Optimizing the use of microwave observations over Polar regions

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The microwave observations in AROME-Arctic

The NWP AROME-Arctic (AA) forecast model is running operationally at MET Norway since November 2015 (2.5km - 65 levels & Fig 1). A 3D-Var assimilation system combines the background state (3h forecast) and the observations (conv & satellites) every 3 hours to produce the initial conditions for the forecast (up to 66h). Boundary conditions are provided hourly by the ECMWF system.

To compensate for the lack of conventional/radiosondes observations in the Arctic, optimizing the use of satellite observations from polar-orbiting satellite platforms is required. It would help to better constraint the atmospheric analysis and thus the forecast (Fig 2).

Currently, AA assimilates microwave radiance observations from: **AMSU-A**, **MHS**, **ATMS** and **MWHS-2** under strict conditions.
Ex: Despite the availability of humidity sounding data from **MHS** provided from 3 satellites (Fig 3), less than 0.5% remain active in the minimization.

Main uncertainties and limitations explored in this poster:

- Surface emissivity over sea-ice and snow => low-peaking channels were blacklisted over 55°N (section 1)
- Hydrometeors processes are highly nonlinear => cloud screening (section 2)
- Mixed signal from sea and land (or sea-ice) surfaces => land/sea mask to reject heterogeneous scene (section 3)
- Observation errors & horizontal error correlation => Thinning distance to 80 km
  limb contaminations at large scan angles => observations produced at the edge of the scan are blacklisted (section 4)

Section 5 shows some preliminary results on the potential use of ML to improve the assimilation of MW over sea-ice.

Fig 3: Available MHS observations over AROME-Arctic

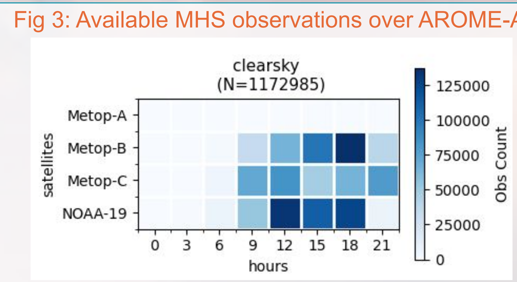


Fig 2: Impact of MHS observations vs radiosondes

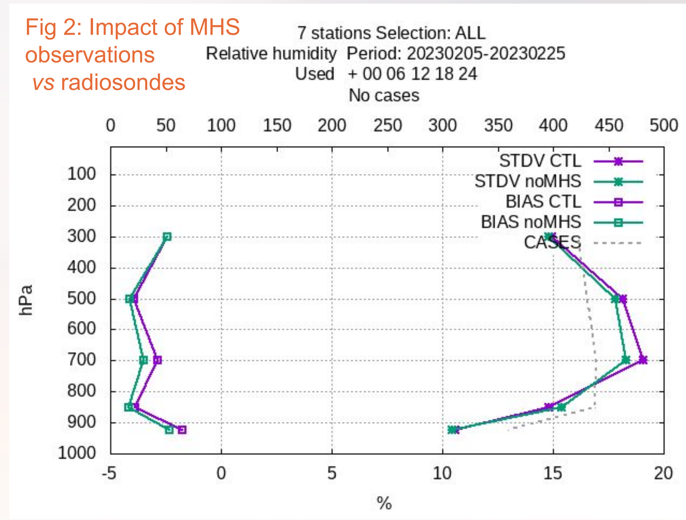
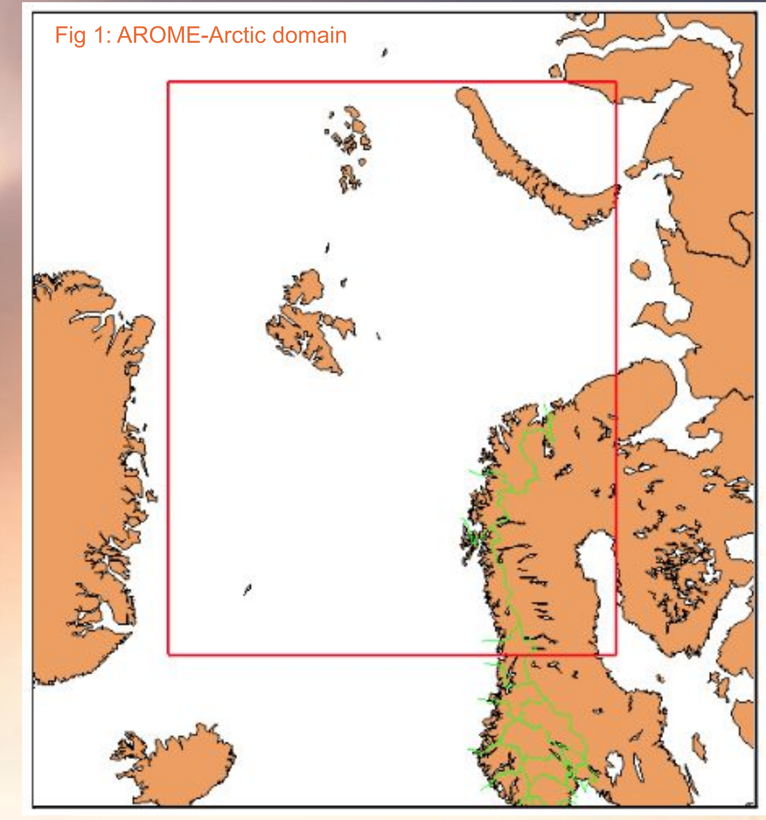
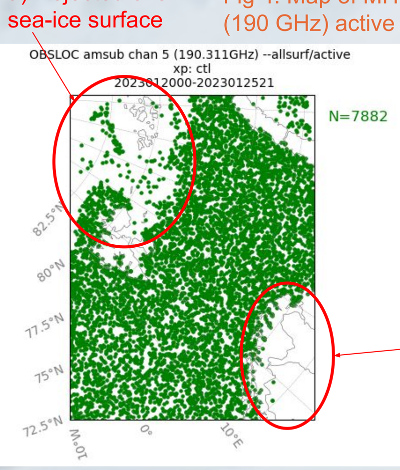


Fig 1: AROME-Arctic domain



1. Low-peaking channels over snow & sea-ice

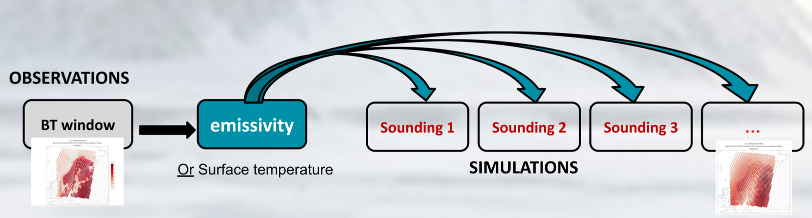
Fig 4: Map of MHS channel 5 (190 GHz) active observations



=> Large departures to observations for surface-sensitive channels *partly due to the use of inadequate surface emissivity and/or temperature inputs*

Low-peaking channels are blacklisted due to uncertainties in the surface modelisation for radiances **over snow-covered land & sea-ice** (Fig 4).

Dynamic emissivity method (LDYN): Retrieve the surface emissivity from a window channel & allocate it to adjacent sounding channel (KarbouEA2006)



Assumption: non-scattering & plane parallel atmosphere, **specular surface**, the medium emits at the temperature of the surface skin & **the variability of emissivity with frequency is low**. Operational over land in AA & MEPS.
=> Not always compliant over snow and sea-ice (BormannEA2021) …

a) Parametrisation over sea-ice surface (LICE):

=> Difference in emissivity with frequency between **MHS** channel 1 (89 GHz) and adjacent sounding channels can be > 10 % depending on sea ice type (seasonnal, permanent)

Instead of using channel 2 (157 GHz) and discard it from any DA attempt, KarbouEA2014 suggested to extrapolate its emissivity from channel 1 (89 GHz):

$$\varepsilon(157,\theta)_{extr} = \varepsilon(89,\theta) - \frac{B_T(157,\theta) - B_T(89,\theta)}{T_s}$$

Fig 5: Retrievals of emissivity (89 GHz => 157 GHz)

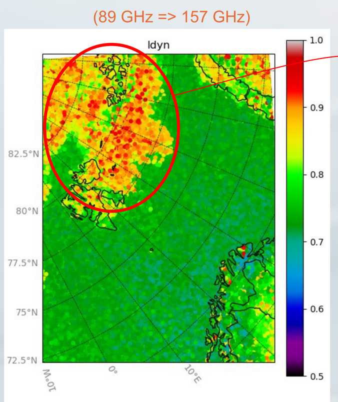
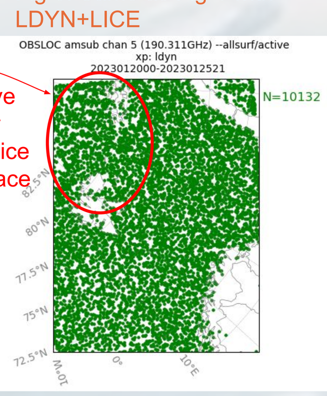


Fig 6: Same as Fig 4 with LDYN+LICE

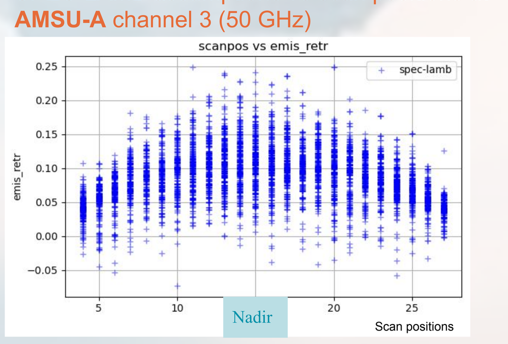


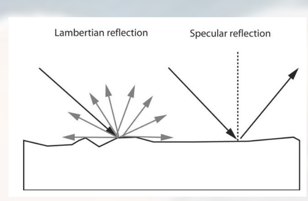
=> Using LDYN+LICE enhance the assimilation of low-peaking channels over sea-ice (Fig 5 & 6)

b) Specular vs Lambertian surface approximation:

=> Assuming the surface to be specular or Lambertian may have an impact on the retrieval of emissivity (up to 25% dif, Fig 7) …

Fig 7: Difference in retrieved emissivity under SPEC-LAMB assumptions *vs* scan positions at **AMSU-A** channel 3 (50 GHz)

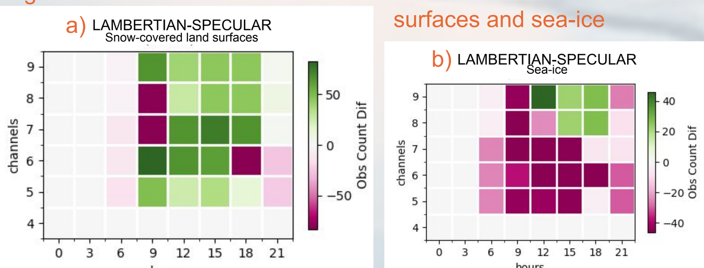




… Which in return affects the amount of active data:
(i.e improved/degraded simulated BT passing QC)

Beneficial
Detrimental

Fig 8: Difference in the amount of active AMSU-A over snow-covered surfaces and sea-ice



=> Assuming Lambertian approximation over snow-covered surface is mostly beneficial (Fig 8a)

But, over sea-ice surface it is overall detrimental for all AMSU-A channels (Fig 8b)

2. Assimilation in All-sky conditions

Preliminary studies were run to enhance the assimilation of MHS radiances in all-sky conditions over AA. Following GeerEA2014, the method is based on:

1) Mie simulation in RTTOV-SCATT for bulk optical properties of hydrometeors
2) the use of inflated observations errors where observations or first guess indicate clouds.

=> BT is computed from **the weighted average between 2 independent sub-columns**
(one is clear and one is cloudy with inflated observation errors => dynamic obs errors)

3D-VAR DA experiments (1 month spin-up + 2 month)
Clear-sky = Full observing systems with MHS in clear-sky
All-sky = same as clear-sky but with MHS in all-sky
=> Overall neutral to positive forecast scores (Fig 9)

Fig 10: Mesoscale low pressure case study 3 and 4/02/2023
a) Synoptic situation

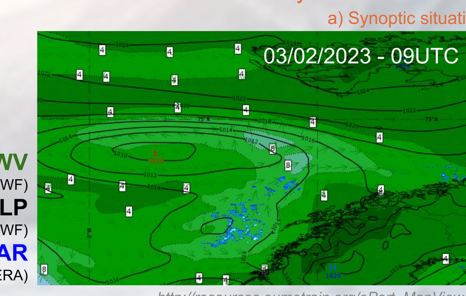
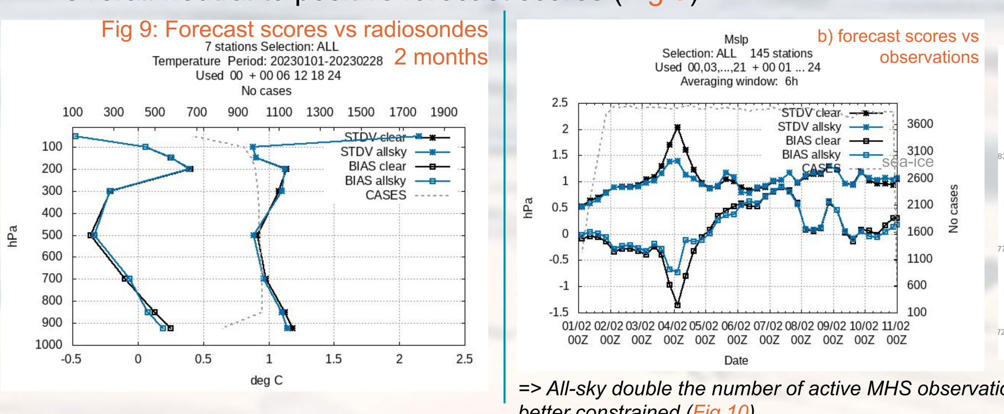
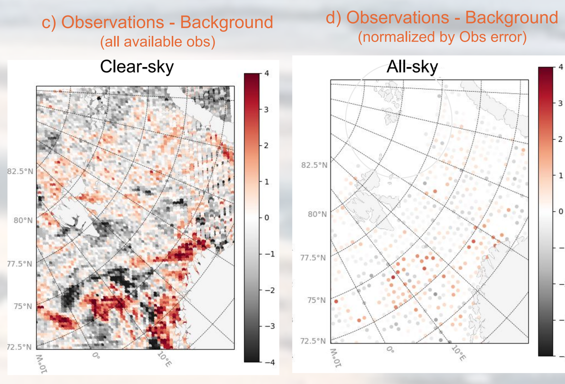


Fig 9: Forecast scores vs radiosondes 2 months





=> All-sky double the number of active MHS observations and most dynamically active area (cloudy/rainy area) are better constrained (Fig 10)

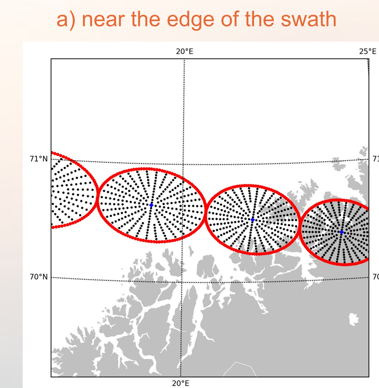
3. The footprint operator

For MW radiances, an appropriate footprint operator might help to better exploit the observations by taking into account the spatial representativity of the radiance measurements in a high-resolution assimilation system (Fig 11).

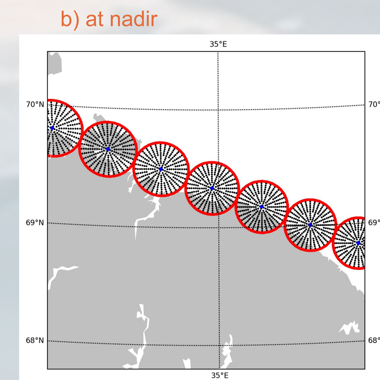
=> QC is a key issue where the footprint operator can detect spatial inconsistencies.

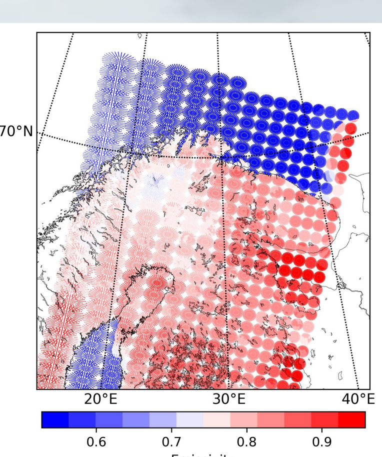
When MW data is assimilated, the footprint observation operator can help to better calculate model-equivalent departures and to remove the representation error over complex or mixed surface scenes. Preliminary results show the footprint operator reduces consistently the standard deviation of fg-departures.

Fig 11: The IFOV ellipses and footprint operator points of AMSU-A pixels
a) near the edge of the swath



b) at nadir





Furthermore, the retrieved surface emissivity can be improved in the final model-equivalent brightness temperatures. It is plotted inside the IFOV i.e., footprint area indicating the heterogeneous surface conditions over the northern part of MetCoOp domain (Fig 12).

Fig 12: The retrieved surface emissivity of AMSU-A observations from METOP-C satellite by the radiance footprint operator showing all footprint operator points. Mixed surface scenes (land, ocean, sea ice) are visible for many AMSU-A pixels inside the MetCoOp domain.

4. Obs errors, thinning distance and additional scan positions

The DesroziersEA_2005 diagnostics have been run to tune the observation errors and the thinning distance for MW radiances over AA. Assuming the DA system is optimal, diagnosed sigma O (and B) in radiance space are compared to the values specified in the system (obs_error) and the overall FG dep stdev. Fig 13 gives an example for ATMS radiances. The horizontal error covariances/correlations has been also run on all MW observations. Fig 14 shows the results for thinned MWHS-2 instruments together with the Hollingsworth/Lönnberg method.
Conclusion: Assumed observations errors are slightly under-estimated for WV channels. The applied thinning distance of about 80 km seems optimal to avoid correlated observation errors.

Fig 13: diagnosed observation & background errors for ATMS over AA (10 days)

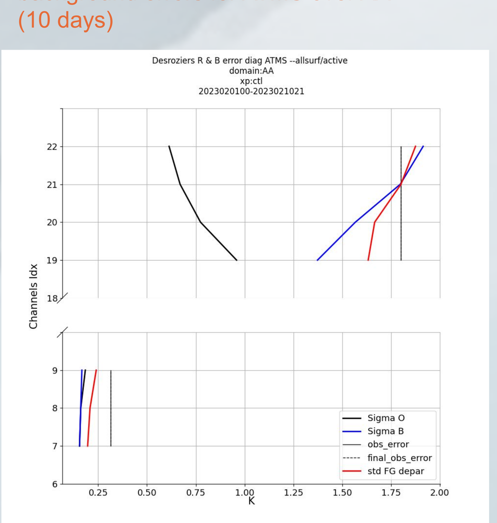
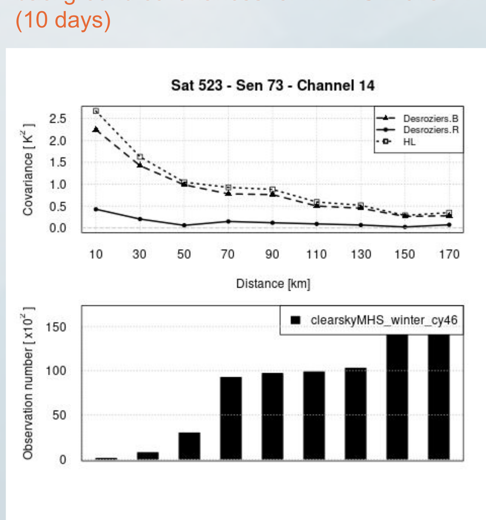


Fig 14: diagnosed horizontal observation & background covariances for MWHS-2 over AA (10 days)



Observations produced at **large angles** *(i.e scan positions 1-10 & 80-90 for MHS, Fig 15)* are still blacklisted due to instrumental bias, limb contamination and uncertainties in radiance simulations (longer atmospheric path).

3D-Var experiment were run on AA domain with MHS additional scan positions and shows some benefits on humidity and temperature compared to the operational version (Fig 16).

Fig 15: Location of additional observations produced at the scan edges

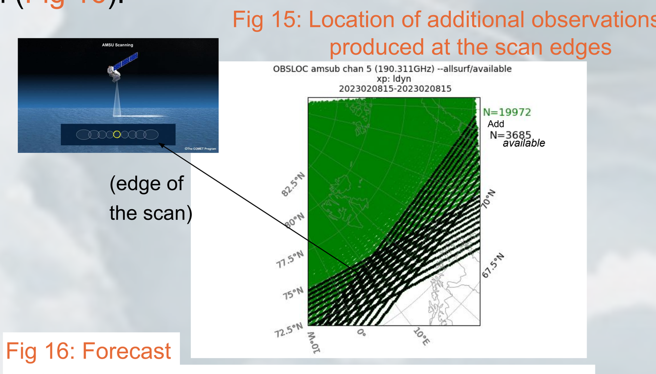
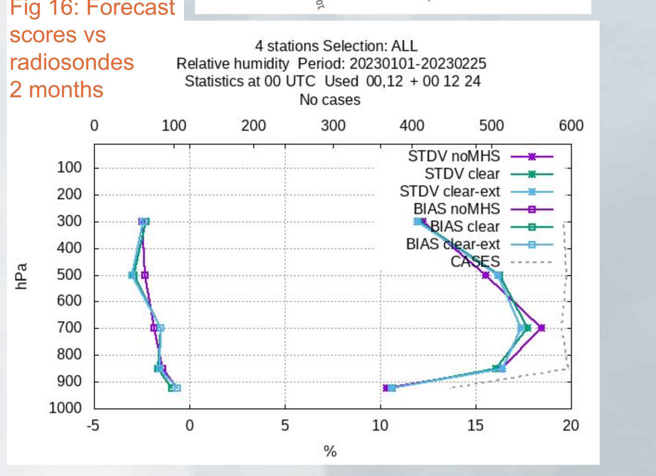


Fig 16: Forecast scores vs radiosondes 2 months



5. ML for sea-ice surface emissivity

Goal: ML to support further improvement of data assimilation over sea ice (window & sounding)

- ML techniques
  - for deriving the simulated brightness temperature
  - for estimating sea ice emissivity to trigger RTTOV
- 'Proof of concept' (BlyverketEA_ITSC2023)
  Predicting simulated brightness temperature using: tausfc, sic, ice_thk, q2m, t2m, qv, sd, Tskin (mix of variables predicted from upper-air and surface model)

=> Encouraging preliminary results on MHS channel 5 radiance simulations (Fig 17 & 18)

Figure 17: FG departures for different predictors

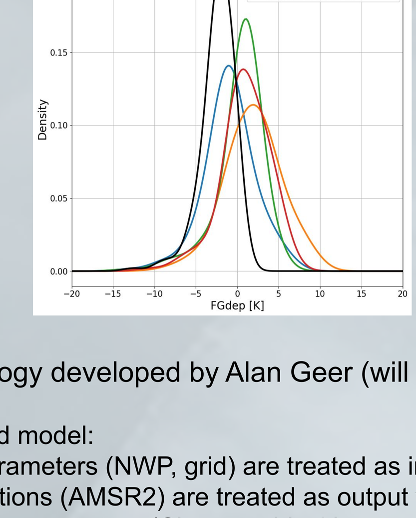


Figure 18: scatter plot MLP vs LDYN

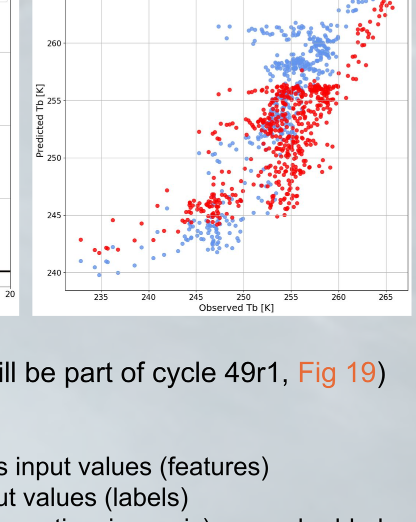
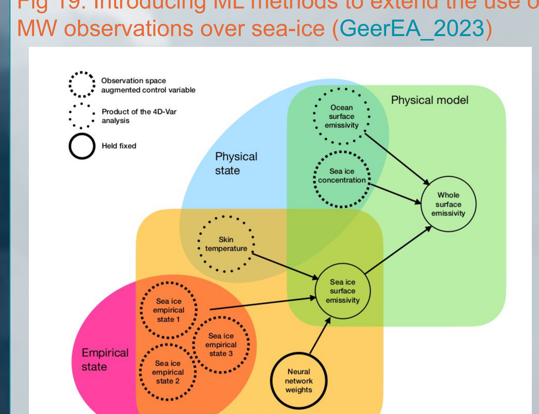


Fig 19: Introducing ML methods to extend the use of MW observations over sea-ice (GeerEA_2023)



New methodology developed by Alan Geer (will be part of cycle 49r1, Fig 19)

ML unsupervised model:
- the fixed parameters (NWP, grid) are treated as input values (features)
- the observations (AMSR2) are treated as output values (labels)
- the trainable parameters (Cice, empirical ice properties, ice emis) are embedded in custom layers of the Neural Network architecture

Mix ML & 4Dvar:
- Extend observation-space auxiliary control variables: Cice + 3 empirical variables that describe the physical state of the sea ice
- Emis = Cice*Eice + (1 - Cice)*Ewater
  Eice → 3 empirical variables + fixed Neural Network weights

Ongoing & Future work

- Extend Lambertian/specular evaluation and implement a switch related to surface properties (snow/sea-ice etc…)
- Extend the use of MHS all-sky with the dynamic emissivity method (or TELSEM) + extend to MW other instruments
- Optimize the footprint operator for operational implementation in AA
- Data denial experiments are planned for observation/background error tuning in AA
  - Diagnose B in observation space using an ensemble (B. Ménétrier)
- Implement & test the new methodology developed by Alan Geer (will be part of cycle 49r1)

projects: AA, MetCoOp, H2O, ESA/AWS, CERISE, Fellowship EUMETSAT and Horizon? & NSC?

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