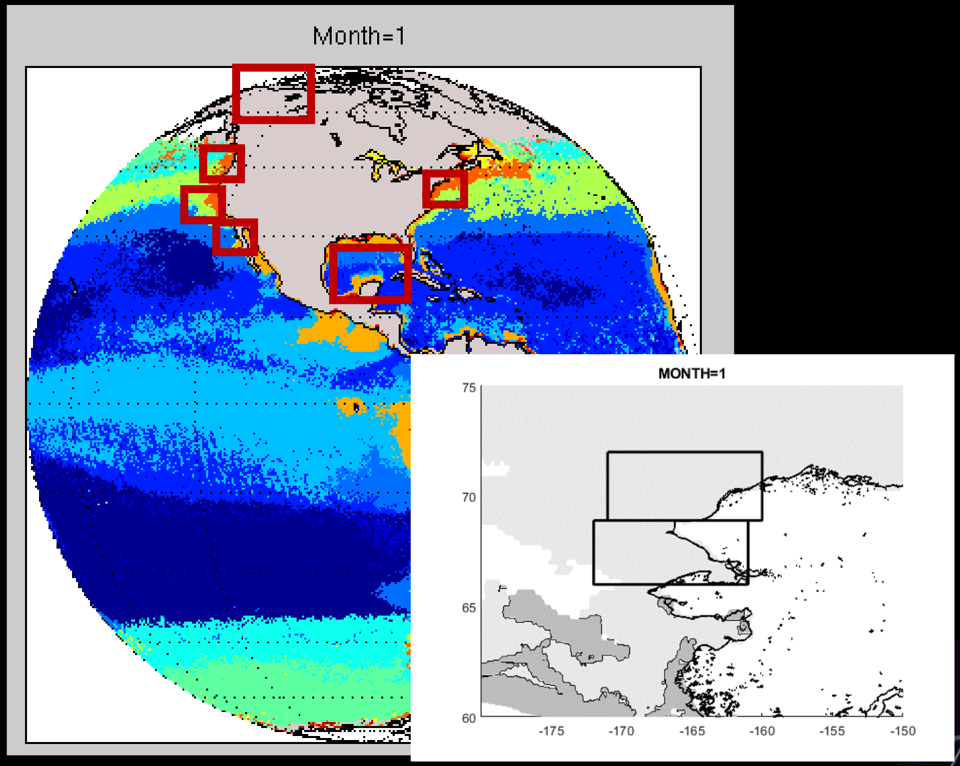
Physics: e.g.
SSS, SST, sea ice, SSHa



Biology:
Chl-a, nFLH, CDOM

Multiscale classification

Seascape Classification/Prediction



Hierarchical, non-linear, dynamic

Regional habitat associations

biogeochemistry, diversity, fisheries habitat