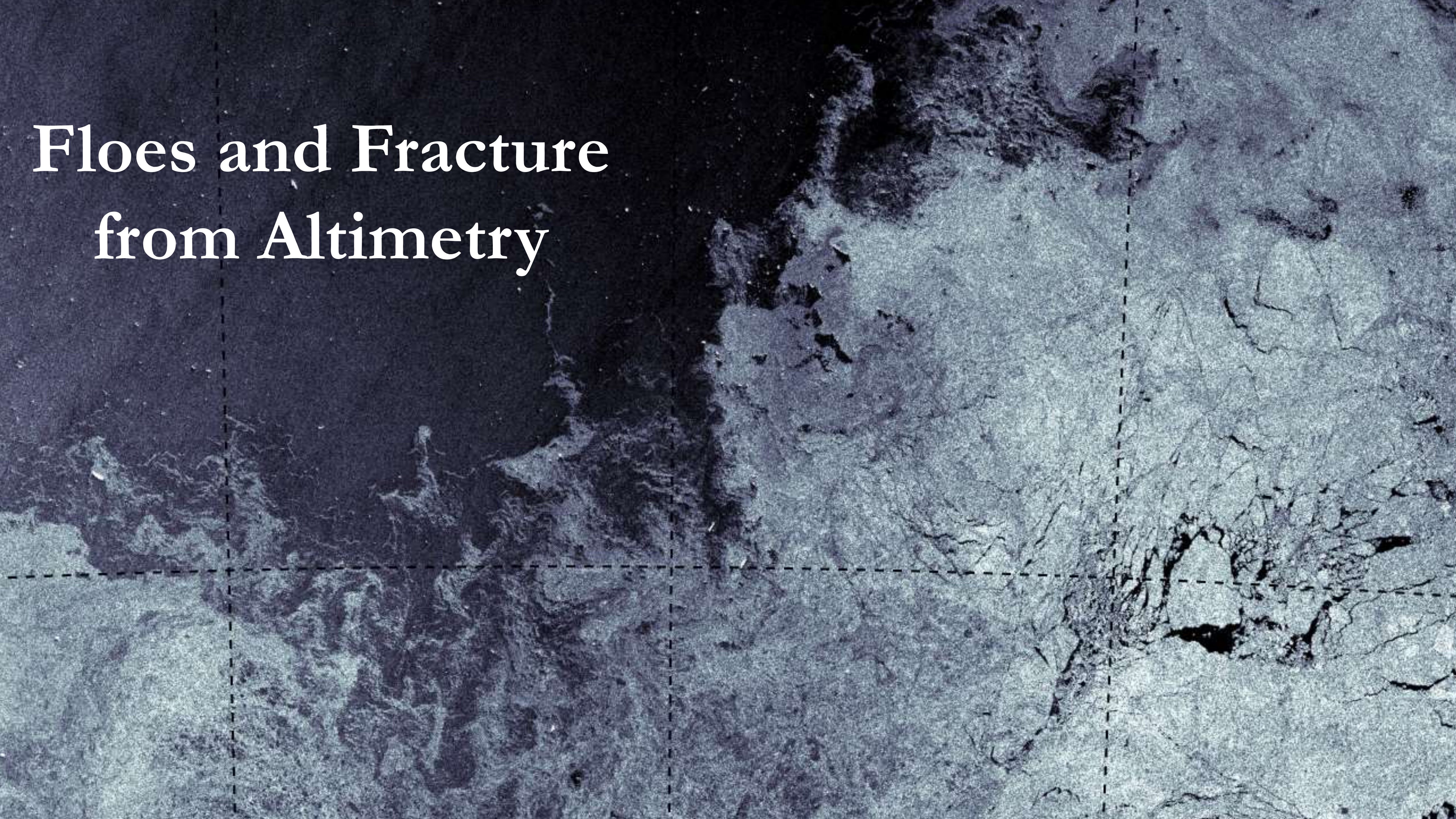
Floes and Fracture from Altimetry



Sea Ice Concentration Estimates from ICESat-2 Linear Ice Fraction.

Buckley et al., Part 1: Multi-sensor Comparison of Sea Ice Concentration Products.

Horvat et al., Part 2: Gridded Data Comparison and Bias Estimation.

Outline

1. New Models Means New Observations.

2. Model-ready Gridded Products from Altimetry
   - Wave Energy
   - Floe Size Distribution
   - Sea Ice Concentration / Linear Ice Fraction

Sea Ice Modeling is Having a Moment

Sea ice is a fractured composite.

The next generation of sea ice models includes information about granular behavior

- Below the grid scale via the floe size distribution
- At resolved scales using brittle physics and discrete element modeling.

Observations *should evolve with models*!

- Roach et al., 2018. An emergent sea ice floe size distribution in a global coupled ocean-sea ice model
- Boutin et al., 2020. Towards a coupled model to investigate wave–sea ice interactions in the Arctic marginal ice zone
- Bateson et al., 2022. Sea ice floe size: its impact on pan-Arctic and local ice mass and required model complexity
- Dansereau et al., 2016. A Maxwell elasto-brittle rheology for sea ice modelling
- Broudeau et al., 2024. Implementation of a brittle sea-ice rheology in an Eulerian, finite-difference, C-grid modeling framework: Impact on the simulated deformation of sea-ice in the Arctic
- Brenner et al., 2023. Scale-Dependent Air-Sea Exchange in the Polar Oceans: Floe-Floe and Floe-Flow Coupling in the Generation of Ice-Ocean Boundary Layer Turbulence
- Moncada et al., 2023. Level set discrete element method for modeling sea ice floes

New Gridded Observations for Comparison to New Models

Matched observations to model changes

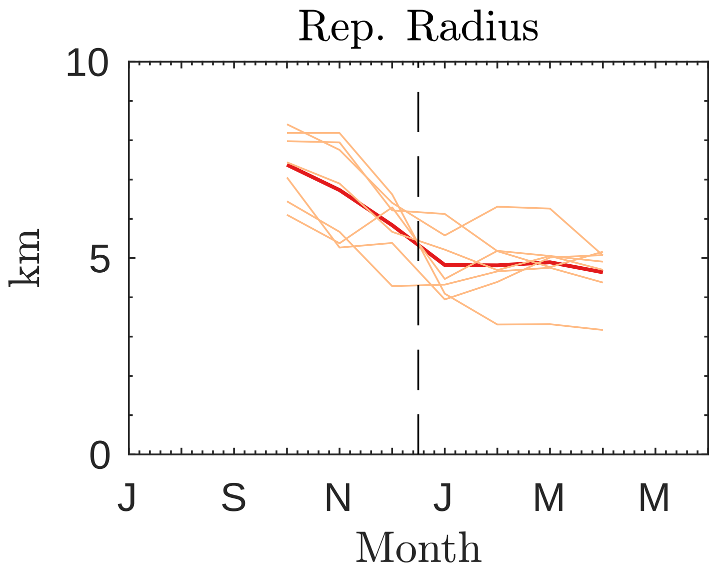
Gridded floe size distribution moments from **Cryosat**.

Gridded wave energy and attenuation from **ICESat-2** (and **ALtiKa**)

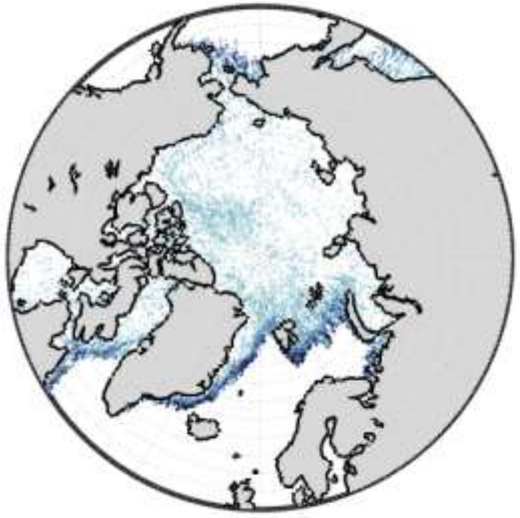
Gridded data on sea ice concentration from **ICESat-2.**

Why this one?

See Tilling et al (2018), Horvat et al (2019)



Arctic mean floe sizes 2008-2016



See Horvat et al (2020), Brouwer et al (2022), Hell and Horvat (2023)

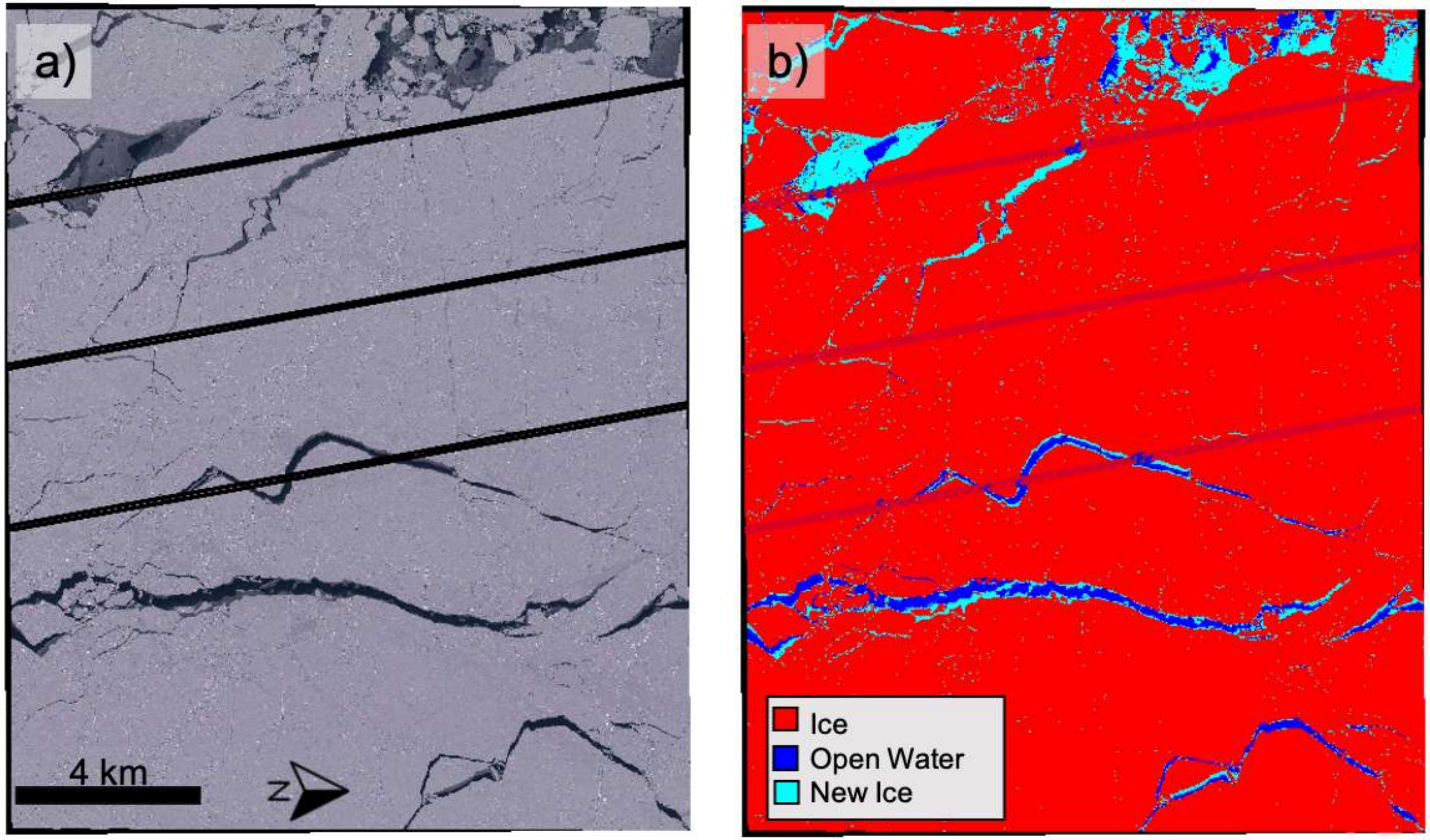
Arctic wave-affected areas in 2021.

Sea ice geometry can affect our best observations

Continuum models use, compare, and assimilate sea ice concentration data.

But this data is challenged by fracture features.

True SIC: 97.5%
NSIDC-CDR: 100%

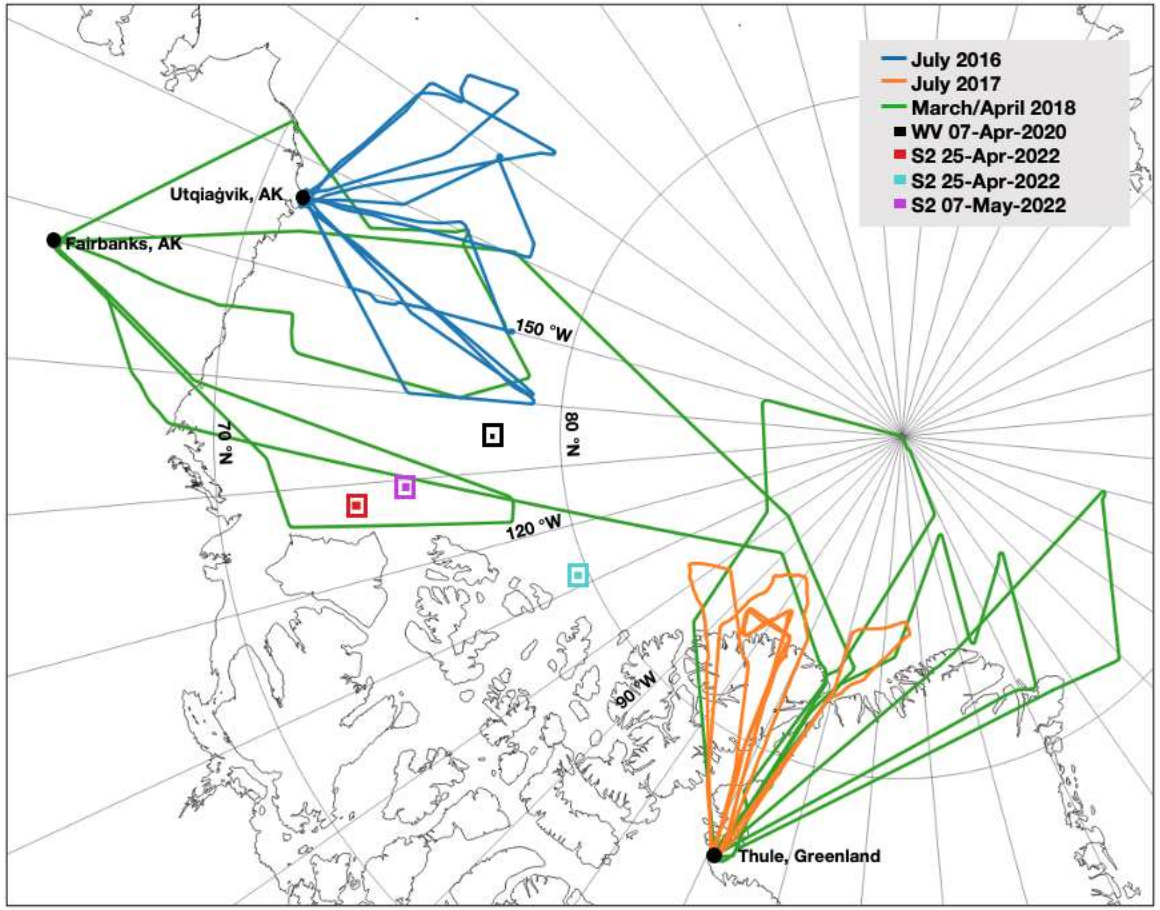


(L) Sea ice in the Beaufort Sea from Worldview-3 Satellite. (R) Same image classified via Buckley et al (2020)

Optical Sea Ice Data from NASA's Operation Icebridge

Evaluate PM biases using more than 70,000 visual images from Operation Icebridge in 2016-2018.

Roughly 20,000 independent passive microwave returns.



JGR Oceans

Research Article | Open Access

Classification of Sea Ice Summer Melt Features in High-Resolution IceBridge Imagery

Ellen M. Buckley, Sinéad L. Farrell, Kyle Duncan, Laurence N. Connor, John M. Kuhn, RoseAnne T. Dominguez

Classified by Buckley et al (2020) algorithm into ice/new ice/pond/ocean

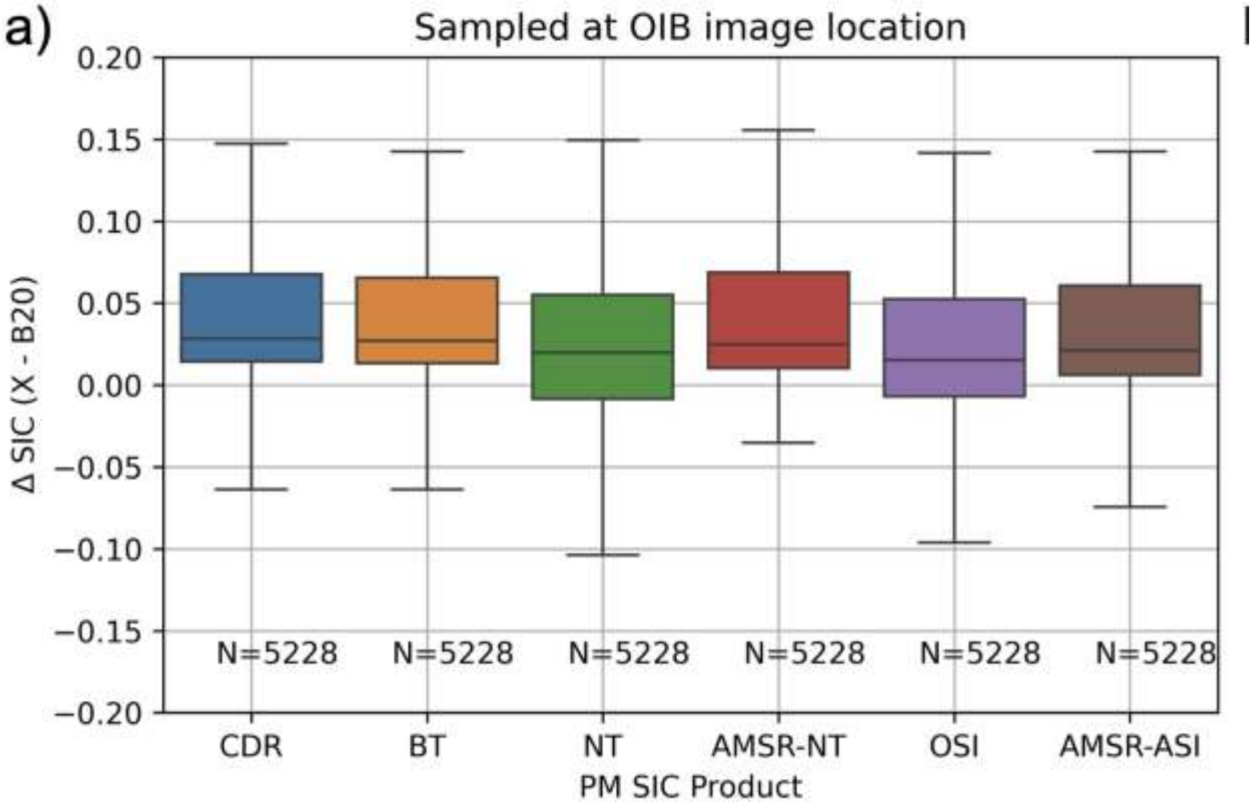
Comparison of PM data to optical data in close ice.

When pond fraction is zero, and visual analysis confirms SIC < 100%.

PM SIC = 97.2% - 98.6%

Actual SIC: 96.6%

Mean errors in open water fraction of 200%. **Mean absolute biases of 2.5-3%.**



Difference in PM-SIC value from visually-classified "ground truth" for winter scenes with SIC < 100%

ICESat-2 "Linear Ice Fraction"

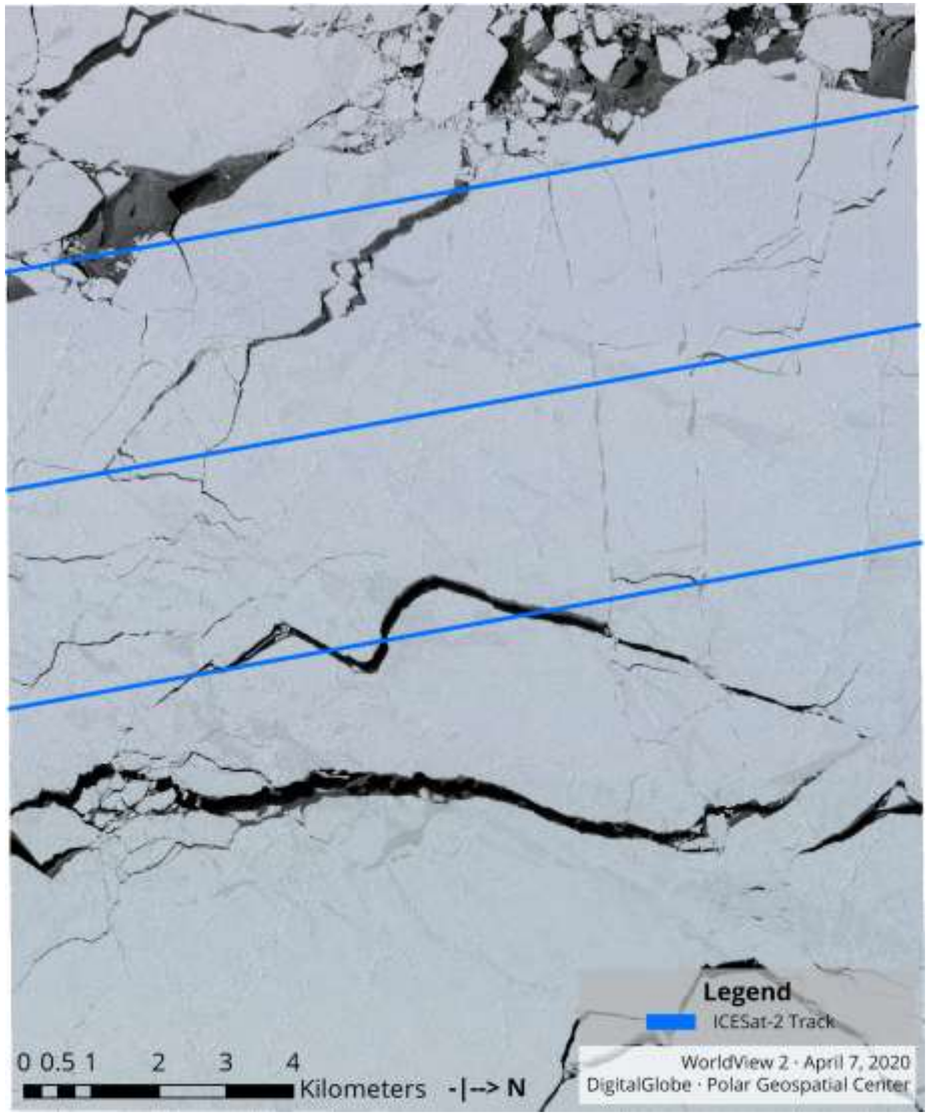
Can altimetry improve SIC in compact ice?

$$LIF = \frac{\text{Length of ice segments}}{\text{Length of all segments}}$$

++ quality controls.

Benefits: SIC ∈ [0,1], high sampling of ice surface. Easy to conceptualize.

Drawbacks: 1-D measurements. Need constraints on applicability with data.



LIF can improve on passive microwave in compact ice

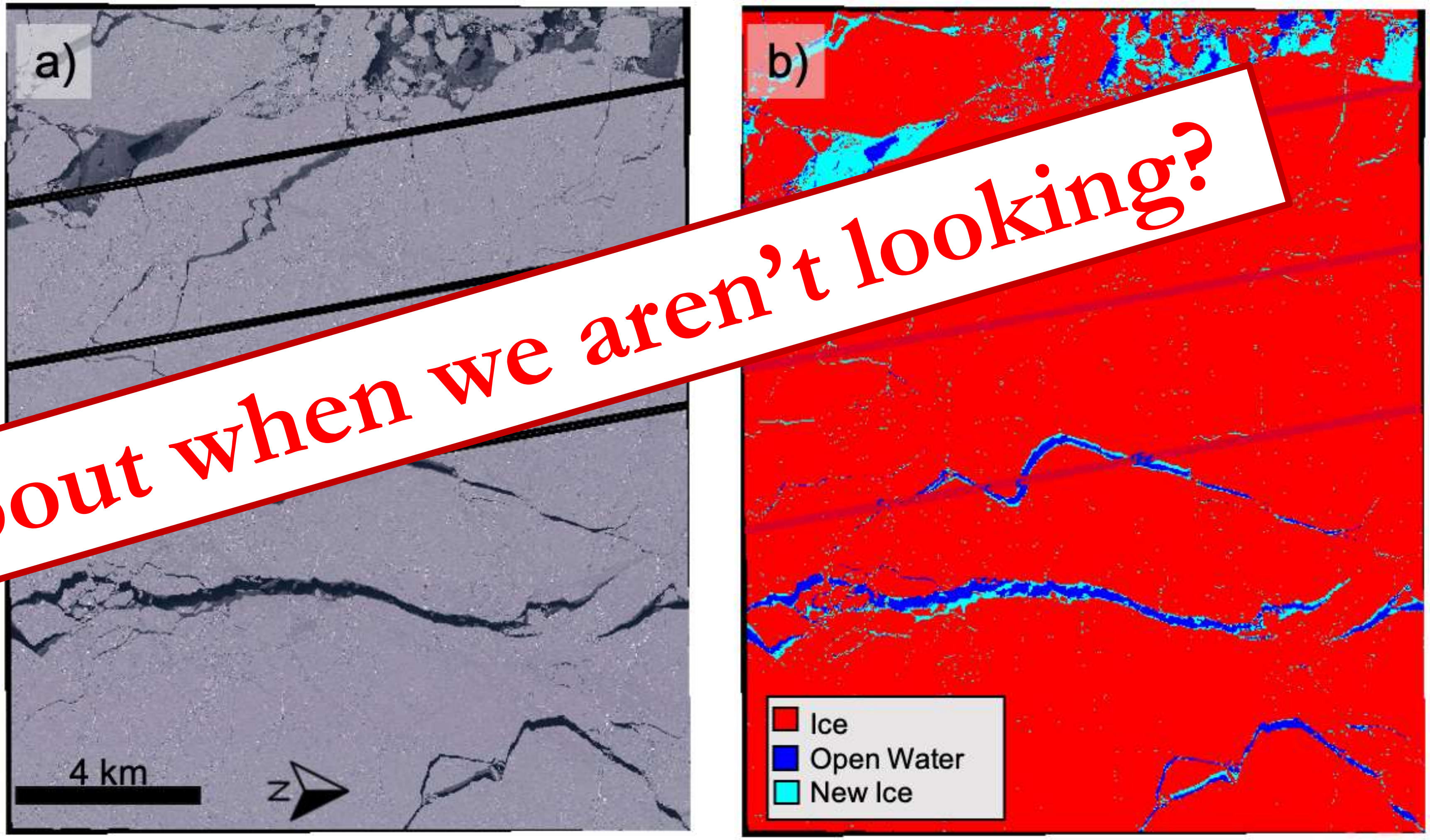
True SIC: 97.5%
NSIDC-CDR: 100%
LIF: 97.5%

In a series of wintertime WV images

Mean ab

IS2: 1.0%
PM: 2.8%

What about when we aren't looking?

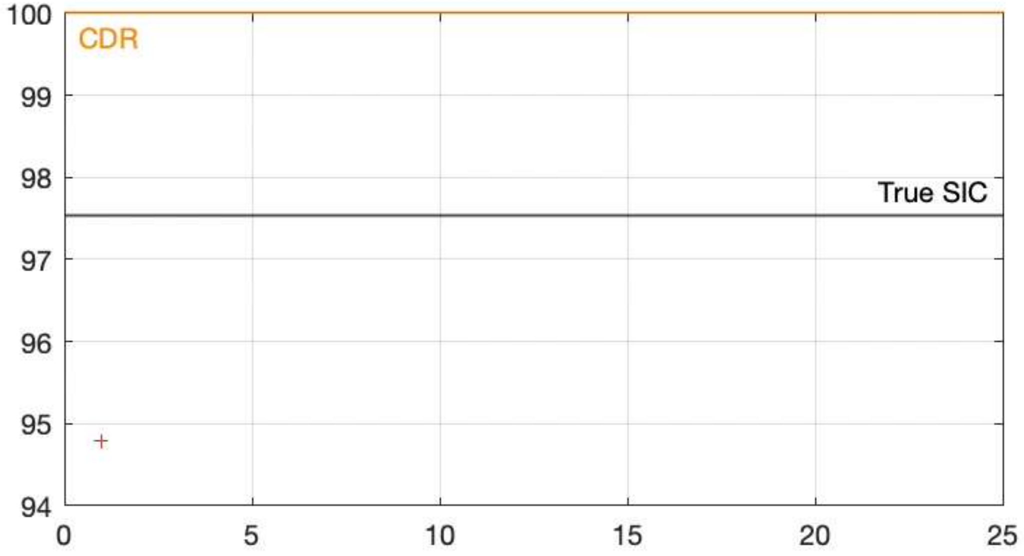


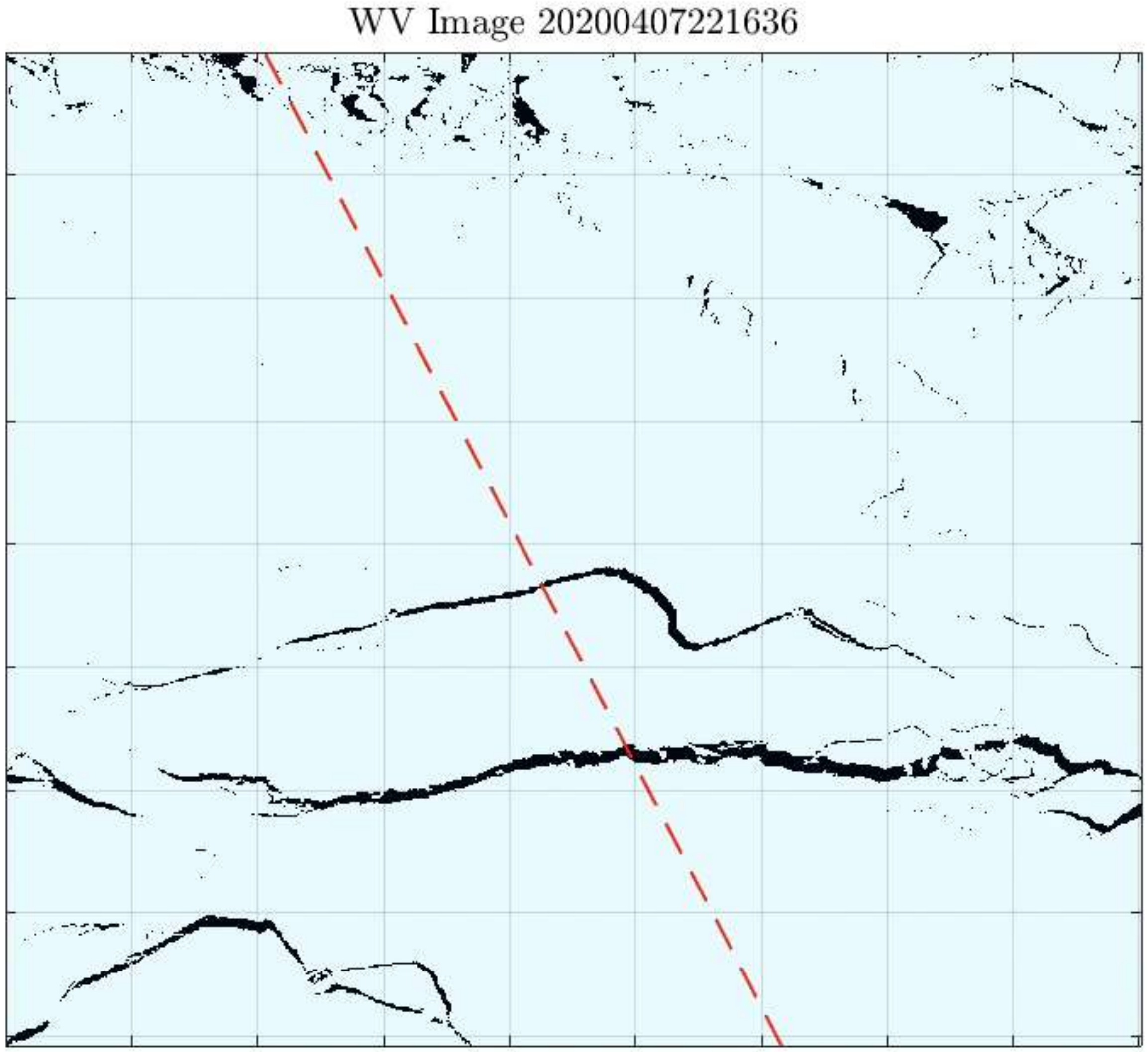
(L) Sea ice in the Beaufort Sea from Worldview-3 Satellite. (R) Same image classified via Buckley et al (2020)

ICESat-2 bias estimates constrained via emulation

How do we quantify error for an unsupervised IS2 product?

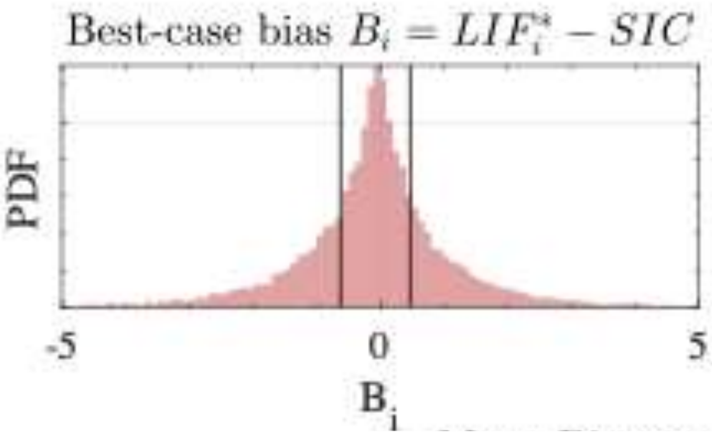
Build an ICESat-2 emulator!

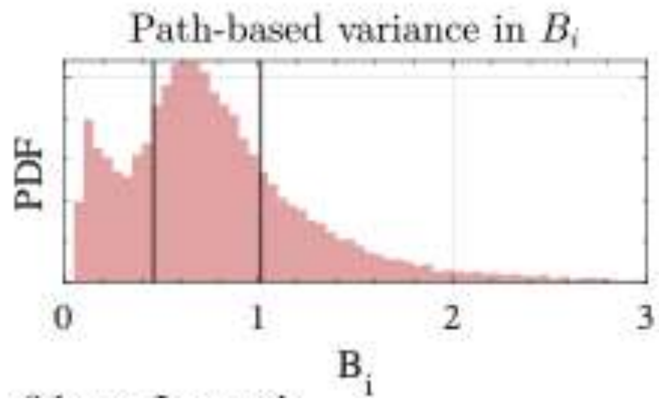




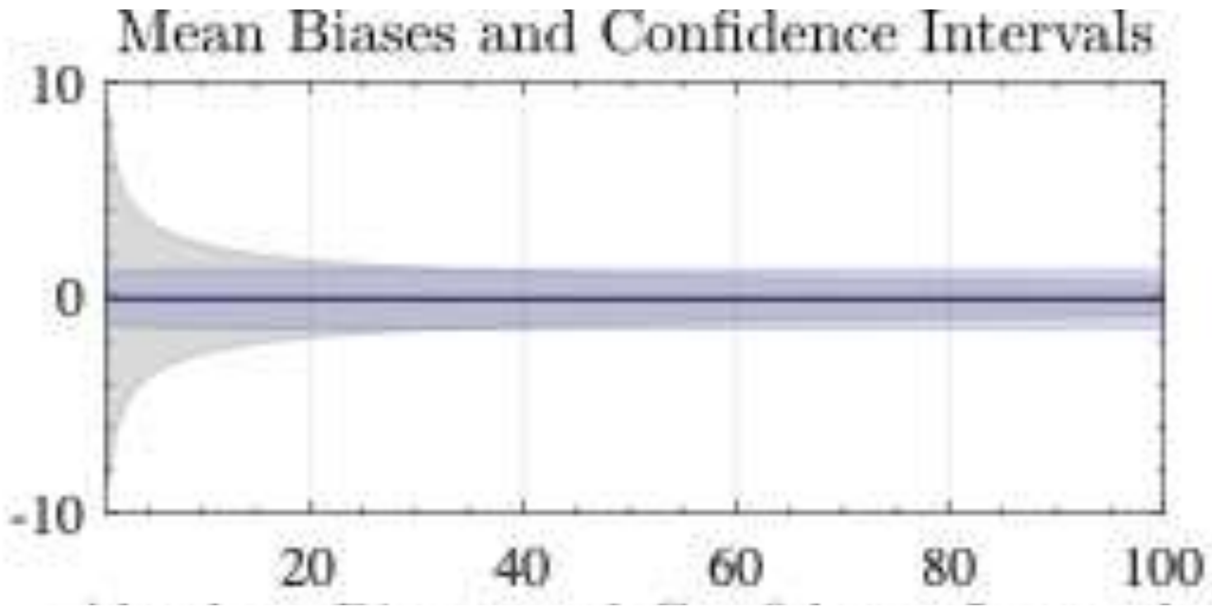
ICESat-2 bias estimates constrained via emulation

With the emulator we can constrain sources of unsupervise error by pairing RGTs with all 70,000 IceBridge surfaces



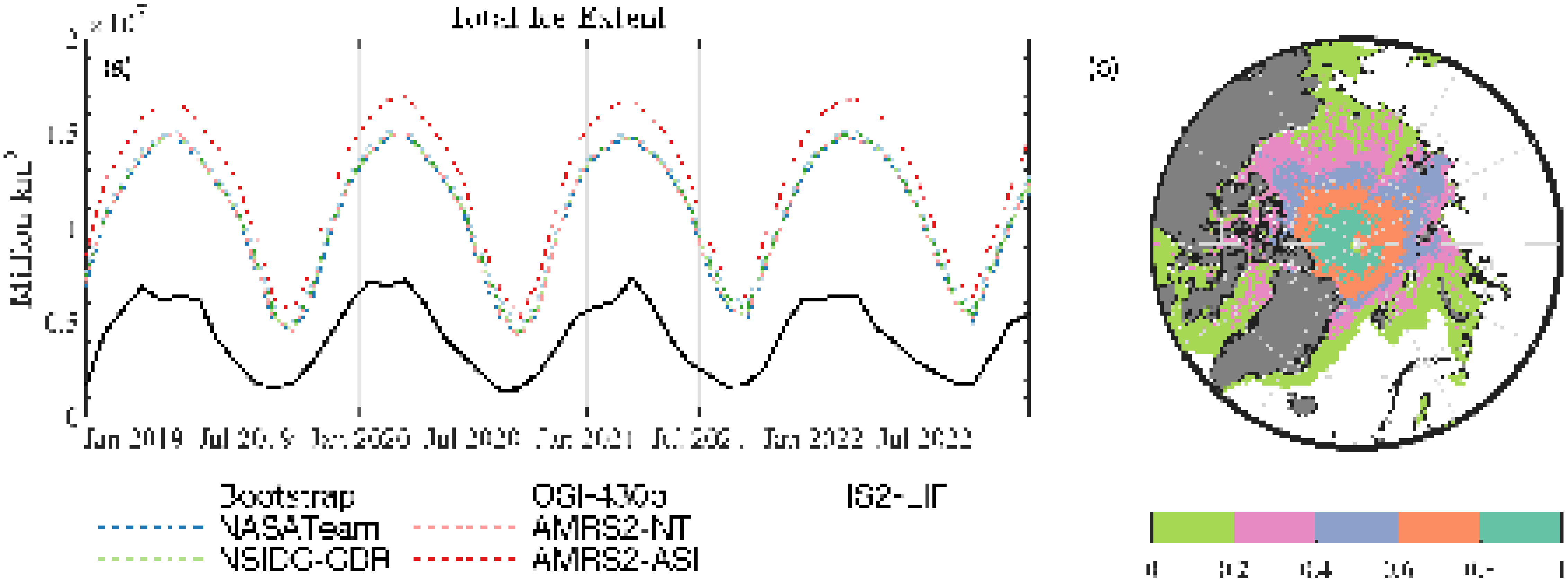


- Sampling error (due to fixed RGT azimuths): (-.6,.6)
- Path error due to unknown ordering of RGTs : (0.25, 1.01)
- Bias a strong function of # overflights.



A gridded linear ice fraction product

Build 25km monthly “LIF” product – requiring > 6 RGTs per month.

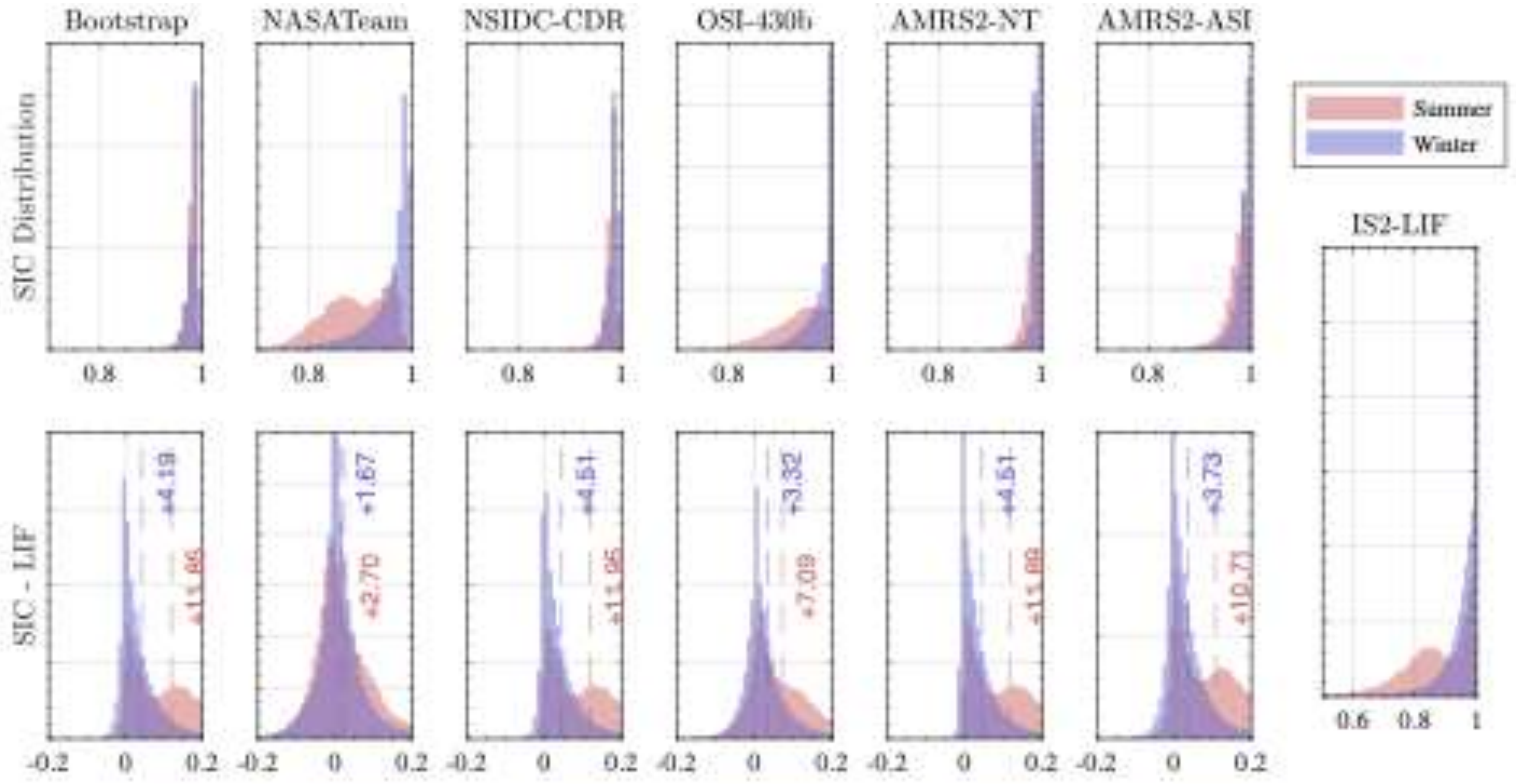


(L) Total coverage of the LIF product vs standard PM-SIC products. (R) Fraction of months since 2018 where all PM-SIC products have data and IS2 has data.

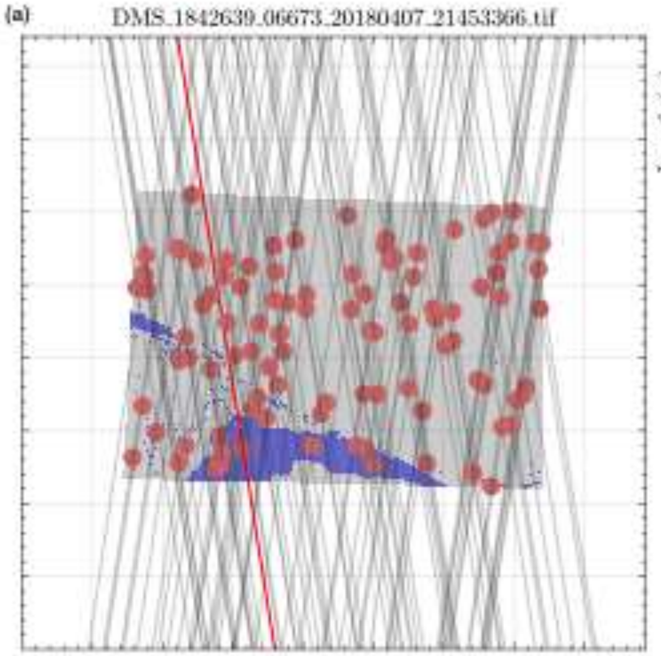
Global SIC Product Comparison

Generally: as seen –in the study region, PM products are systematically 2-5% higher in winter, 3-12% in summer.

(Top) is distribution of SIC for PM-SIC products. (Bottom) is difference from IS2-LIF – vertical lines are median difference.



Some Development Highlights!

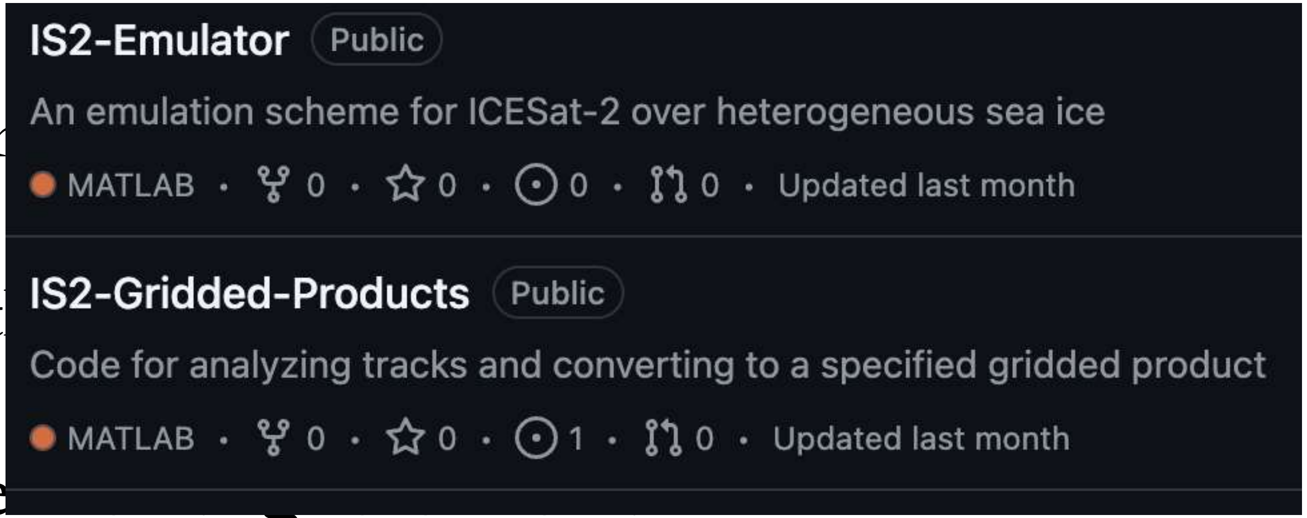


We developed code bases 60:

1) Emulate IS2 overflights over any surface over time, drawing from RGT azimuths to bound unsupervised uncertainty .

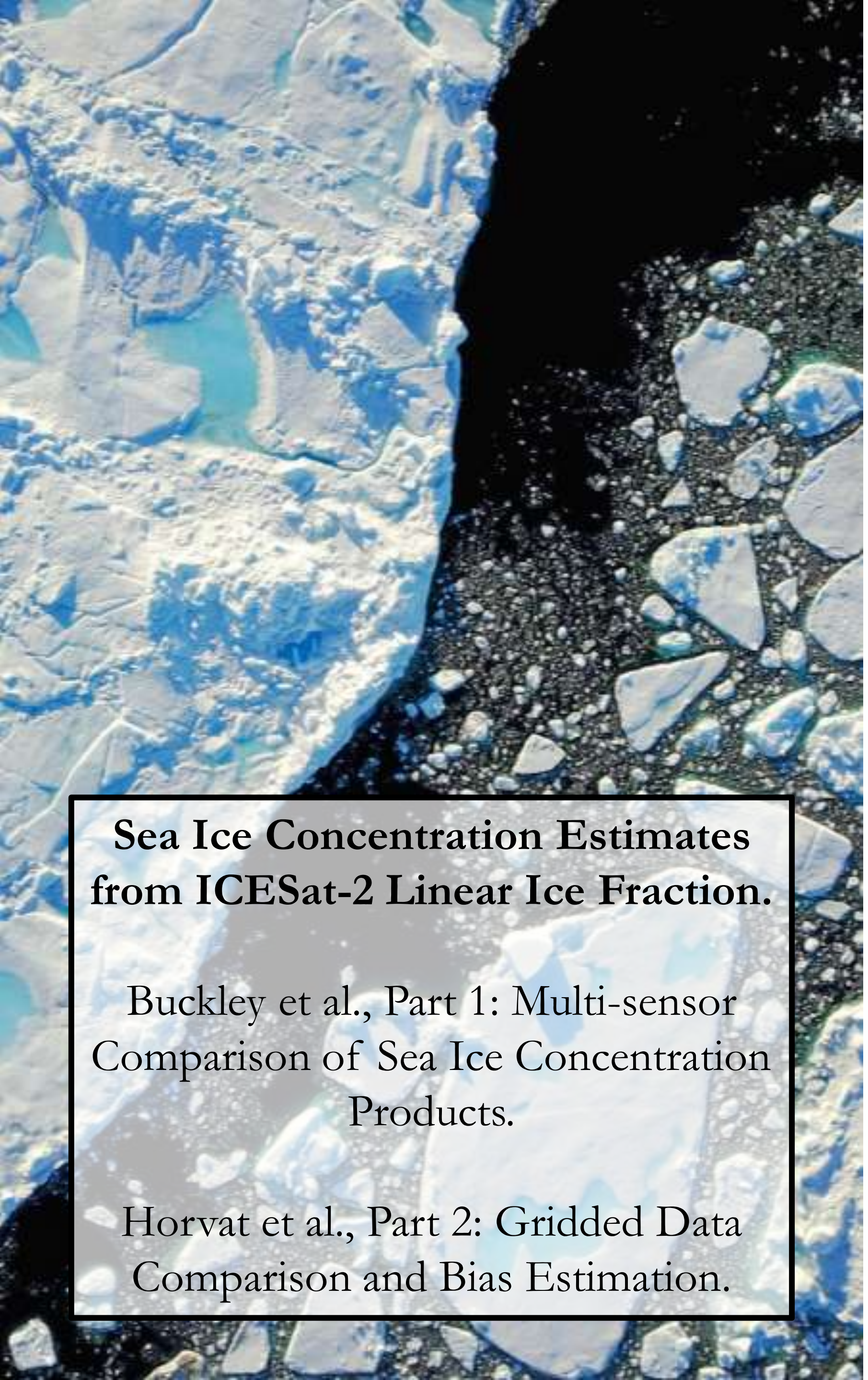
2) Modularly build gridded products by

- Computing along-track statistics
- Gridding in time and space to a ch resolution
- Outputting in desired formats wit



If you like this – use them! Name

Wrap up



Sea Ice Concentration Estimates from ICESat-2 Linear Ice Fraction.

Buckley et al., Part 1: Multi-sensor Comparison of Sea Ice Concentration Products.

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Models are moving to represent sea ice a fragmented composite granular material.

We have exciting new observational datasets. We'd like to find use cases and ways to bias-correct PM.

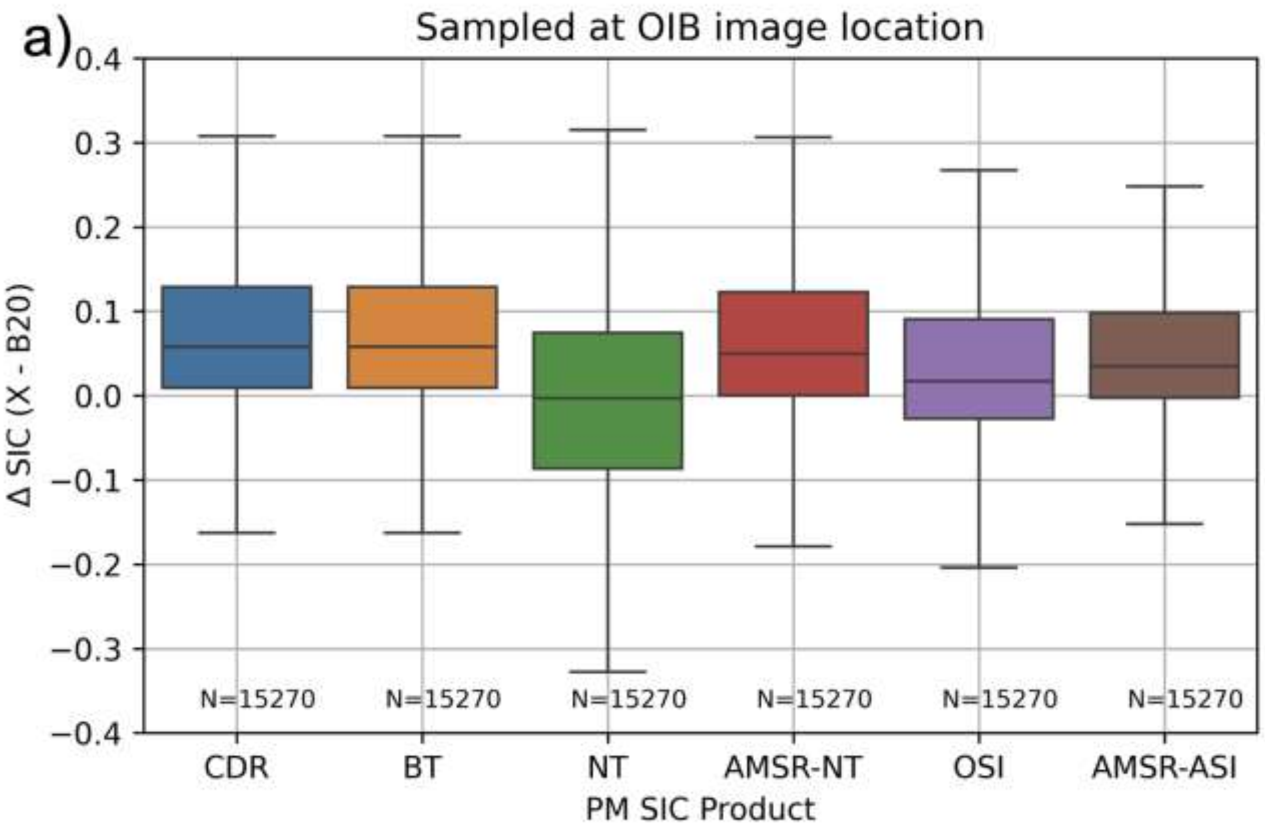
Altimeters are perfect when coupled with techniques for unsupervised error estimation.

polar-oceans.com

Comparison of PM data to optical data with ponds present.

When pond fraction is nonzero, differences are overestimates of SIC in most cases.

Mean absolute biases of 20-25%



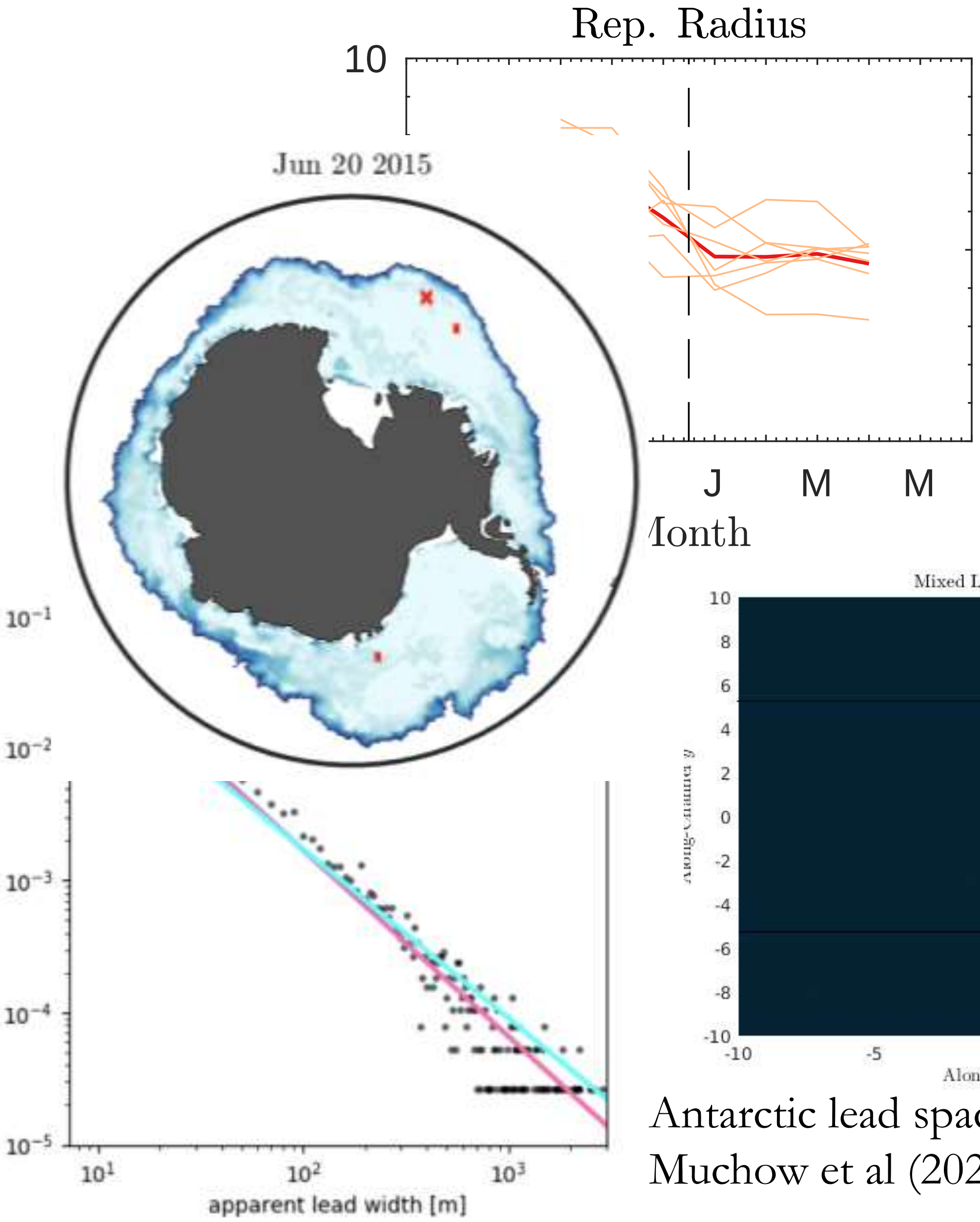
Difference in PM-SIC value from visually-classified "ground truth" for summer with MPF > 0%

Why are these small errors important?

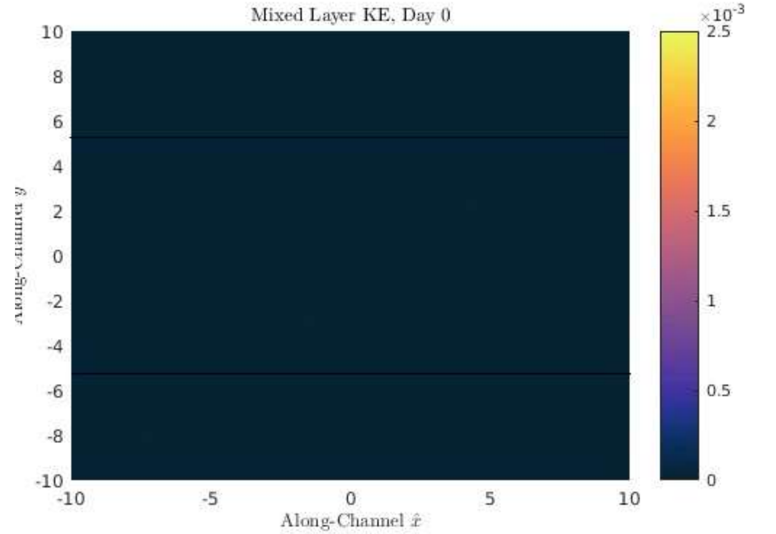
1) HR-PM is at 6 km. The scale of typical floes/lead spacings.

2) Lead distribution is *red*. More variability at smaller scales.

3) Input of PE/PAR in small leads has significant influence on under-ice ocean and ecology (see later)



Arctic mean floe sizes. From Horvat et al (2020)



Antarctic lead spacing distribution. From Muchow et al (2021)

Sea Ice Concentration

$$\boxed{I(f;T) = \frac{2}{c^2} f^2 T}$$

Key observable for polar change. Generally observed via passive microwave satellites

PM senses the *brightness temperature*, related to surface temperature.

$$T_B = \epsilon T$$

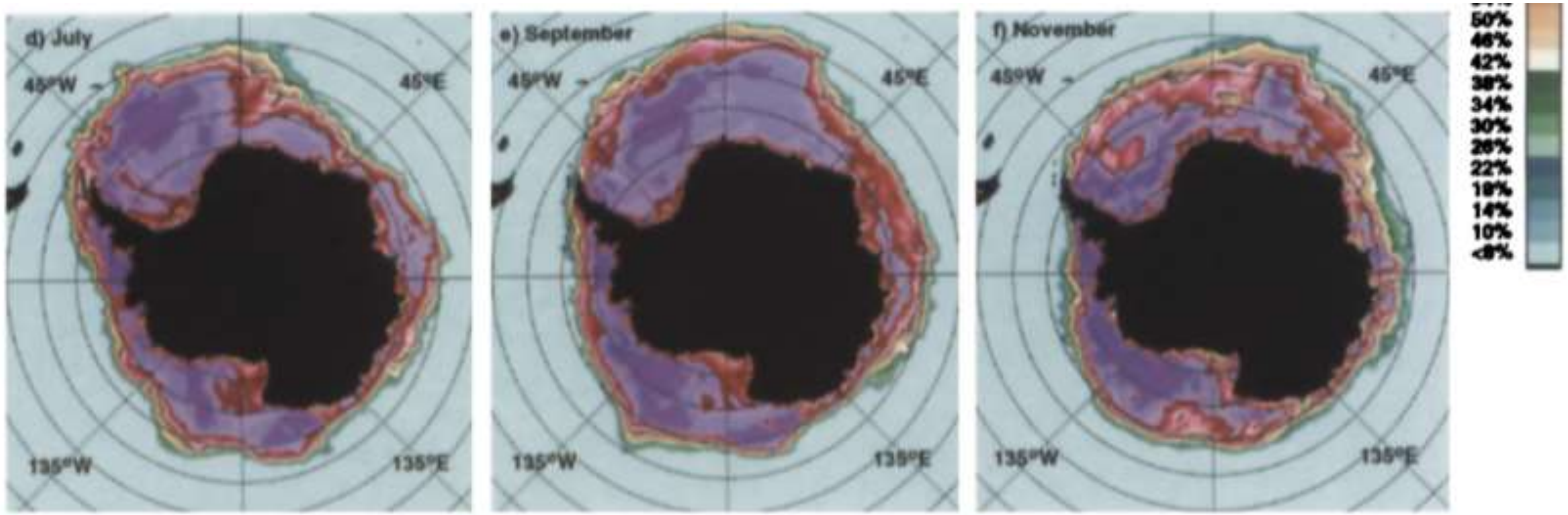


Figure 5. Monthly Antarctic sea ice concentrations derived from SSM/I data, using the Bootstrap algorithm, presented for every other month from January through November 1992.

T_B the weighted sum of brightness temperatures of other surfaces in the satellite footprint

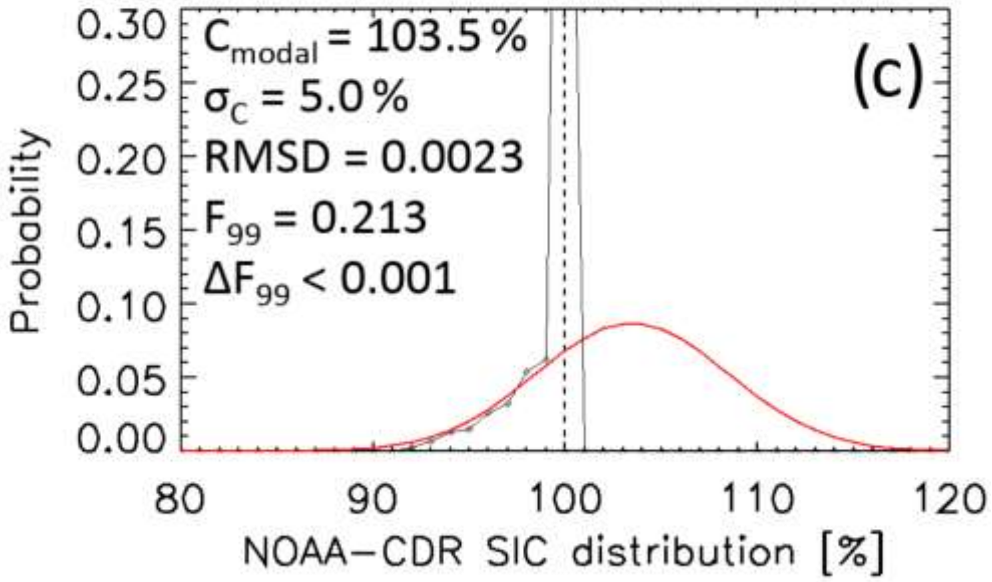
$$T_B = (1-c)T_W + \sum_{\text{ice types}} c_i T_i$$

PM Overestimates of Sea Ice Concentration

Uncertainty in T values leads to SIC > 1!

$$C = \frac{T_B - T_o}{T_i - T_o}$$

For ”close ice” measurements (SIC =~ 100%), NSIDC benchmark SIC product *overestimates* SIC by 3.5%.



Distributions of estimated SIC from the NSIDC-CDR SIC product for sea ice known to have SIC > 99%. From Kern et al (2020)