Phytoplankton Biomass Predictions in Equatorial Pacific using Random Forest Modeling

by

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### **Abstract**

### Phytoplankton biomass drivers are integral to our understanding of how climate change will impact global photosynthesis and carbon sequestration. The equatorial Pacific is a region with high primary productivity due to the convergence of easterly trade winds and equatorial currents, though few oceanographic cruises take place here. This study assesses the predictive performance of random forest regression models for phytoplankton biomass along with which environmental variables play the largest role in biomass. We hypothesized that using chlorophyll, nutrients, salinity and temperature measurements we can predict Prochlorococcus, Synechococcus, and Eukaryotes biomass in the equatorial Pacific. Each population exhibited varying importance rankings for predictor features. Results suggest that satellite derived chlorophyll a concentration is a useful predictor for Prochlorococcus, and that Synechococcus biomass is most influenced by phosphate and Eukaryotes are most influenced by nitrate. The model captures overall biomass trends well, with discrepancies observed near the equator, likely due to complex interactions among environmental factors.

### **Plain Language Summary**

Phytoplankton are tiny marine plants that play a crucial role in photosynthesis and carbon storage. Understanding what affects their growth is important for predicting how climate change will impact our planet. This study focused on the equatorial Pacific, where strong winds and currents create favorable conditions for phytoplankton. However, there is limited research in this region. Using data obtained from a cruise in the equatorial Pacific in spring of 2023, computer models were built and used to predict phytoplankton biomass. Different sizes of phytoplankton were found to be influenced by different factors. Some were able to be derived well mostly from remotely measure chlorophyll pigments in the water, while others were better observed relying more on nutrients.

### **Introduction**

Phytoplankton biomass plays a critical role in the oceanic carbon cycle and the global climate system. Phytoplankton only represent about 1% of global photosynthetic biomass but are responsible for roughly half of the world's primary production and are a significant factor in the global carbon cycle, influencing climate patterns and atmospheric gas composition (Falkowski 2012). Phytoplankton biomass varies greatly in time and space, depending on a range of environmental factors, such as nutrient availability, light, temperature, and ocean currents (Behrenfeld et al., 2006). Changes in phytoplankton biomass can have significant impacts on the food web, carbon cycling, and the overall health of the ocean (Boyd et al., 2015). For example, low phytoplankton biomass can lead to reduced food availability for zooplankton and fish, which can in turn affect higher trophic levels and commercial fisheries (Hunt et al., 2002). Conversely, high phytoplankton biomass can result in human, ecological and economic consequences (Stauffer et al. 2019). In addition to biomass, phytoplankton size is also an important factor that can impact their ecological role and influence the marine food web.

Phytoplankton are diverse physiologically with size ranges from 0.6 to 200 µm, with three size classes, picoplankton (diameter <2 μm), nanoplankton (diameter from 2 to 20 μm), and microplankton (diameter >20 μm) (Brotas et al., 2022). While smaller plankton generally occupy the mixed layer longer due to their lower sinking rate, their carbon export is proportional to their contributions to total net primary productivity just as larger phytoplankton. Such pathways of export for picophytoplankton include aggregation and their incorporation into detritus as marine snow. Dune et al., 2005 also demonstrated that carbon export is relative to productivity, with larger phytoplankton, such as diatoms, that utilize mineralization, being more productive than smaller cells, resulting in increased carbon export to depth.

In the marine environment, there exists an inverse relationship between nutrient load and phytoplankton size. Smaller plankton are favored in oligotrophic oceans since they have a higher surface area to volume ratio making nutrient uptake relative to their size higher than larger phytoplankton (Acevedo-Trejos et al., 2018). Nitrate is a significant limiting nutrient for these organisms and its concentrations are correlated with other necessary nutrients as observed in the Redfield ratio (Tyrrell 2019). These correlations make nitrate a good proxy for estimating nutrient concentrations in the water column. Robinson et al., 2018 found that mean maximum photosynthetic rates have a positive relationship with phytoplankton size, meaning smaller size classes plankton have higher photosynthetic rates than their larger counterparts.

Prochlorococcus and Synechococcus are two important examples of small phytoplankton that dominate in oligotrophic oceans and play a significant role in global primary production. Prochlorococcus is the smallest known photosynthetic organism and is the most abundant photosynthetic organism in the world, responsible for up to 20% of global oxygen production (Partensky et al., 1999). This cyanobacterium is extremely well adapted to oligotrophic environments and has a high surface area to volume ratio, allowing for efficient nutrient uptake. Synechococcus is also abundant in oligotrophic oceans and can contribute up to 50% of primary production in these environments (Flombaum et al., 2013). Like Prochlorococcus, Synechococcus has a high surface area to volume ratio and is well adapted to oligotrophic environments. However, Synechococcus is more versatile in its nutrient requirements and can use a wider range of organic and inorganic compounds compared to Prochlorococcus ​​(Wawrik et al. 2009). Both of these cyanobacteria are projected to increase in abundance in due to increased sea surface temperatures as a result of climate change (Flombaum et al. 2013). Generally, warmer temperatures can increase phytoplankton growth rates by increasing metabolic rates and nutrient uptake (Boyd et al., 2013). However, the relationship between temperature and phytoplankton biomass is complex and depends on various factors such as nutrient availability, light, and water column stability.

Nutrient availability is a critical factor that influences phytoplankton biomass in the marine environment. Among the nutrients that are essential for phytoplankton growth, nitrogen (N) and phosphorus (P) are the most commonly limiting in oligotrophic oceans (Bristow et al. 2017). The Redfield ratio, which refers to the ratio of dissolved inorganic carbon, nitrogen, iron, a N to P in phytoplankton and marine organic matter, provides a useful framework for understanding the relative importance of these nutrients for phytoplankton growth. Generally, the concentration of CO2 in seawater is not a limiting factor for phytoplankton growth, as it is present in high concentrations (Bristow et al. 2017). Nitrate (NO3-) is a significant source of N for phytoplankton, and its concentrations are correlated with other necessary nutrients such as phosphate. Accurate estimation of phytoplankton biomass is crucial for understanding the dynamics of marine ecosystems and their response to environmental changes. However, traditional methods for predicting phytoplankton biomass based on empirical models have limited accuracy and generalization, especially in remote regions such as the Equatorial Pacific (Friedrichs et al., 2009).

​The Equatorial Pacific (5°S to 5°N latitude and 170°W to 120°W longitude) is a pelagic region of the Pacific Ocean and it’s known for its unique features that support relatively high levels of primary productivity (Chavez et al., 2011). This productivity is largely driven by the upwelling of nutrient-rich waters from the deep ocean to the surface, which provides a source of nutrients for phytoplankton growth (Karl and Lukas, 1996). The upwelling is caused by the convergence of the easterly trade winds and the equatorial currents, which create a region of intense mixing and nutrient exchange between the surface and deeper waters (Chavez et al., 2011). The pelagic waters of the north and south of the Pacific are generally characterized by low concentrations of nutrients and primary production, often referred to as a marine desert (Morel et al. 2010). This area is influenced by the El Niño and the Southern Oscillation (ENSO). ENSO is a large-scale interaction between the ocean and the atmosphere, and it cycles between El Niño, “normal”, and La Niña. El Niño is characterized by weakened equatorial easterlies winds, this results in negative sea level pressure and reduced upwelling. This results in increased atmospheric temperature along with higher SST due to a lack of cold, nutrient rich water upwelling (Wang & Fiedler, 2006). ENSO is most concentrated near the equator in the Pacific, with the largest changes in SST occurring there, and its variability has been increasing since the industrial revolution (Figure 1).

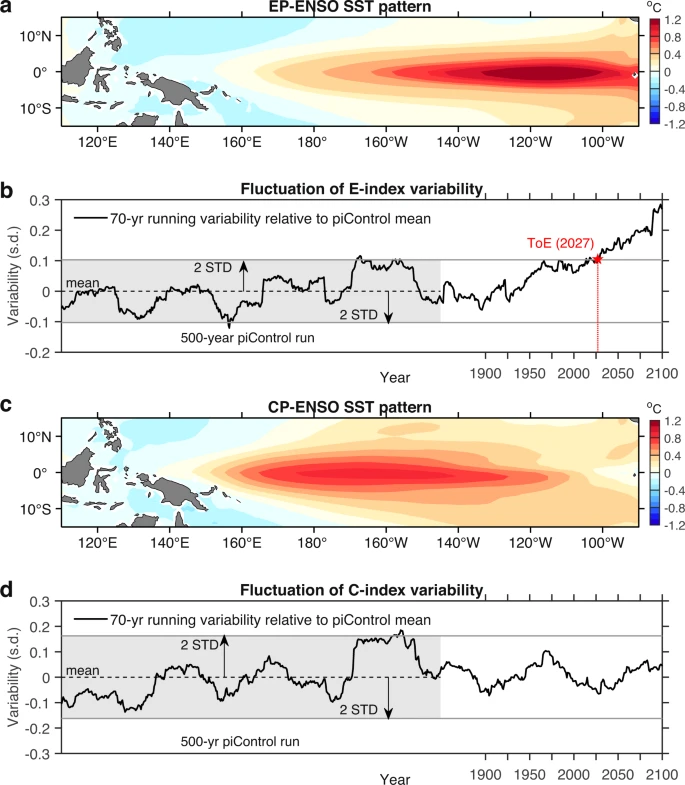


Figure 1: (Geng et al., 2022) El Niño SST variability from climate model GFDL-ESM4. Panel a shows the spatial pattern of ENSO in the eastern equatorial Pacific. Panel B describes El Niño variability relative to the mean of the E-index variability from pre-industrial levels. Panel C and D describe the same as panels A and B but relative to the central Pacific.

Few oceanographic research cruises take place in the equatorial Pacific, leaving a large gap of knowledge in the region. Especially considering global climate change leading to higher sea SST globally and increasingly frequent and intense El Niño events, it is important to understand and predict how biomass is changing and impacted by the changing climate. Satellite data has shown to be a promising remote sensing tool to predict phytoplankton biomass and random forest models have been show to be effective in predicting phytoplankton biomass (Zhang et al. 2021). Though there is a lack of existing models for the equatorial Pacific.

Through predicting biomass, we could expand biomass measurements on previous research cruises that did not have the instruments to collect this data. biomass is an important observation that can inform us of sequestration of surface carbon to the deep ocean in addition to environment nutrient load, photosynthetic efficiency, and even the marine food web structure. By expanding our knowledge of biomass through previous cruises taking place in the equatorial Pacific, we can gain a better understanding of inferred phytoplankton community changes over time.

To address the lack cruises that take place in the equatorial Pacific for phytoplankton biomass to be directly measured, a blend of remote sensing and in situ measures from a Pisces climatological model was used to create random forest models to predict the biomass of Prochlorococcus, Synechococcus, Eukaryotes. **I hypothesize that satellite derived chlorophyll a, nutrient concentration, and Sea surface temperature are large determining factors of phytoplankton biomass because they represent key environmental conditions that influence the growth and distribution of phytoplankton in the world's oceans.**

**Materials and methods:**

Data Retrieval:

SeaFlow testing and training data for phytoplankton biomass was obtained from R/V Thompson cruise TN413. Temperature and Salinity were collected in situ during the cruise from an underway CTD. The other features that will be used in the model are nitrate, phosphate, iron, and satellite chlorophyll. These were retrieved from a Simons CMAP query using the Mercator-Pisces Biogeochemistry Daily Forecast (cl1) model with colocalization done with TN413 Latitude and Longitude values.

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Figure 2: TN413 cruise tract from Honolulu, Hawaii to Suva, Fiji.

Random Forest Regression Model:

Random forest regression is a machine learning algorithm commonly used for modeling and predicting various oceanographic variables such as sea surface temperature, chlorophyll-a concentration, and dissolved oxygen concentration. Random forest regression builds an ensemble of decision trees based on random subsamples of the training data, with each tree being grown to the maximum extent possible without pruning (Breiman, 2001). The algorithm is particularly useful for capturing nonlinear relationships and interactions between variables. (Huang et al. 2022). However, random forest models may not perform well with data values that are outside the range of values it has seen during the training process. This is because the decision tree splits are based on the features of the training data, and if there are values in the test data that are vastly different from those seen during training, the model may struggle to make accurate predictions.

I will use the RF regressor model since we are predicting biomass, which is a continuous measurement. Using anaconda python software, the RF will be a classifier model from sklearn.ensemble.RandomForestRegressor. 70 percent of the data will be used for training, and 30 percent of the data will be tested on by the resulting model. The features are Satellite chlorophyll, temperature, salinity, nitrate, iron and phosphate.

**Results**

The cruise data was divided into different phytoplankton populations (Prochlorococcus, Synechococcus, and Eukaryotes) and random forest regression models were trained on each dataset. Each phytoplankton population had different importance values assignment to each feature. The Prochlorococcus model assigned about 40% of weight in the decision nodes to chlorophyll making satellite chlorophyll the most important feature for that model with the other features below 15% and mostly near 10%. The Synechococcus model assigned about 40% of weight in the decision nodes to phosphate and only 5% to satellite chlorophyll. Its second largest ranked important feature is temperature at about 30%. The Eukaryotes model assigned about 65% of decision weights to nitrate, about 15% to chlorophyll, and 4% to other features (Figure 3). Temperature was the second largest contributor to predicting phytoplankton biomass in both Prochlorococcus and Synechococcus and ranked low for prediction Eukaryotes biomass. No models ranked iron very high as an important predictor for biomass.

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Figure 3: Feature importance values for determining what had the most influence on predicting phytoplankton biomass in the random forest model. All feature importance’s summed equate to 1.

Applying the model to the entire dataset allows us to compare how biomass changes over latitude and aids in determine the models fit and what latitudes it has trouble in. In observed biomass there is considerably larger variability from -10º to 10º. Near Hawaii biomass was relatively low for all observed biomass of the phytoplankton from 10º to 20º. The model followed these trends well with more noticeable errors near or at the equator (figure 4).

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Figure 4: Biomass against latitude. Blue line represents observed values from SeaFlow and the red dots represent random forest predictions.

To assess the performance of the model, we calculated the errors by comparing the predicted values with the observed values. The biomass of Prochlorococcus exhibited a wide range during the cruise, spanning from 2.5 pgC per liter to 19 pgC per liter. In contrast, the biomass values of Synechococcus ranged from near zero to 5.5 pgC per liter, while the Eukaryotes showed greater variability, ranging from 5 pgC per liter to 40 pgC per liter (Figure 4). These observed variabilities align with the range of prediction errors, with Synechococcus displaying the largest error ranges, followed by Prochlorococcus and Eukaryotes.

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Figure 5: Prediction errors for each phytoplankton population represented in SeaFlow. Errors calculated by subtracting observed phytoplankton biomass by random forest predicted phytoplankton biomass.

**Discussion:**

This analysis demonstrates the effectiveness of random forest regression models for predicting phytoplankton biomass in the equatorial Pacific. All three phytoplankton populations analyzed had stark differences in their importance rankings. Prochlorococcus, Synechococcus, and Eukaryotes occupy different niches of the photosynthetic zone due to their varying sizes. This highlights the different varying drivers of biomass for Prochlorococcus, Synechococcus, and Eukaryotes (Falkowski, 2012). Chlorophyll concentration was identified as the most important feature for Prochlorococcus prediction, though this is not a factor that impacts Prochlorococcus but rather aids us in predicating their numbers, unlike the other features which are direct drivers of biomass. Chlorophyll measurements for Synechococcus was found to be one of the least important features, this is likely due to Synechococcus’ greater nutrient requirements such as Phosphate which is a major limiting nutrient for Synechococcus since they cannot utilize inorganic P like they can with N (Wawrik et al. 2009). Eukaryotes’ largest biomass driver is nitrate, in this study Eukaryotes were generalized due to limited data available, but they are a diverse group of phytoplankton when it comes to their size. And since these organisms are larger, they have a smaller surface area to volume ratio, making their nutritional requirements much higher than Prochlorococcus or Synechococcus ​​(Wawrik et al. 2009).

The application of the model to the entire dataset allowed us to analyze the spatial distribution of phytoplankton biomass across different latitudes. The observed biomass showed substantial variability in the range of -10º to 10º latitude due to the convergence of the easterly trade winds and the equatorial currents causing upwelling between the surface and deeper waters (Chavez et al., 2011). Biomass levels near Hawaii remained relatively low between 10º and 20º latitude likely because of its limited nutrients available (Morel et al. 2010).

The model generally captured these trends well, but some discrepancies were observed, particularly near or at the equator. These errors may be attributed to the complex interactions between multiple environmental factors in the equatorial region, such as a large increase in nutrient availability, light, and water column stability (Chavez et al., 2011).

According to Behrenfeld et al. (2006), the equatorial region presents unique challenges for accurately predicting phytoplankton biomass due to the complex interactions between various environmental factors. The equator experiences significant changes in nutrient availability, light intensity, and water column stability, which can affect the growth and distribution of phytoplankton. This is where we also saw the most off predicted values for all three plankton populations. This may suggest that there is another feature(s) that could be useful in predicting these populations biomass.

It is worth noting that our study focused on the equatorial Pacific, an area with limited research cruises and a significant knowledge gap in phytoplankton biomass. This gap in understanding is especially critical given the increasing sea surface temperatures and the frequency and intensity of El Niño events associated with global climate change (Flombaum et al., 2013). By expanding our knowledge of phytoplankton biomass in the equatorial Pacific, we can gain a better understanding of inferred phytoplankton community changes over time and their response to the changing climate and ENSO events (Wang & Fiedler, 2006).

**Conclusion**

This analysis reinforces the importance of considering multiple environmental factors when predicting phytoplankton biomass, as different phytoplankton populations respond differently to nutrient availability, temperature, and other factors. Eukaryotes demonstrated the most variability in biomass through the cruise transect, this was reflected in the random forest model which had increased discrepancies near the equator due to more complex processes going on there. Prochlorococcus and Synechococcus models both found Nitrate and Phosphate to be important predictors for biomass, and Prochlorococcus had near half the weight of predictions on satellite chlorophyll, making it an interesting predictor for Prochlorococcus specifically. The random forest models captured the variation of phytoplankton population’s biomass throughout space well with some discrepancies near the equator due to increased complex process that occur there. Future studies should incorporate more research cruises that take advantage of SeaFlow to increase the generalizability of random forest models. In addition to space being limited to train the model, only one season of one year was incorporated into .

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**References**

Behrenfeld, M. J., O’Malley, R. E., Siegel, D. S., McClain, C. R., Sarmiento, J. L., Feldman, G. C., et al. (2006). Climate-driven trends in contemporary ocean productivity, *444*(7120), 752–755. https://doi.org/10.1038/nature05317

Bristow, L. A., Mohr, W., Soeren Ahmerkamp, & Marcel. (2017). Nutrients that limit growth in the ocean, *27*(11), R474–R478. https://doi.org/10.1016/j.cub.2017.03.030

Buitenhuis, E. T., Corinne Le Quéré, Olivier Aumont, Beaugrand, G., Bunker, A., Hirst, A. G., et al. (2006). Biogeochemical fluxes through mesozooplankton, *20*(2), n/a-n/a. https://doi.org/10.1029/2005gb002511

Falkowski, P. G. (2012). Ocean Science: The power of plankton, *483*(7387), S17–S20. https://doi.org/10.1038/483s17a

Flombaum, P., Gallegos, J. L., Gordillo, R. A., Rincon, J., Zabala, L. L., Jiao, N., et al. (2013). Present and future global distributions of the marine Cyanobacteria *Prochlorococcus* and *Synechococcus*, *110*(24), 9824–9829. https://doi.org/10.1073/pnas.1307701110

Huang, H., Wang, W., Junping Lv, Liu, Q., Liu, X., Xie, S., et al. (2022). Relationship between Chlorophyll a and Environmental Factors in Lakes Based on the Random Forest Algorithm, *14*(19), 3128–3128. https://doi.org/10.3390/w14193128

L., B. (2016). Breiman, L. (2001) Random Forests. Machine Learning, 45, 5-32. - References - Scientific Research Publishing. Retrieved May 16, 2023, from https://www.scirp.org/(S(czeh2tfqw2orz553k1w0r45))/reference/referencespapers.aspx?referenceid=1734556

Zhang, J., Zhi, M., & Zhang, Y. (2021). Combined Generalized Additive model and Random Forest to evaluate the influence of environmental factors on phytoplankton biomass in a large eutrophic lake, *130*, 108082–108082. https://doi.org/10.1016/j.ecolind.2021.108082

**Appendices**

[**https://github.com/CristianSwift/SeniorThesis**](https://github.com/CristianSwift/SeniorThesis)

**(has not been pushed to git yet)**

### **References**

### Wang, H., T. Liu, Y. Huang, Y. Fang, R. Liu, S. Wang, W. Wen, and M. Sun. 2014. Plasmon-driven surface catalysis in hybridized plasmonic gap modes. Sci. Rep. 4: 7087.

### Acevedo-Trejos, E., E. Marañón, and A. Merico. 2018. Phytoplankton size diversity and ecosystem function relationships across oceanic regions. Proceedings of the Royal Society B: Biological Sciences **285**: 20180621. doi:https://doi.org/10.1098/rspb.2018.0621

### Brotas, V., G. A. Tarran, V. Veloso, and others. 2022. Complementary Approaches to Assess Phytoplankton Groups and Size Classes on a Long Transect in the Atlantic Ocean. Frontiers in Marine Science **8**. doi:https://doi.org/10.3389/fmars.2021.682621

### Buesseler, K. O., C. H. Lamborg, P. W. Boyd, and others. 2007. Revisiting Carbon Flux Through the Ocean’s Twilight Zone. Science **316**: 567–570. doi:https://doi.org/10.1126/science.1137959

### Dunne, J. P., R. A. Armstrong, A. Gnanadesikan, and J. L. Sarmiento. 2005. Empirical and mechanistic models for the particle export ratio. Global Biogeochemical Cycles **19**: n/a-n/a. doi:https://doi.org/10.1029/2004gb002390

### Dutkiewicz, S., P. Cermeno, O. Jahn, M. J. Follows, A. E. Hickman, D. A. A. Taniguchi, and B. A. Ward. 2020. Dimensions of marine phytoplankton diversity. Biogeosciences **17**: 609–634. doi:https://doi.org/10.5194/bg-17-609-2020

### Geng, T., W. Cai, L. Wu, and others. 2022. Emergence of changing Central-Pacific and Eastern-Pacific El Niño-Southern Oscillation in a warming climate. Nature Communications **13**. doi:https://doi.org/10.1038/s41467-022-33930-5

### Hu, S., H. Liu, W. Zhao, T. Shi, Z. Hu, Q. Li, and G. Wu. 2018. Comparison of Machine Learning Techniques in Inferring Phytoplankton Size Classes. Remote Sensing **10**: 191. doi:https://doi.org/10.3390/rs10030191

### Irarte, J. L., and H. E. González. 2004. Phytoplankton size structure during and after the 1997/98 El Niño in a coastal upwelling area of the northern Humboldt Current System on JSTOR.

### Marañón, E. 2015. Cell Size as a Key Determinant of Phytoplankton Metabolism and Community Structure. Annual Review of Marine Science **7**: 241–264. doi:https://doi.org/10.1146/annurev-marine-010814-015955

### Meyer, M. G., W. Gong, S. M. Kafrissen, and others. 2022. Phytoplankton size-class contributions to new and regenerated production during the EXPORTS Northeast Pacific Ocean field deployment. Elementa: Science of the Anthropocene **10**. doi:https://doi.org/10.1525/elementa.2021.00068

### Richardson, T. L., and G. A. Jackson. 2007. Small Phytoplankton and Carbon Export from the Surface Ocean. Science.

### Robinson, A., H. A. Bouman, G. H. Tilstone, and S. Sathyendranath. 2018. High photosynthetic rates associated with pico and nanophytoplankton communities and high stratification index in the North West Atlantic. Continental Shelf Research **171**: 126–139. doi:https://doi.org/10.1016/j.csr.2018.10.010

### Sarica, A., A. Cerasa, and A. Quattrone. 2017. Random Forest Algorithm for the Classification of Neuroimaging Data in Alzheimer’s Disease: A Systematic Review. Frontiers in Aging Neuroscience **9**. doi:https://doi.org/10.3389/fnagi.2017.00329

### Srivastava, D., and Lekha Bhambhu. 2010. Data classification using support vector machine. ResearchGate.

### Swalwell, J. E., F. Ribalet, and E. V. Armbrust. 2011. SeaFlow: A novel underway flow-cytometer for continuous observations of phytoplankton in the ocean. Limnology and Oceanography: Methods **9**: 466–477. doi:https://doi.org/10.4319/lom.2011.9.466

### Swalwell, J., François Ribalet, and E. V. Armbrust. 2013. SeaFlow: A novel underway flow-cytometer for continuous observations of phytoplankton in the ocean. ResearchGate.

### Turner, J. T. 2015. Zooplankton fecal pellets, marine snow, phytodetritus and the ocean’s biological pump. Progress in Oceanography **130**: 205–248. doi:https://doi.org/10.1016/j.pocean.2014.08.005

### Tyrrell, T. 2019. Redfield Ratio. Encyclopedia of Ocean Sciences 461–472. doi:https://doi.org/10.1016/b978-0-12-409548-9.11281-3

### Wang, C., and P. C. Fiedler. 2006a. ENSO variability and the eastern tropical Pacific: A review. Progress in Oceanography **69**: 239–266. doi:https://doi.org/10.1016/j.pocean.2006.03.004

### Wang, C., and P. C. Fiedler. 2006b. ENSO variability and the eastern tropical Pacific: A review. Progress in Oceanography **69**: 239–266. doi:https://doi.org/10.1016/j.pocean.2006.03.004

### Watanabe, M., J.-L. Dufresne, Y. Kosaka, T. Mauritsen, and H. Tatebe. 2020. Enhanced warming constrained by past trends in equatorial Pacific sea surface temperature gradient. Nature Climate Change **11**: 33–37. doi:https://doi.org/10.1038/s41558-020-00933-3

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### Rough Project Budget:

Travel

* R/V Thompson cruise cost: $48,000
* One-way flight from Seattle to Honolulu $350
* One-way flight from Nadi to Seattle $1022

Instruments

* Run by another team: $0

**Processing software**

* Anaconda Python Software: $0