Arctic-SummIT

Jack Landy, University of Bristol

LIVING PLANET FELLOWSHIP

CRYOSPHERE

Arctic-SummIT: Arctic Summer Ice Thickness

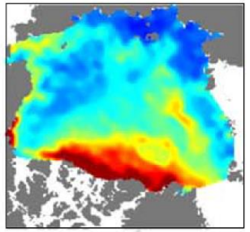
University of Bristol
Environment and Climate Change Canada
ALFRED-WEGENER-INSTITUT HELMHOLTZ-ZENTRUM FÜR POLAR- UND MEERESFORSCHUNG
European Space Agency

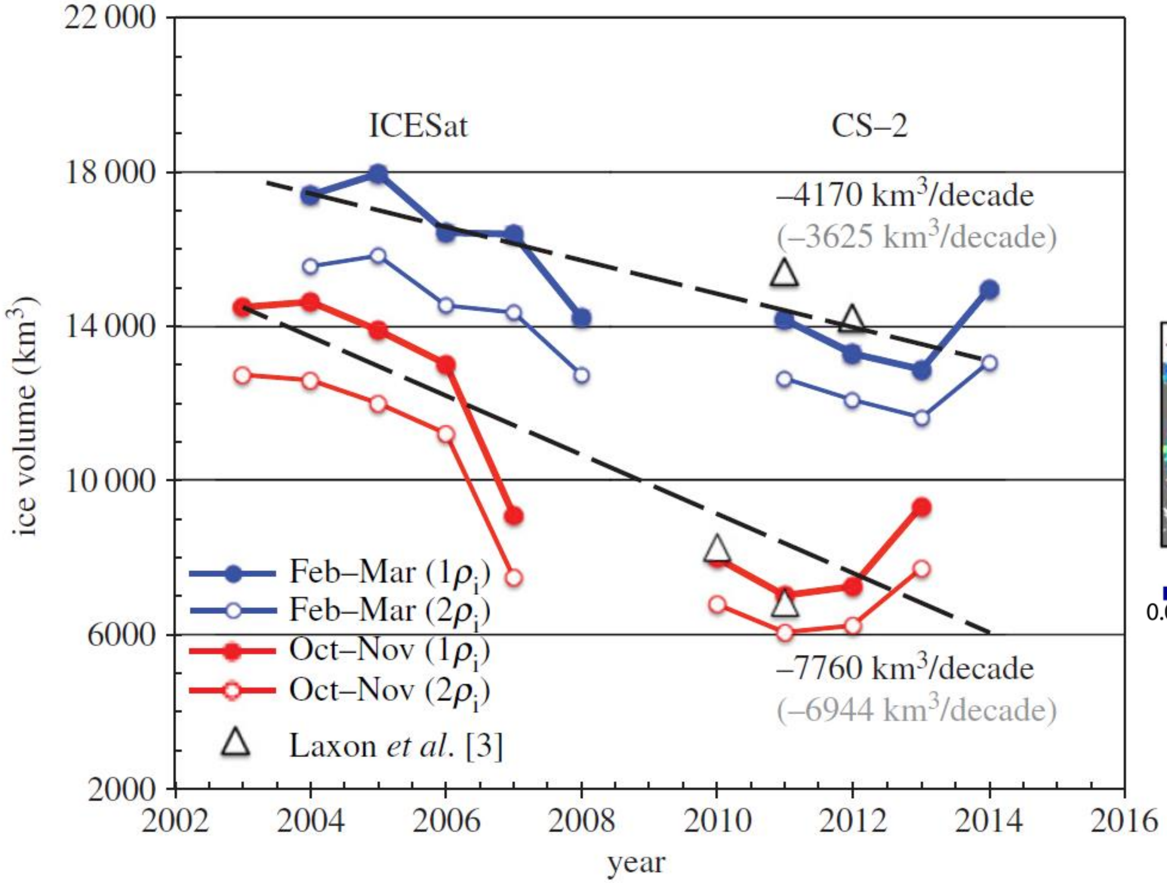
With contributions from:

- Geoffrey Dawson, University of Bristol
- Alexander Komarov, Environment Canada Climate Change
- Steve Howell, Environment Canada Climate Change
- Thomas Krumpen, Alfred Wegener Institute, Germany

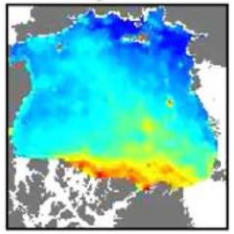
Arctic Sea Ice Volume Trends 2003-2015

2004



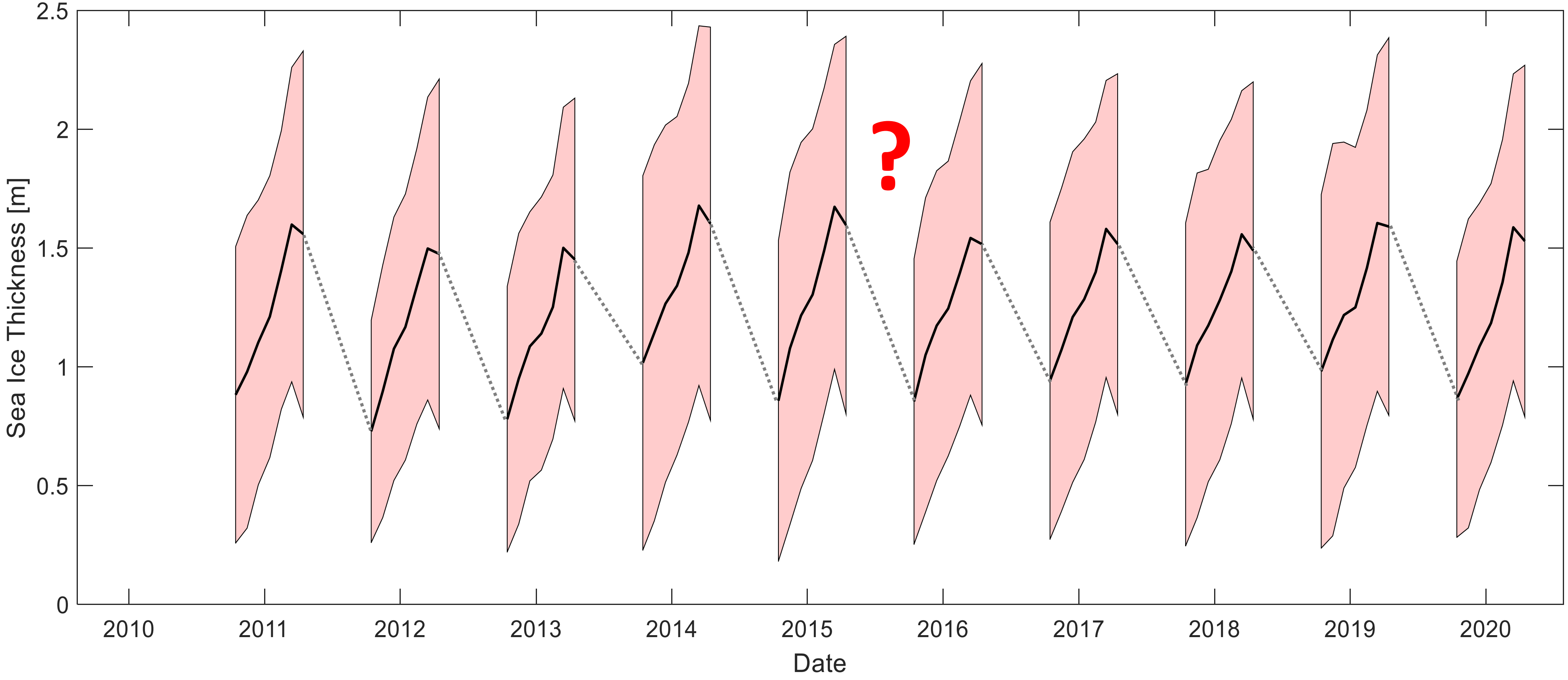


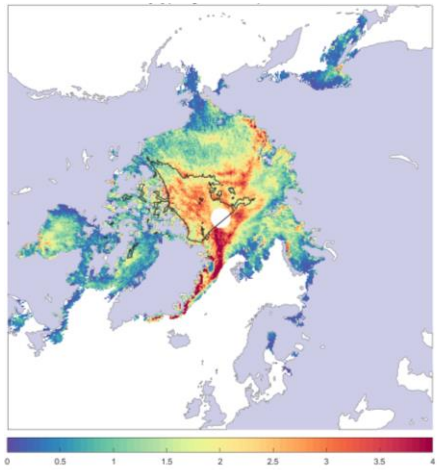
2018



Kwok and Cunningham, PTRS-A, 2014

A long-term sea ice record… but is it complete?



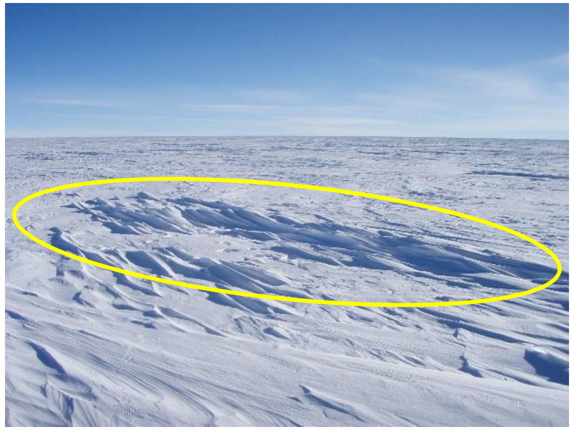


Sea Ice Thickness [m]
February 2018

Arctic-SummIT

esa

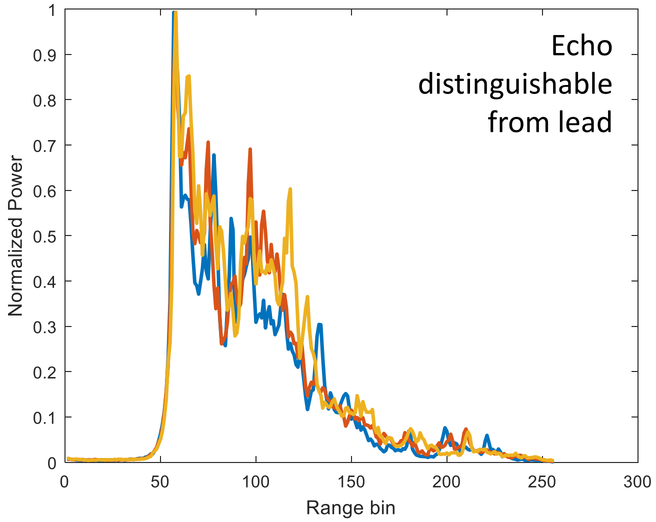
So why can't we do this in summer as well…?



sci-news.com

Diffuse Echo

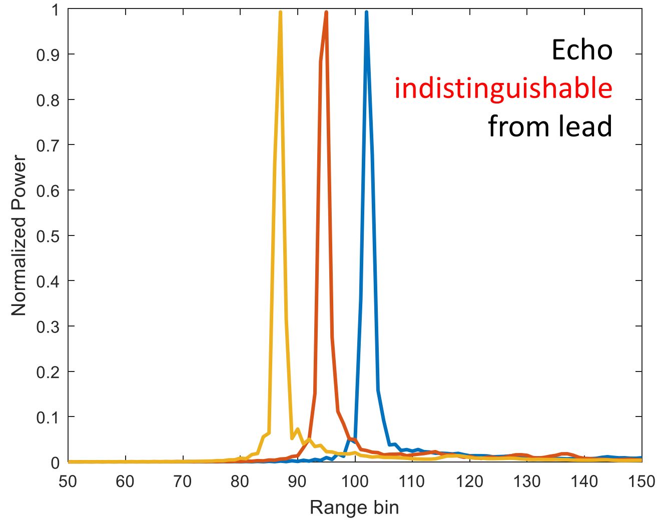
Scattering contributions from across entire Cryosat-2 footprint



nikkophotography.blogspot.com

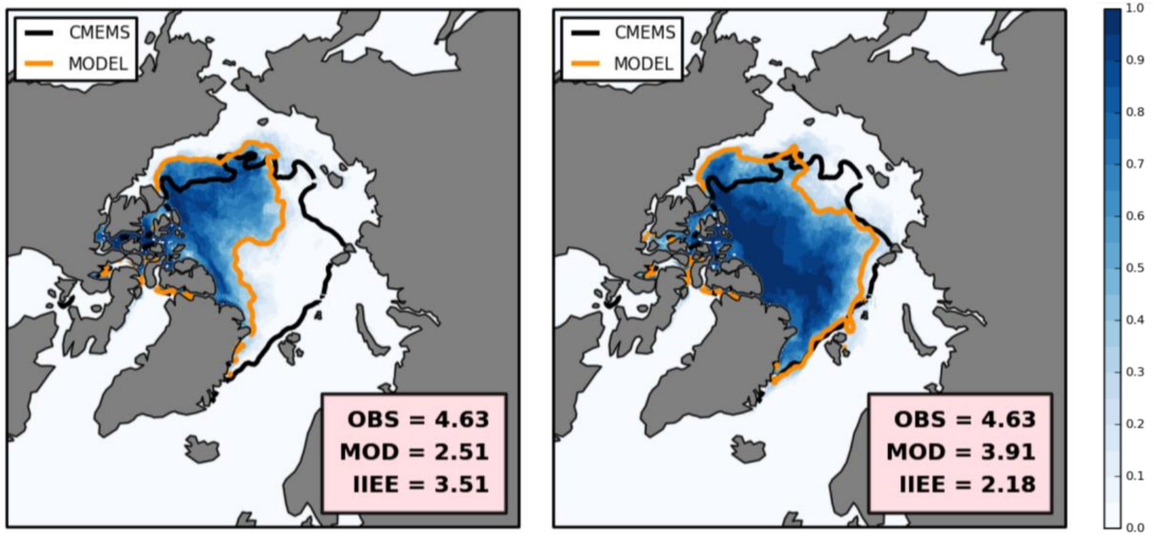
Specular Echo

Coherent reflection from melt pond closest to nadir location

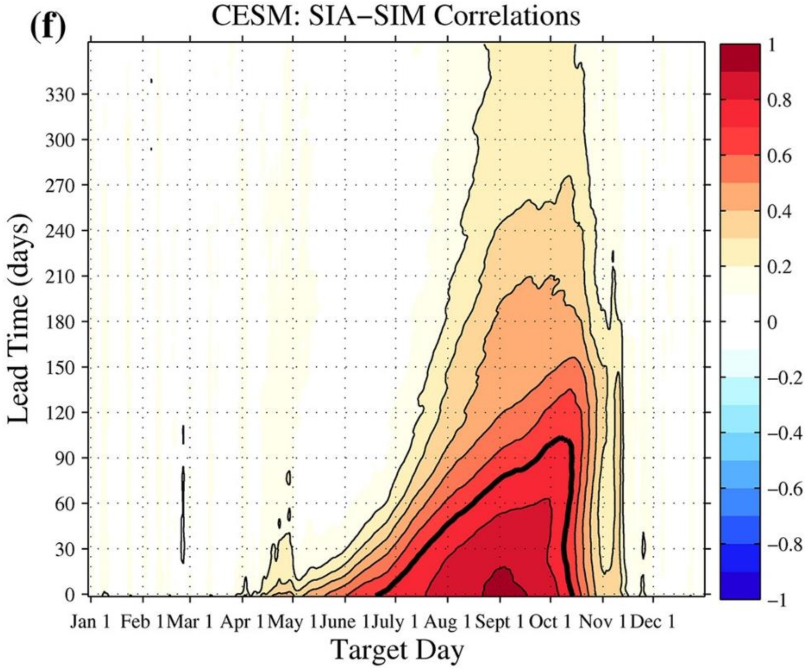


Potential impact of summer sea ice thickness observations

GloSea Model | Initialized with CS2 Data



Blockley and Peterson, TC, 2018



Bushuk et al., GRL, 2020

"The spring predictability barrier implies that <u>SIT observations collected past the melt onset date</u> are particularly critical for seasonal predictions of regional summer Arctic sea ice. <u>Extending these data as far as possible into the melt season</u> would likely lead to substantial improvements in seasonal prediction skill." **Bushuk et al., GRL, 2020**

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Obj a – Use machine learning to separate sea ice and lead echoes in summer

Obj b – Derive and validate sea ice freeboards

Obj c – Develop sea ice thickness product with uncertainties

Obj d – Calculate sea ice volume fluxes through Arctic gateways

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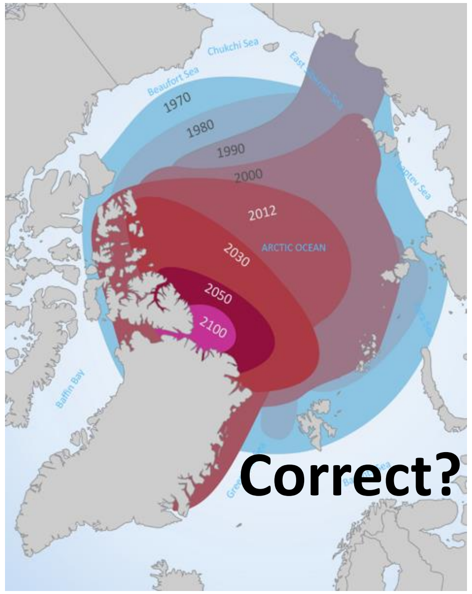
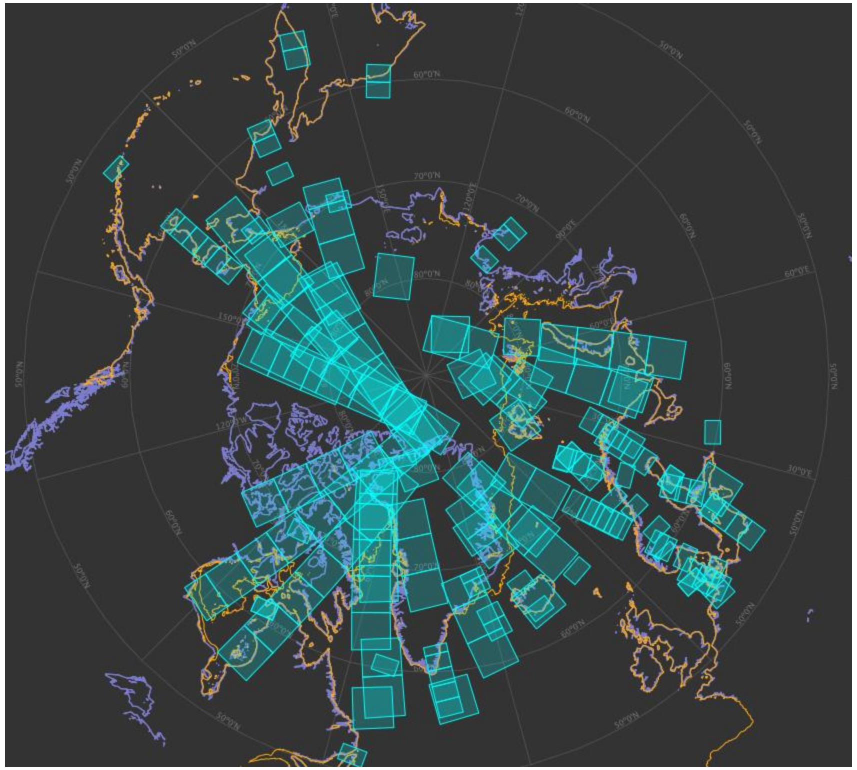
<u>PRE-MELT</u> (Preconditioning the trigger for rapid Arctic ice melt)

Jack Landy (Bristol), Michel Tsamados (CPOM), Yevgeny Aksenov (NOC)



- Pilot results from the first year of Arctic-SummIT project used as building block for new grant proposal to the UK Natural Environment Research Council (NERC)
- NERC Standard Grant: PRE-MELT (€770k started Jan 2020)
- Key objective: are enhanced sea ice dynamics in Central Arctic leaving the ice vulnerable for faster-than-expected melt..?
- Postdoctoral Researcher on project: Geoffrey Dawson

Obj a – Use machine learning to separate sea ice and lead echoes in summer



Polar View (24/11/20)

Sensor	Coincident Images per Month
Sentinel-1A/B	~90
Sentinel-2	~5
Landsat-8	~7
RADARSAT-2	~7

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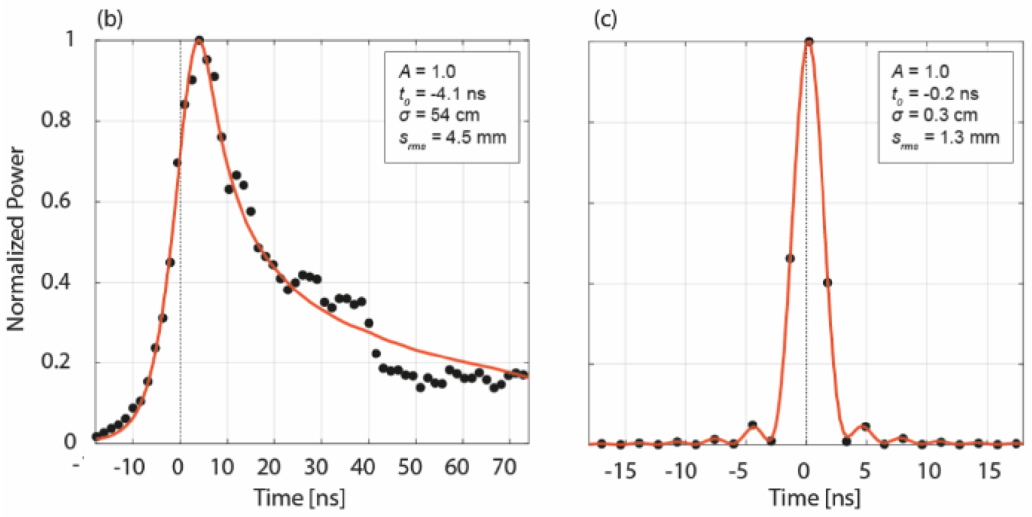
Obj a – Use machine learning to separate sea ice and lead echoes in summer

ESA GPOD SARvatore Data

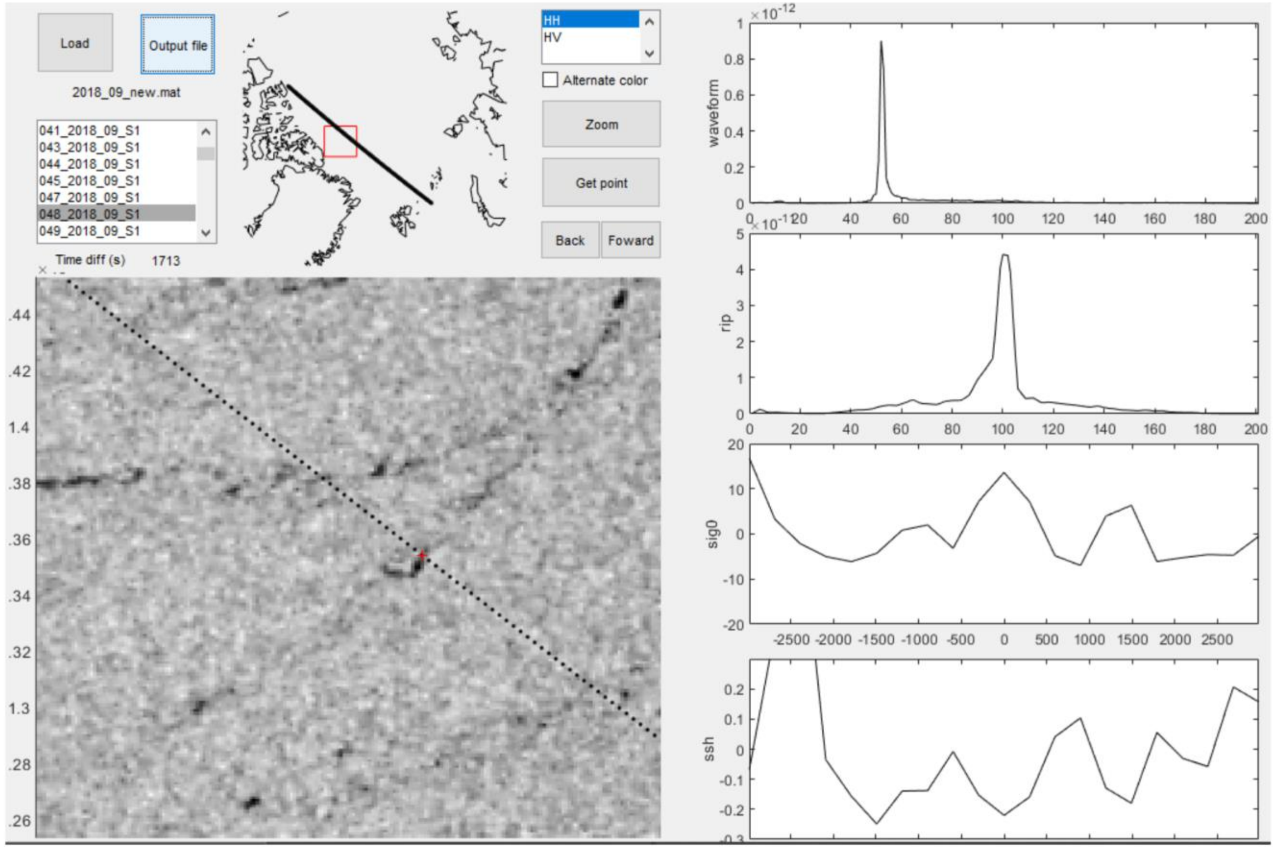
- SAMOSA+ Retracking
- Theoretical model for the backscattered radar echo from a rough ocean surface
- Adapted for inland water/coastal regions/sea ice
- Model fit to ESA CryoSat-2 L1B observations
- Repository of SAR & SARIn data for the Arctic Ocean 2011-2019 at 20 Hz
- Custom processing of individual tracks at 80 Hz

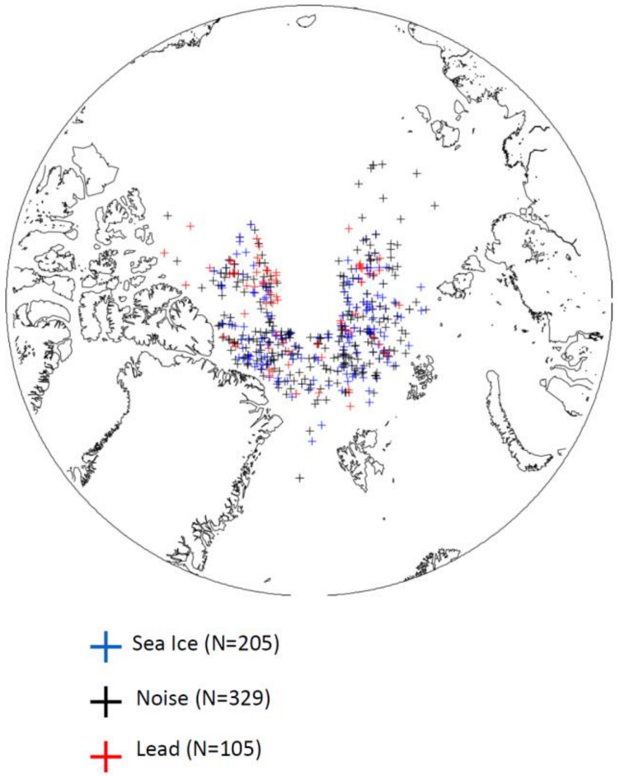


Landy et al., JGRO, 2020

With great thanks to Salvatore Dinardo, Jérôme Benveniste, Giovanni Sabatino and the rest of the ESA GPOD Team!

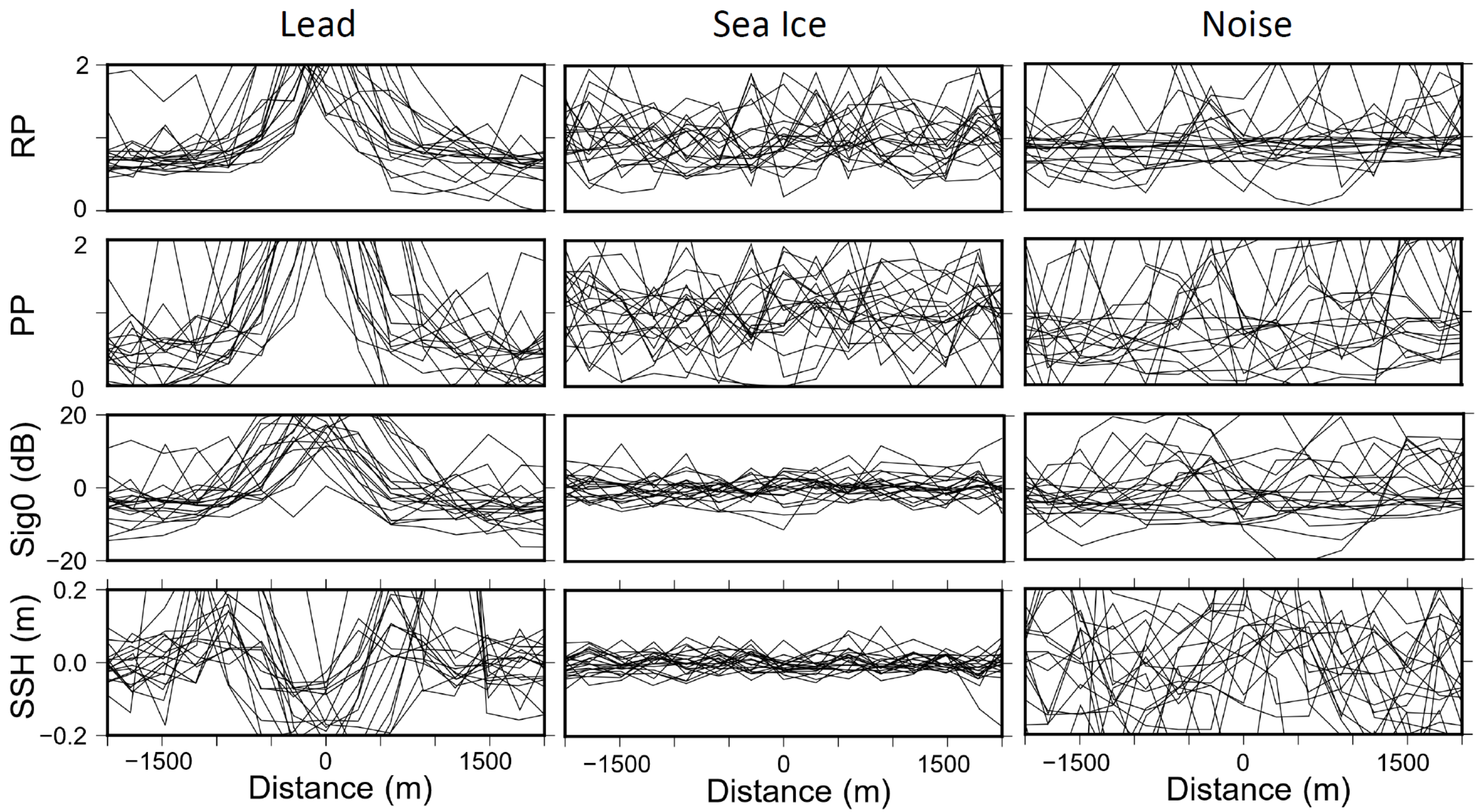
Obj a – Use machine learning to separate sea ice and lead echoes in summer





Manual Identification of Training Data

Obj a – Use machine learning to separate sea ice and lead echoes in summer



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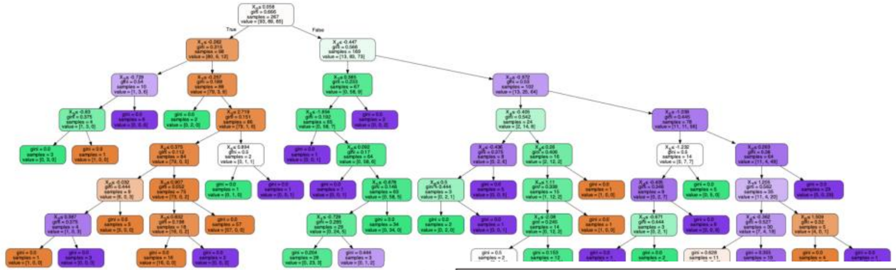
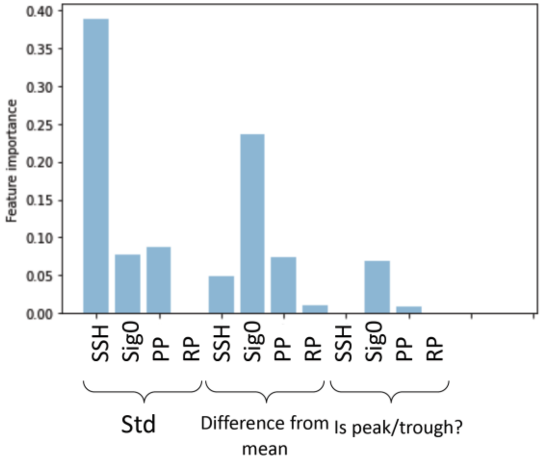
Obj a – Use machine learning to separate sea ice and lead echoes in summer

Shallow Learning: Decision Tree

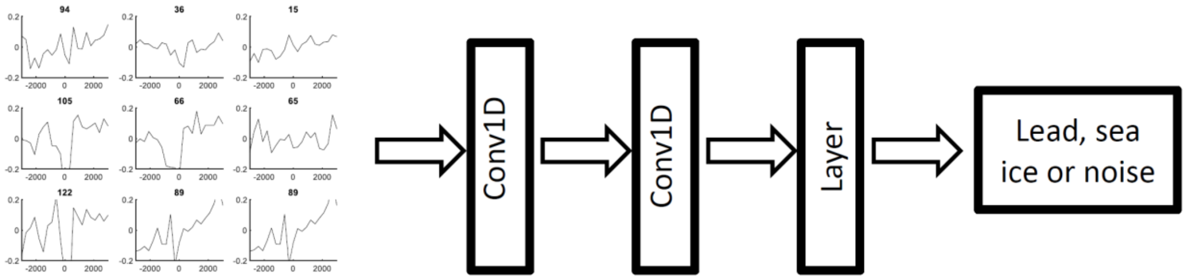
SciKit





Deep Learning: 1D Convolution Neural Network (CNN)

KERAS + TensorFlow

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==========================================================================
Total params: 1,091 Trainable params
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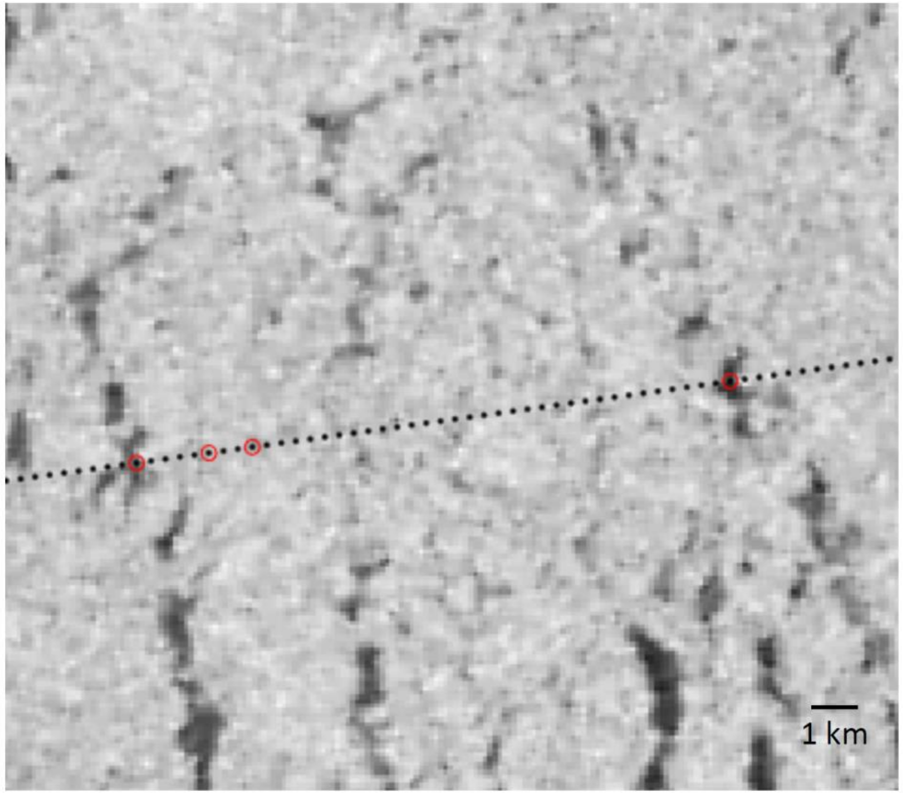
Classification Results:

Decision Tree = 70%

1D CNN = 81%

Obj b – Derive and validate sea ice freeboards



Classification results on the testing samples

Steps for deriving sea ice freeboard fields:

1. Apply classification routines
2. Noise filtering
3. Fit robust polynomial function to all ‘sea ice’ samples within 8 km of each ‘lead’ sample
4. Radar freeboard obtained from difference between sea ice fit and leads
5. Gridded by inverse-distance weighting

Obj b – Derive and validate sea ice freeboards

Unpublished Results

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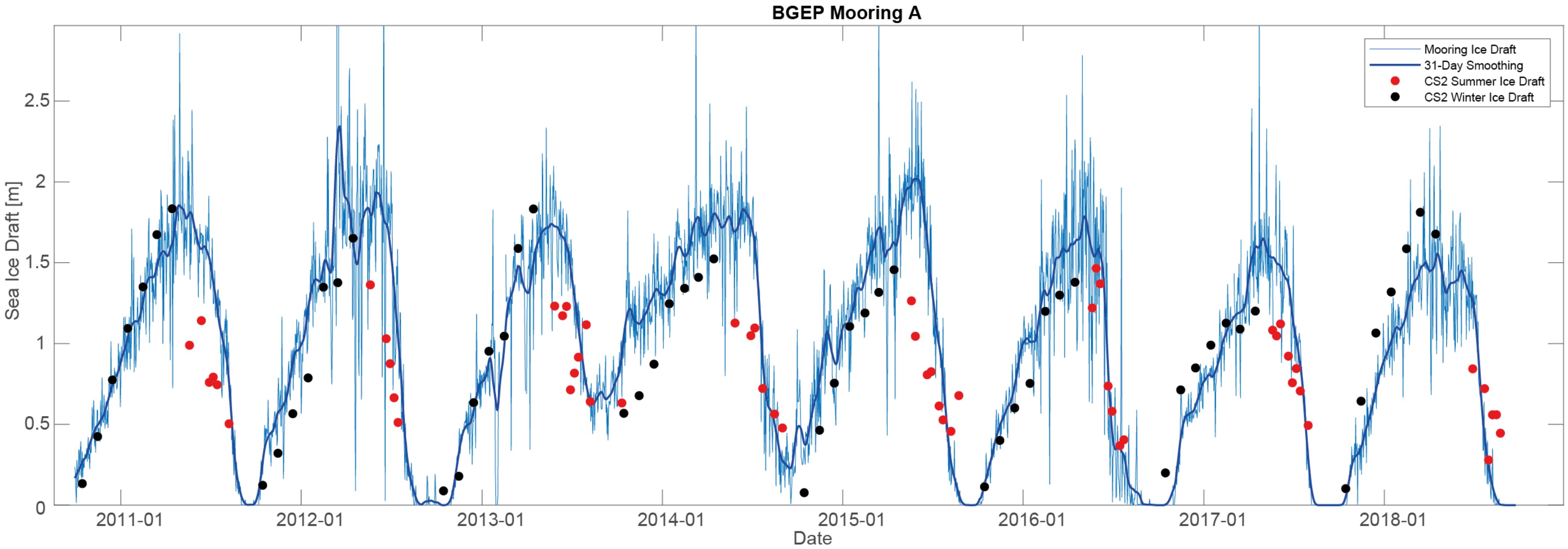
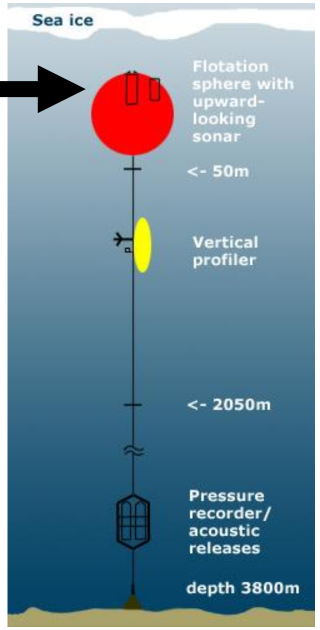
Unpublished Results

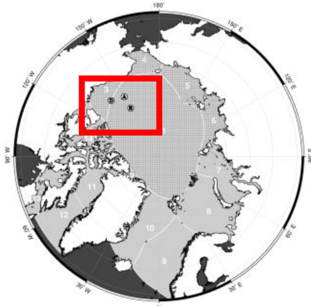
Obj b – Derive and validate sea ice freeboards

Validation against the Beaufort Gyre Exploration Program Moorings

Upward-Looking Sonar







Obj c – Develop sea ice thickness product with uncertainties

Comparison with airborne EMI ice thickness data from the AWI "IceBird" Program (courtesy of Thomas Krumpen)

- Assume ice density of 916 kg/m^3
- CS2 SIT underestimates AEM in all campaigns
- 40-50 cm over marginal ice in 2011
- ~100 cm over old central pack ice in 2016-2018

Unpublished Results

Why is the sea ice thickness being underestimated?

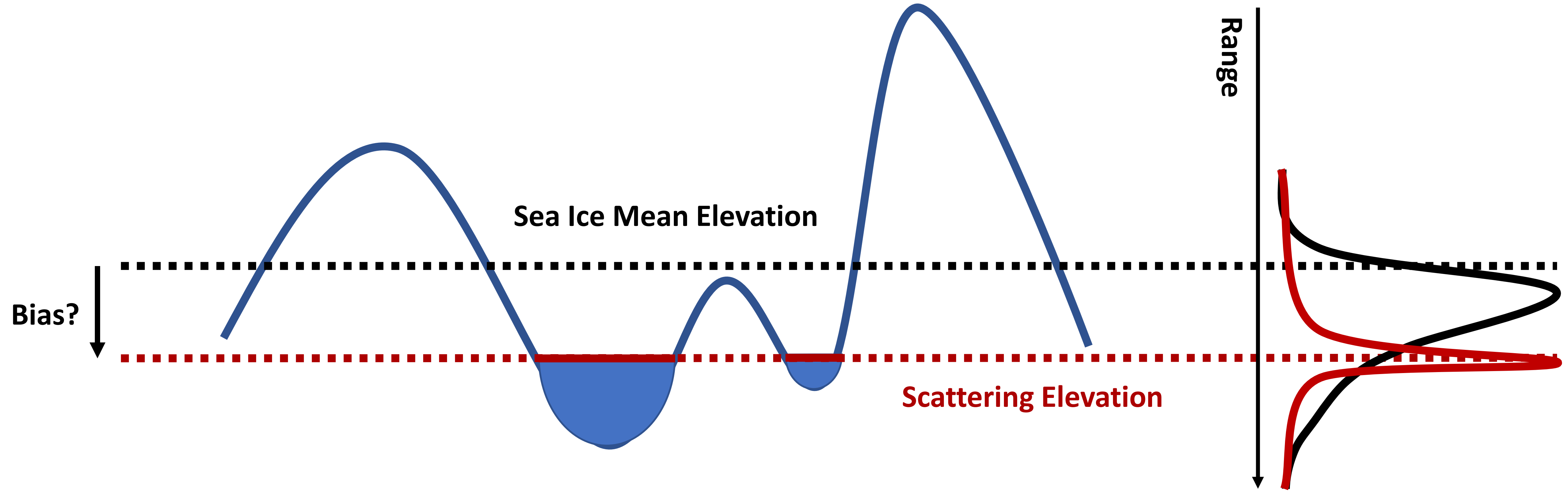
Obj c – Develop sea ice thickness product with uncertainties

Possible sources of the SIT underestimation

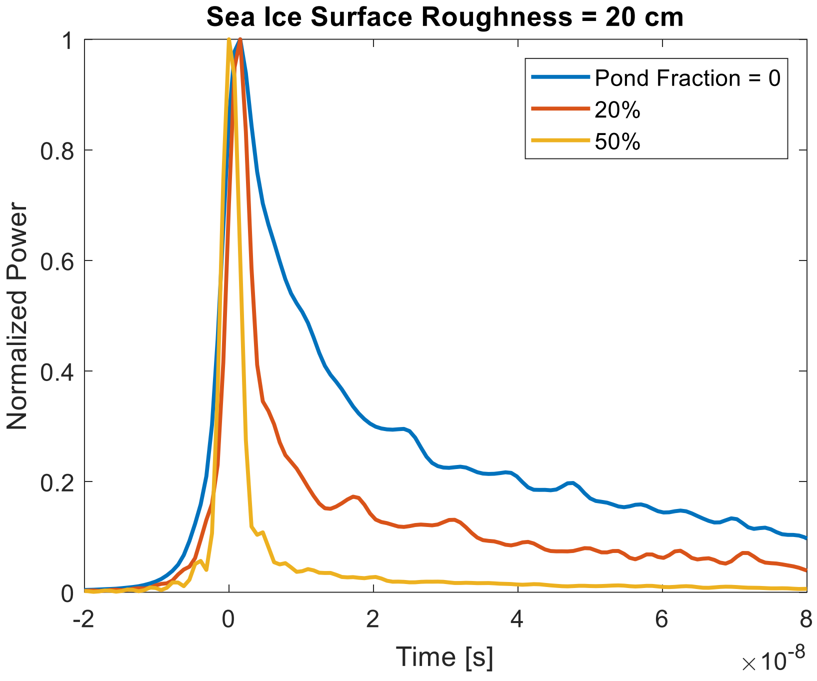
1. Range to sea ice underestimated, with radar sensitive to specular scatterers covering just 1% of the sensor footprint
2. Differences in SSH measurements between SAMOSA+ retracking of ESA and GPOD L1B waveforms
3. Effective sea ice density is high: >930 kg/m^3
4. Residual snow load on the sea ice or melt pond water sitting above sea level
5. Melt ponds introduce a bias in the principal radar scattering horizon

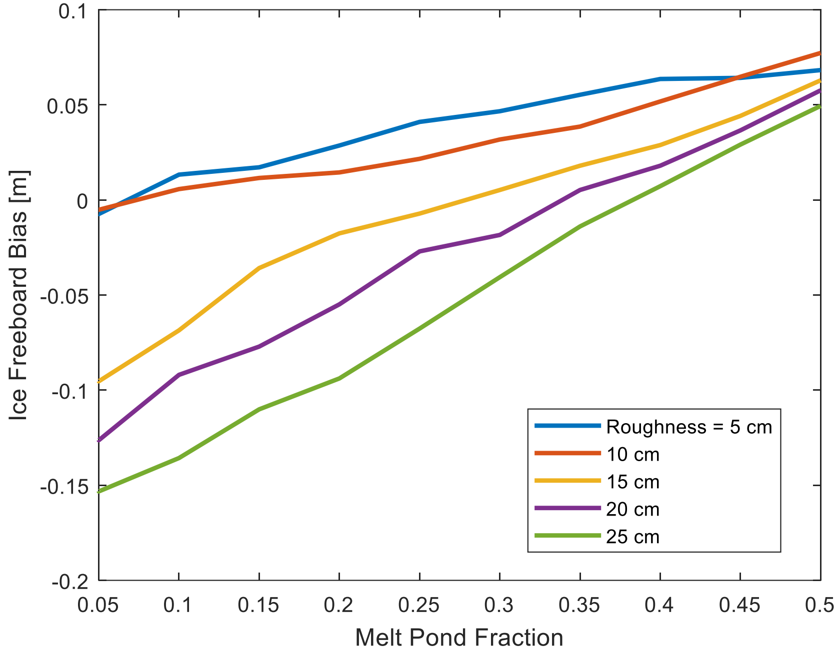
Obj c – Develop sea ice thickness product with uncertainties

Radar freeboards biased low by reflections from pond surfaces sitting below mean ice level



Obj c – Develop sea ice thickness product with uncertainties

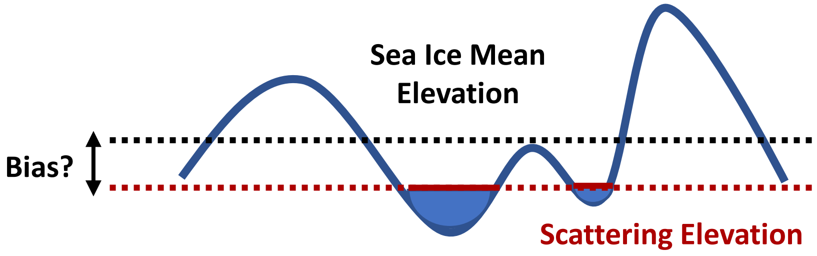




Typical freeboard underestimation of 0-15 cm

Landy et al., TGARS, 2019

Possible solution: determine bias as function of ice roughness/pond coverage from auxiliary observations



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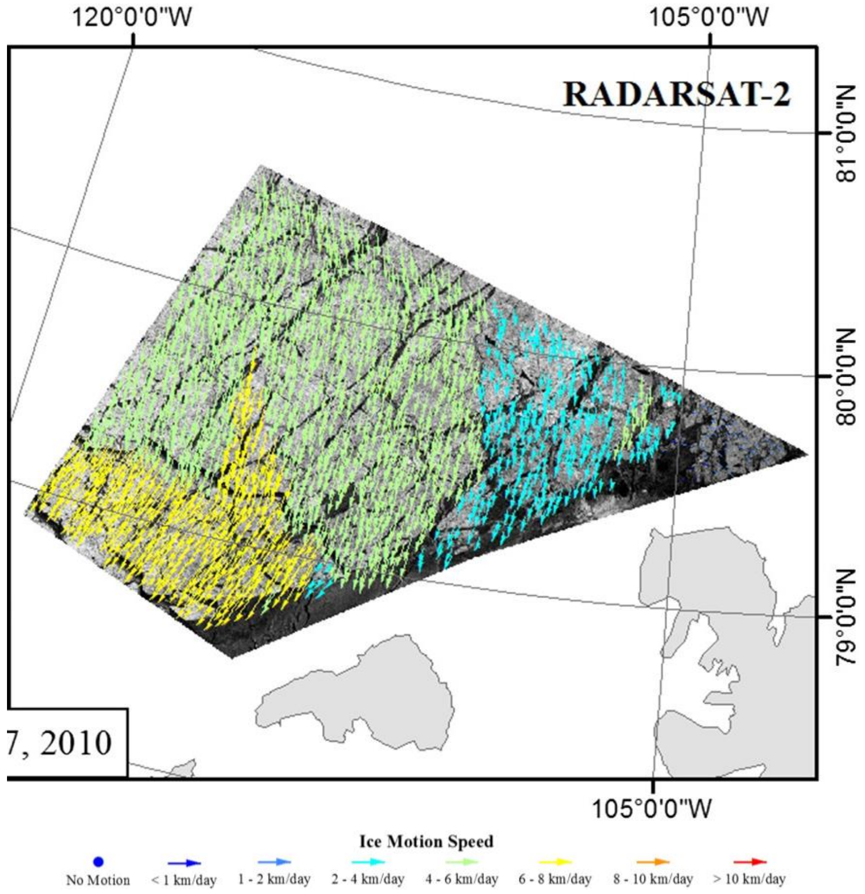
Obj d – Calculate sea ice volume fluxes through Arctic gateways



Combine new sea ice thickness data with ice concentration and motion to calculate ice volume fluxes through Arctic gateways

- Project partner Dr. Steve Howell (ECCC)
- 7-day sea ice motion from SAR (RADARSAT-2, Sentinel-1 A/B, RCM) since 2016
- Consistent coverage over Nares Strait, Fram Strait, Bering Strait
- Will calculate sea ice volume fluxes for ~full year for these key gateways

Publications relating to Fellowship Research

Landy, J.C., Tsamados, M. and Scharien, R.K., 2019. A facet-based numerical model for simulating SAR altimeter echoes from heterogeneous sea ice surfaces. IEEE TGARS, 57(7), 4164-4180.

Landy, J.C., Petty, A.A., Tsamados, M., and Stroeve, J.C., 2019. Sea ice roughness overlooked as a key source of uncertainty in CryoSat-2 ice freeboard retrievals. JGR-Oceans, 125(5), p.e2019JC015820.

Kirillov, S., Babb, D., Dmitrenko, I., Landy, J., Lukovich, J., Ehn, J., et al. (2020). Atmospheric forcing drives the winter sea ice thickness asymmetry of Hudson Bay. Journal of Geophysical Research: Oceans, 125, e2019JC015756.

Babb, D. G., Landy, J. C., Barber, D. G., & Galley, R. J. (2019). Winter sea ice export from the Beaufort Sea as a preconditioning mechanism for enhanced summer melt: A case study of 2016. Journal of Geophysical Research: Oceans, 124, 6575– 6600.

Mallett, R.D., Lawrence, I.R., Stroeve, J.C., Landy, J.C. and Tsamados, M., 2020. Brief communication: Conventional assumptions involving the speed of radar waves in snow introduce systematic underestimates to sea ice thickness and seasonal growth rate estimates. Cryosphere, 14(1), pp.251-260.

Summary and Future Plans

- Obtaining valid Arctic sea ice thickness data in summer from CryoSat-2 is a huge challenge!!
- A shallow-deep ML classification algorithm has been trained on Sentinel-1 and RADARSAT-2 imagery for separating CryoSat-2 echoes from leads and melt pond-covered sea ice
- Classification accuracies are up to 81% versus independent testing samples
- Derived sea ice freeboards reflect expected spatial & temporal patterns in summer melt evolution
- CryoSat-2 estimates for sea ice thickness typically underestimate coincident airborne EM observations
- Future work = develop a generalized bias correction for freeboard-to-thickness conversion
- Constrain ice thickness data product uncertainties
- Investigate sea ice volume fluxes during summer at key Arctic gateways

Thanks to the European Space Agency for their funding and support throughout the LPF!

Any questions…?