

RAMI workshop on Radiative Transfer Modelling support to EO metrology and Cal/Val activities

FORUM sensitivity to surface emissivity

Sgattoni C.¹, Ridolfi M.², Sgheri L.¹, Zugarini C.¹.



Varese, June 8th, 2023

¹Institute for Applied Mathematics (IAC) - National Research Council (CNR), Florence.

²National Institute of Optics (INO) - National Research Council (CNR), Florence.

Table of contents

- ▶ FORUM mission overview and adopted methods
- ▶ FORUM sensitivity to surface emissivity
 - ▶ Globe: clear sky
 - ▶ Antarctica: cloudy sky
- ▶ Emissivity apriori global map

Forum mission

FORUM (Far-infrared Outgoing Radiation Understanding and Monitoring):

- ▶ Fourier Transform Spectrometer (FTS);
- ▶ 9th ESA's Earth Explorer mission (EE9);
- ▶ End-to-end (E2E) simulator;
- ▶ Complete emission spectrum at the top of the atmosphere (TOA) → unique picture of the Earth's radiative budget;
- ▶ $100\text{-}1600\text{ cm}^{-1}$ ($6.25\text{-}100\text{ }\mu\text{m}$) region of the atmosphere (FIR and part of MIR) → more than 95% outgoing longwave flux lost by our planet.

Targets:

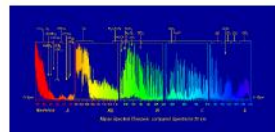
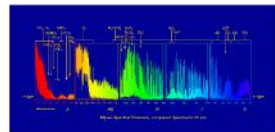
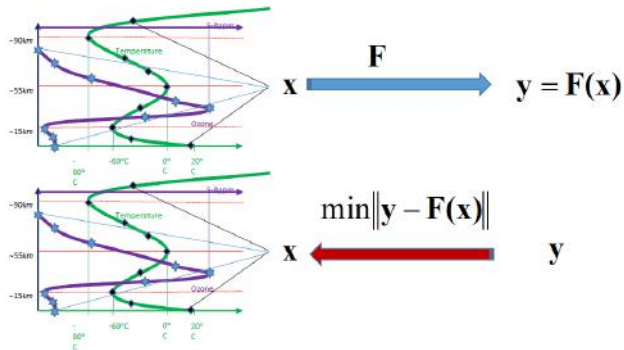
- ▶ Upper Troposphere and Lower Stratosphere Water Vapor;
- ▶ **Surface emissivity in polar and dry regions** ;
- ▶ Cirrus clouds characteristics.

Final aim: improving the accuracy of climate models

Direct and inverse problem

Radiative transfer equation: solved using Line-By-Line Radiative Transfer Model (LBLRTM).

Inverse problem (Retrieval problem): solved using an optimal estimation (OE) method.



Optimal Estimation method

The inverse problem is very **ill-conditioned**.

Given a Gaussian measurement error $\varepsilon = y - F(x)$, with $S_y = \mathbb{E}[\varepsilon\varepsilon^t]$. Suppose there is an a priori estimate x_a of x with error $\varepsilon_a = x - x_a$ and $S_a = \mathbb{E}[\varepsilon_a\varepsilon_a^t]$. We can compute:

$$P(y, x_a) = \frac{1}{(2\pi)^{\frac{n}{2}} |S_a|} e^{-\frac{(x_a - x)^t S_a^{-1} (x_a - x)}{2}} \frac{1}{(2\pi)^{\frac{m}{2}} |S_y|} e^{-\frac{(y - F(x))^t S_y^{-1} (y - F(x))}{2}},$$

where:

- ▶ $|\dots|$ indicates the determinant;
- ▶ n is the dimension of x ;
- ▶ m is the dimension of y ;
- ▶ S_y can be tuned according to the instrument properties;
- ▶ S_a can be set according to the atmospheric variability features, but mostly diagonal.

Optimal Estimation method

We can rewrite P as:

$$P(y, x_a) = \frac{1}{(2\pi)^{\frac{n+m}{2}} |S_a| |S_y|} e^{-\frac{1}{2} \left[(x_a - x)^t S_a^{-1} (x_a - x) + (y - F(x))^t S_y^{-1} (y - F(x)) \right]}$$

Optimal estimation method for the inversion:

The maximization of the probability that a given parameter vector is compatible with the measurements is equivalent to the minimization of the quantity:

$$\chi^2(x) = (x_a - x)^t S_a^{-1} (x_a - x) + (y - F(x))^t S_y^{-1} (y - F(x)).$$

ERA5 data

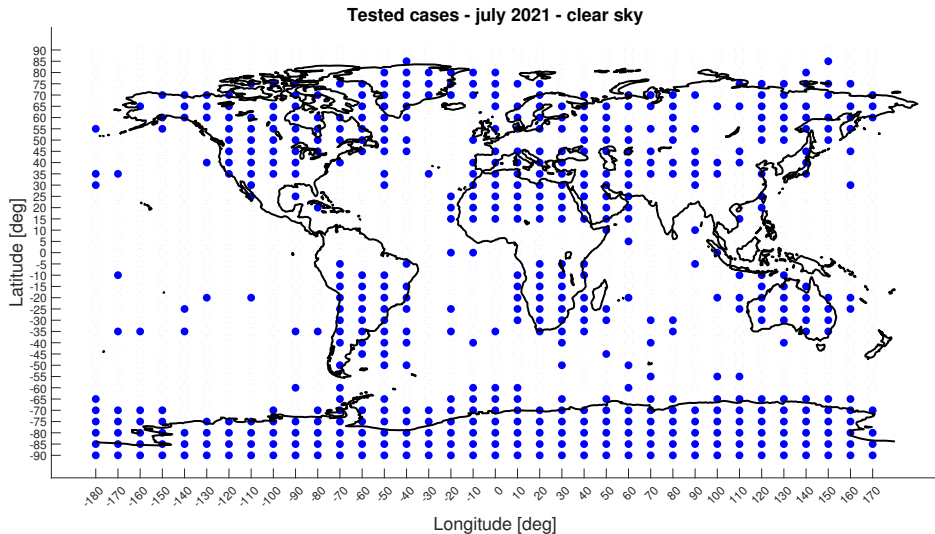
- ▶ **Period:** July 1-20, 2021, 12:00.
- ▶ **Area:**
 - ▶ longitude ([deg]): -180, -170, -160, -150, -140, -130, -120, -110, -100, -90, -80, -70, -60, -50, -40, -30, -20, -10, 0, 10, 20, 30, 40, 50, 60, 70, 80, 90, 100, 110, 120, 130, 140, 150, 160, 170;
 - ▶ latitude ([deg]): -90, -85, -80, -75, -70, -65, -60, -55, -50, -45, -40, -35, -30, -25, -20, -15, -10, -5, 0, 5, 10, 15, 20, 25, 30, 35, 40, 45, 50, 55, 60, 65, 70, 75, 80, 85, 90.



Copernicus Climate Change Service (C3S) (2017): ERA5: Fifth generation of ECMWF atmospheric reanalyses of the global climate. Copernicus Climate Change Service Climate Data Store (CDS), date of access. <https://cds.climate.copernicus.eu/cdsapp#!/home>.

ERA5 data selection

For each case: choose the first clear sky day (total cloud optical depth (OD) at 900 cm^{-1} less than equal to 0.03). Total number of cases: 563:



CLAIM (CLOUDS and Atmosphere Inversion Module) settings

- ▶ **Simulation:** forward model + first iteration retrieval module.
- ▶ **Input settings:**
 - ▶ retrieved components: emissivity with retrieval grid step of 5 cm^{-1} ;
 - ▶ retrieval points: 301 (number of emissivity points);
 - ▶ emissivity apriori and initial guess data from Climatology;
 - ▶ gases initial guess data from ERA5 or IG2;
 - ▶ emissivity apriori error: 0.15.

Analysis

► Quantities:

- Precipitable water vapor (PWV [mm]);
- Surface temperature (t_s [K]);
- Emissivity average error ($\sqrt{S_x}$);
- Thermal contrast: $t_s - t_m$ ([K]), where t_m is the average temperature in the first 6 Kms.

► Spectral regions:

- FIR1: 100 – 300 cm^{-1} ,
- FIR2: 300 – 620 cm^{-1} ,
- MIR1: 720 – 1100 cm^{-1} ,
- MIR2: 1100 – 1600 cm^{-1} .

Surface emissivity average error

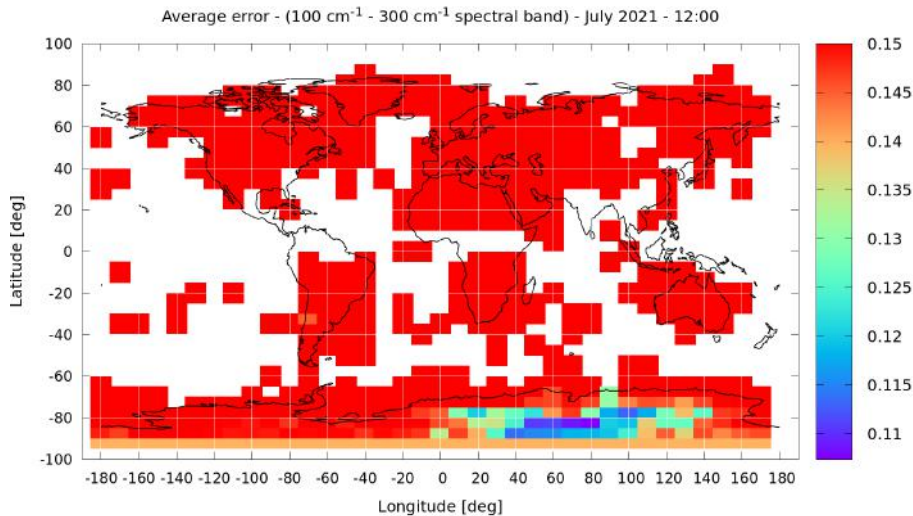
$$S_x = ((K_k^T S_y^{-1} K_k) + S_a^{-1})^{-1},$$

where K is the Jacobian, S_y is the measurements VCM and S_a is the apriori VCM.

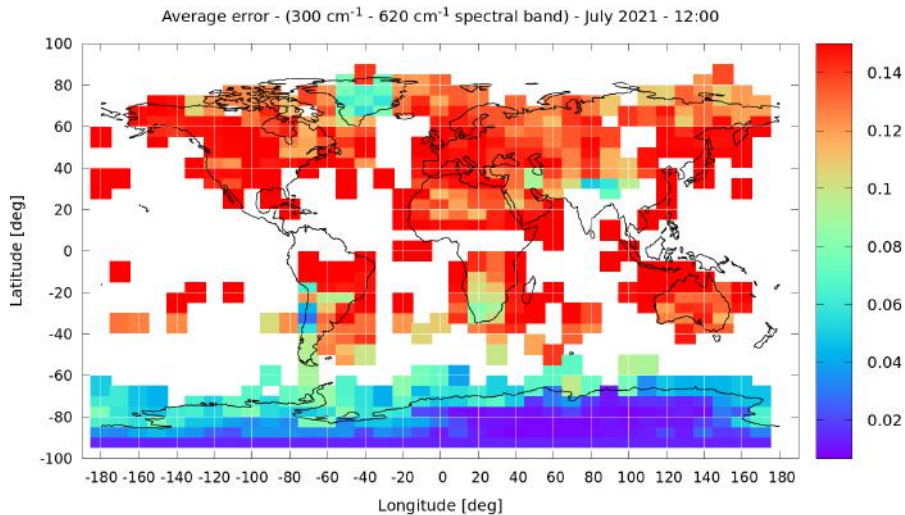
If $\|K_k^T S_y^{-1} K_k\| \sim 0 \Rightarrow S_x \sim S_a$ and **we do not have sensitivity**.

Selection of plots

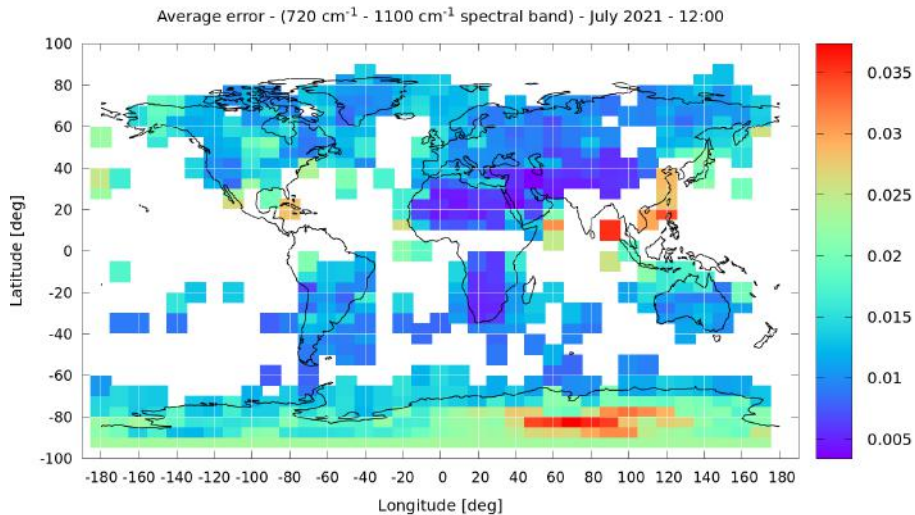
Avg error in the FIR1



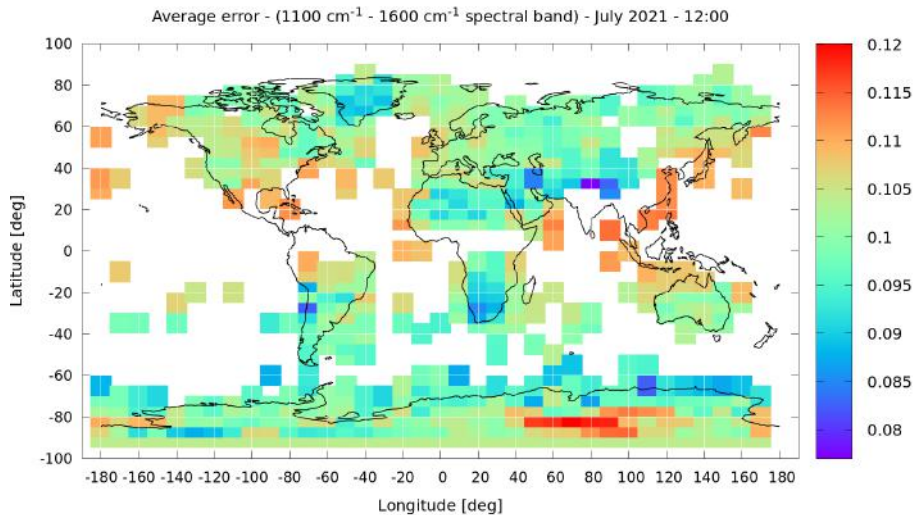
Avg error in the FIR2



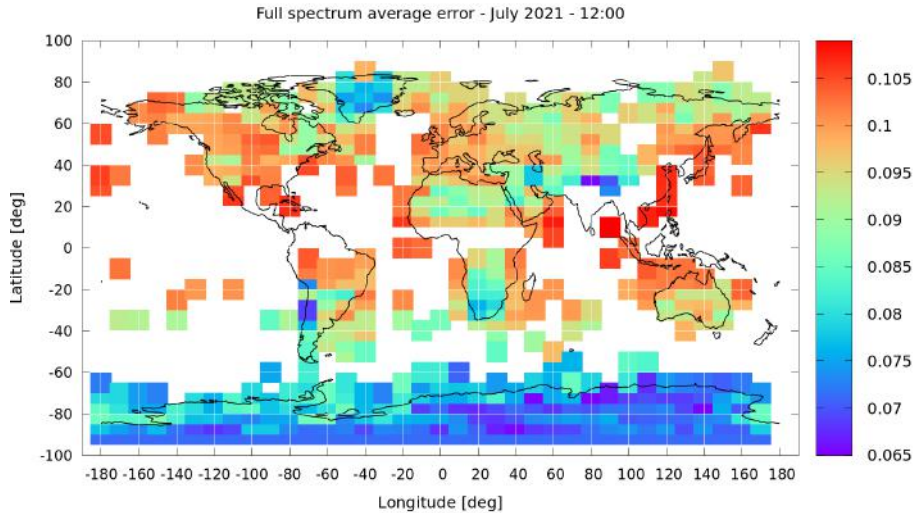
Avg error in the MIR1



Avg error in the MIR2



Full spectrum avg error



ERA5 data

- ▶ **Period:** July 1-20, 2021, 12:00.
- ▶ **Area:**
 - ▶ longitude ([deg]): -180, -170, -160, -150, -140, -130, -120, -110, -100, -90, -80, -70, -60, -50, -40, -30, -20, -10, 0, 10, 20, 30, 40, 50, 60, 70, 80, 90, 100, 110, 120, 130, 140, 150, 160, 170;
 - ▶ latitude ([deg]): -90, -85, -80, -75, -70.

Total number of tentative cases: $36 \times 5 \times 20 = 3600$

ERA5 data selection:

- ▶ Computation of the total cloud OD at 900 cm^{-1} for each case.
- ▶ Deleting the clear sky cases (corresponding to $\text{OD} \leq 0.03$).
- ▶ Cutting cases with $\text{OD} \geq 1$.
- ▶ Choosing 20 random cases "equally spaced" in the final OD vector.

Our final sample is composed of 20 cases with OD between 0.03001 and 0.9182

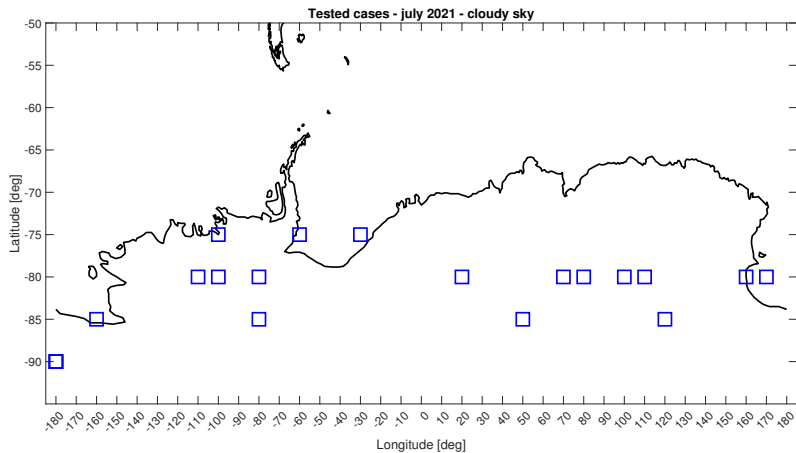
Sample, part 1

LON	LAT	OD	N.CLOUDS	CLOUD TYPE	N.LAYERS
80	-80	0.0300	1	ICE	2
-160	-85	0.0442	1	ICE	6
-60	-75	0.0620	2	ICE - ICE	2 - 3
-100	-80	0.0797	1	ICE	2
50	-85	0.1024	2	ICE - ICE	1 - 3
-180	-90 (day 20)	0.1302	1	ICE	3
110	-80	0.1417	3	ICE - ICE - ICE	1 - 4 - 2
-180	-90 (day 2)	0.1672	1	ICE	3
-30	-75	0.1816	1	ICE	7
20	-80	0.2184	1	ICE	5

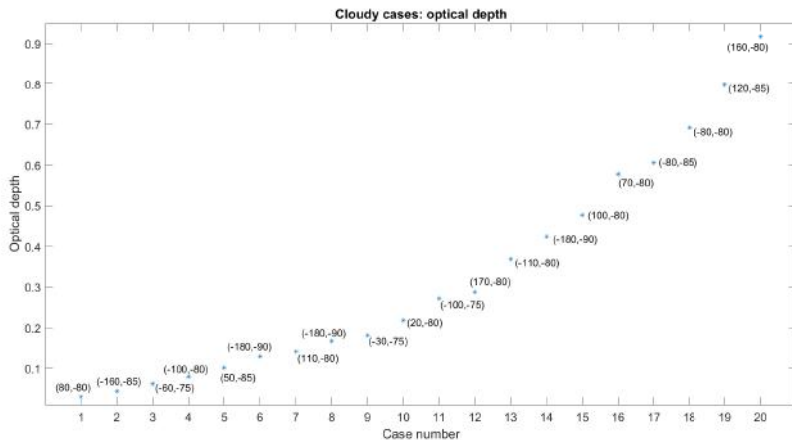
Sample, part 2

LON	LAT	OD	N.CLOUDS	CLOUD TYPE	N.LAYERS
-100	-75	0.2722	1	ICE	9
170	-80	0.2878	1	ICE	13
-110	-80	0.3687	1	ICE	6
-180	-90 (day 4)	0.4239	1	ICE	5
100	-80	0.4771	1	ICE	4
70	-80	0.5774	1	ICE	6
-80	-85	0.6051	1	ICE	7
-80	-80	0.6915	1	ICE	8
120	-85	0.7969	1	ICE	5
160	-80	0.9182	1	ICE	5

Sample

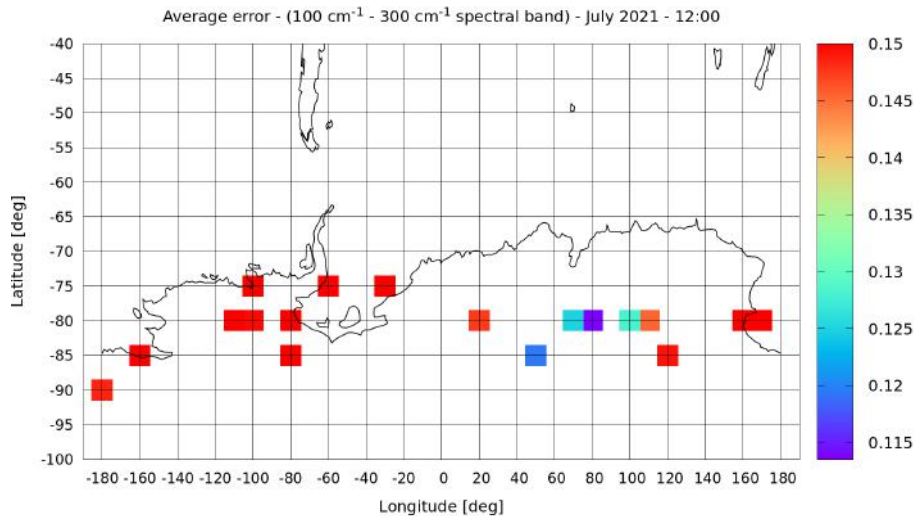


Sample

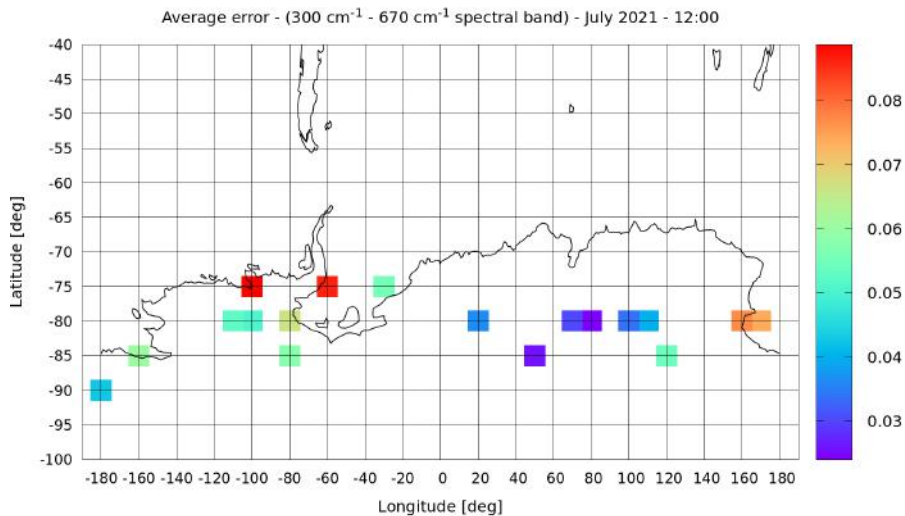


Selection of plots

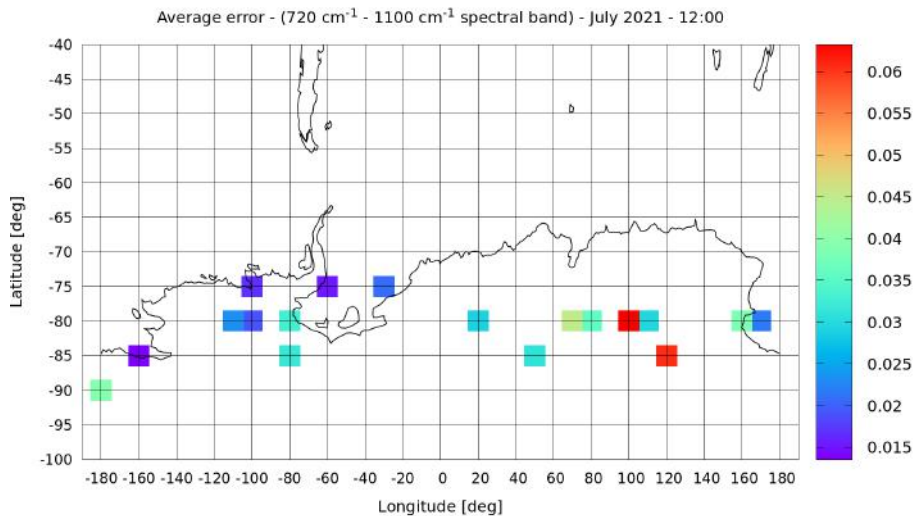
Avg error in the FIR1



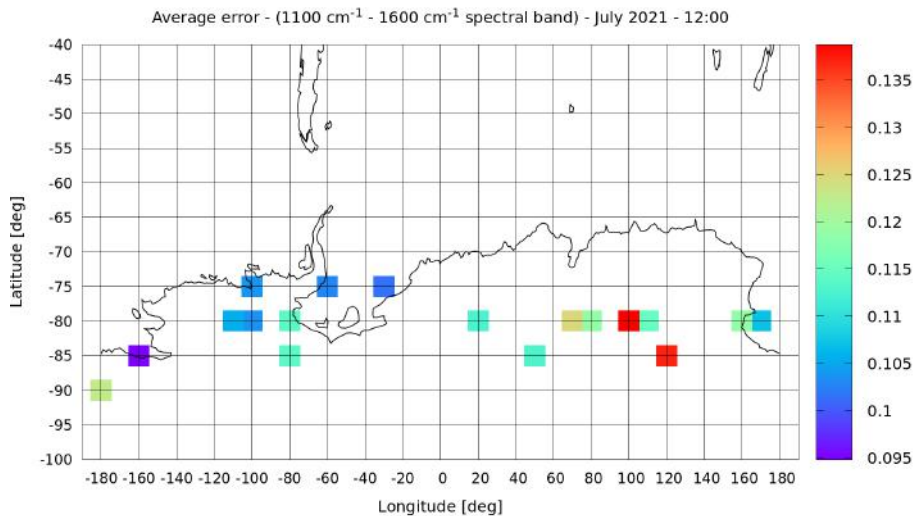
Avg error in the FIR2



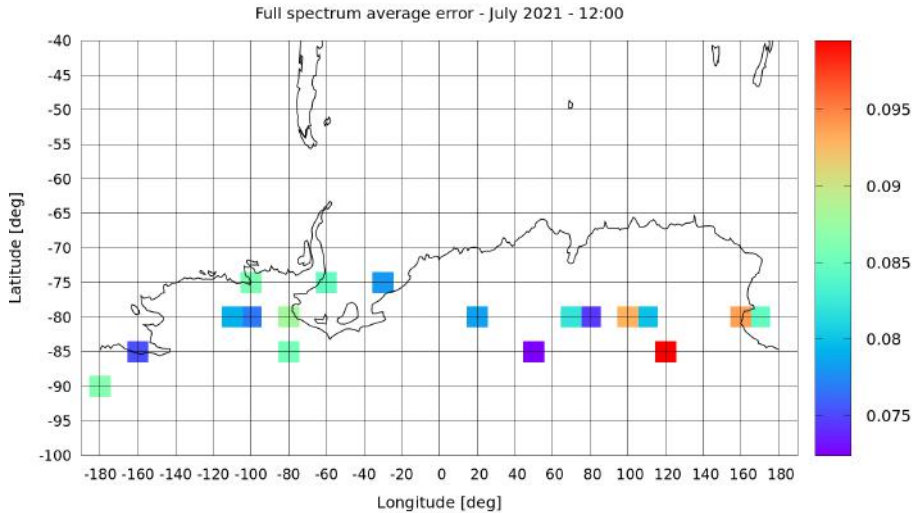
Avg error in the MIR1



Avg error in the MIR2



Full spectrum avg error



Emissivity global map - Huang database

Aim: creation of global surface emissivity map from measured data.

EMI MODEL
Desert (DES)
Desert and grass (D+G)
Grass (GRS)
Dry grass (DGR)
Deciduous (DEC)
Conifer (CON)
Water (WAT)
Fine snow (FSN)
Medium snow (MSN)
Coarse snow (CSN)
Ice (ICE)
Forest (FOR)



Huang, X., Chen, X., Zhou, D. K., and Liu, X.: An Observationally Based Global Band-by-Band Surface Emissivity Dataset for Climate and Weather Simulations, *J. Atmos. Sci.*, 73, 3541–3555, <https://doi.org/10.1175/JAS-D-15-0355.1>, 2016.

Emissivity global map

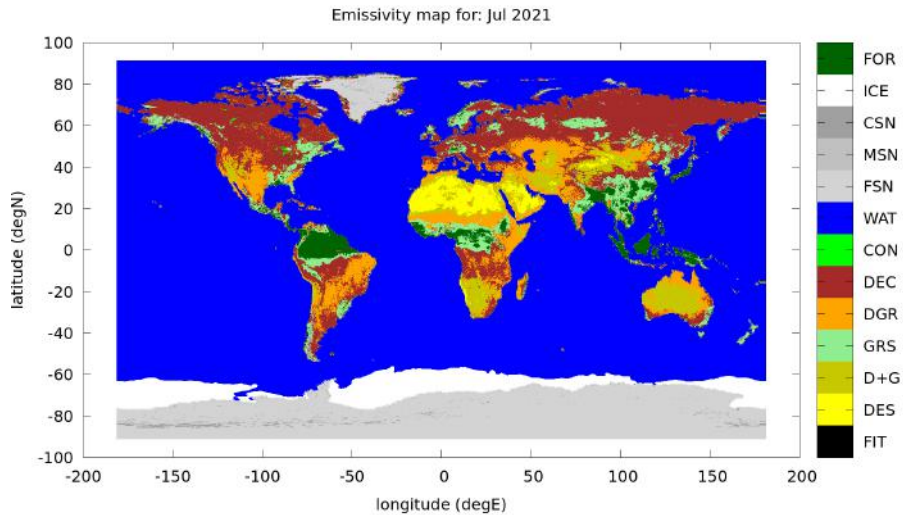
First approach:

- ▶ Download of a surface emissivity global map from MODIS-ASTER-IREMIS database: MONTHLY data available in 0.05x0.05 degree grid in 10 channels: 3.6, 4.3, 5.0, 5.8, 7.6, 8.3, 9.3, 10.8, 12.1, and 14.3 microns.
- ▶ For each ERA5 pixel (0.25x0.25 degree grid) association of one of the emissivity models (Huang database) computing the minimum error in L2 norm.
- ▶ Additional constraints using ERA5 monthly data about **surface temperature, humidity and snow cover**.

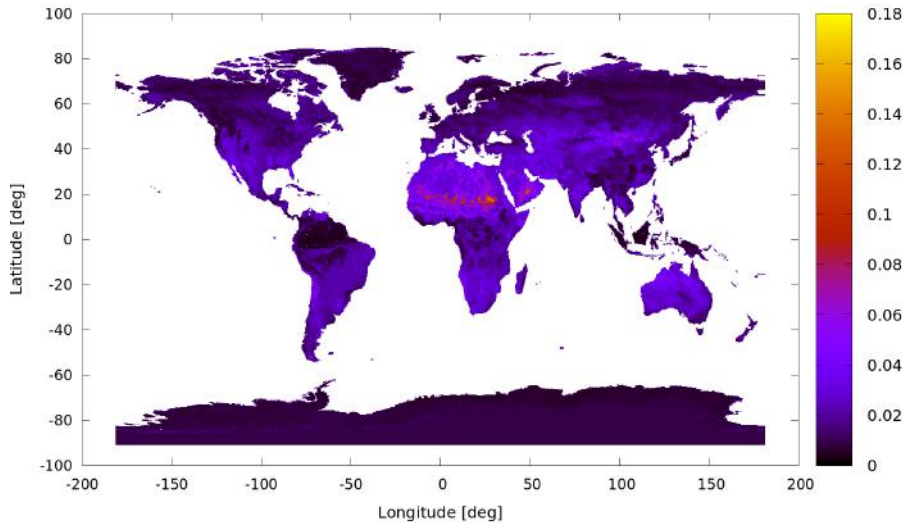


IREMIS: Global Infrared Land Surface Emissivity: UW-Madison Baseline Fit Emissivity Database, Space Science & Engineering Center, University of Wisconsin -Madison.

First map



Error map



Surface type global map

Second approach:

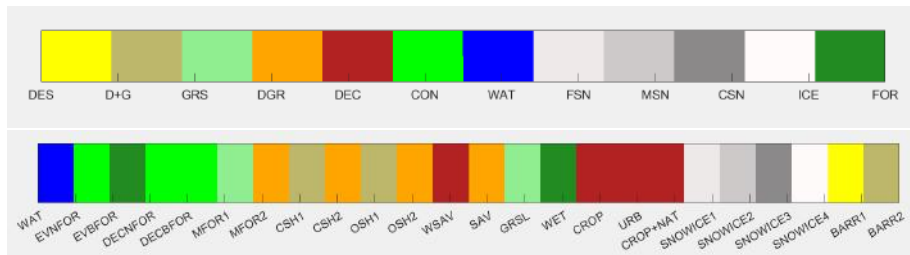
- ▶ Download of a surface cover global map from MODIS-AQUA-TERRA database: YEARLY data available in 0.05x0.05 degree grid using the IGBP (International Geosphere-Biosphere Programme) classification scheme composed of 17 surface types.
- ▶ For each ERA5 pixel (0.25x0.25 degree grid) association of a probability vector for the 17 surface types.



Friedl, M., D. Sulla-Menashe. MCD12C1 MODIS/Terra+Aqua Land Cover Type Yearly L3 Global 0.05Deg CMG, 2015, distributed by NASA EOSDIS Land Processes DAAC, <https://doi.org/10.5067/MODIS/MCD12C1.006>.

Surface type global map

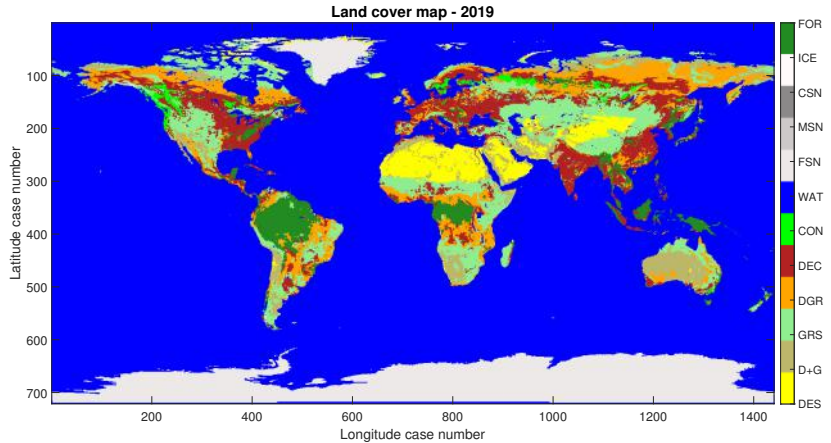
- ▶ Association of the emissivity models (Huang database) to the 17 surface types and computation of the new probability vectors.
- ▶ Choice of the surface type with maximum probability.



International Geosphere-Biosphere Programme (IGBP) classification

WAT	Water bodies
EVNFOR	Evergreen Needleleaf Forests
EVBFOR	Evergreen Broadleaf Forests
DECNFOR	Deciduous Needleleaf Forests
DECBFOR	Deciduous Broadleaf Forests
MFOR	Mixed Forests
CSH	Closed Shrublands
OSH	Open Shrublands
WSAV	Woody Savannas
SAV	Savannas
GRSL	Grasslands
WET	Permanent Wetlands
CROP	Croplands
URB	Urban and Built-up Lands
CROP+NAT	Cropland/Natural Vegetation Mosaics
SNOWICE	Permanent Snow and Ice
BARR	Barren

Second map



Merging maps: Bayesian approach

Given a surface type t_k and an emissivity model e_k , the joint probability of having the surface t_k and the emissivity e_k simultaneously is:

$$p(t_k; e_k) = p(t_j)p(e_k) = p(t_j) \frac{1}{(2\pi)^{\frac{m}{2}}} \sigma^m \exp \left[-\frac{\sum_{i=1}^m ((e_k)_i - e_i)^2}{2\sigma^2} \right],$$

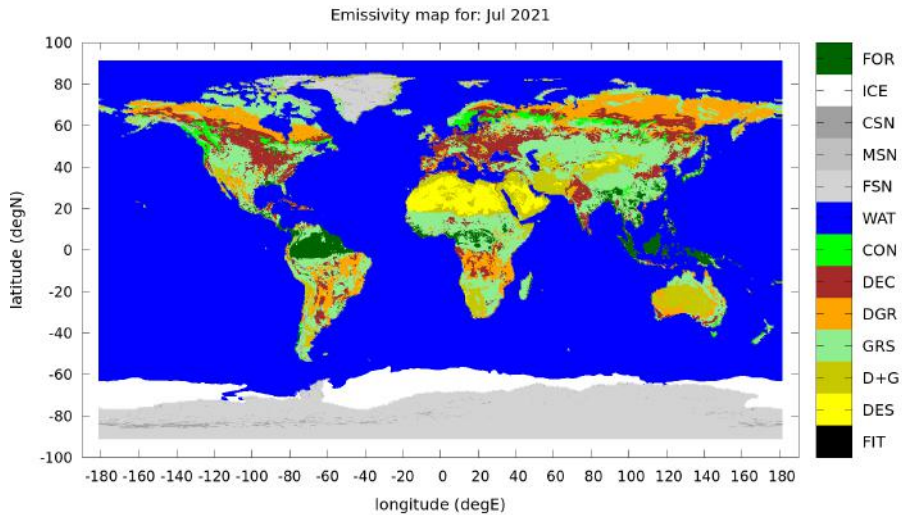
where:

- ▶ m is the number of MODIS measurements;
- ▶ e_i is the i -th MODIS measurement;
- ▶ $k = 1, \dots, 12$ are the indices corresponding to the emissivity model and the surface type;
- ▶ $(e_k)_i$ is the emissivity model k interpolated at the MODIS measurement i .

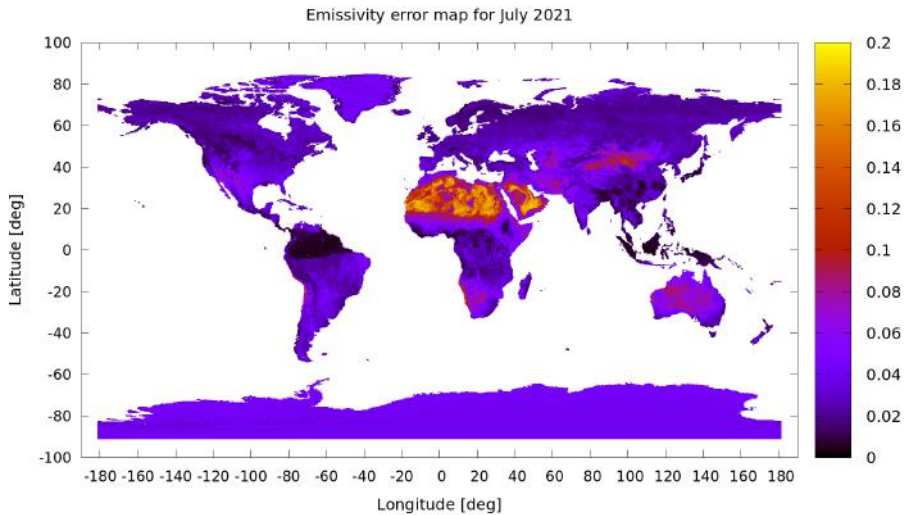
For each case in the globe, we choose the model such that

$$\max_k p(t_k; e_k)$$

Final map



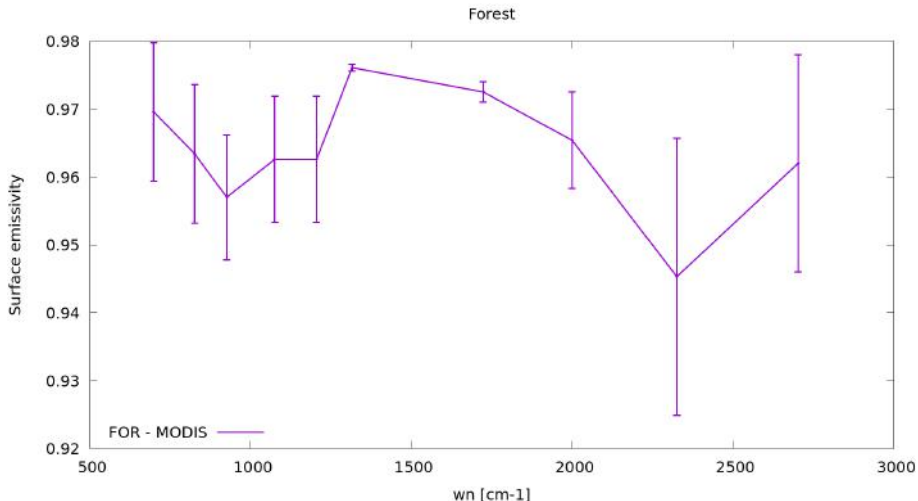
New error map



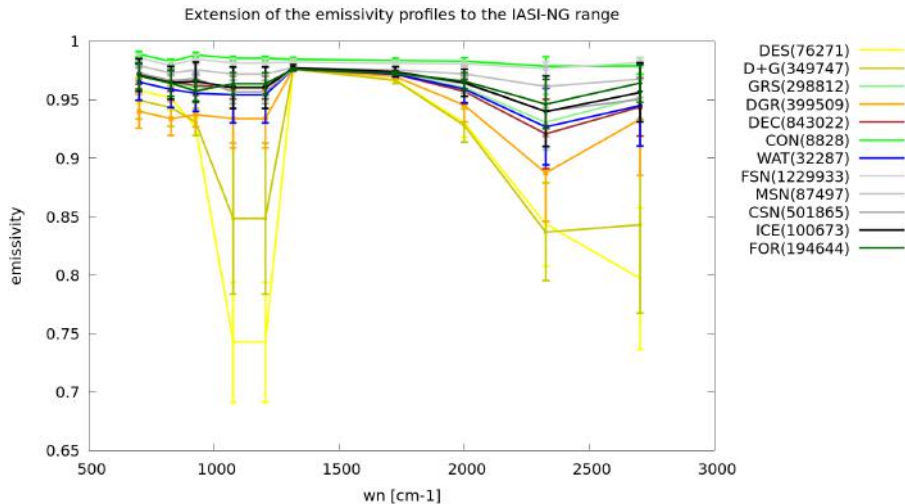
Extension to MIR - in progress

Using:

- ▶ MODIS-ASTER-IREMIS monthly data (January in this case);
- ▶ mean and standard deviation over surface emissivity data in the globe corresponding to the considered model (Forest model in this case).



Extension to MIR - in progress

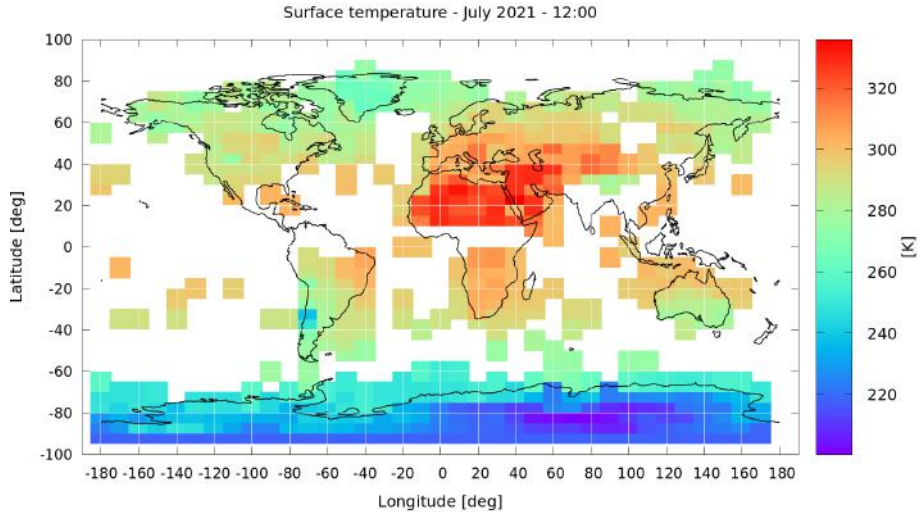


Conclusions, ongoing and future works

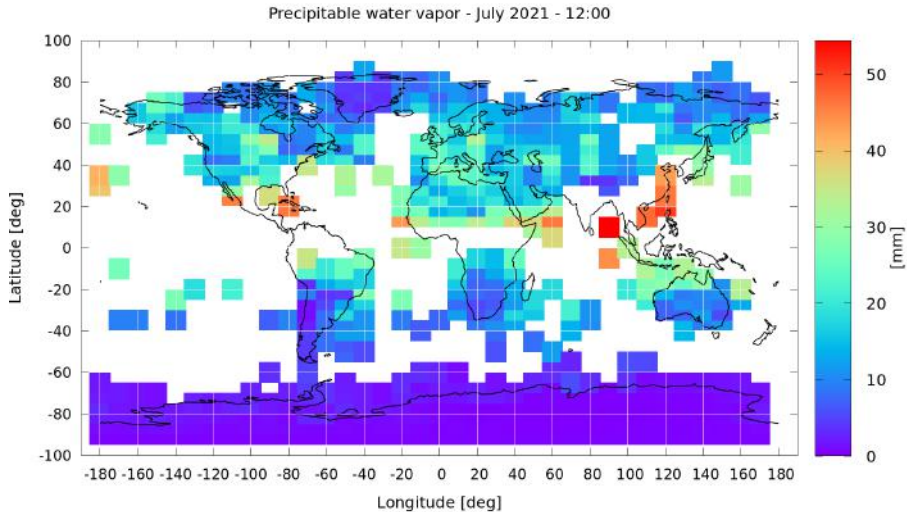
- ▶ FORUM sensitivity to surface emissivity is not so good, it increases only in the polar regions both in clear and cloudy sky conditions;
- ▶ A Bayesian approach improves the accuracy of the surface emissivity global map.
- ▶ Extension of the cloudy sky analysis: more cases in Antarctica and all over the world using a faster code like sigma-iasi (current computational effort: about 10 days for 20 cloudy sky cases).
- ▶ Extension of the emissivity models to the middle-infrared region using observed data from MODIS-ASTER.
- ▶ In progress: use of physics guided neural networks for the radiative transfer model or for the scene identification (clear/cloudy) at the beginning of the retrieval process. Collaboration with the Mathematics Department of Emory University in Atlanta, Georgia, USA.

Thank you!

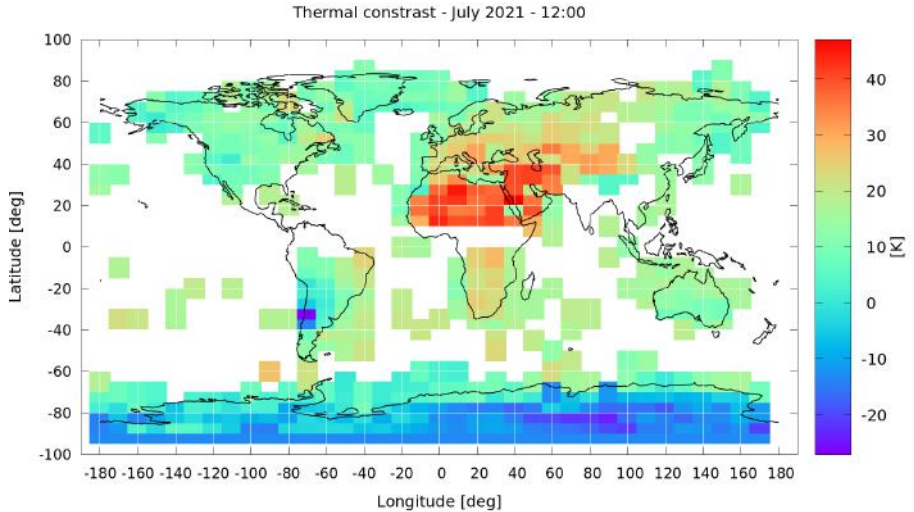
Surface temperature



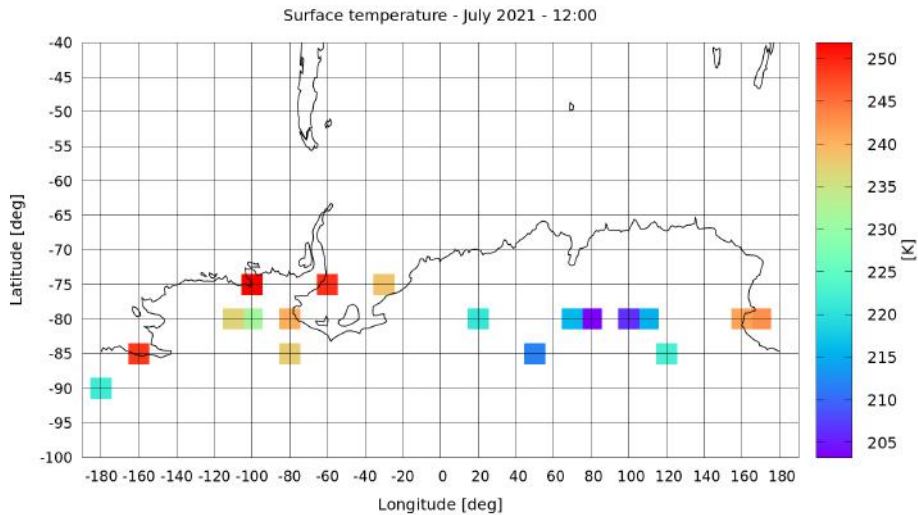
Precipitable Water Vapor



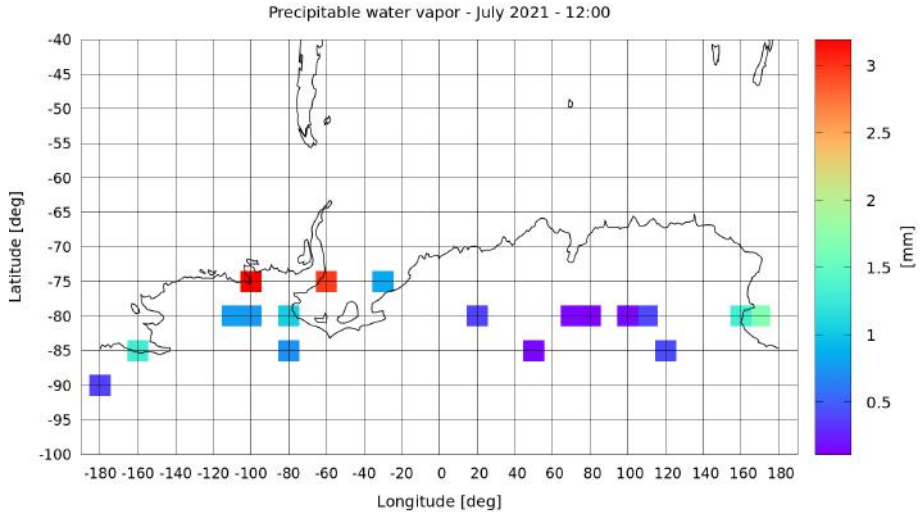
Thermal contrast



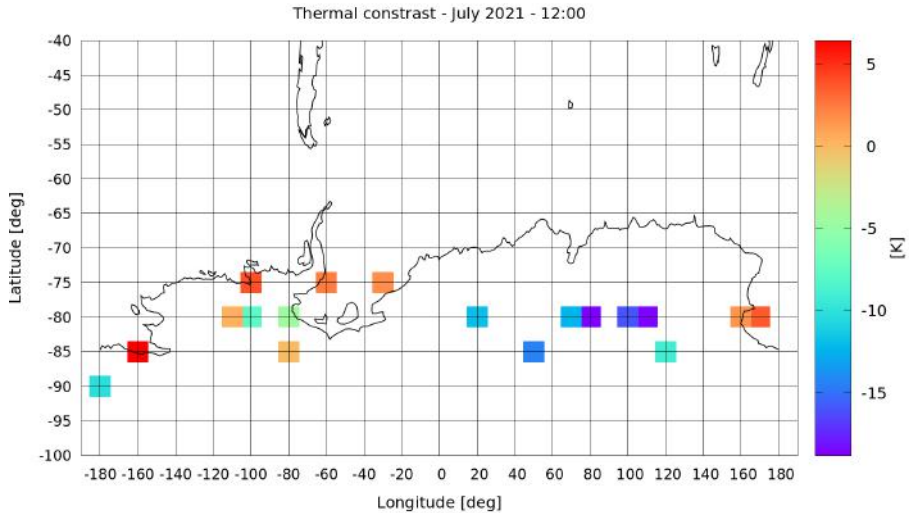
Surface temperature



Precipitable Water Vapor



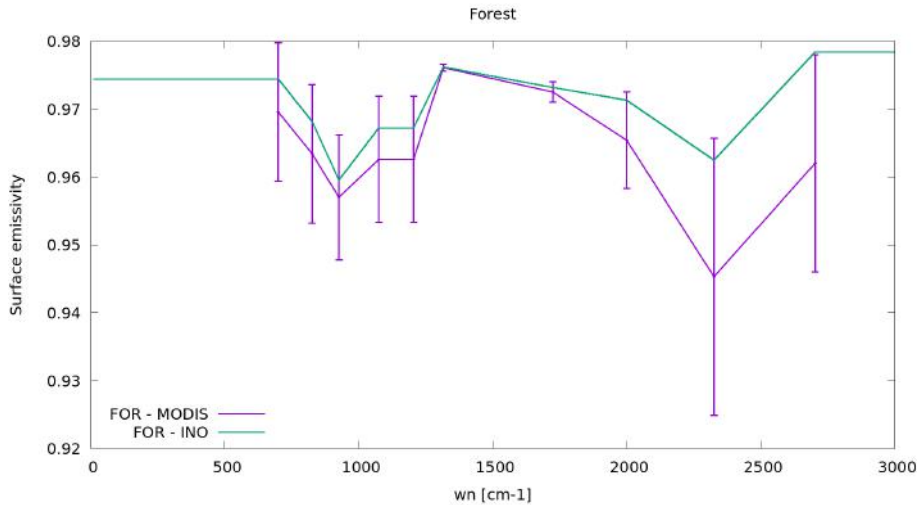
Thermal contrast



Constraints

EMI MODEL	SNOW COVER	TSKIN range [K]	HUMIDITY range
Desert (DES)	N	[303.0, 1000.0]	[0.000, 0.200]
Desert and grass (D+G)	N	[270.0, 1000.0]	[0.010, 0.250]
Grass (GRS)	N	[0.0, 1000.0]	[0.100, 0.450]
Dry grass (DGR)	N	[0.0, 1000.0]	[0.010, 0.350]
Deciduous (DEC)	N	[0.0, 1000.0]	[0.100, 0.350]
Conifer (CON)	N	[0.0, 1000.0]	[0.200, 0.450]
Water (WAT)	N	[267.0, 1000.0]	[1.000, 1.000]
Fine snow (FSN)	Y	[0.0, 270.0]	[0.800, 1.000]
Medium snow (MSN)	Y	[0.0, 270.0]	[0.800, 1.000]
Coarse snow (CSN)	Y	[0.0, 270.0]	[0.800, 1.000]
Ice (ICE)	Y	[0.0, 270.0]	[0.800, 1.000]
Forest (FOR)	N	[277.0, 1000.0]	[0.400, 0.550]

Extension to MIR



The minimization

Gauss-Newton method (GN) + Levenberg-Marquardt technique (LM):

$$x_{k+1} = x_k + \left(K_k^t S_y^{-1} K_k + S_a^{-1} + \alpha_k \text{diag}(K_k^t S_y^{-1} K_k) \right)^{-1} \cdot \left[K_k^t S_y^{-1} (y - F(x_k)) + S_a^{-1} (x_a - x_k) \right],$$

where k is the iteration index, α_k is the Marquardt parameter at iteration k and $K_k = \nabla F(x_k)$.

Why LM?

- ▶ the damping term α_k helps in the inversion of the matrix to be computed;
- ▶ for large values of α_k , $x_{k+1} - x_k$ goes to $-\frac{\nabla \chi^2(x)}{\alpha(x)}$, which is a descend direction for the cost function.

Drawback: premature convergence.