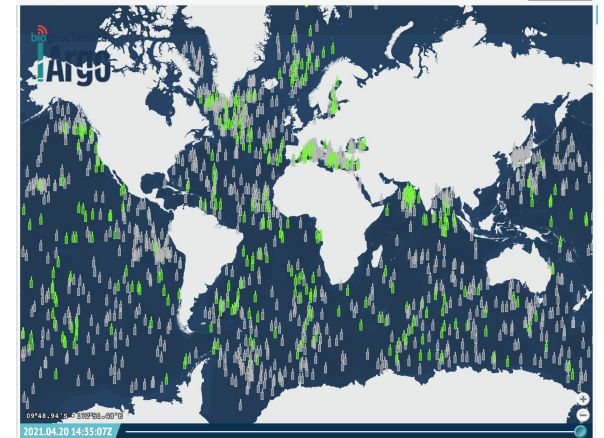
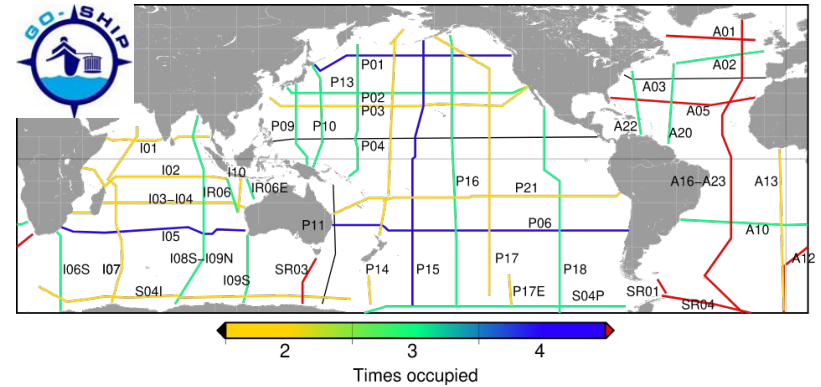
The background image shows a polar landscape. In the foreground, there is a large, white, textured ice formation on the left side. The water is a deep blue, with some lighter blue patches near the ice. In the distance, a small white iceberg is visible on the water. The sky is a clear, pale blue with some wispy clouds. The overall scene is a high-contrast, naturalistic depiction of a cold, aquatic environment.

Predicting Critical Biogeochemistry of the Southern Ocean for Climate Monitoring

Ellen Park, Jae Deok Kim, Nadège Aoki, Yumeng Cao, Yamin
Arefeen, Matthew Beveridge, David Nicholson, Iddo Drori

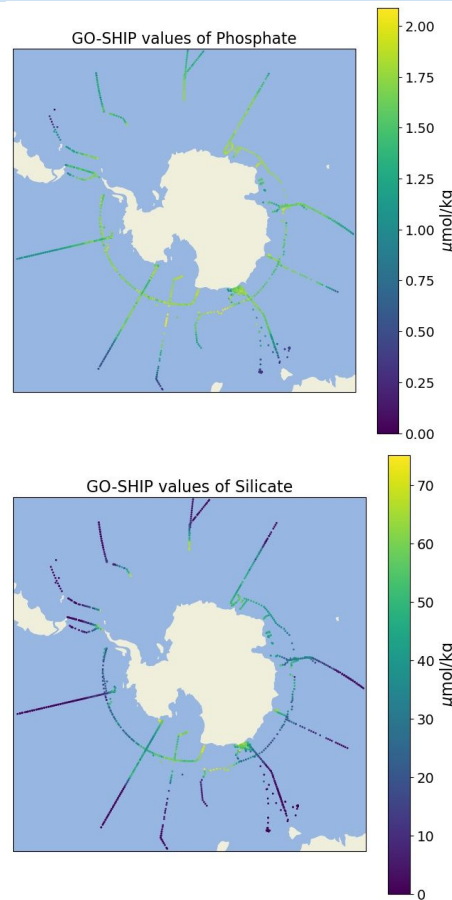
Introduction

- Ocean plays an important role in the Earth's climate system
- How do we currently measure and monitor the oceans?
 - Ship surveys, autonomous floats and vehicles
 - Moored-arrays, satellite remote sensing
- Limitations: time, space, measured variables, cost
- Data sets
 - Global Ocean Ship-Based Hydrographic Investigations Program (GO-SHIP)
 - Biogeochemical Argo floats (BGC-Argo)

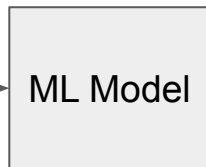


Project Goals

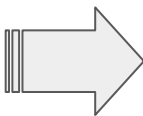
- Can we use ML to predict phosphate and silicate concentrations in the Southern Ocean from a limited number of features?
 - Measured by GO-SHIP, not by BGC-Argo
 - Phosphate: limiting nutrient for phytoplankton production
 - Silicate: diatoms, informative for biogeography
 - Southern Ocean: global carbon sink, BGC-Argo floats, seasonally inaccessible
- Relevance to climate change



Input Features:
T, S, P, O_2 ,
 NO_3 , Lat,
Lon



Output Features:
 PO_4
 SiO_4



Apply ML model to:

1. Earth system model (ESM) data
2. BGC-Argo data

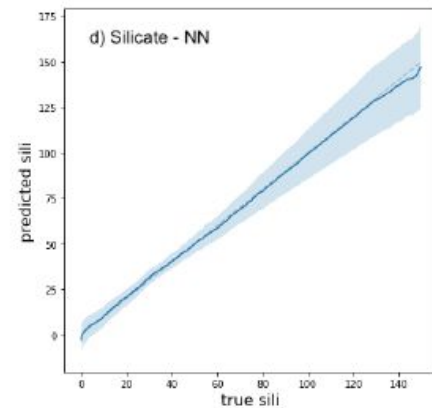
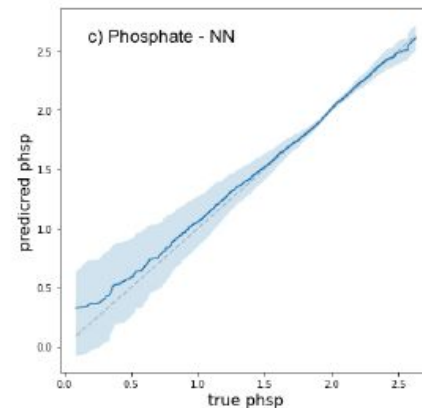
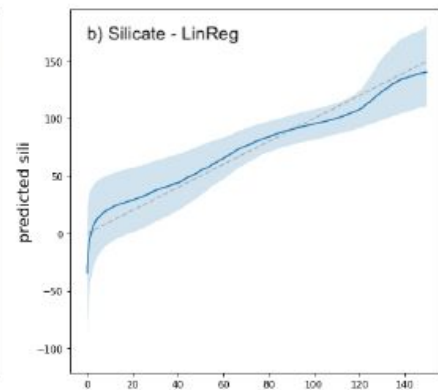
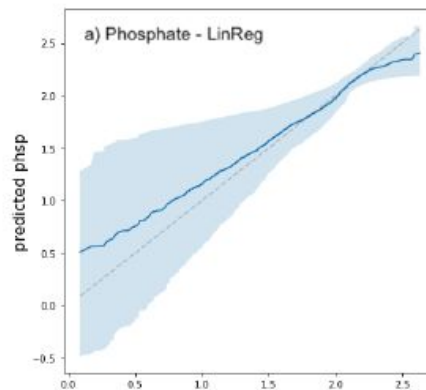
Model & Results

● Model

- 1 layer NN (linear regression)
 - 1 layer, feed-forward, linear activation
- Neural Network
 - 2-layers, feed-forward, 64 hidden units, ReLu Activation
- Trained on 42,412 points - 9:1 train/test split
- Uncertainty bounds via dropout (p=0.2)

● Results

- NN had lower error and smaller uncertainty

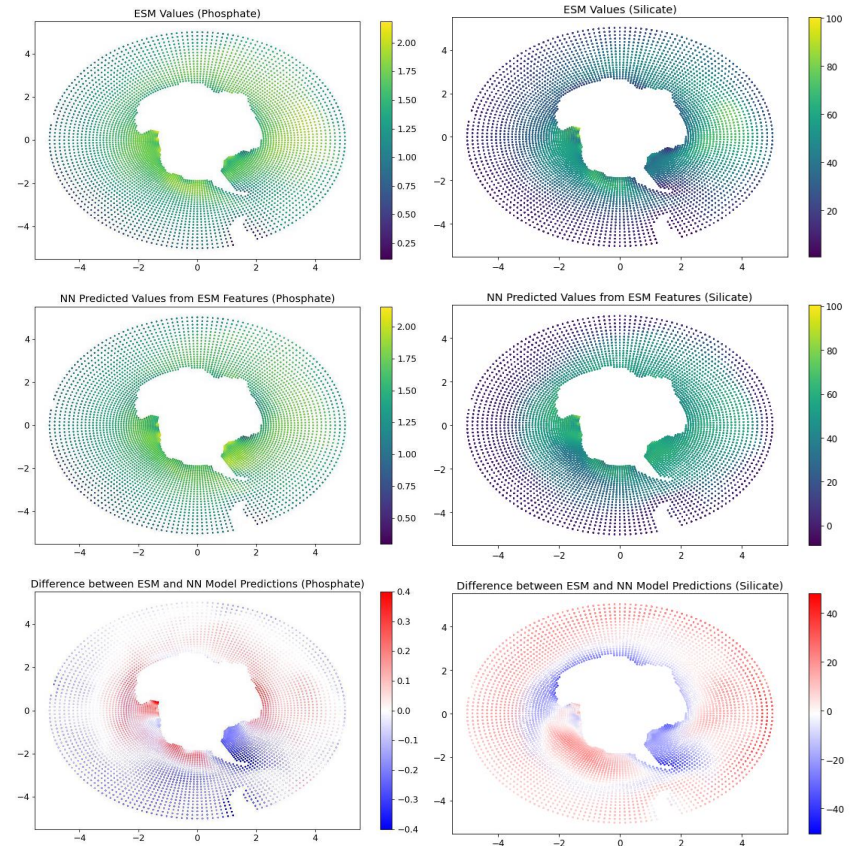


Model Mean Squared Error

	Linear Regression	Neural Network
PO_4	0.019	0.0031
SiO_4	240	50

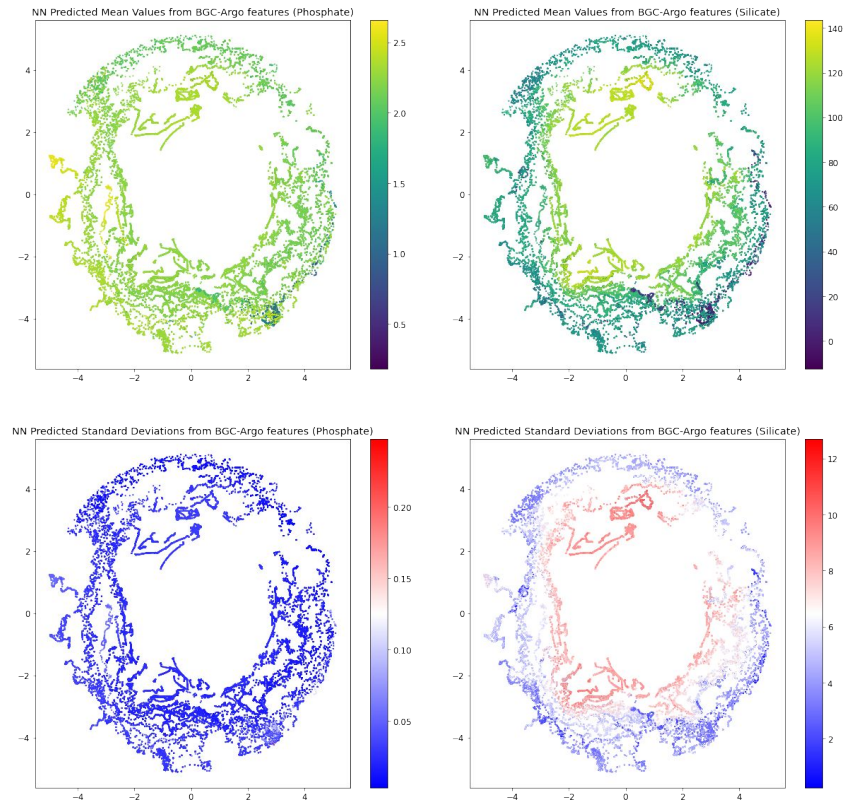
Neural Networks for ESM data

- Compared the ESM output values of phosphate and silicate to our predicted values from applying our neural network to the ESM features
- Results
 - Phosphate: NN predicts greater values away from continent
 - Silicate: NN lower values away from the Antarctic continent
- Conclusion
 - NN generally able to capture the spatial variations in both phosphate and silicate



Neural Networks for BGC-Argo data

- NN predicts a similar spatial pattern to that of the GO-SHIP data
- For silicate, high uncertainty near continent
 - Possibly ice dynamics causing higher variance as well as a latitudinal dependence
- Additional factors: data quality control



Limitations

- Lack temporal component and spatial relations
- Model improvements
 - Spatio-temporal graph neural network
 - Train models on a subset of GO-SHIP data

Conclusion

- Successful neural network predictions of phosphate and silicate in the Southern Ocean including calculation of uncertainty bounds
- Application of neural network to different datasets highlighted areas for model improvement
- Application for climate monitoring