Using ML for forward-modelling of interface observations

I. de Gélis[1,2], L. Kilic[1,2], C. Prigent[2,1], C. Jimenez[1,2]

ECMWF Annual Seminar

17/09/2026

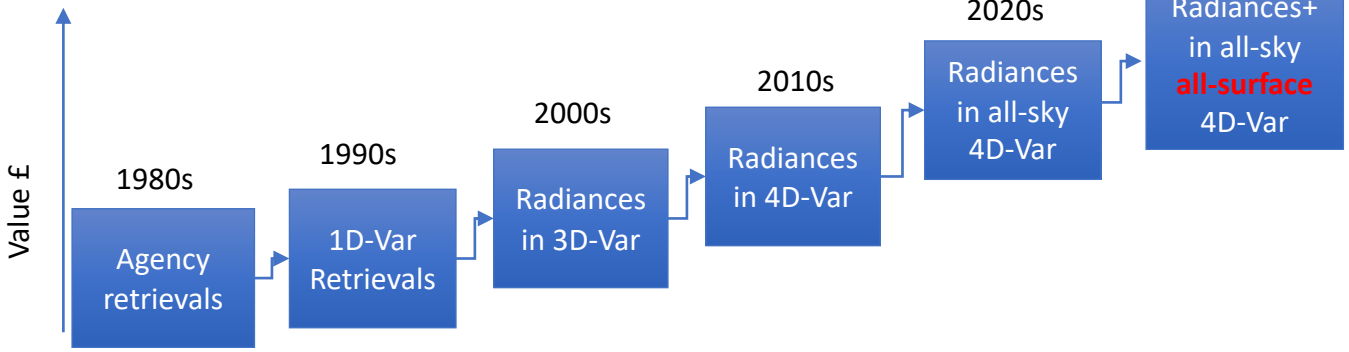
[1]Estellus, Estellus-MW,
[2]LIRA, Observatoire de Paris



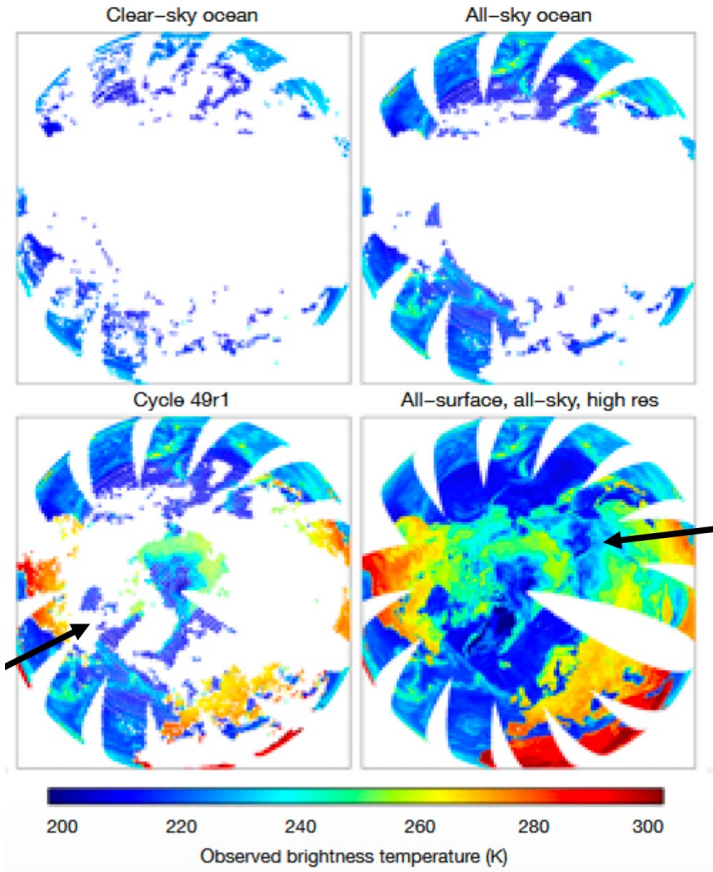




Today key challenge in NWP : the assimilation of all-surface radiances



From S. English, ECMWF annual seminar, 2021



AMSR2 observed brightness temperatures in the 37 GHz v-polarised channel for the 12-hour DA window around 12 UTC, 17 November 2024

ECMWF in 2025

The dream

From 50 years of ECMWF

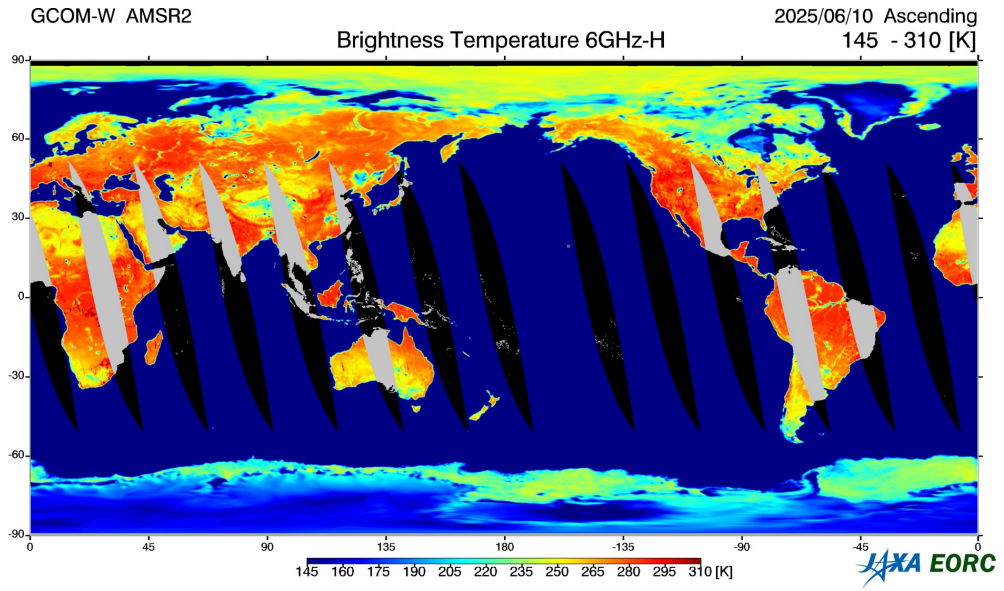
Presented by JF. Caron on Monday

To achieve so, it requires an **accurate estimation of the surface contribution**

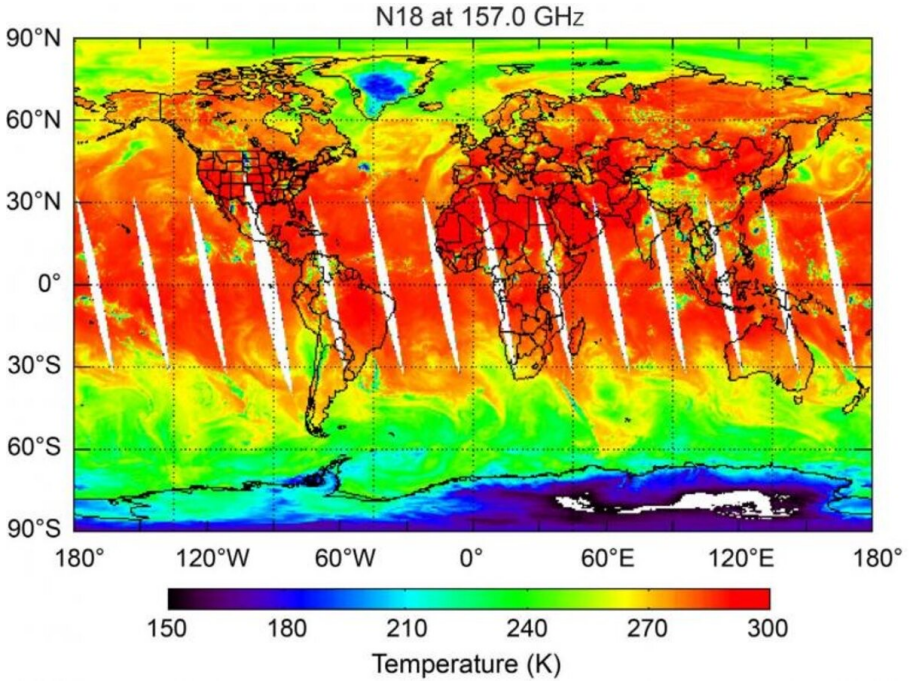
- **for all surface-sensitive observations**
- **for all surfaces (i.e. at global scale)**

Any surface sensitive channel

- Atmospheric ‘windows’ for **surface characterization**. The surface contribution is the **information.**



- For **atmospheric characterization**, the surface contribution is a source of **noise.**

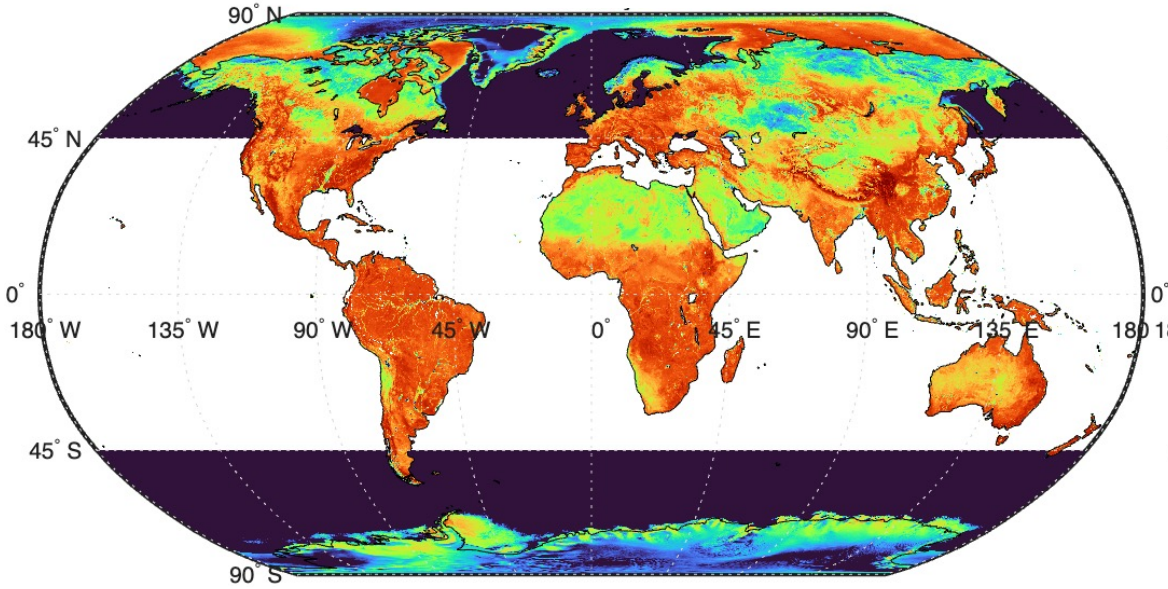


⇒ In both cases, the surface contribution has to be quantified!

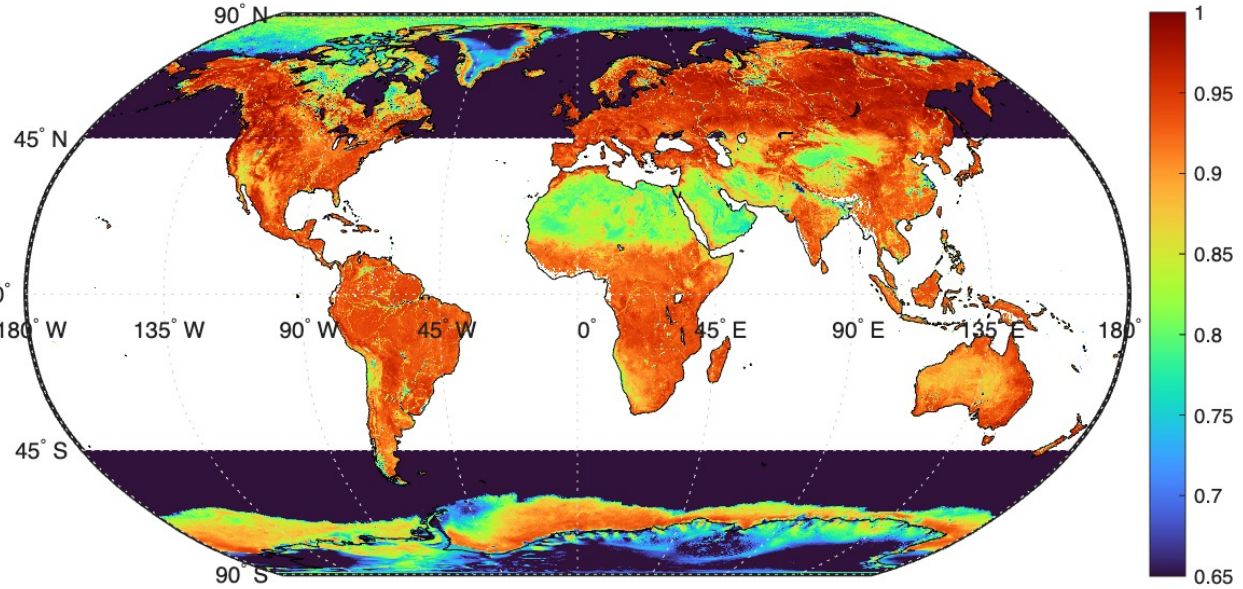
A varying surface contribution

Spatio-temporal variability:

Emissivity 36.5 GHz H-pol.
January



Emissivity 36.5 GHz H-pol.
July

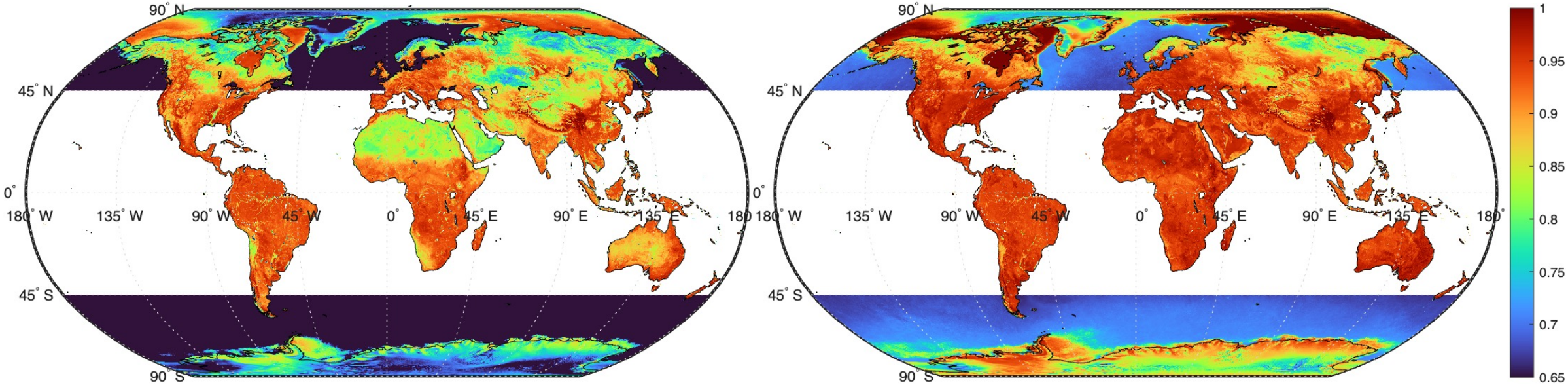


A varying surface contribution

Depending on observing conditions (e.g. polarization, incidence angle):

Emissivity 36.5 GHz **H**-pol.
January

Emissivity 36.5 GHz **V**-pol.
January

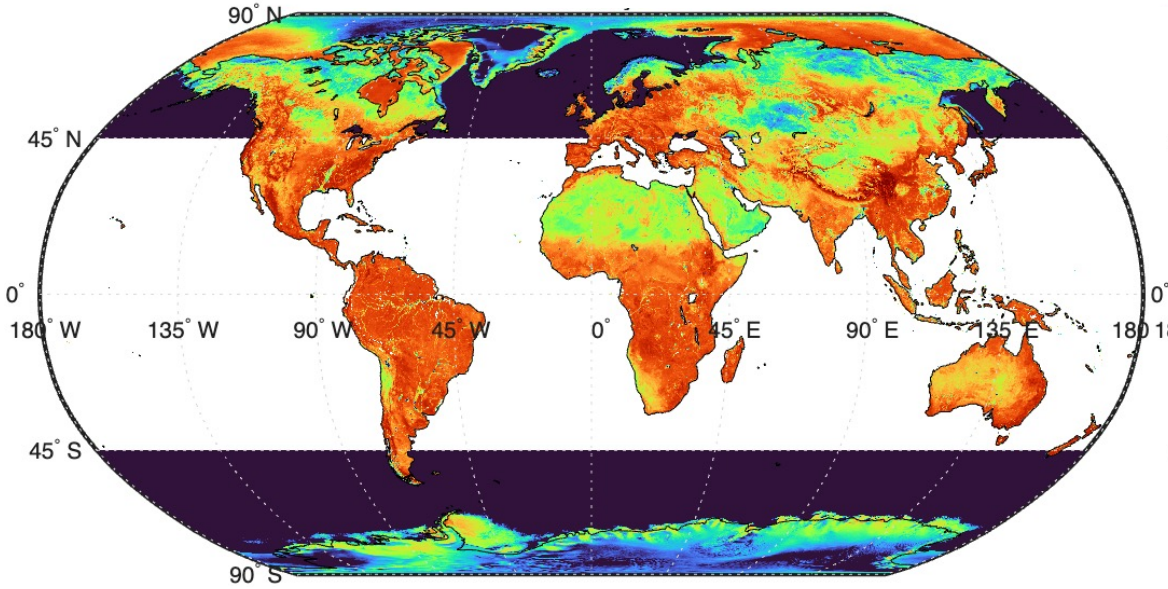


Horizontal vs Vertical polarization

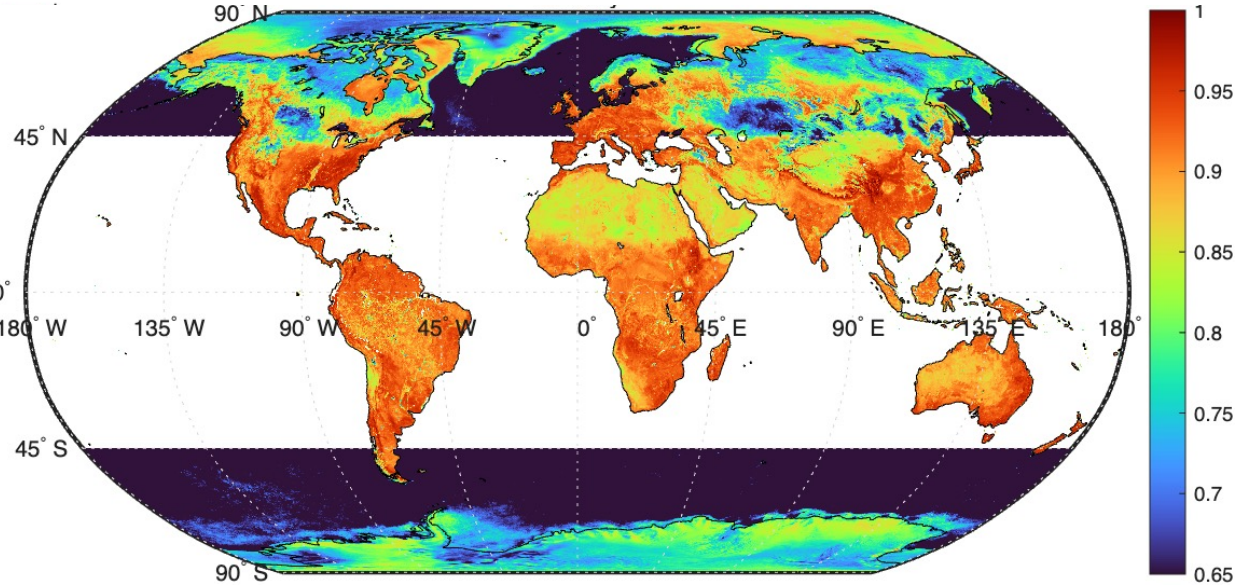
A varying surface contribution

Depending on frequency:

Emissivity **36.5** GHz H-pol.
January



Emissivity **89.0** GHz H-pol.
January



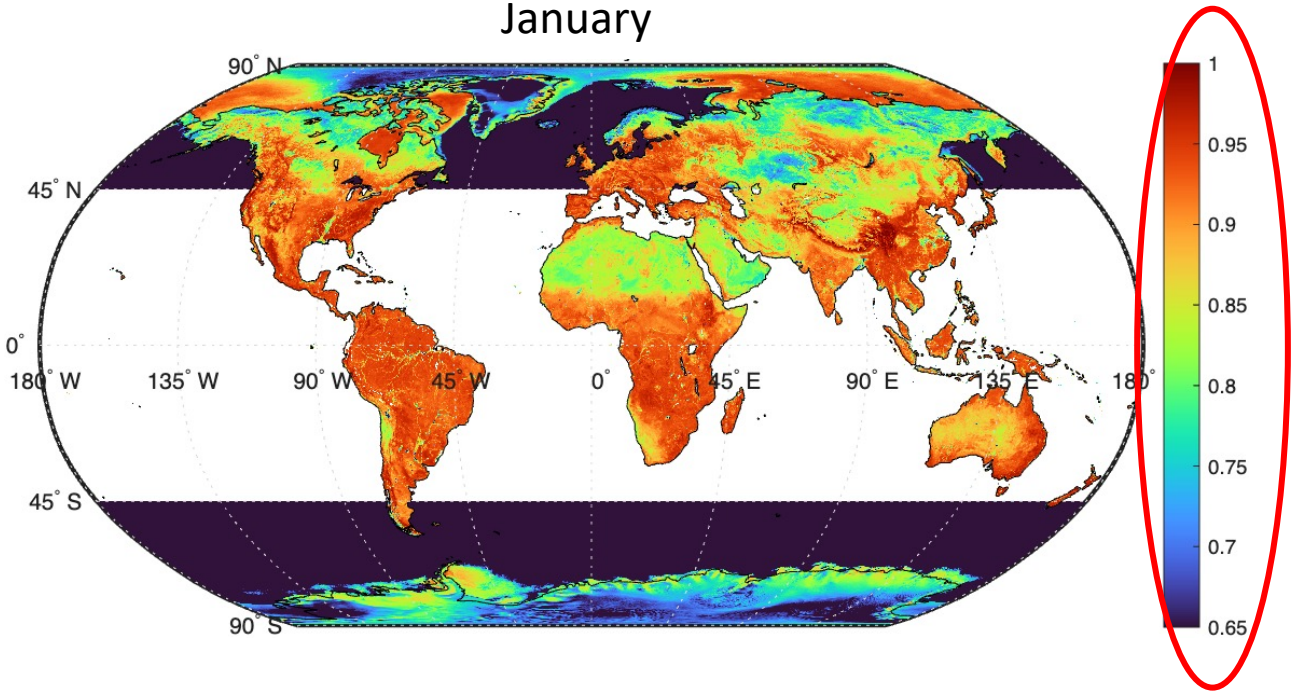
36.5 GHz vs 89.0 GHz

Microwave emissivity: a particularly challenging surface contribution

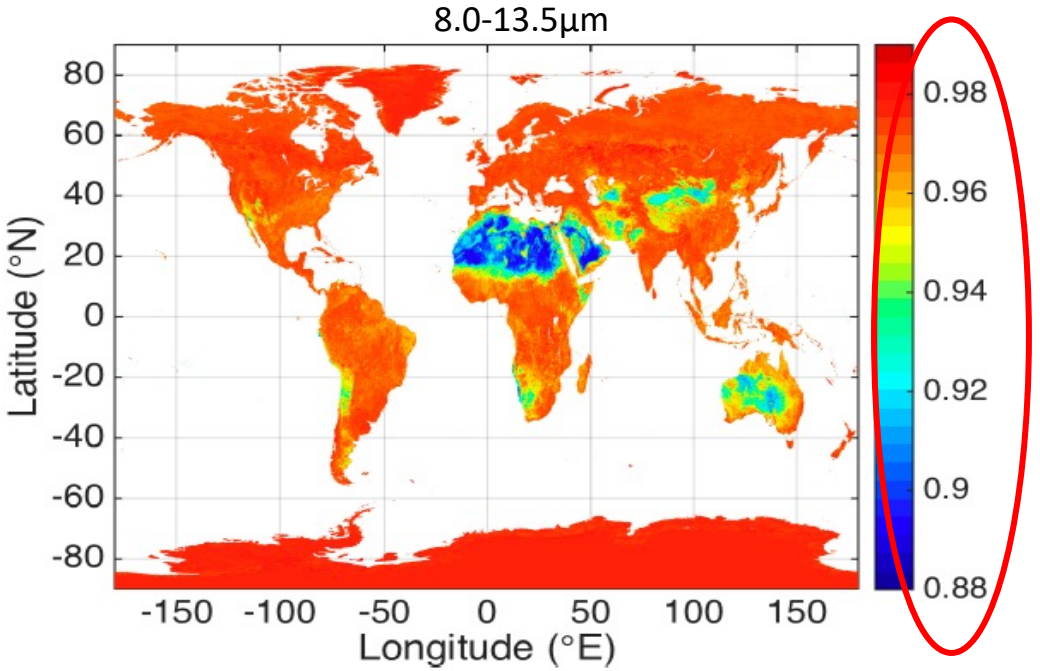
Depending on frequency:

MW emissivity vs thermal **IR** emissivity

Emissivity 36.5 GHz H-pol.
January

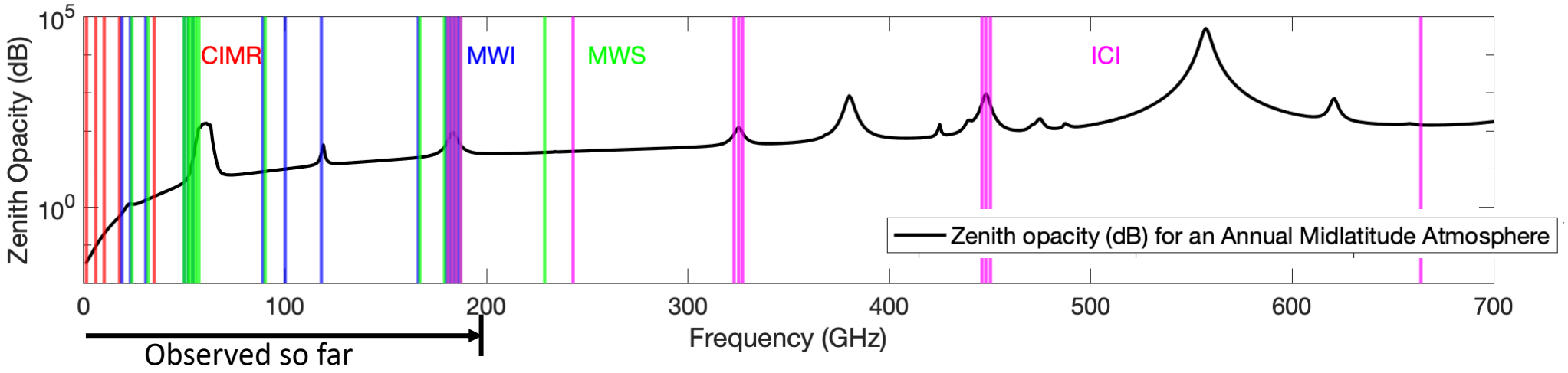


8.0-13.5µm



⇒ **Higher variability** in microwave emissivity
⇒ A challenging parameterization problem
⇒ This is our focus

The bright future of passive microwave observations in Europe



CIMR = Copernicus Imaging Microwave Radiometer
MWI = MicroWave Imager (MetOp-SG B)
MWS = MicroWave Sounder (MetOp-SG A)
ICI = Ice Cloud Imager (MetOp-SG B)

- Extension of the frequency range up to 664 GHz, with **ICI** (Launch in the end of 2026)
- Simultaneous observations between 1.4 and 36 GHz, with **CIMR** (Launch in 2030)

Forward-modelling of interface observations

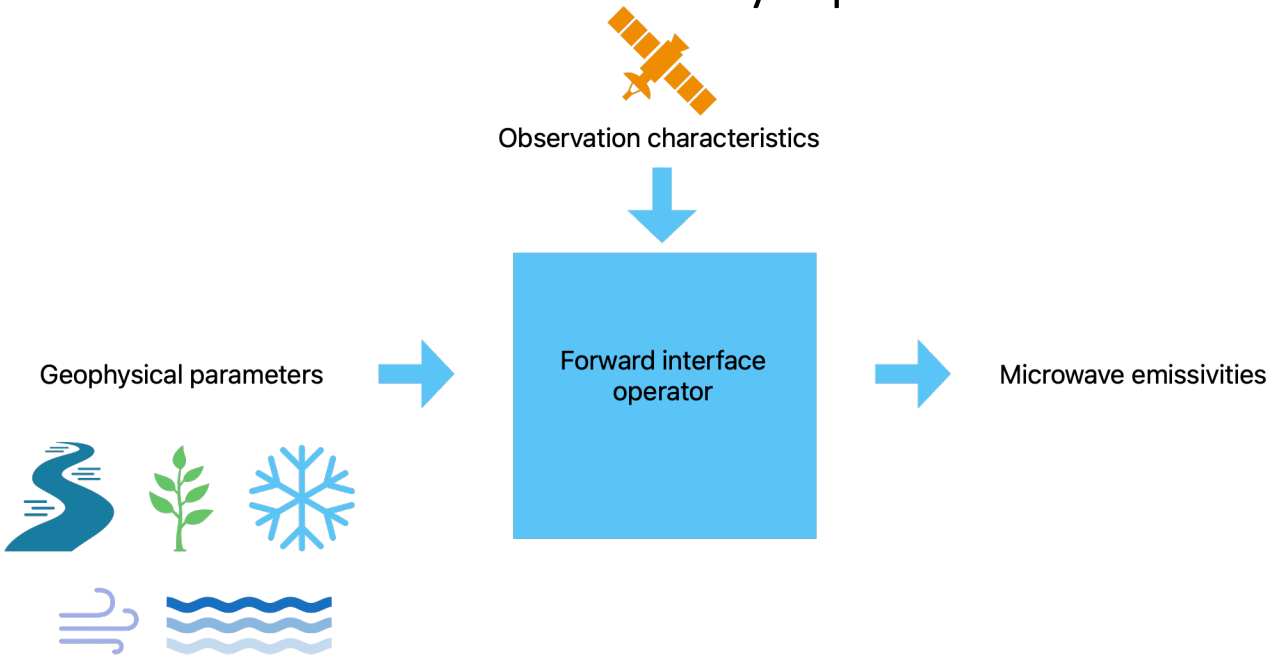
Parameterizing MW emissivities:

- Across **surface types**: at global scale
- Across **applications**: surface & atmospheric retrievals (surface-sensitive channels), and NWP
- Across **frequencies**: short microwave to millimeter waves (e.g., CIMR, ICI)
- Across **observing conditions**: incidence angle and polarization.

⇒ **Consistent forward operators** for forward/inverse modeling in coupled assimilation systems.

⇒ **Surface-aware operator** accounting for surface conditions to accurately capture surface contributions



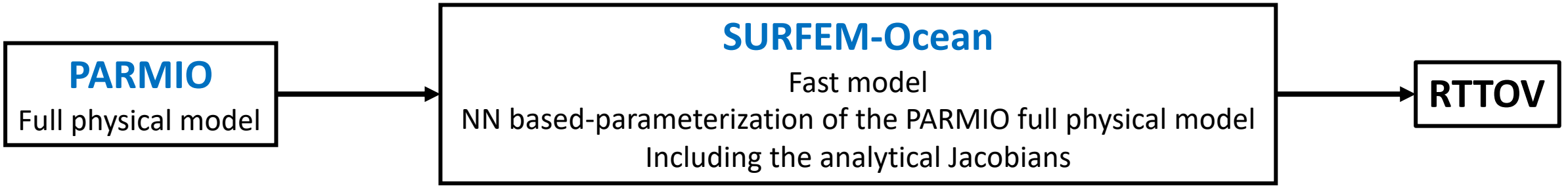


From physical model to fast ML forward model

For open ocean: a rather homogeneous surface (at least compared to the other surfaces)

- **PARMIO** (English et al., 2020; Dinnat et al., 2023): robust but slow

→ SURFEM-Ocean (Kilic et al., 2020 & 2023): **Fast model based on Neural Networks** (NN)



English et al., BAMS, 2020
Dinnat et al., BAMS, 2023

Kilic et al., JGR, 2019
Kilic et al., ESS, 2023

Geer et al., ECMWF, 2024



→ Same physical dependencies
→ Analytical Jacobians
→ Much faster

Heterogeneous surfaces

For sea ice, snow and land:

- ➜ Complex surface structure
- ➜ Surface Reflection & scattering
- ➜ Volume scattering
- ➜ Strong dependence on surface state

⇒ **Radiative transfer very challenging**

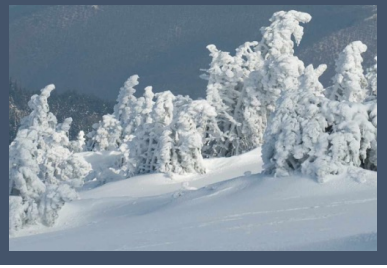
⇒ **Detailed physical models become difficult to apply globally**



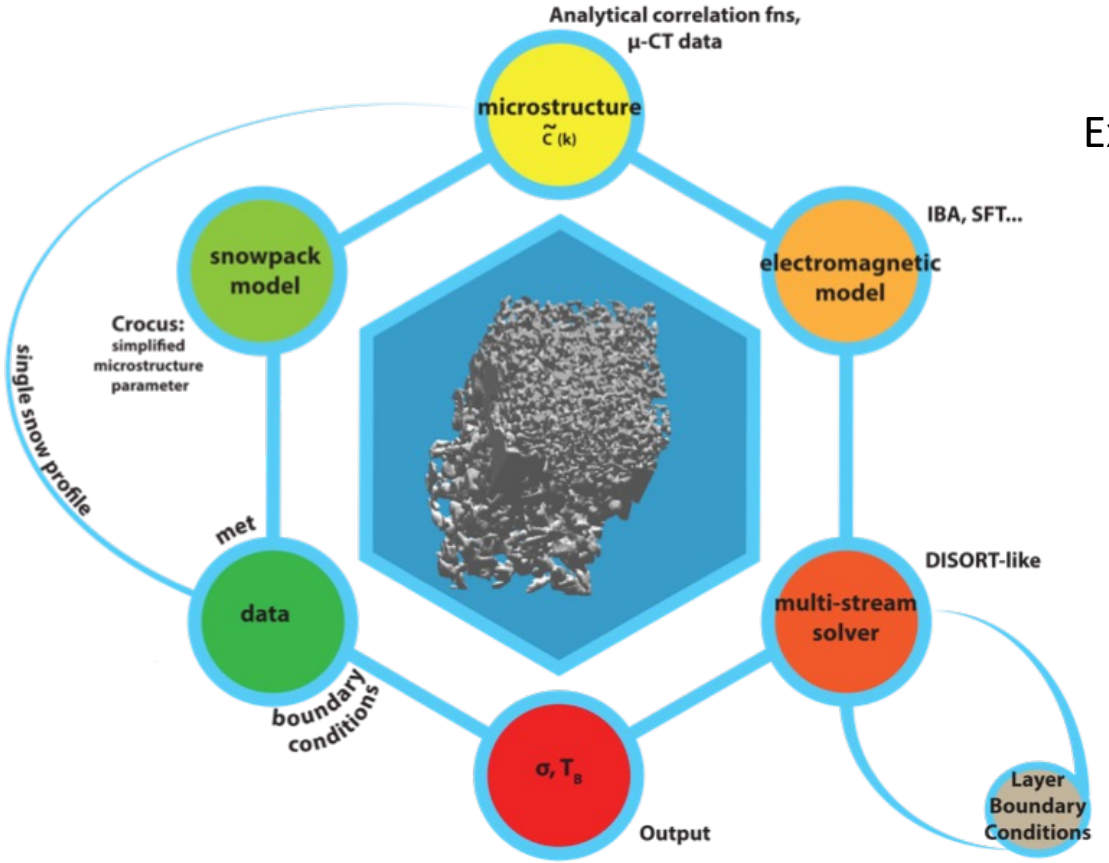



Snow and sea ice microwave radiative transfer models





For snow and sea ice: HUT (Pullianen et al. 1999), MEMLS (Wiesmann and Mätzler 1999), **SMRT** (Picard et al. 2018), …



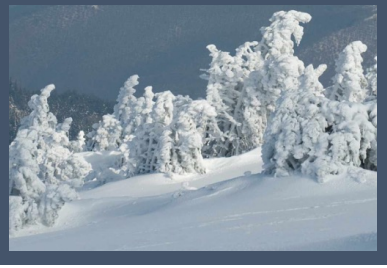
Example of **Snow Microwave Radiative Transfer model (SMRT)**

→ Based on a lot of information on **multi-layer snow macro- and micro-structural properties**

→ Most of input variables are **not available at large scale**

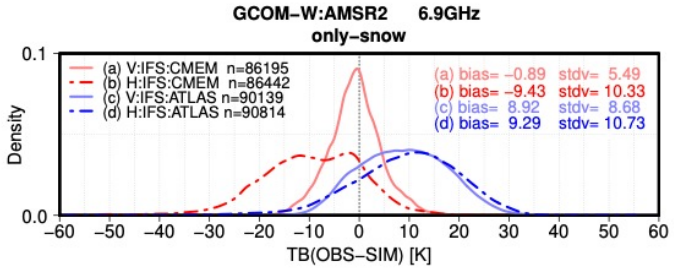
⇒ **Although very important to understand, analyse, and replicate physical processes, not practical at large scales.**

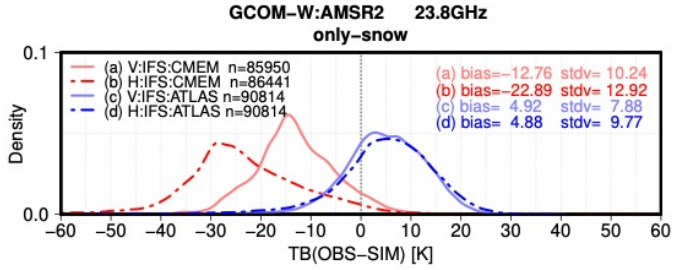
Large-scale snow emissivity models

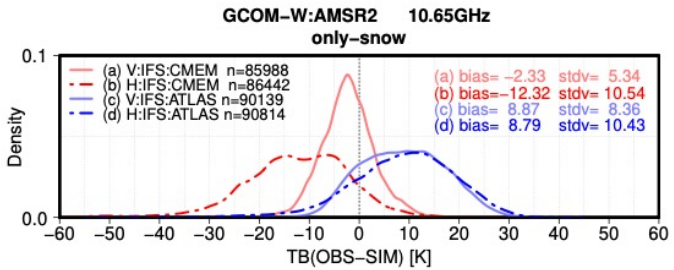


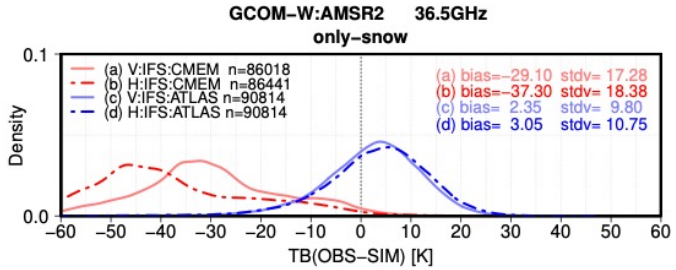
For snow:

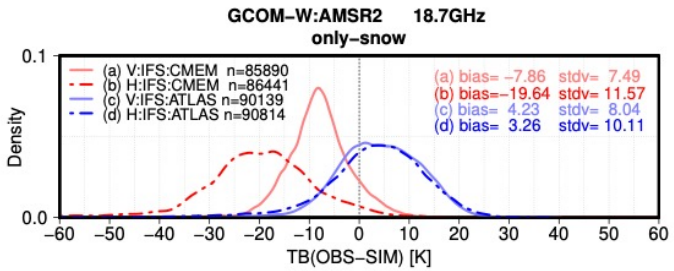
CMEM (Community Microwave Emission Modelling platform) – ECMWF

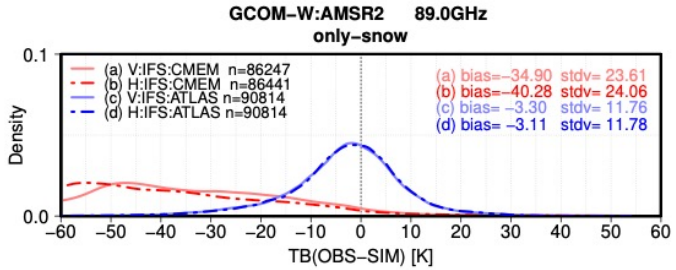












CMEM :

- Only suitable for low frequencies in V polarization
- **Very large bias for H polarization** (all frequencies)

ATLAS – TELSEM :

- **Not suitable for low frequencies (not developed for it)**
- **Climatological**: **no inter-annual variation depending on snow properties**

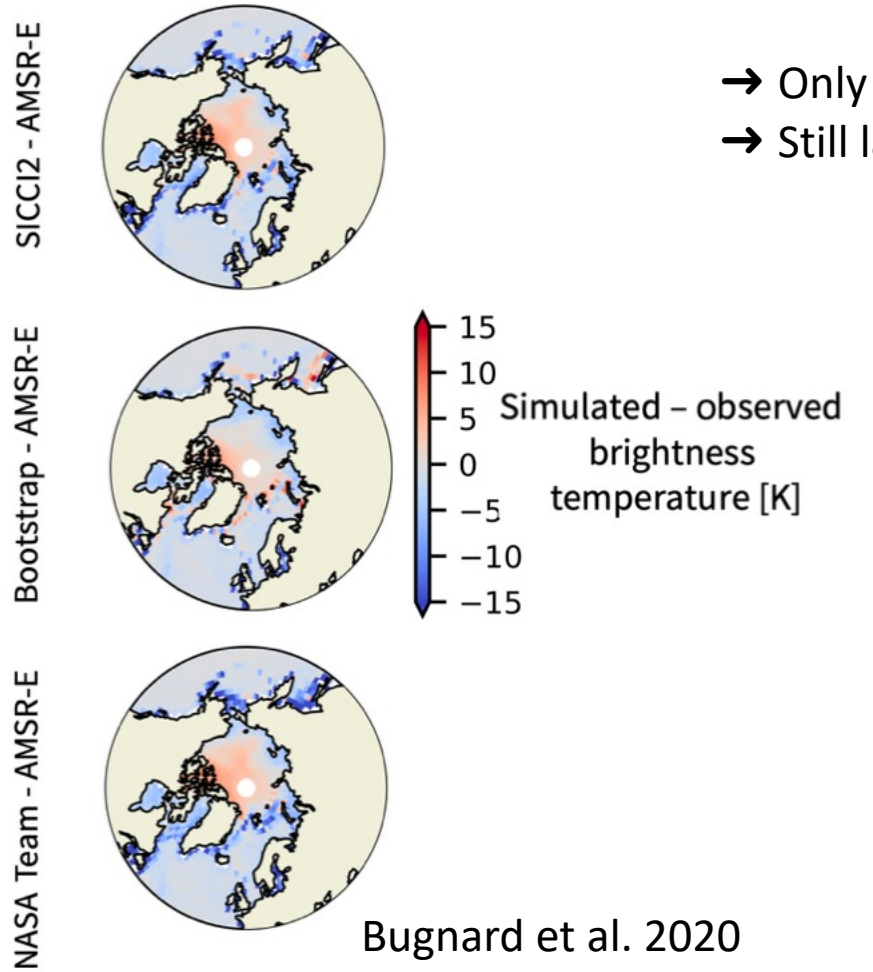
Hirahara et al. 2020

Large-scale sea ice emissivity models



For sea ice:

ARCtic Ocean Observation Operator for 6.9 GHz V-pol (ARC3O)



→ Only available at 6.9 GHz V pol. where very low variability observed

→ Still large biases

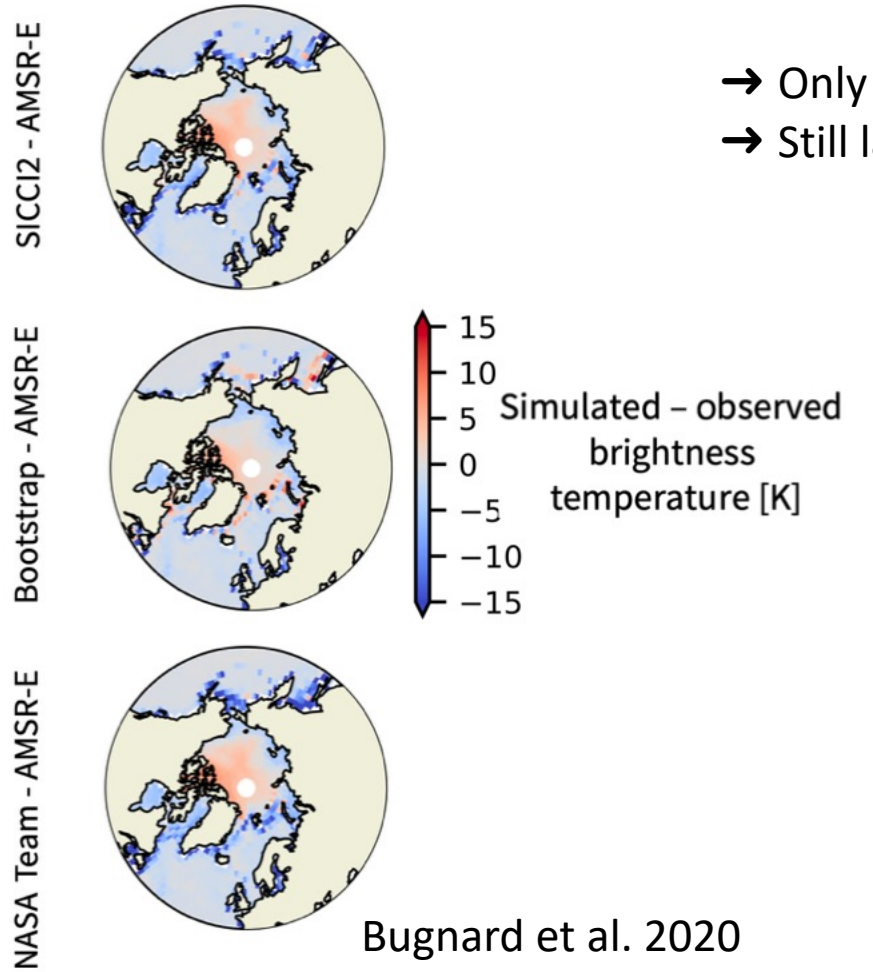
Bugnard et al. 2020

Large-scale sea ice emissivity models



For sea ice:

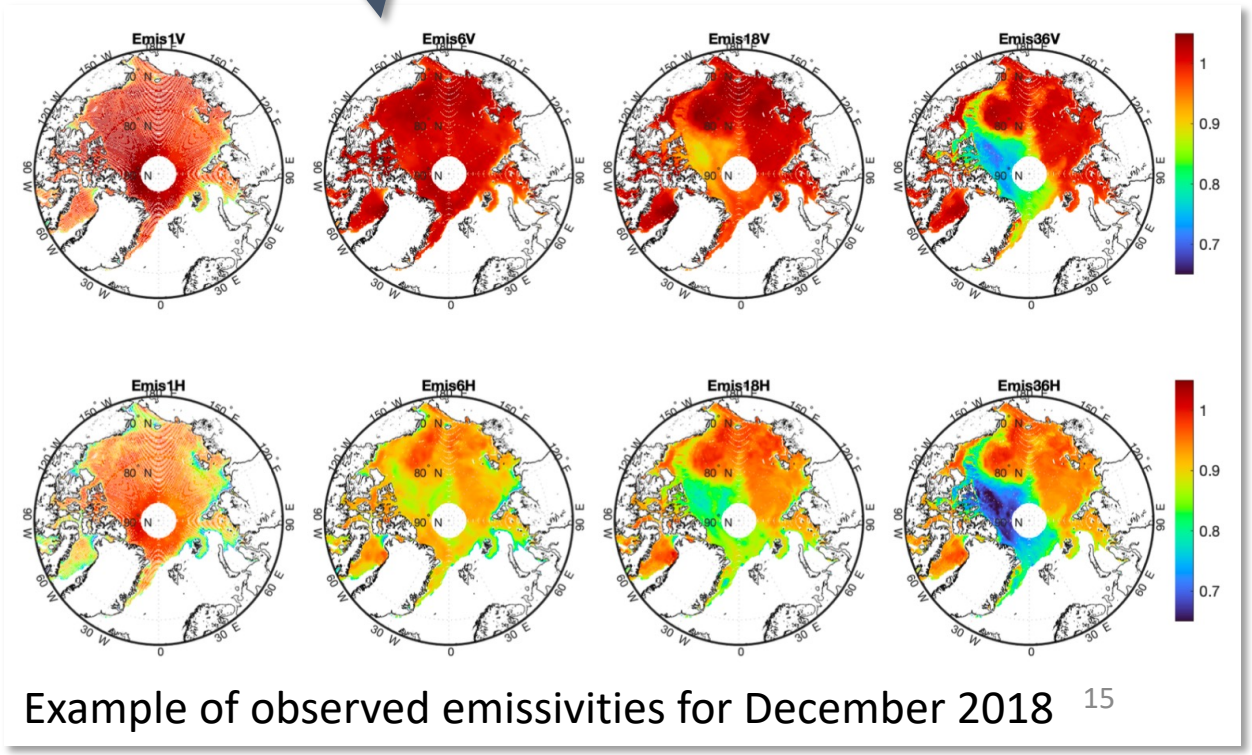
ARCtic Ocean Observation Operator for 6.9 GHz V-pol (ARC3O)



Bugnard et al. 2020

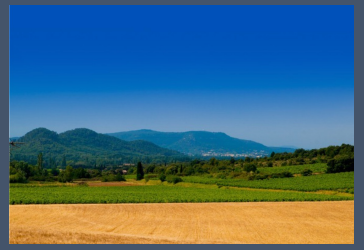
→ Only available at 6.9 GHz V pol. where very low variability observed

→ Still large biases



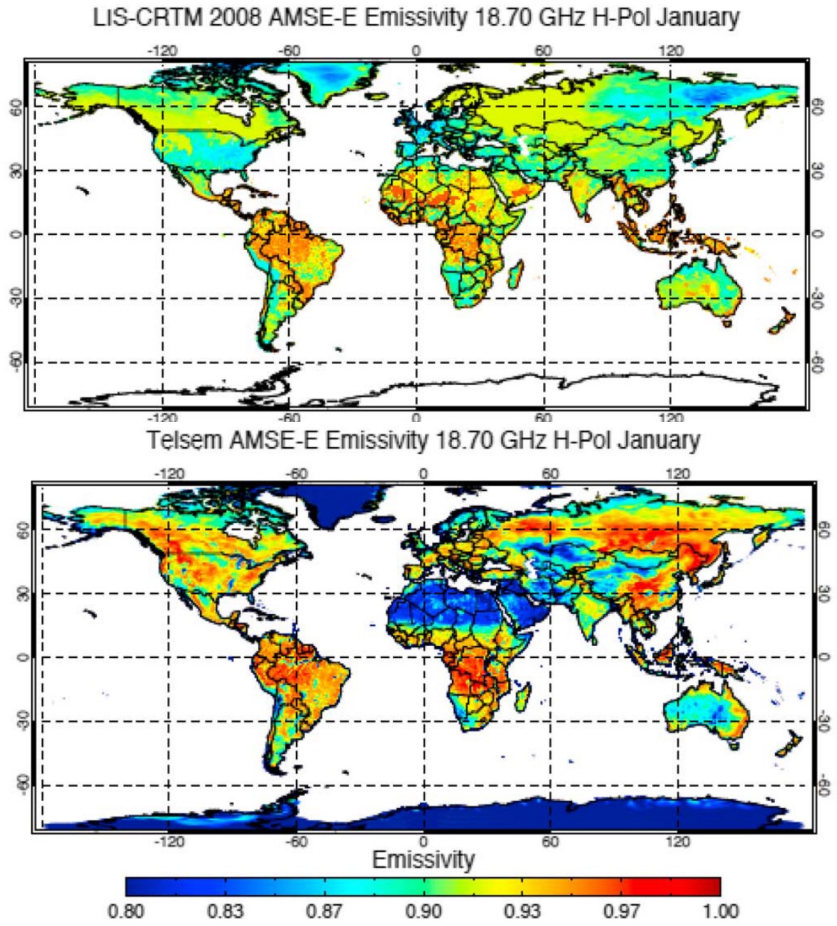
Example of observed emissivities for December 2018

Large-scale land emissivity models



For land:

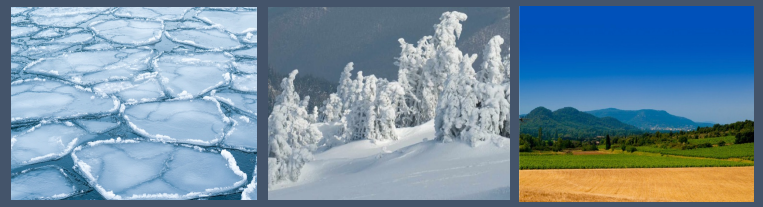
The Community Radiative Transfer Model (CRTM V2.0)



➜ Large differences when compared to atlases (TELSEM)

Prigent et al., 2015

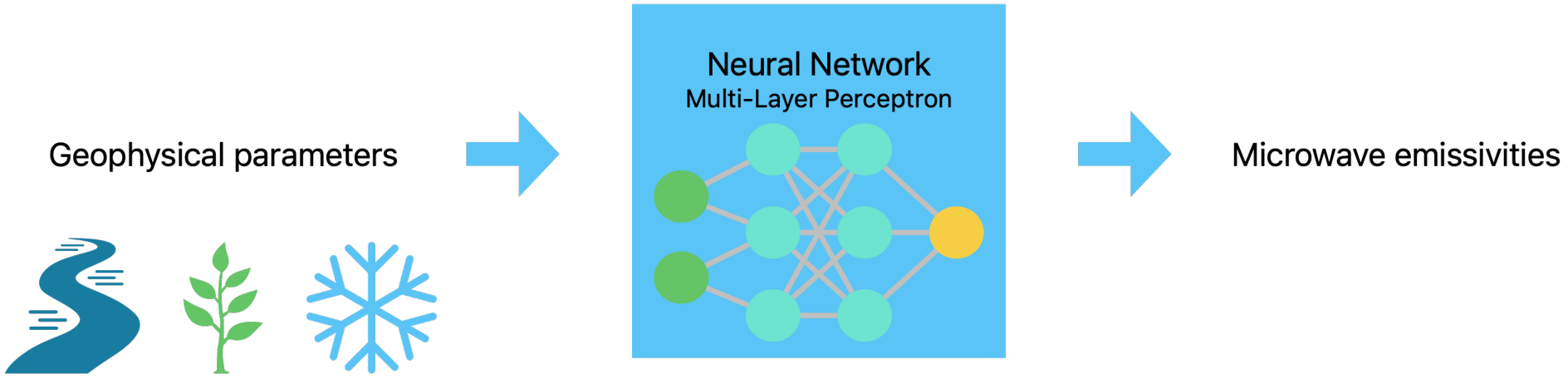
A ML approach to model large scale surface contributions - Objectives



Our objective: Develop an operator to derive **surface contribution** (i.e., emissivities) depending on surface **geophysical condition** at **large scale**

→ **Global**: Applicable throughout the year and across surface types

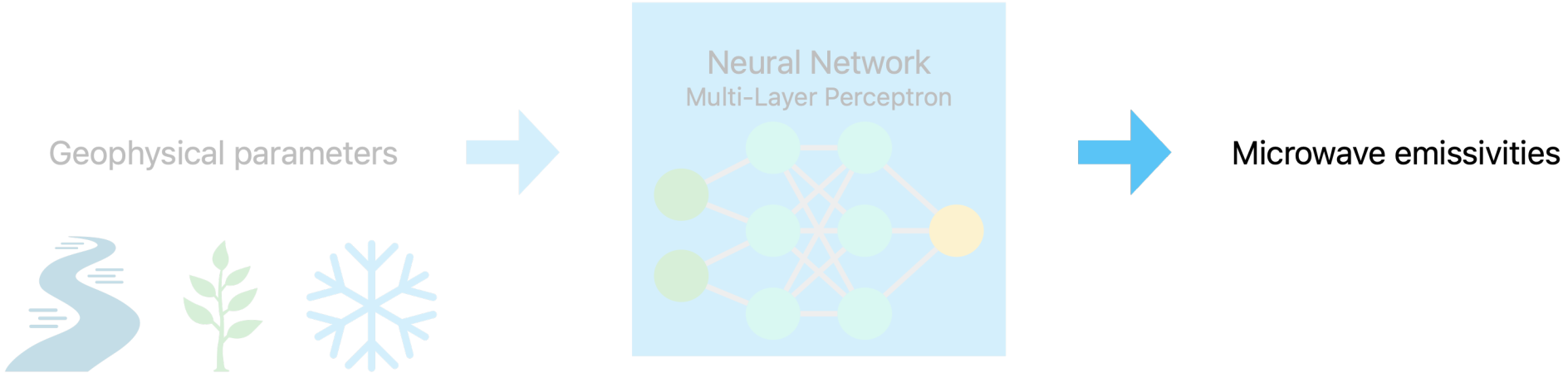
→ **NWP-compatible**: Driven by geophysical variables available in the NWP system



A ML approach to model large scale surface contributions - Methodology



- **Methodology:**
  1. Satellite-derived microwave emissivity database: SMAP, SMOS, AMSR2, AMSR3, AMSU-A, MHS



From observed brightness temperature to surface emissivity

In theory

- Radiative transfer equation in the specular assumption:

$$T_B = \underbrace{T_{surf} \times \epsilon \times \tau}_{1} + \underbrace{T_{atm}^{\downarrow} \times (1-\epsilon) \times \tau}_{2} + \underbrace{T_{atm}^{\uparrow}}_{3}$$

T_B Observed brightness temperature

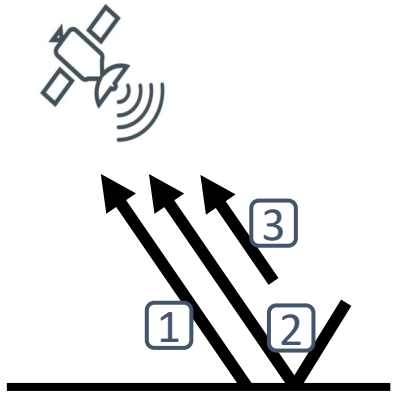
T_{surf} Surface temperature

$T_{atm}^{\downarrow}$ Downwelling atmospheric TB

ϵ Emissivity

$T_{atm}^{\uparrow}$ Upwelling atmospheric TB

τ Atmospheric transmission



$$\Rightarrow \epsilon = \frac{T_B - T_{atm}^{\uparrow} - T_{atm}^{\downarrow} \times \tau}{(T_{surf} - T_{atm}^{\downarrow}) \times \tau}$$

From observed brightness temperature to surface emissivity

In practice

- Radiative transfer equation in the specular assumption:

$$T_B = T_{surf} \times \epsilon \times \tau + T_{atm}^{\downarrow} \times (1 - \epsilon) \times \tau + T_{atm}^{\uparrow}$$

T_B Observed brightness temperature

ϵ Emissivity

$T_{surf_{eff}}$ Surface temperature

Based on ECMWF reanalysis (ERA5), interpolated at satellite swath and time

→ No penetration assumption

$T_{atm}^{\downarrow}$ Downwelling atmospheric TB

$T_{atm}^{\uparrow}$ Upwelling atmospheric TB

τ Atmospheric transmission

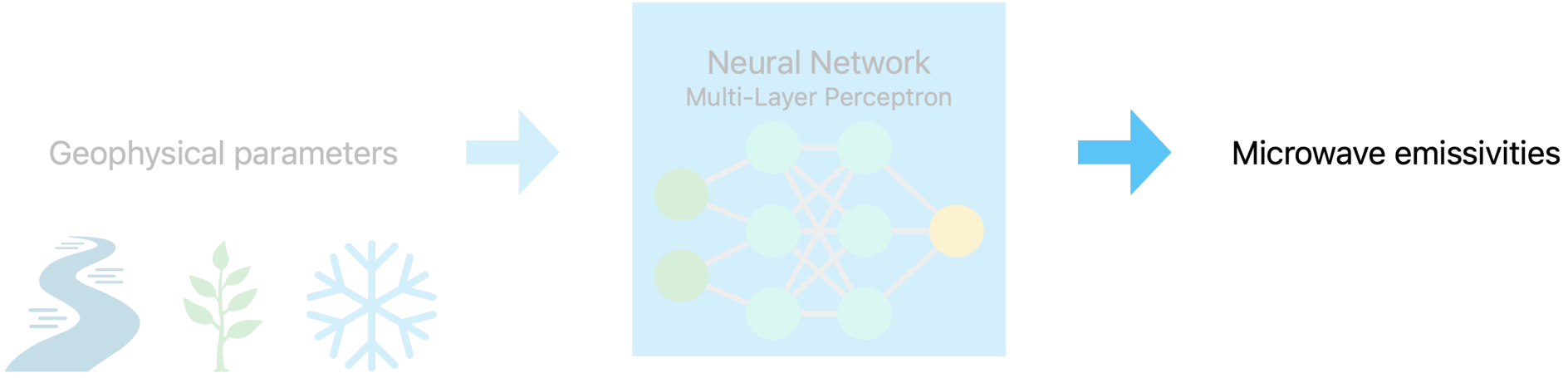
Rosenkranz (2017) : Sourced from atmospheric meteorological values from ERA5 (interpolated at satellite swath and time)

$$\Rightarrow \epsilon_{eff} = \frac{T_B - T_{atm}^{\uparrow} - T_{atm}^{\downarrow} \times \tau}{(T_{surf_{eff}} - T_{atm}^{\downarrow}) \times \tau}$$

A ML approach to model large scale surface contributions - Methodology



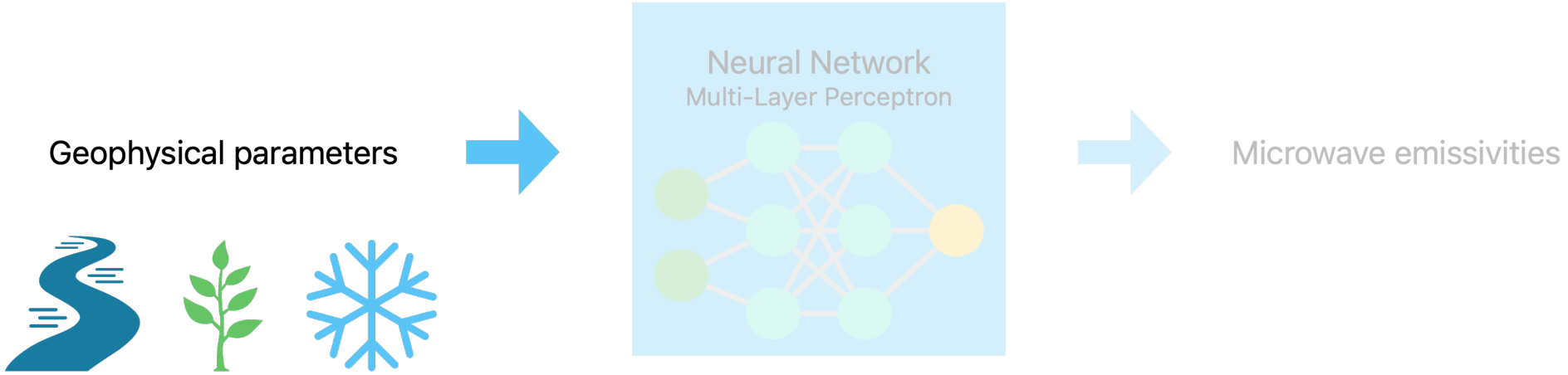
- **Methodology:**
  1. Satellite-derived microwave emissivity database: SMAP, SMOS, AMSR2, AMSR3, AMSU-A, MHS
     → Satellite-derived emissivity calculated for the full time series
     → With ERA5 inputs for the atmosphere and the surface temperature (Tskin)
     → Data cleaning, clear sky observation selection



A ML approach to model large scale surface contributions - Methodology



- **Methodology:**
  2. Select potential predictors for the parameterization of the emissivities
     - ➜ Preferably from reanalysis (ERA5)
     - ➜ From well-recognized community models when reanalysis information not enough
     - ➜ Selection based on an in-depth analysis of the links between the observations and the available geophysical variables



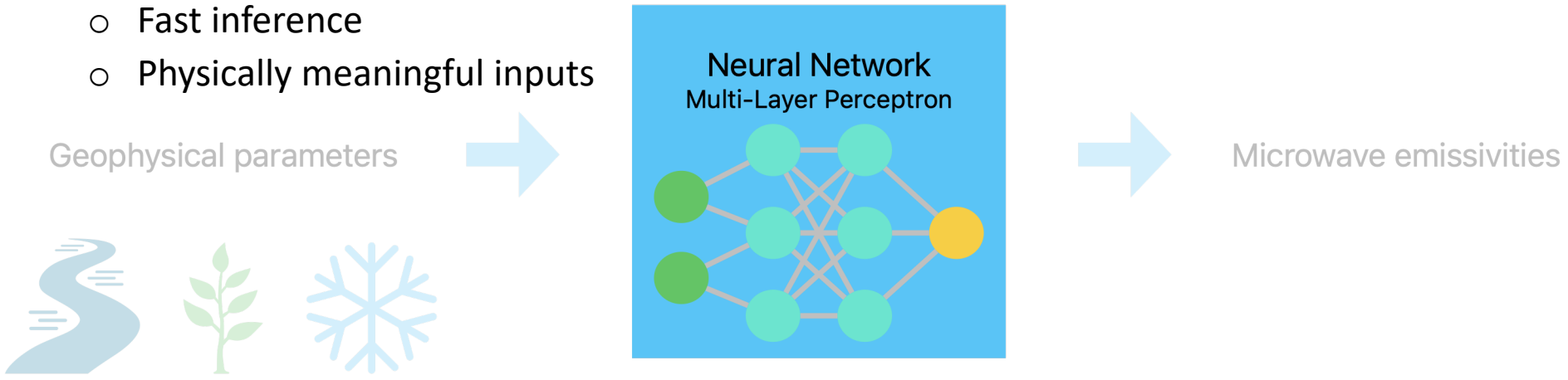
A ML approach to model large scale surface contributions - Methodology



- **Methodology:**
  3. Statistically relate the satellite-derived emissivities to relevant geophysical parameters at global scale

     → Use of machine learning method to account for complex relationships between geophysical parameters and emissivity

     → **Multi-layer perceptron**
     - Simple architecture
     - Fast inference
     - Physically meaningful inputs

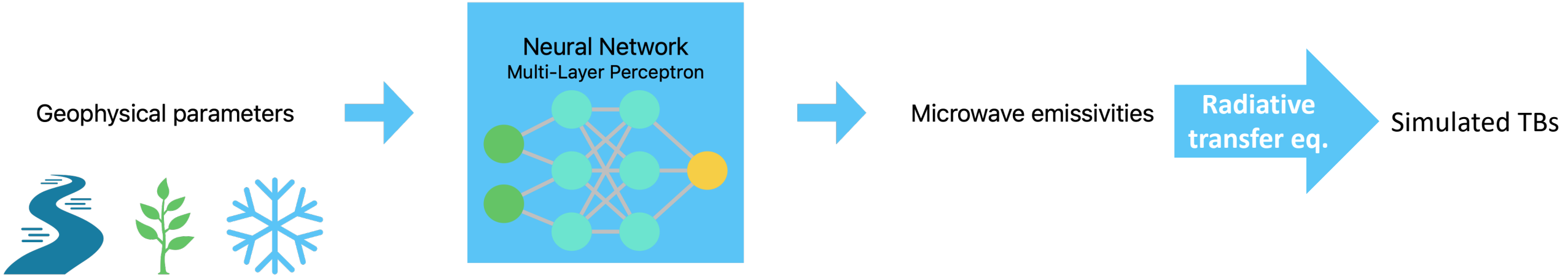


A ML approach to model large scale surface contributions - Methodology



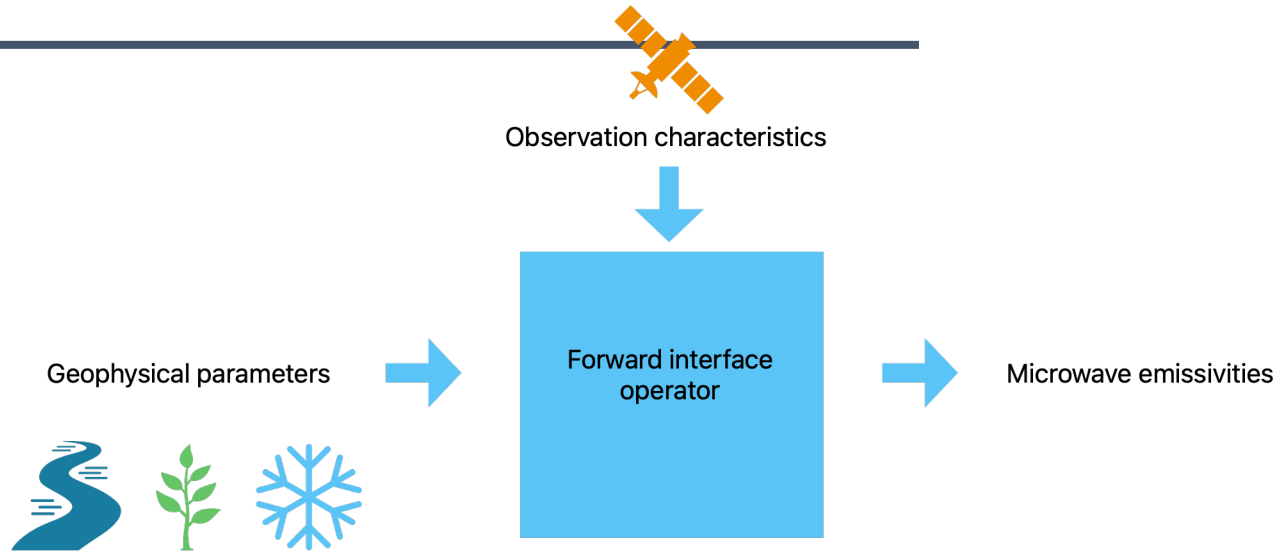
Same method for sea ice, snow-covered and snow-free areas, but with different predictors, resulting in three operators.

- **Methodology :**
  1. Satellite-derived microwave emissivity database
  2. Select potential predictors for the parameterization of the emissivities
  3. Statistically relate the satellite-derived emissivities to relevant geophysical parameters at global scale

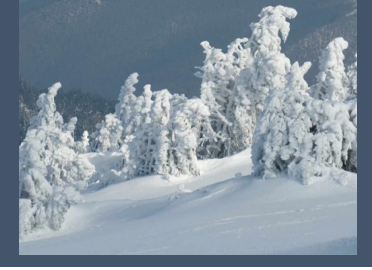


Examples and results

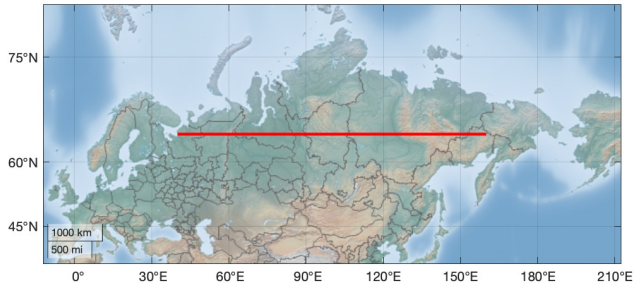


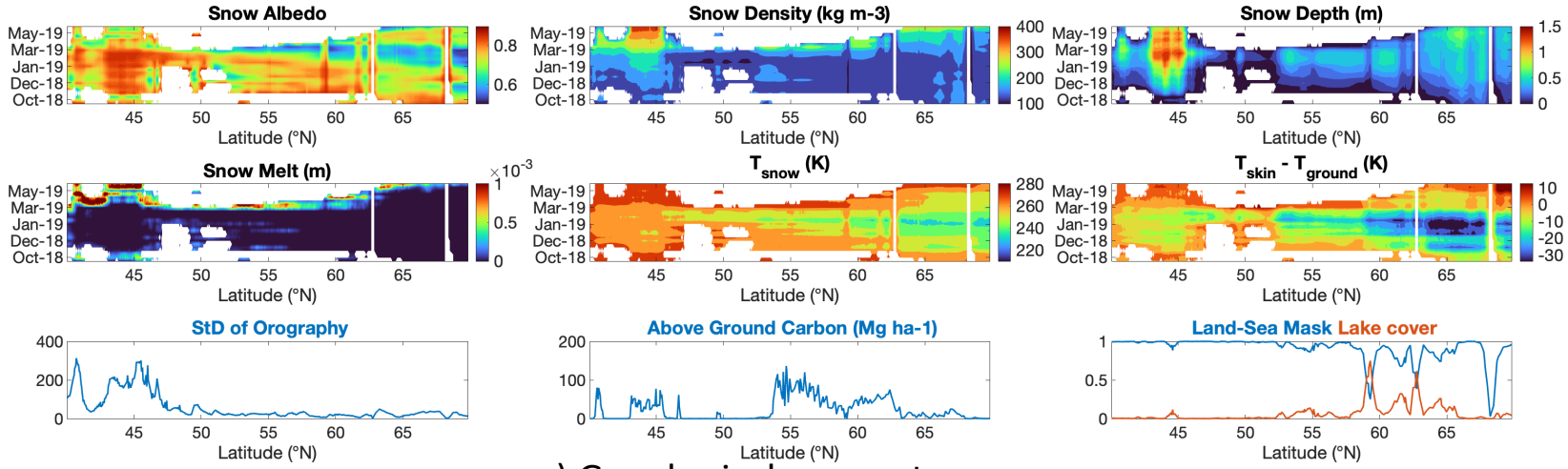


Snow emissivity parameterization: Predictor selection

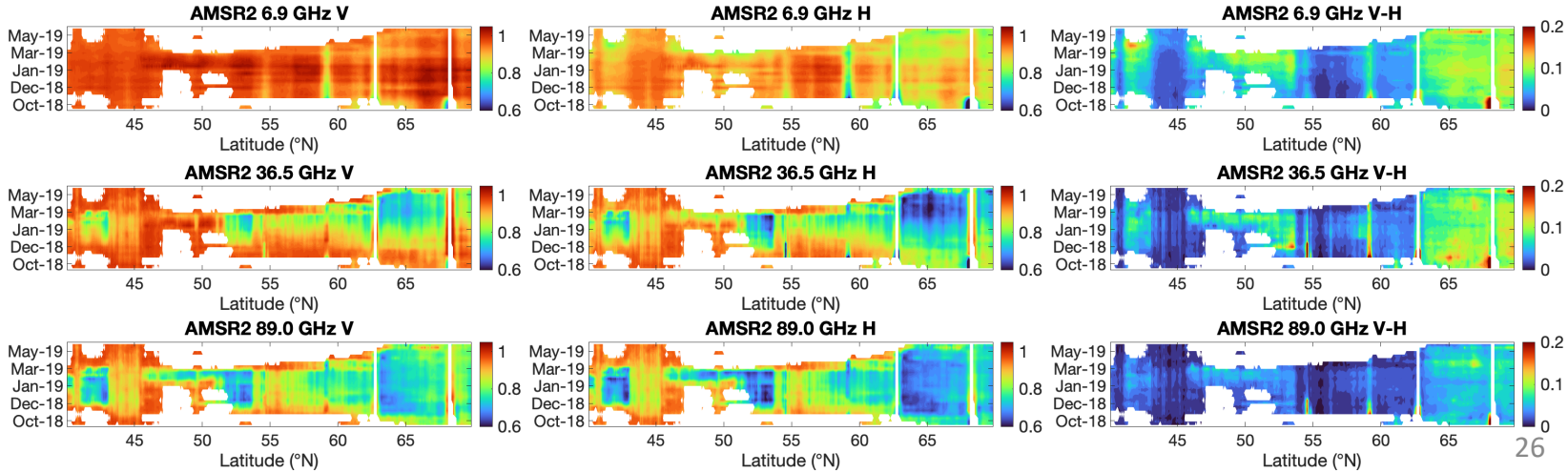


- **Joint analysis of surface emissivities and potential geophysical predictors:**



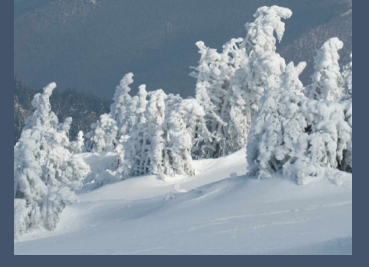


a) Geophysical parameters

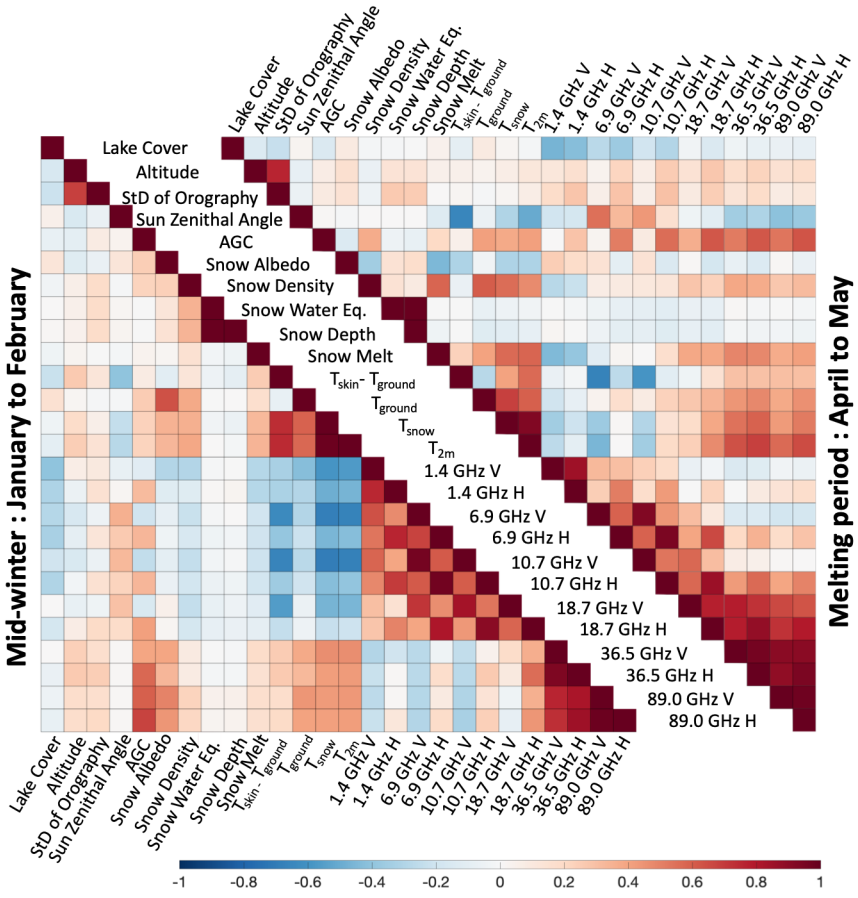


b) Emissivities

Snow emissivity parameterization: Predictor selection



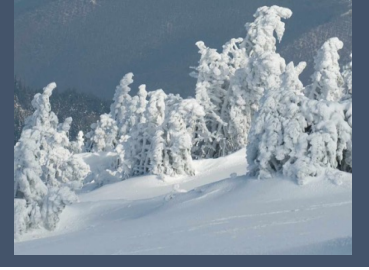
- **Joint analysis of surface emissivities and potential geophysical predictors:**



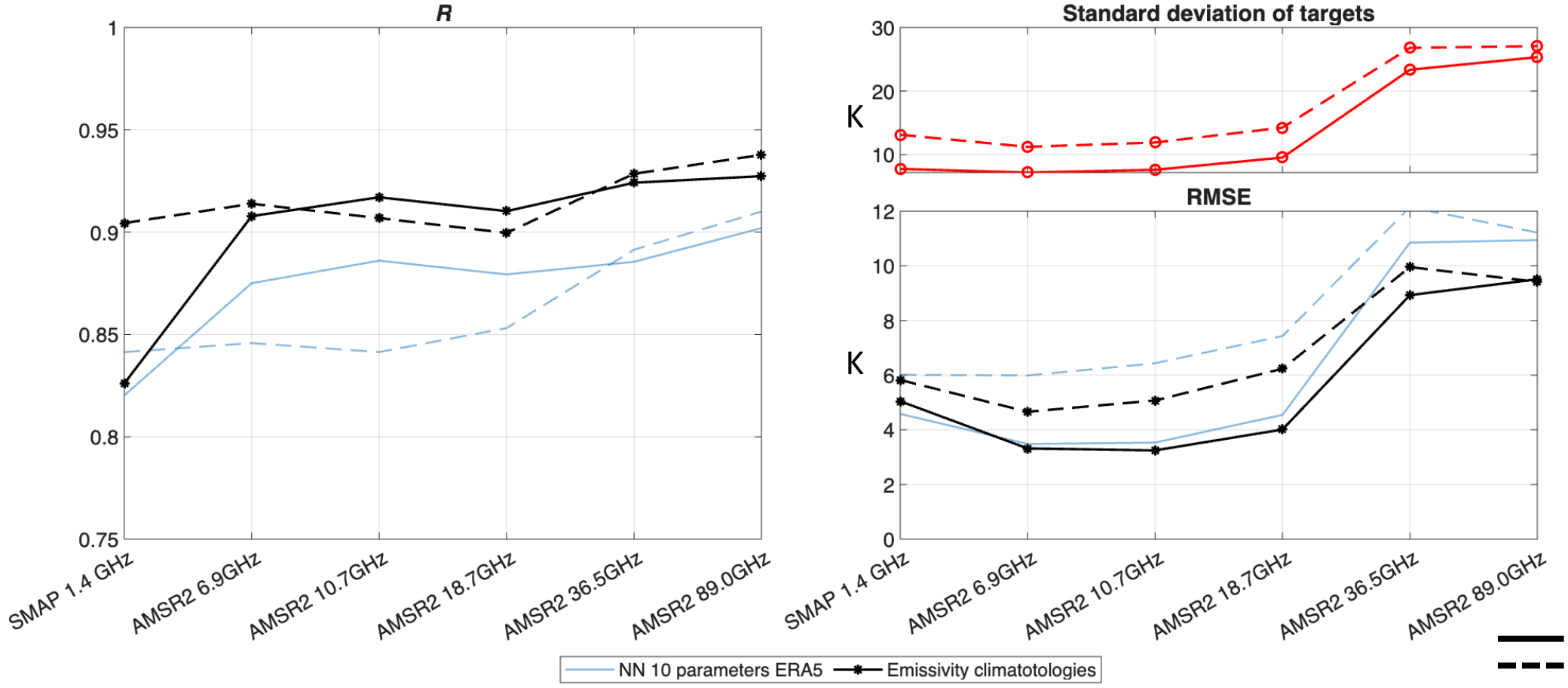
⇒ The selected predictors for the snow parameterization

Name	Geophysical parameters		
	Fixed	Snow	Temperature
NN 10 parameters	Lake Cover StD of Orography AGB	Albedo Density Depth Melt	Snow (T_{snow}) Ground (T_{ground}) Gradient ($T_{skin} - T_{ground}$)

Snow emissivity parameterization: Quantitative results

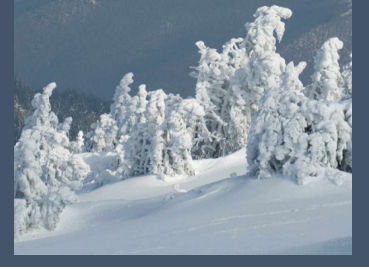


- Our results with ERA5 as input (back in TB space)

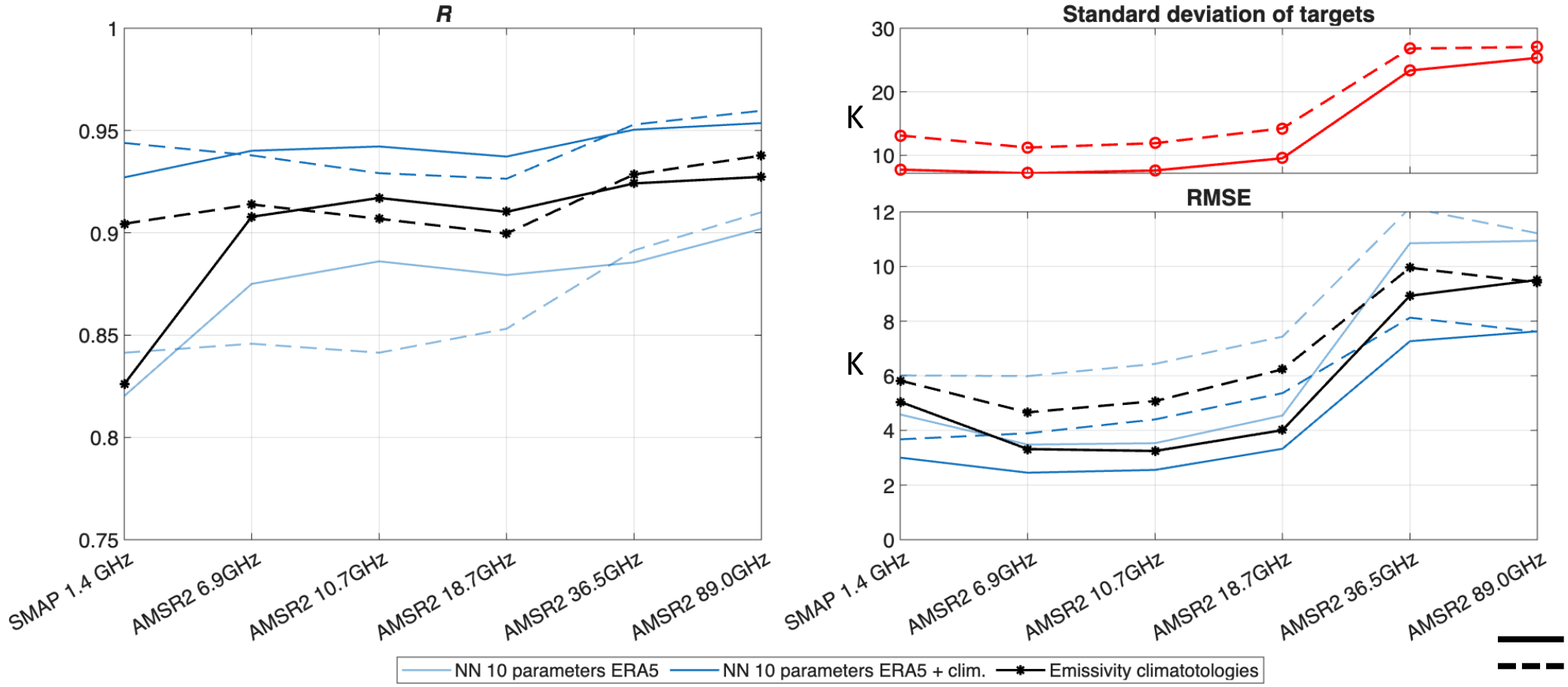


- Given the complexity of the surface, geophysical predictors alone are not sufficient

Snow emissivity parameterization: Quantitative results



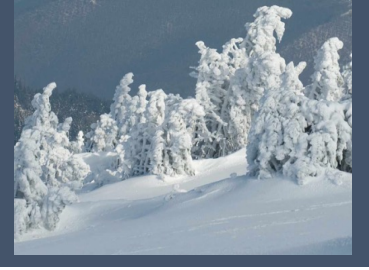
- Our results with ERA5 as input (back in TB space)

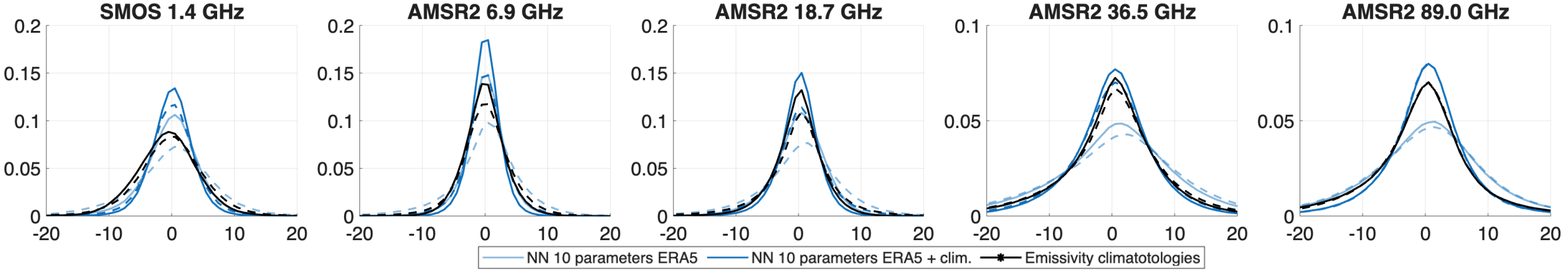


- Emissivity climatological information complements dynamic geophysical predictors

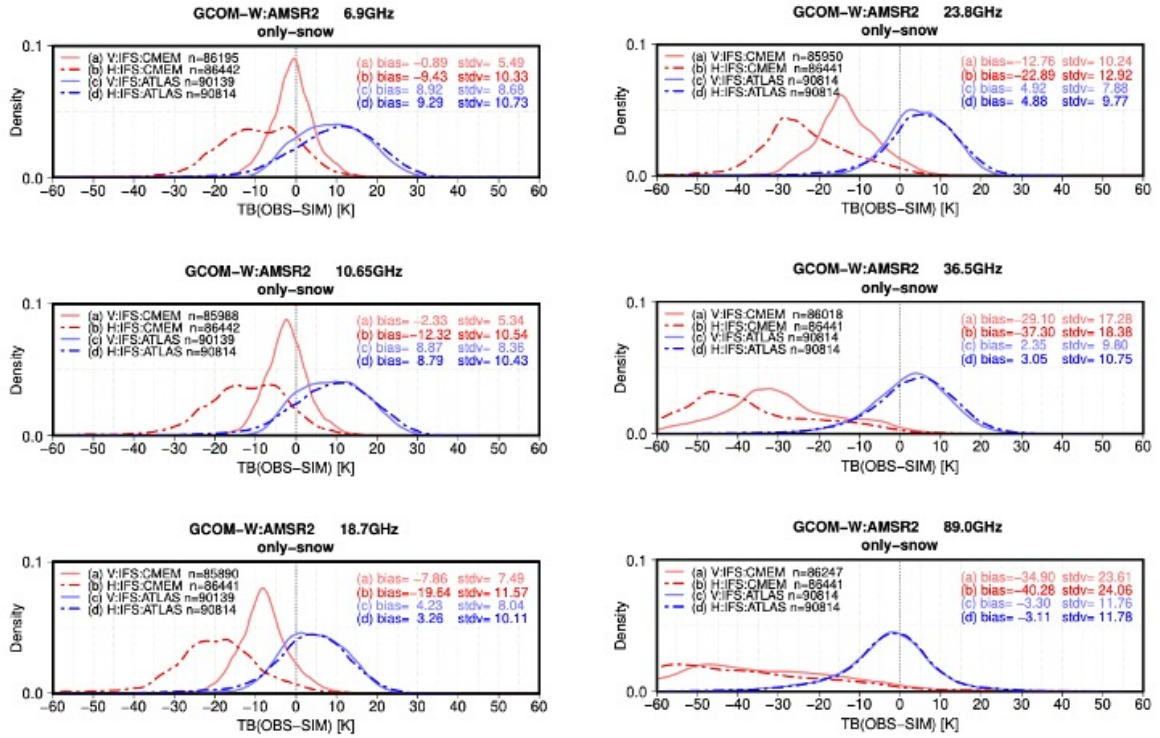
→ ML forward operator : Considerable improvement over emissivity climatologies

Snow emissivity parameterization: Histograms of errors TB(OBS-SIM)





CMEM (Community Microwave Emission Modelling Platform) -- ECMWF

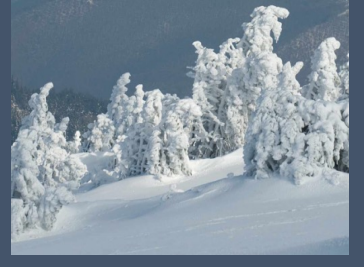


CMEM

ATLAS – TELSEM

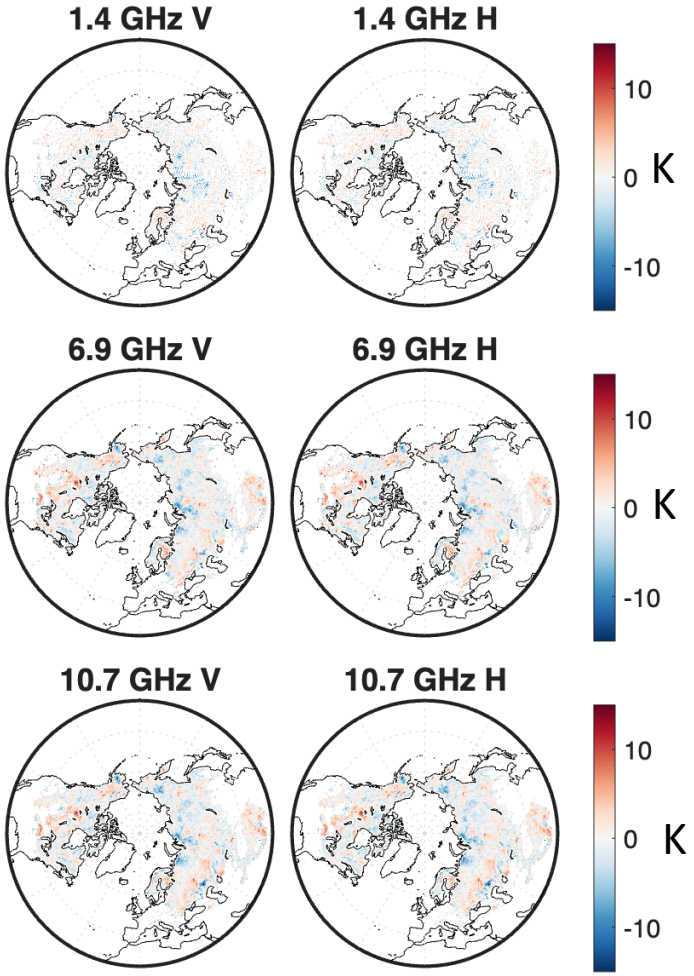
Hirahara et al., 2020

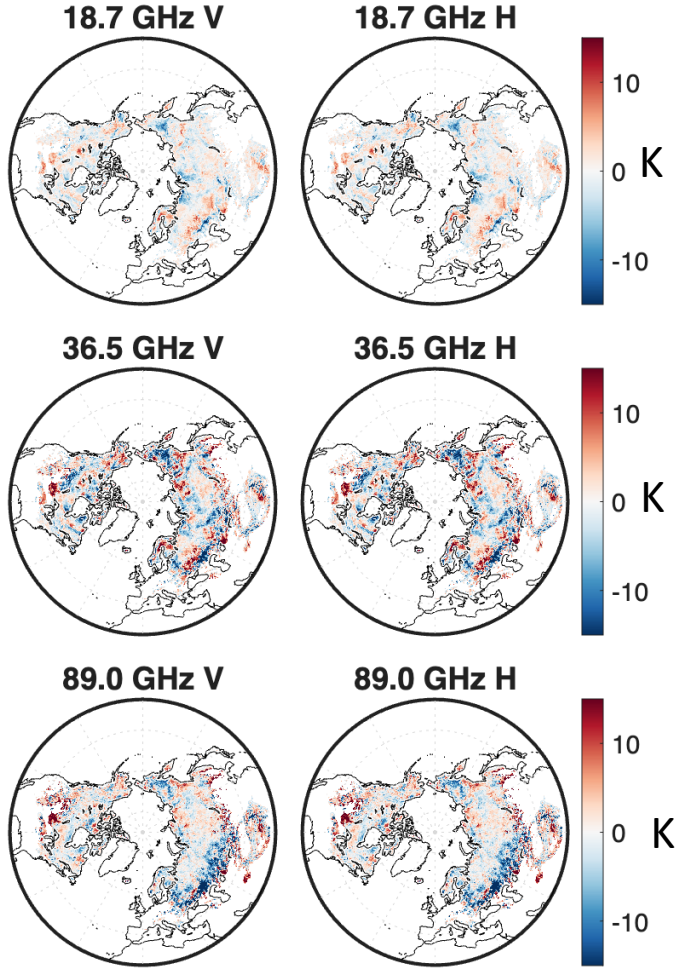
Snow emissivity parameterization: Maps of errors



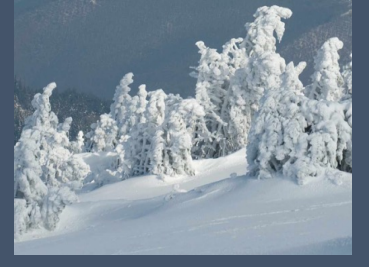
- Differences with SMAP and AMSR2 observations (back in TB space)

January 2019





Snow emissivity parameterization: Impact of the snowpack representation



- Experimentation using ERA6Land prototype

  (within ISSI snow & sea ice team, with the help of Gabriele Arduini (ECMWF) and Julien Meloche (ECCC))

➜ ERA5: single layer snowpack

➜ ERA6-Land prototype: multi-layer snowpack

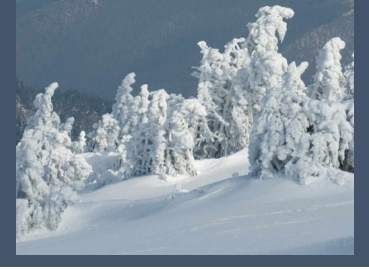
Some new predictors to better represent the snowpack:

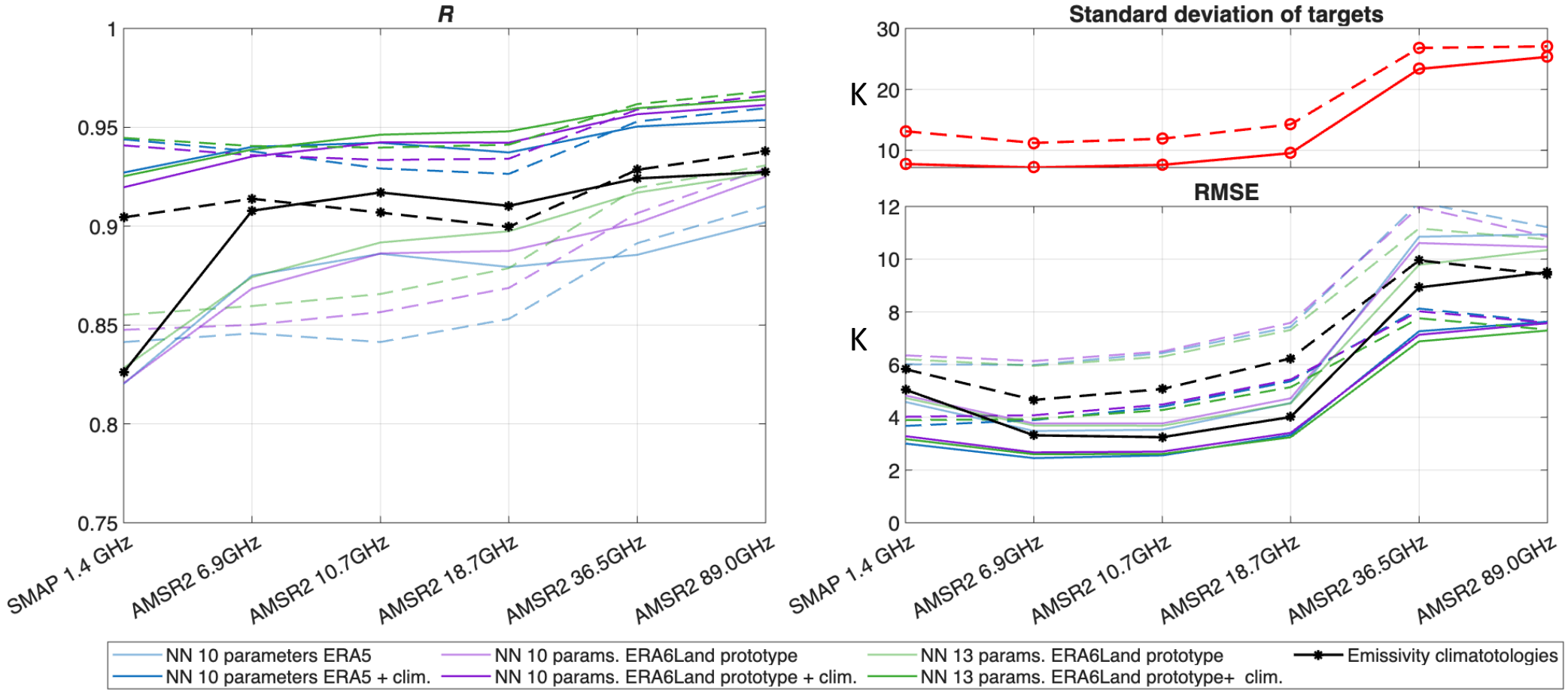
Name	Geophysical parameters		
	Fixed	Snow	Temperature
NN 13 parameters	Lake Cover StD of Orography AGB	Albedo Density Depth Melt **Liquid Water Content** **Snow Specific Area*** **Nb active layers**	Snow (T_{snow}) Ground (T_{ground}) Gradient ($T_{skin} - T_{ground}$)

* Snow Specific Area ≈ Snow radius: derived from ERA6Land prototype variables

-> How does this relate to microwave satellite observations at global scale ?

Snow emissivity parameterization: Impact of the snowpack representation

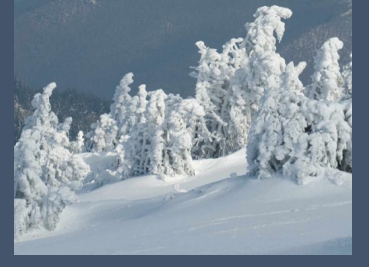




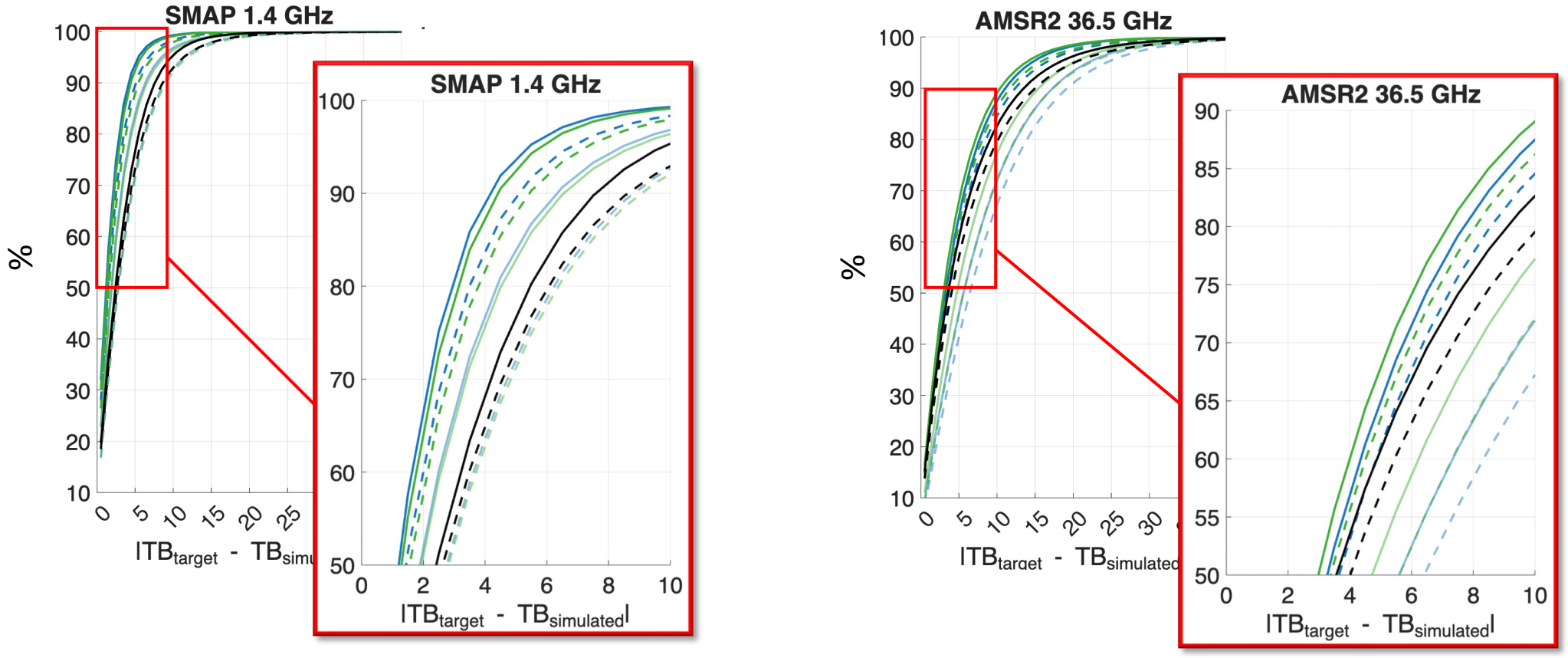
Ongoing study

- Without emissivity climatologies as input : ERA6Land prototype helps at high frequencies (from 18.7 GHz)
- Emissivity climatologies can still complement dynamic geophysical predictors

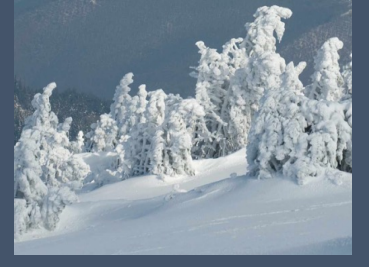
Snow emissivity parameterization: Statistics on errors



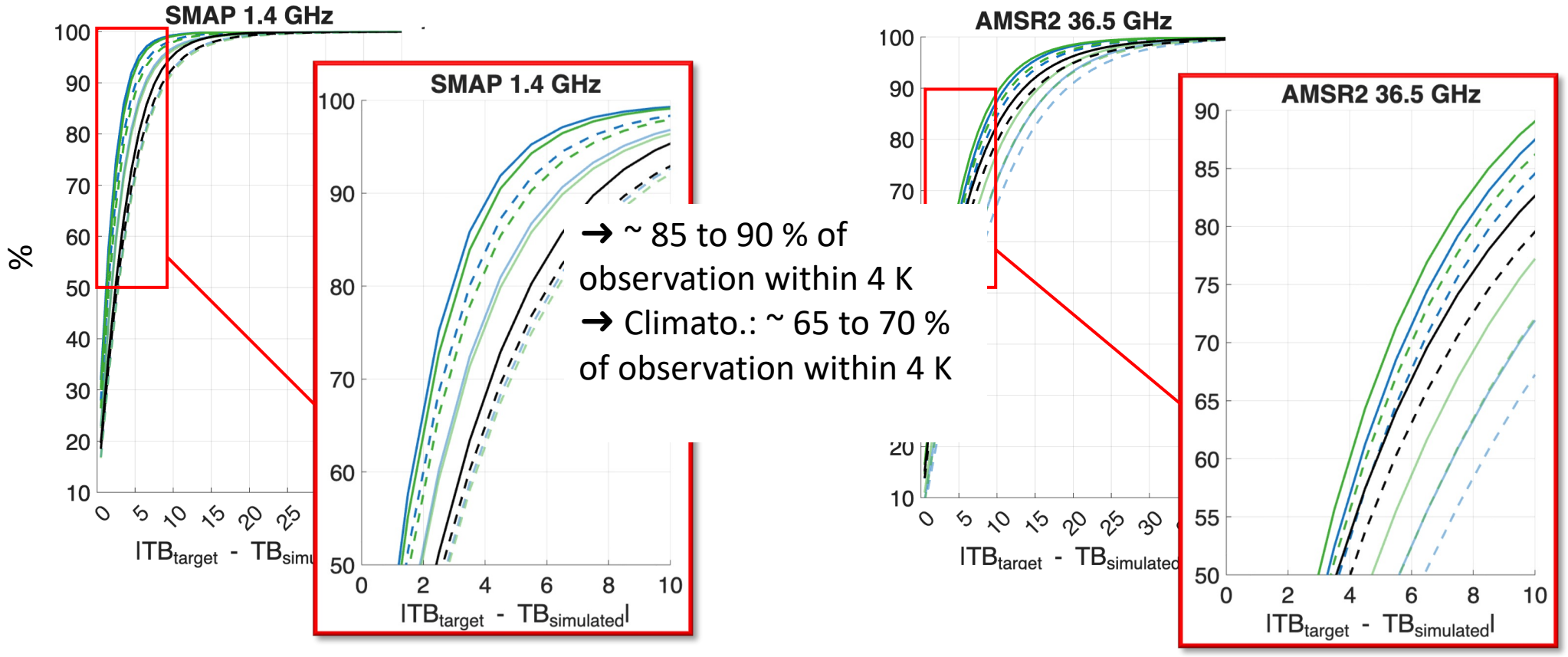
Cumulative fraction of the observed differences below the threshold on the x-axis.



Snow emissivity parameterization: Statistic on errors



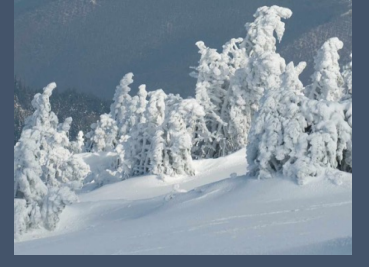
Cumulative fraction of the observed differences below the threshold on the x-axis.



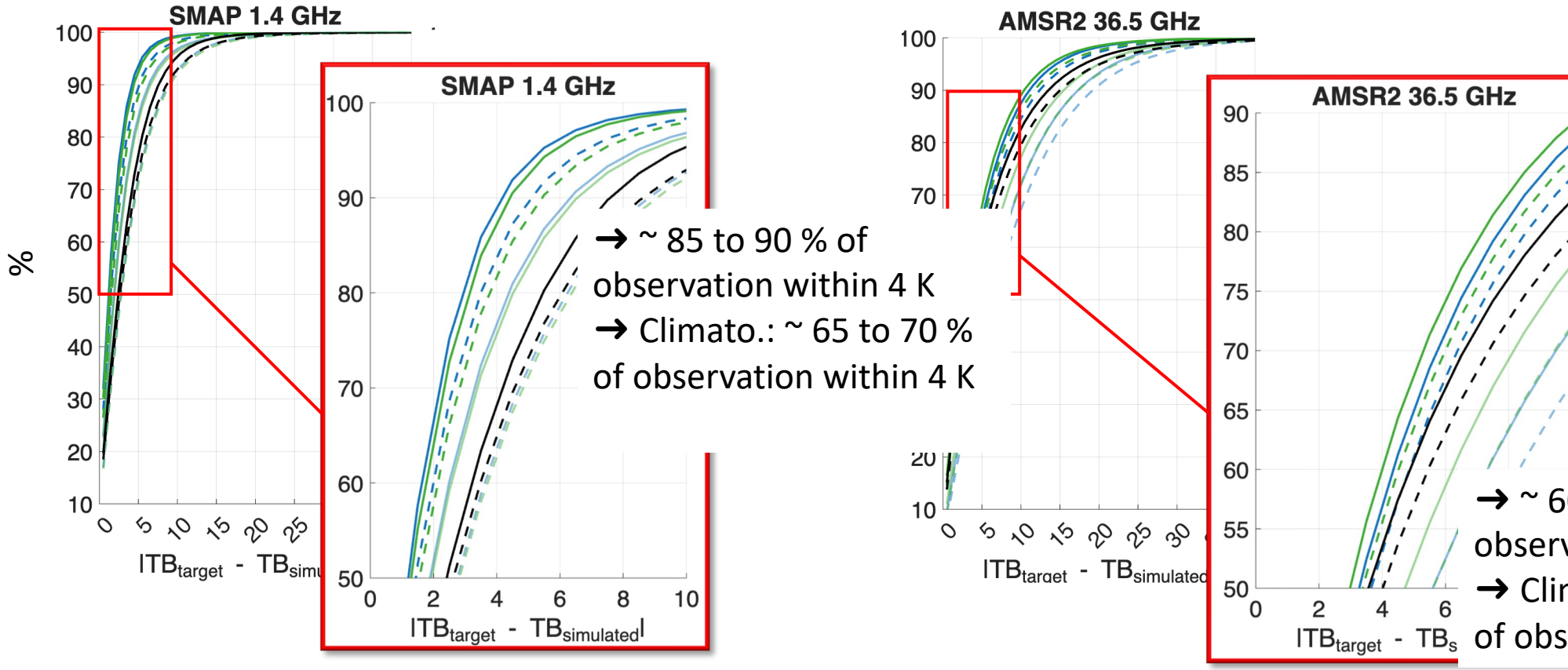
➜ ~ 85 to 90 % of observation within 4 K

➜ Climato.: ~ 65 to 70 % of observation within 4 K

Snow emissivity parameterization: Statistic on errors



Cumulative fraction of the observed differences below the threshold on the x-axis.



→ ~ 85 to 90 % of observation within 4 K
→ Climato.: ~ 65 to 70 % of observation within 4 K

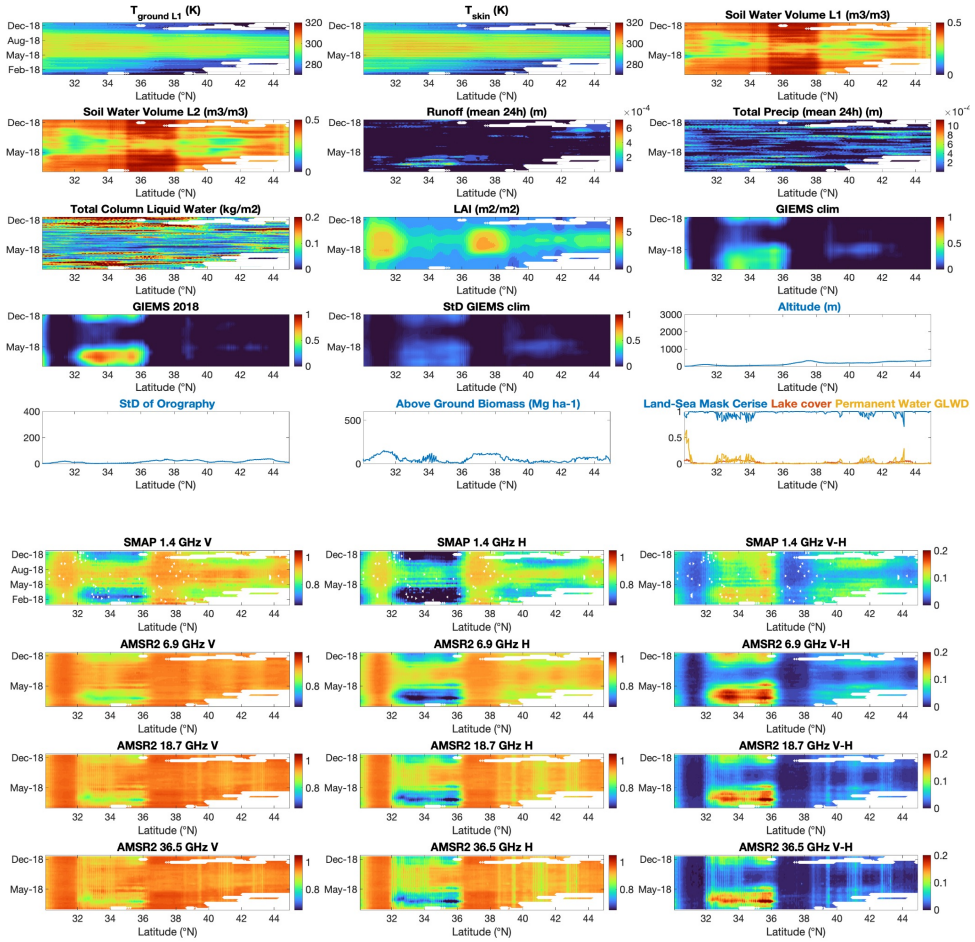
→ ~ 60 to 65 % of observation within 5 K
→ Climato.: ~ 55 to 60% of observation within 5 K

NN 10 parameters ERA5
NN 10 parameters ERA5 + clim.
NN 13 params. ERA6Land prototype
NN 13 params. ERA6Land prototype + clim.
Emissivity climatologies

Land emissivity parameterization: Predictor selection



- **Joint analysis of surface emissivities and potential geophysical predictors:**



⇒ The selected predictors for the land parameterization

Name	Geophysical parameters		
	Vegetation	Water and moisture presence	Other
NN 7 parameters	AGB LAI	**Soil Water Volume L1** GIEMS climatology * Permanent Water GLWD2	StD of Orography **Soil Temperature L1**

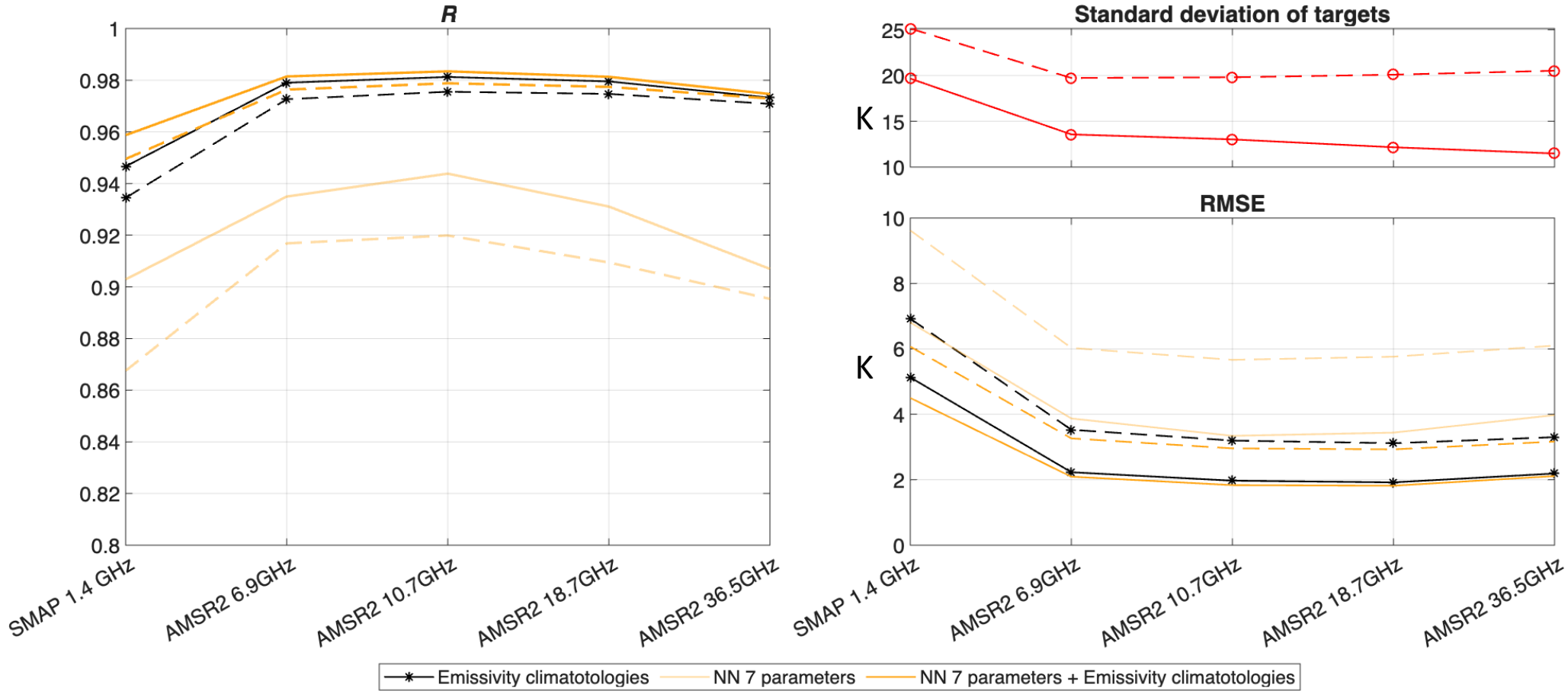
Bold = time-varying
Underlined = monthly climatologies
Regular = fixed.

*GIEMS : open surface water fraction

Land emissivity parameterization: Quantitative results



- Our results with ERA5 as input (back in BT)



- Emissivity climatological information is a very strong baseline
- The quality of the forward model is constrained by the information available in the predictors.

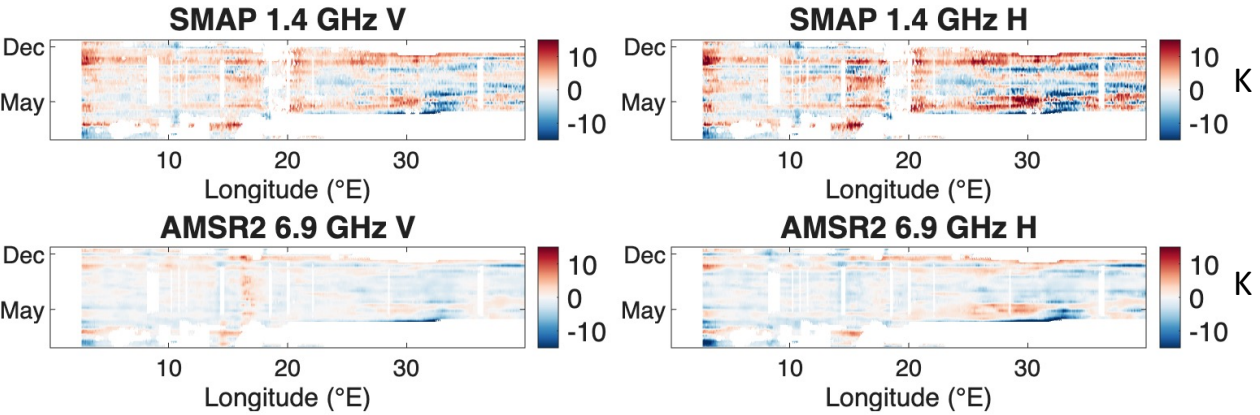
V polarization
H polarization

Land emissivity parameterization: Qualitative results



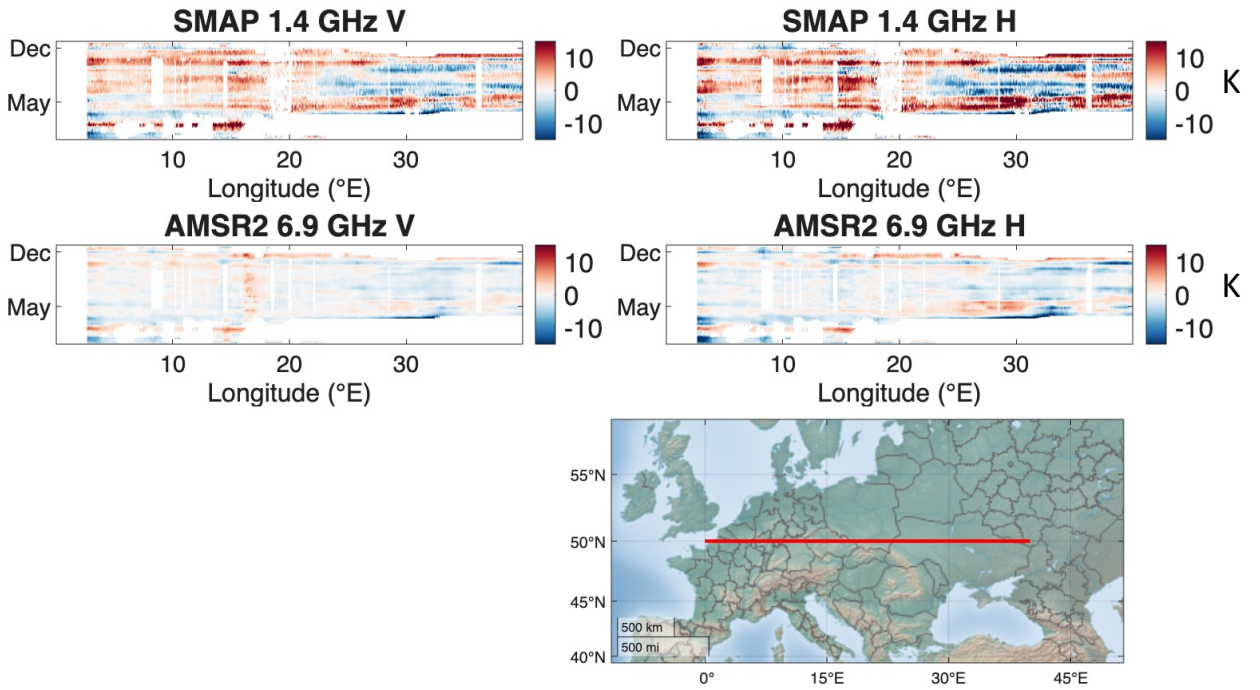
- Hovmöller graph – Differences with observation (back in TB space) – Europe

Target – Retrieval

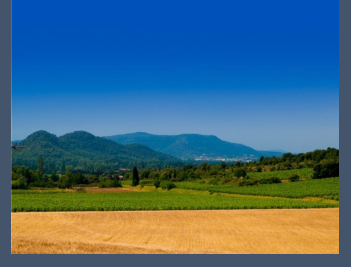


- Some local improvements

Target – Climatology

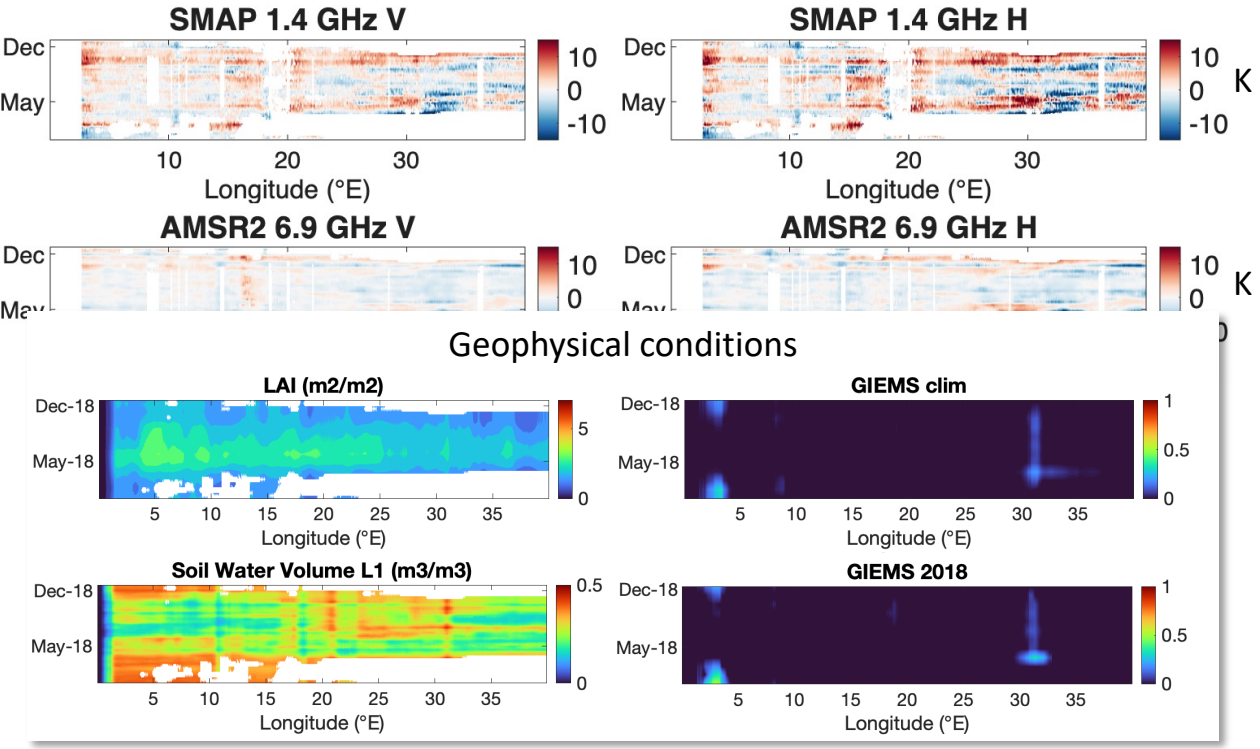


Land emissivity parameterization: Qualitative results

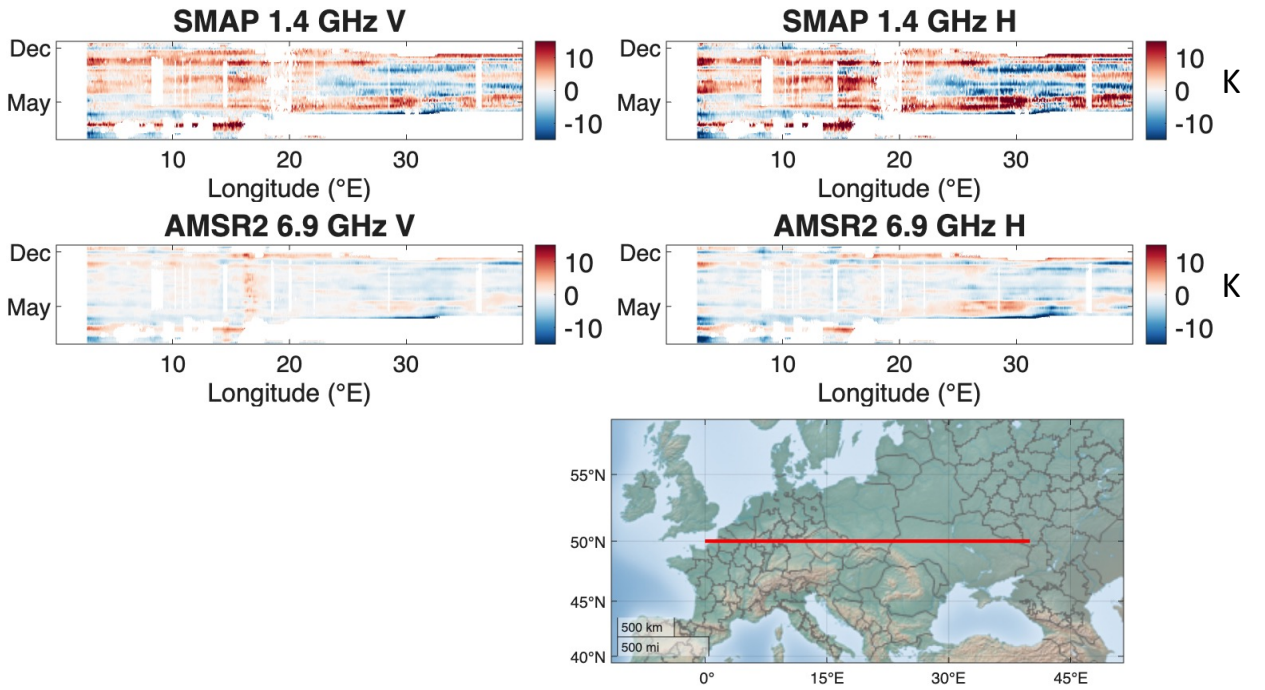


- Hovmöller graph – Differences with observation (back in TB space) – Europe

Target – Retrieval



Target – Climatology



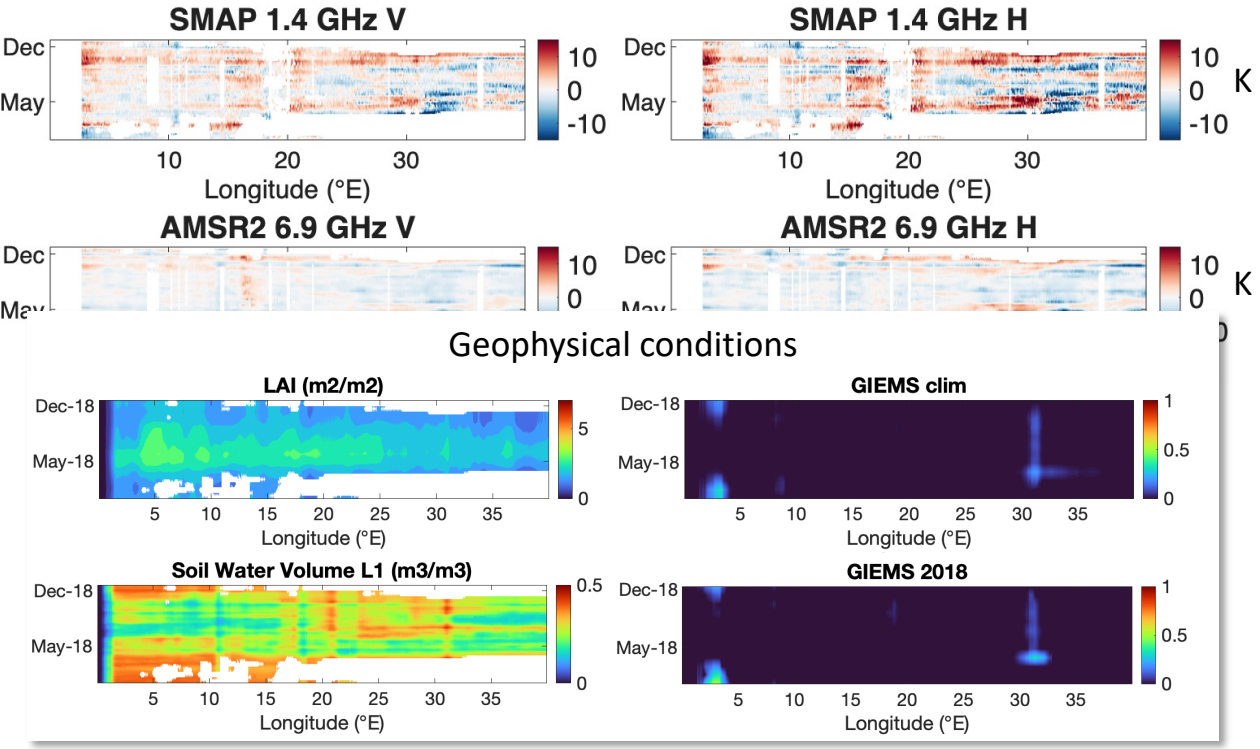
- Some local improvements

Land emissivity parameterization: Qualitative results

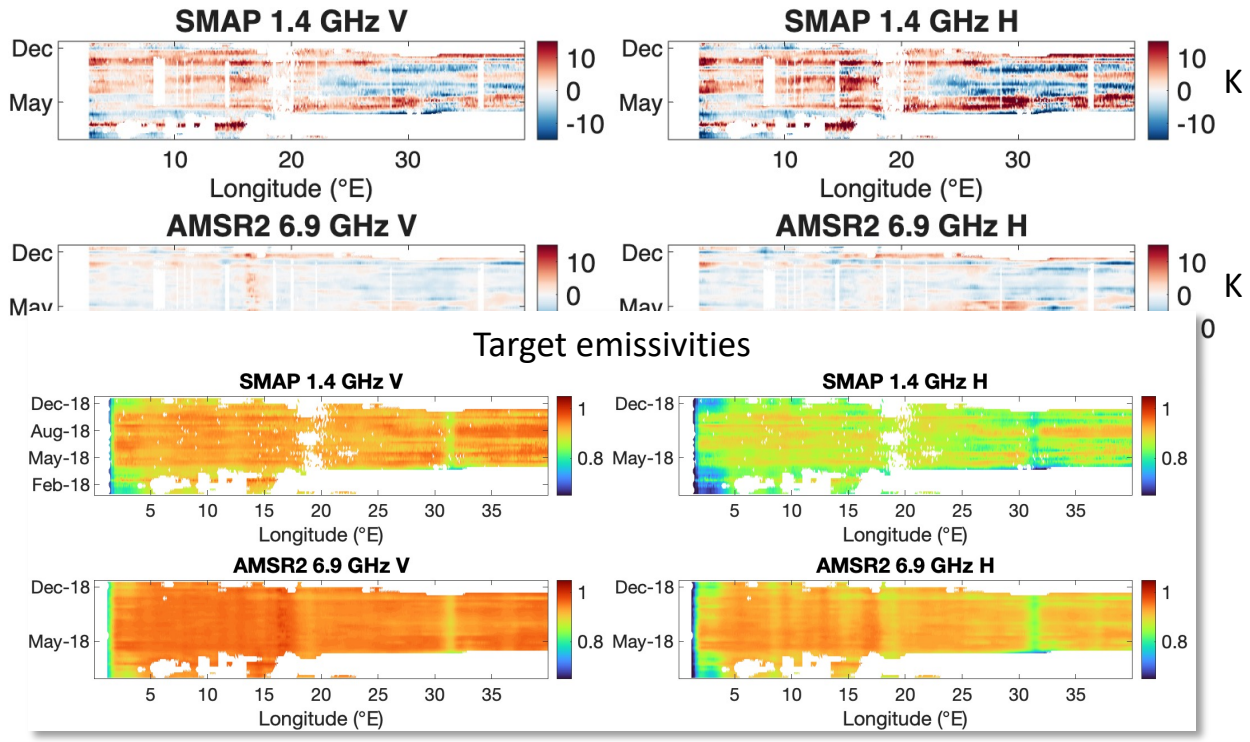


- Hovmöller graph – Differences with observation (back in TB space) – Europe

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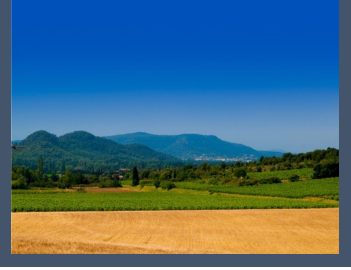


Target – Climatology



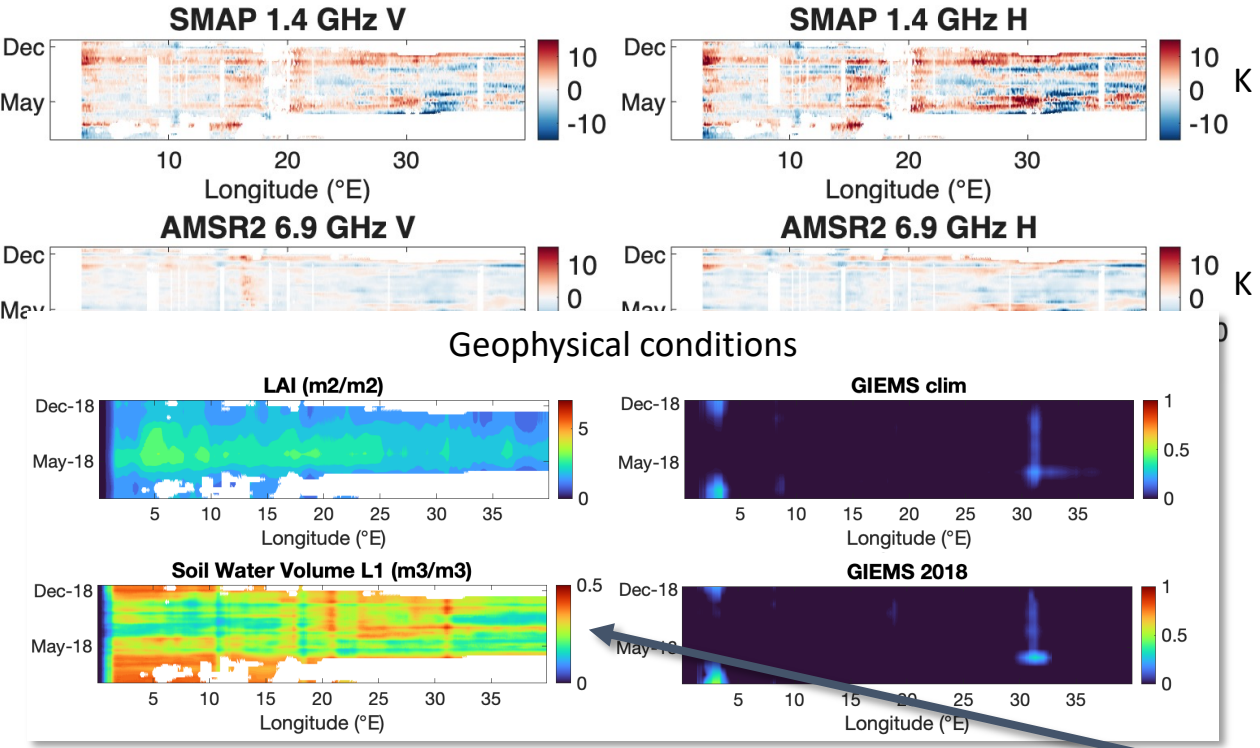
- Some local improvements

Land emissivity parameterization: Qualitative results

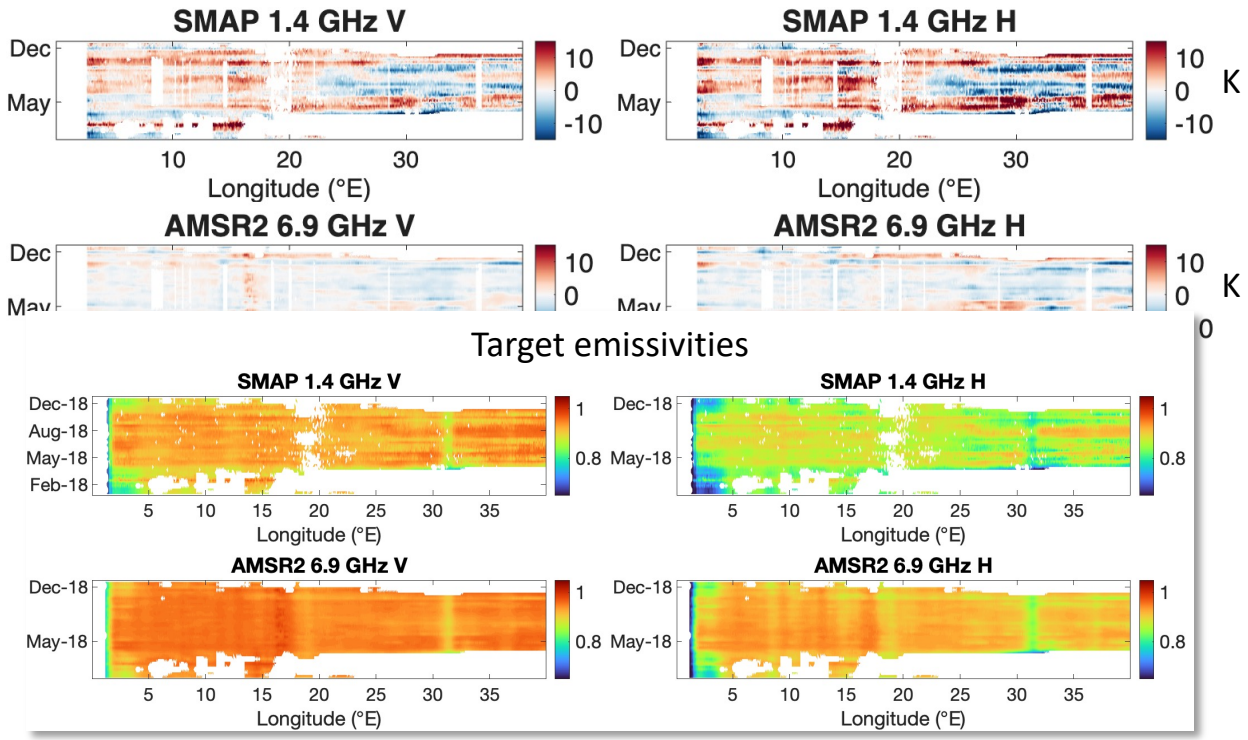


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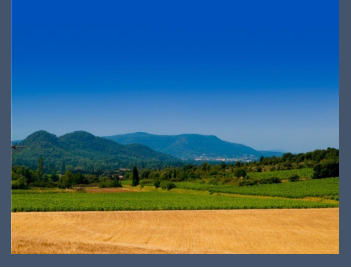
Target – Climatology



- Some local improvements

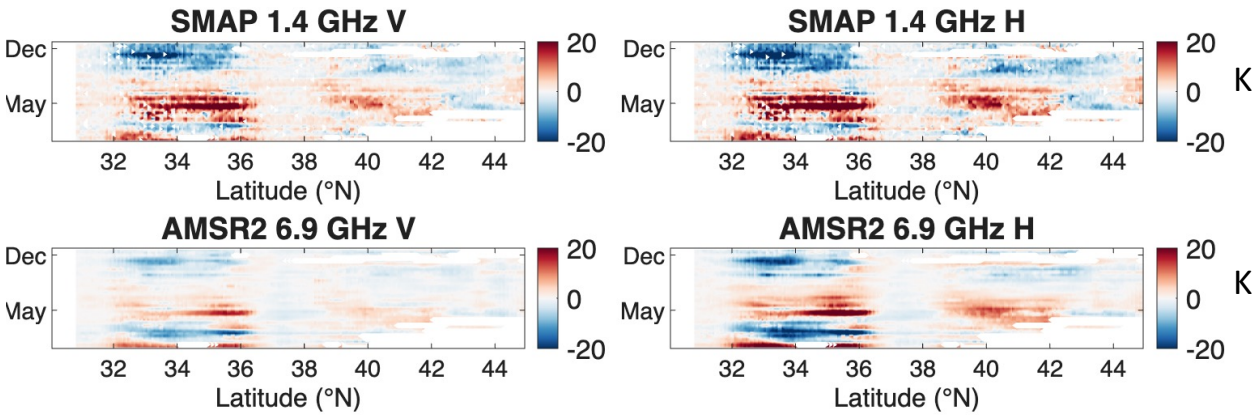
⇒ In this case the key driver of emissivity variability is the soil moisture (time-varying variable)

Land emissivity parameterization: Qualitative results

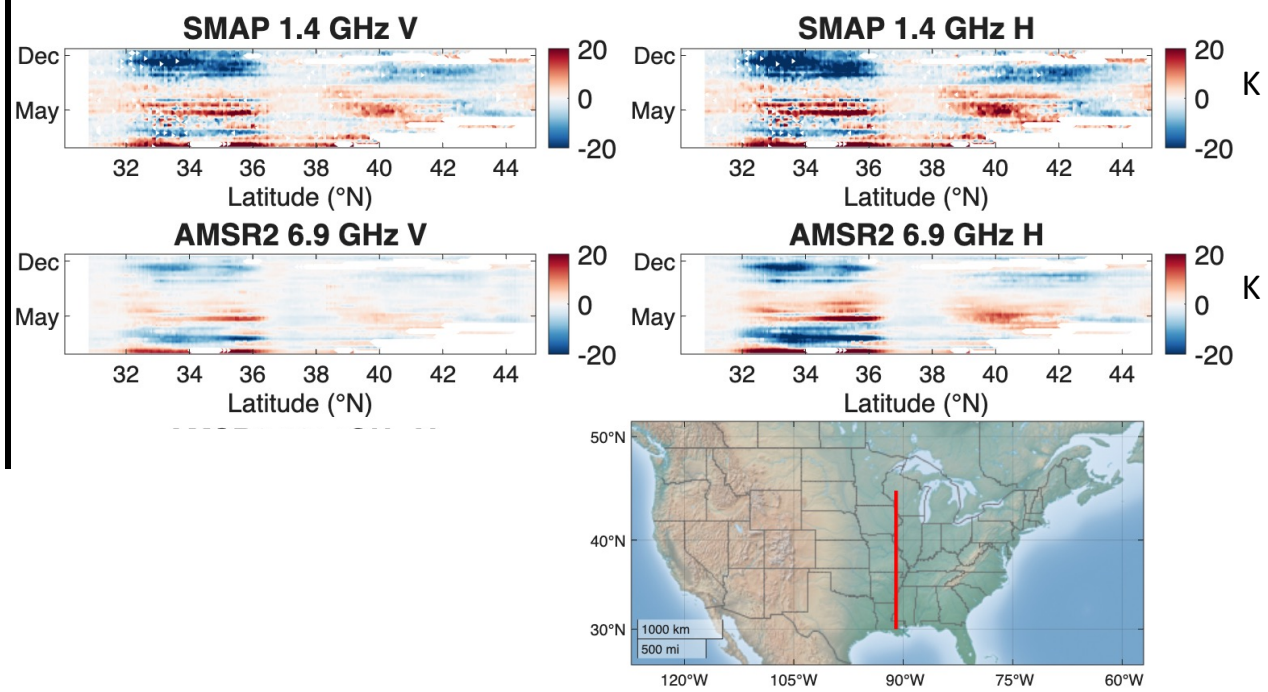


- Hovmöller graph – Differences with observation (back in TB space) – Mississippi area

Target – Retrieval

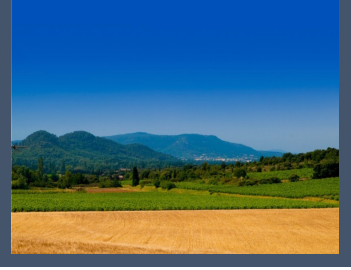


Target – Climatology



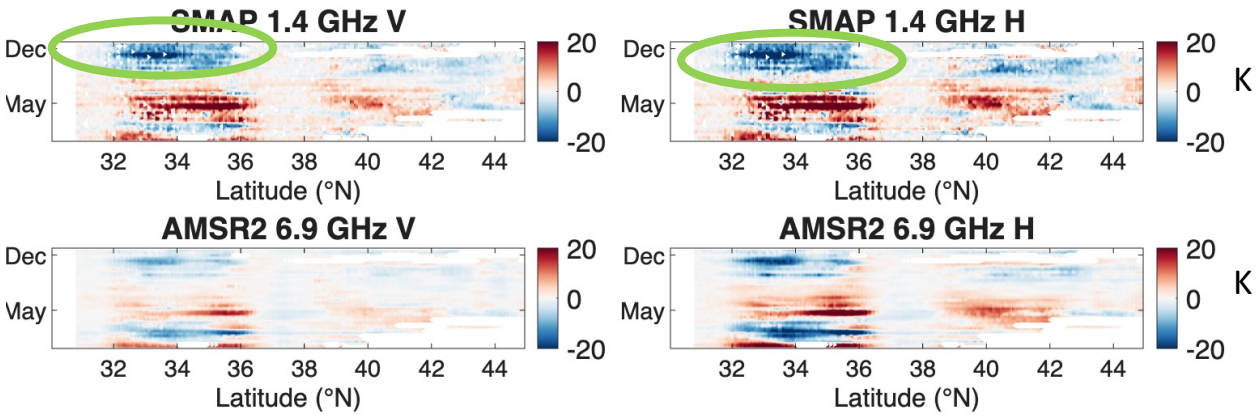
- Some local improvements
- Still large errors, even at higher frequencies

Land emissivity parameterization: Qualitative results

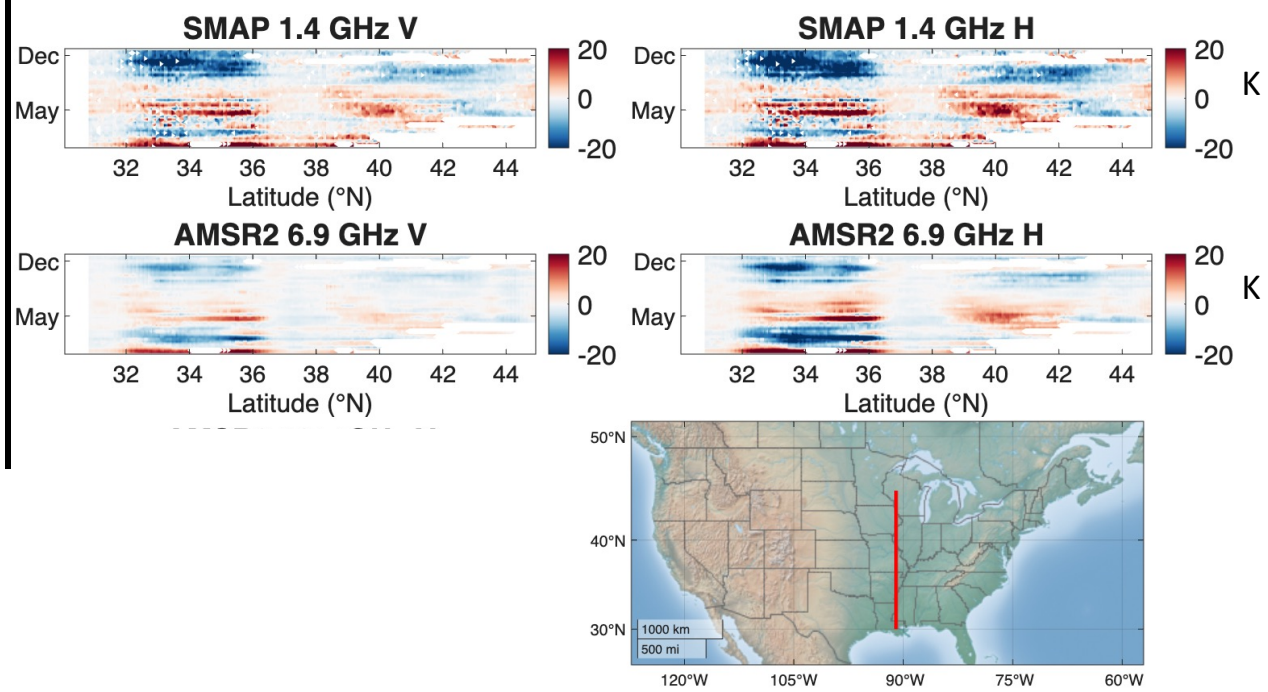


- Hovmöller graph – Differences with observation (back in TB space) – Mississippi area

Target – Retrieval



Target – Climatology



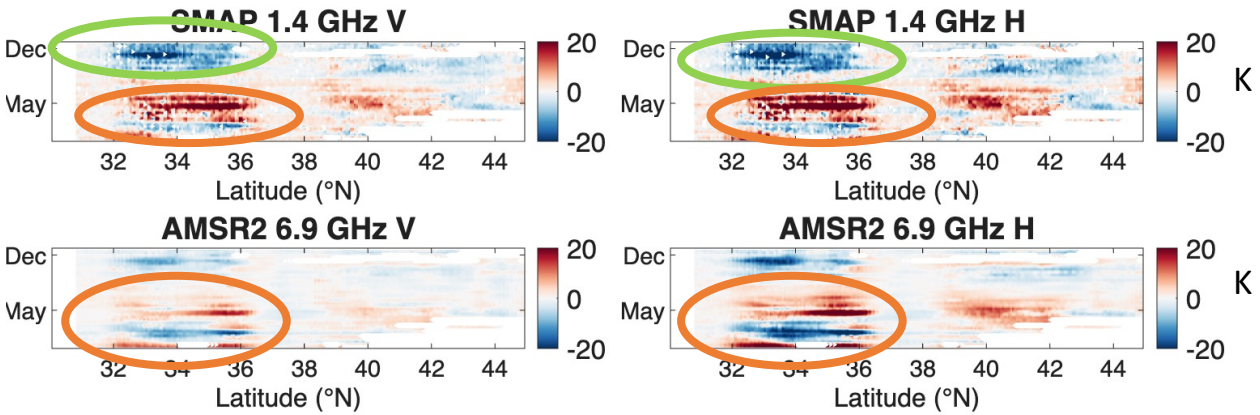
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Land emissivity parameterization: Qualitative results

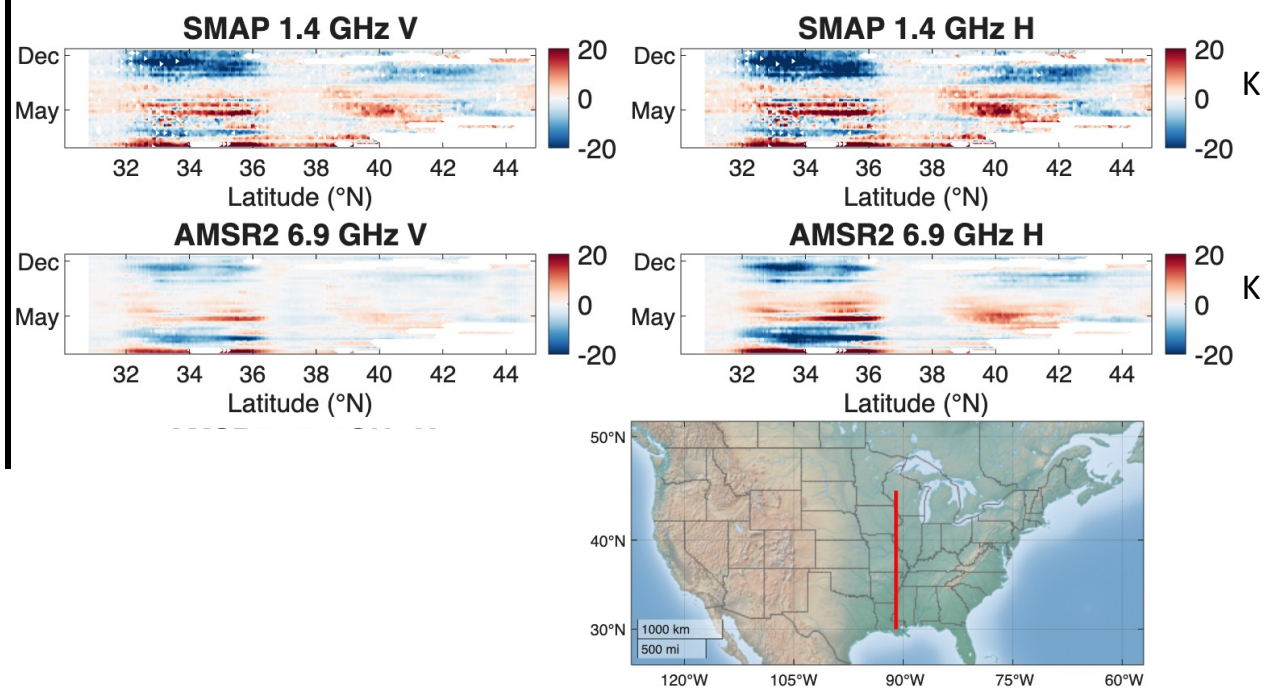


- Hovmöller graph – Differences with observation (back in TB space) – Mississippi area

Target – Retrieval



Target – Climatology



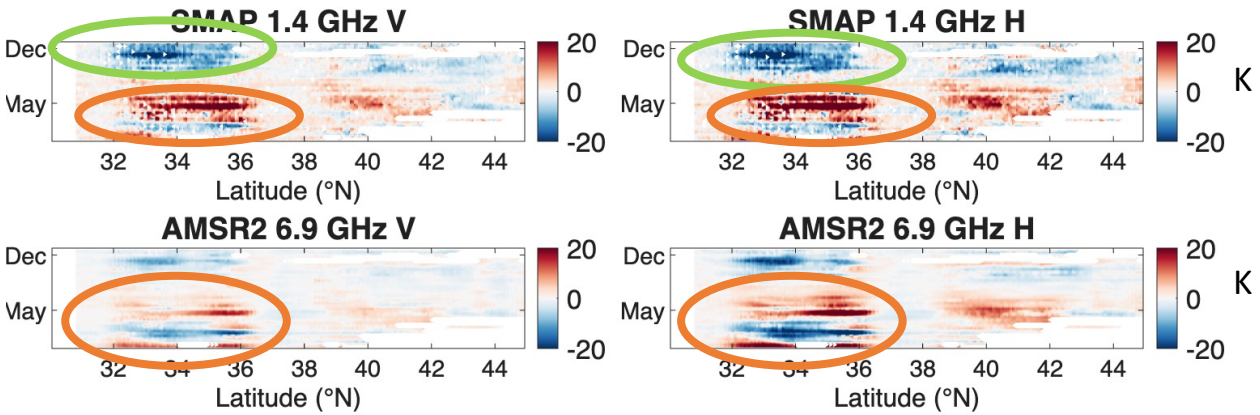
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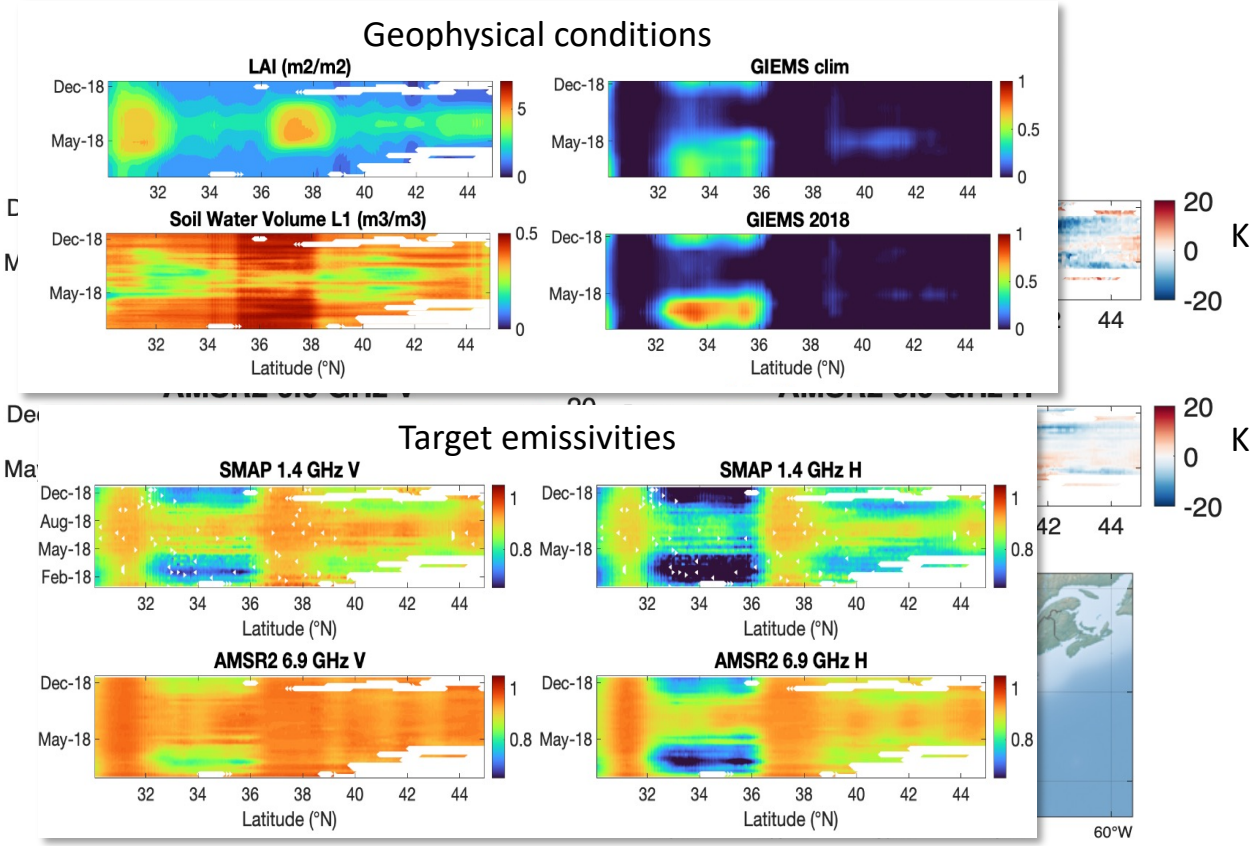
Land emissivity parameterization: Qualitative results



- Hovmöller graph – Differences with observation (back in TB space) – Mississippi area

Target – Retrieval



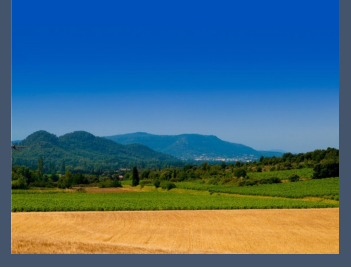


- Some local improvements
- Still large errors, even at higher frequencies

- **Largest errors occur in areas experiencing anomalously high or low flooding:** GIEMS clim. vs. GIEMS 2018.

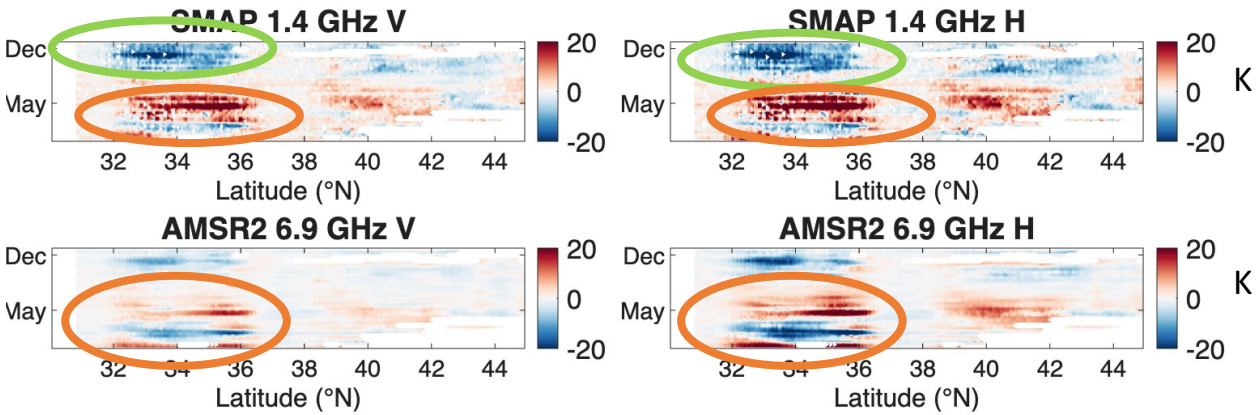
⇒ **Land emissivity variability is not fully represented by the available NWP predictors.**

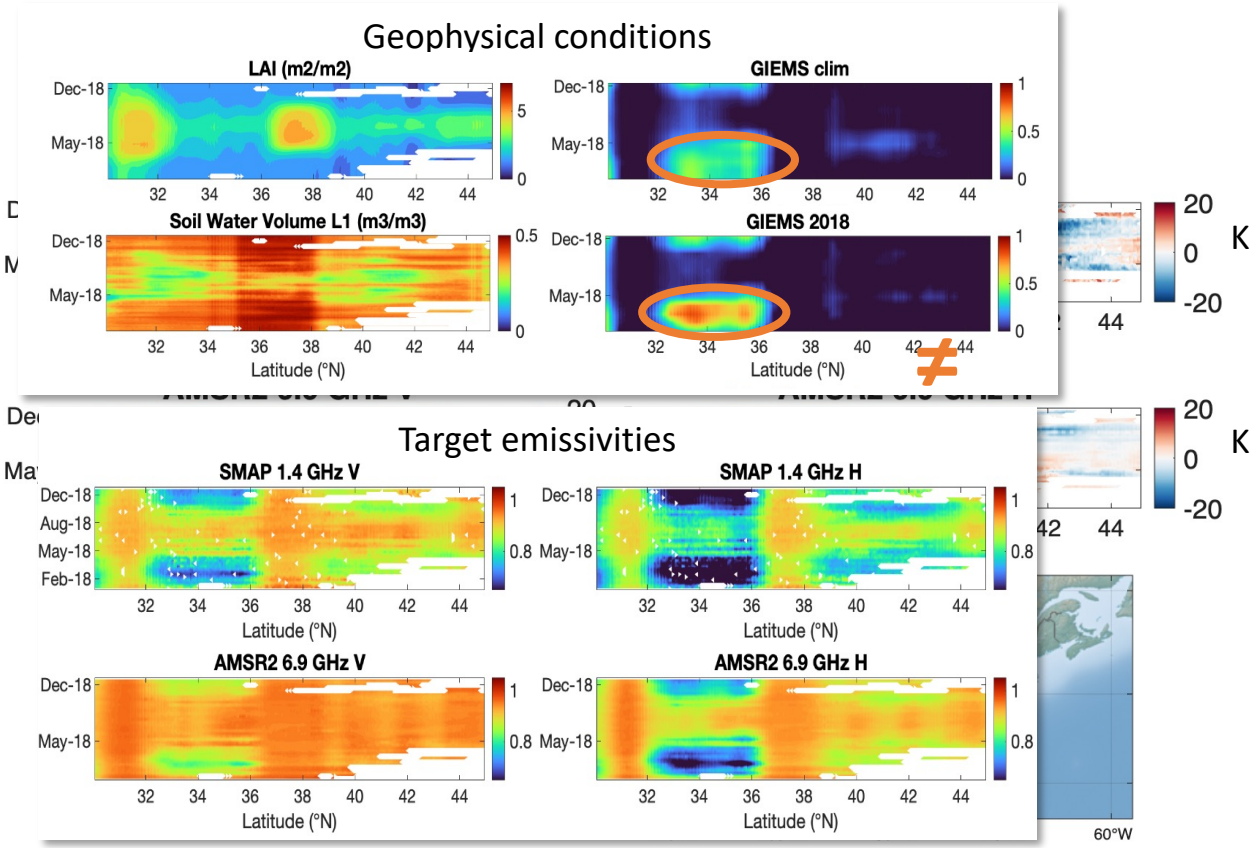
Land emissivity parameterization: Qualitative results



- Hovmöller graph – Differences with observation (back in TB space) – Mississippi area

Target – Retrieval





- Some local improvements
- Still large errors, even at higher frequencies

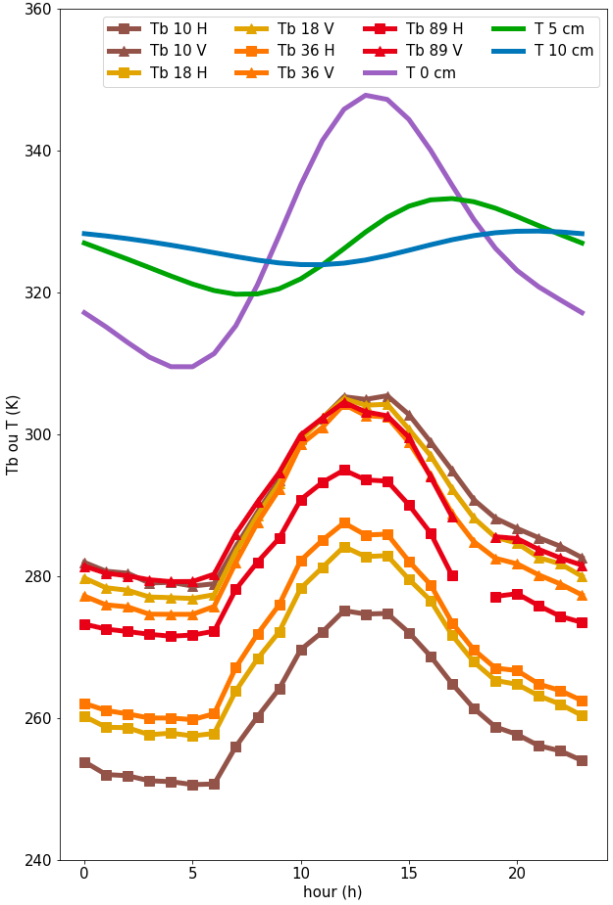
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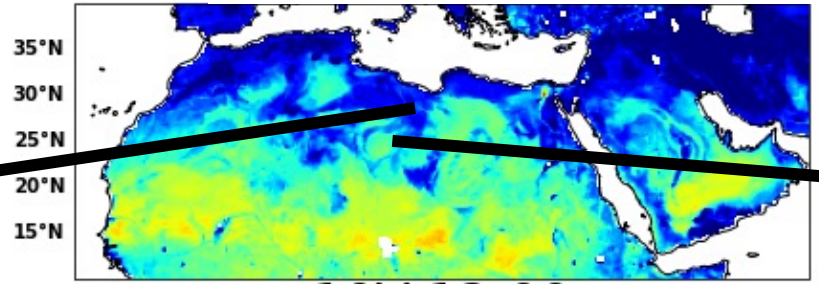
Subsurface emission over arid surfaces



- **High penetration depth not only at 1.4 GHz…**

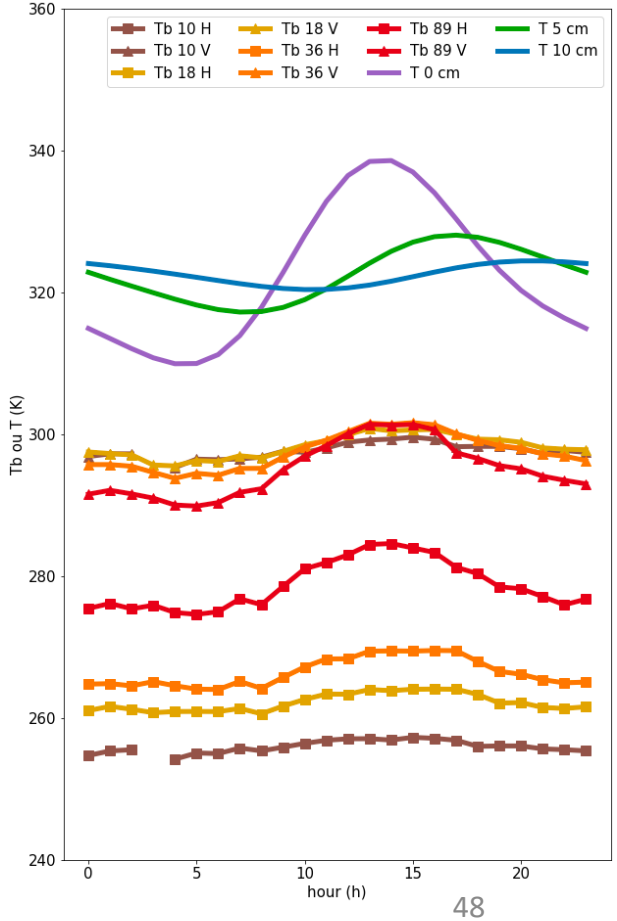


TBs V-pol 10 GHz at 6:00



Diurnal cycles of the **temperature** at the surface and in the sub-surface

Diurnal cycles of the **microwave TBs** from 10 to 89 GHz



Subsurface emission over arid surfaces



- **High penetration depth not only at 1.4 GHz**
  → must be accounted for when estimating the **emissivity**.

$$T_B = \underbrace{T_{surf} \times \epsilon \times \tau}_{1} + \underbrace{T_{atm}^{\downarrow} \times (1-\epsilon) \times \tau}_{2} + \underbrace{T_{atm}^{\uparrow}}_{3}$$

T_B Observed brightness temperature

ϵ Emissivity

$T_{surf_{eff}}$ Surface temperature

Based on ECMWF reanalysis (ERA5), interpolated at satellite swath and time

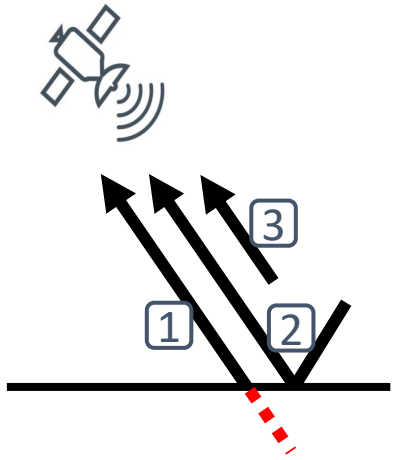
→ No penetration assumption

$T_{atm}^{\downarrow}$ Downwelling atmospheric BT

$T_{atm}^{\uparrow}$ Upwelling atmospheric BT

τ Atmospheric transmission

Rosenkranz (2017) : Based on atmospheric meteorological values from ERA5 (interpolated at satellite swath and time)

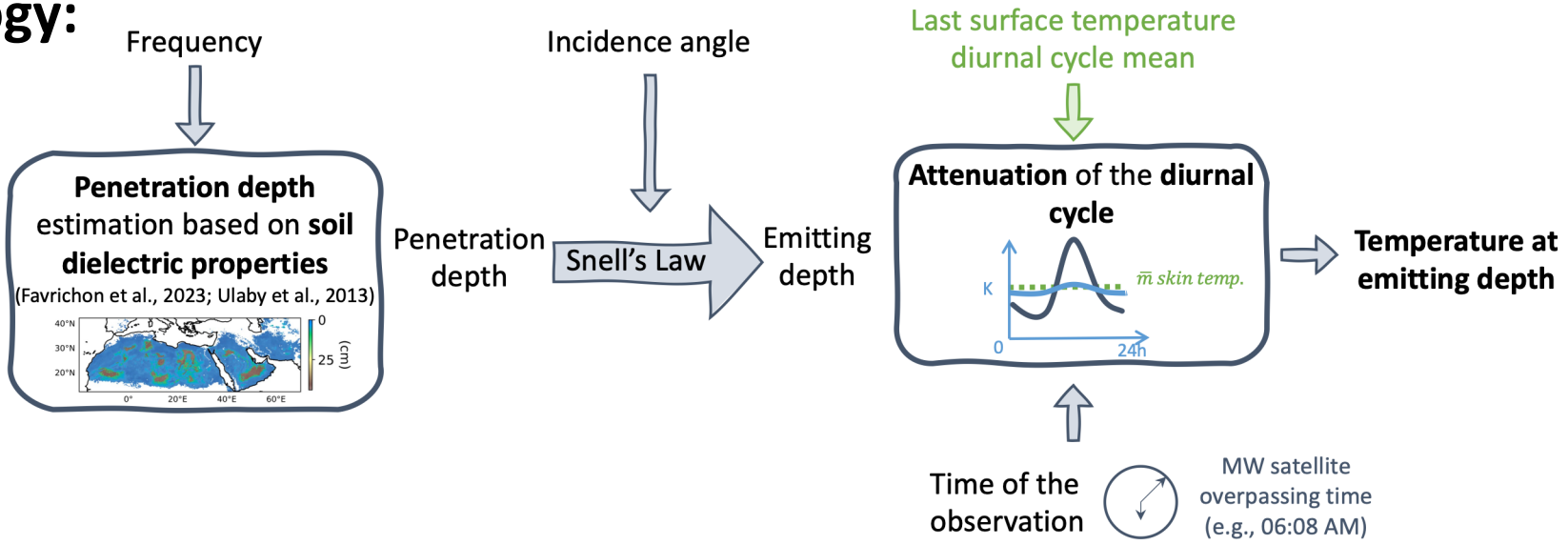


$$\Rightarrow \epsilon_{eff} = \frac{T_B - T_{atm}^{\uparrow} - T_{atm}^{\downarrow} \times \tau}{(T_{surf_{eff}} - T_{atm}^{\downarrow}) \times \tau}$$

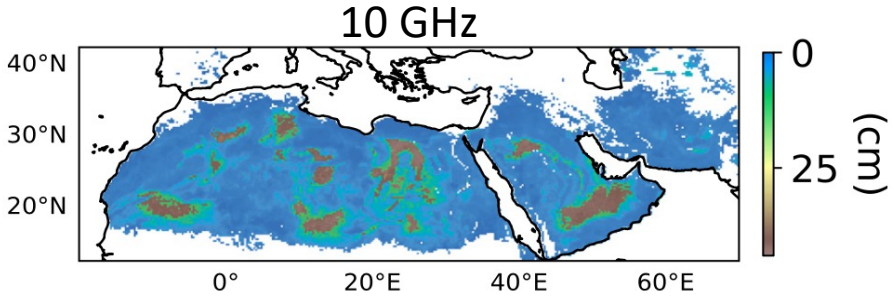
Arid-surface emissivity retrieval

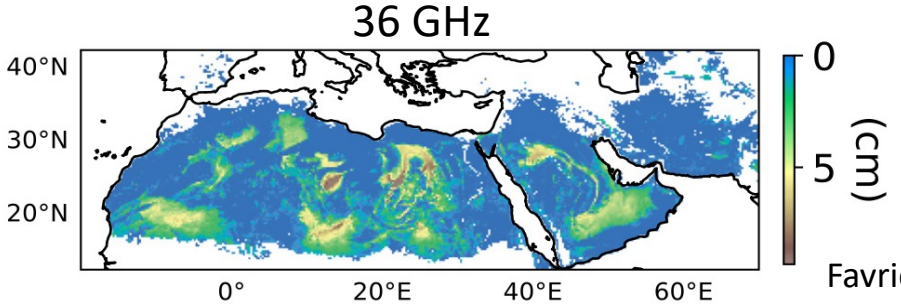


- **High penetration depth not only at 1.4 GHz**
  → must be accounted for when estimating the **emissivity**.
- **Methodology:**



Penetration depth examples:





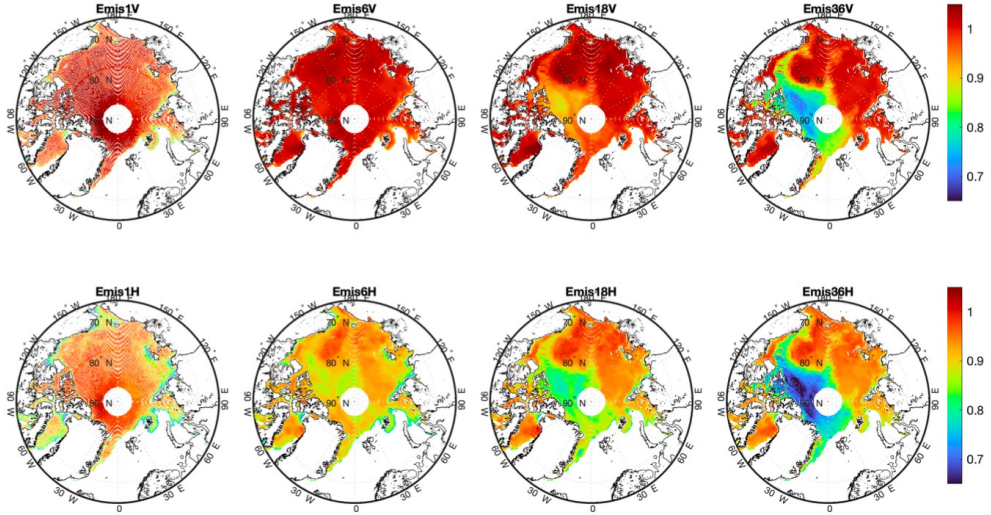
Favrichon et al., 2023

Sea Ice emissivity parameterization: Emissivity and geophysical predictors analysis



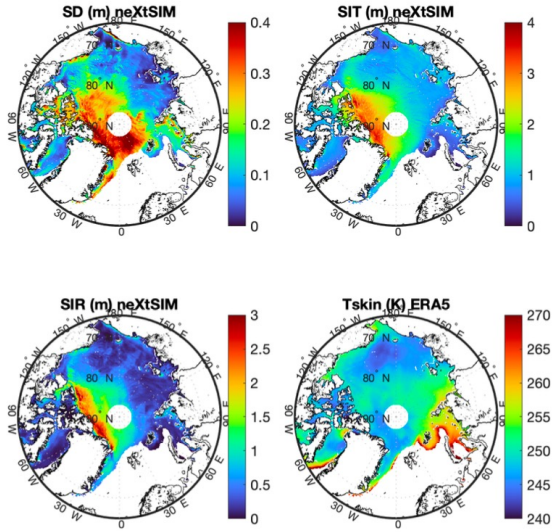
- **Input dataset**: **neXtSIM** (NERSC) outputs are used to complement the sea-ice information missing from ERA5

21-31 December 2018



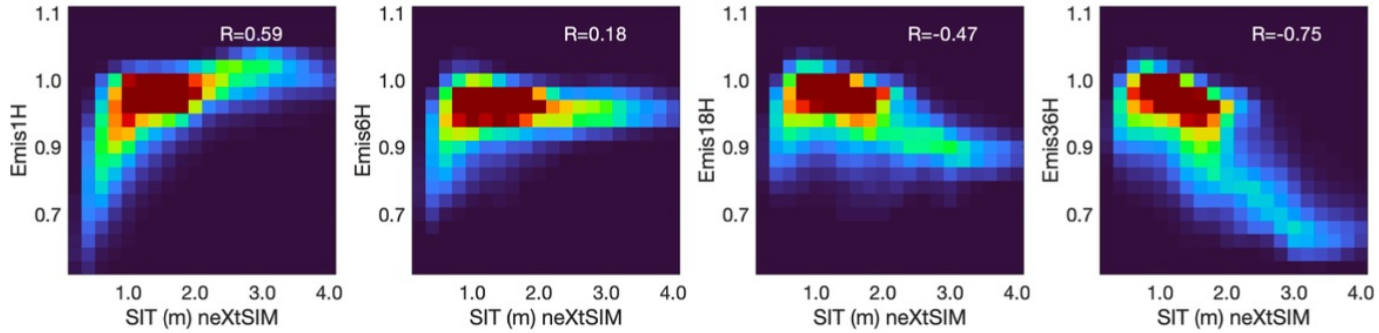
Satellite-derived emissivity

21-31 December 2018



Geophysical inputs from neXtSIM and ERA5

Correlation with sea ice thickness:

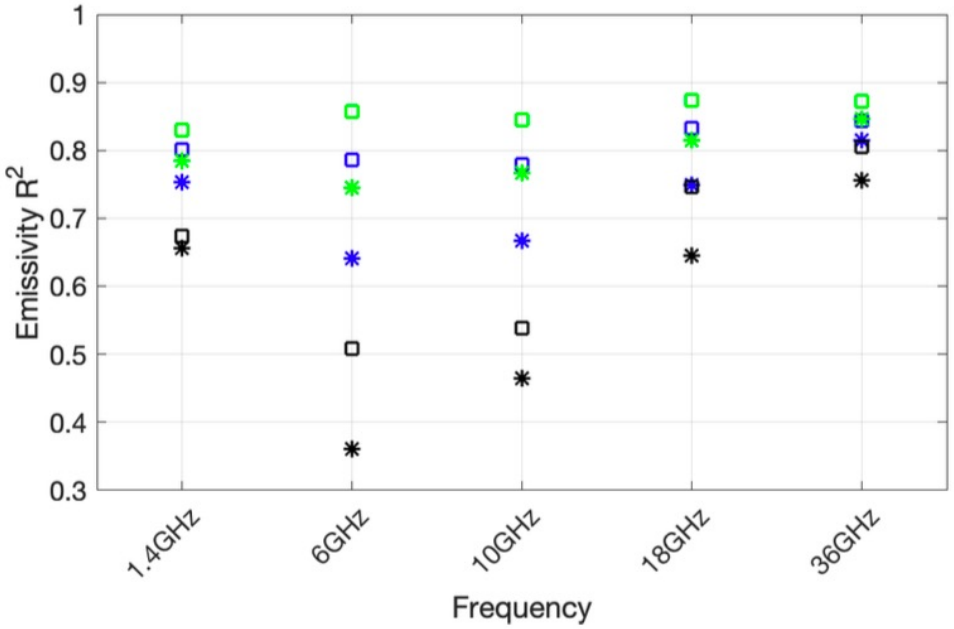


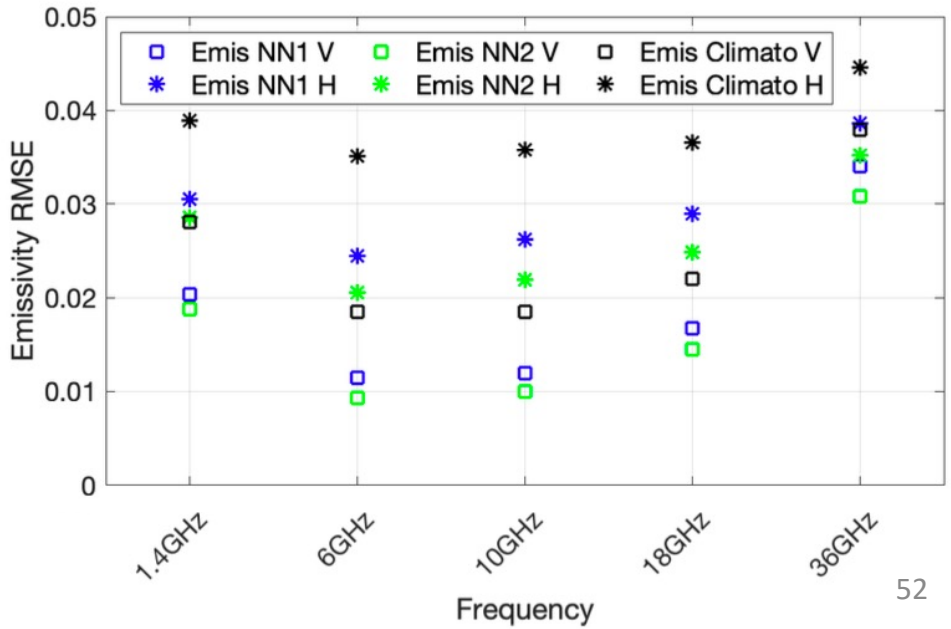
Sea Ice emissivity parameterization: Results



⇒ The selected predictors for the sea ice parameterization

Name	Geophysical parameters		
	ERA5	neXtSIM	Others
NN Geo 1	Sea Ice Skin T° Total Colum Water Vapor	Sea Ice Thickness Snow Depth	
NN Geo 2	Sea Ice Skin T° Total Colum Water Vapor	Sea Ice Thickness Snow Depth **Ridge Ratio**	**Winter day**





Sea Ice thickness parameterization



Sea Ice Thickness from passive microwaves

- CIMR frequency assessment using CIMR-like SMAP and AMSR2 data
- Large correlation observed between the TBs and the Sea Ice Thickness measured by lidar (ICESat-2)
- NN trained on the lidar Sea Ice Thickness from ICESat-2 using CIMR-like data

Earth and Space Science

RESEARCH ARTICLE
10.1029/2022EA002542

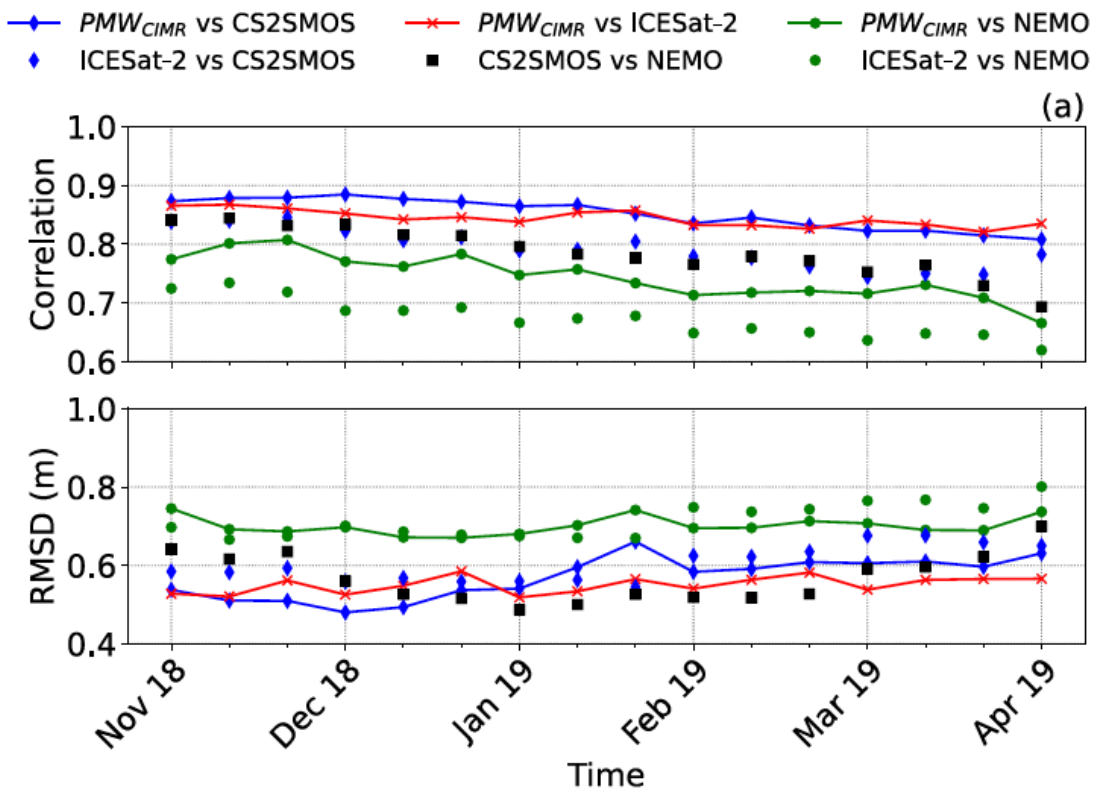
Arctic Sea Ice Thickness Estimation From Passive Microwave Satellite Observations Between 1.4 and 36 GHz

Clément Soriot[1], Catherine Prigent[1,2], Carlos Jimenez[1,2], and Frédéric Frappart[3]

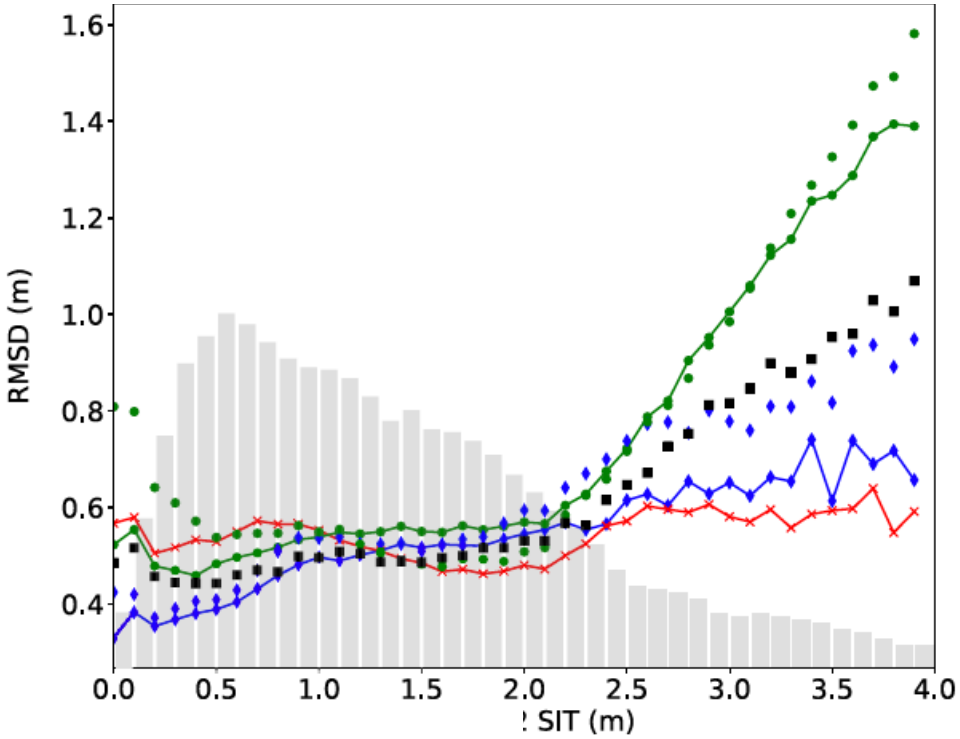
[1]LERMA, Paris Observatory, CNRS, PSL, Paris, France, [2]Estellus, Paris, France, [3]ISPA, INRAE/Bordeaux Sciences Agro, Bordeaux, France

Key Points:

- High correlation is evidenced over the Arctic between passive microwave (PMW) satellite signatures and sea ice thickness (SIT) derived from lidar and



For all thicknesses:

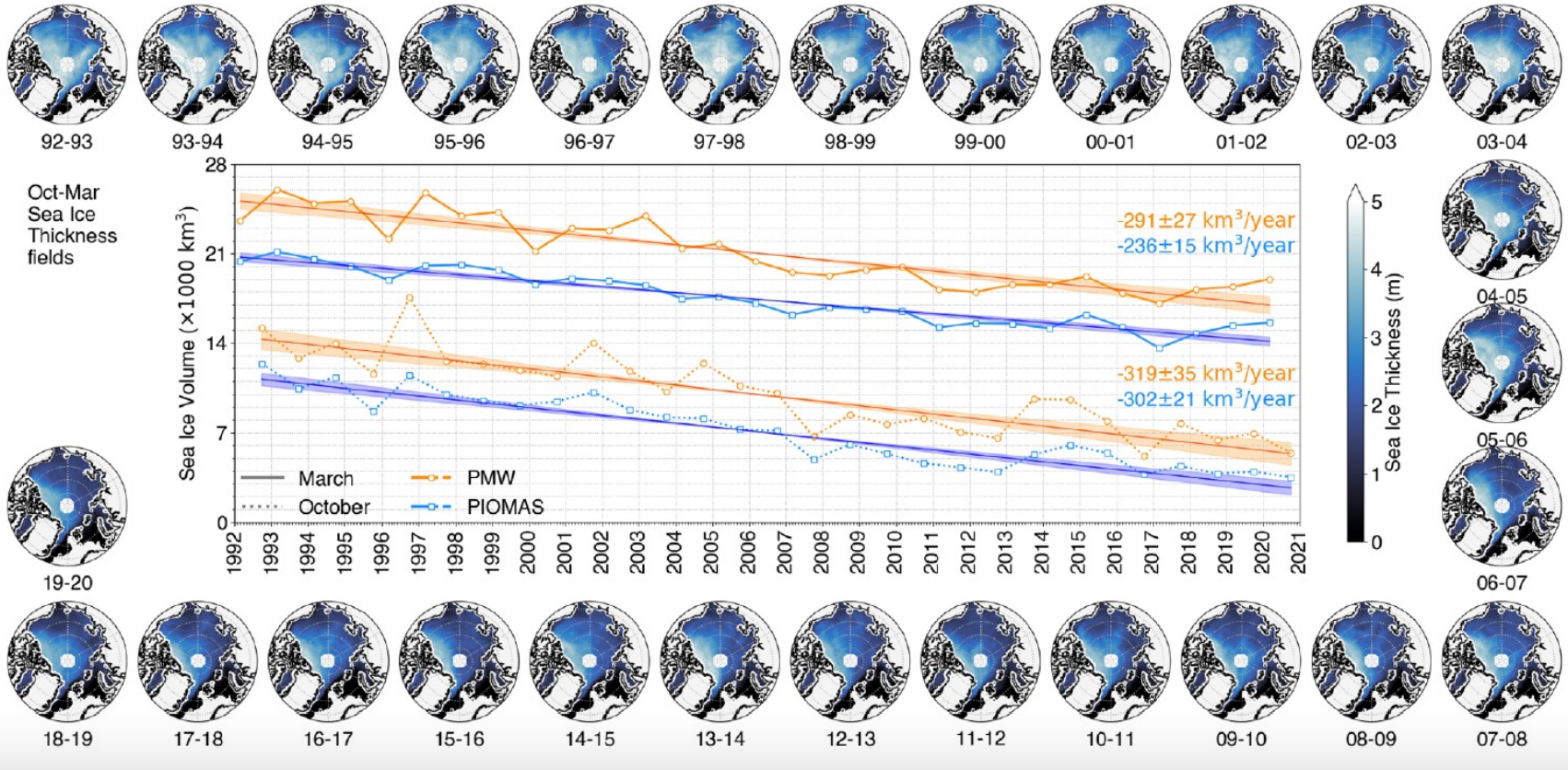


Sea Ice thickness parameterization



Long term time series retrievals:

- Similar method developed with 18 and 36 GHz only (less accuracy)
- Comparison of trends in Sea Ice Volume from model (PIOMAS) and satellite-derived products (SSMI/SSMIS)
- Significant reduction in the uncertainties on the Sea Ice Volume, with respect to the last IPCC report.



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Winter arctic sea ice volume decline: uncertainties reduced using passive microwave-based sea ice thickness

Clement Soriot[1,2✉], Martin Vancoppenolle[3], Catherine Prigent[1,4], Carlos Jimenez[2,4] & Frédéric Frappart[5]

Overall results for heterogeneous surfaces

ML parameterization, anchored to geophysical predictors



- Large improvement over emissivity climatologies

RMSE

- Up to 18 GHz: <0.02 (< 5 K in TB)
- Higher freq.: <0.03 (< 8 K in TB)



- Emissivity climatologies already strong baseline
- Local improvement

RMSE

- 1.4 GHz: <0.02 (< 6 K in TB)
- Higher freq.: <0.01 (< 3 K in TB)



- Based on neXtSIM for inputs
- Good performance without emissivity climatologies as input

RMSE

- Up to 18 GHz: <0.025 (< 5 K in TB)
- Higher freq.: <0.035 (< 9 K in TB)







Conclusions









Observation characteristics

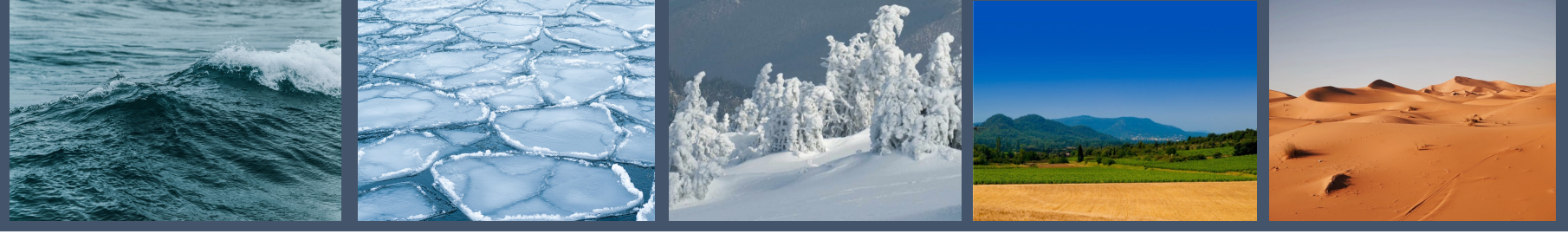
Geophysical parameters



Forward interface operator

Microwave emissivities

Conclusions



Over ocean

- **Physically-based emissivity models are robust.**

- **Fast emissivity models derived from physical models, using ML.**

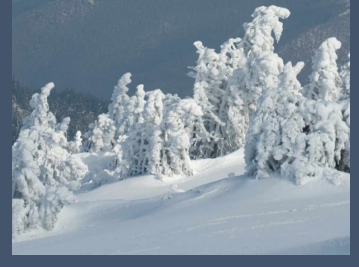
Over sea ice, snow and land

- **Physically-based emissivity models still very challenging** for large scale applications, under multiple instrument conditions.

- **Physics-aware ML parameterization of the surface emissivity** anchored to satellite-derived emissivity, as a function geophysical variables representing the surface.

A ML parameterization of emissivity







Operator	Frequency	Incidence Angle	Polarization	Status
SURFEM-Ocean	0.5-700 GHz	0-90°	4 Stokes	RTTOV
SURFEM-Sea Ice	1-90 GHz	0-90°	V, H	Available
SURFEM-Snow	1-90 GHz	0-90°	V, H	Available
SURFEM-Land	1-90 GHz	55°	V, H	Under test

→ Earth and Space Science

RESEARCH ARTICLE
10.1029/2022EA002785

Key Points:
- An international team of experts has converged on the selection of a Passive and Active Reference Microwave to Infrared Ocean model

Development of the SURface Fast Emissivity Model for Ocean (SURFEM-Ocean) Based on the PARMIO Radiative Transfer Model

Lise Kilic[1,2], Catherine Prigent[1,2], Carlos Jimenez[1,2], Emma Turner[3], James Hocking[3], Stephen English[4], Thomas Meissner[5], and Emmanuel Dinnat[6]

→ Earth and Space Science

RESEARCH ARTICLE
10.1029/2025EA004259

Key Points:
- Physical modeling of sea ice microwave emissivities is challenging: a pragmatic solution is proposed, using satellite-derived emissivities

Parameterization of the Winter Arctic Sea Ice Microwave Emissivity Between 1.4 and 36 GHz, for Large Scale Applications

Lise Kilic[1,2], Carlos Jimenez[1,2], Catherine Prigent[1,2], Anton Korosov[3], Pierre Rampal[4], Iris de Gelis[1,2], and Gilles Garric[5]

→ Contents lists available at ScienceDirect
Remote Sensing of Environment
journal homepage: www.elsevier.com/locate/rse

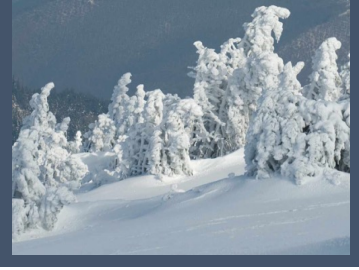
Forward modelling of passive microwave emissivities over snow-covered areas at continental scale

Iris de Gélis[a,b,*], Catherine Prigent[b,a], Carlos Jimenez[a,b], Melody Sandells[c]

→ de Gélis et al., in preparation

Next plans



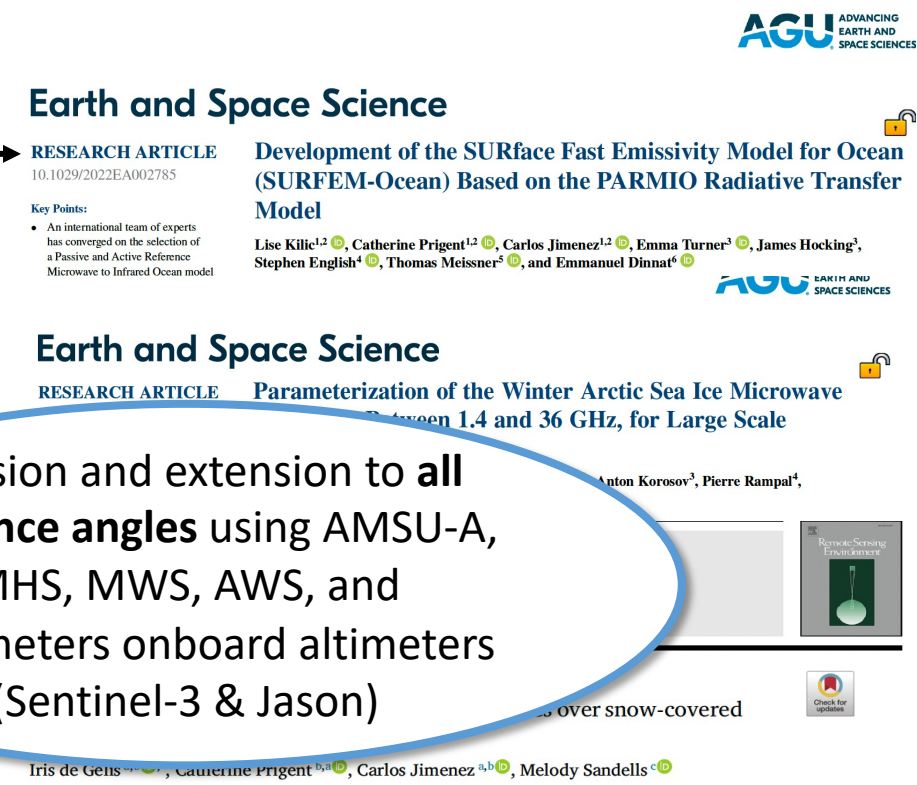




Operator	Frequency	Incidence	Polarization	Status
SURFEM-Ocean	0.5-[illegible]			RTTOV
SURFEM-Sea Ice	1-90 Ghz	0-90°	V, H	Available
SURFEM-Snow	1-90 Ghz	0-90°	V, H	
SURFEM-Land	1-90 Ghz	55°	V, H	Under test → de Gélis et al., in preparation

Extension toward **higher frequencies** using AMSR3, MHS, MWS, AWS

Revision and extension to **all incidence angles** using AMSU-A, MHS, MWS, AWS, and radiometers onboard altimeters (Sentinel-3 & Jason)


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Earth and Space Science

RESEARCH ARTICLE
10.1029/2022EA002785

Development of the SURface Fast Emissivity Model for Ocean (SURFEM-Ocean) Based on the PARMIO Radiative Transfer Model

Key Points:
- An international team of experts has converged on the selection of a Passive and Active Reference Microwave to Infrared Ocean model

Lise Kilic[1,2], Catherine Prigent[1,2], Carlos Jimenez[1,2], Emma Turner[3], James Hocking[3], Stephen English[4], Thomas Meissner[5], and Emmanuel Dinnat[6]

AGU EARTH AND SPACE SCIENCES

Earth and Space Science

RESEARCH ARTICLE

Parameterization of the Winter Arctic Sea Ice Microwave [illegible] between 1.4 and 36 GHz, for Large Scale

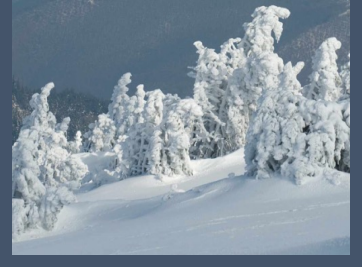
[illegible] Anton Korosov[3], Pierre Rampal[4],

[illegible] over snow-covered

Iris de Gelis [illegible], Catherine Prigent [b,a], Carlos Jimenez [a,b], Melody Sandells [c]

A ML parameterization of the emissivity





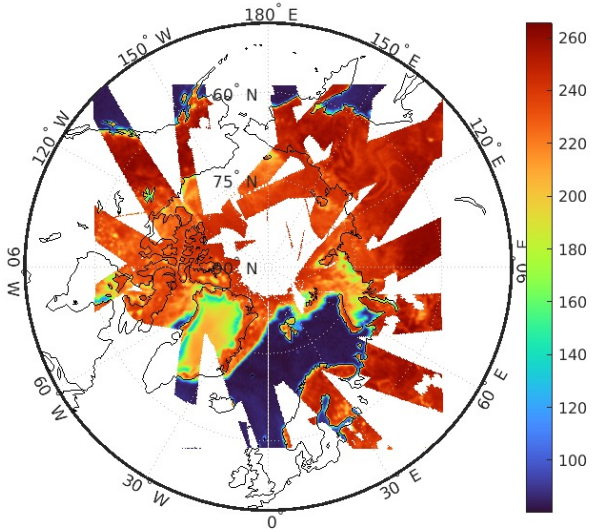


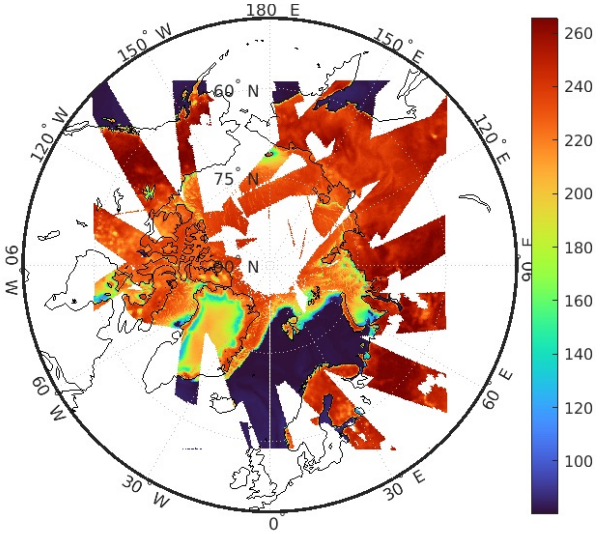
Example over the North pole :

Observations

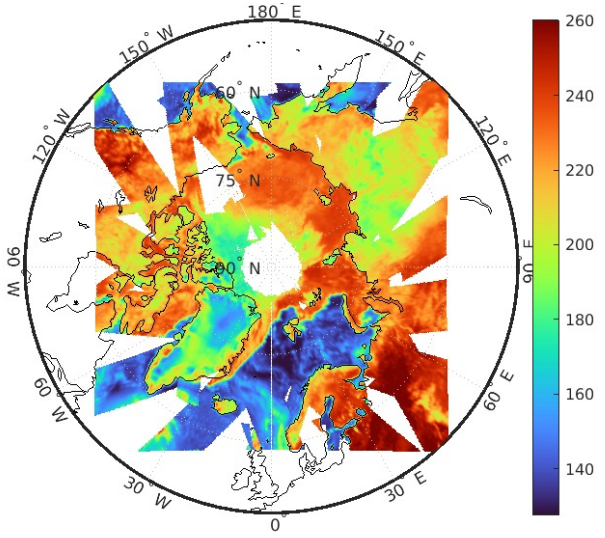
Simulations

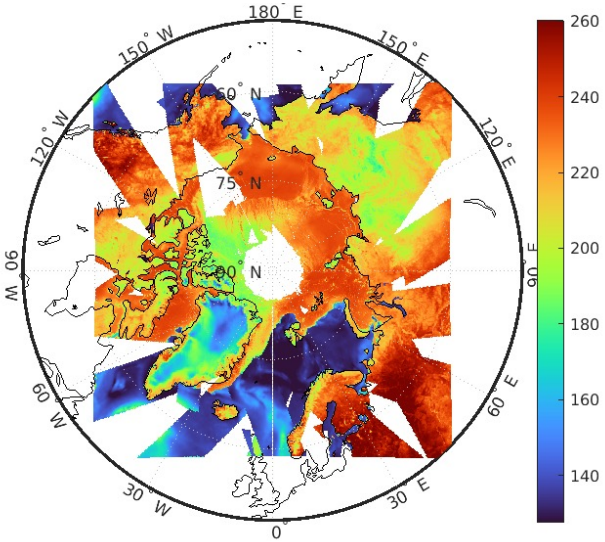
SMAP
Tb 1.4 GHz H (K)





WINDSAT
Tb 37 GHz H (K)





CopERnIcus climate change Service Evolution - CERISE

Funded by the European Union

Coordinated by ECMWF

Thank you!

iris.degelis@obspm.fr





