Recent Progress in Advancing a Hybrid Machine Learning Approach over Sea-Ice Surfaces for AMSU-A

Image credit: chatgpt

EUMETSAT

Fellow Day

2nd March 2026

Cristina González-Flórez [1], Fabrizio Baordo[1], Stephanie Guedj[2] , Alan Geer[3] and Suman Singha[1]

(1) Danish Meteorological Institute, Copenhagen, Denmark (2) Norwegian Meteorological Institute, Oslo, Norway, (3) ECMWF, Reading, UK.

The Danish Meteorological Institute

Fellowship from 1st November 2024

Satellite Observations

Data Assimilation (DA)

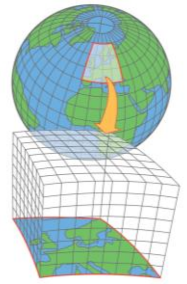
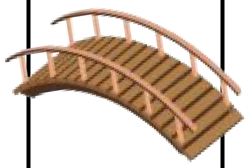


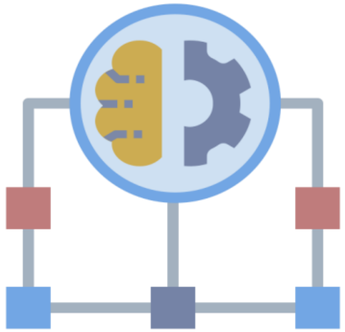
Image credit: FMI
https://en.ilmatieteenlaitos.fi/



EUMETSAT
fellowship

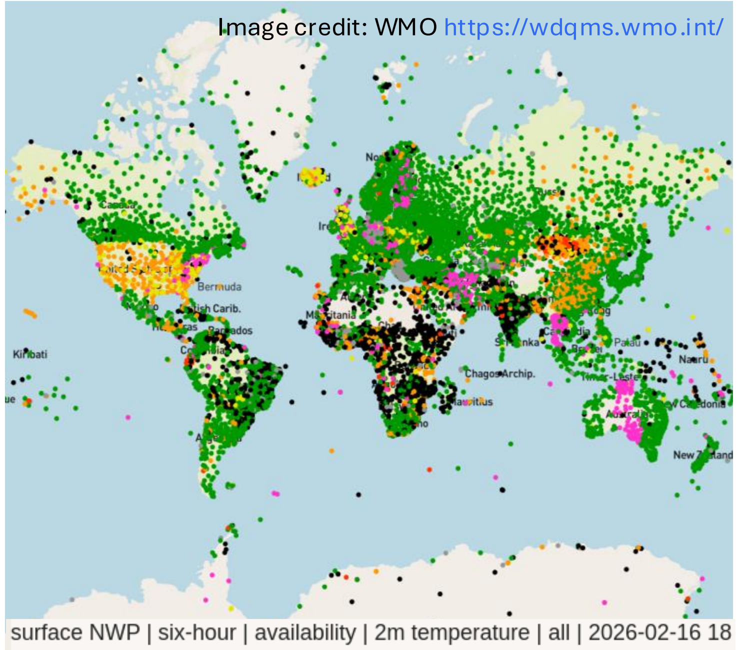
Polar regions

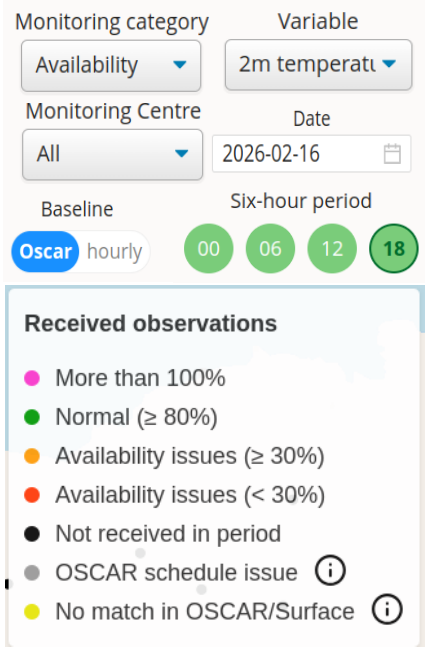
Machine Learning (ML)



Satellite Observations

Provide near-global Earth system monitoring, complementing sparse in situ observations.

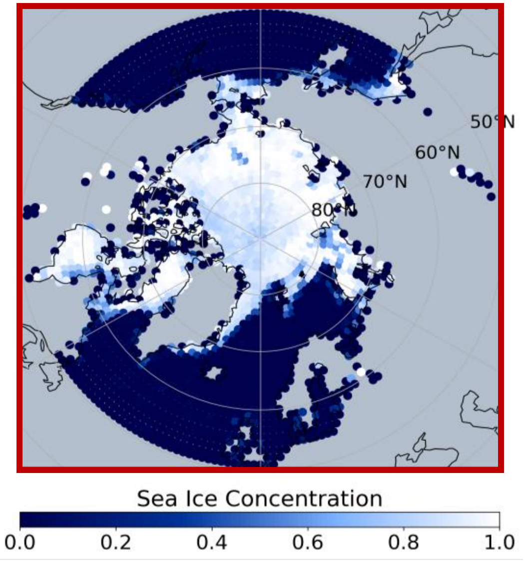




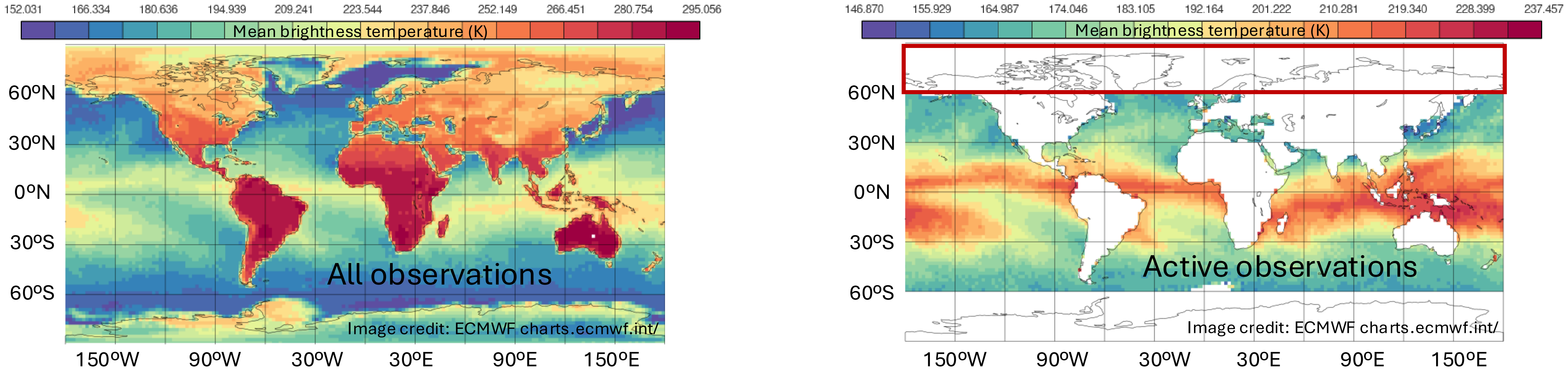
Satellite Observations

Provide near-global Earth system monitoring, complementing sparse in situ observations.

1 Feb 2025



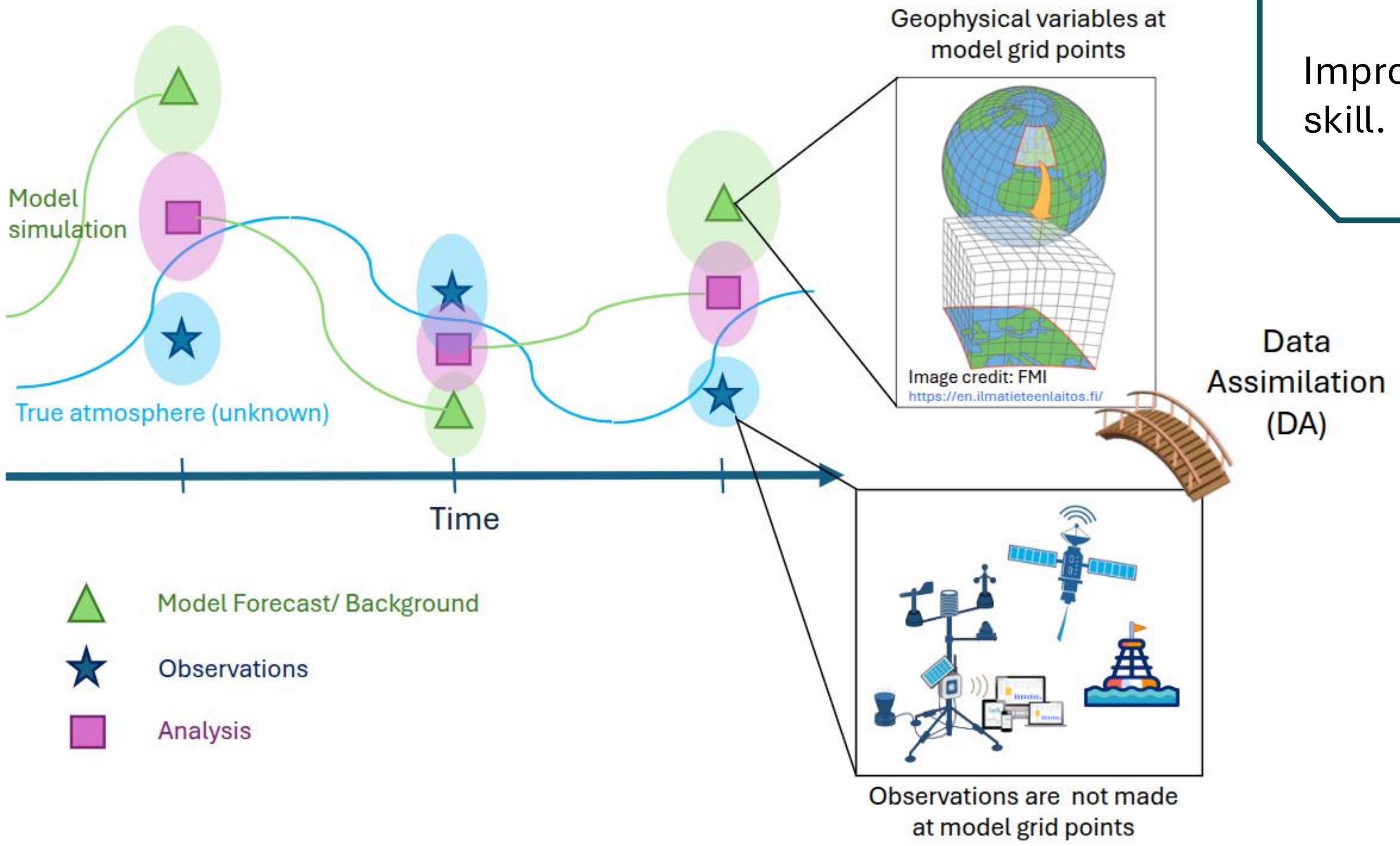
AMSU-A (METOP-B) 19 Feb 2026 00UTC Channel 1 23,8 GHz (V)



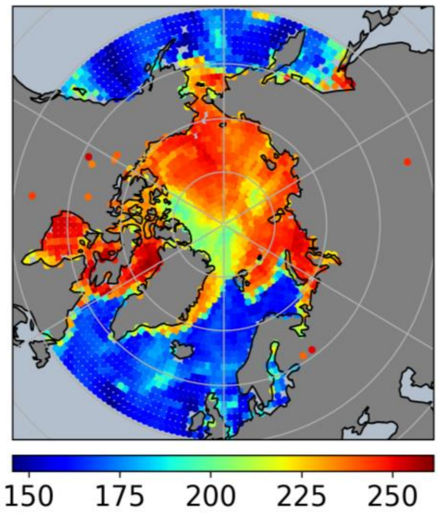
Data Assimilation (DA)

Integrates in situ and satellite observations into forecasting systems.

Improves initial conditions, enhancing forecast skill.

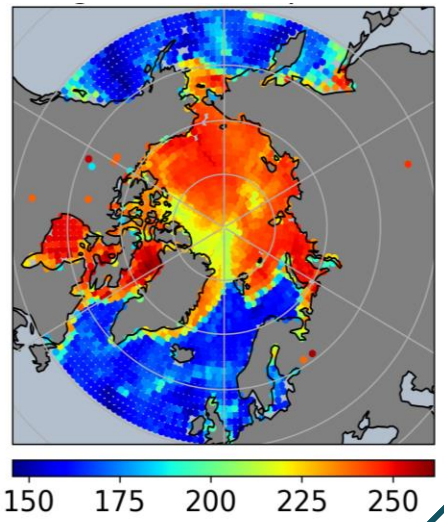


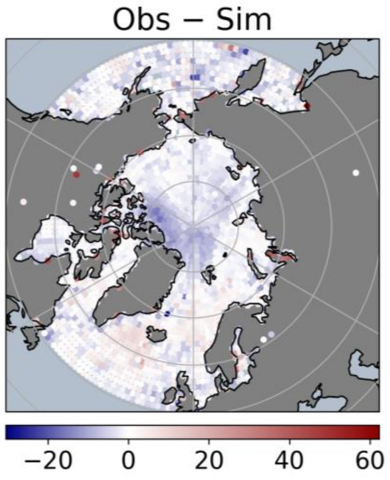
Observed Brightness Temperature
AMSU-A (METOP-B)
1/04/2024 Channel 2 (31V)



First Guess departure

Simulated Brightness Temperature
AMSU-A (METOP-B)
1/04/2024 Channel 2 (31V)





If the observed and simulated brightness temperatures are close enough, then the observations are assimilated

Machine Learning (ML)

Hybrid ML approach for a sea-ice observation operator (used to simulate satellite observations in Numerical Weather Prediction/DA systems)

Geer, A. J. (2024a). Simultaneous inference of sea ice state and surface emissivity model using machine learning and data assimilation.

Polar regions

Arctic amplification drives rapid changes in surface conditions (e.g., sea-ice extent), with implications for regional and global weather, and the emergence of new maritime routes requiring reliable forecasts.

1 Understanding the hybrid ML architecture

2 Retrieving satellite data and corresponding ECMWF-IFS outputs

3 Building the training dataset

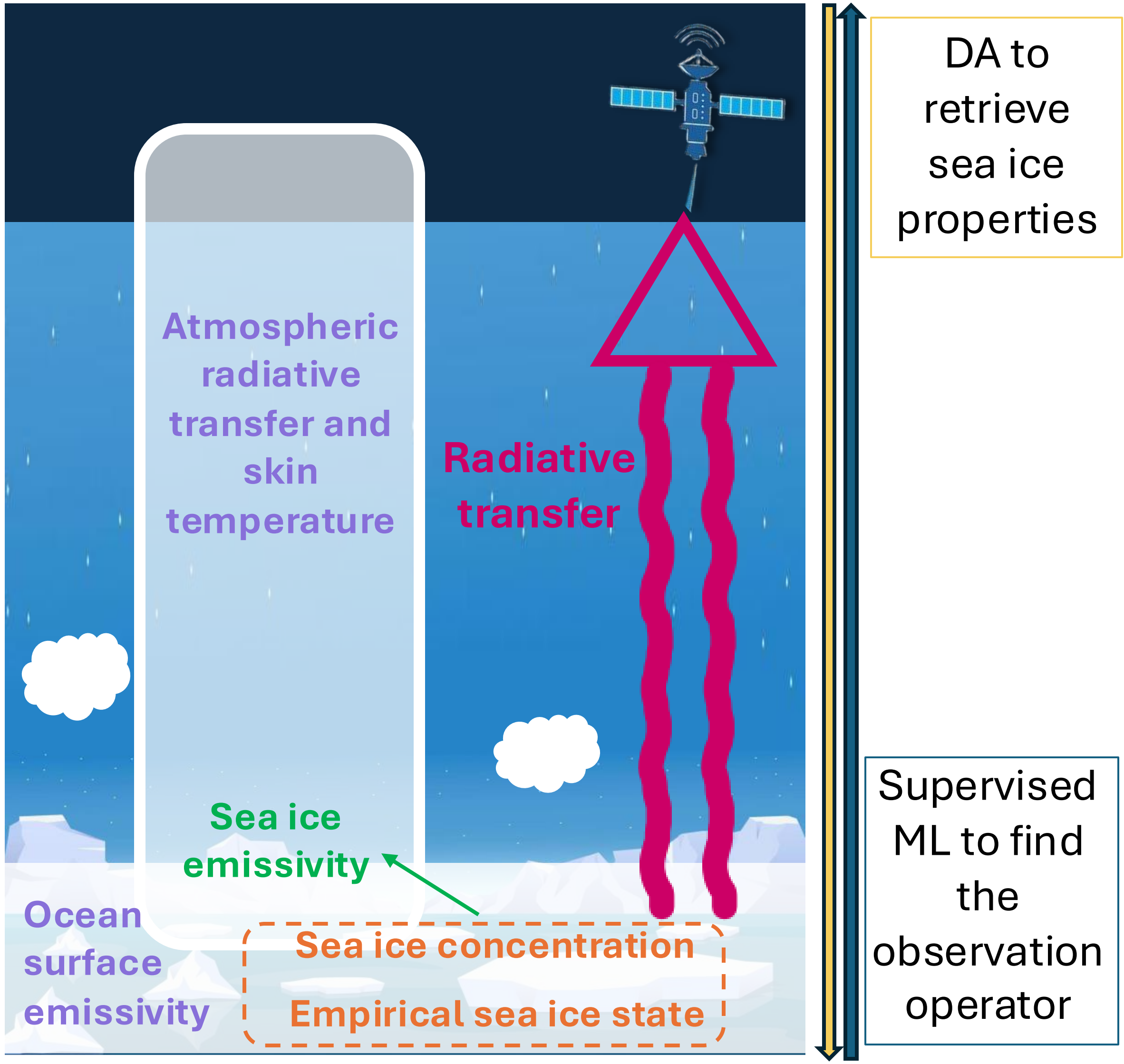
4 Extending the hybrid ML model to cross-track scanning sensors

5 Running and evaluating the model

Satellite observations

Atmosphere

Sea-Ice



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Inputs

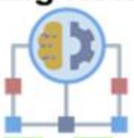
	x_1	x_2	...	x_i
Obs. 1				
Obs. 2				

Obs. m				

- tsfc: surface temperature
- tausfc: surface-to-space transmittance in the clear atmospheric column
- windspeed10m: 10 m wind speed

⋮

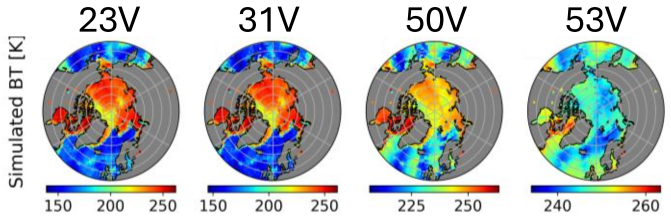
Empirical-physical training Network



$J = J_{obs} + J_{seaice\_bounds} + J_{seaice\_tsfc} + J_{emis} + J_{bias}$

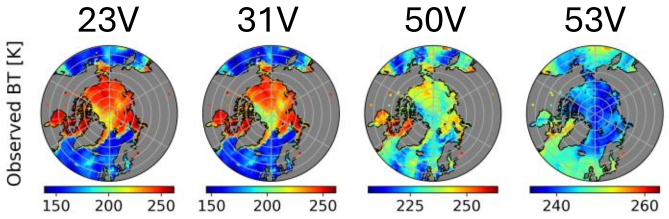
Output

Simulated Brightness temperature x n channels



Observed

Brightness temperature x n channels



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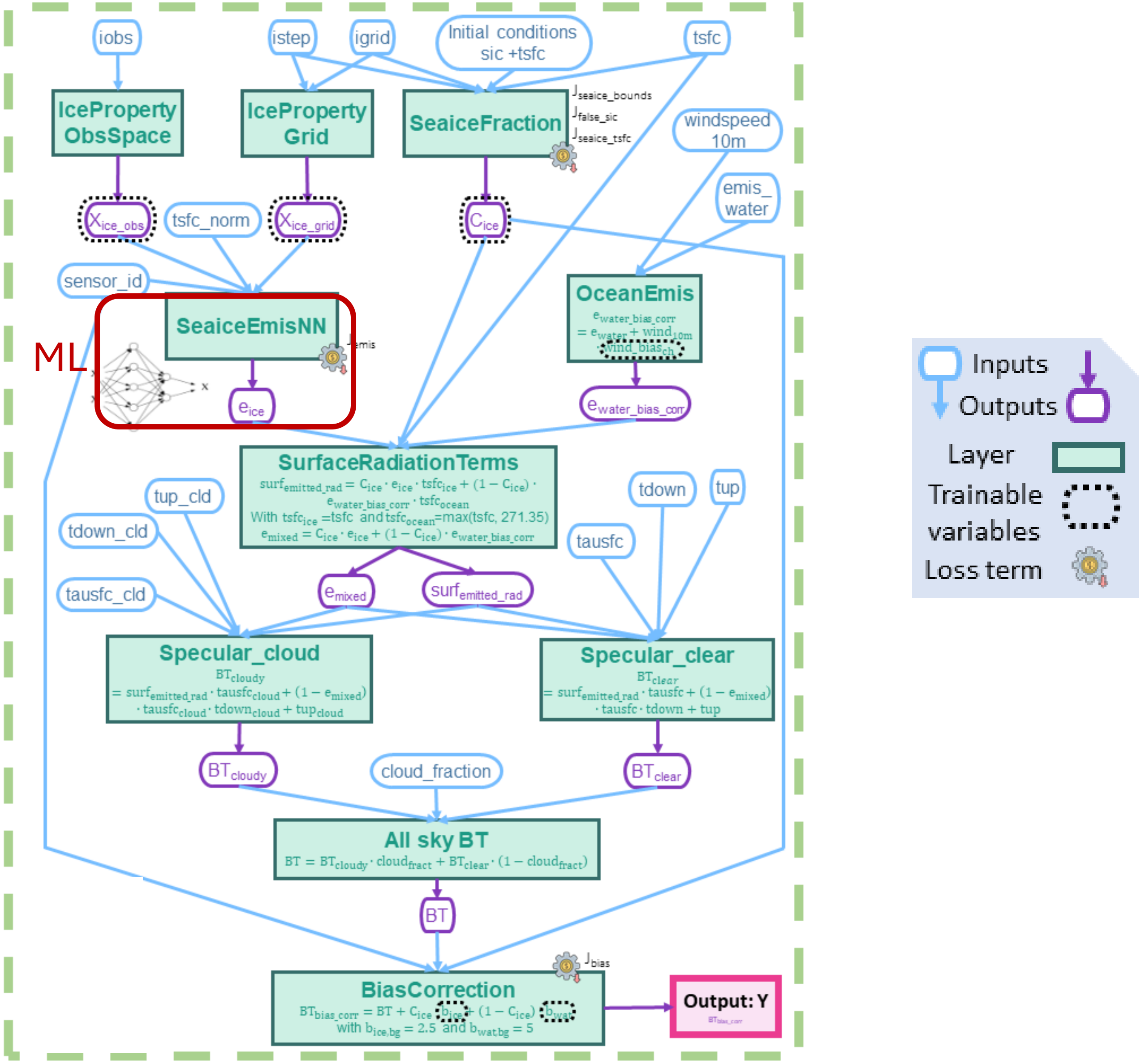

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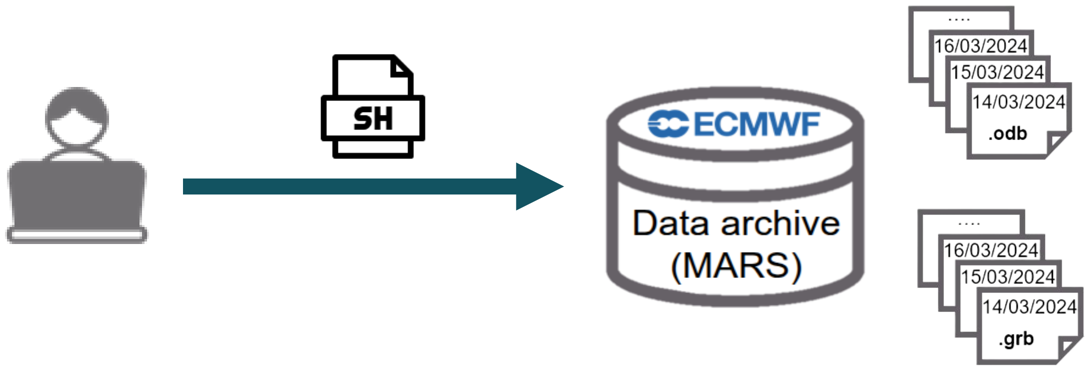

Satellite Observations

Brightness temperature measured by AMSU-A onboard METOP-B, METOP-C, NOAA-15, NOAA-18 & NOAA-19

Output from the ECMWF IFS 12 h background forecast

Radiative transfer variables (tup, tup_cld, tausfc ....), skin temperature, ocean emissivity, wind speed

Output from the ECMWF IFS 6h analysis

Initial conditions for sea-ice concentration and surface temperature

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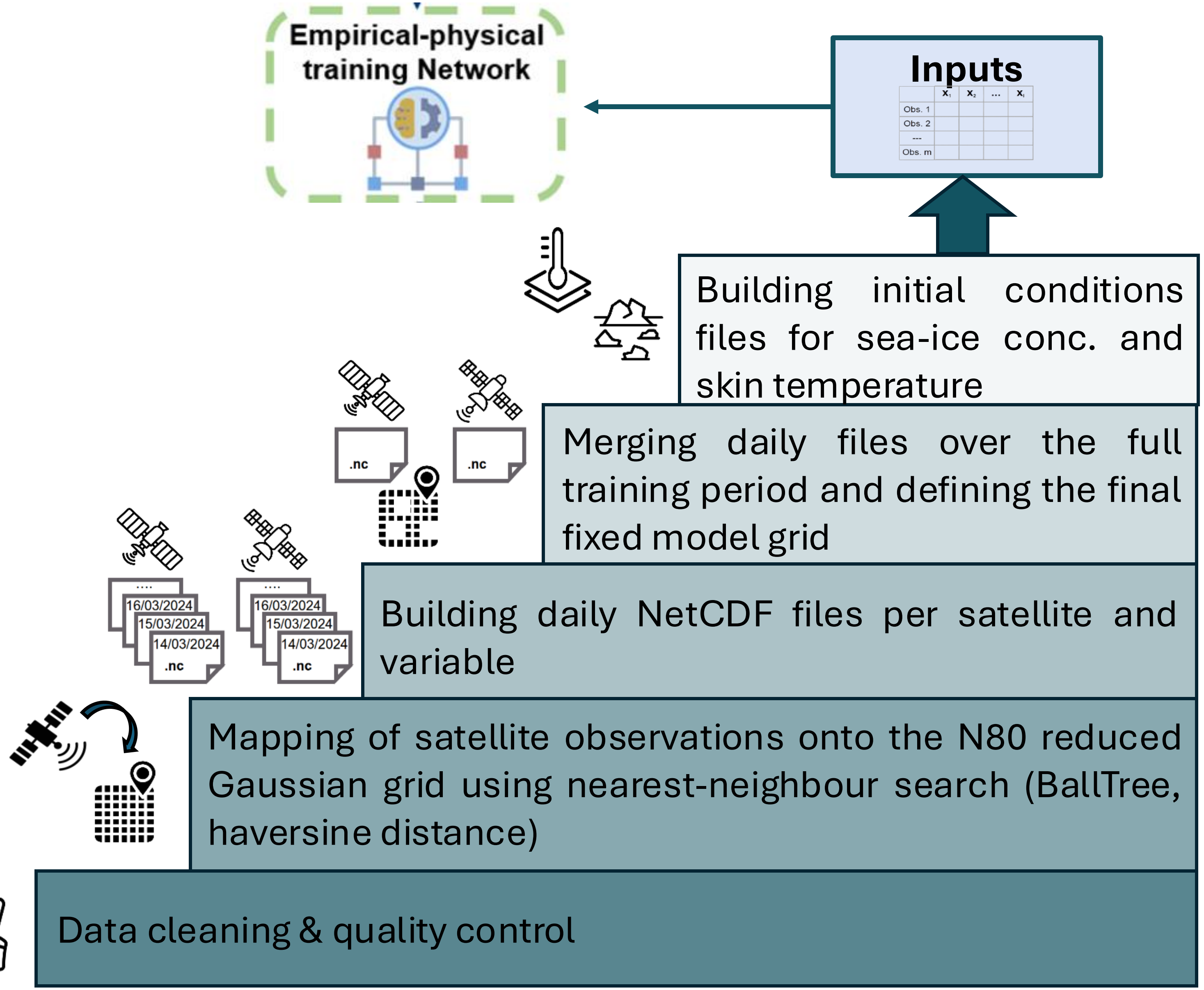

Motivation | Methodology | Results | Conclusions | Next steps

1 Understanding the hybrid ML architecture

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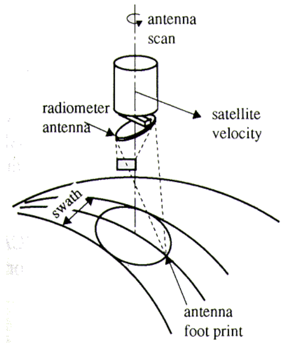
AMSR2
Conical scanner sensor



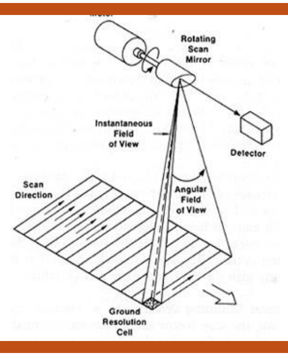
Geer, A. J. (2024a). Simultaneous inference of sea ice state and surface emissivity model using machine learning and data assimilation.

Angle dependency

$$E_{\mathrm{QV}} = E_{\mathrm{V}} \cos^2 \theta_s + E_{\mathrm{H}} \sin^2 \theta_s$$

$$E_{\mathrm{QH}} = E_{\mathrm{V}} \sin^2 \theta_s + E_{\mathrm{H}} \cos^2 \theta_s$$

AMSU-A
Cross track
scanner sensor



1 Understanding the hybrid ML architecture

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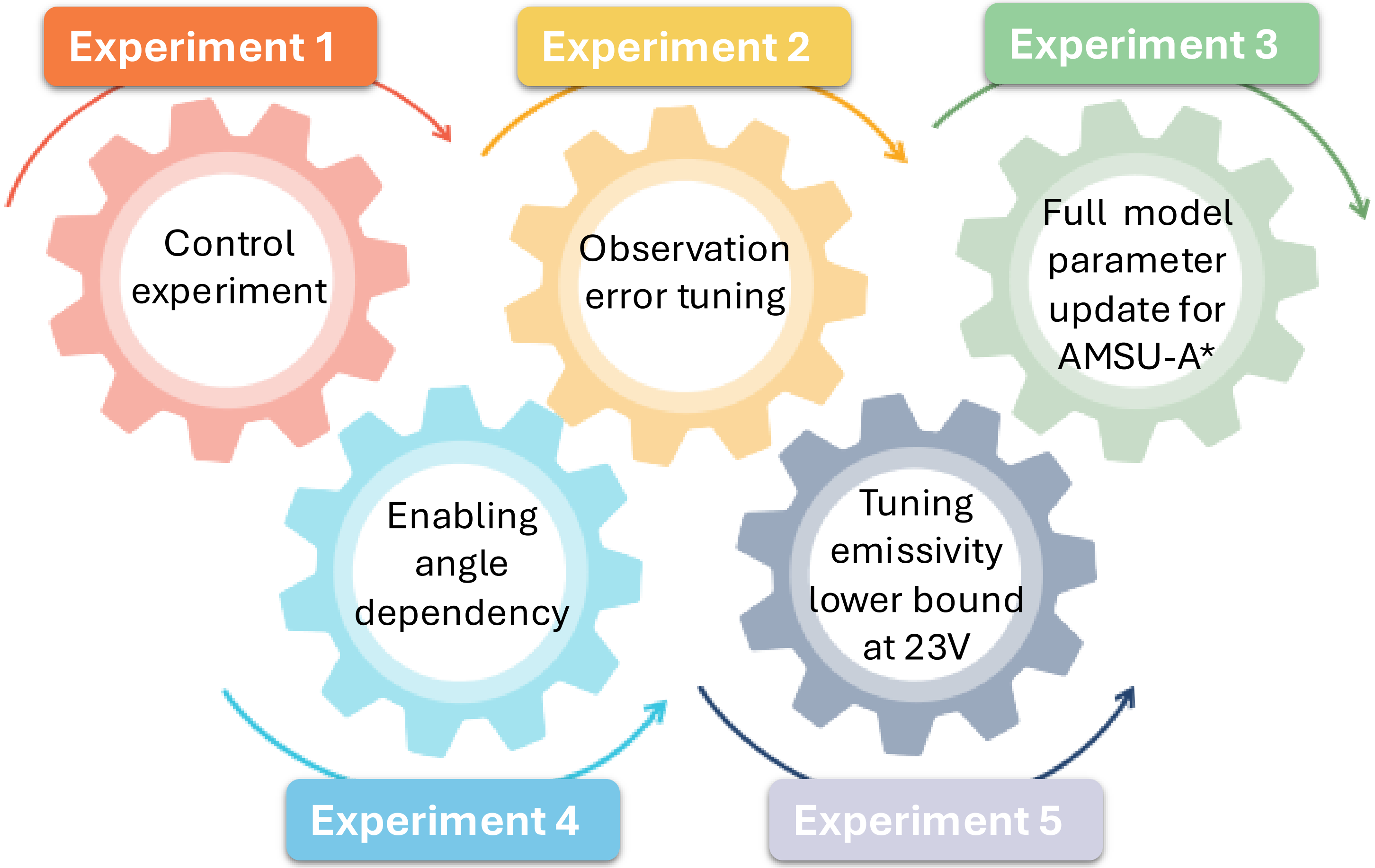
Training period 01/04/2024-31/03/2025

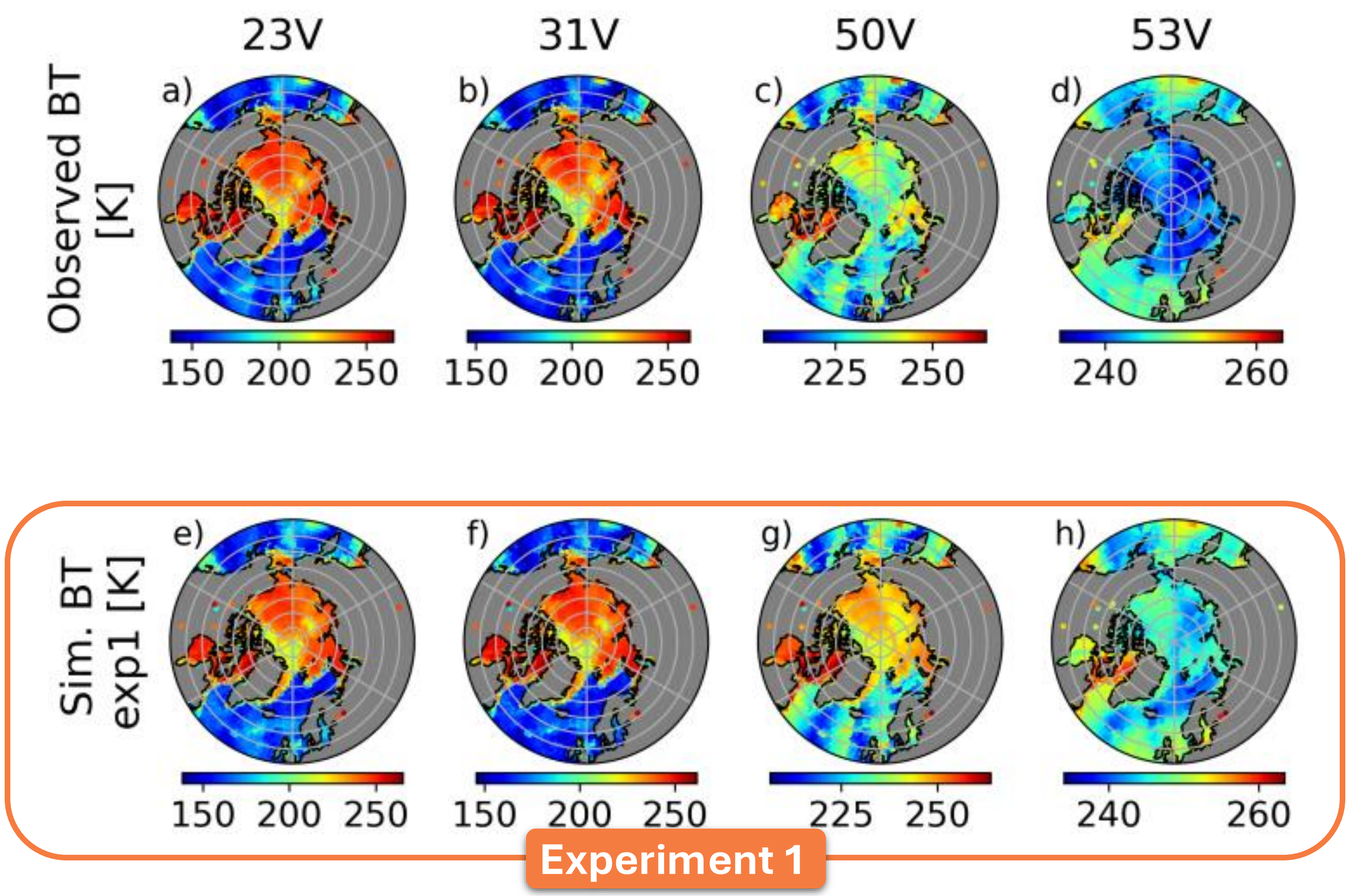
AMSU-A onboard METOP-B. Channels 23V, 31V, 50V, 53V

> 50.5°N latitude, excluding land points



*Includes: observation error tuning, per-channel background bias correction (sea-ice & open ocean), background error, emissivity lower bound at 23V and constant penalty against false sea-ice

01/04/2024



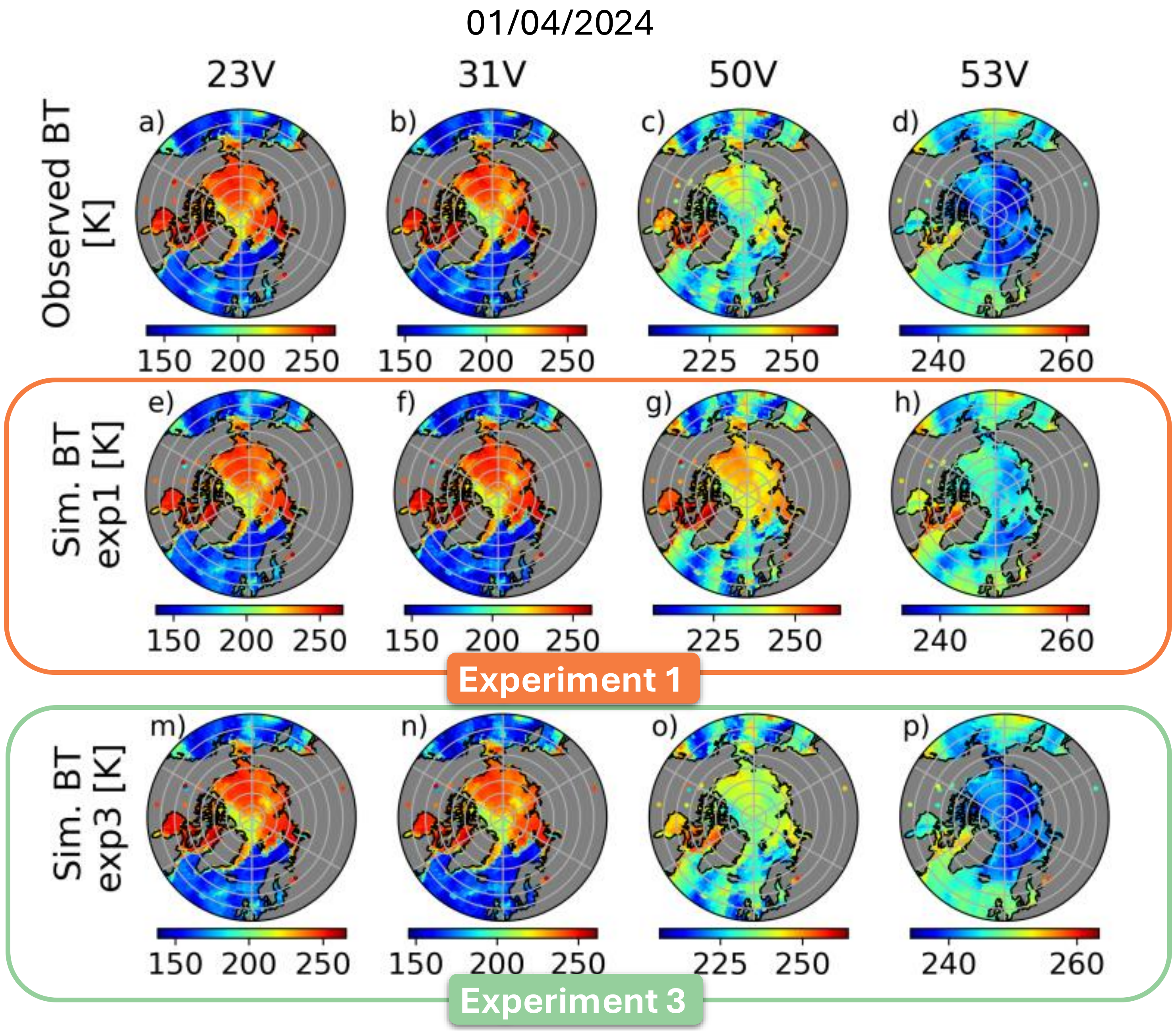
The first major objective was to **successfully run** the hybrid ML **model** with **AMSU-A inputs** and obtain physically realistic outputs.

Even without AMSU-A–specific tuning or explicit scan-angle dependency, **good agreement** is achieved at **low frequencies.**

At **higher frequencies, increased biases** and missing spatial structures are observed

likely linked to stronger atmospheric sensitivity of these channels and the need for further model refinement.

First year EUMETSAT fellowship report:
https://www.eumetsat.int/media/53229



Impact of model parameter tuning

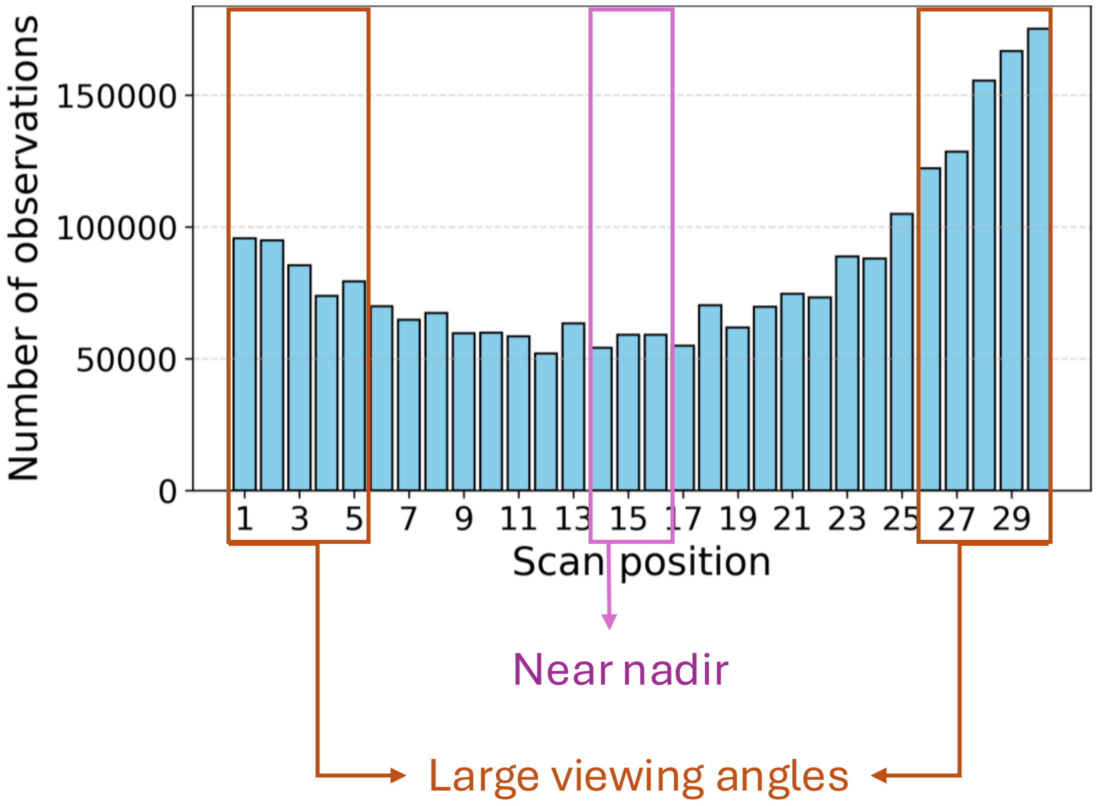
vs

- Annual mean Obs–Sim differences are reduced by **91–99%** in Experiment 3 relative to Experiment 1 (channels 31V, 50V and 53V).
- Parameter tuning plays a key role in improving model performance

Impact of angle dependency

vs

AMSU-A onboard METOP-B
Channel 1 (23V)
01/04/2024 - 31/03/2025



Annual statistics

Large viewing angles

Reduction in mean bias
≈ 60 % Channel 1
≈ 17 % Channel 3

Reduction in standard deviation & RMSE
≈ 1-4% All channels

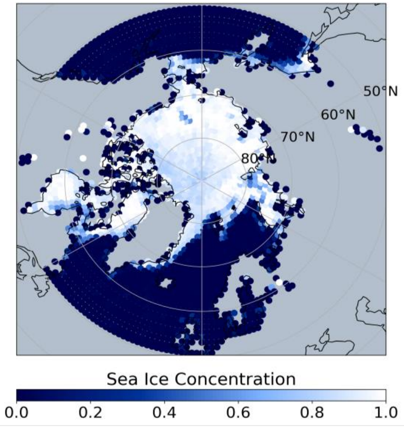
Near nadir

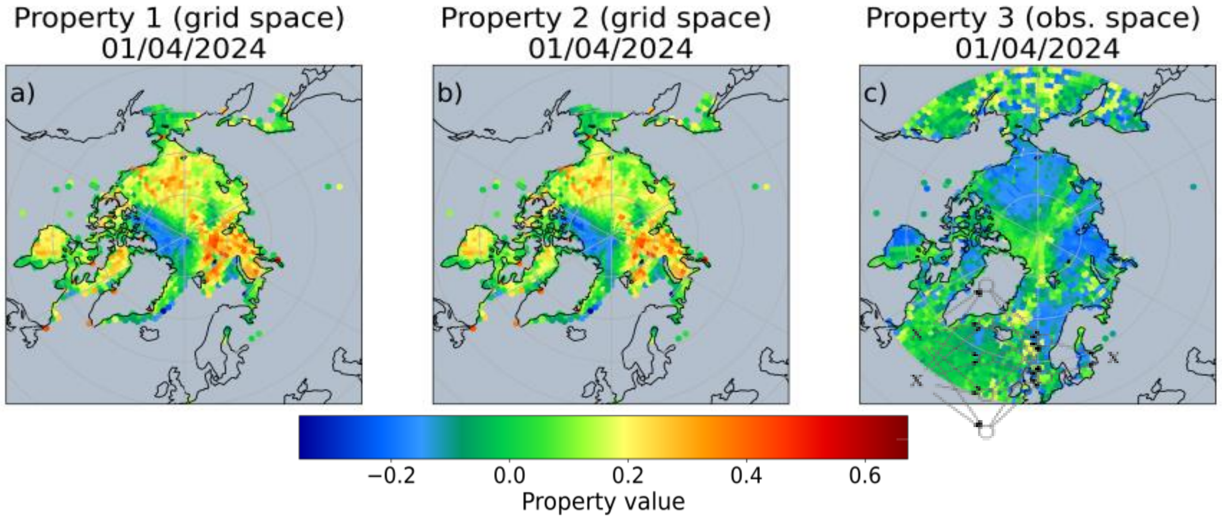
Slight increase in mean bias
Few tenths K

Reduction in standard deviation & RMSE
≈ 0.6-3% All channels

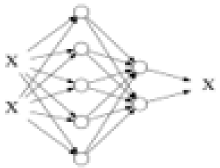
Broader overview of the hybrid ML model: example on 1 April 2024 for AMSU-A onboard Metop-B, Channel 1 (23V)

Sea Ice Concentration



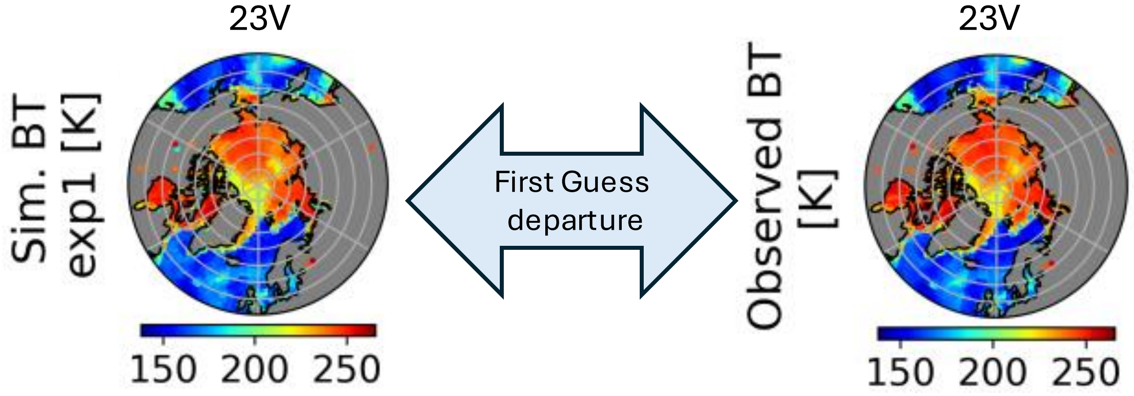


ML



Mixed surface emissivity

$$e_i = (1 - C_{\text{ice}})e_{\text{water},i} + C_{\text{ice}}e_{\text{ice},i}.$$



- The hybrid ML sea-ice observation operator was successfully implemented with AMSU-A inputs, producing physically consistent outputs.

- Even without AMSU-A-specific tuning or scan-angle dependency, the initial configuration showed good agreement at low frequencies (23V, 31V), while larger biases and missing spatial structures remained at higher frequencies.

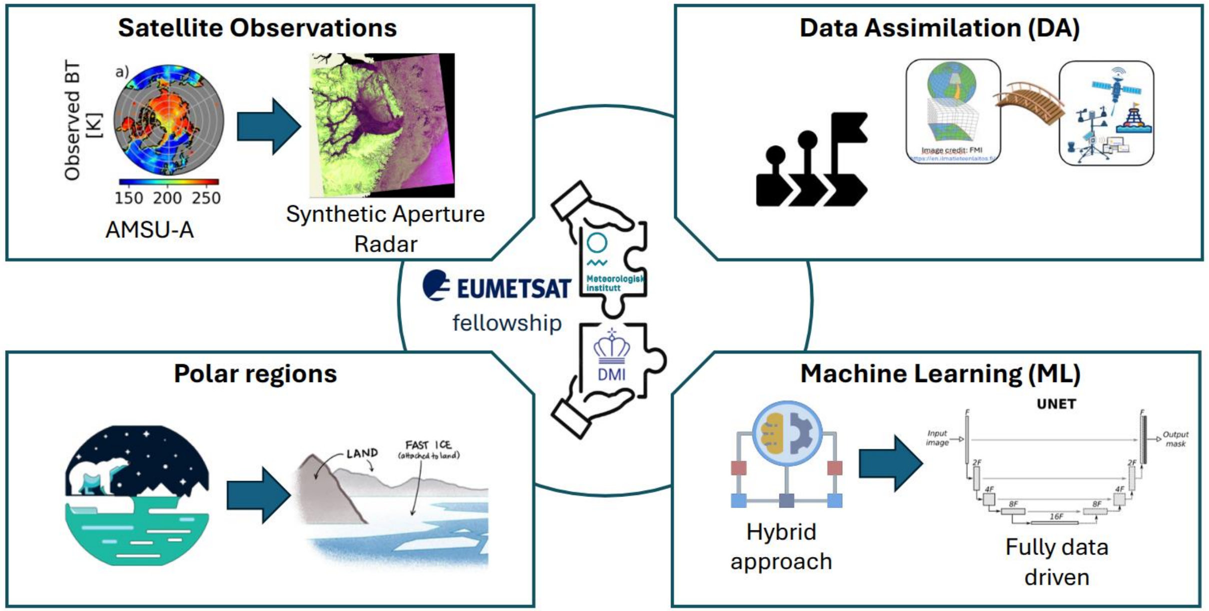
- Parameter tuning is a key driver of model performance, reducing annual mean Obs–Sim differences by 91–99% for channels 31V, 50V, and 53V.

- Including scan-angle dependency further improves performance at large viewing angles, although small degradations near nadir require further investigation.

November
2027

Consolidate AMSU-A hybrid ML results

New focus: ML-based fast ice detection



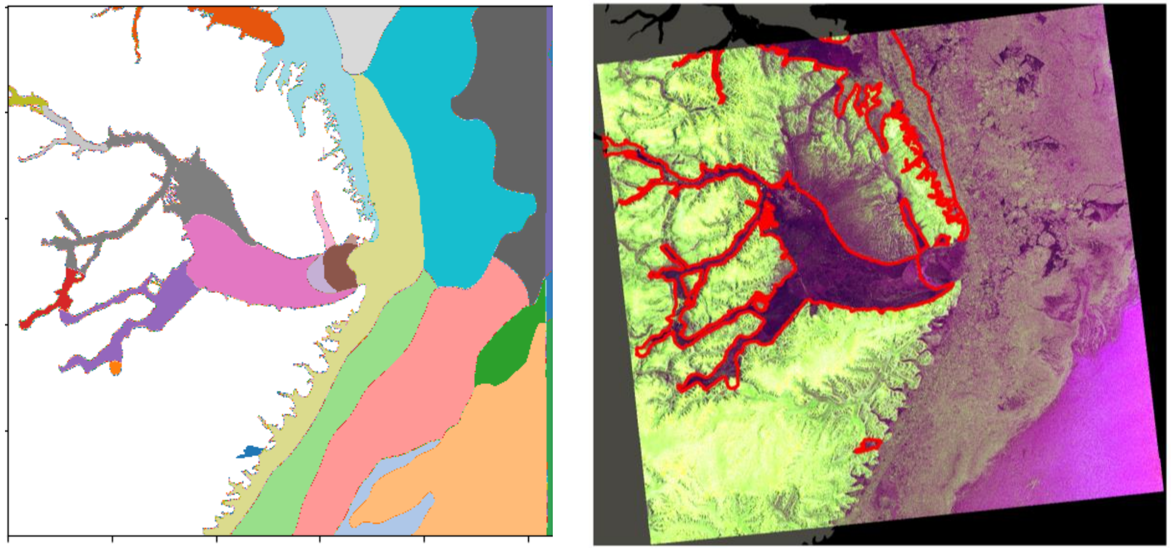
New focus: ML-based fast ice detection

Ice charts & Synthetic Aperture Radar (SAR) data (e.g. Sentinel-1)

Fully ML based approach (U-net architecture)

Greenland and the Canadian Arctic Archipelago

08/02/2021 08:21:07H



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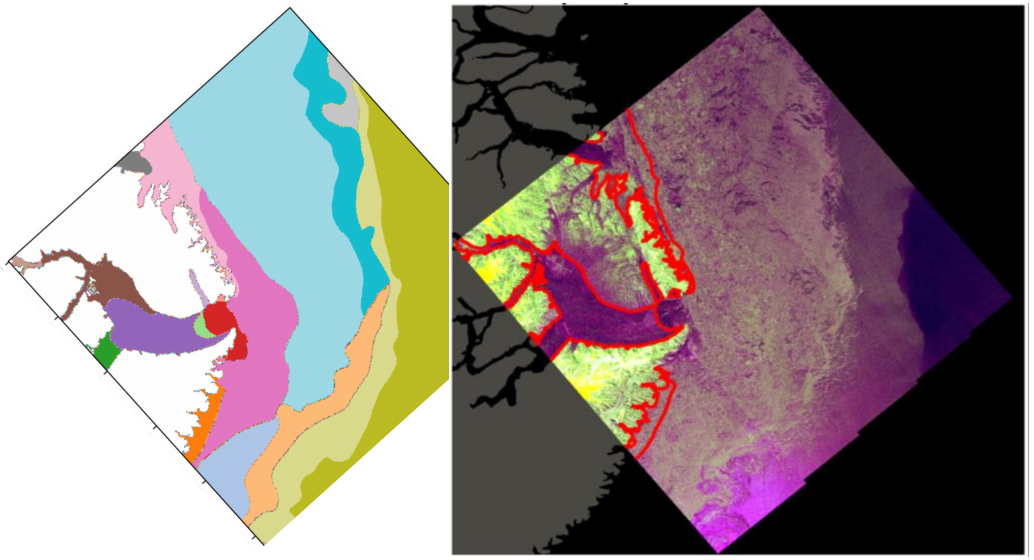

1) Identify days and regions characterized by fast ice based on operational ice charts

2) Collocate SAR imagery covering these areas, including images from preceding days to capture temporal persistence

3) Assemble these data into a dedicated ML training dataset

Thank you

Cristina González Flórez
cgf@dmi.dk