Advancing Hybrid Machine Learning Observation Operators for Sea Ice: Incorporating Scan-Angle Dependency for AMSU-A

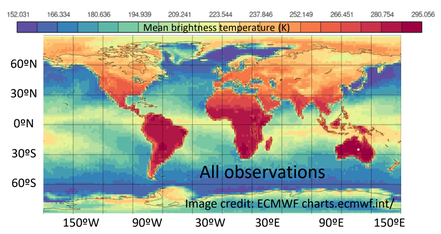
Cristina González Flórez[1](cgf@dmi.dk), Fabrizio Baordo[1], Stephanie Guedj[2] , Alan Geer[3]

[1]Danish Meteorological Institute, Copenhagen, Denmark, [2]Norwegian Meteorological Institute, Oslo, Norway,
[3]European Centre for Medium-Range Weather Forecasts, Reading, UK.

Introduction

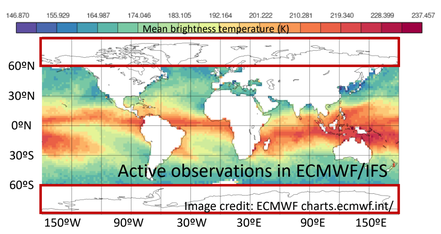
Machine learning (ML) is increasingly used in **satellite data assimilation (DA)**, a key component of **Numerical Weather Prediction (NWP).** This study focuses on **polar regions**, where improved assimilation is key for more accurate weather forecasts.

Satellites provide **near-global** Earth system **monitoring**, **filling observational gaps** (e.g. oceans and polar regions)



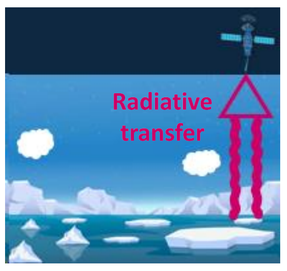
AMSU-A (METOP-B) 19 Feb 2026 00UTC
Channel 1: 23,8 GHz (V)

However, many **surface-sensitive channels** are **not assimilated** in NWP systems



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

WHY?



Challenges in **radiative transfer modelling** over **snow** and **sea ice**

ECMWF has developed (and implemented operationally in IFS 49r1) a **hybrid ML observation operator** for **sea ice**, originally trained with radiances from **AMSR2**, which is a **conical scanning sensor**

This study **extends** the hybrid ML model to **AMSU-A**, which is a **cross-track scanning sensor**

Hybrid ML approach

TensorFlow

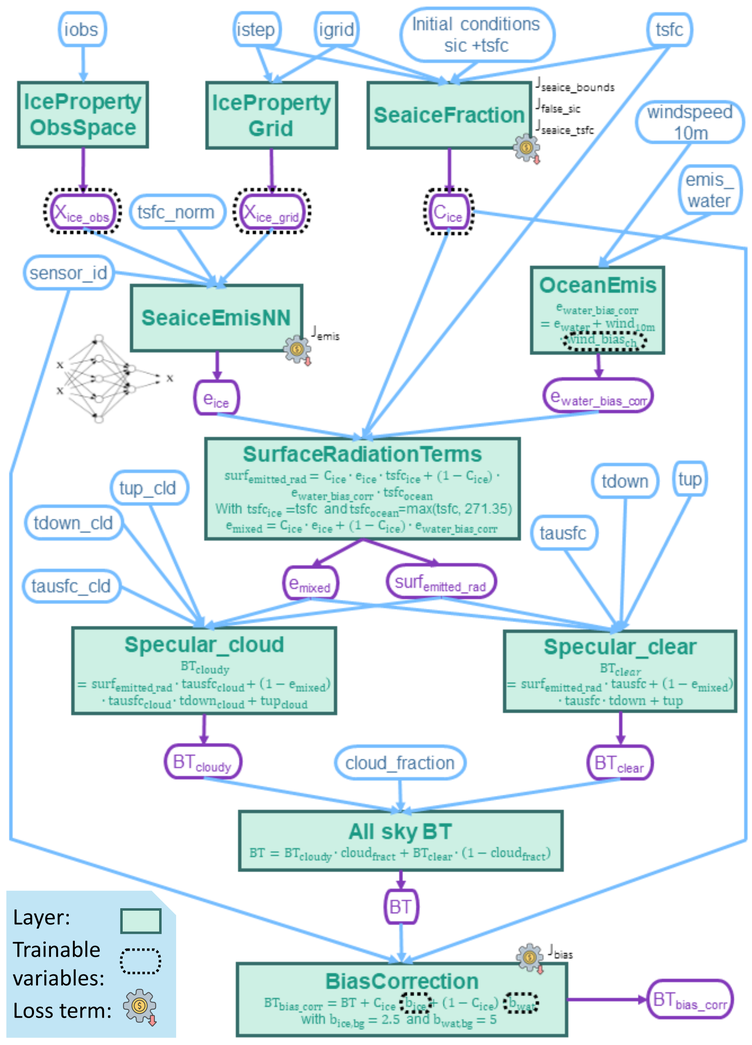


Figure 1: Detailed architecture of the hybrid ML observation operator for sea ice

Inputs

Satellite observations

iobs, istep: satellite observation index and temporal index
igrid: spatial index defining the fixed grid
sensor_id: satellite platform identifier

ECMWF IFS 12h background forecast data

tsfc, tsfc_norm: surface temperature (raw/normalized)
windspeed10m: 10m wind speed
emis_water: ocean surface emissivity
cloud_fraction: effective cloud fraction
Radiative transfer variables:
tausfc, tausfc_cloud: atmospheric transmittance (clear/cloudy)
tup, tup_cld: upwelling brightness temperature (clear/cloudy)
tdown, tdown_cld: downwelling brightness temperature (clear/cloudy)

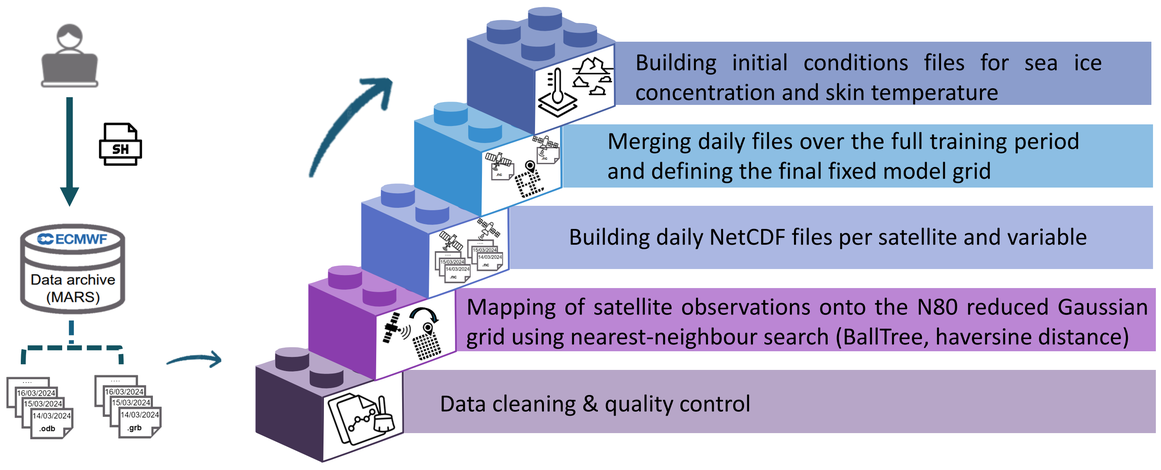
ECMWF IFS 6h analysis

Initial conditions for **sea ice concentration** + **surface temperature**

Outputs

X_{ice_obs}, X_{ice_grid}: empirical sea ice properties (observation/grid space)
C_{ice}: sea ice concentration (grid space)
e_{ice} $e_{water\_bias\_corr}$, e_{mixed} : surface emissivity for sea ice, ocean (bias-corrected) and mixed surfaces
BT_{cloudy}, BT_{clear},BT, BT_{bias_corr} : simulated brightness temperatures (cloudy, clear, all-sky, all-sky bias corrected)

Building the dataset



Running the model

Training period

1/04/2024 - 31/03/2025

Area

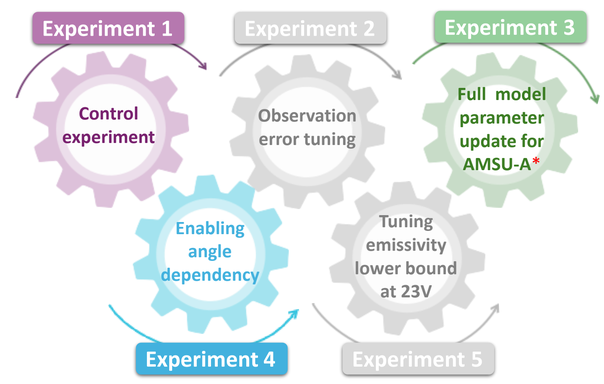
> 50.5°N latitude, excluding land points (lsm = 0)

Sensor & satellite

AMSU-A onboard Metop-B channels 23.8 GHz QV, 31.4 GHz QV, 50.3 GHz QV & 52.8 GHz QV

Other settings

2 dense layers (7 and 2 neurons) with sigmoid activation



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

This poster focuses on Experiments 1, 3, and 4; full results available at: https://www.eumetsat.int/media/53229

Preliminary results

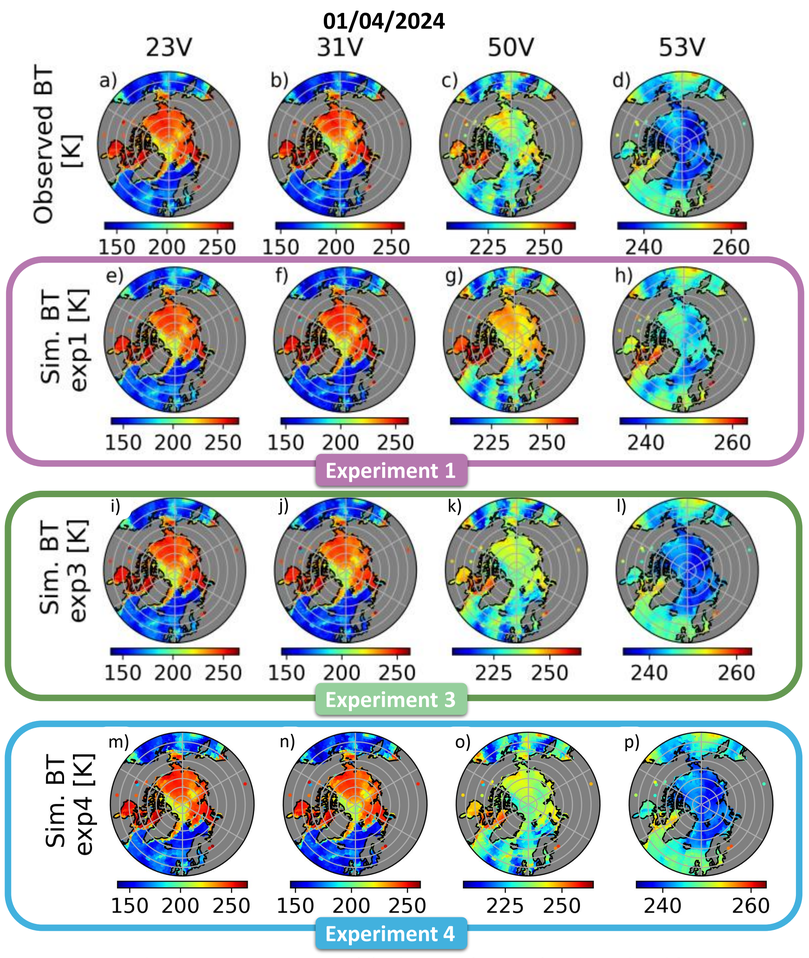


Figure 2: AMSU-A brightness temperatures (K), observed (top row) and simulated for Experiments 1, 3, and 4 (subsequent rows) over the Arctic on 1 Apr 2024, channels 23V, 31V, 50V, and 53V.

Experiment 1

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

Experiment 1 vs **Experiment 3**

Impact of model parameter tuning

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

Experiment 3 vs **Experiment 4**

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

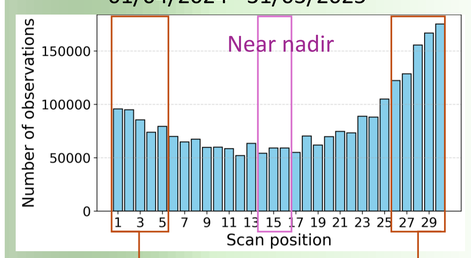
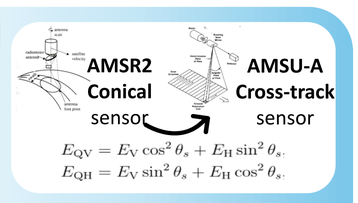


Figure 3: Distribution of AMSU-A observations per scan position over training period for channel 23V



Annual statistics

Large viewing angles

Reduction in mean bias
≈ 60% Channel 23V
≈ 60% Channel 50V

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)

Figure 4: Observed (a) and simulated (b) brightness temperature from AMSU-A onboard MetOp-B (ch. 23V); (c) sea ice concentration; (d–f) empirical sea ice properties. Panels (b–f) from Hybrid ML Experiment 4 (01/04/2024)

Conclusions and future work

- This study demonstrates the **feasibility of extending ECMWF's hybrid empirical–physical ML observation operator to AMSU-A over Arctic sea ice.**
- Even without AMSU-A-specific tuning or scan-angle dependence, the model reproduces reasonably well observed BT patterns and magnitudes for the most surface-sensitive channels (23V, 31V).
- **AMSU-A-specific tuning** significantly **improves performance**. For the first time, **scan-angle-dependent polarization mixing** based on instrument geometry **is considered**, leading to modest but **systematic improvements**, particularly at **large viewing angles**.

Our next steps include:

- Incorporate zenith angle as an additional predictor
- Extend the approach to the Southern Hemisphere
- Assess the benefit of AMSU-A-specific training vs. the conical-scanner trained model

Funding

This work has been carried out with funding from the EUMETSAT Fellowship Programme.

References

[1] A. J. Geer, "Simultaneous inference of sea ice state and surface emissivity model using machine learning and data assimilation," J. Adv. Model. Earth Syst., vol. 16, no. 7, 2024.

[2] A. J. Geer, "Joint estimation of sea ice and atmospheric state from microwave imagers in operational weather forecasting," Q. J. R. Meteorol. Soc., vol. 150, no. 763, pp. 3796–3826, 2024.