

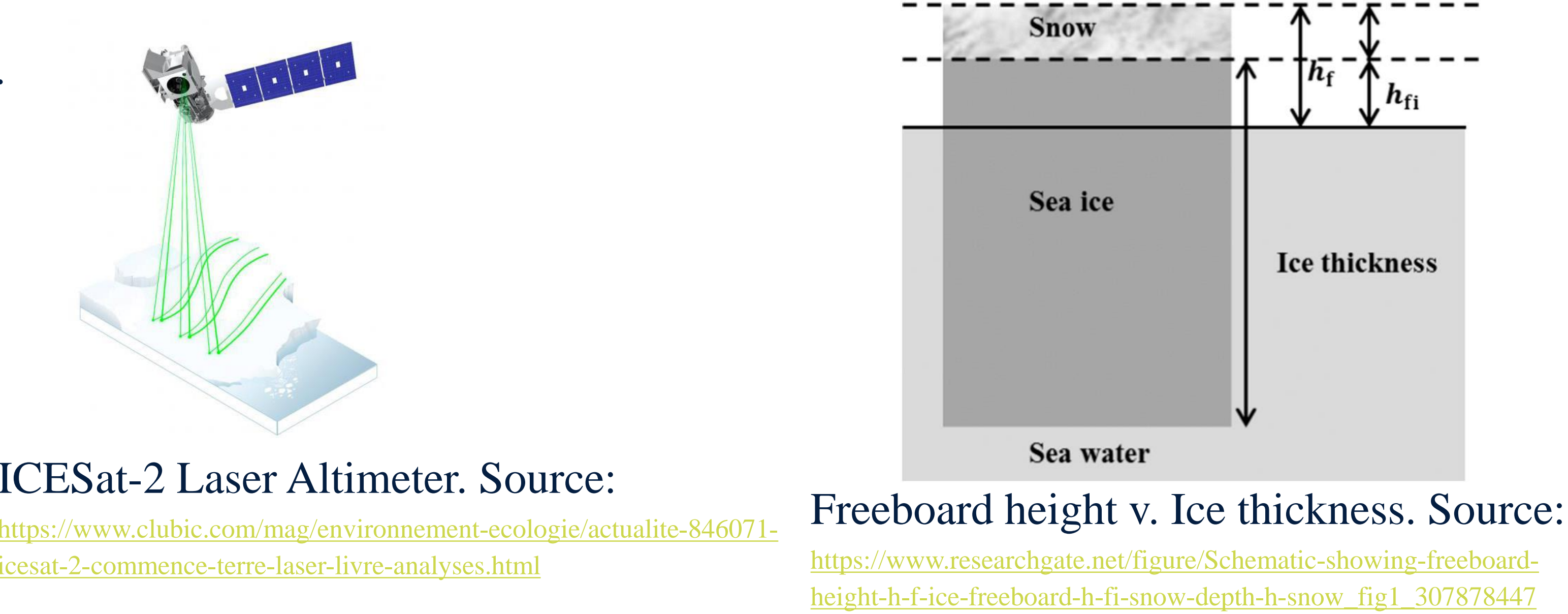
# Seasonal Variation and Thickness Estimation of First-year v. Multi-year Ice in the Amundsen and Bellingshausen Seas

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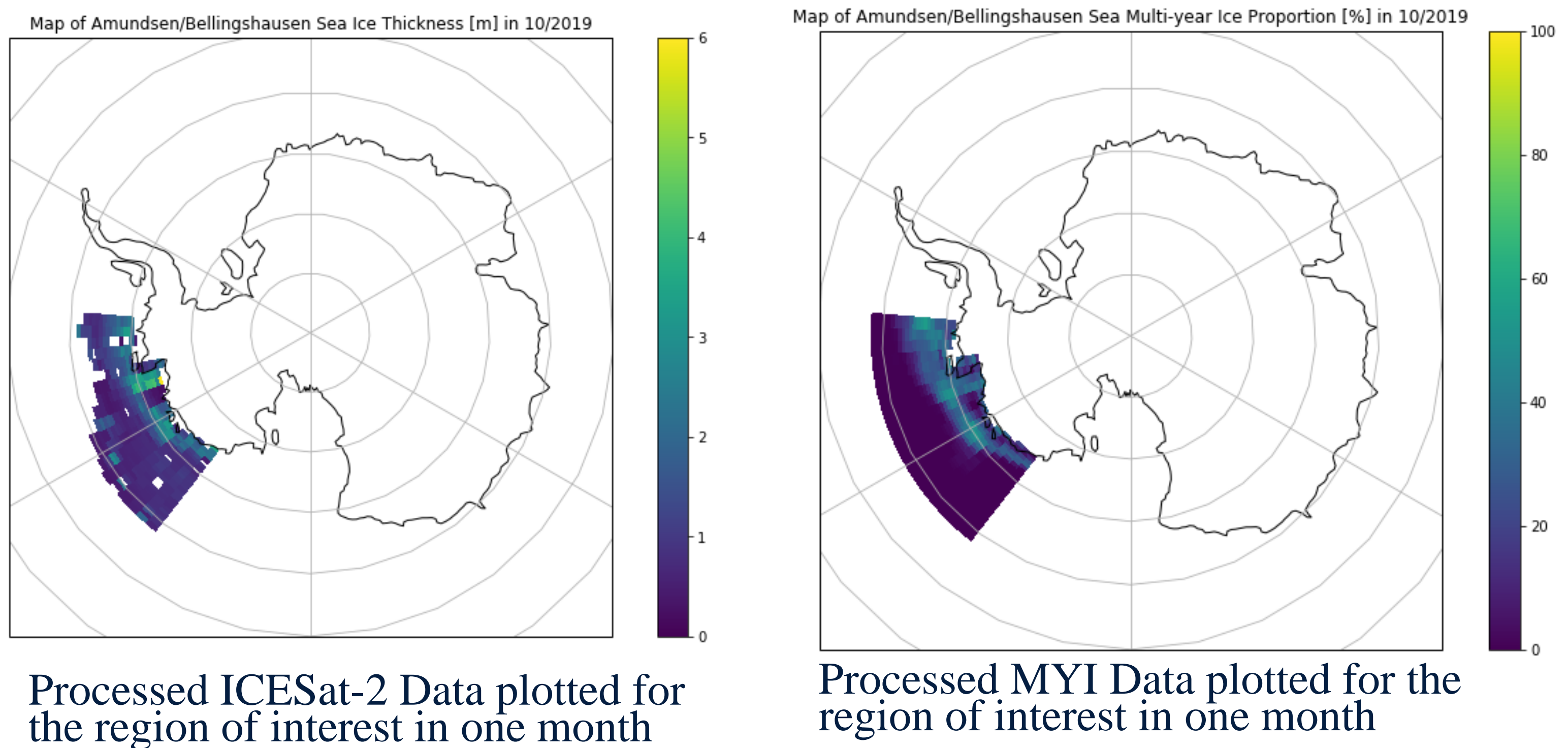


## INTRODUCTION

- Motivation: How do seasonal ice growth and melting in Amund-/Bellingshausen Seas affect ocean properties and delivery of water to ice shelves in Antarctica?
- Two main seasons: winter (April to October) and summer (November to March).
- Thickness is a linear function of 2 variables - freeboard height ( $h_f$ ) and snow depth.



- ATLAS/ICESat-2 satellite laser altimeter measures freeboard height via photon counting and photon travel time.
- Microwave Radiometer AMSR-E measures Sea ice concentration and ratio of Multi-year ice (MYI) v. First-year ice (FYI) concentration via brightness temperature.



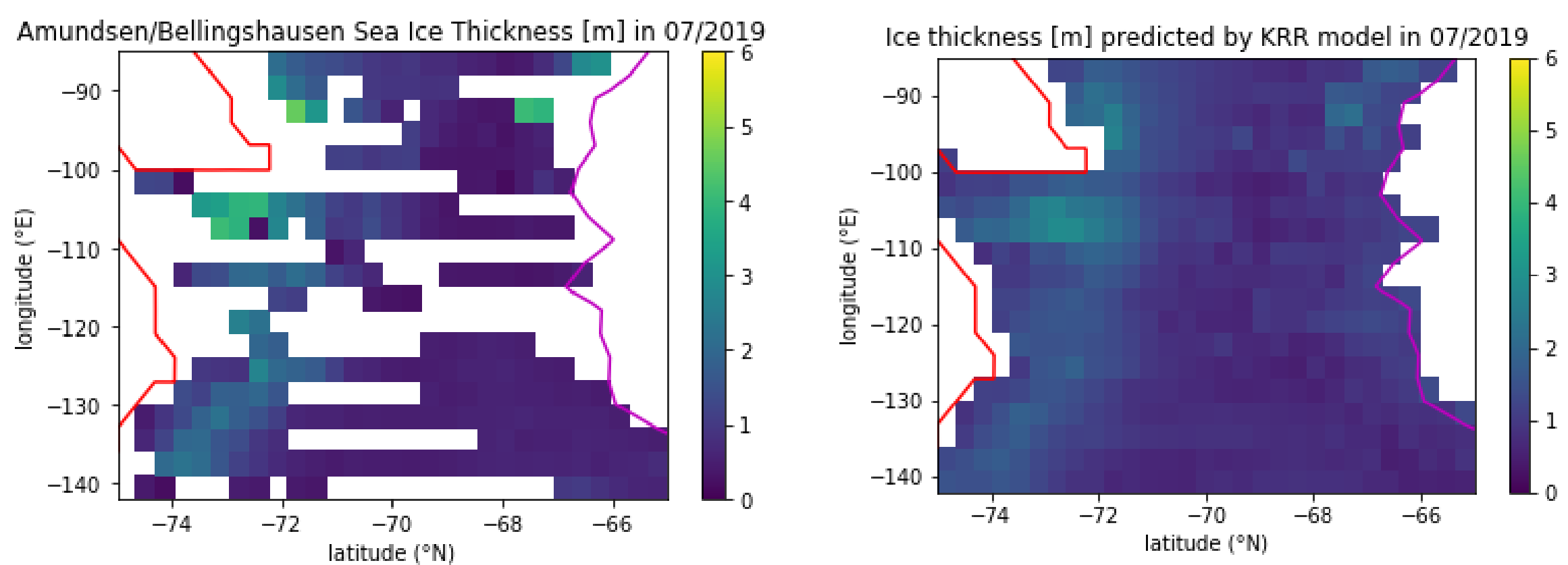
## CHALLENGES

1. *Snow Depth*: No snow depth dataset was found for the Amund-/Bellingshausen Sea region. Only freeboard height data were available to estimate ice thickness.
2. *Mapping*: Three datasets do not sample at same coordinates. How to map together?
3. *Missing Data*: Cloudy months (much sparser data in one month compared to the months immediately before, after, and that same month in a consecutive year).

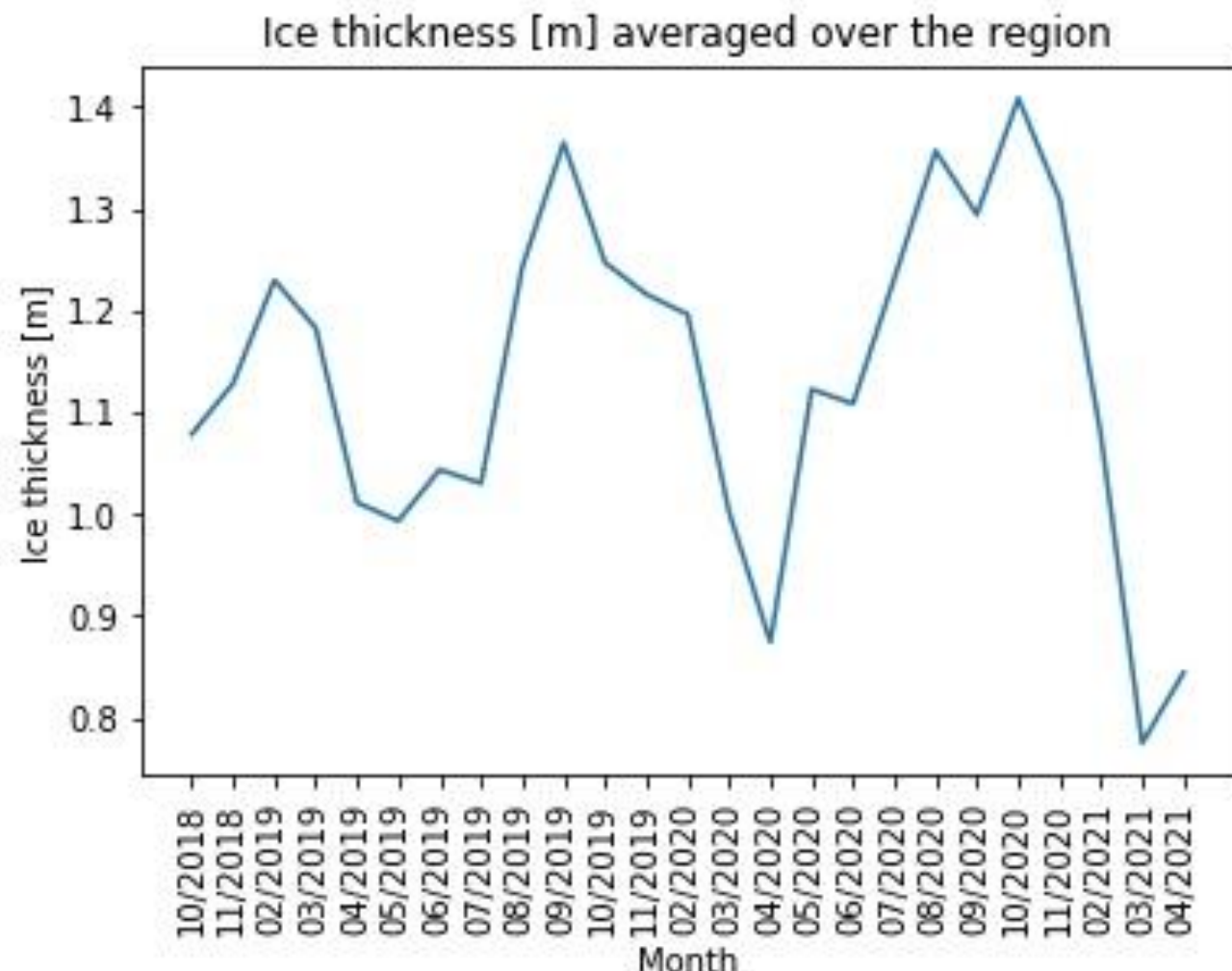
## METHODS

1. *Snow Depth*: Apply an empirical linear fit (Li et al., 2018) to approximate ice thickness from freeboard height: **Ice thickness =  $2.79 * h_f + 0.169$  [m]**
2. *Mapping*: **Discretize** the region, each pixel covering a rectangular range of latitude and longitude. Average all data for each physical feature within a **pixel** in a **month**.
3. *Missing Data*: Train a **KRR** model, i.e. **multivariate regression** with **regularization** (to reduce overfitting) and the **Laplacian kernel** (so that model complexity only grows with number of training samples, not with number of features). Inputs: spatio-temporal coordinates, ice concentration, multi-year ice proportion.

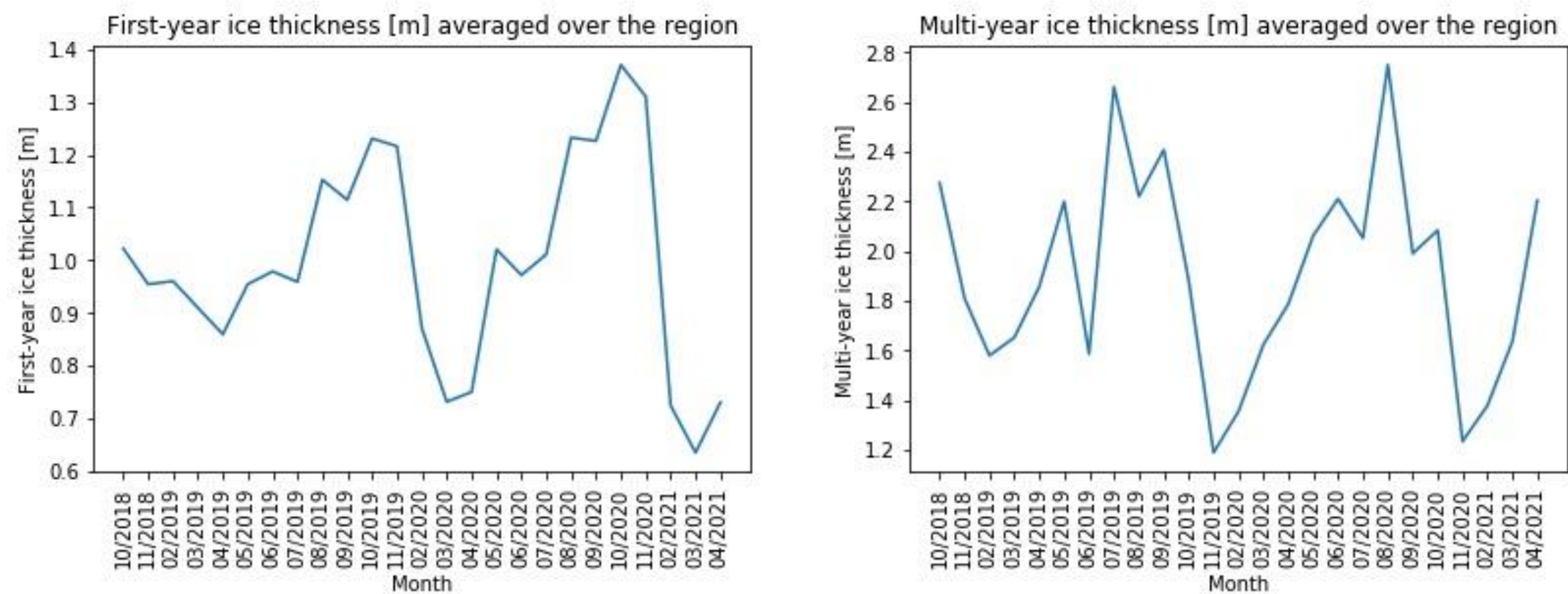
## PRELIMINARY RESULTS



**Figure 1:** Original v. KRR-predicted ice thickness in a ‘cloudy’ month with optimized hyperparameters  $\alpha=0.33$ ,  $\gamma=0.037$ , rms test error = 0.38 m (33.4% of mean thickness)



**Figure 2:** Evolution of ice thickness averaged over the region by month



**Figure 3:** First- v. Multi-year ice thickness trend with 50% Threshold approach

## OBSERVATIONS

- The KRR-predicted plot in July 2019 qualitatively captured the two thick ice (coastal) areas showed in the original data: the bigger one southeast, the smaller one northeast, both mostly in the Bellingshausen Sea.
- By each late summer (February), much first-year ice has melted, leaving a large southern portion of the two seas covered in mostly multi-year ice at  $(-115^{\circ}\text{E to } -85^{\circ}\text{E}) \times (-73^{\circ}\text{N to } -70^{\circ}\text{N})$ .
- FYI: melting in summer to an annual trough (March); thickening in winter to an annual peak (October).
- MYI: appearing to thicken throughout summer (potential explanation: most FYI melted while most MYI remained intact -> pixels with high thickness got MYI label); thickening to an annual peak in mid-winter (July or August), then thinning to an annual trough by end of winter (November).

## NEXT STEPS

1. *Snow Depth*: Differentiate the relative contribution to freeboard height changes by ice thickness v. snow depth. How? Look for more nuanced empirical fit between ice thickness and freeboard height and quantify their errors.
2. *Mapping*: Distinguish first- from multi-year ice on a pixel scale: attribute thicker data to multi-year ice and thinner data to first-year ice based on concentration (Assumption: multi-year ice is thicker than first-year ice).
3. *Missing Data*: Improve the KRR model by getting more training data (e.g. with smaller thus more pixels), more features (e.g. roughness of ice surface) or handling the missing values differently (not just filling in the mean of each feature). Try other machine learning models, e.g. multilayer perceptron, recurrent neural network.

## REFERENCES

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