Satellite analysis of shifts in phytoplankton community composition and energy flow in the new Arctic

Jens Nielsen, Lisa Eisner (NOAA AFSC)

Priscila Lange, Mike Lomas (Bigelow Lab)

Calvin Mordy, Phyllis Stabeno (NOAA PMEL)

Kathi Lefebvre (NOAA NWFSC)

Cara Wilson, Dale Robinson (NOAA PolarWatch)

Jeanette Gann (NOAA AFSC)

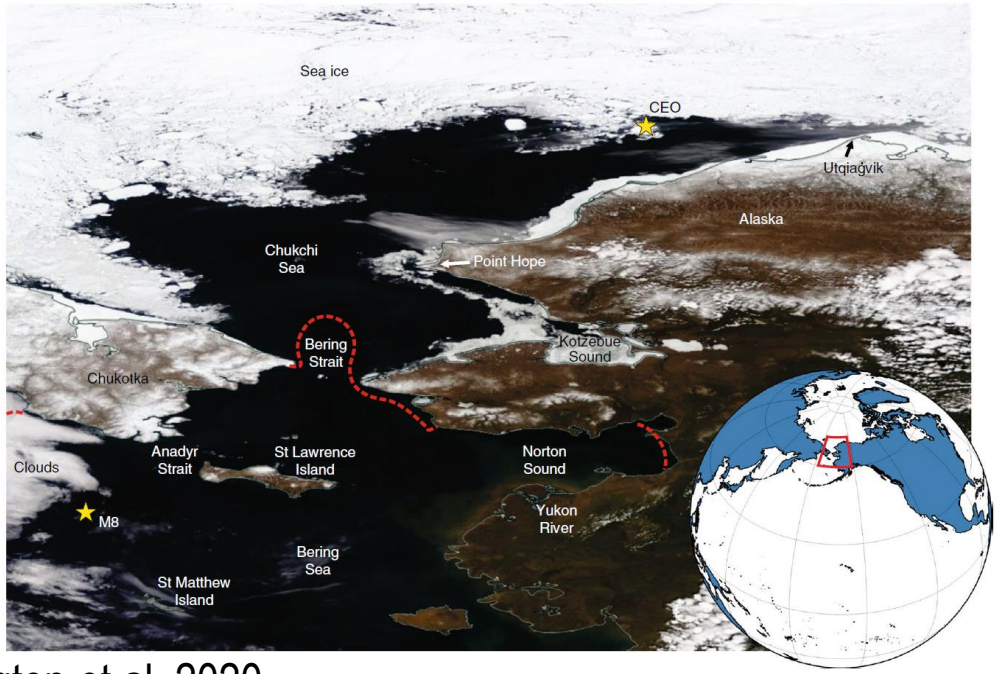
NOAA FISHERIES

- **Alaska Fisheries Science Center**

- Feb 8, 2023

Funded by NOAA Joint Polar Satellite System (JPSS) Proving Ground and Risk Reduction (PGRR) initiatives (3 years, June 2021- 2024)

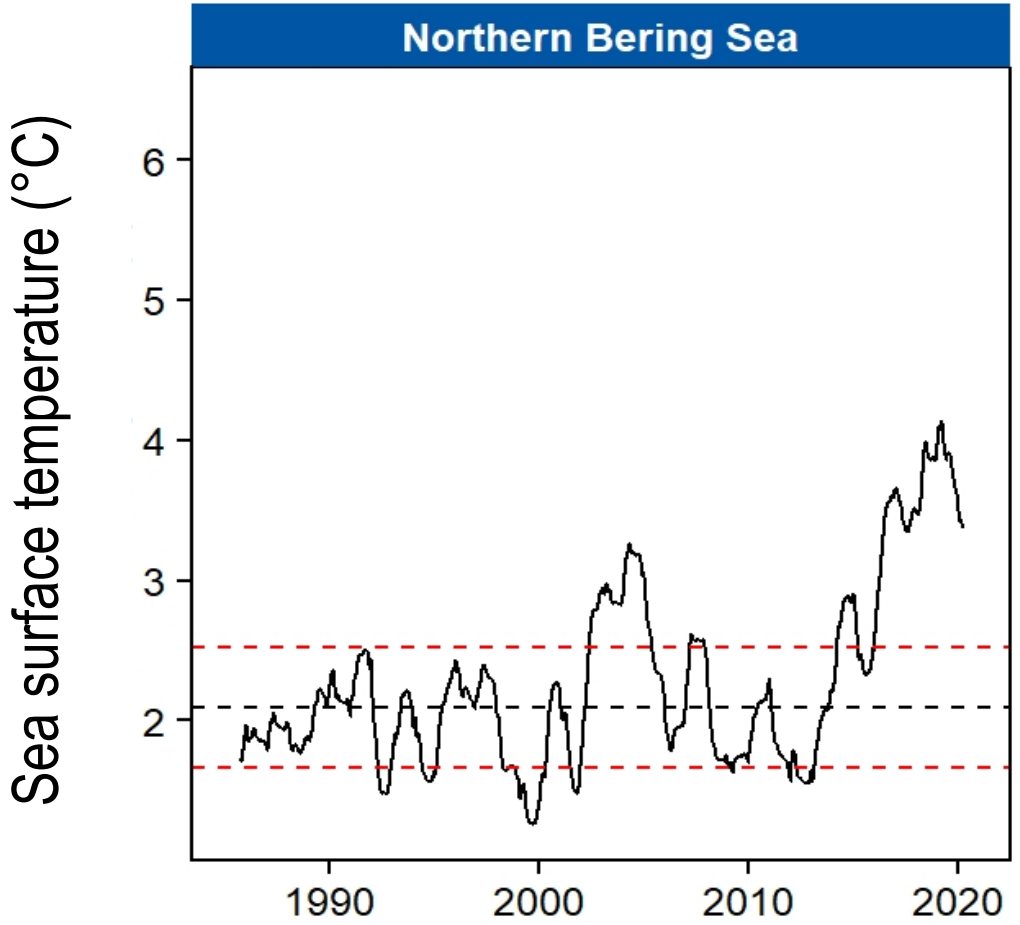
The Arctic is warming



Huntington et al. 2020

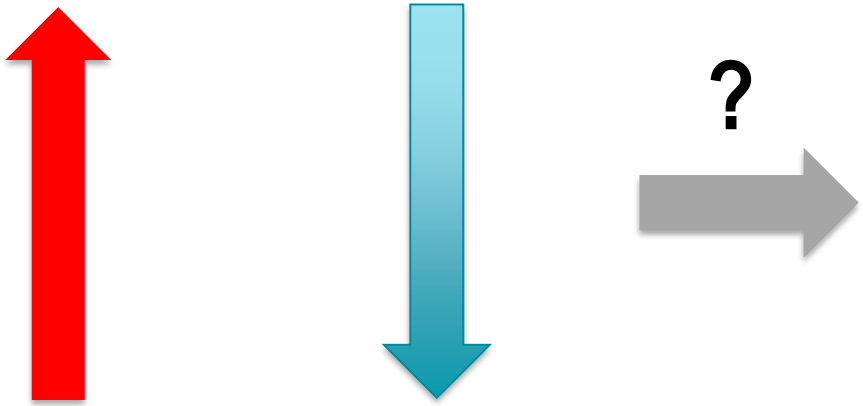


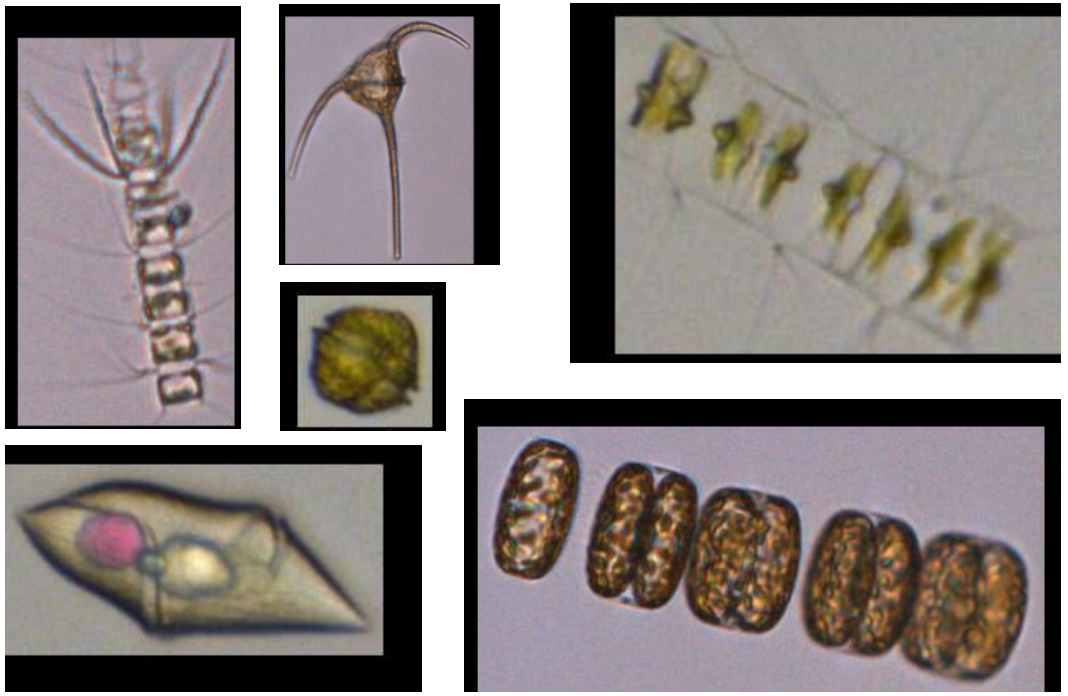
Danielson et al. 2020



J. Watson, satellite SST

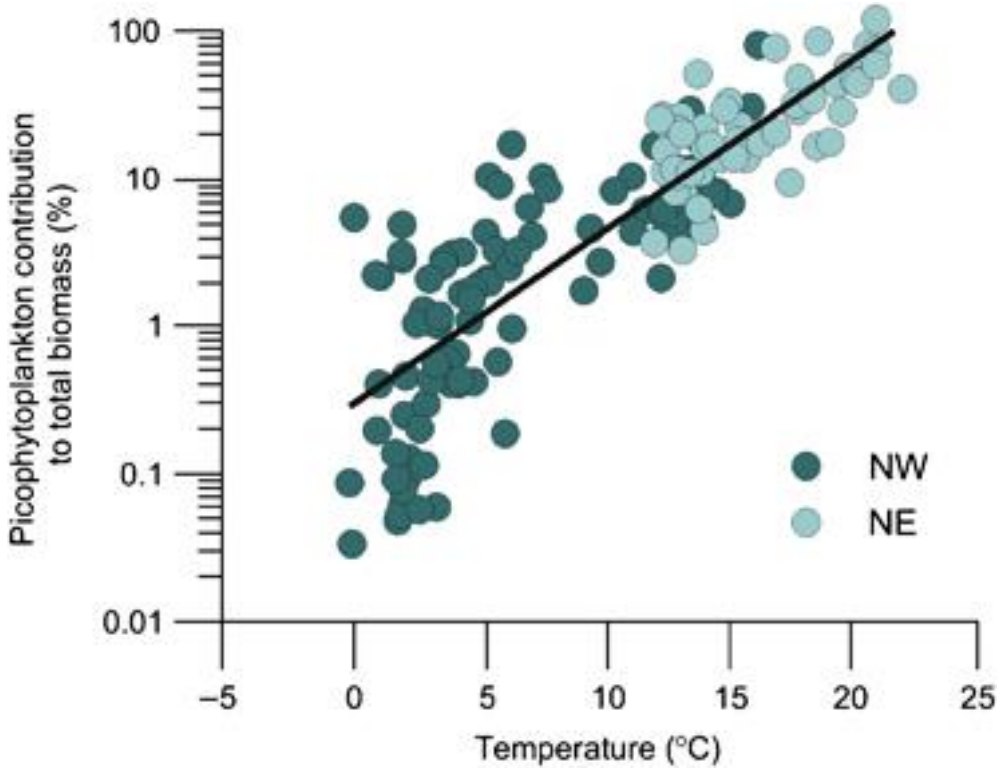
Warmer ocean - influence on phytoplankton composition?





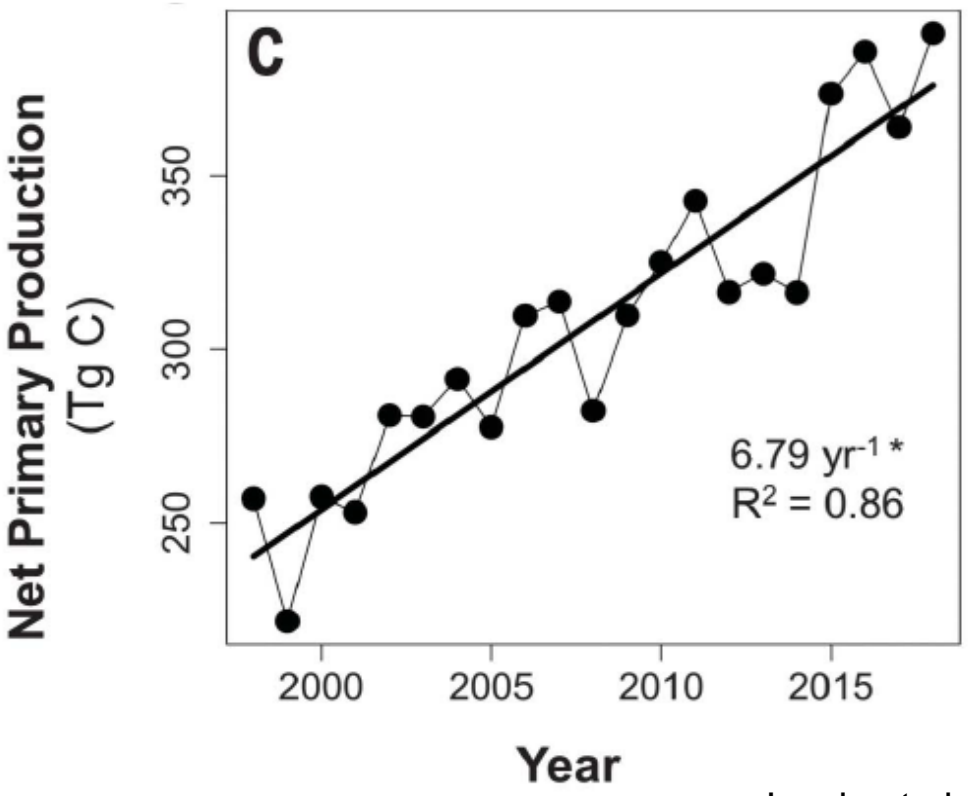
Increasing picoplankton and primary production

North Atlantic



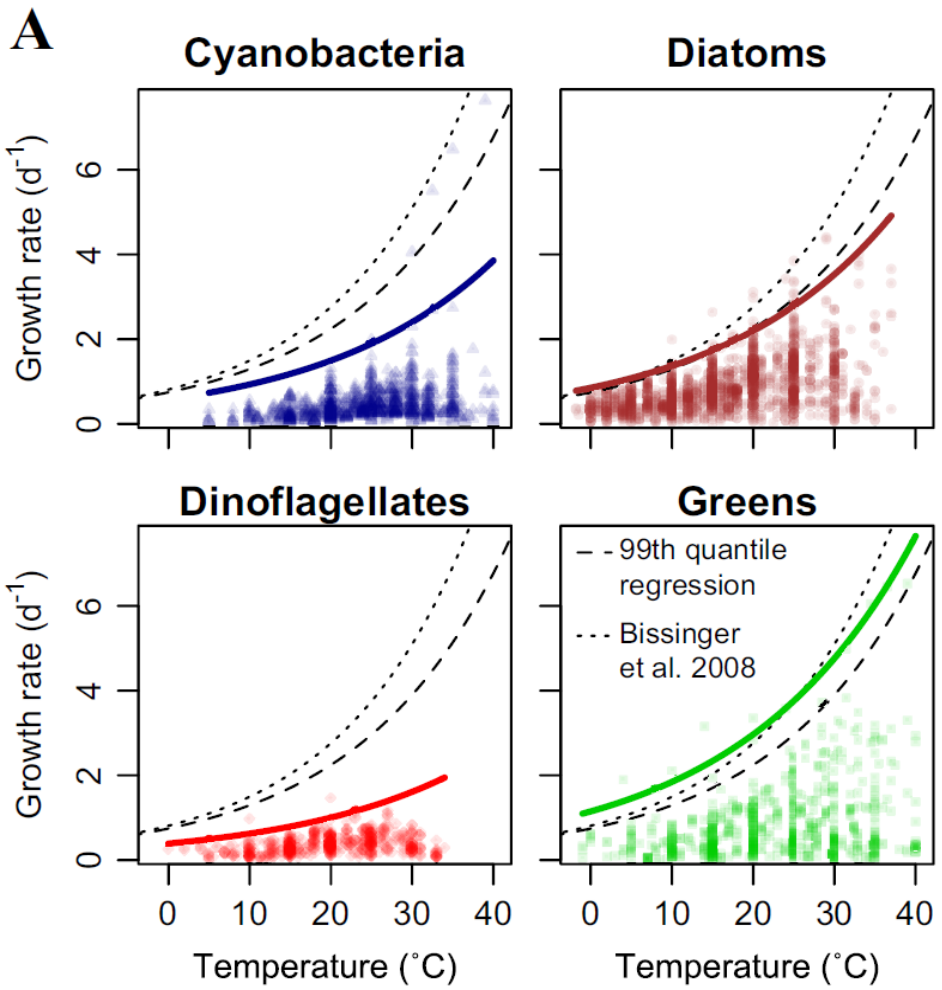
Moran et al. 2010

Arctic (including Chukchi S.)

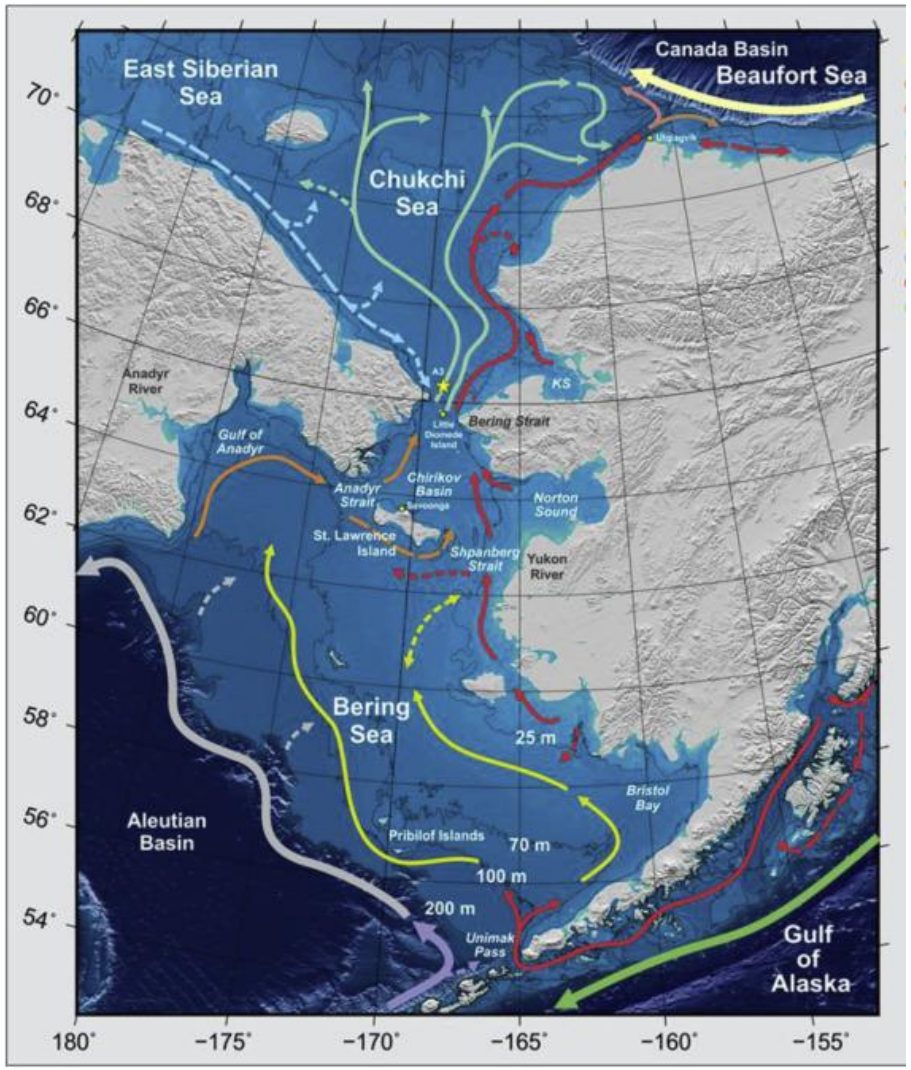


Lewis et al. 2020

Temperature and nutrients influence species growth

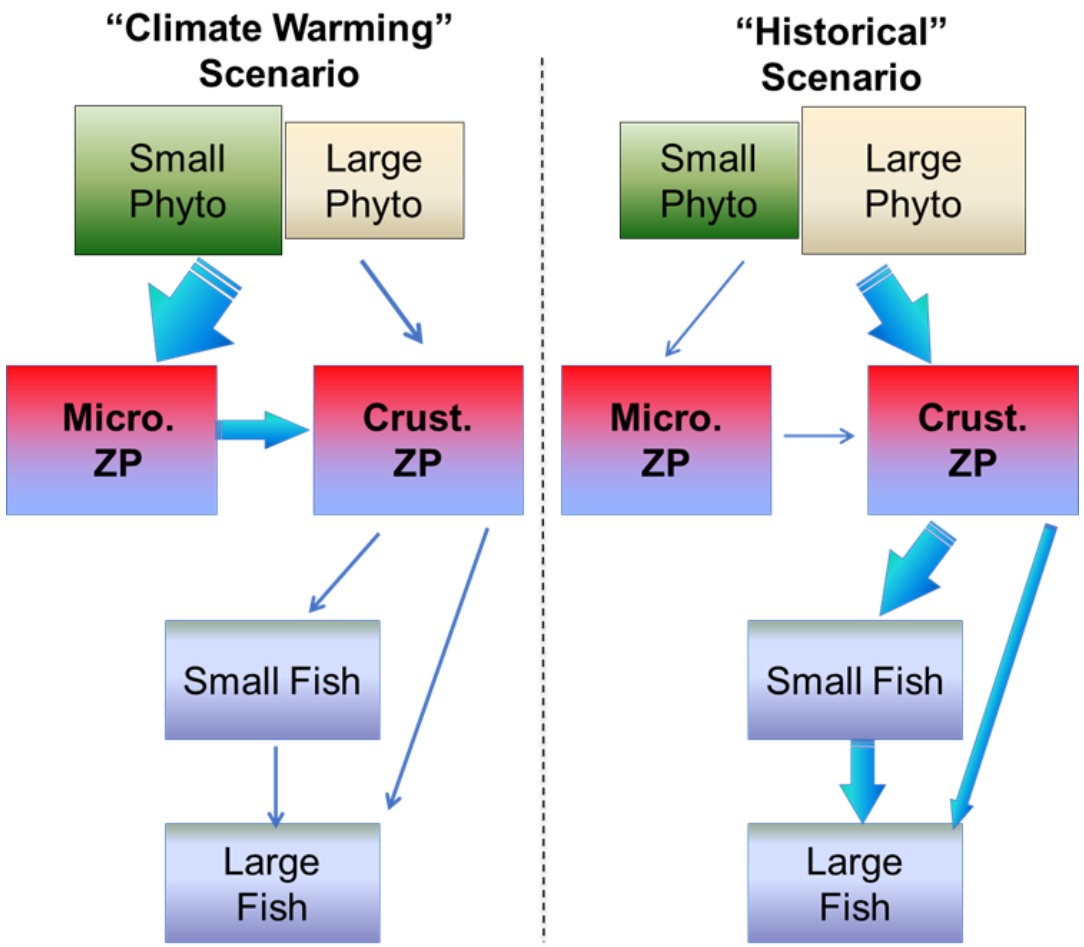


Kremer et al. 2017



Danielson et al. 2020

Potential climate-driven changes in ecosystems



Project goals: Can we assess phytoplankton changes using satellites?

- Use satellite ocean color data (VIIRS, MODIS, GlobColour) for N. Bering & Chukchi seas, ground-truth with *in situ* data:

1) analyze **community size structure** based on remote-sensing **empirical chlorophyll-*a* -based algorithms** and reflectance ($R_{rs}(\lambda)$)**;**
2) Use $R_{rs}(\lambda)$ to determine changes in ***Synechococcus*** **(small photosynthetic cyanobacteria)** (Lange et al. 2020);
3) Explore correlative methods to assess the **probability of occurrence of harmful algae** such as *Alexandrium* spp. using satellites (Sentinel 3-A-OLCI).
4) Estimate **diatom** abundances from $R_{rs}(\lambda)$

Size-fractionated chlorophyll *in-situ* datasets

In-situ dataset:

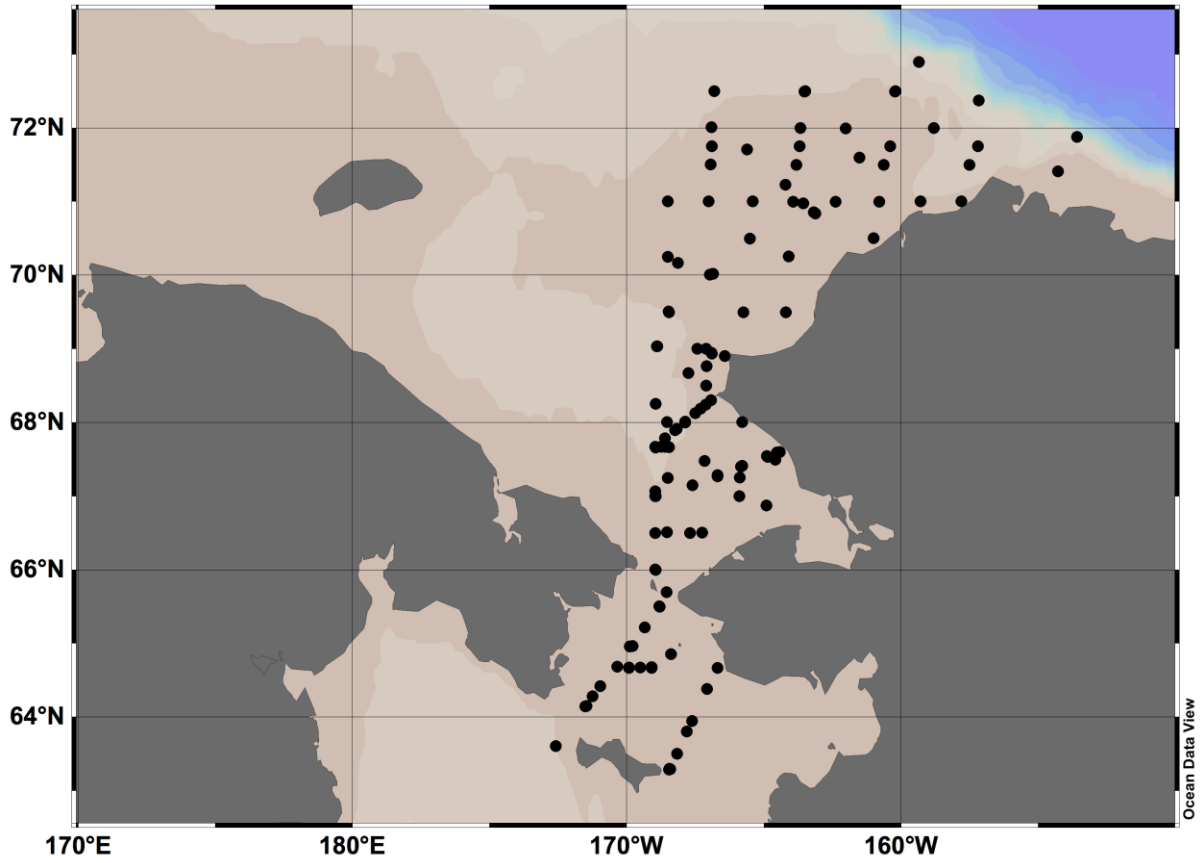
- 221 samples
- **Surface samples** (depth < 10 m)
- Size-fractionated filtration

Micro: > 20 µm

Nano: 5-20 µm

Pico: < 5 µm

- Years: 2017 and 2019
- Months: June to September.

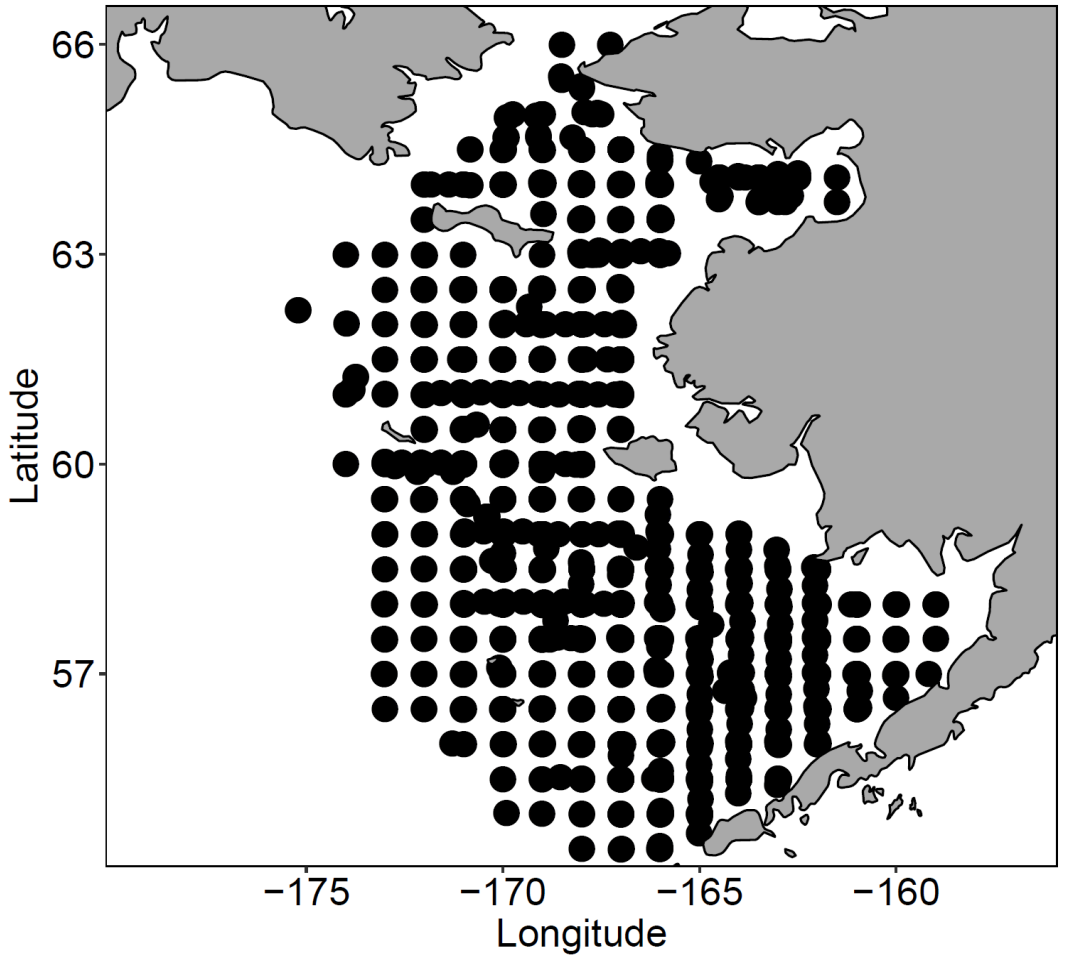


Size-fractionated data – Bering Sea (<10 µm & >10 µm)

2nd In-situ dataset:

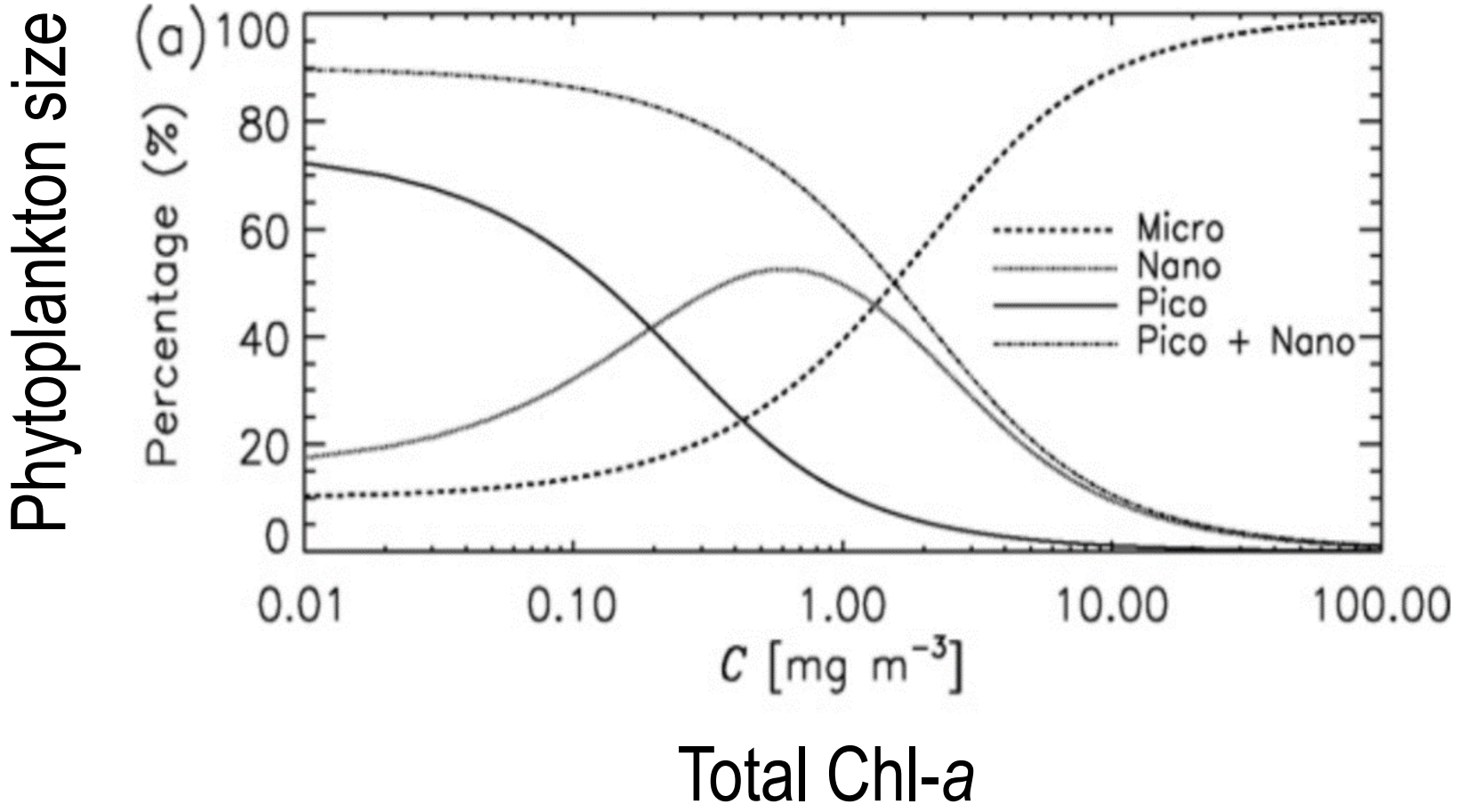
- ~1500 samples
- **Surface samples** (depth < 10 m)
- Size-fractionated filtration (<10 µm & >10 µm)

- Years: 2003 and 2021
- Months: August - September.

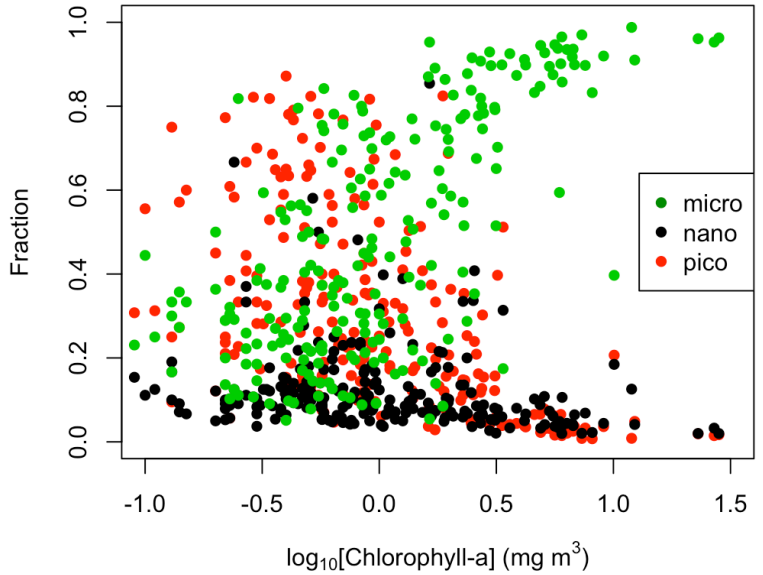


Size fraction models

Brewin et al. 2010



Bering / Chukchi data



Phytoplankton size fractions:

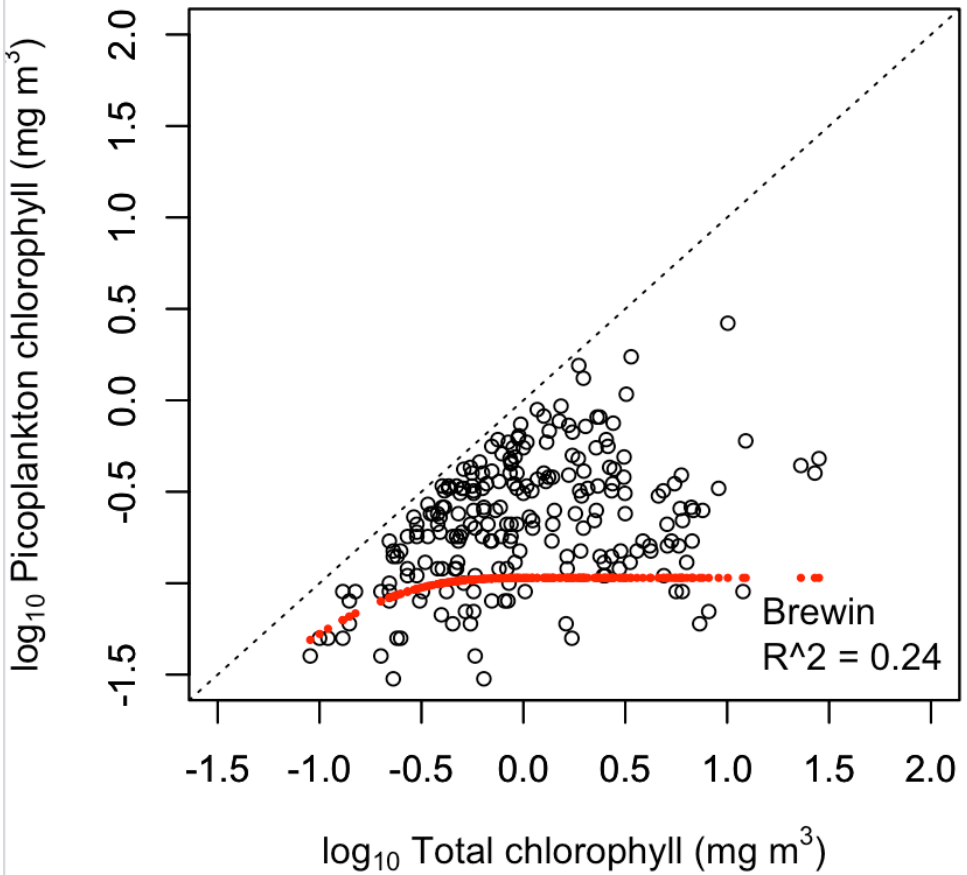
Micro: > 20 µm

Nano: 5-20 µm

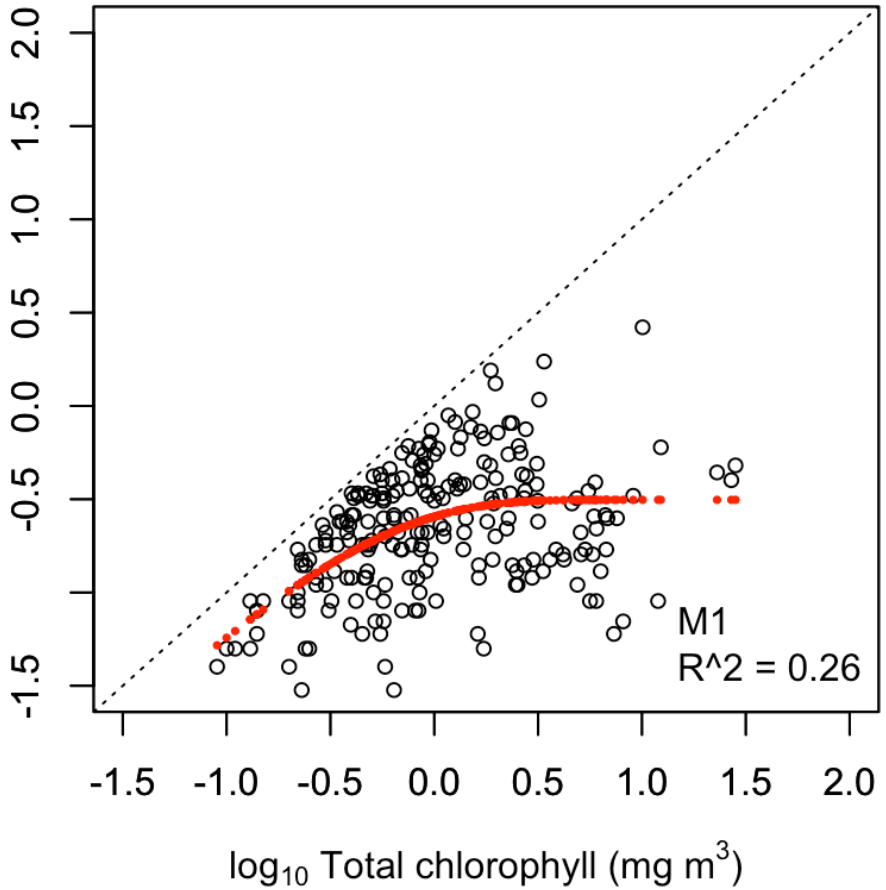
Pico: < 5 µm

Brewin et al. 2010 global vs regional

"Global" parameters



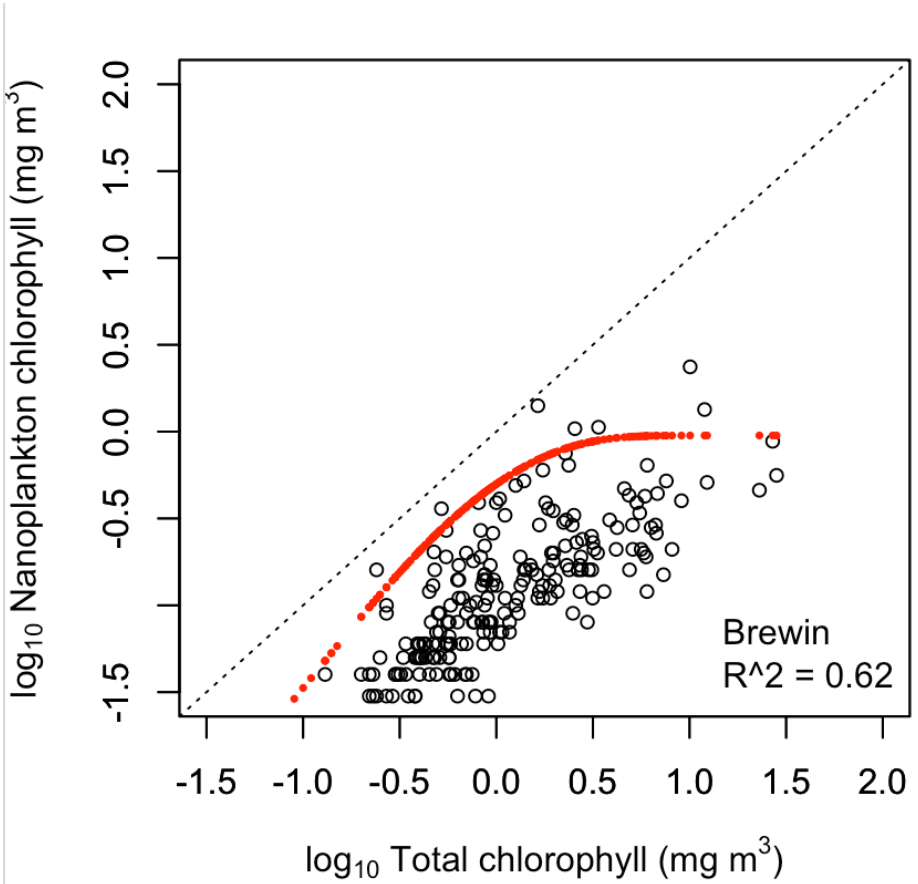
Regionally-parameterized model



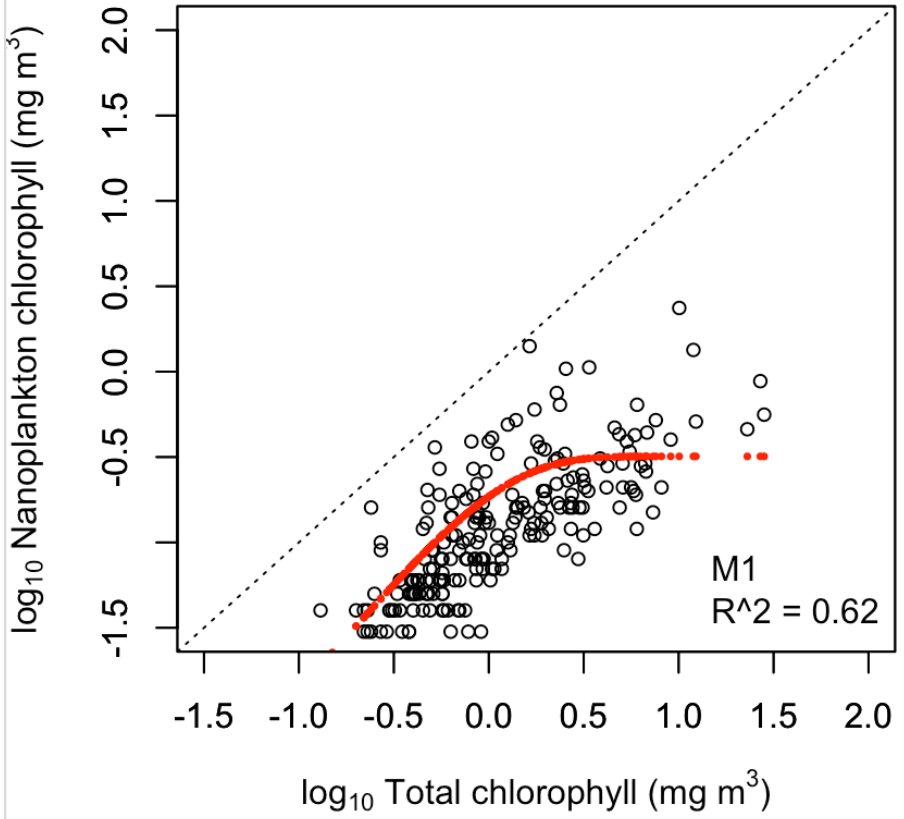
More picoplankton relative to total chl-a in "our" data

Brewin et al. 2010 global vs regional parameters

"Global" parameters



Regionally-parameterized model

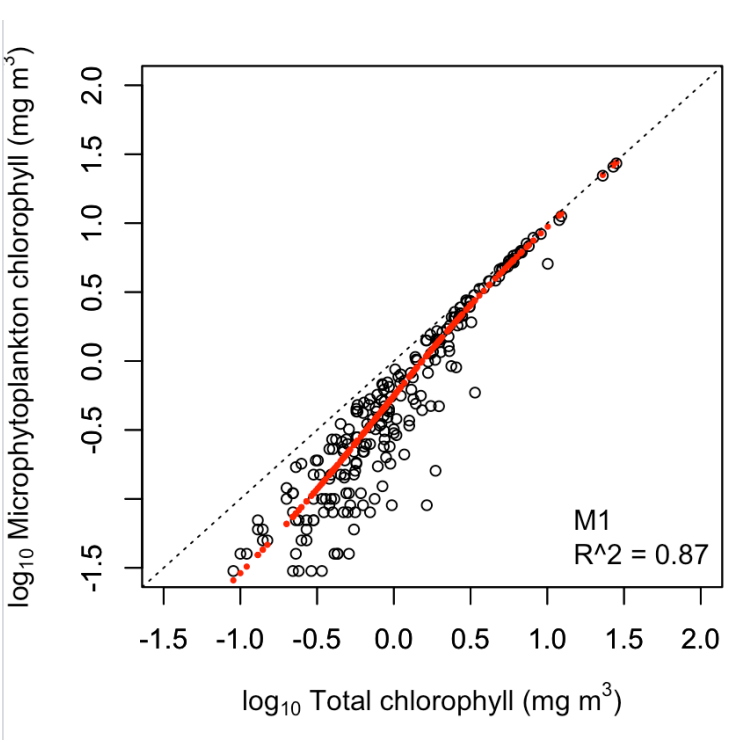


Less nanoplankton

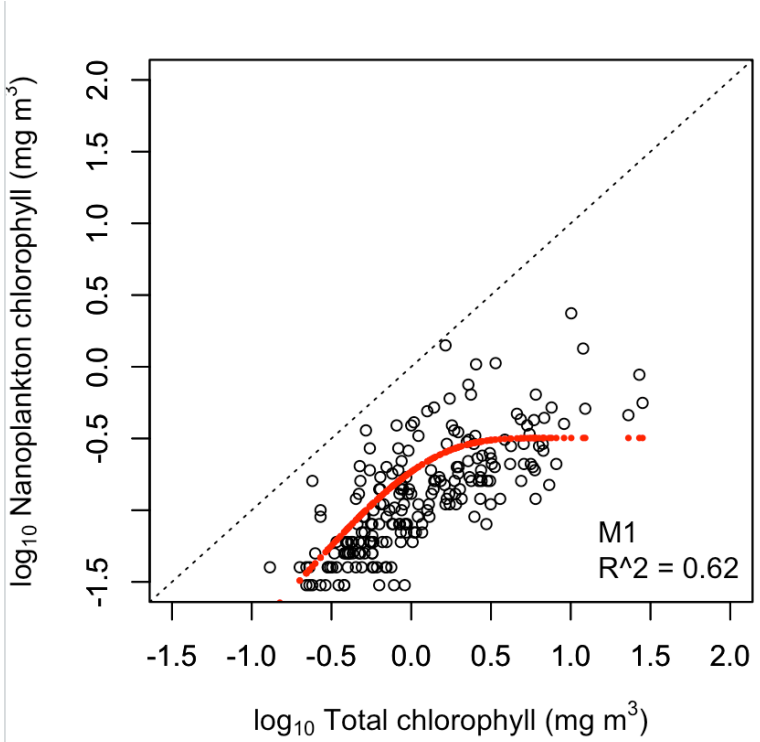
Brewin et al. 2010 regional

Regionally-parameterized model

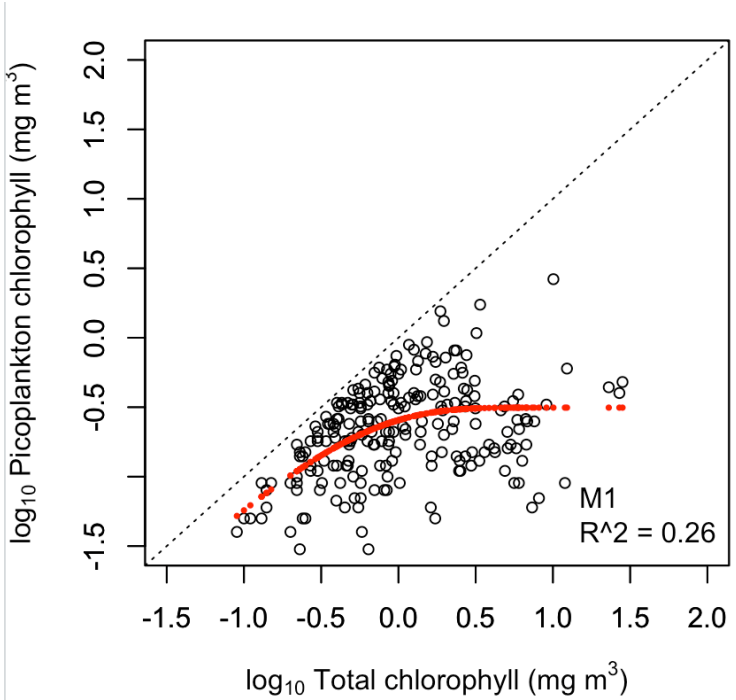
Micro (>20 μm)



Nano (5 -20 μm)



Pico (<5 μm)



Chl-a size fraction modeling - comparisons

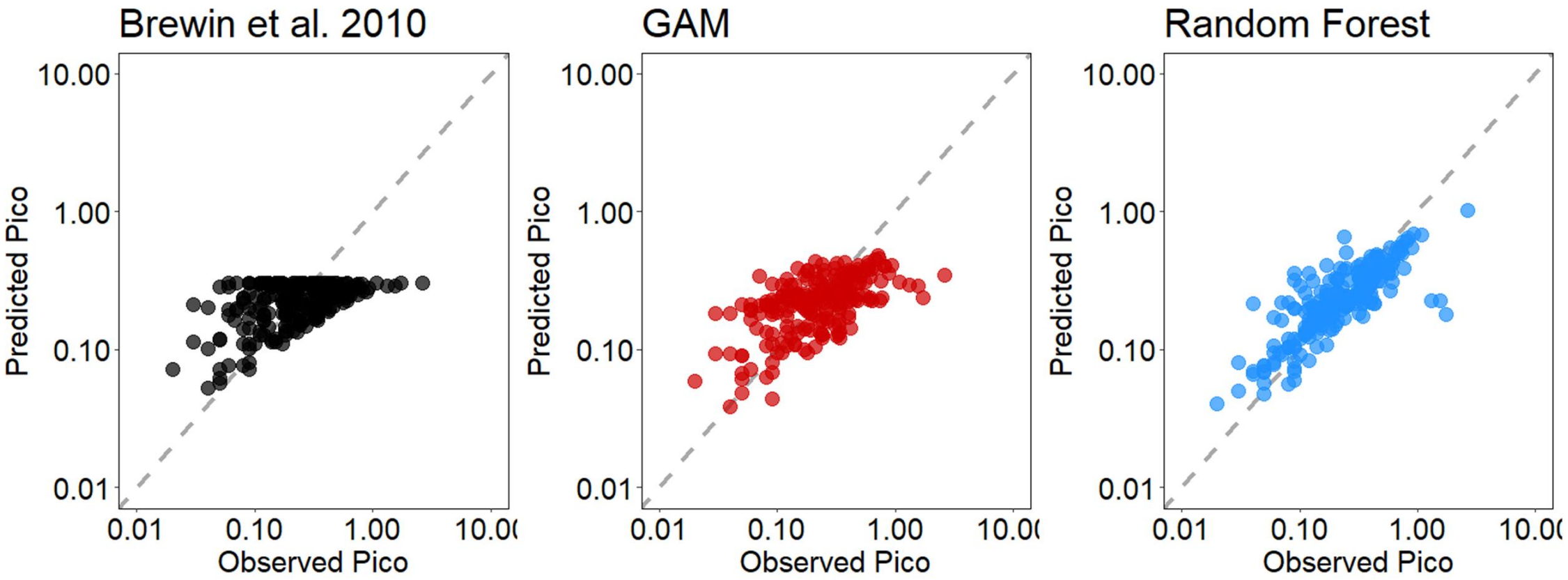
Basic model used for all 3 size fractions:

Size chl-a ~ total chl-a + SST

Comparative approaches

- Brewin et al. 2010 (only total chl-a).
- Generalized additive model (GAM)
- Random forest model

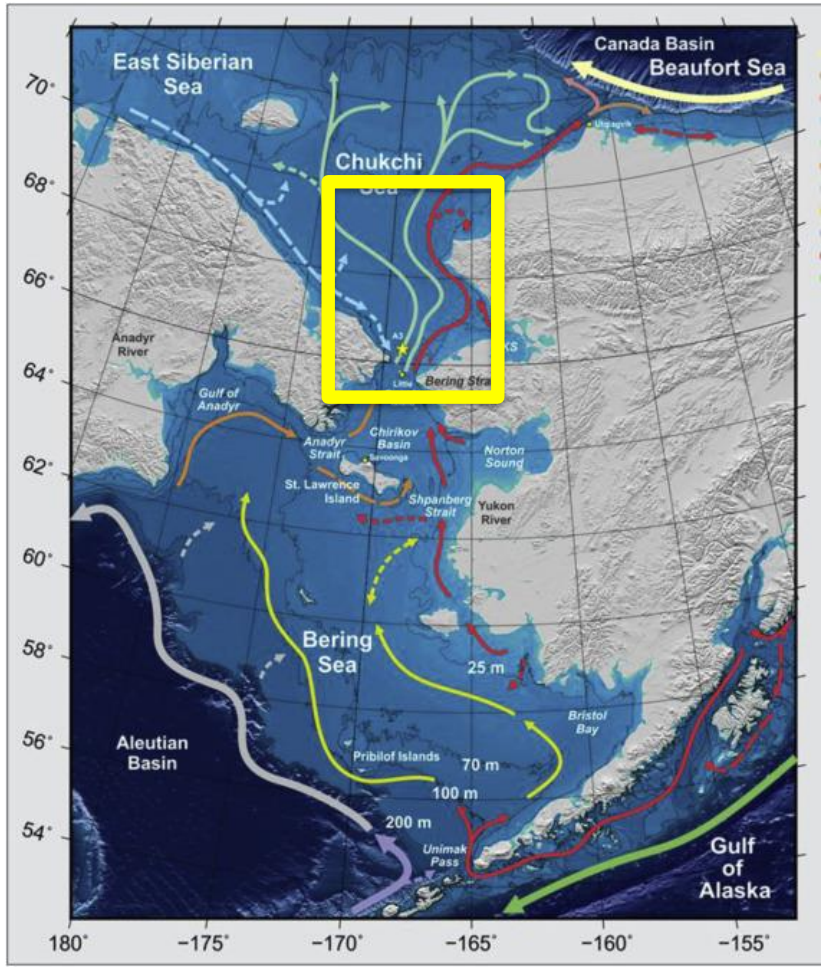
Picoplankton (<5 µm) predictions from different models

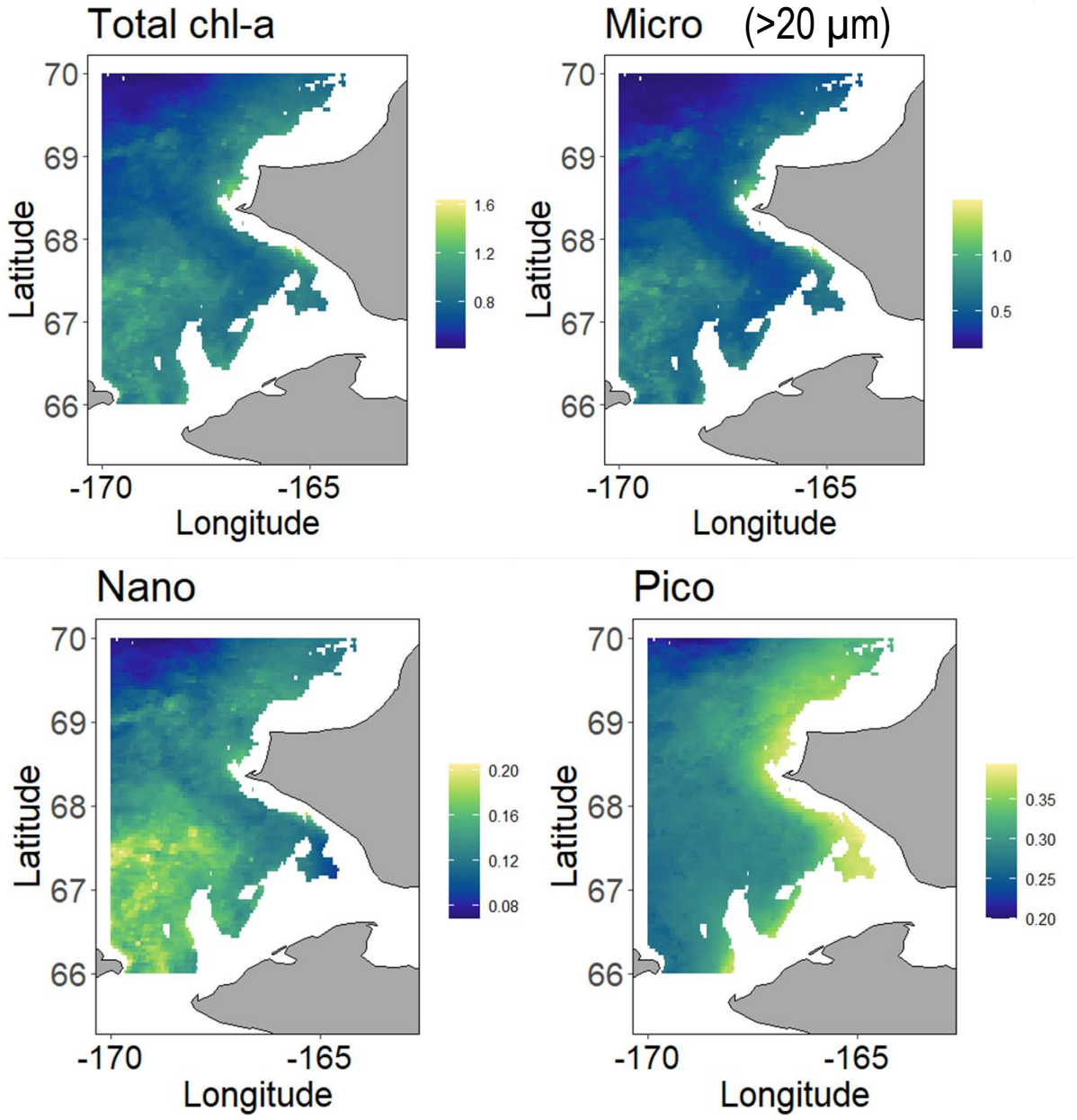


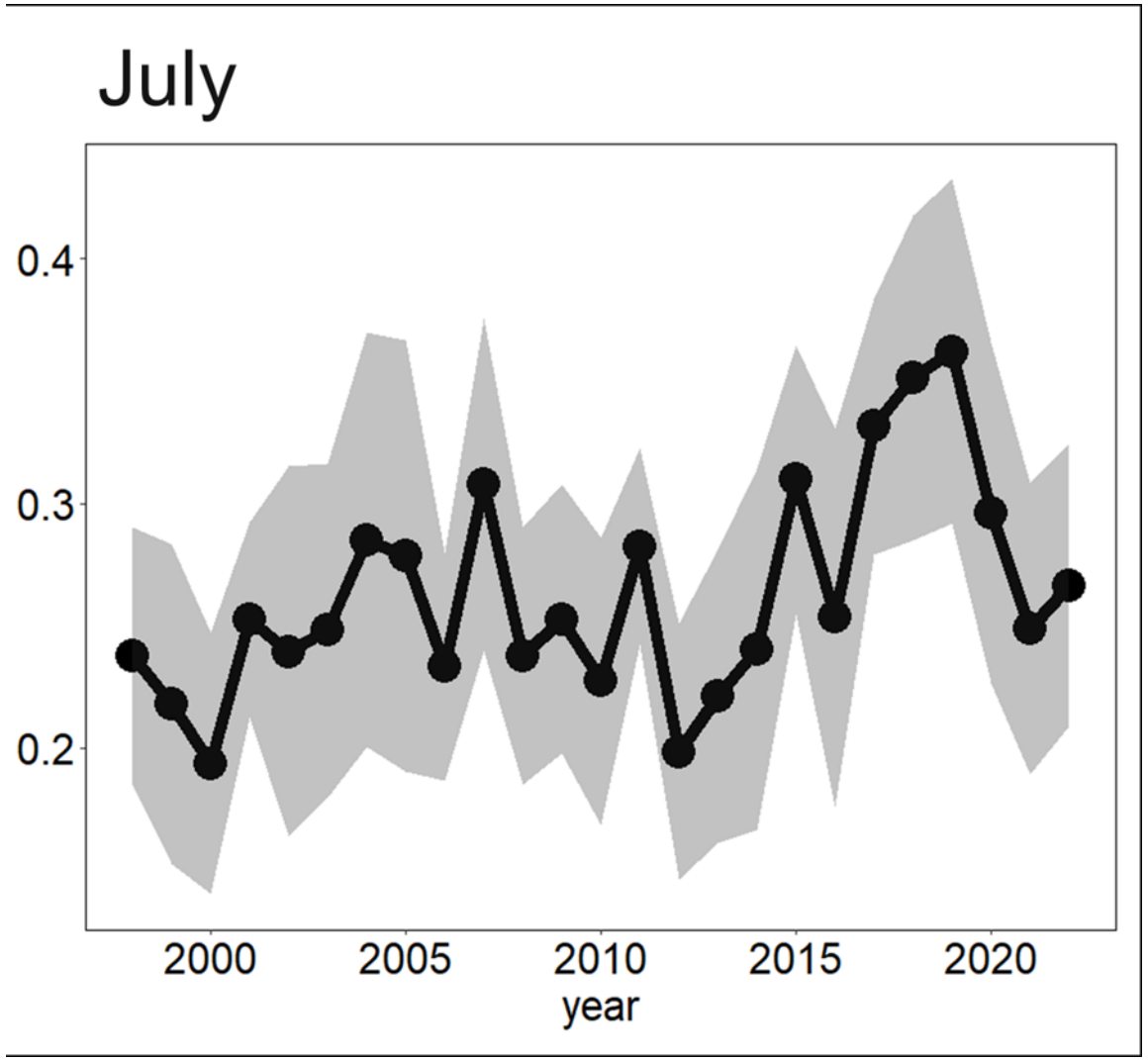
Model performance - Bootstrap analysis (80/20)

Size class	Metric	$Brewin_{chla}$	GAM_{chla}	GAM_{chla_sst}	RD_{chla_sst}
Pico (< 5 µm)	RMSE	0.304	0.299	0.292	**0.288**
Pico (< 5 µm)	R^2	0.25	0.28	0.31	**0.33**
Nano (5- 20 µm)	RMSE	0.296	**0.261**	0.263	0.271
Nano (5- 20 µm)	R^2	0.61	**0.64**	**0.64**	0.61
Micro (> 20 µm)	RMSE	0.259	**0.241**	0.245	0.258
Micro (> 20 µm)	R^2	0.87	**0.88**	0.87	0.86

Combining GAM_{chla_sst} model and Globcolour chl-*a* data

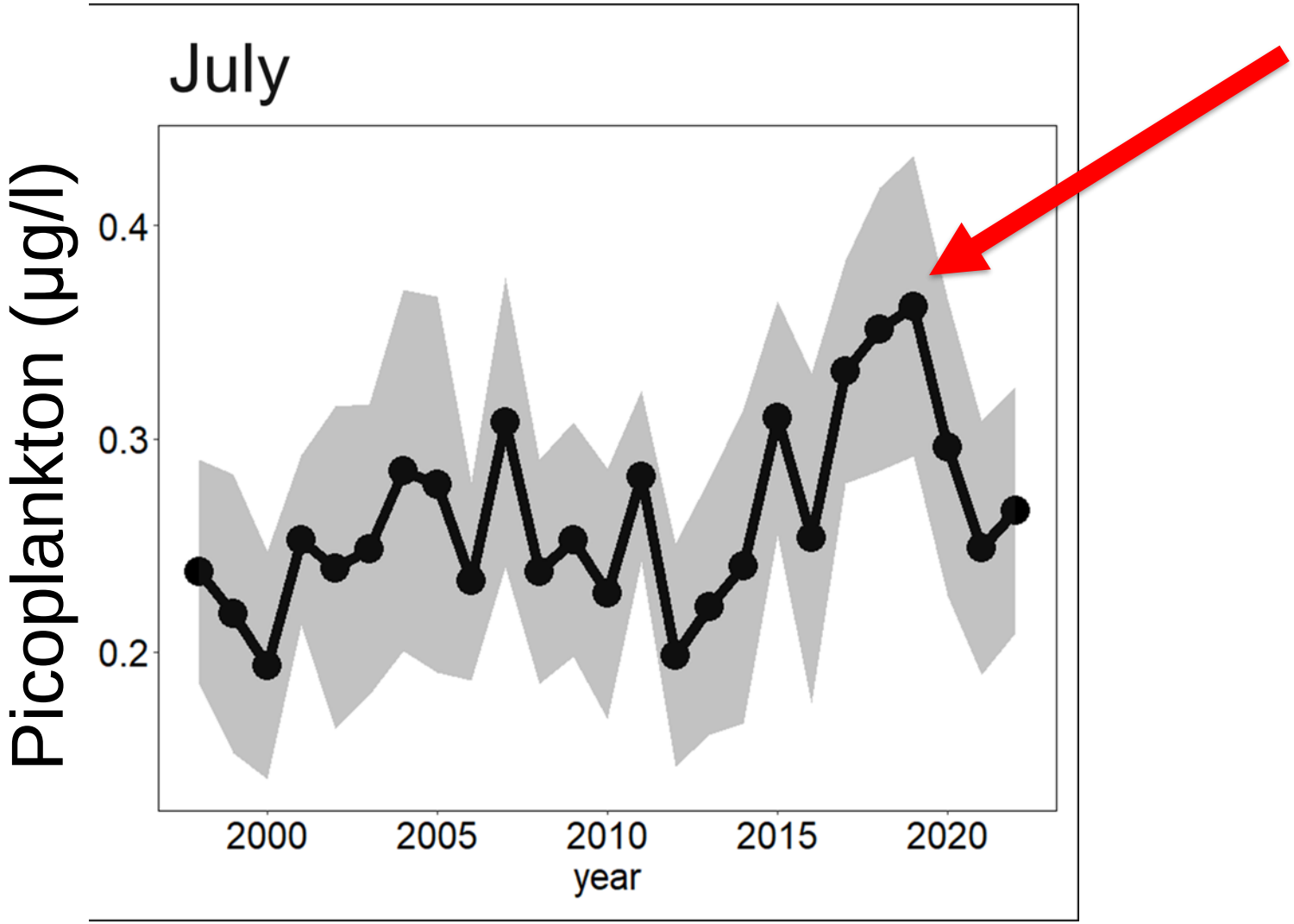




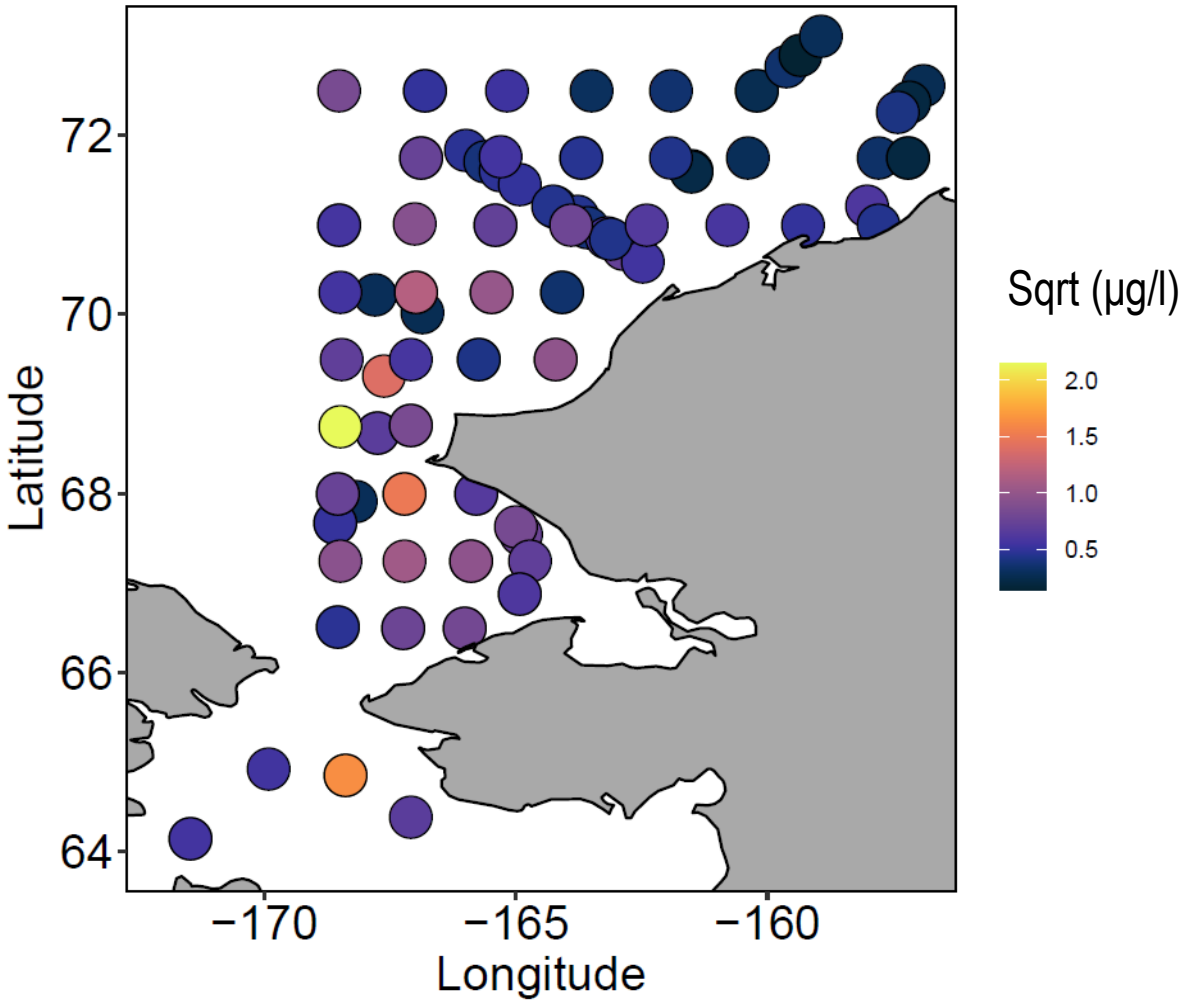


Mann-Kendall trend test
s = slope
p = p-value

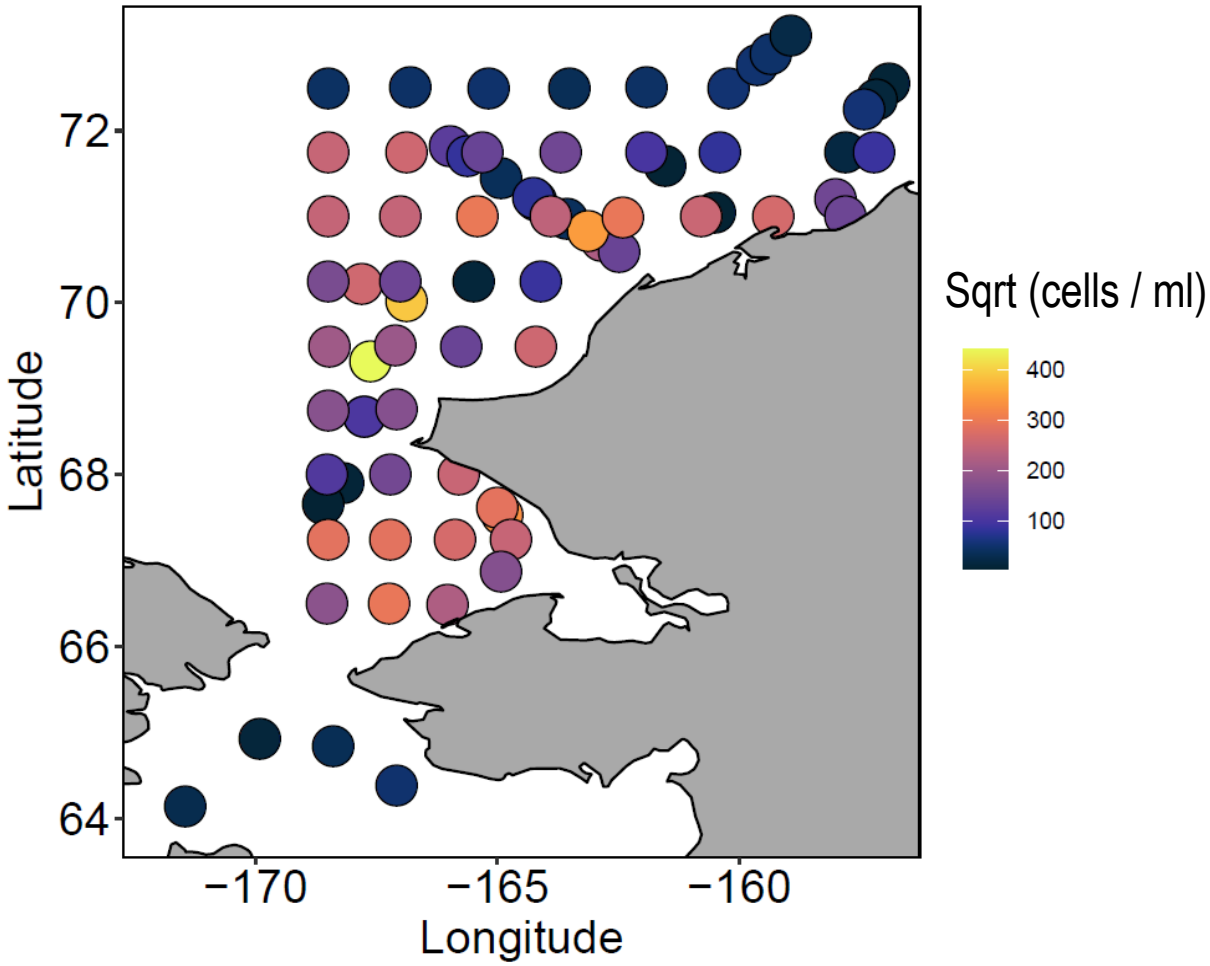
Mann-Kendall	Pico		Nano		Micro	
	p	*s*	*p*	*s*	*p*	*s*
June	**<0.01***	0.48	0.76	-0.05	**<0.01***	-0.46
July	**<0.05***	0.35	0.91	0.02	0.17	-0.20
August	0.13	0.22	0.15	0.21	0.52	0.01
September	0.90	0.02	0.76	-0.05	0.31	0.15


July
Picoplankton (µg/l)
0.4
0.3
0.2
2000
2005
2010
2015
2020
year

Picoplankton 2019



Synechococcus spp. 2019 (from flow cytometry)

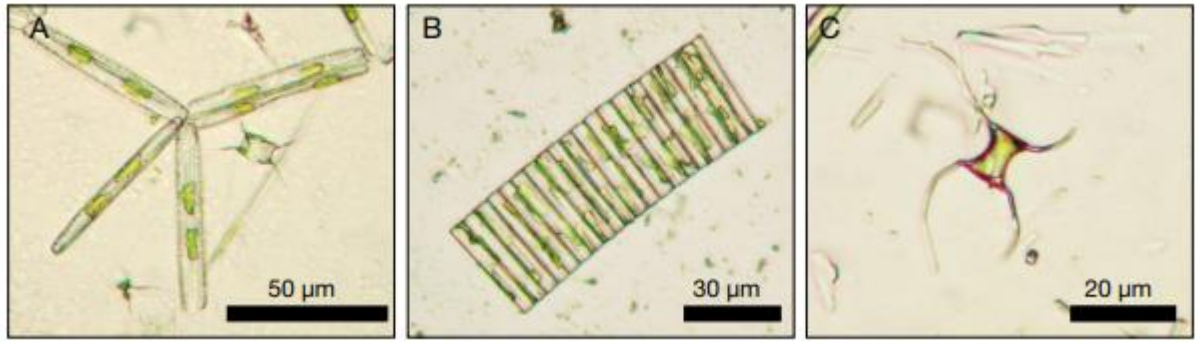


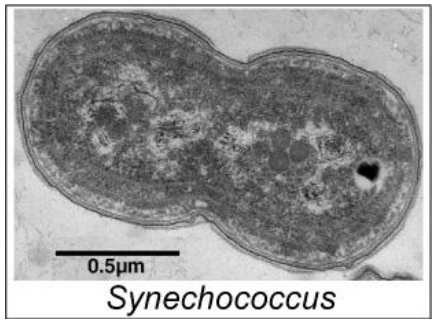
Project goals: Can we assess phytoplankton changes using satellites?

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Phytoplankton community change – NBS/Chukchi Sea





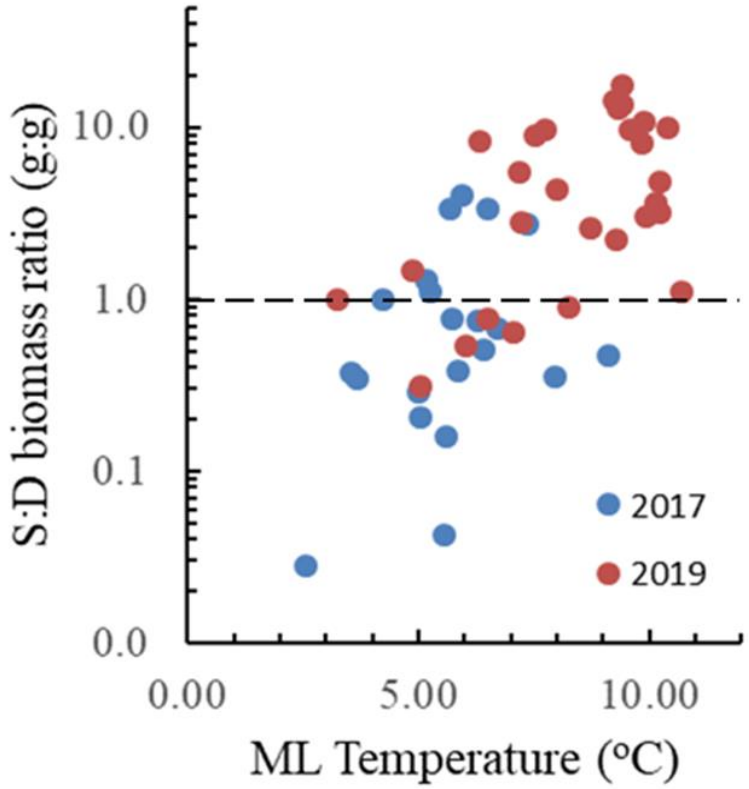
Synechococcus

Synechococcus is ~ 1/100 the size of many diatoms

- In the '***warm***' summer of 2017, there was relatively high diatom biomass.
- In the "***very warm***" summer of 2019 *Synechococcus* commonly exceeded diatom biomass.

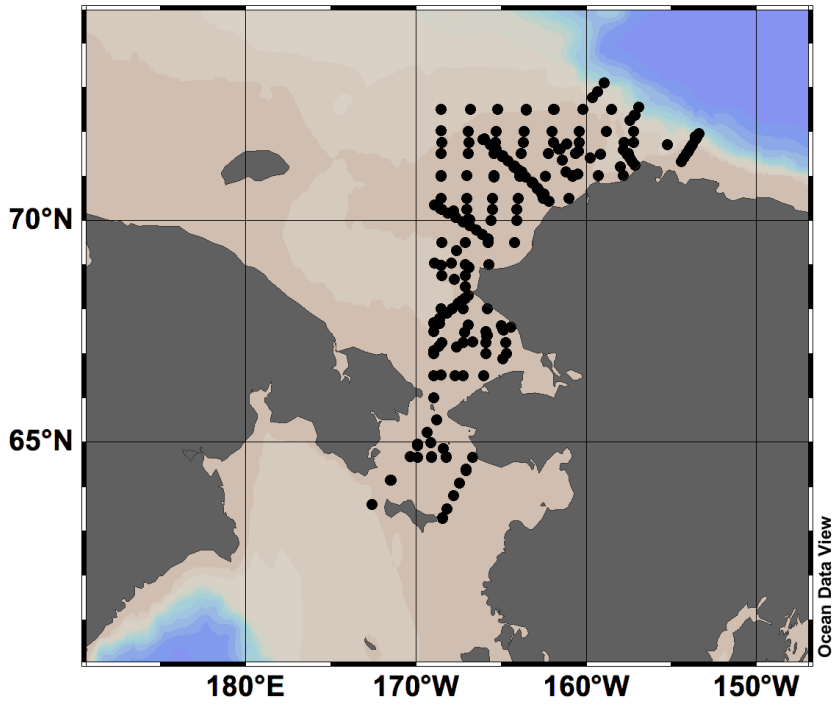
Porgorzelec et al. 2017. MEPS. 569: 77-88 (top photo); https://www.whoi.edu/science/b/people/ewebb/syne.html (bottom photo)

Synechococcus to diatom biomass ratio (S:D) vs temperature



Lomas et al. in prep

Synechococcus abundance from VIIRS R_{rs} (2012-2022)



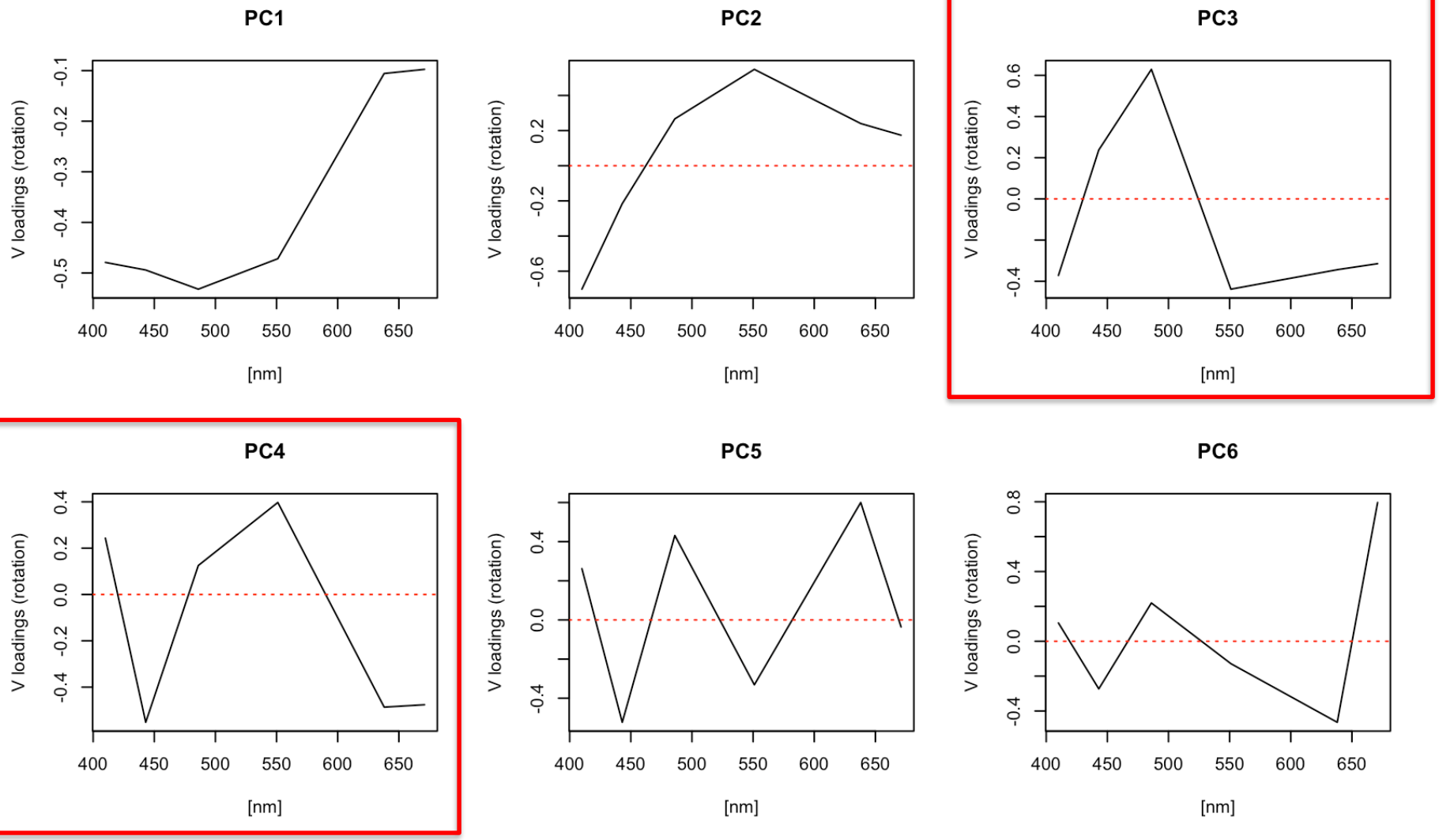
Suomi-NPP VIIRS R_{rs} data

Spatial resolution: 750 m / 2 km match-up
Temporal resolution: daily / 3 days match-up

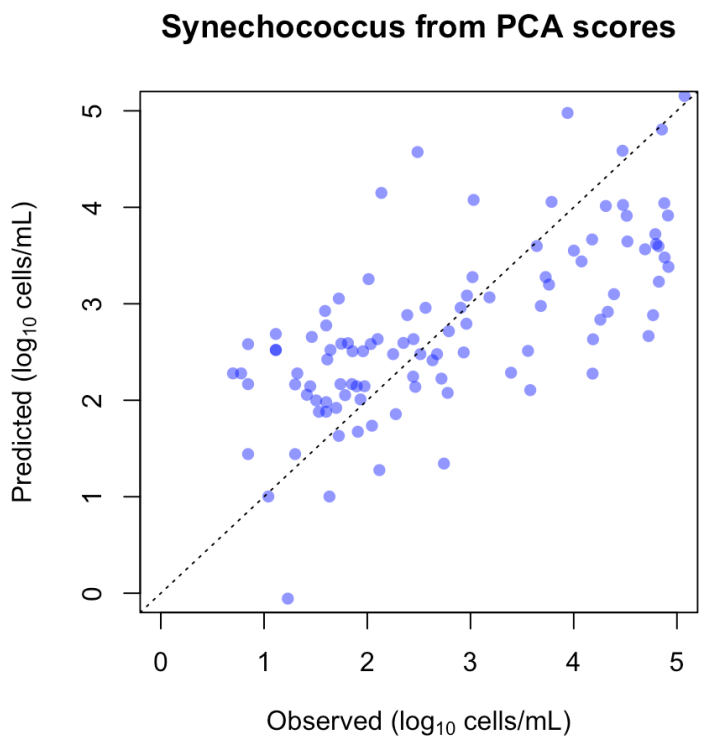
In-situ *Synechococcus*: n = 739
Match-up with VIIRS R_{rs}: n = 104

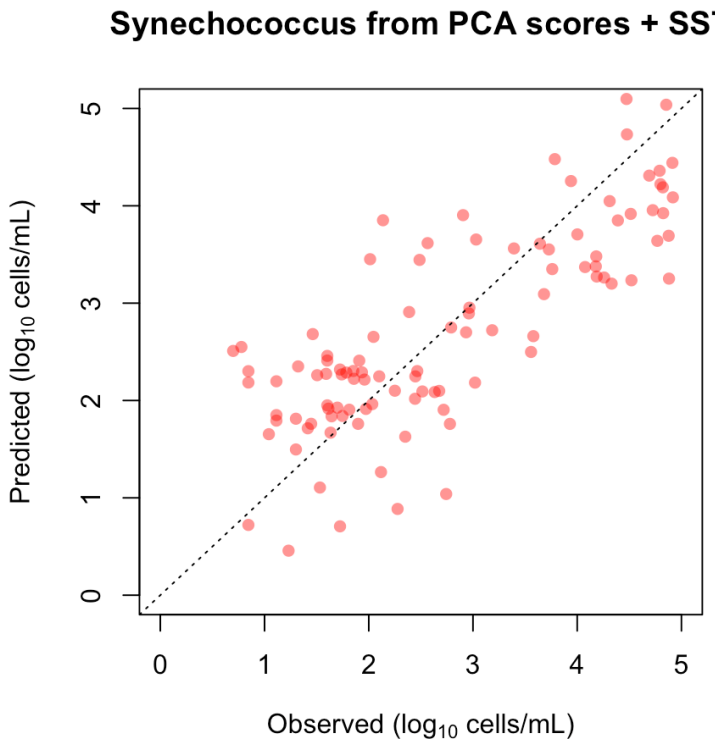
Method: Principal Component Regression following Lange et al. 2020

VIIRS R_{rs} : PCA loadings



Synechococcus (cells mL^{-1}) from VIIRS R_{rs} predictions





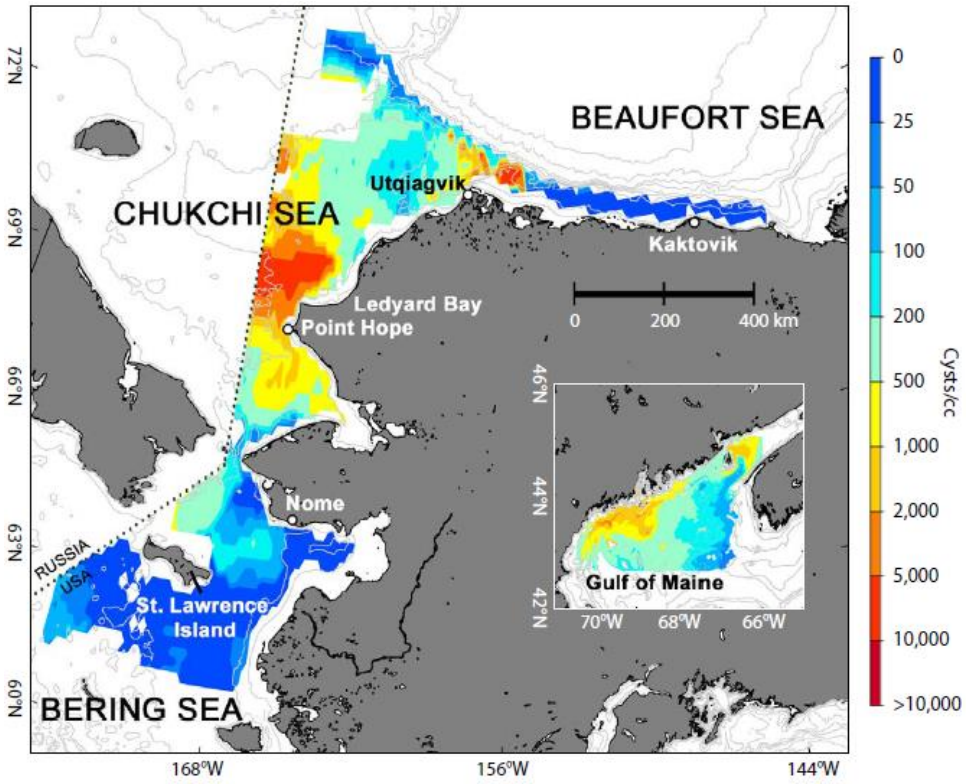
Predictors	R^2	MAE	Bias	RMSE	N
PC3, PC4	0.45	0.77	< 0.001	0.95	104
PC3, PC4, SST	0.63	0.65	< 0.001	0.79	104

Project goals: Can we assess phytoplankton changes using satellites?

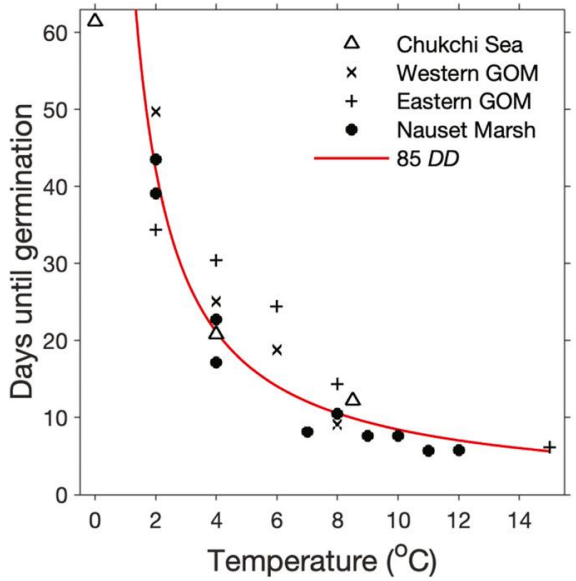
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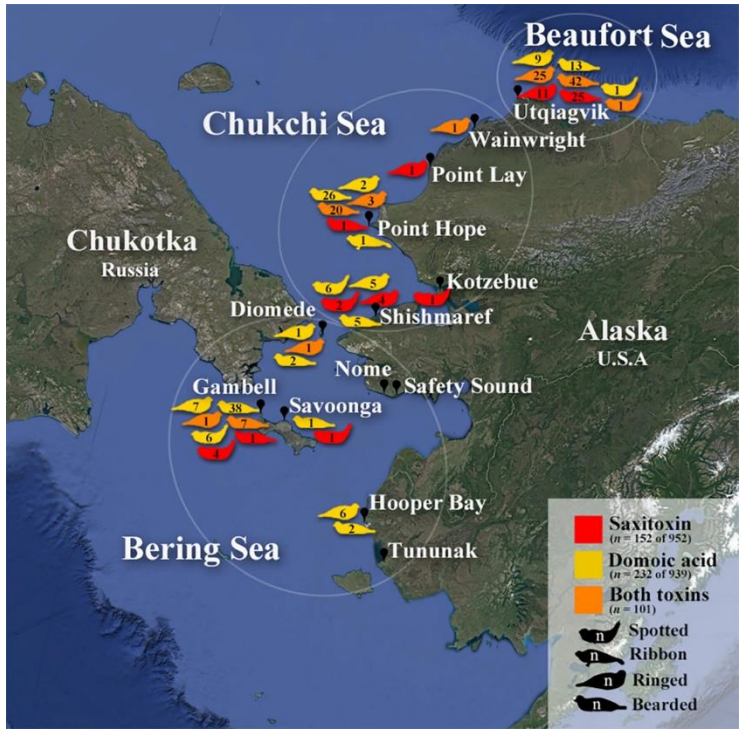
Harmful algae blooms – increasing in the Pacific arctic



Alaskan (2018–2020) *Alexandrium catenella* cyst abundance in surface sediments. Sites visited across multiple years were averaged to create maps.

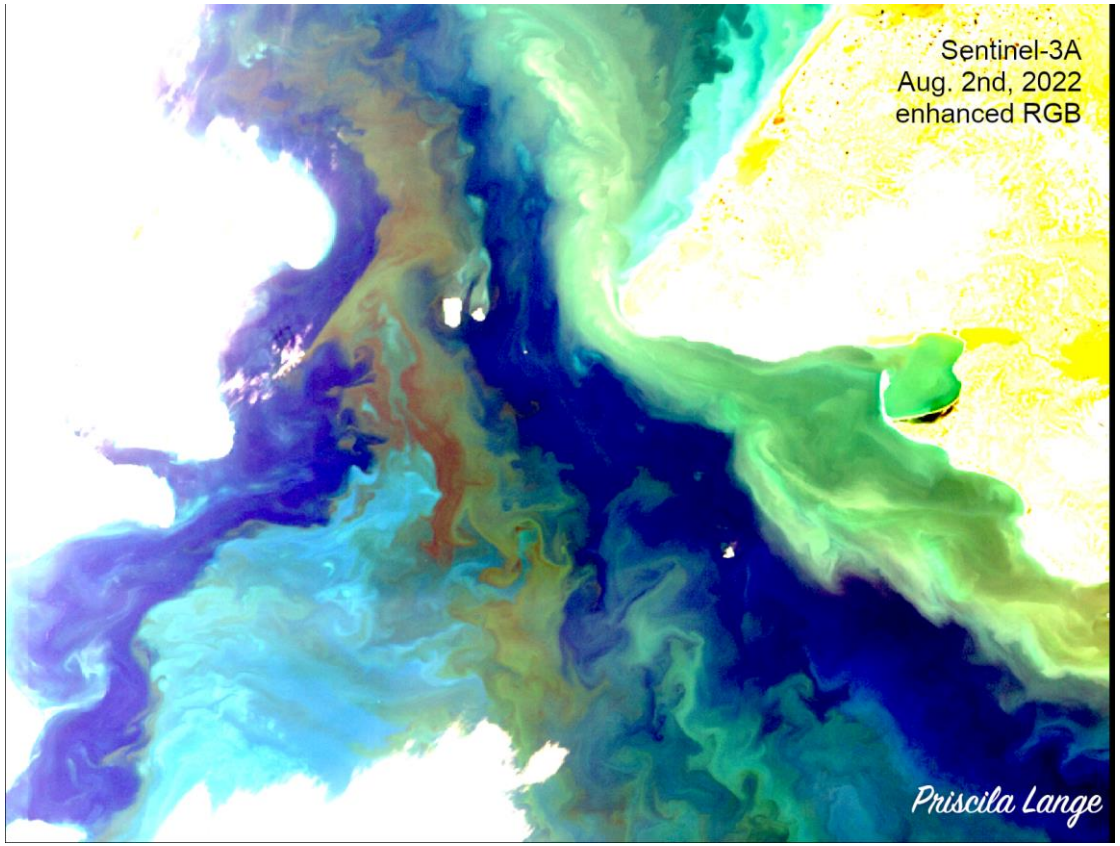


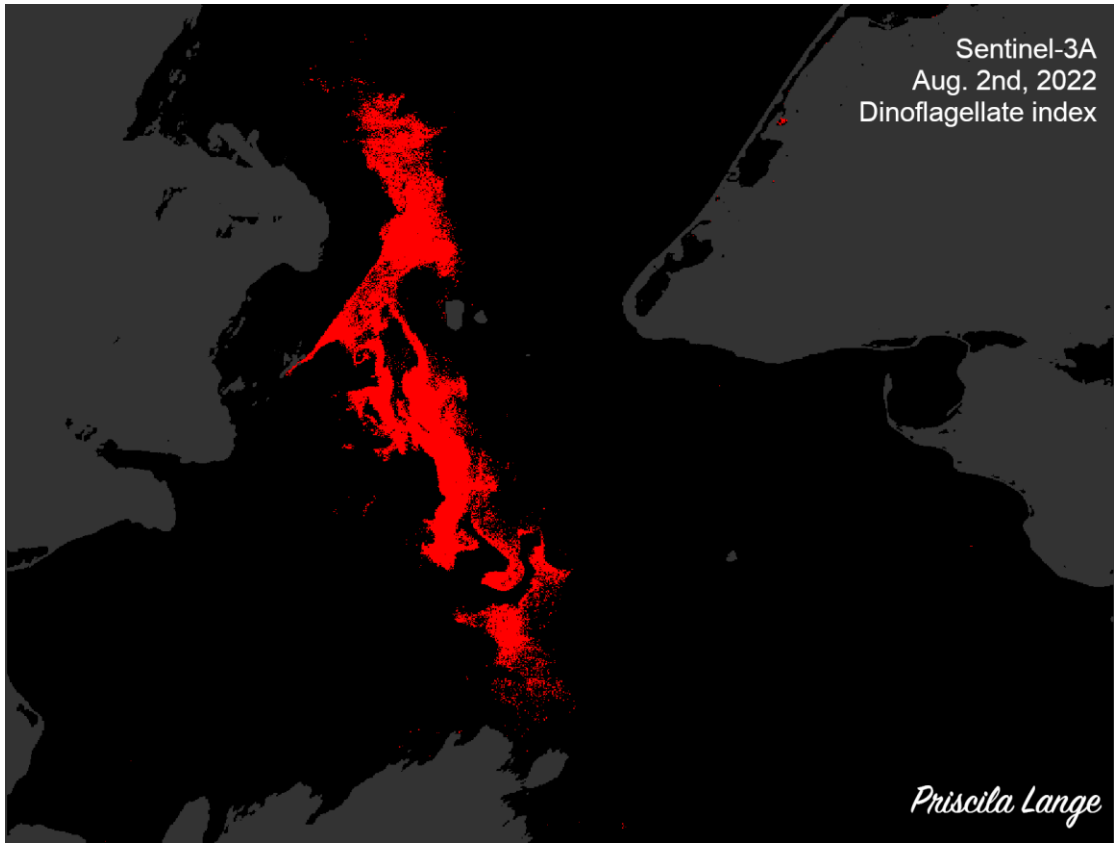
Anderson et al. 2021, 2022



Hendrix et al. 2021

Harmful algae blooms – satellites





HAB:
Alexandrium

Phytoplankton species information – crucial for developing algorithms and for understanding responses to climate change



Summary

- Regionally tuned models perform best for all three size fractions, with total chlorophyll being the most important predictor, while SST helps improve the fit for picoplankton (<5um).

- Preliminary analyses suggest increasing picoplankton in June and July, particularly during the warm 2017-2019. Such changes in size composition, along with earlier sea ice retreat and bloom timing, will influence plankton food web structure and function.

- Promising results of estimating *Synechococcus* abundance from VIIRS R_{rs} data.

Next steps

- Develop size-fraction models using size fraction dataset (<10, >10 μm) collected in the Bering Sea (2003-2019).

- Use *Synechococcus* estimation model in combination with long-term (2012-2022) VIIRS data to assess potential inter-annual and decadal changes in *Synechococcus* abundances.

- Develop algorithms to detect harmful algae blooms (e.g. Alexandrium).