Theme 4: Sea Ice

- Sea Ice Drift
- Sea Ice Type
- Multi-sensor synergy
- In situ campaigns

Co-chairs:
- Anton Korosov, NERSC
- Malin Johansson, The Arctic University of Norway
- Robert Shuchman, Michigan Technological University, USA
- Wolfgang Dierking, Alfred Wegener Institute, Germany
- Ron Kwok, University of Washington Seattle, USA

01/05/2023

Theme : Sea Ice
Topic : Sea Ice Drift and Deformation (SIDĐ)

Demchev Denis, Frost Anja, Karvonen Juha, Korosov Anton, Xiao-Ming Li
+ slides from Bouchat Amelie and Helfrich Sean

01/05/2023

Contributing work

- Juha Karvonen, Copernicus Marine Service SITAC SAR-Based Baltic Sea Ice Products (FMI)
- Denis Demchev, Leif Eriksson, Anders Hildeman, Wolfgang Dierking, Investigation of Multifrequency SAR Image Alignment by Ice Drift Compensation In The Marginal Ice Zone (Chalmers University of Technology, AstraZeneca, UiT, AWI)
- Xiao-Ming Li, Sea Ice Cover And Drift By Sentinel-1 SAR And The Support for Arctic Shipping (Aerospace Information Research Institute)
- Anton Korosov and Marcel Kleinherenbrink, Potential Application of the Earth Explorer 10 candidate Harmony for Sea Ice Model Validation, (NERSC, Delft University of Technology)
- Amélie Bouchat, Sea-ice deformation derived from the RADARSAT Constellation Mission and Sentinel-1 SAR Imagery at 24- and 72-hr intervals from 2017 to 2021 (McGill Univ.), IICWG-DA-11
- Sean Helfrich, Sea-ice deformation derived from the RADARSAT Constellation Mission and Sentinel-1 SAR Imagery at 24- and 72-hr intervals from 2017 to 2021 (NOAA), IICWG-DA-11
- Korosov et al., Towards improving sea ice deformation predictability (NERSC), The Crysophere discussions

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Remaining knowledge gaps (summary)

Outlook and recommendations (summary)

Key objectives

Development of SID algorithms

- To develop a sea ice drift algorithm (two sequential SAR GRD images + pattern matching)
- To validate the algorithm (e.g., on new MOSAiC data)
- To test parameters of the algorithm (e.g., temporal intervals between images)

Application of SID algorithms

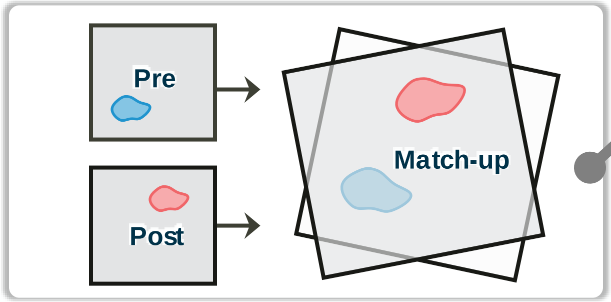
- Operational sea ice monitoring with resolution higher than on the ice charts
- Producing longer time-series of ice drift
- Alignment of multi-frequency (C- and L-band) SAR imagery for ice type classification
- Alignment (‘morphing‘) of multi-temporal C-band SAR imagery for more robust ice type classification
- Calibration / validation of sea ice models
- Testing applicability of future missions (Harmony)
- Assimilation into sea ice models

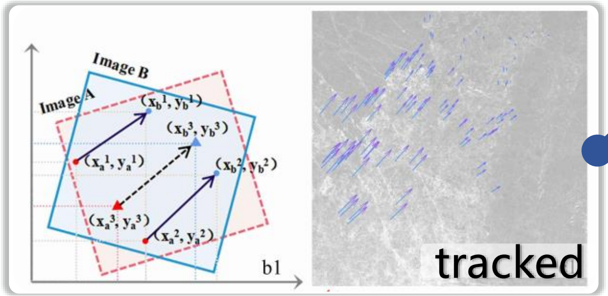
Innovations

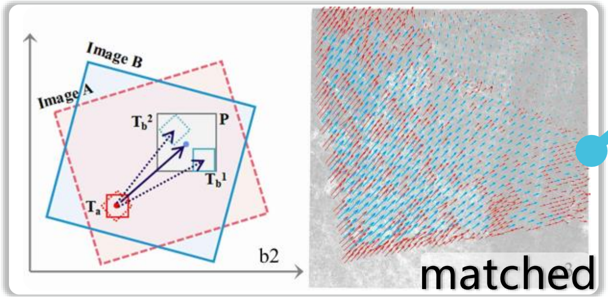
(Results)

Sea Ice Cover And Drift By Sentinel-1 SAR And The Support for Arctic Shipping (Li et al.)

Applying a combination of Feature Tracking and Pattern Matching to retrieve sea ice drift based on Sentinel-1 EW HV sequential data, the results were validated against MOSAiC buoys in 2020.







Sequential SAR

↓

Feature Tracking

↓

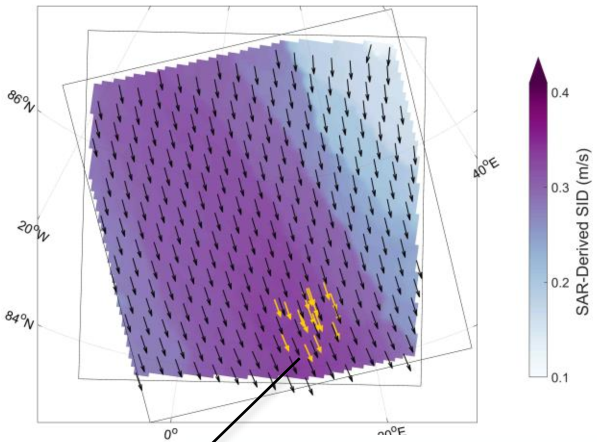
Interpolation

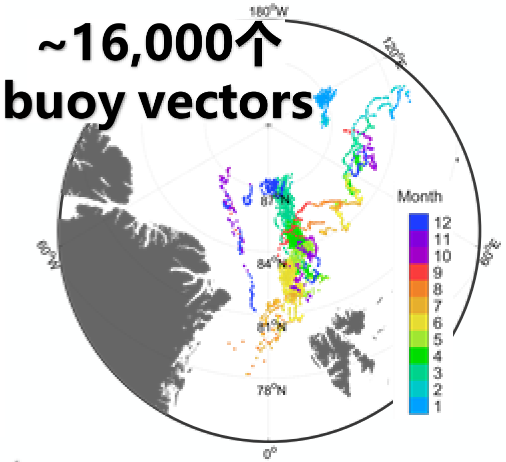
↓

Pattern Matching

↓

Quality control





seasons	Temporal Intervals	S1 pairs (vectors)	Error bias (RMSE)	
			cm/s	°
Jan-Jun, Oct-Dec	16 -24h	4,765 (15,254)	0.00 (0.57)	0.27 (4.73)
Jul-Sep	<16h	499(644)	0.52 (1.85)	4.62 (20.73)

Qiu and Li (2022), *IEEE TGRS*

Sea Ice Cover And Drift By Sentinel-1 SAR And The Support for Arctic Shipping (Li et al.)

- **Apart from the applied algorithms, the accuracy also relies on the temporal intervals between sequential SAR images, especially for high variability.**

Qiu and Li (2022), *IEEE TGRS*

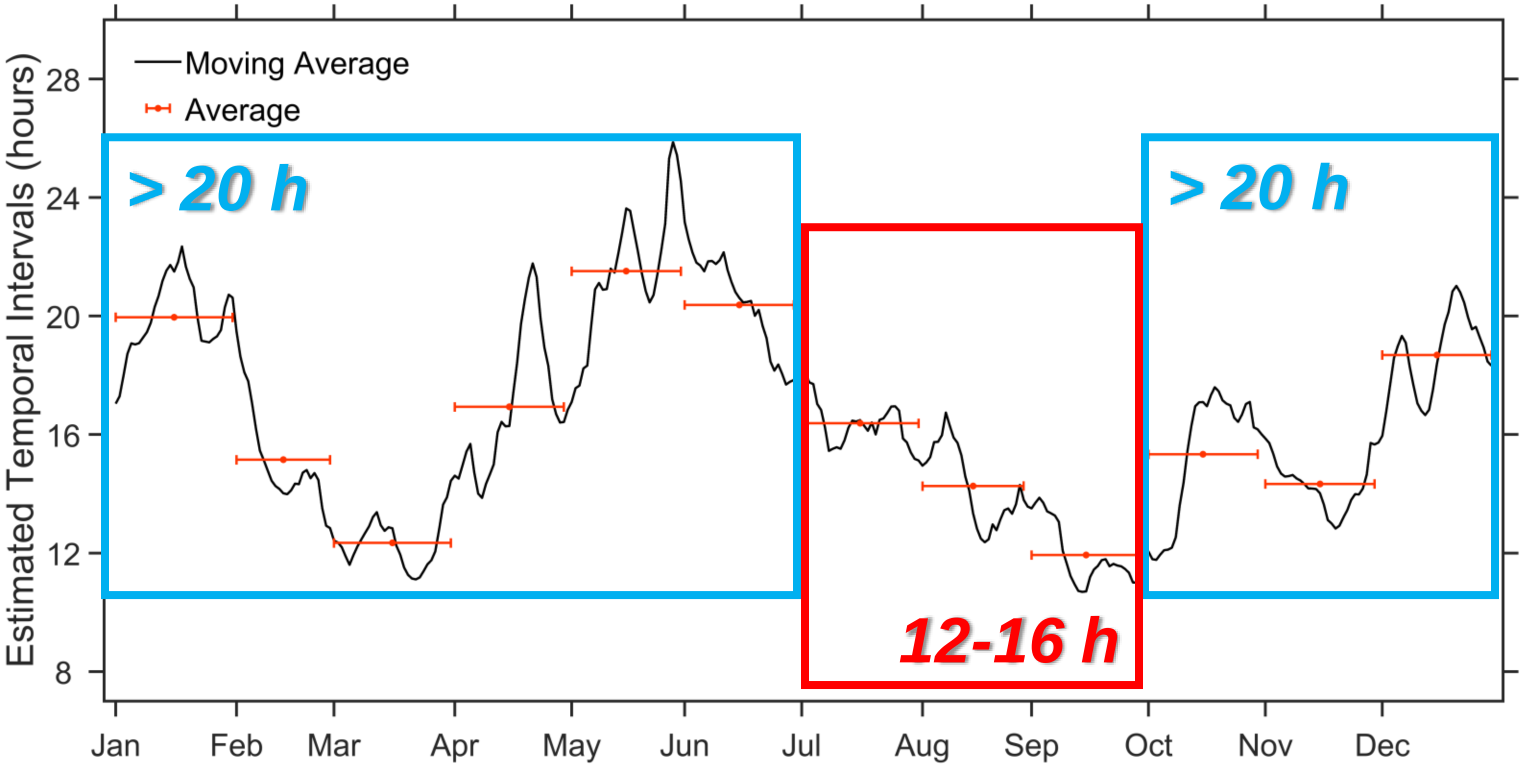
"Approriate" Temporal Intervals?

- could minimise the retrieval error
- can be estimated from an error convergence distance and the MOSAiC buoys measurement

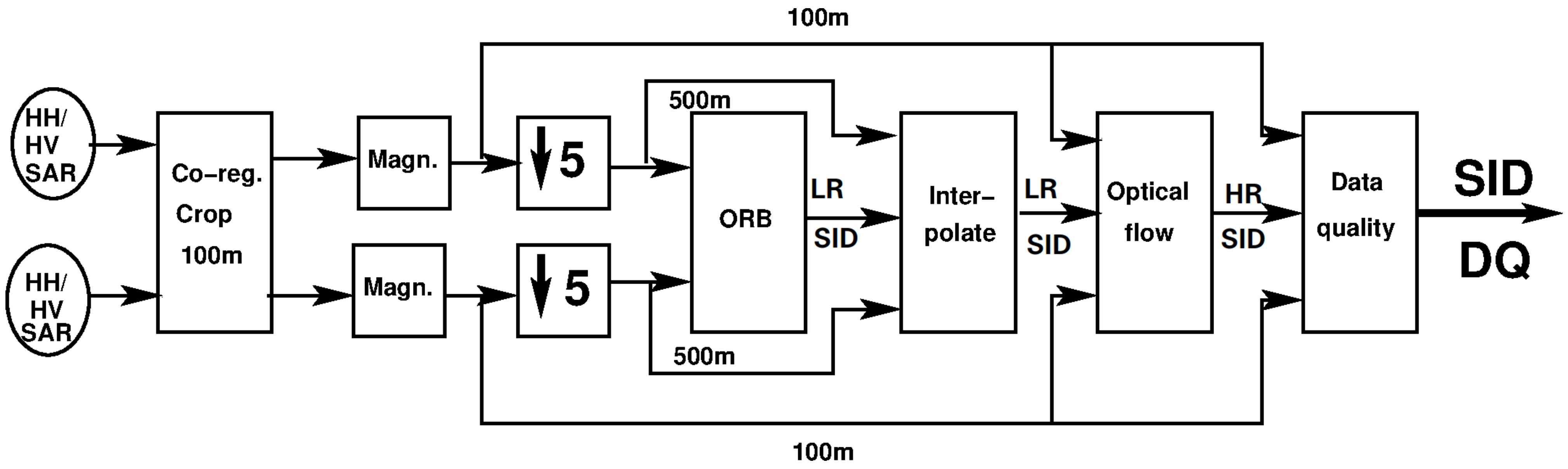
Non-melting season: >20 h

Melting season: 12-16 h

Estimated "Approriate" Temporal Intervals

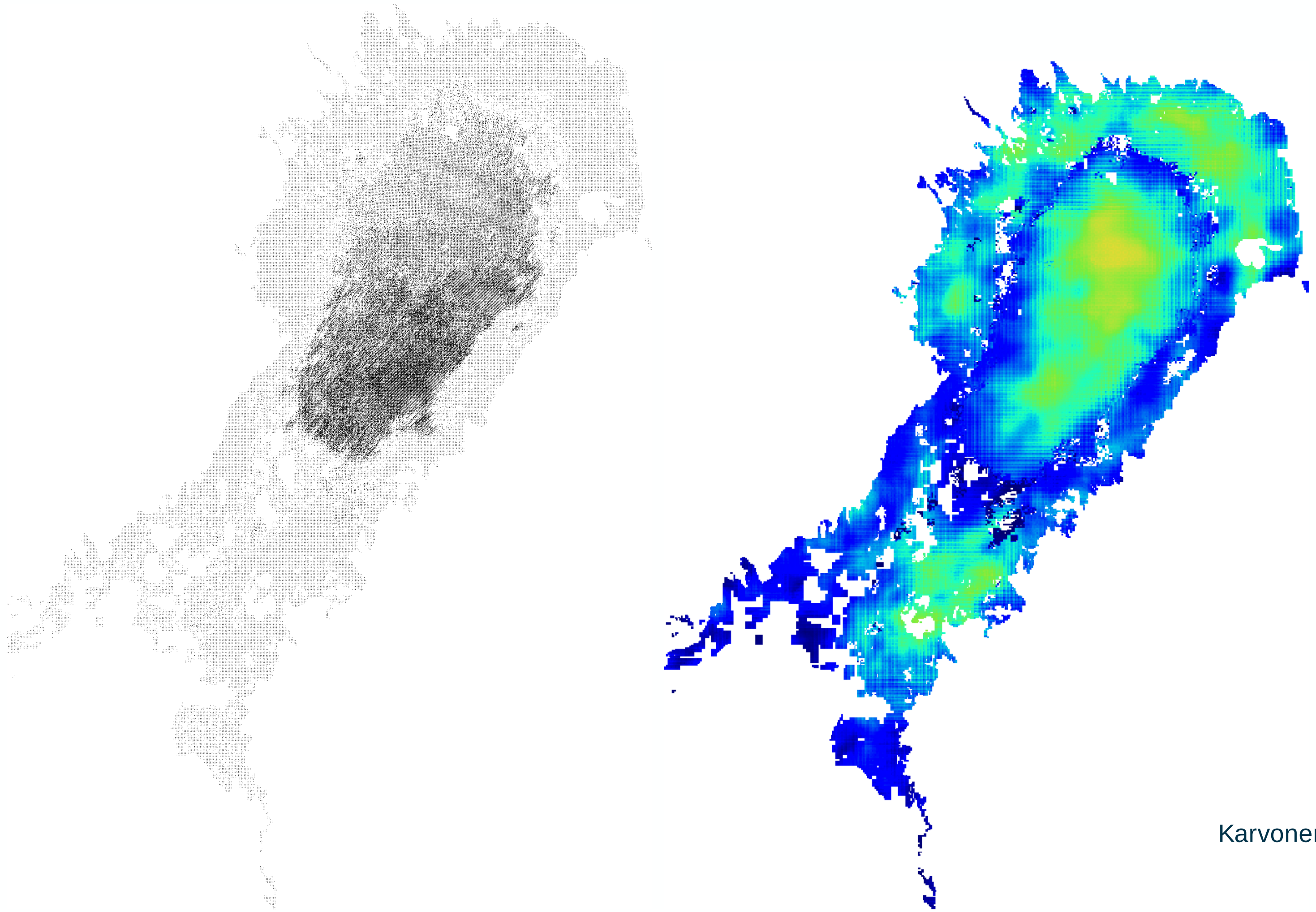


Simplified SID algorithm diagram



Karvonen: ESA_SEASAR_2023

An example of SID (20230326 16:05:47 20230327 16:04:52)



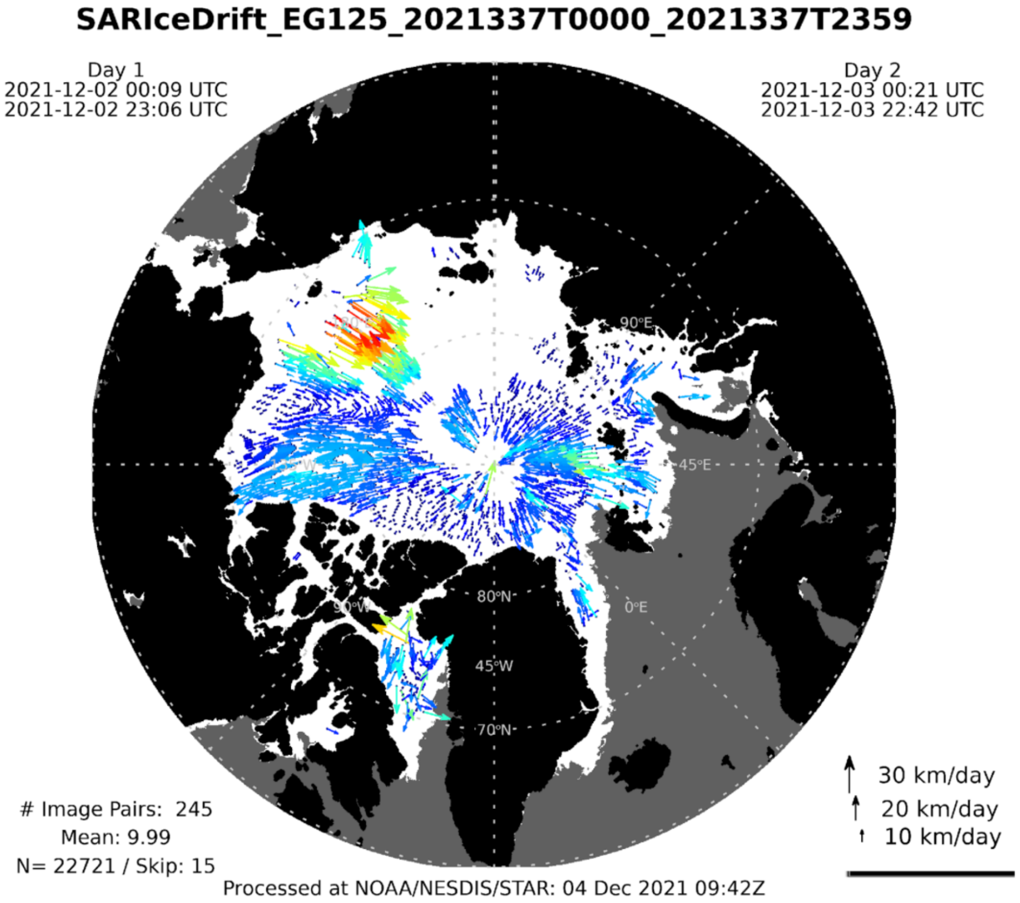
Karvonen: ESA_SEASAR_2023

NOAA STAR Sea Ice Drift Daily Product

- The NOAA STAR has developed 1-day sea ice drift motion product based on SAR imagery
  - The amount of daily coverage depends on the SAR coverage
  - Vector locations are calculated on 12.5 km EASE grid positions
- Relies on wide swath SAR imagery from Sentinel-1 and the Radarsat Constellation Mission
- The product is currently used internally at NOAA and the U.S. National Ice Center
  - Plans to produce and archive it as part of the NOAA CoastWatch / PolarWatch Program

SAR imagery can provide all weather, high res ice motions and ice dynamics estimates

Drift calculated for 02 to 03 Dec 2021



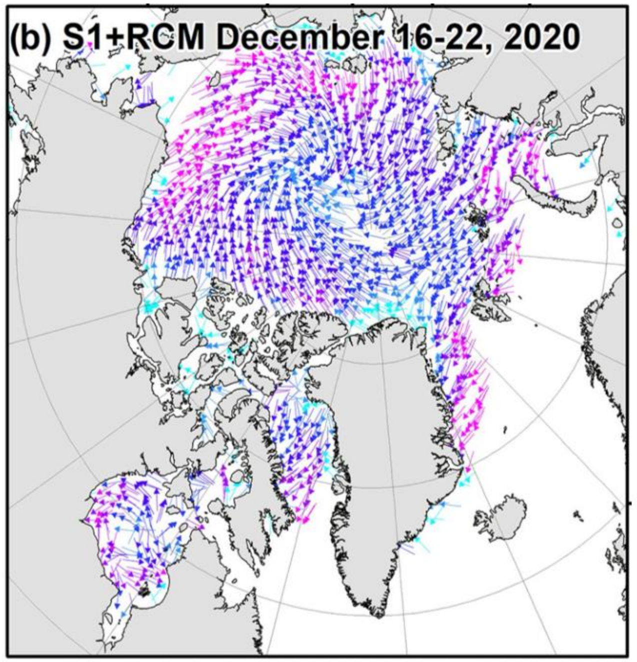
NOAA National Environmental Satellite, Data, and Information Service

17

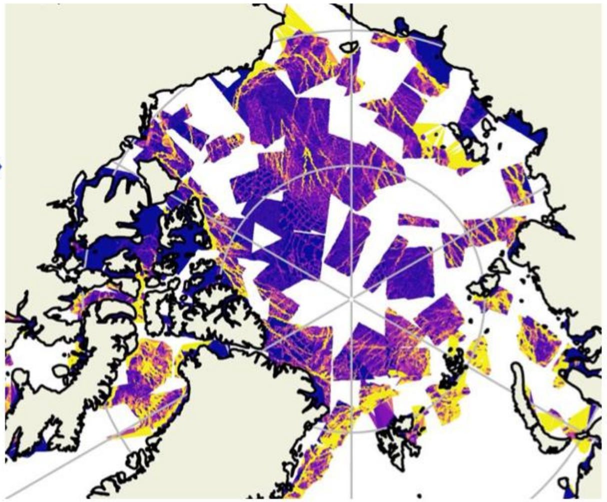
Helfrich et al. (NOAA), IICWG-DA, 2023

Other large scale SAR data sets

EGPS (Envisat): Gridded, 24hrs, 10km, 2007 – 2012
DTU (Envisat, RADARSAT-2, Sentinel-1): Gridded, 24hrs, 10km, 2018 – 2023



New deformation data set

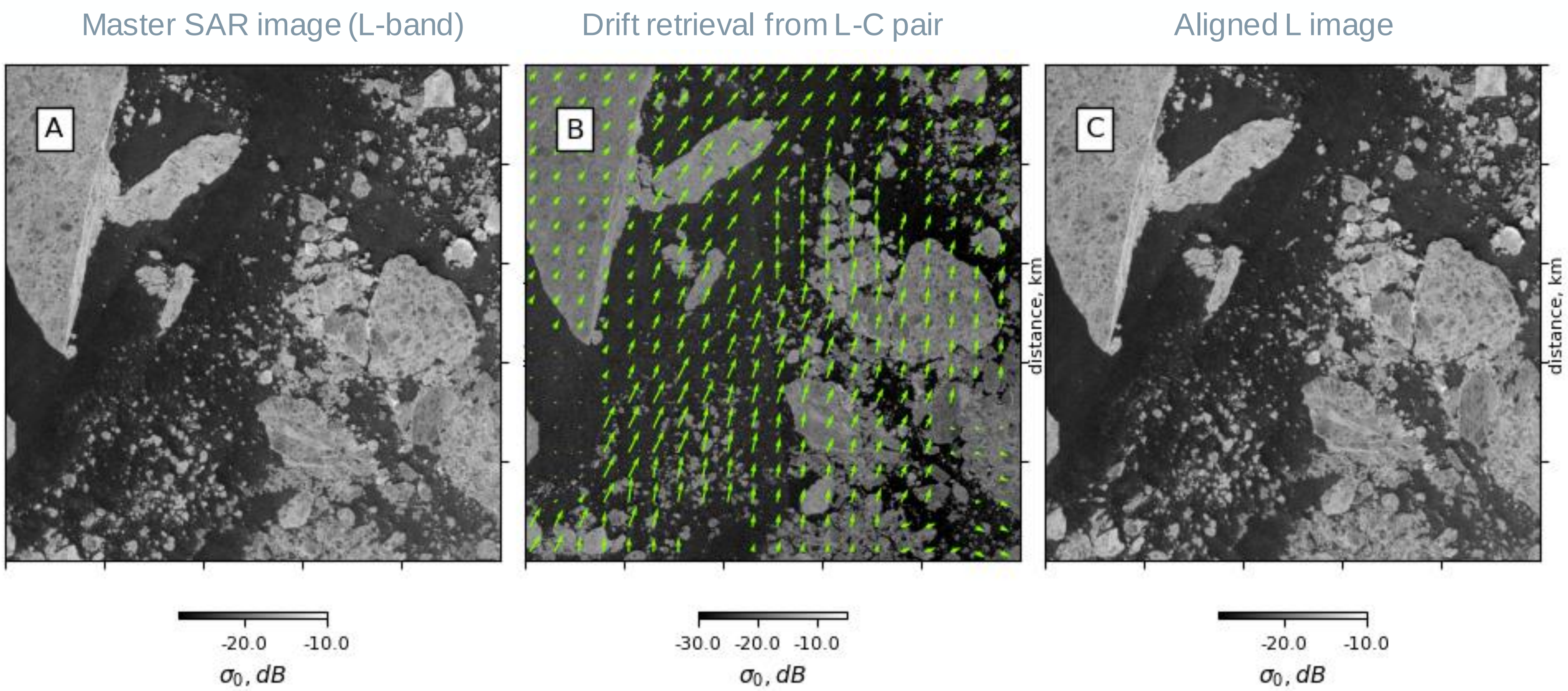


Lagrangian deformation estimates, at multiple temporal and spatial resolutions

Bouchat et al. (McGill Univ.), IICWG-DA, 2023

Investigation of Multifrequency SAR Image Alignment by Ice Drift Compensation In MIZ (Demchev et al.)

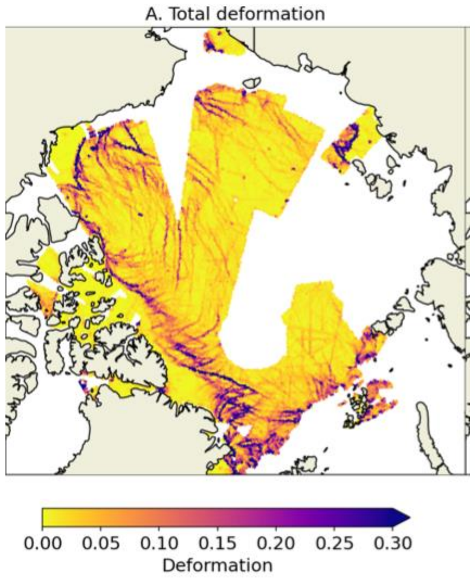
- A new algorithm for sea ice SAR imagery alignment has been proposed and tested in presence of granular ice covers consisting of relatively small, thin ice floes, which are common in the marginal ice zone

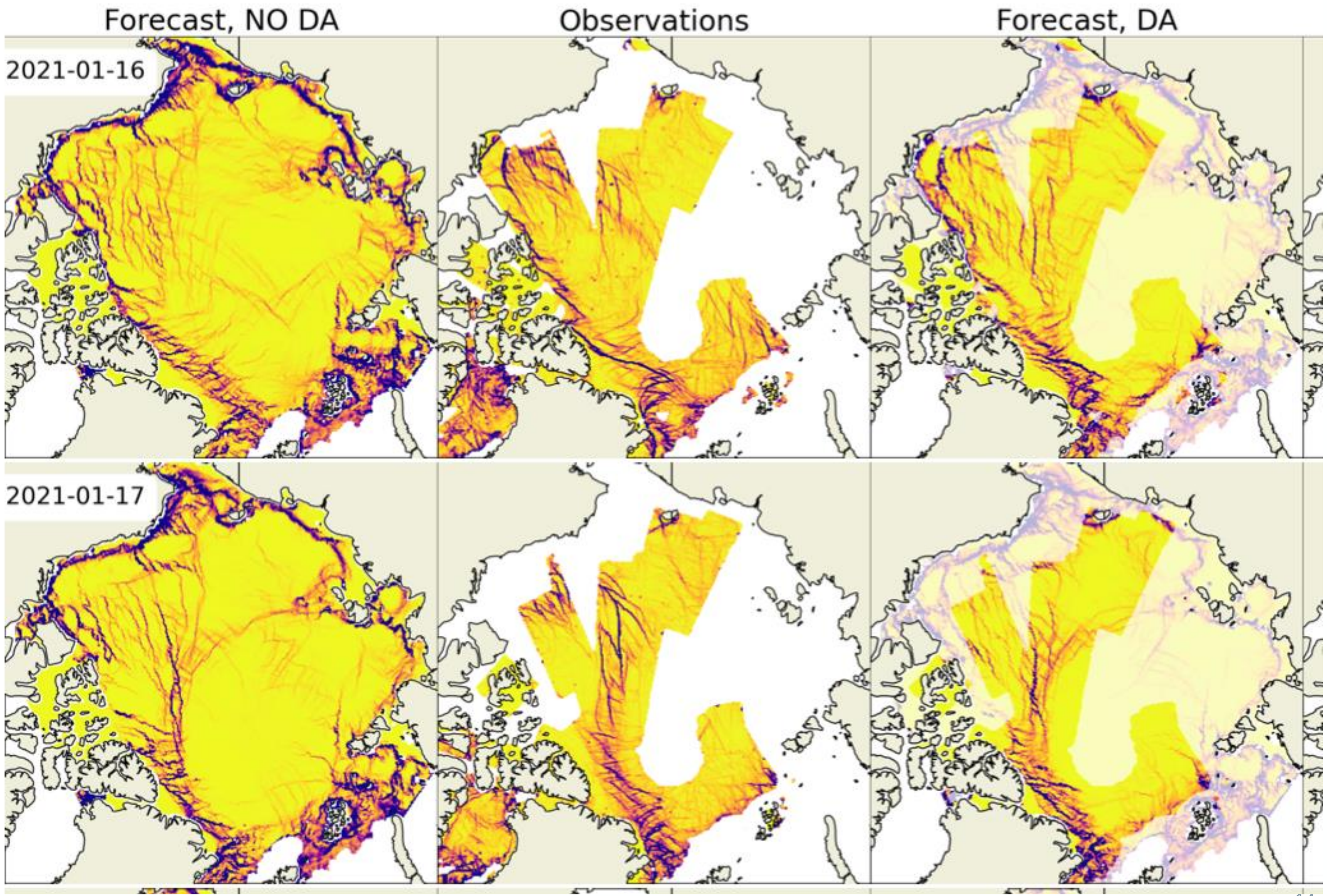


Improving predictability of sea ice deformation (Korosov, et al.)

Sea ice deformation (CMEMS) is assimilated into a sea ice model (neXtSIM).

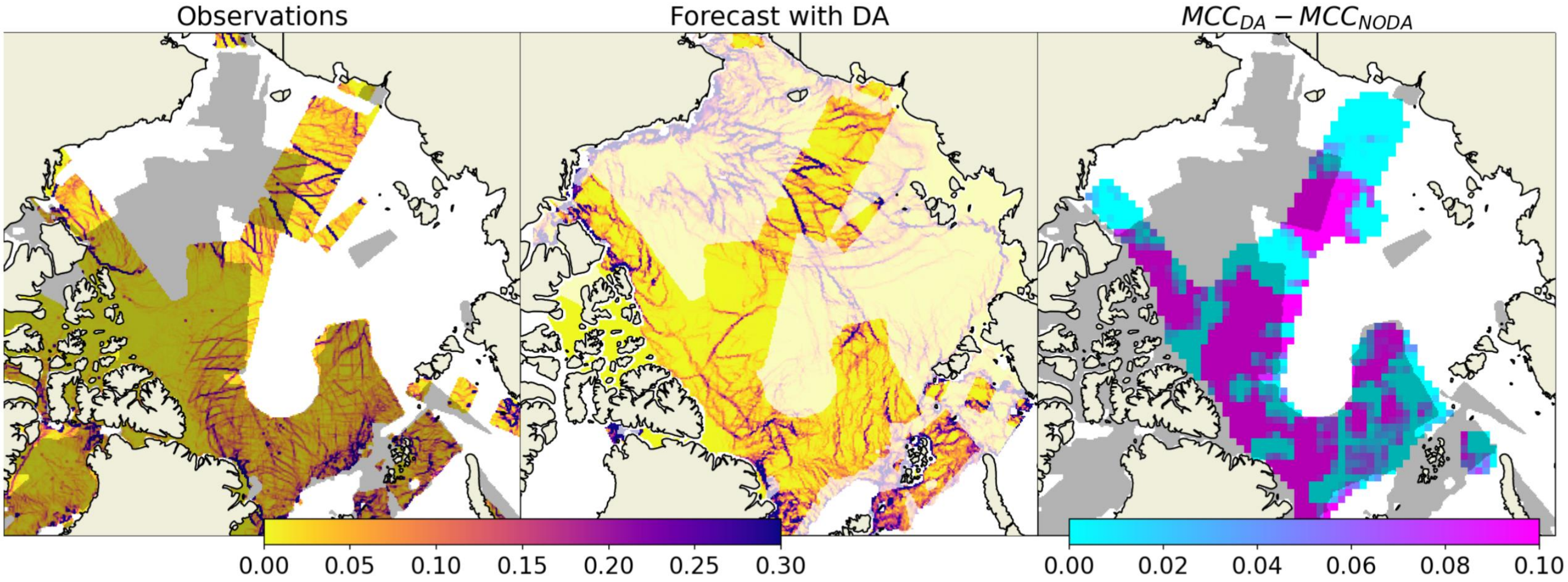
2021-01-15



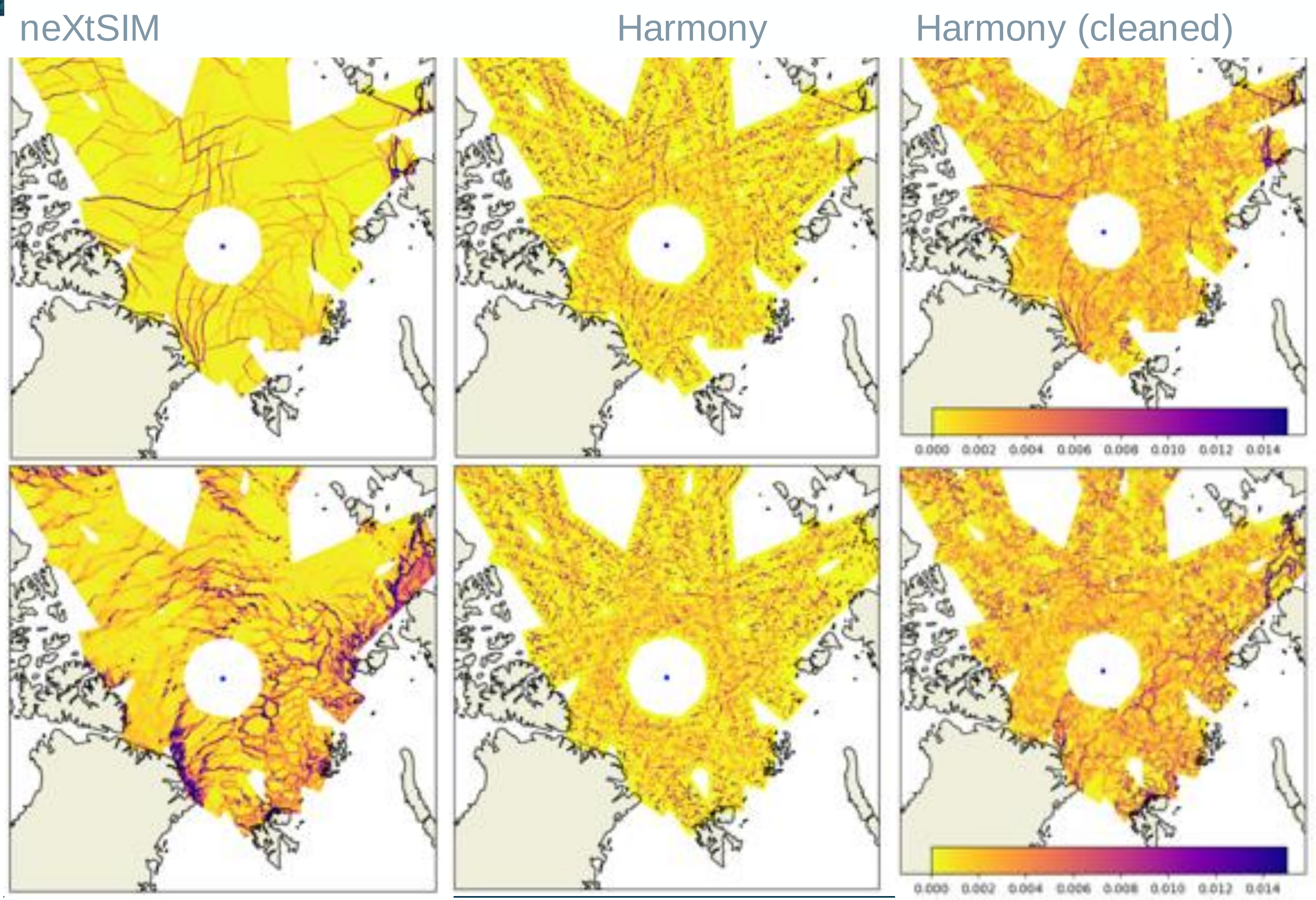


Improving predictability of sea ice deformation (Korosov, et al.)

Area covered by assimilated data is shown by gray color. 24 hour later (figure below) we compare the observations (left) with forecast of deformation (middle). The model realistically extrapolates assimilated LKFs (shown by maps of MCC on the right).



Potential Application of Harmony for Sea Ice Model Validation (Korosov et al.)



- NeXtSIM: simulating instantaneous sea ice drift.
- Harmony E2E simulator: simulating Doppler shift signal.
- Inversion 1: Raw Doppler shift to sea ice drift and deformation
- Inversion 2: Cleaned Doppler shift to sea ice drift and deformation

Maps of shear (τ) computed from the two neXtSIM runs (upper and lower rows) from original velocities (left) and from Harmony denoised velocities U^{M2} (middle) and U^{A} (right).

Challenges and knowledge gaps for SID algorithms

High thermal or speckle noise

- How to suppress noise without loosing resolution?
- What are implications on ice drift and deformation accuracy?

Too low contrast (wet snow in summer, broken ice in MIZ) for a robust MCC

- How to improve informativeness of a SAR image patch
- How to efficiently utilize HH and HV simultaneously?

Rapidly changing surface (melting in summer, floe rotation and heterogeneous drift in MIZ)

- How to adapt time delta between images and what is the optimal one?

Inherently different patterns of C- and L-band SAR imagery

- How to compare (MCC) and how to evaluate alignment?

Challenges and knowledge gaps for SID applications

Alignment algorithms: floe rotation (and other fast surface changes) complicates image 'morphing'

- How to generate (morph) images more efficiently?
- How to evaluate aligned multi-frequency imagery? (a new metric is needed)

No proper Lagrangian SID product from Sentinel-1 and/or RS2 and/or RCM

- How to calibrate / validate perform model validation in recent times (with better weather forecasts)?

BIG DATA requires more hardware resources

- How to optimize algorithms?
- Where to get resources?

Loss of S1B and reduced data coverage

- How to access RCM and adapt algorithms for RCM?

Outlook and recommendations (algorithms)

Algorithm improvement

- Use AI for ice drift retrieval
- Develop methods for post-processing (discarding, optimization) of drift vectors
- Improve intervals between images for ice drift
- Optimize algorithms for parallel processing (AND allocate more resources for processing)

Input data

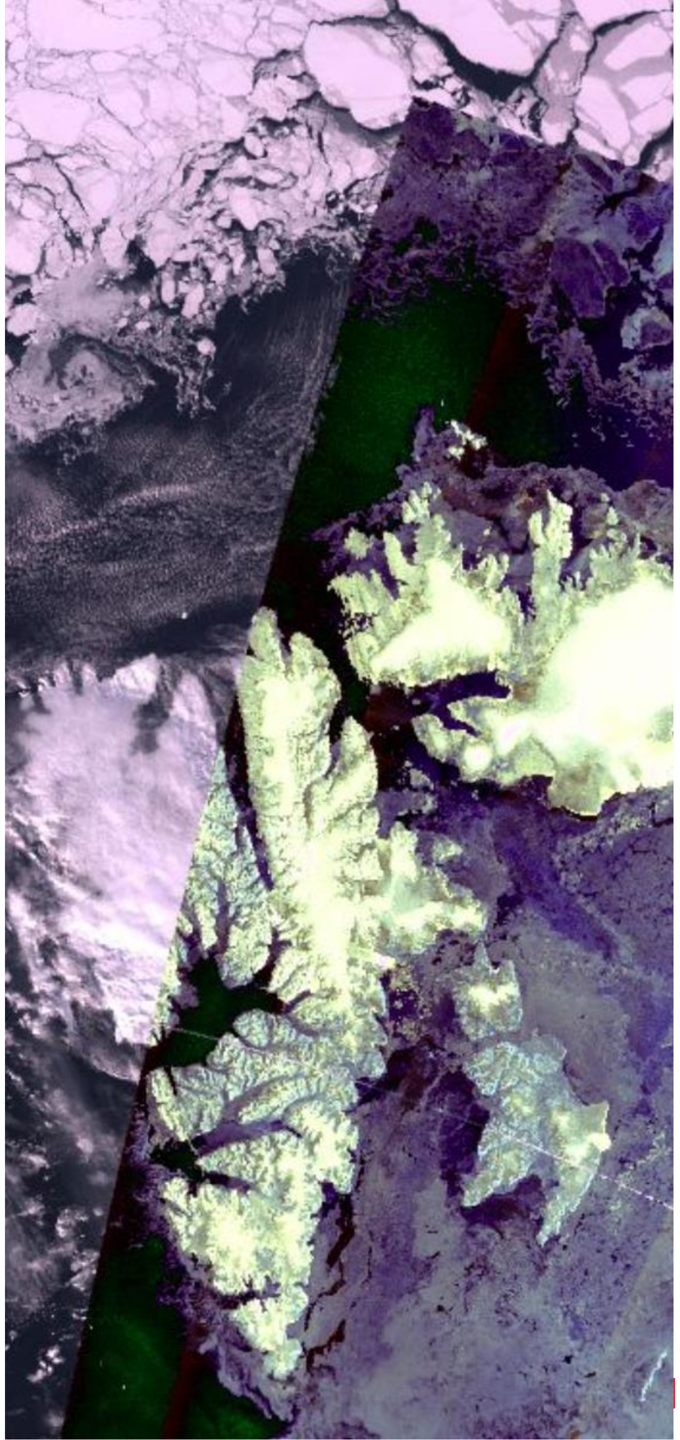
- Launch operational L-band SAR constellation

Better products

- Increase temporal resolution for ice drift products.
- Develop high-resolution, long-term ice drift dataset

Outlook and recommendations (applications)

- Combine SID and thermodynamics for SIT retrieval.
- Move towards integrated systems: (satellite) observations – assimilation – model
- Use SSIM as a metric for alignment evaluation
- Test SID and alignment algorithms under various weather and drift conditions
- Reduce noise in Harmony data
- Use Harmony data for detection of MIZ (mobile ice despite high concentration)
- Estimate and improve practical predictability of linear kinematic features
- Develop new metrics for model calibration / validation using ice drift and deformation data



3D data viewer:
https://cvl.eo.esa.int/

Code repository:
https://github.com/CryosphereVirtualLab/

Polar Thematic Exploitation Platform:
https://cvl.eo.esa.int/node/30

PROJECT PARTNERS

- Nansen Environmental and Remote Sensing Center
- NORCE Norwegian Research Centre
- The Norwegian Meteorological Institute
- Science and Technology
- The Norwegian Polar Institute

We offer the following workflows:

WF1:

- Online data search
- 3D-visualization
- Geo-transformation
- Download of the selected products

WF2:

- Online data search and download
- Installation of virtual machine on your PC
- Analysis of the selected products locally

WF3:

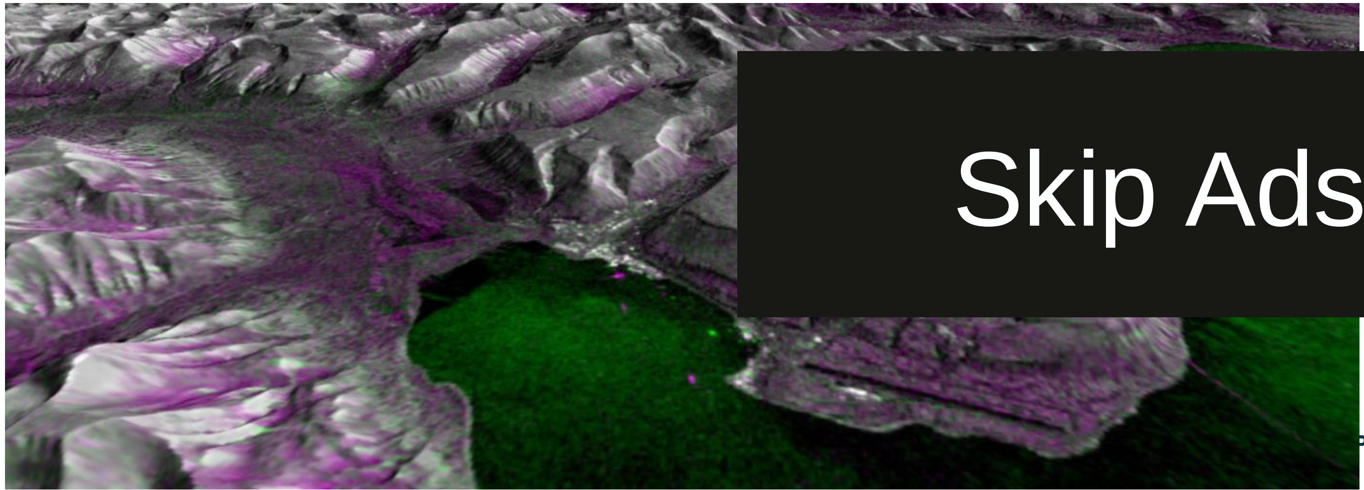
- Online data search
- Online analysis in a Jupyter notebook at P-TEP

WF4:

- Scheduled batch processing of data at P-TEP including automated search and visualisation

Cryosphere Virtual Laboratory

- Exploitation, analysis, visualization and sharing of data
- Satellite, in-situ and model data
- Collaboration between cryosphere scientists
- Reduce the time and effort for data searching
- Develop own tools for processing and analysis



Theme : Sea Ice
Topic : Sea Ice Type (SITy)

Demchev Denis, Frost Anja, Karvonen Juha, Korosov Anton, Xiao-Ming Li
+ slides from Bouchat Amelie, Helfrich Sean, Clement Fougerouse

01/05/2023

Contributing work

- Anja Frost, James Imber, Dmitrii Murashkin, Karl Kortum, Gregorek, Towards Multitemporal Sea Ice Classification By Means Of Spaceborne SAR Image Time Series (DLR, MARUM)
- Qiang Wang, Malin Johansson, Johannes Lohse, Anthony P. Doulgeris, Torbjørn Eltoft, The Impact of Input Features in Deep Learning Based Sea Ice Mapping (UiT)
- Tore Wulf, Jørgen Buus-Hinkler, Suman Singha, Matilde Brandt Kreiner, Operational SAR-based Sea Ice Concentration Retrieval Using Convolutional Neural Networks (DMI)
- Sean Helfrich, Sea-ice deformation derived from the RADARSAT Constellation Mission and Sentinel-1 SAR Imagery at 24- and 72-hr intervals from 2017 to 2021 (NOAA), IICWG-DA-11
- Alexander Komarov, The RADARSAT Constellation Mission data assimilation in ECCC ice prediction system (ECCC), IICWG-DA-11
- Clement Fougerouse and Anton Korosov, Informativeness of SAR and PMW data for sea ice type retrieval (ENSG, NERSC), In Prep.
- Denis Demchev, Anton Korosov, Detection of sea ice ridging in first-year ice from Sentinel-1 images and ice deformation (Chalmers Univ., NERSC), In Prep.

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Key objectives (summary)

Innovations (key slides from your presentations)

Remaining knowledge gaps (summary)

Outlook and recommendations (summary)

Key objectives

Development of SITy algorithms (SAR GRD image, image processing)

- Robust, high-resolution, all-season
- To derive more information from SAR: Ice extent, ice/water, MYI, FYI, YI, OW, rough ice, uncertainties, L2/L3, SIC, Stage-of-Development, floe size
- To include more data on input: SST, multi-temporal observations, AMSR2, wind speed, sea ice deformation
- To validate the algorithm: visual inspection, coastal observers, icebreakers, ice charts (also cross-validation)
- *Deep learning (U-net)*

Application of SITy algorithms

- Operational sea ice monitoring with resolution higher than on the ice charts
- To support ship navigation directly
- To combine with drift forecast for predicting optimal ship route
- To support ice cervices
- To assimilate into models

Innovations

(Results)

Methodology

Tore Wolf, (DMI)

Training dataset:
We have compiled a training dataset consisting of **1202** unique matches of Sentinel-1 EW imagery and manually produced regional ice charts from 2018 up to and including 2021, covering Greenland waters (DMI ice charts) and parts of the Canadian Arctic (CIS ice charts). The dataset also includes resampled AMSR-2 brightness temperatures.

The DMI and CIS ice charts contain information about sea ice concentration (SIC), stage of development (SoD), also called ice type, and floe size (FLOE).

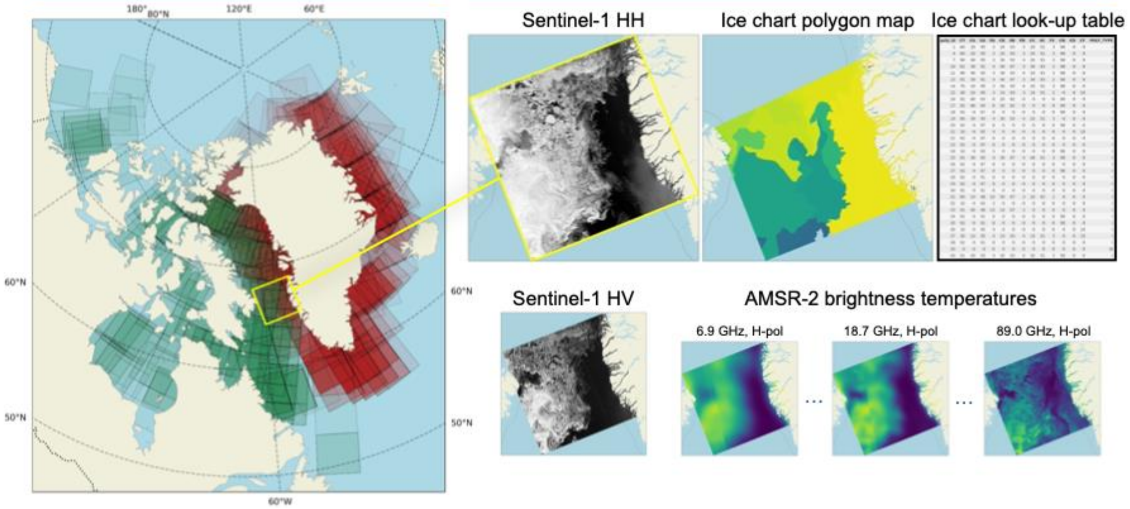
The compiled training dataset is based on two publicly available datasets that were produced in the ESA-sponsored AI4Arctic project:
https://doi.org/10.11583/DTU.13011134.v3 (ASIDv2)
https://doi.org/10.11583/DTU.c.6244065.v2 (ASID Challenge)

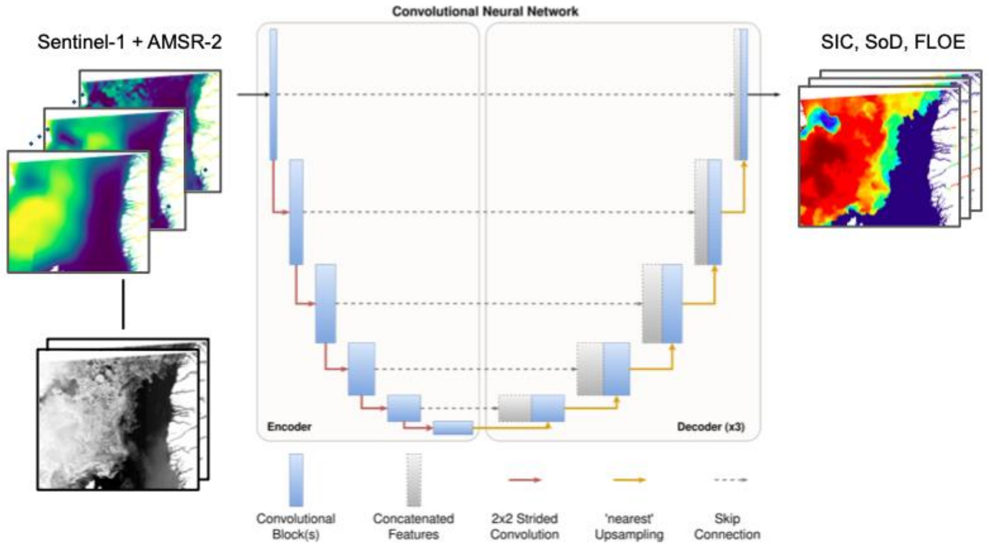
CNN Overview:
The CNN is designed as a multi-tasking model that is trained on multiple sea ice parameters simultaneously. The CNN follows a U-Net-like encoder-decoder structure. The encoder network consists of 6 stages, each comprised of multiple inverted residual blocks, for multi-scale feature extraction. The CNN has three decoders, which outputs pseudo-probabilistic distributions over a predefined set of classes for each sea ice parameter - SIC, SoD and FLOE.

SIC prediction and uncertainty estimation:
We calibrate the pseudo-probabilistic SIC output of the CNN by using *label smoothing* (during training) and *temperature scaling* (post-processing). Given a well-calibrated model, the SIC prediction and the accompanying uncertainty is computed as a weighted average and a weighted std., respectively, of the predefined set of SIC classes, with weights given by their respective probabilities predicted by the model.

Training dataset overview

Example scene, May 16th, 2021





Results

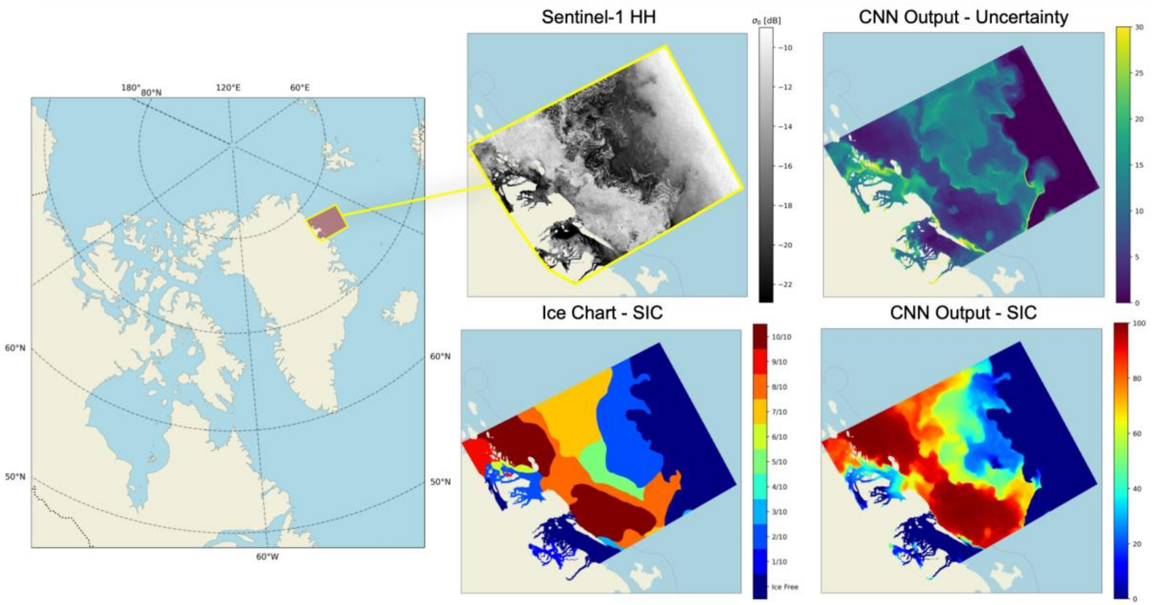
Tore Wolf, (DMI)

50 carefully selected examples from the dataset have been set aside for predictive performance and uncertainty estimation evaluation.

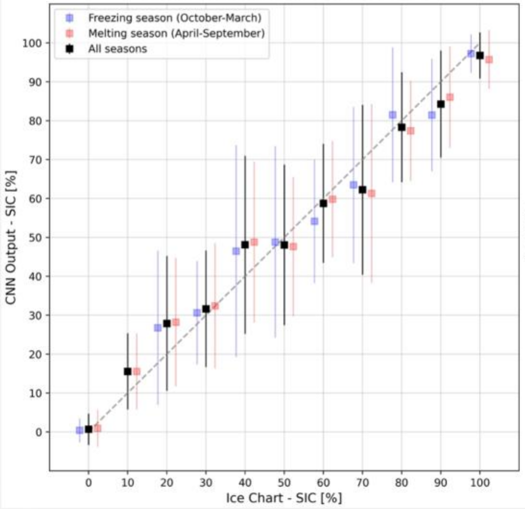
SIC predictive performance:
Our model achieves a *RMSE* of **4.1%** (freezing season), **5.1%** (melting season) and **4.6%** (overall) when evaluated against the test dataset at pixel level.

SIC uncertainty estimation:
Training our model with *label smoothing* improves the calibration of the SIC output, but the trained model is slightly 'under-confident'. This tendency is mitigated using *temperature scaling*.

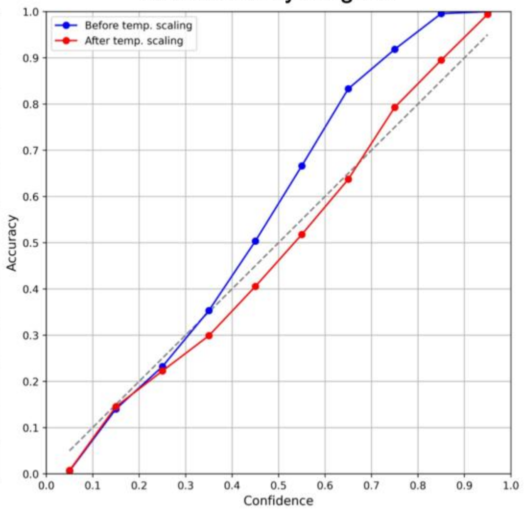
Sea Ice Concentration, single scene example, August 25th, 2020



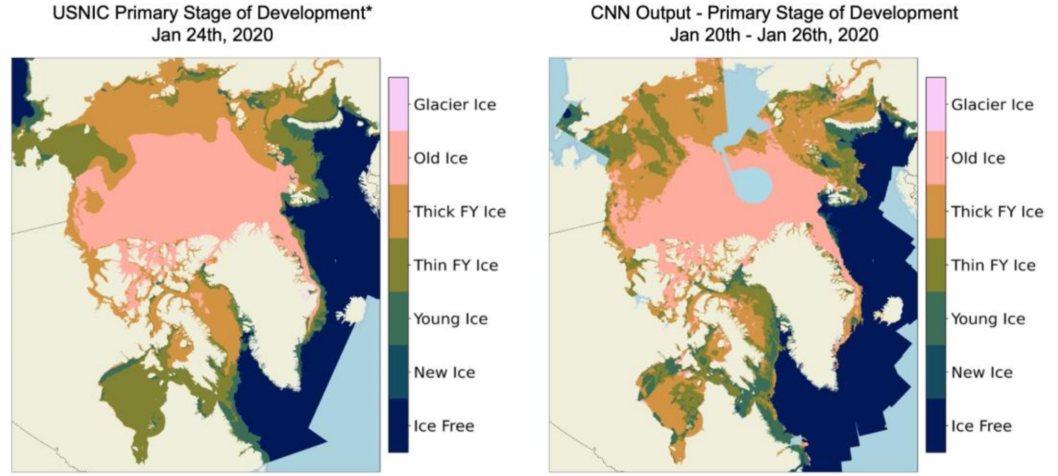
CNN SIC vs. Ice Chart SIC



SIC Reliability Diagram



Stage of Development (ice type), preliminary mosaic example



*USNIC ice charts might follow different ice charting practices than the regional ice charts from DMI and CIS that the CNN was trained on.

The Impact of Input Features in Deep Learning Based Sea Ice Mapping (Wang et al.)

- Water ice boundary is well delineated by both the baseline and the advanced model
- The advanced model can identify the newly formed ice better than the baseline model (see areas marked by red rectangles)
- Both baseline model and the advanced model (adding SST as feature input) may mis-classify the smooth ice as water, shown in the green rectangle in Fig. 2c

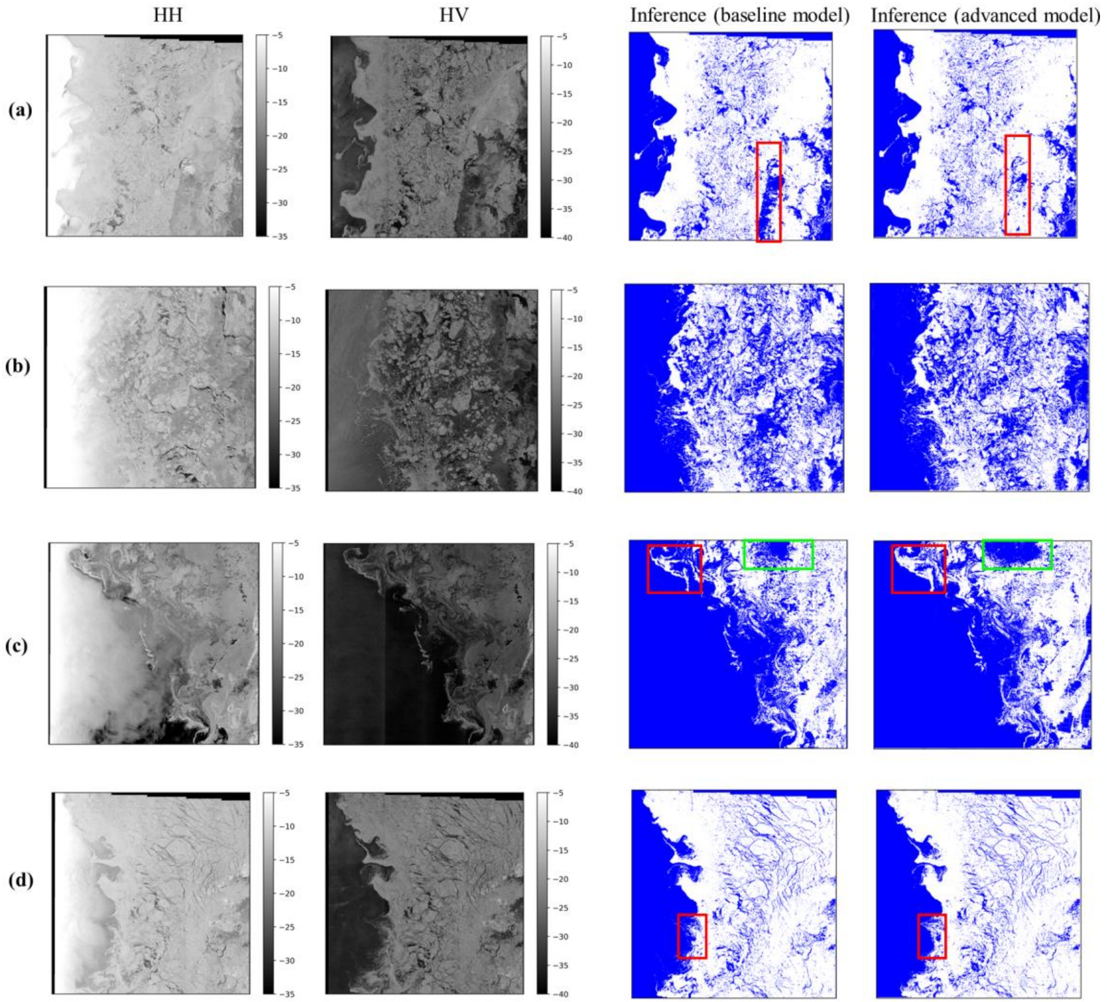
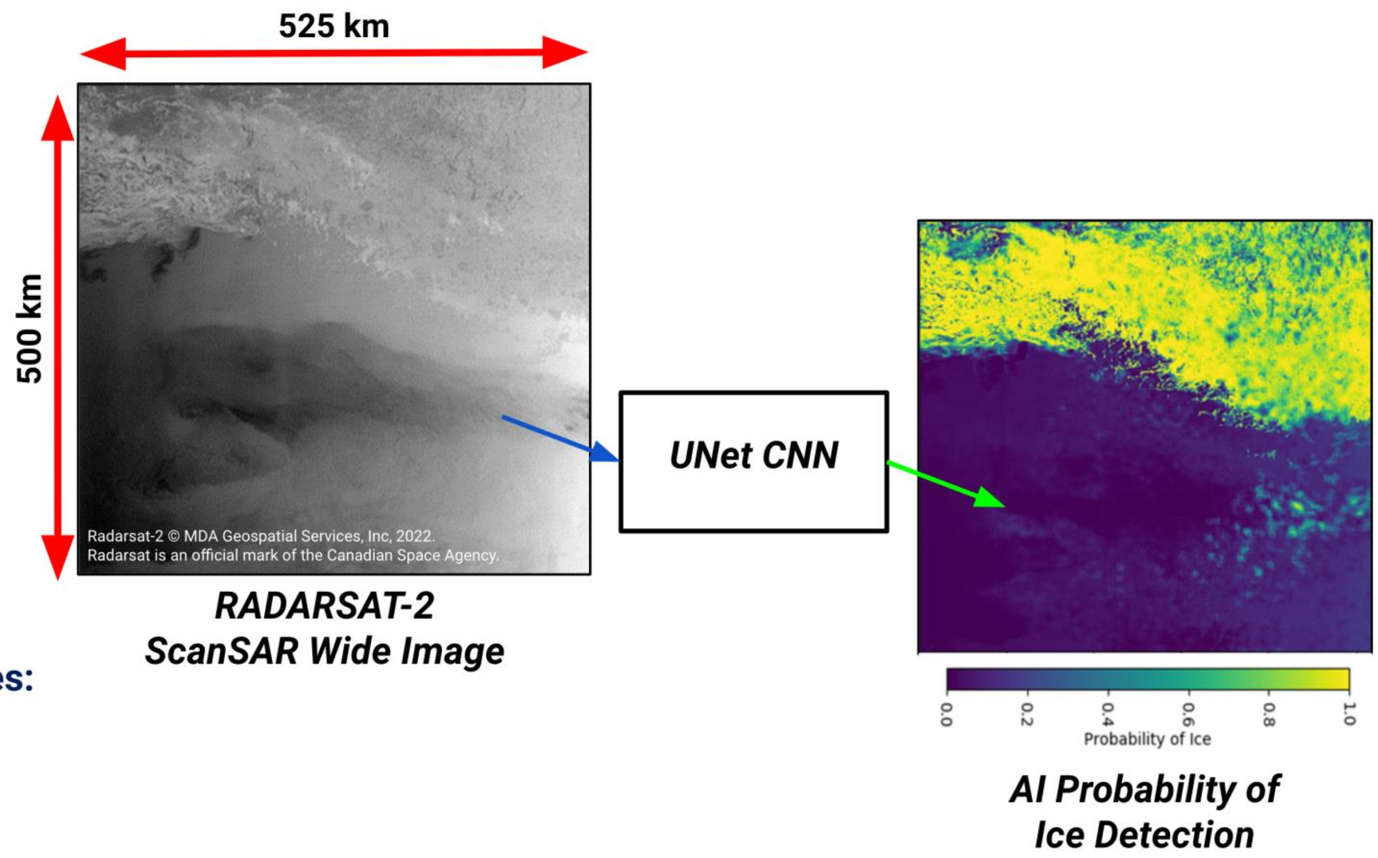


Figure 2: From left to right: HH (in dB), HV (in dB), baseline model inference, and advanced model inference for the four S1 example images. The a-d letters corresponds to the Scene IDs in Tab. I. Water is blue and ice is white. Regions of particular interest are highlighted by colored rectangles.

Supervised Training Dataset

- **160 initial labeled images**
  - Radarsat-2 ScanSAR Wide azimuth and range multilook images and corresponding labels
  - From Beaufort Sea, April to Nov 2014
  - Sigma-naught 50 m x 50 m pixel spacing, HH only
  - ~ 500 km x 500 km scenes (~10K x 10K pixel images)
- **30 images set-aside for validation/testing**
- Labels – ***ice*** or ***no ice***; "no-ice" interpreted as navigable by ship (thin ice possible)
- **Separate models trained on three input types:**
  - Native, Log Transformed, and Log Transformed/Rescaled



Wide scan SAR RADARSAT-2 Image. Previously approved by NGA for public release, 21-030.

Sea ice classification on single SAR acquisitions, Anja Frost (DLR)

Requirements:

- Automatic approach
- Providing results in near real-time

Core of the classification:

- adjusted UNET++ convolutional neural network [1]
- Sentinel-1 channels are divided into tiles, classified, and then the results are joined back [2, 3]

Output:

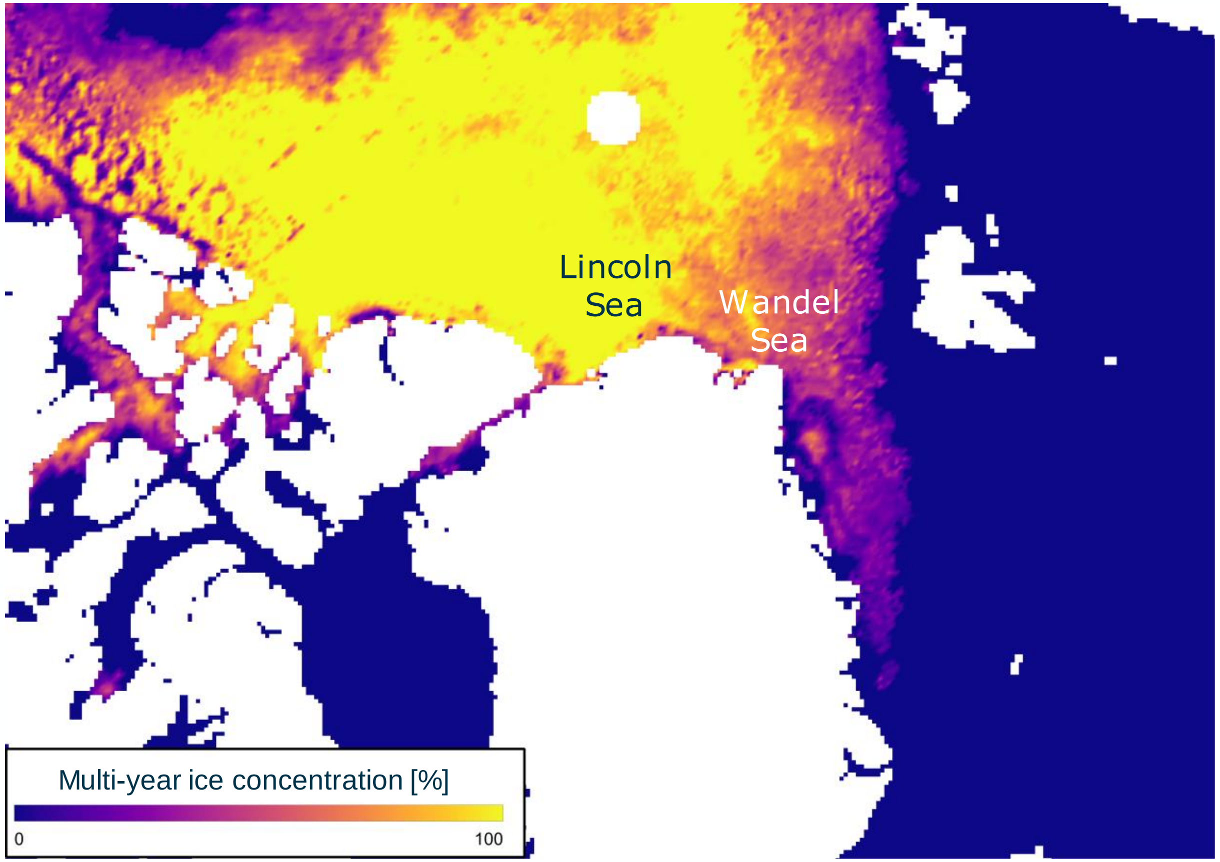
six ice types: Multi-year ice, first-year ice, young ice, open water (calm), open water (rough), and rough ice

Deficiency:

- Sometimes, results are inconsistent

[1] Z. Zhou et al., 2019.
[2] D. Murashkin et al., 2021
[3] A. Frost, J. Imber, D. Murashkin, D. Gregorek, M. Bathmann, 2023

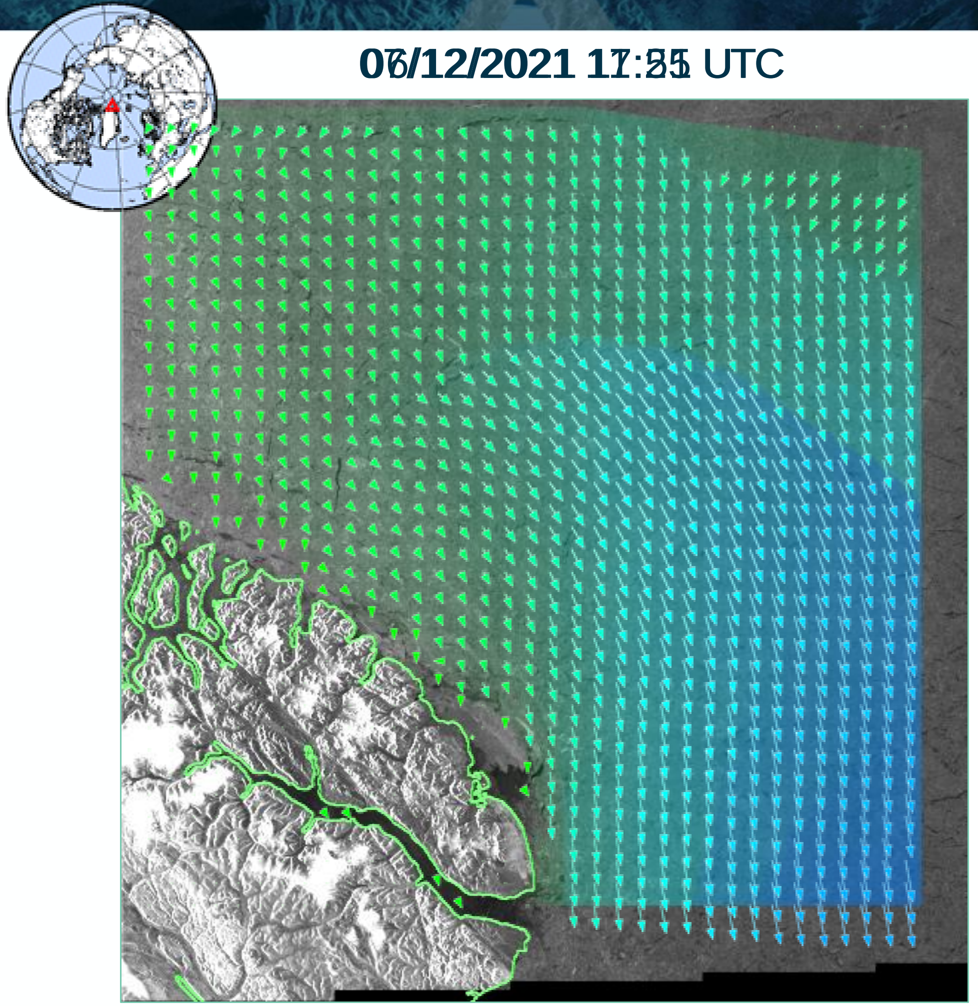
Preliminary study using 34 subsequent Sentinel-1 acquisitions taken between Lincoln and Wandel Seas

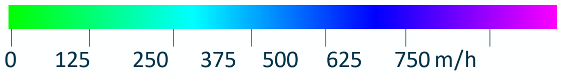


Multi-year ice data from 12/6/2021 from https://www.meereisportal.de (funding: REKLIM-2013-04).

Sea ice classification on single SAR acquisitions

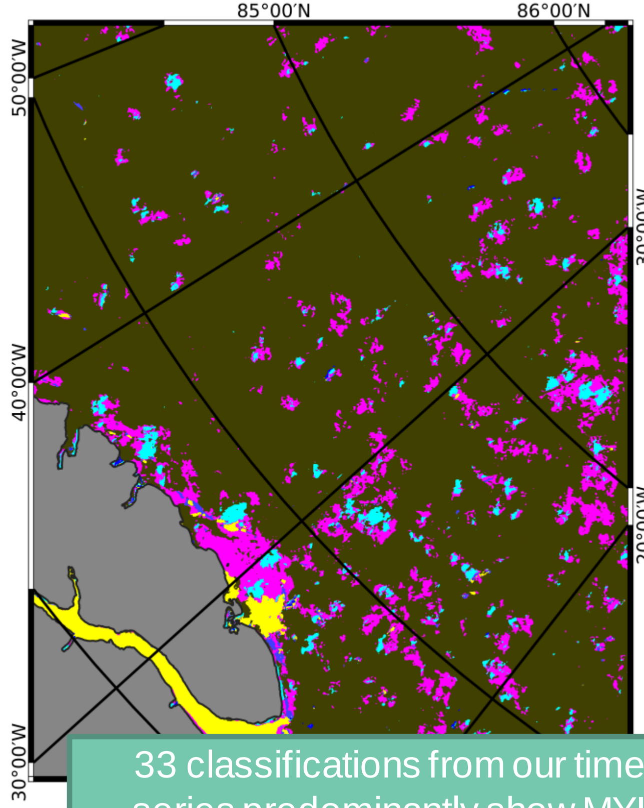
07/12/2021 17:51 UTC
06/12/2021 11:25 UTC



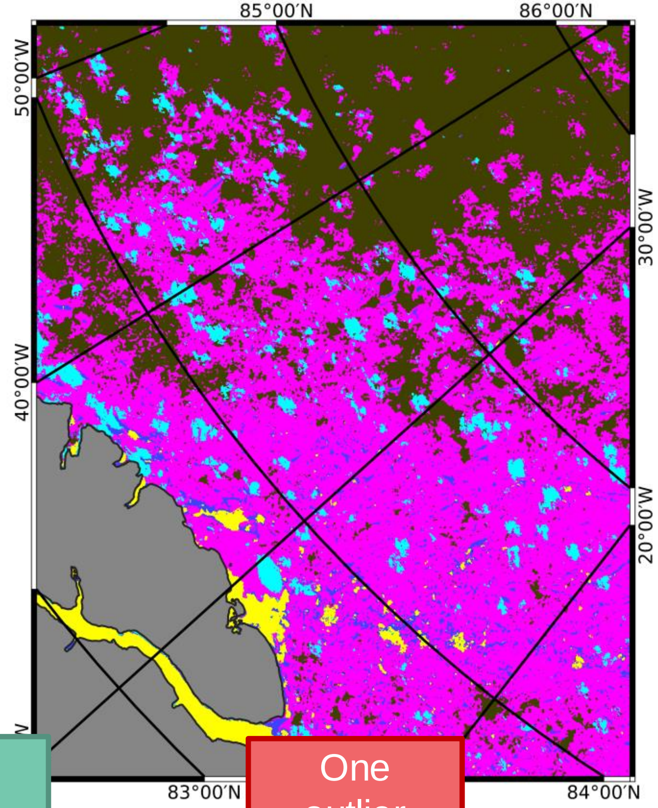


No substantial changes

Classification
07/12/2021 17:51 UTC



Classification
06/12/2021 11:25 UTC



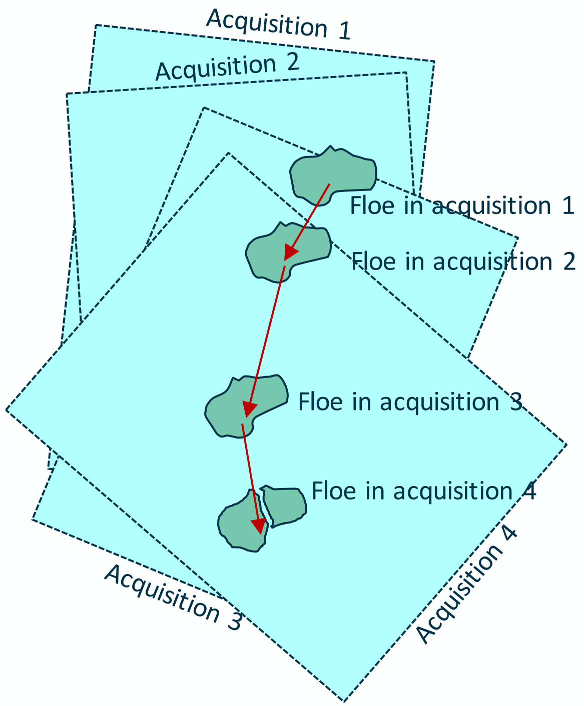
33 classifications from our time series predominantly show MYI

One outlier

Multi-year ice	Open water (calm)
rst-year ice	pen water (rough)
Young ice	gh ice

DLR

Towards Multitemporal Sea Ice Classification



Basic idea:

→ track sea ice from one SAR acquisition to the next and collect more measurements about e.g. a floe

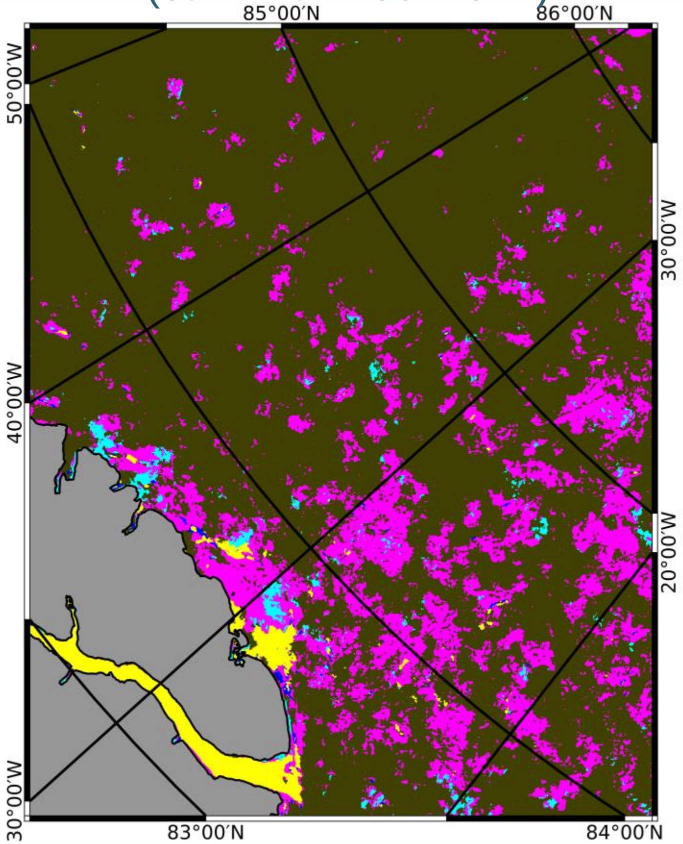
→ Use the collected data jointly to classify the ice

Key to success: high-precision sea ice drift vector field

Frost et al., IEEE OCEANS 2023 publication includes validation of drift tracking

Multitemporal classification approach:
imply modelling of discrete probability distributions over ice type and applying methods from probability theory

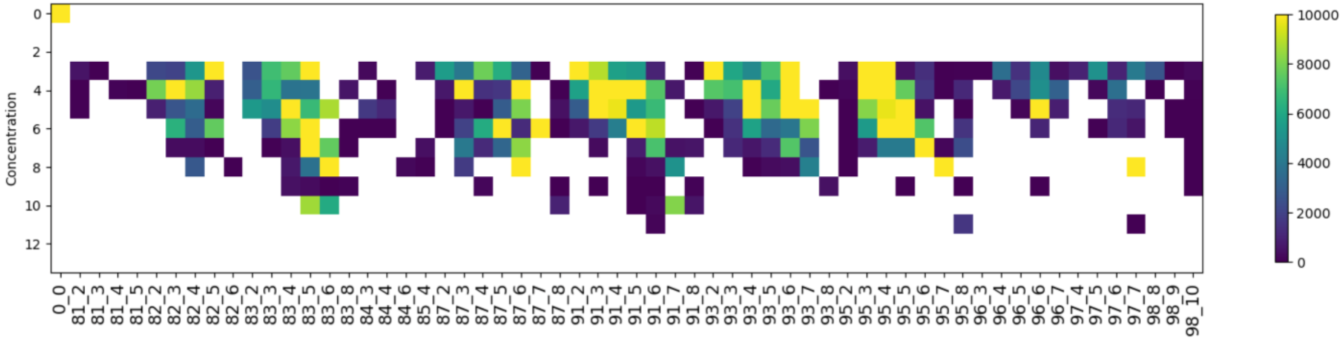
Combined classification (6th + 7th Dec. 2021)



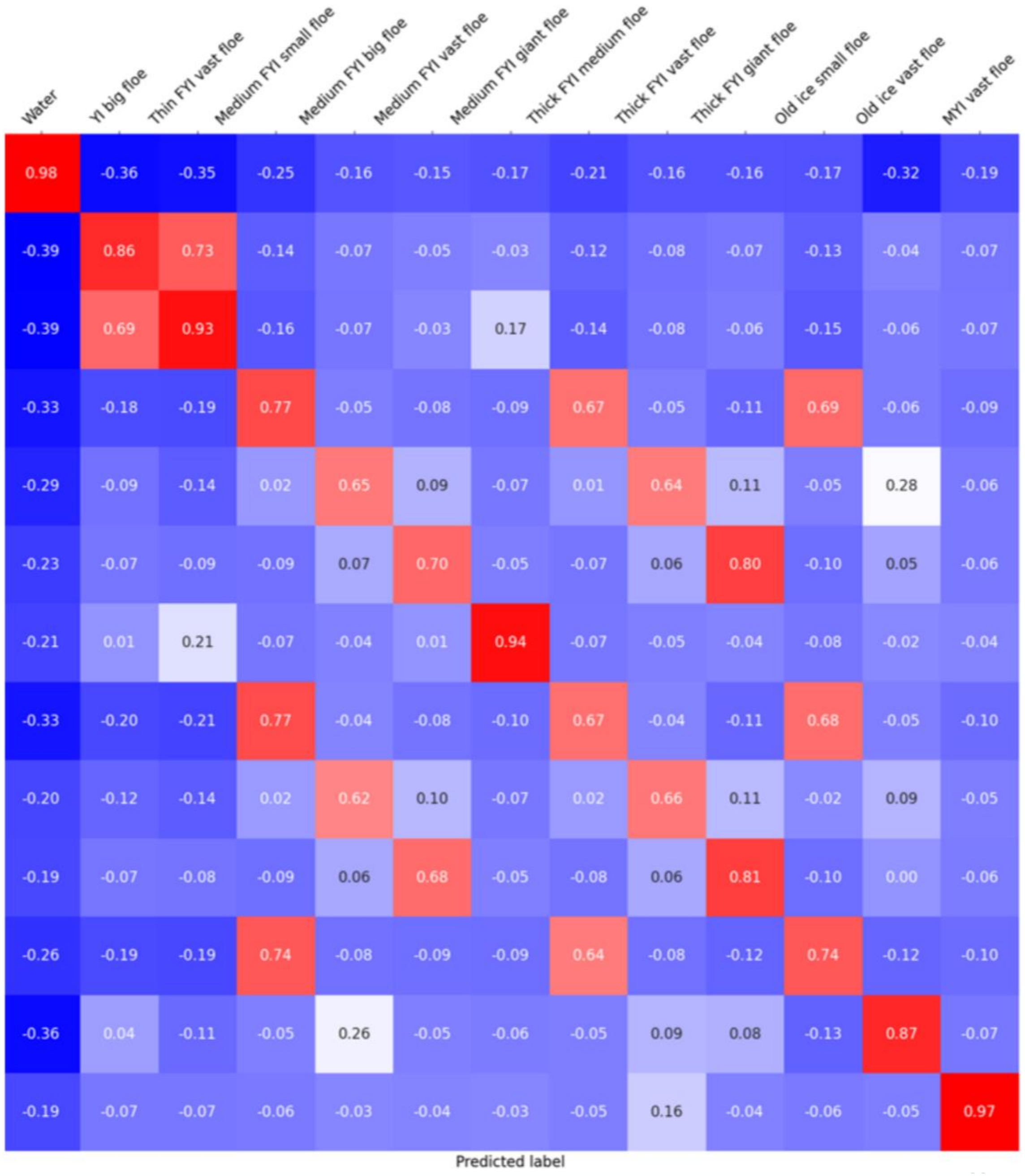
Result: Combined classification better represents the real sea ice situation

Deficiency: More in situ data needed to train and calibrate the CNN

Informativeness of SAR texture (Fougerouse C., in prep)



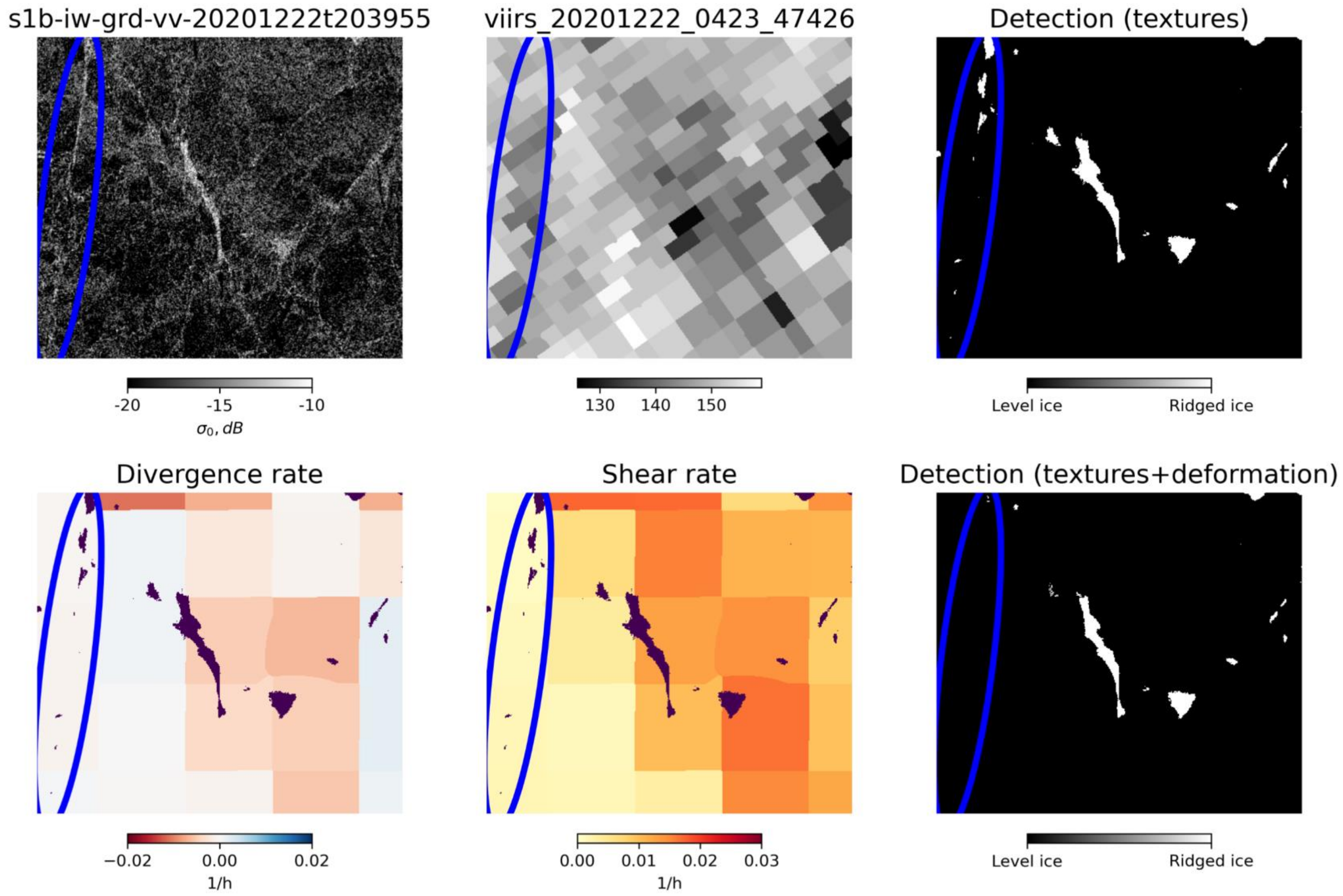
All combinations of SoD and FSD in ASIPv2



Correlation between true and predicted partial concentration of **13** SoD_FSD combinations

Conclusion:
Most of categories classify well, but some categories do intersect and should be grouped or excluded.

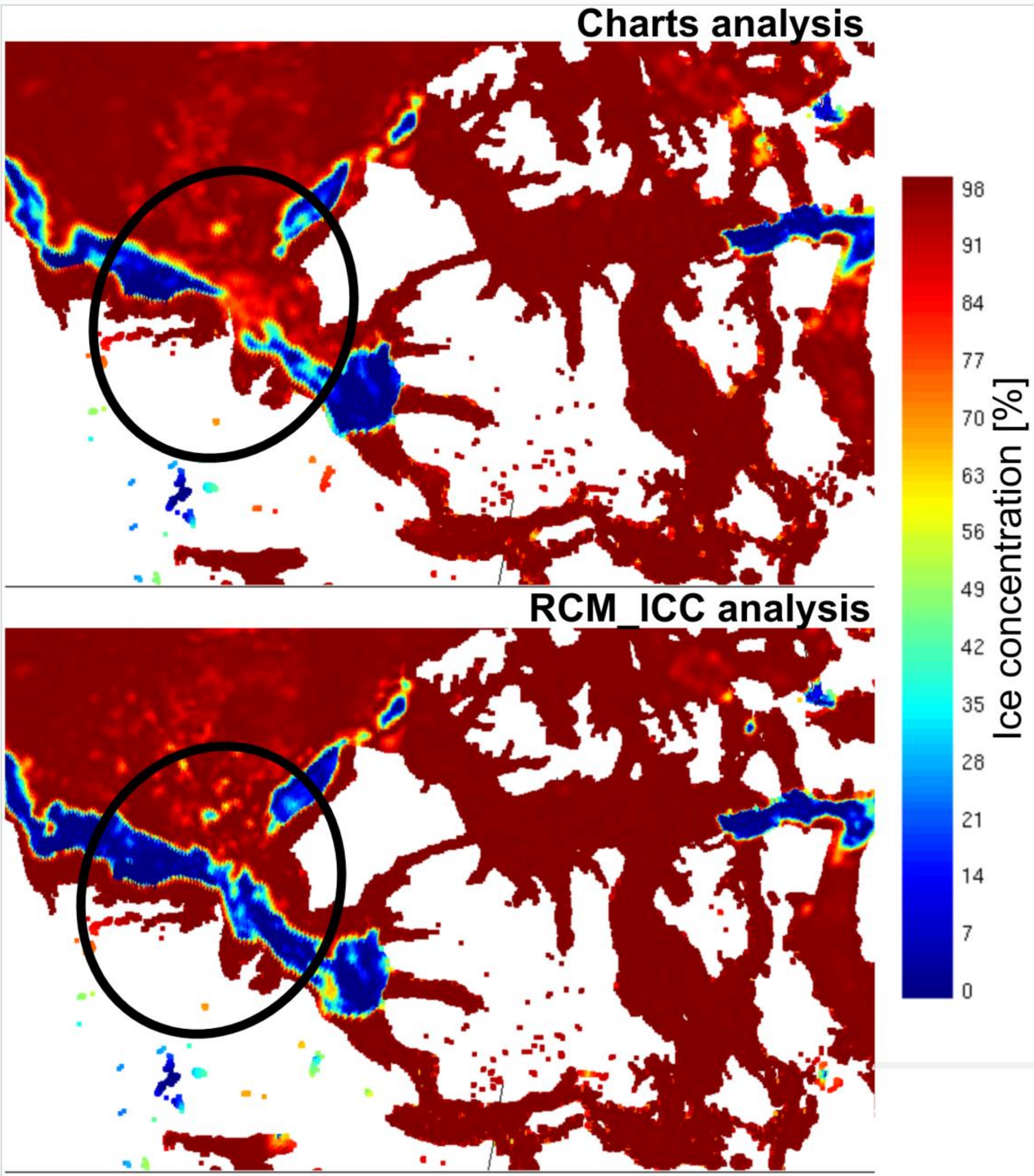
Detection of sea ice ridging in first-year ice from Sentinel-1 images and ice deformation (Demchev, et al)



Conclusion:
Including sea ice deformation as input data improves ridge detection on Sentinel-1 IW data.

ANALYSIS EXAMPLE: WESTERN ARCTIC JUNE 11, 2021

Aleks Komarov (EEEC), IICWG-DA, 2023



NASA Worldview VIIRS

Challenges and knowledge gaps

Ice is very diverse and some categories (e.g., new ice) are not sufficiently represented

- How to improve representation of all ice types?
- How to deal with low prediction accuracy, when the category is under-represented in training data?

Inconsistent classification results for multi-temporal images

- How to deal with inconsistent classification and how to improve consistency?

Machine learning is a black box

- What can we learn from DL models?
- What is a physical relation between input features?
- What is the theoretical informativeness of a SAR image (how many ice types can we infer in principle)?

How to improve classification in case of: strong winds, new or young ice?

How to improve quality of label data (e.g., inherent systematic bias in ice charts)?

Outlook and recommendations (algorithms)

More input variables:

- wind speed, solar radiation, VIIRS, AMSR2, RS2, RCM, hi-res SST, altimetry, multi-frequency and multi-polarization data, sea ice deformation

More output variables:

- probability to belong to an ice category, deformation, ridges, leads, aerodynamic roughness
- Fit-for-purpose ice products (either for ice charts, or for models)

Better training / validation data:

- High resolution verification data from other satellites or in situ coincident with SAR
- Ridges, leads, roughness from altimetry that does not have inherent bias from the manual ice charts
- A solid training dataset (wet ice in summer, windy water) with many scenes (AI4Arctic!)
- Evaluation of ice charts (cross-calibration of ice experts)

Outlook and recommendations (applications)

Support of ice cervices and navigation:

- Integrate the products into ice service routines (use ML-based ice type as input to ice analyst)
- Forecast of ice type and ship route by combining ice type observation with ice drift forecast
- Forecast of SAR image by combining SAR image with ice drift forecast

Assimilation:

- Assimilate different products in different regions (both operational and reanalysis)
- Evaluate of impact from assimilation of various products (SIC vs SoD vs SIC)
- Characterize uncertainty better

Sea ice physics:

- From machine learning to human learning: interpret results of ‘black box’ CNNs
- Forward model for sea ice backscatter: SAR image texture is a result of ice deformation history

Theme: Sea ice
Topic: Multi-sensor synergy

Stefan Wiehle et al,
Johannes Lohse and Wolfgang Dierking
Malin Johansson et al.

Contributing work

Preliminary results of Sea Ice Classification using combined Sentinel-1 and Sentinel-3 data

By Stefan Wiehle, Dmitrii Murashkin, Anja Frost, Christine König, Thomas König

Combining C- and L-band SAR imagery for automated sea ice classification and segmentation

By: Johannes Lohse and Wolfgang Dierking

High resolution L- and C-band polarimetric variability during MOSAiC

By: Malin Johansson, S. Singha, G. Spreen, S. Howell

Table of content

Key objectives (summary)

Innovations (key slides from submitted presentations)

Remaining knowledge gaps (summary)

Outlook and recommendations (summary)

Key objectives

Multi-sensor sea ice type classification, separation and characterization

- To develop new (fused) algorithms (combinations of methods or frequencies)
- Combine SAR + optical images (Sentinel-1 missions) for improved sea ice classification
- Investigate and quantify the benefits of combining C- and L-band SAR imagery for automatic sea ice type separation
- New polarimetric parameters for improved ice type characterization and separation
- Multi-frequency (X-, C- and L-band) aligned SAR imagery for ice type classification and iceberg detection

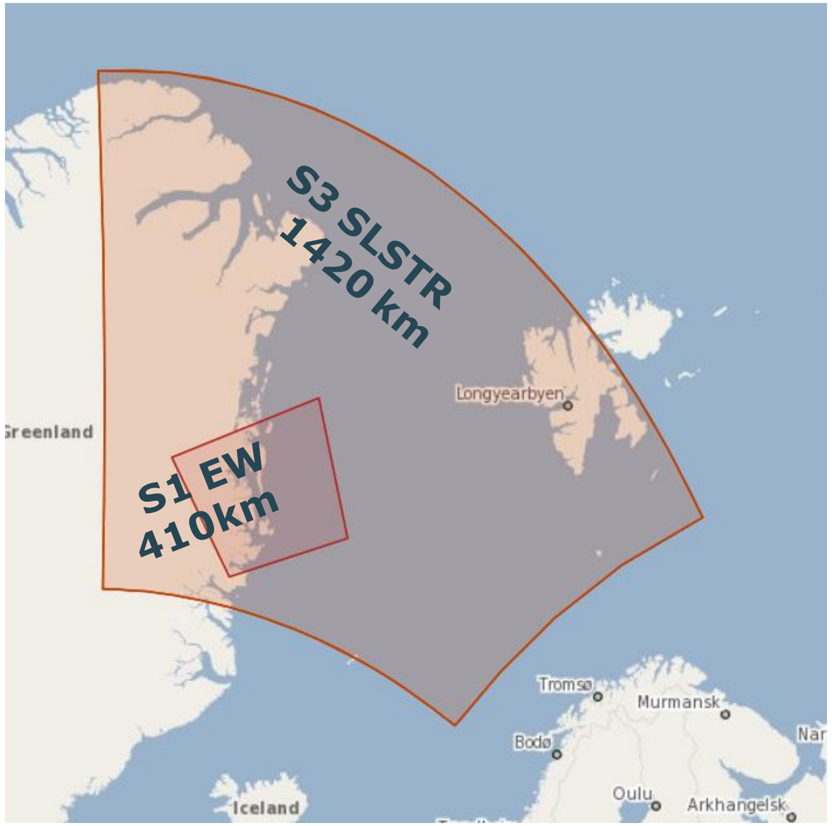
Application of multi-sensor algorithms

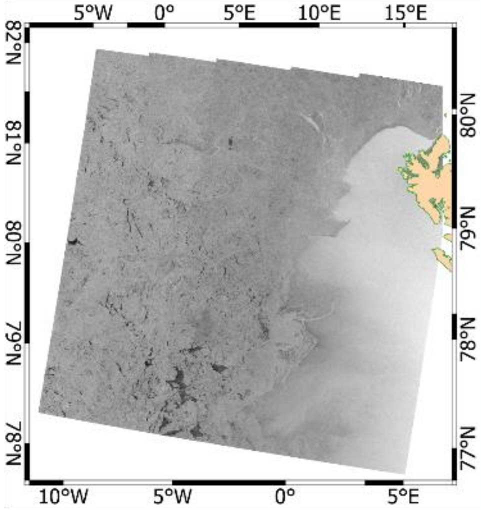
- Improve separation of ice types and ice-water
- Testing applicability of future missions (ALOS-4, NISAR, ROSE-L)
- Improve ship safety and reduce travel time by providing reliable and up-to-date sea ice information

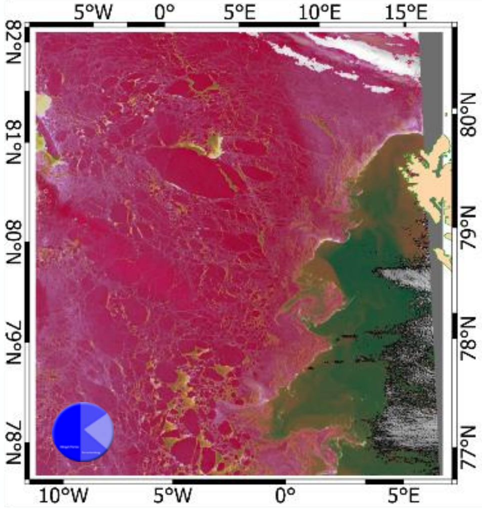
Innovations

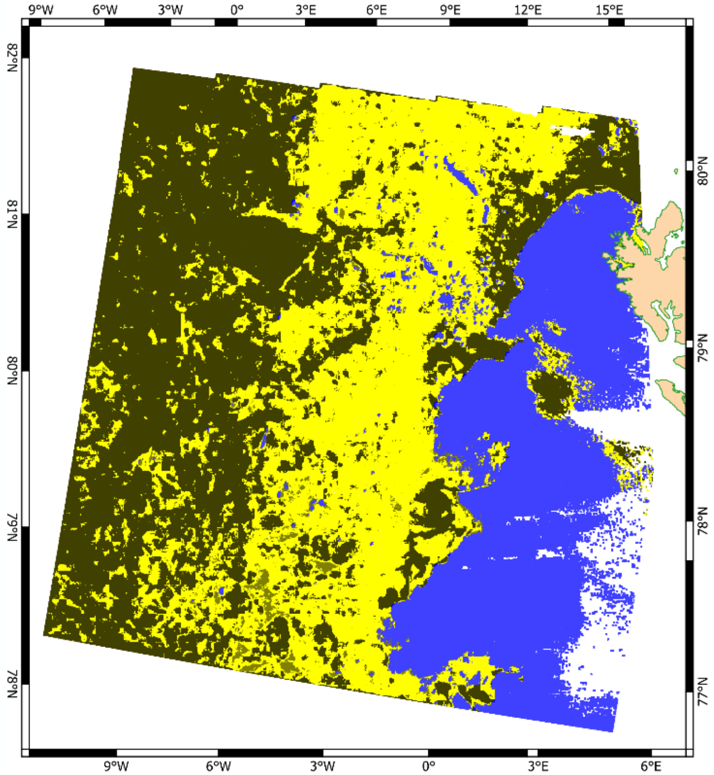
(Results)

Innovation (Wiehle et al.)







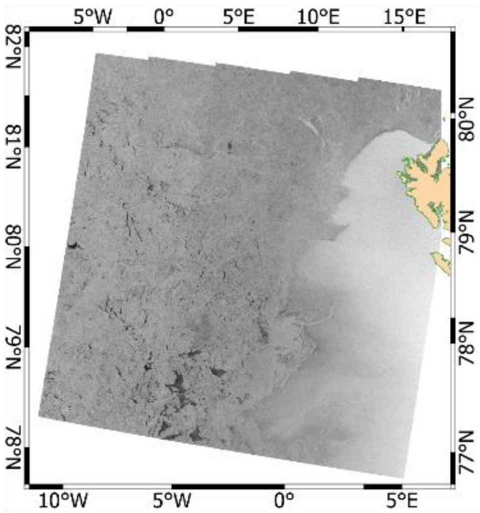


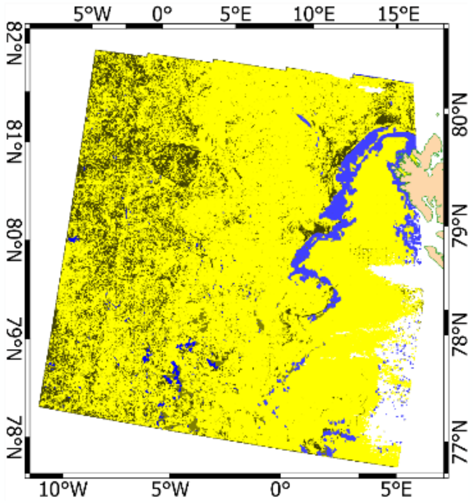
- CNN classification, 6 classes
  - Multi-year ice
  - First-year ice
  - Young ice
  - Open water, smooth
  - Open water, rough
  - Rough ice

Innovation (Wiehle et al.)

- Open water challenging to classify in SAR
- High dependency on acquisition parameters
- Difficult to train

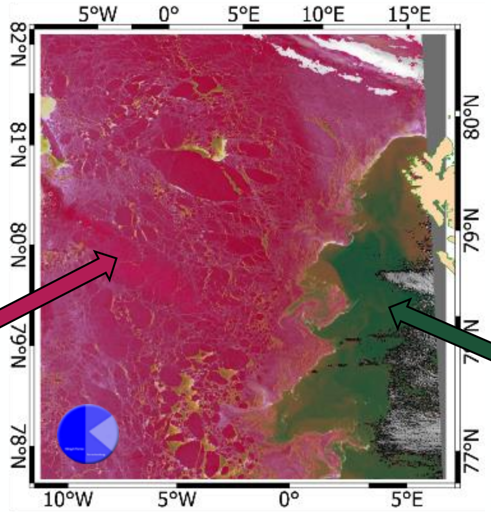
SAR only classification





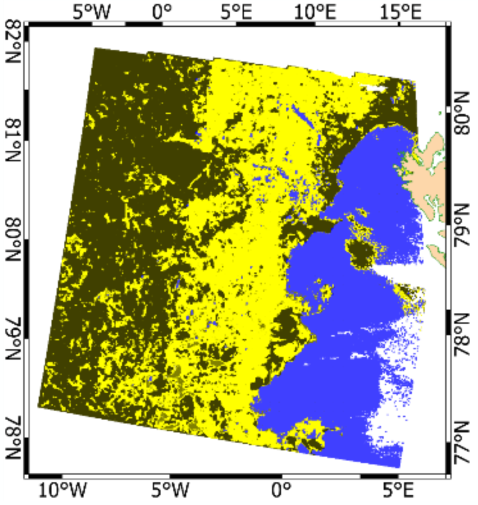
- Fusion: improved classification of open water

Ice with dry snow cover

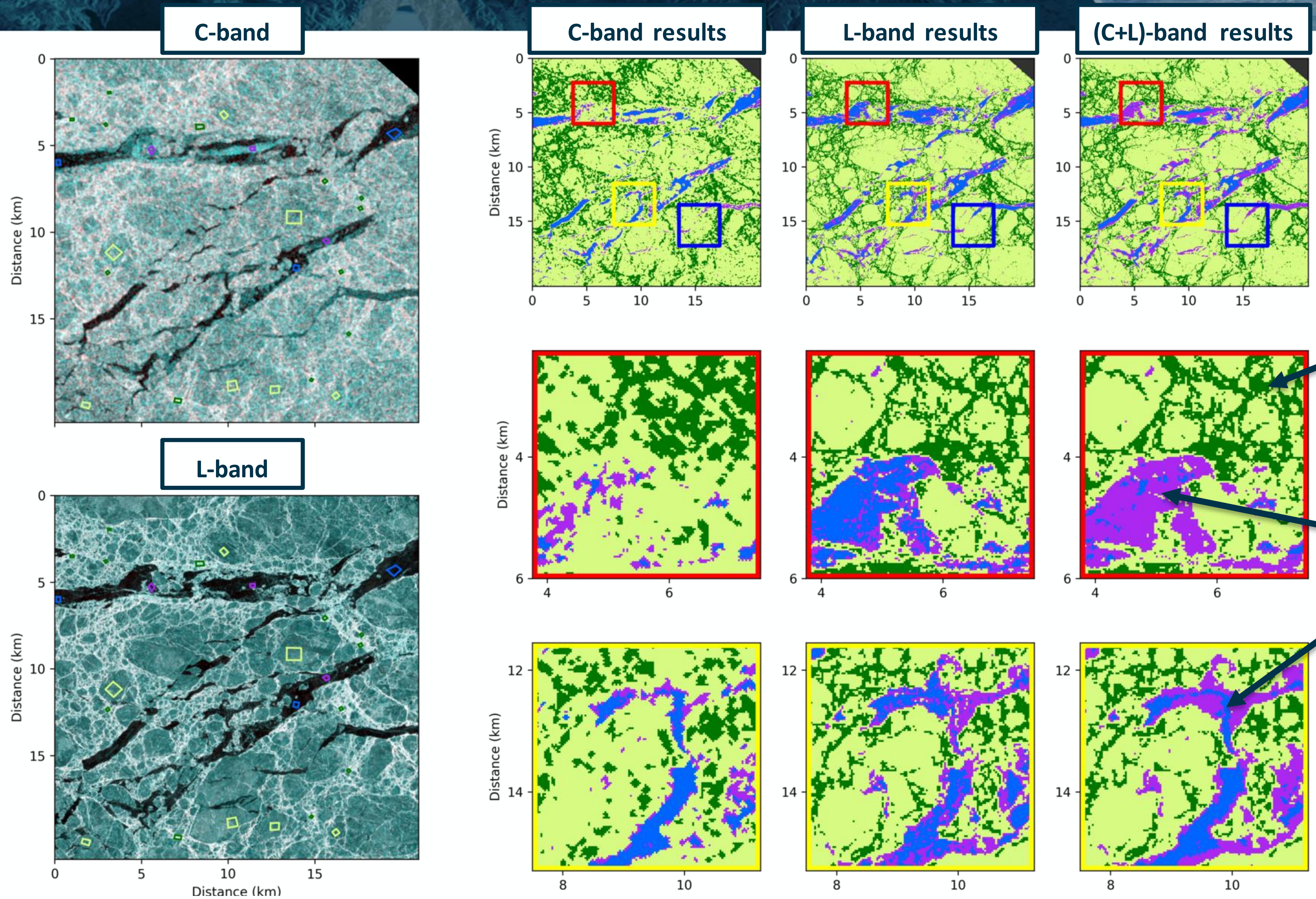


Open water

Fused classification

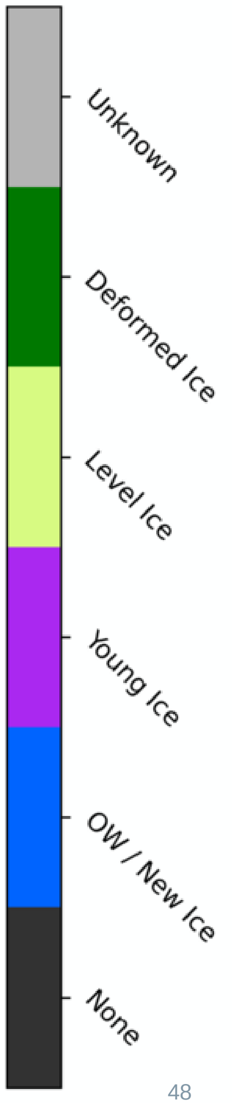


Innovation (Lohse and Dierking)



L-band or the combination of C- and L-band is clearly best at detecting *Deformed Ice*

Only the combination of C- and L-band captures *Young Ice* and *Open Water* within lead systems correctly

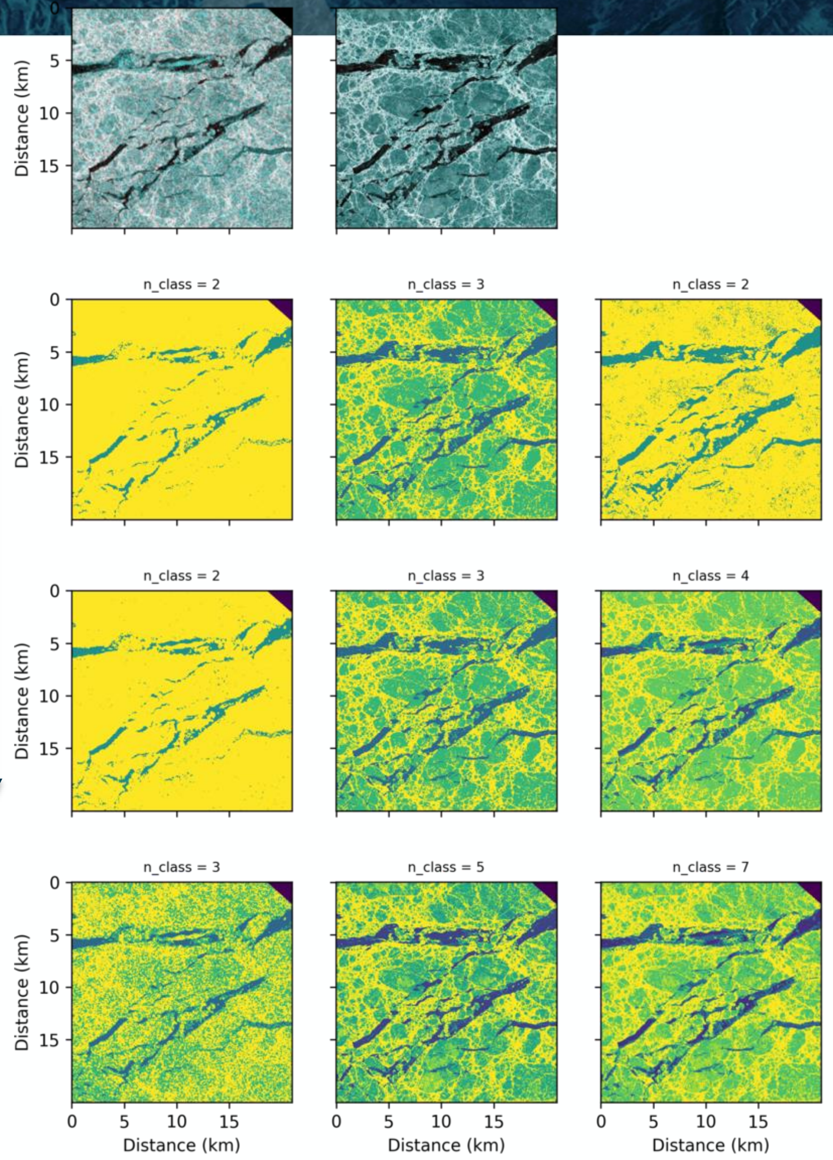


Innovation (Lohse and Dierking)

Increasing sensitivity

↓

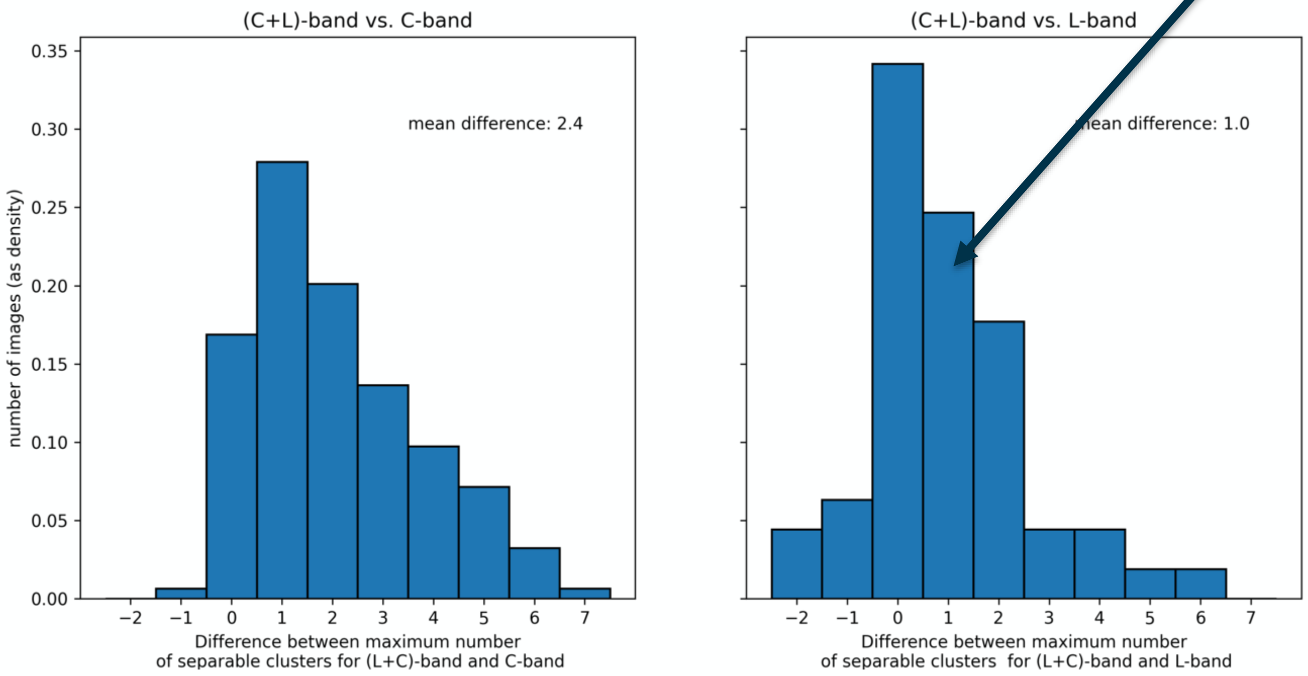
more clusters



Use distance measure to find maximum number of statistically separable clusters for:

- C-band
- L-band
- (C+L)-band

Number of image pairs for which (C+L)-band segmentation produces 1 more statistically significant cluster than L-band stand-alone segmentation



Innovation (Lohse and Dierking)

- L-band is always better at detecting *Deformed Ice* than C-band
    - Combination of C- and L-band is equally good or better

- Results for *Leads* and *Young Ice* are more variable:
    - Sometimes C-band is better, sometimes L-band is better (likely depending on small-scale roughness of YI)
    - Combination of C- and L-band is always best

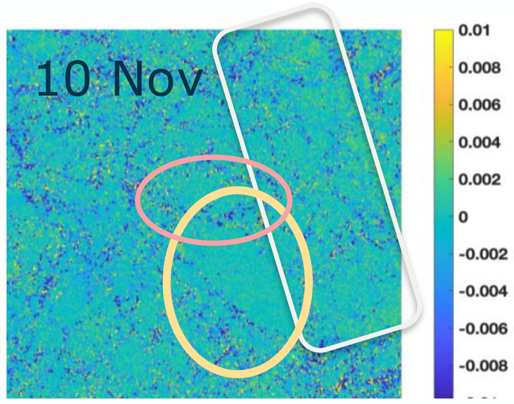
- L-band maintains slightly better separation of *Level Ice* and *Deformed Ice* during melt onset

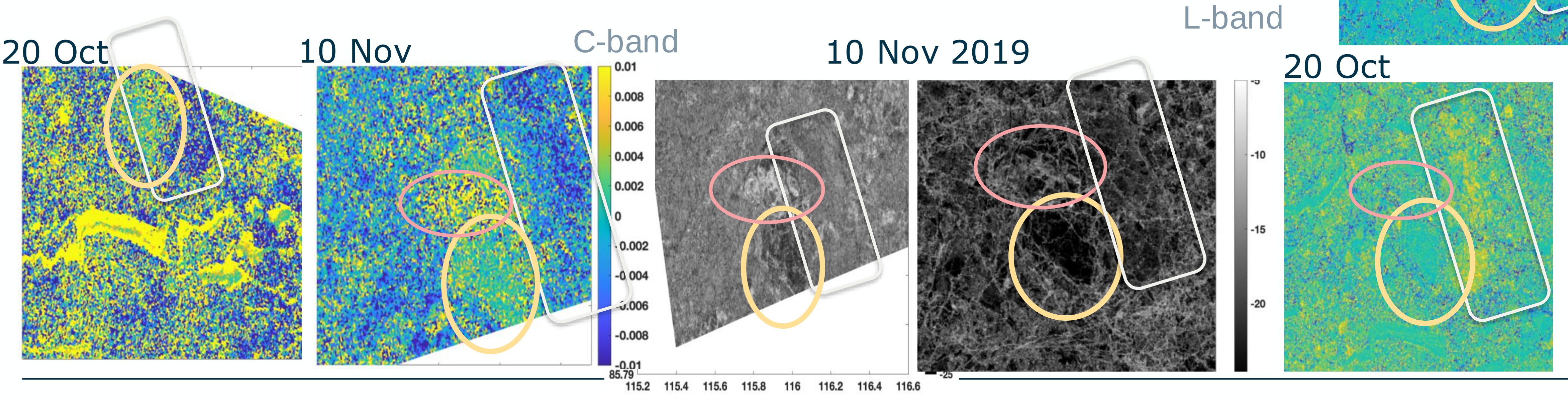
- Segmentation: (C+L) contains significantly more information than single-frequency approaches
    - On average 2.4 more clusters than C-band stand-alone and 1.0 more clusters than L-band stand-alone

Innovation (Johansson et al.)

Polarization difference (PD): VV-HH usefulness for sea ice type characterization -> separation of young ice

- Open water -> high PD
- Newly frozen sea ice -> high PD
- Young ice -> low PD
- Deformed ice -> large variability





Innovation (Johansson et al.)

L-band:

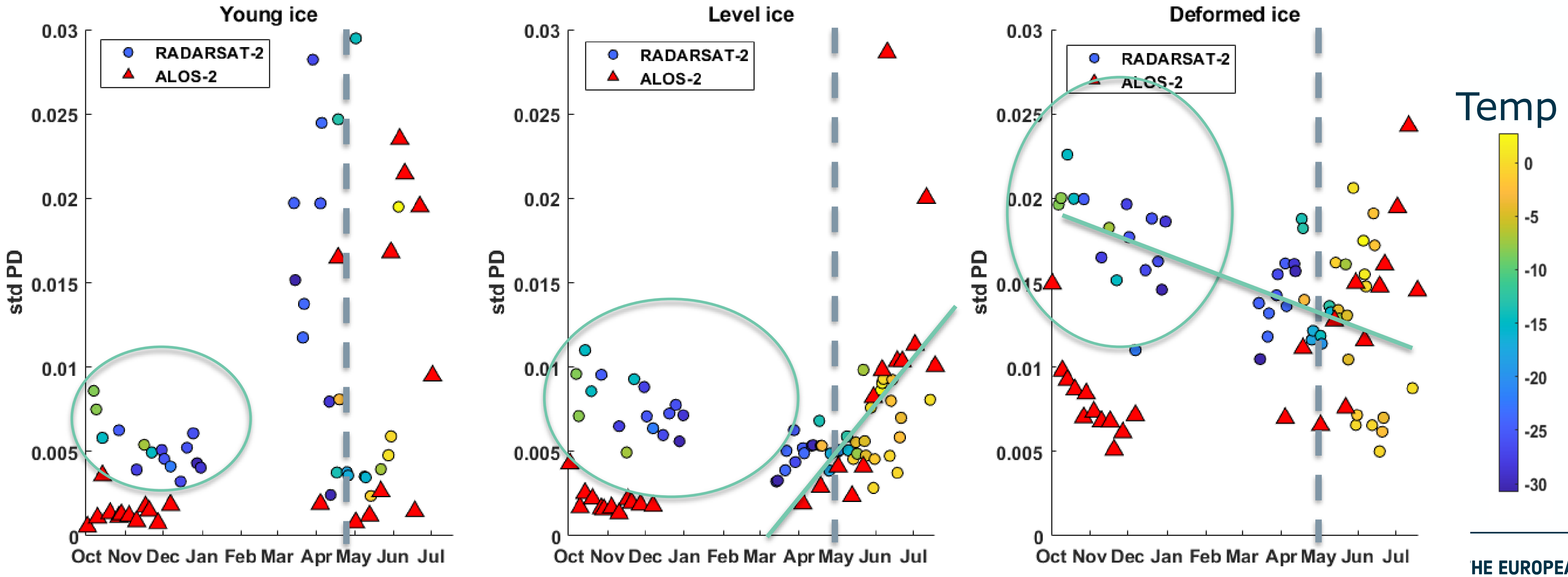
PD std small in freezing season

Larger std but same mean values in early melt season

Positive temp -> std and mean values increased

C-band:

- PD std large in freezing season
- High mean and lower std values for young ice regardless of low or high backscatter
- Level ice -> increased std with positive temp
- Deformed ice -> decrease std



Innovation (Johansson et al.)

Polarization difference

- Can be used separate young ice types from surrounding sea ice in both frequencies
    - L- and C-band have different dependencies on season and sea ice types
    - Reduced sensitive to incidence angle variations and noise
    - Possible from RCM, i.e. the HH+VV mode
    - The co-pol channels are also preferable for melt seasons for melt pond studies
    - Results transferable to data from, e.g., N-ICE2015 and CIRFA cruise 2022
        - Snow cover thicker during N-ICE2015

- Smaller L-band pixel spacing could aid the deformed sea ice extraction

Challenges and knowledge gaps

Multi-sensor synergy

- We have better coverage (temporal + spatial) when combining multiple sensors
- Several hours time delay between acquisitions
    - Critical especially for ocean applications with quickly changing parameters
    - Areas with high sea ice drift speeds (e.g. Fram Strait)
- Data alignment can produce good results, but multi-sensor data with temporal gaps are challenging
- SAR + optical satellite combination might be advantageous for multiple sea ice tasks
    – Clouds, fog and darkness

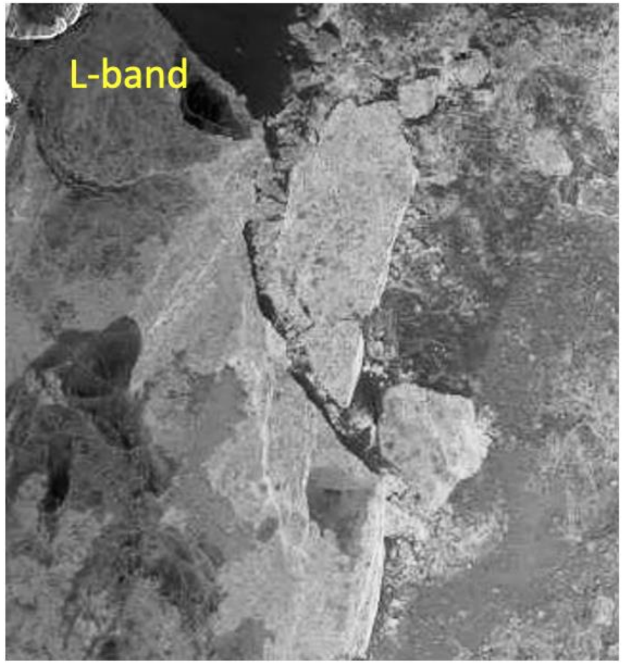
⇒ How to overcome the time separation?

Summer – melt season

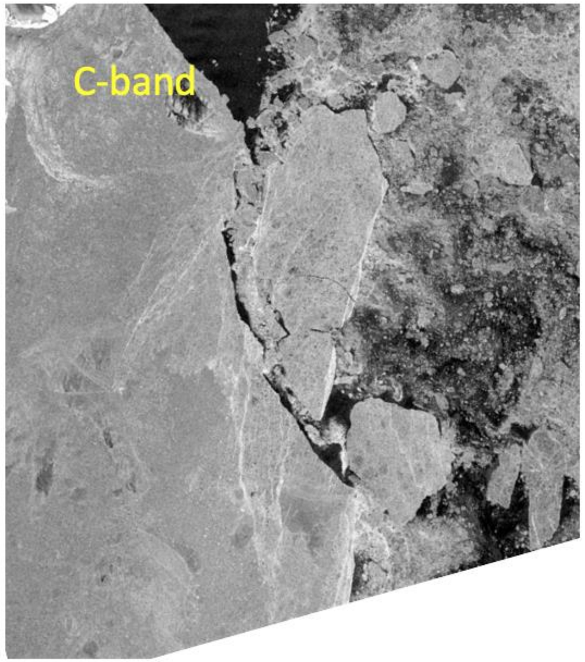
- The use of the two co-pol channels are preferable
    - Possible from RCM, i.e. the HH+VV mode, or compact pol missions
- Polarization difference can be used to separate young ice form thicker sea ice – RCM or compact pol data

Challenges and knowledge gaps

- How can we best assimilate different sensors and benefit from their strengths
  - IR thin vs thick ice -> heat fluxes
  - Optical -> open water, snow covered sea ice, ridges (with favourable illumination)
  - SAR -> penetrates (?) snow, can see the ice structure, ice water separation is challenging



PALSAR-2 WB HH-Pol. 20190708 14:27



S1 EW HH-Pol. 20190708 08:10

Example of multi-frequency SAR image combination

Belgica Bank (NE Greenland), melting phase: first-year ice (darker signature) easier to distinguish from multi-year ice (brighter areas) at L-band

Courtesy: Nick Hughes and Frank Amdal, Norwegian Ice Service

Outlook and recommendations

- Time separation between different SAR (satellite) sensors
  - ⇒ Tandem mission for ROSE-L is preferable (for automated ice type classification)
- Fleet of mixed micro-satellites (think Capella Space) might be an option when time delay <1h is ok
- Consider using RCM mode HH+VV over polar regions in summer
- Combine sea ice deformation and thermodynamics for sea ice classification/separation
- Operational L-band SAR constellation
  - Identify how L-band SAR can contribute for improved sea ice products
  - ALOS-2 has small pixel spacing – is this more important than resolution?
- Move towards integrated systems: (satellite) observations – assimilation – model
- Collaboration between different sensor acquisitions

Theme: Sea Ice

Topic: In situ data to support sea ice retrievals

Catherine Taelman et al,
Torbjørn Eltoft et al
Ekaterina Kim et al.

Contributing work

Tracking backscatter signatures of individual sea ice floes - Using in-situ drift observations

By Catherine Taelman, Johannes Lohse and Anthony P. Doulgeris

UiT The Arctic University of Norway

The CIRFA-2022 Cruise to the western Fram Strait: Objectives, Ground Measurements, and Preliminary Results

By: T. Eltoft, C. Taelman, M. Johansson, J. P. Lohse, S. Gerland, and W. Dierking

CIRFA - UiT the Arctic University of Norway

Quadruple Helix Framework for Sea Ice Monitoring: Next Steps

By: Ekaterina Kim. Roger Skjetne, Knut Høyland

NTNU

Table of content

Key objectives (summary)

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Remaining knowledge gaps (summary)

Outlook and recommendations (summary)

Key objectives

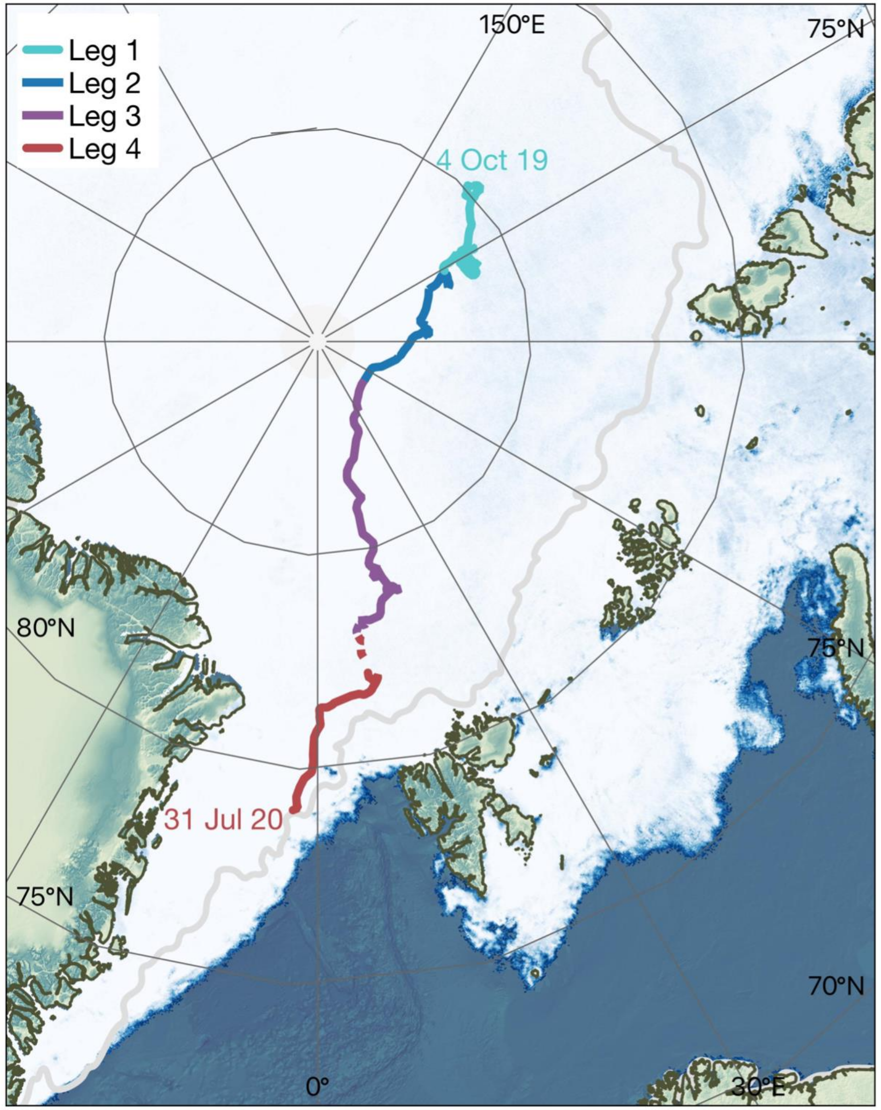
Collect In-situ data to aid remote sensing tool development

- Aid developments and validation of new sea ice algorithms
- Dedicated remote sensing validation campaigns
    - Temporal and spatial overlap
    - Instantaneous ice drift validation
    - Deployment of drifters on sea ice and icebergs
    - Tomographic radar measurements

To build a multiscale digital method and system that integrate remote sensing, numerical models and in-situ data

- Improved spatial and temporal resolution to achieve more precise forecasting of ice conditions in the Arctic
    - including better understanding of long-term variations in polar ice cover
    - Improve design and operation of offshore wind infrastructure

In-situ data campaigns



MOSAIC expedition Oct 2019 – Oct 2020

- Goal to continually monitor changes in the coupled ocean-ice-atmosphere system throughout the seasons

N-ICE 2015
NORWEGIAN YOUNG SEA ICE CRUISE

MOSAiC

the Nansen LEGACY

Icebird (2 yearly)

Photo by Sara Wang

Sea ice Environmental Research Facility (SERF), Uni Manitoba

Innovations

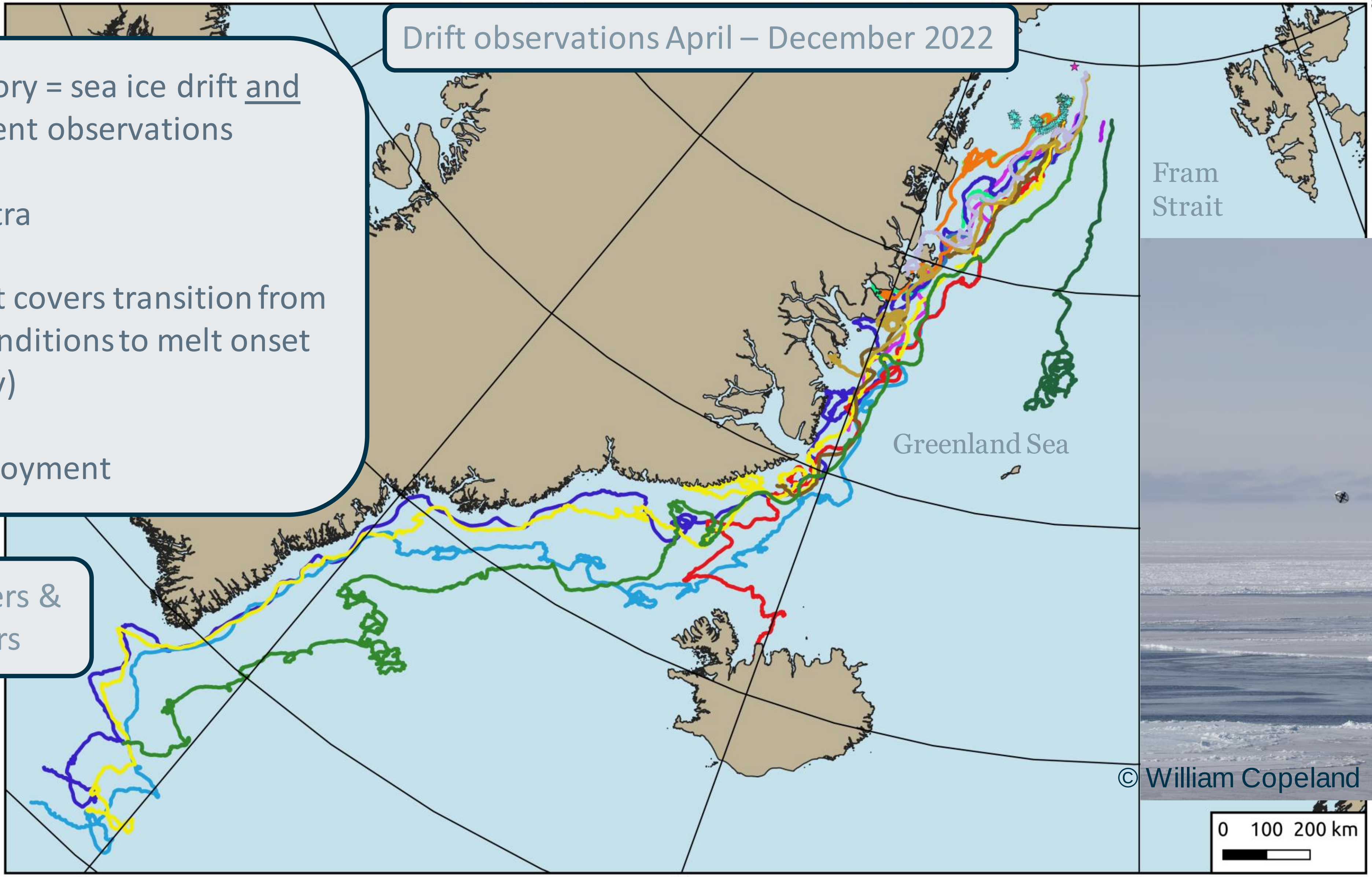
(Results)

Innovation (Taelman et al.)

- Full trajectory = sea ice drift <u>and</u> ocean current observations
- Wave spectra
- Sea ice part covers transition from freezing conditions to melt onset (April – July)
- Drone deployment

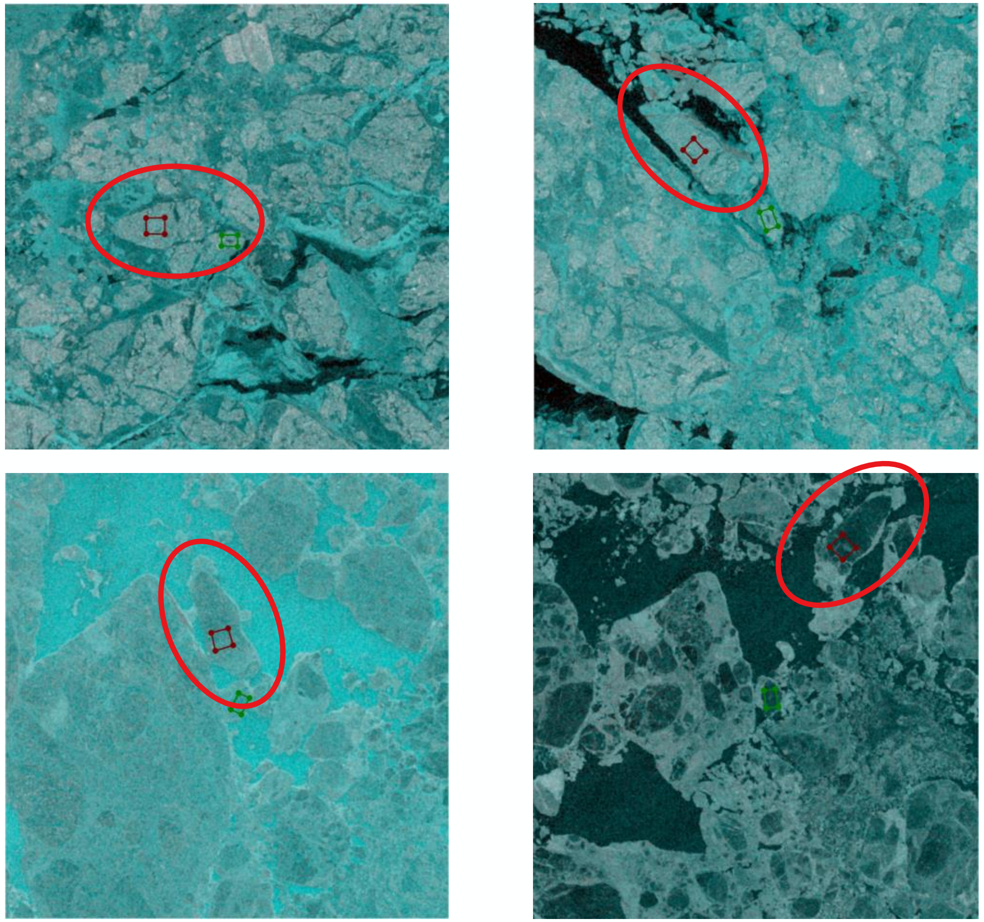
17 sea ice drifters &
3 iceberg drifters

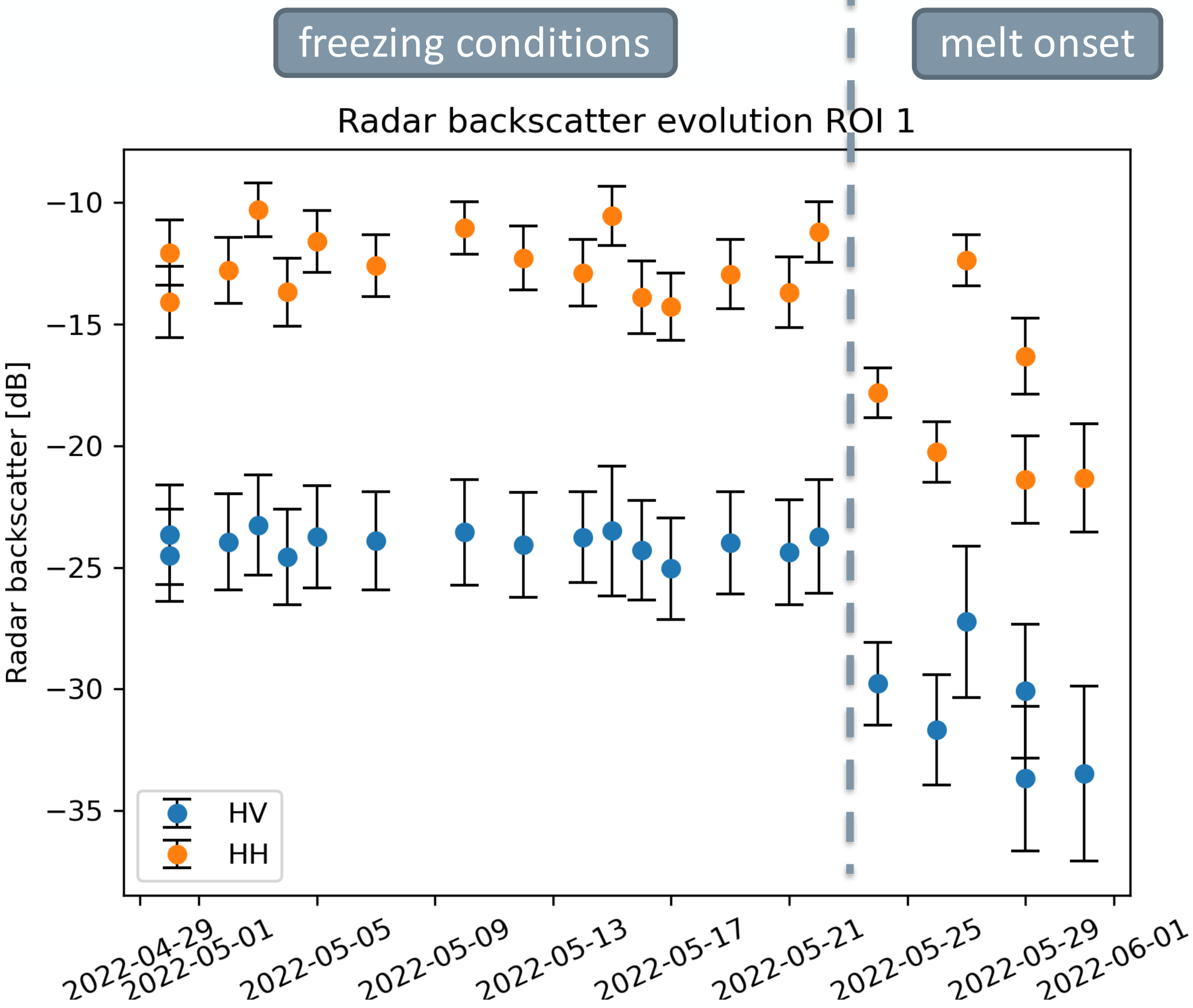
Drift observations April – December 2022



Innovation (Taelman et al.)

- Expand the tracked area by manually identifying distinct ice structures in the vicinity of the drifter location





Innovation (Taelman et al.)

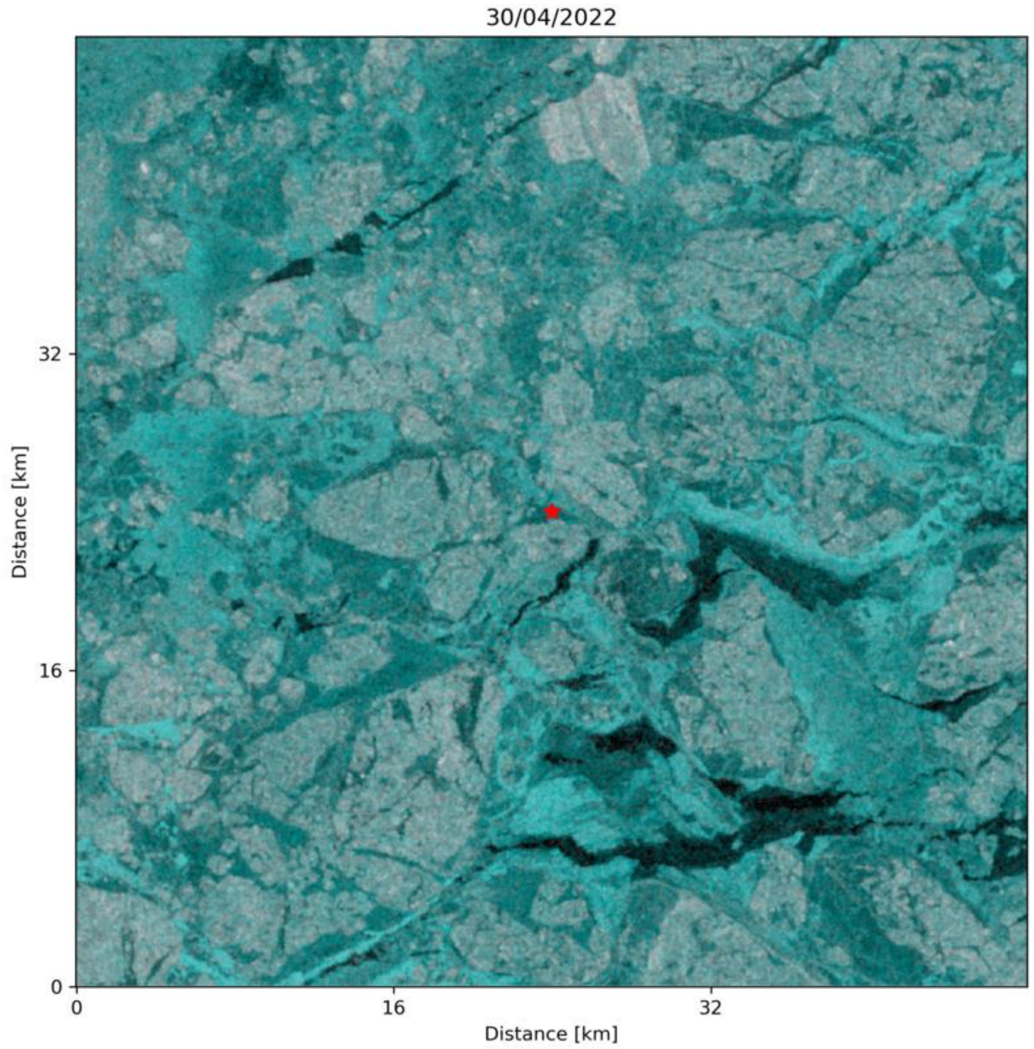
- Drones can be used to deploy drifters away from ships/land -> larger spread

- Larger number of drifters enables study of the temporal evolution and incident angle dependence of the radar backscatter for drifting ice floes, even in the melt season

- Preliminary results show that:
    - Freezing season: Radar backscatter variation is mostly due to incident angle

    - Melt season: Radar backscatter changes rapidly and the internal spread is larger. Difficult to attribute variations to either physical changes on the ice, or to incident angle.

Example SAR timeseries for 1 drifter (★)



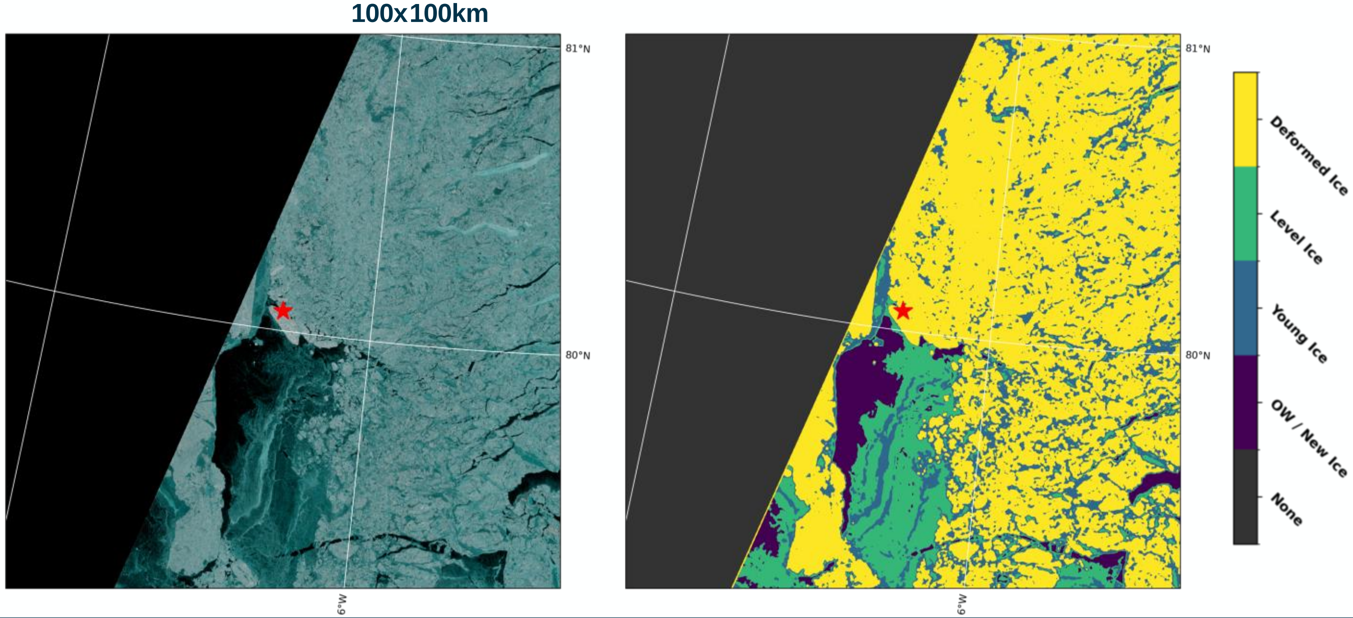
Innovation (Eltoft et al.)

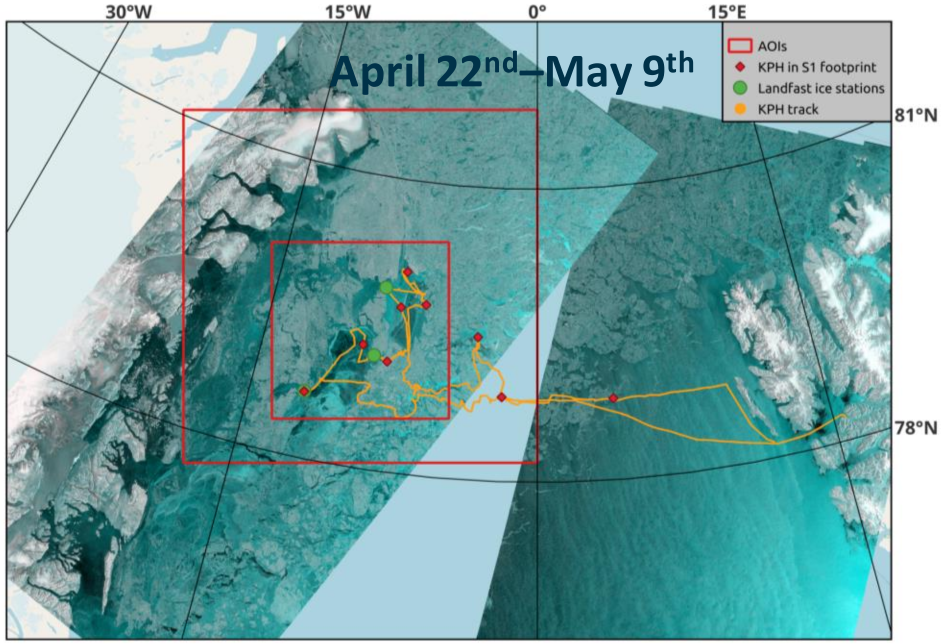
Near real time validation of ship-based sea ice observations with Classifier results.

Sentinel-1: 2022/05/04 07:29 UTC

IceObs: Deformed Ice, small patches of Level Ice or Open Water

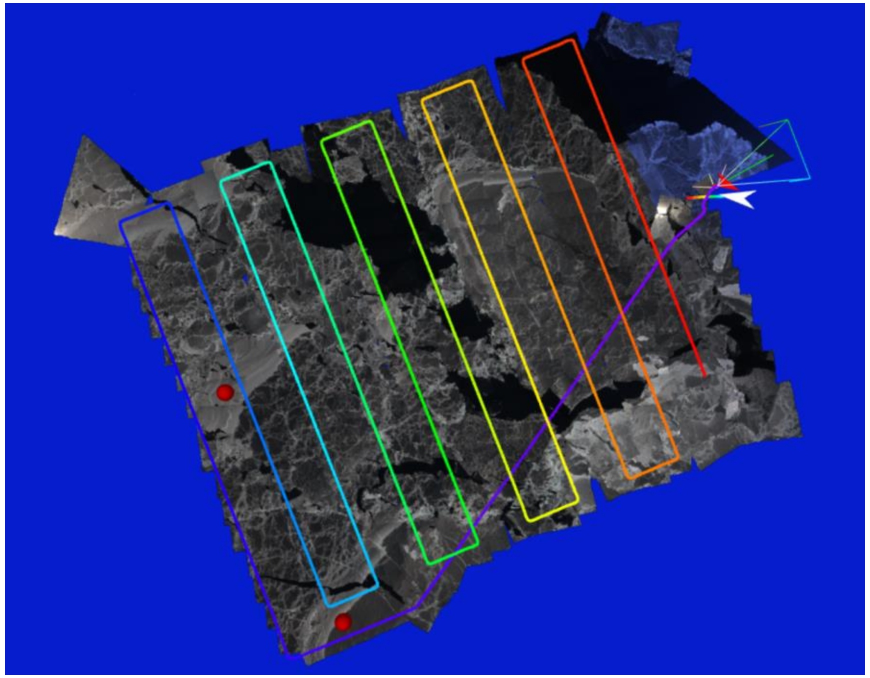
Classification: Deformed Ice

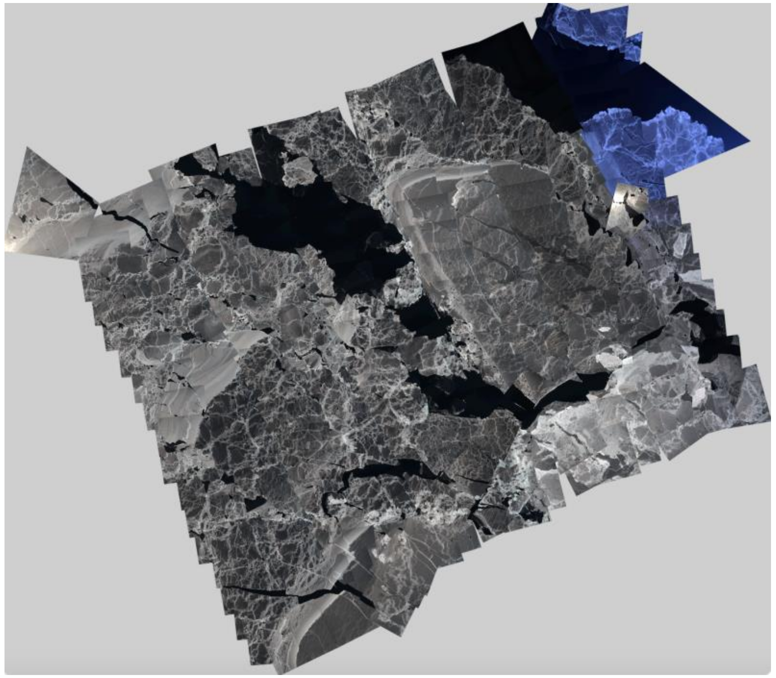




Innovation (Eltoft et al.)

- The VTOL drone could take-off and land on the heli-deck.
- Its long-distance flying capability allowed for km-meter wise optical mapping of sea ice with, 50 cm spatial resolution.
- Coinciding in time and place with SAR acquisitions
- Instantaneous sea ice drift estimates – Harmony mission

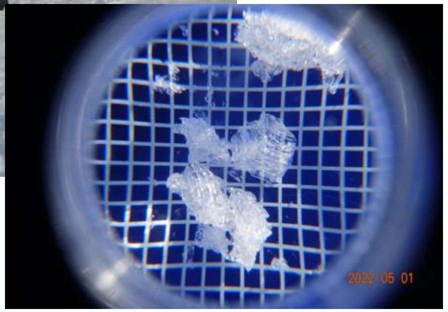




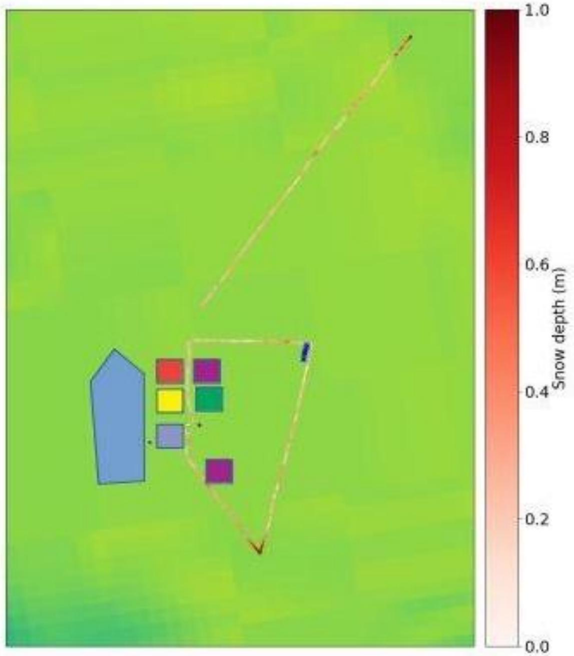
Innovation (Eltoft et al.)

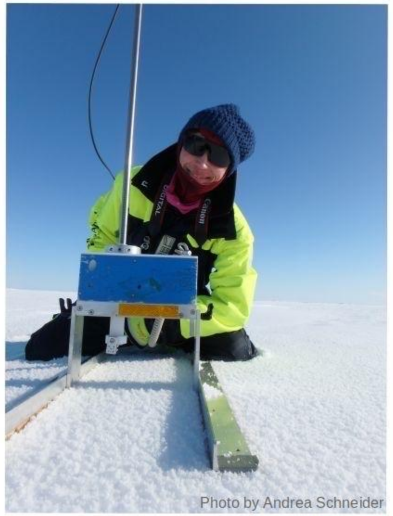
Multi-scale snow measurements

- Snow radar drone
- Snow depth (Magnaprobe)
- Snow hardness (Snow Micropenetrometer)
- Snow pits



Drone equipped with an UWB Snow radar

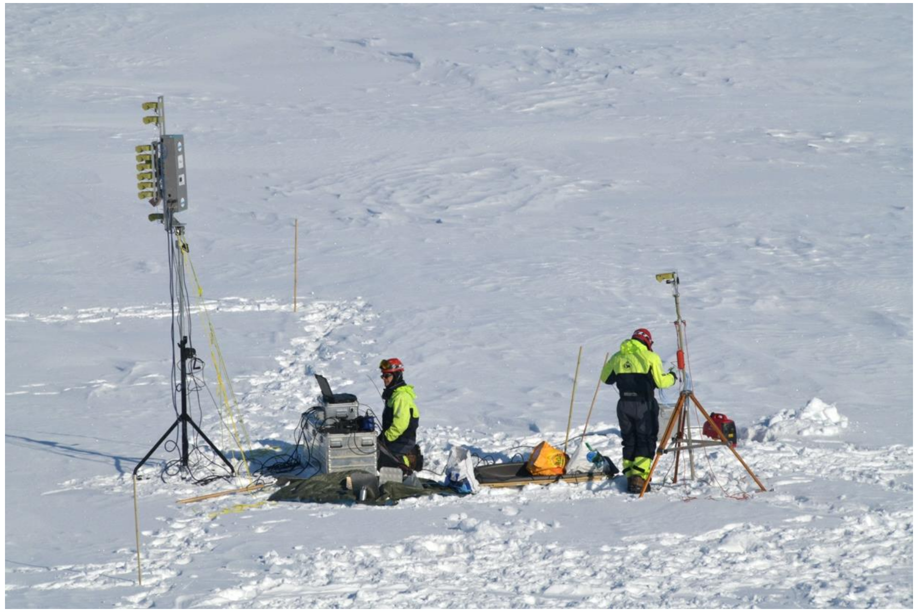


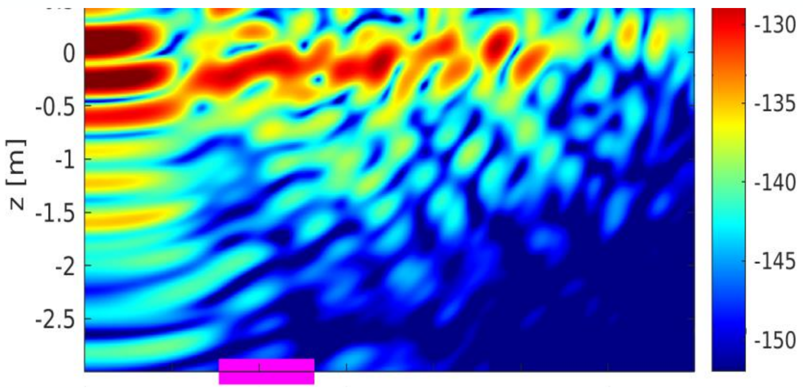


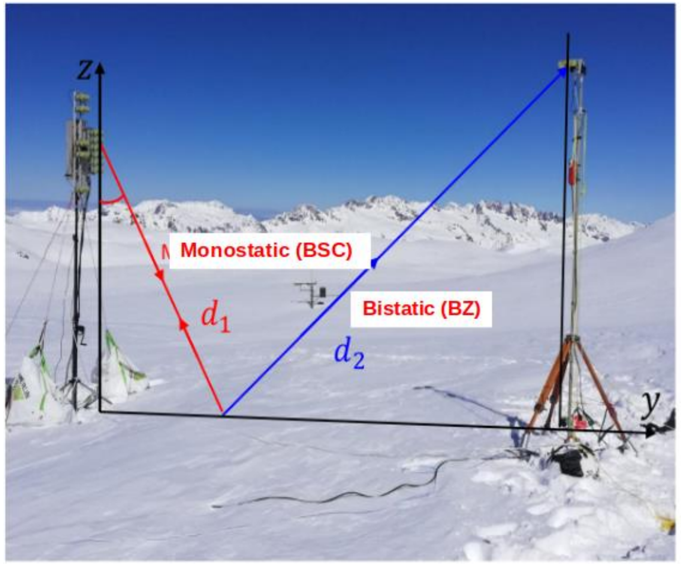
Snow Micropenetrometer

Innovation (Eltoft et al.)

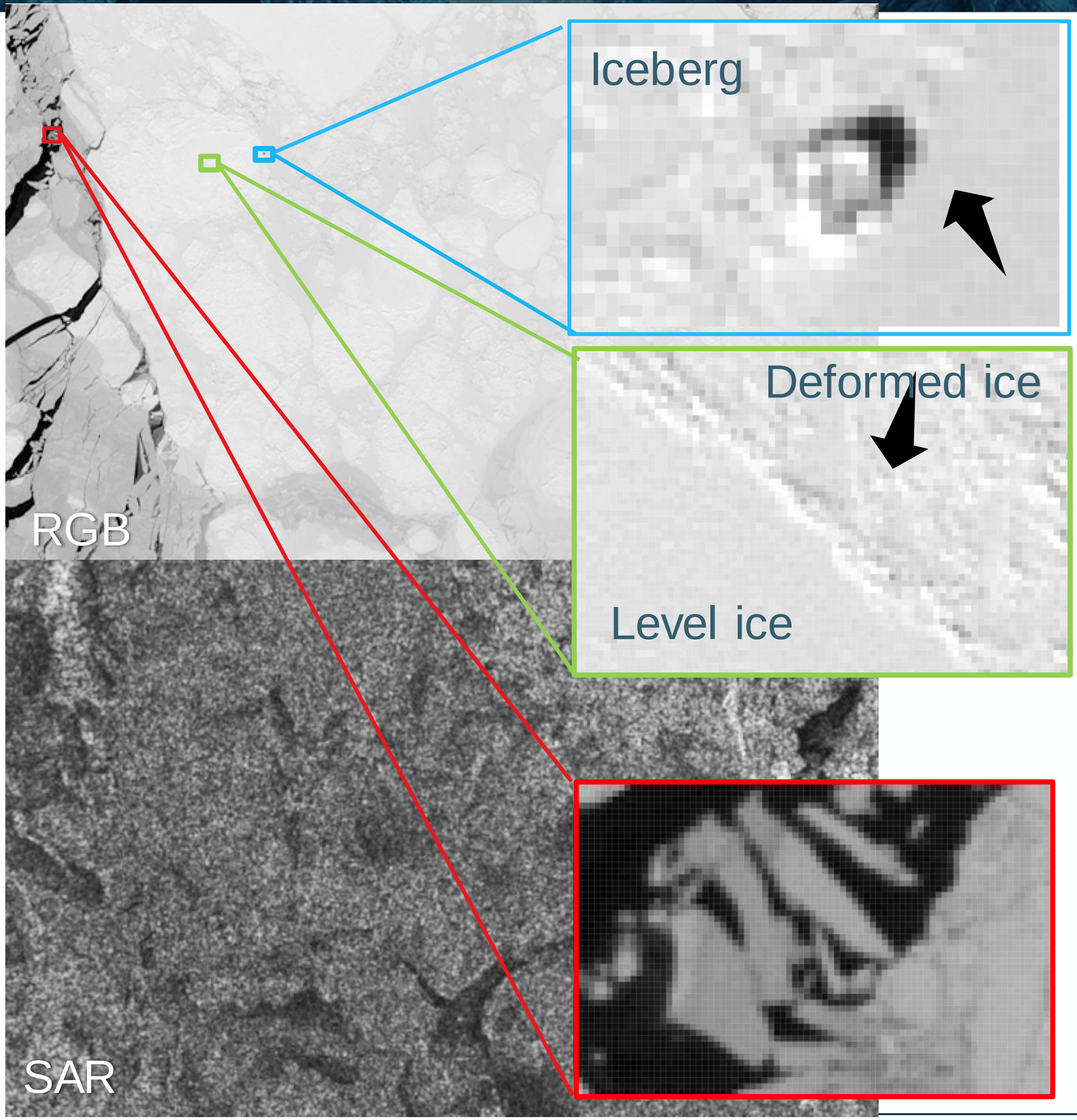
- **High-resolution ground-based radar** signatures to be compared to satellite data
- Discriminate sources of scattering within a *layered* medium consisting of snow on sea ice
- Testing assumptions associated with the radar response of sea-ice at C band





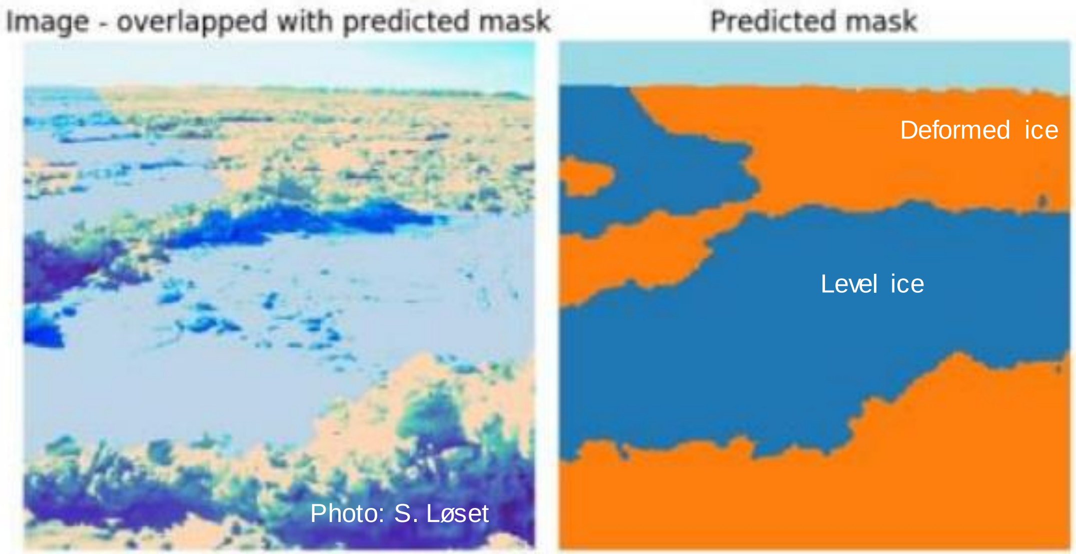


Innovation (Kim et al.)



- AI based segmentation of optical images from ships (Panchi et al, 2021)
- Retrieval of ice parameters
- Customized output

<u>Detection of</u>
Level ice
Deformed ice
Icebergs
Pancake ice
Brash ice
Ice floe
Melt ponds



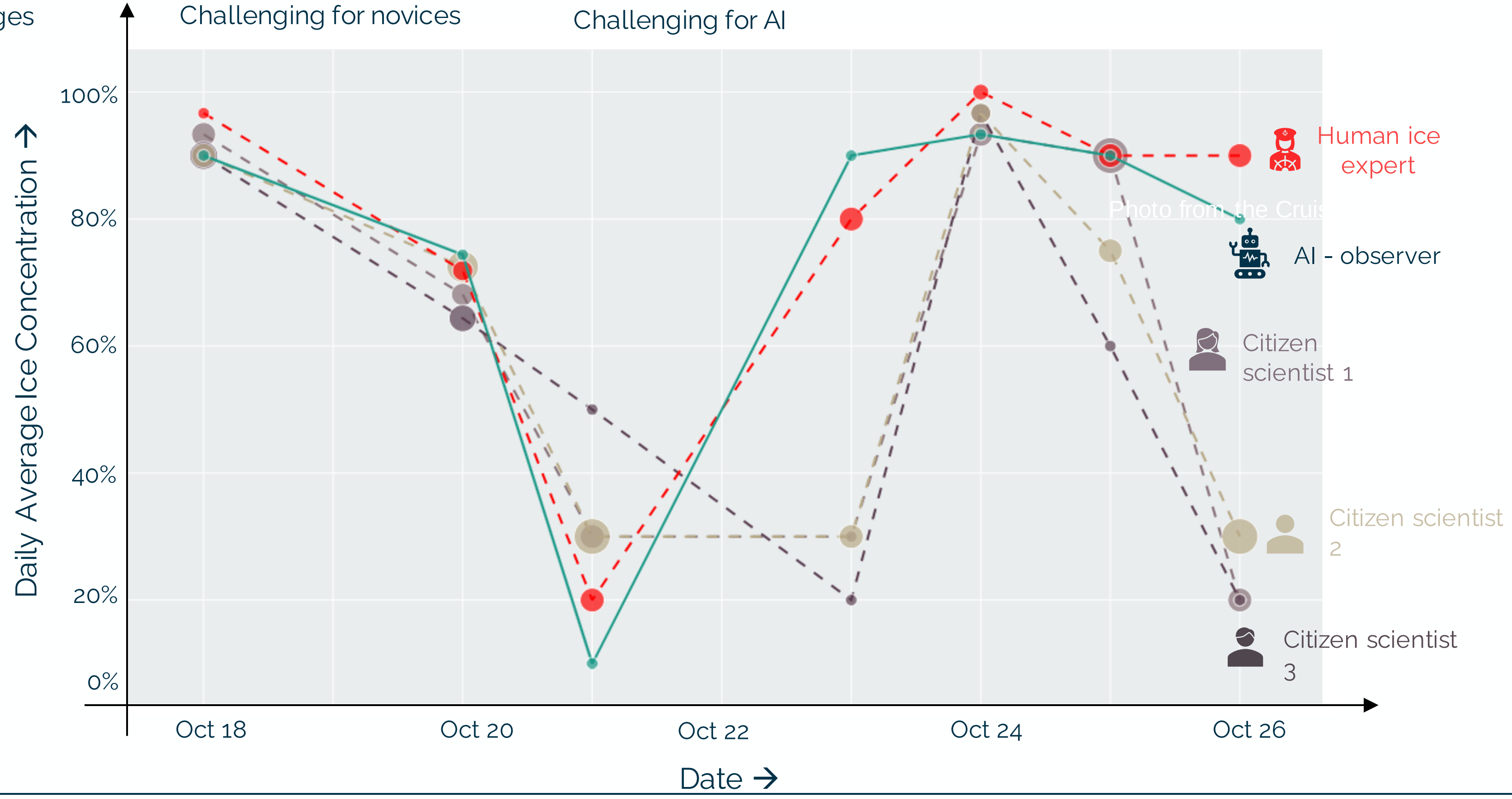
Innovation (Kim et al.)


Normal images


Challenging for novices


Challenging for AI

Tested during GoNorth-2022 (Panchi et al, 2023)

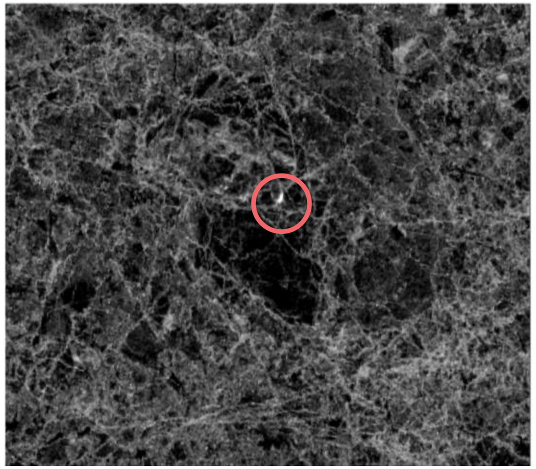


Challenges and knowledge gaps for in-situ data

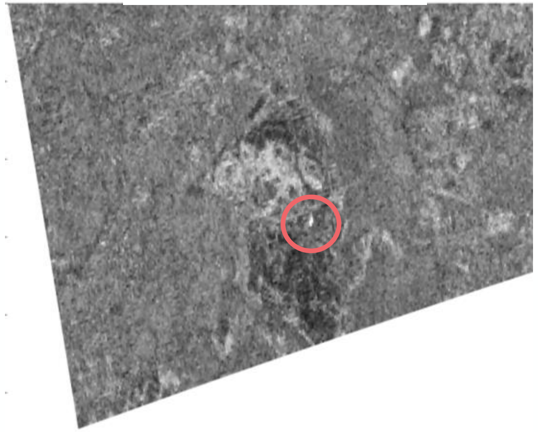
For drifting sea ice is temporal overlap between satellite images and in-situ data collection very important

- Time separation <u>without in-situ drift</u> make validation and training data extraction challenging
- Drift station data collection over time can help cover multiple seasons

PALSAR-2

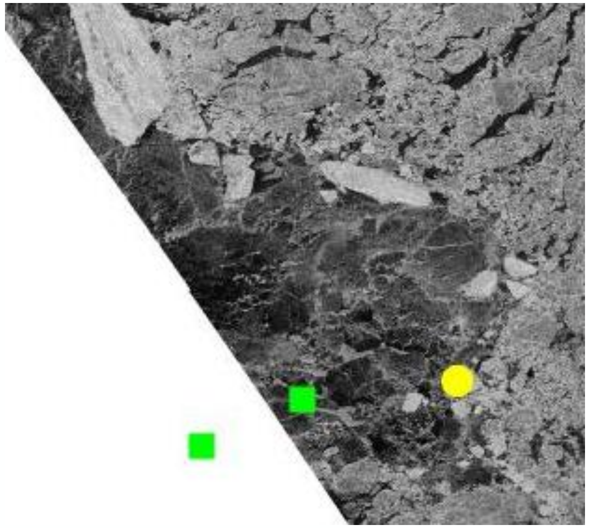


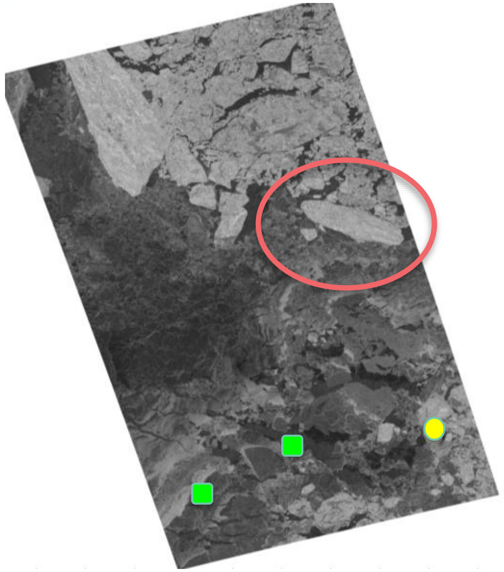
Radarsat-2



8 h time separation

PALSAR-2



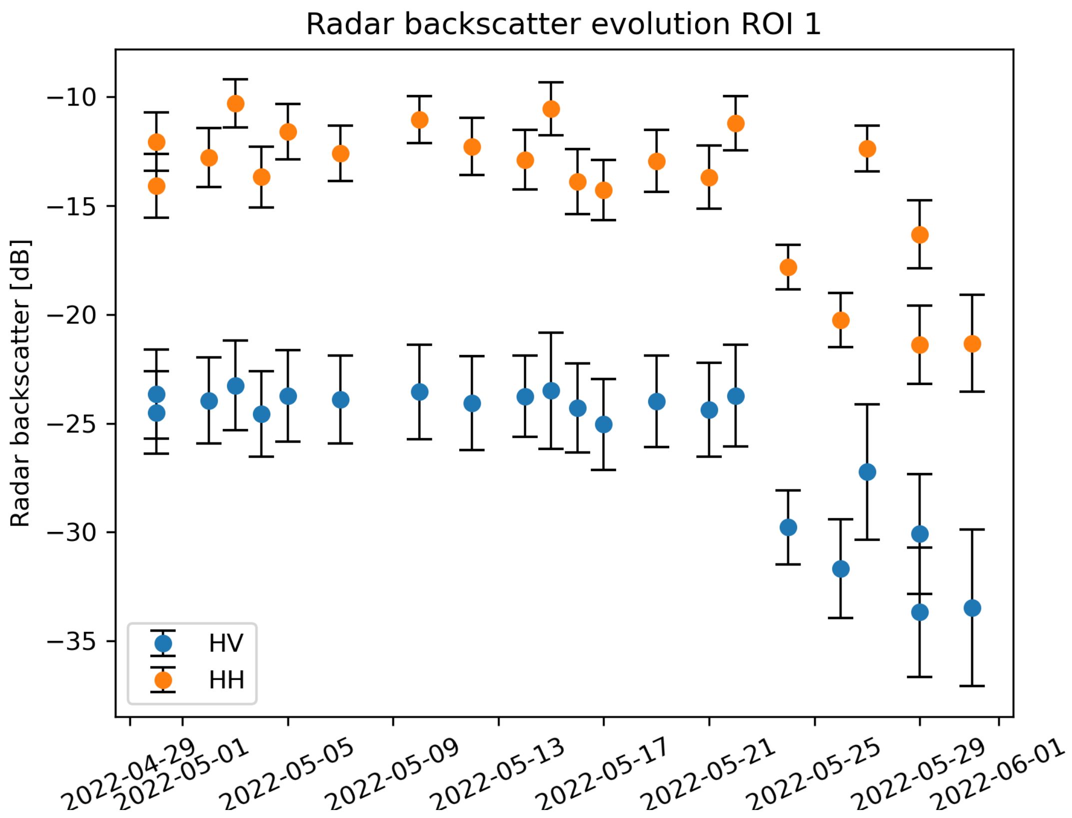


5 h time separation

Challenges and knowledge gaps for in-situ data

Rapid changing surfaces (melting in summer, ice drift year-round)

- Time separation between different satellite sensors and in-situ data collection
- High temporal cover during in-situ data campaigns – support from satellite service providers
    - JAXA-ESA LC-project



Challenges and knowledge gaps for in-situ data

Upscaling - downscaling

- Different modes (fine + coarse evolution) help with upscaling and downscaling
- How can we go from in-situ -> drones -> airborne -> satellites -> models?
- Large spatial possible cover over the site – help mitigate issues with overlapping drifting in-situ campaigns

Outlook and recommendations

Targeted in-situ data collection

- In-situ data campaigns targeting satellite data product validation
- Permanent stations overlapped with repeated satellite image overlaps
- In-situ collection should be adapted to solve the scientific question
- Connect ground radar observations -> drones -> SAR (other satellite images) for upscaling
- Consider overlaps in time and space for upscaling
    - SAR, Altimetry, PMW, IR, Optical sensors for satellites, drones and airborne sensors

Drone usage

- Increased use of georeferenced drone images for training and validation of satellite data products
- Plan drone flights to relate to the science and operational question
- Use drones for instantaneous sea ice drift retrieval - connect with SAR image observations (Harmony)
- Drones have long-distance capability allowed for km-meter wise optical and IR mapping
- Can fly below cloud cover and fly simultaneous with SAR (other satellite sensor) acquisitions

Outlook & remaining knowledge gaps

The role of snow must be better understood

- Snow metamorphism and the effect on the radar signature (perhaps) not fully understood
- Also under dry freezing conditions
- Wind compacted layers
- Rain on snow events
- Ice lenses within the snowpack and brine layer at the snow-ice interface, e.g., February N-ICE2015
- Might mostly relate to C- and X- band, L-band less affected

Summer season

Drifters

- Deploy more drifters on underrepresented sea ice
  - First year ice (thinner)
  - Fast drifting sea ice
- Data arrays, e.g., MOSAiC, NICE-2015 etc (drifting and deformation on a high-resolution scale)