MC-FORUM

Deep Learning-based observation operator for satellite *FORUM* data assimilation

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Motivation: *Where we are and where we go.*

- Radiances are assimilated using a Radiative Transfer Model (RTM). These models are highly non-linear descriptor of radiative processes in atmosphere.

- Recent years have seen a growing interest in using AI for emulating RTM (computational efficiency, nonlinearities, auto-differentiability)

- See e.g. *[X. Liang et al., 2022; Liang et al, 2023; Li et al., 2024, Weston et al (see talk of yesterday)]* for RTM emulation on the microwave band and for satellite image in visible *[Scheck., 2021]* and near-infrared *[Baur, 2023].*

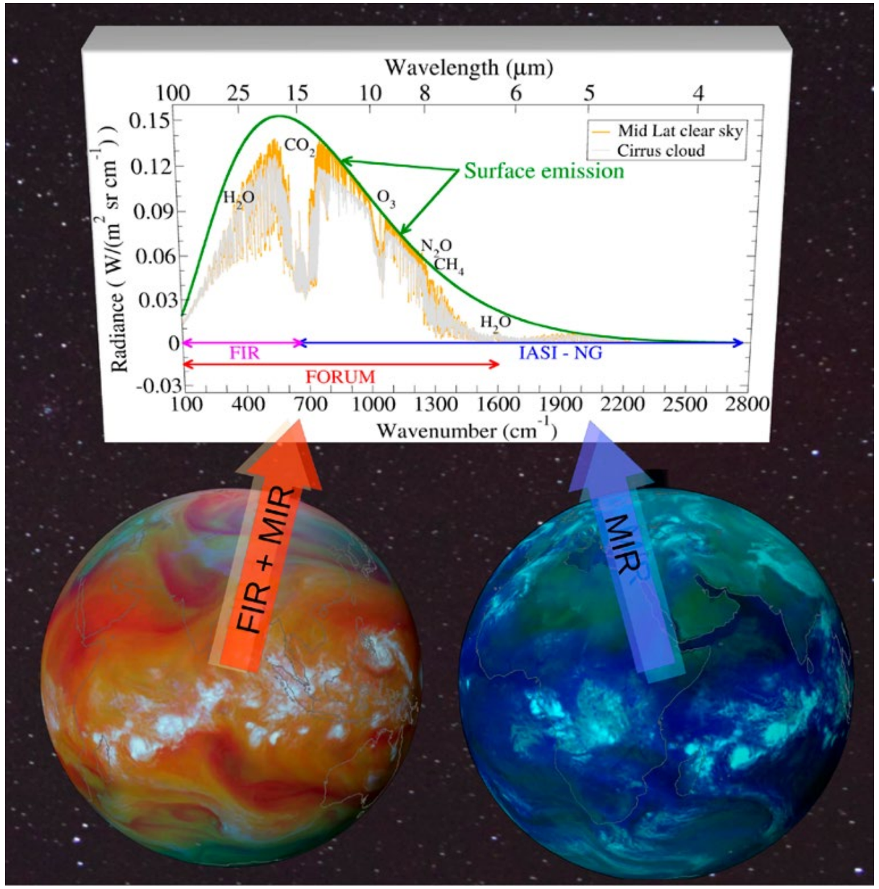
- Recent studies identified Recurrent Neural Networks (RNNs) as the most suitable architecture for this task. *[e.g. Ukkonen, 2022; Yao et al, 2023; Li et al., 2024].*

We study a development of an AI-based emulator of full infrared state-of-art RTM the $\sigma - FORUM$ model

- $\boldsymbol{\sigma}$ RTM *[Masiello et al, 2024]*

(more detailed) Motivations: *ESA 9° Earth Explorer mission "FORUM"*

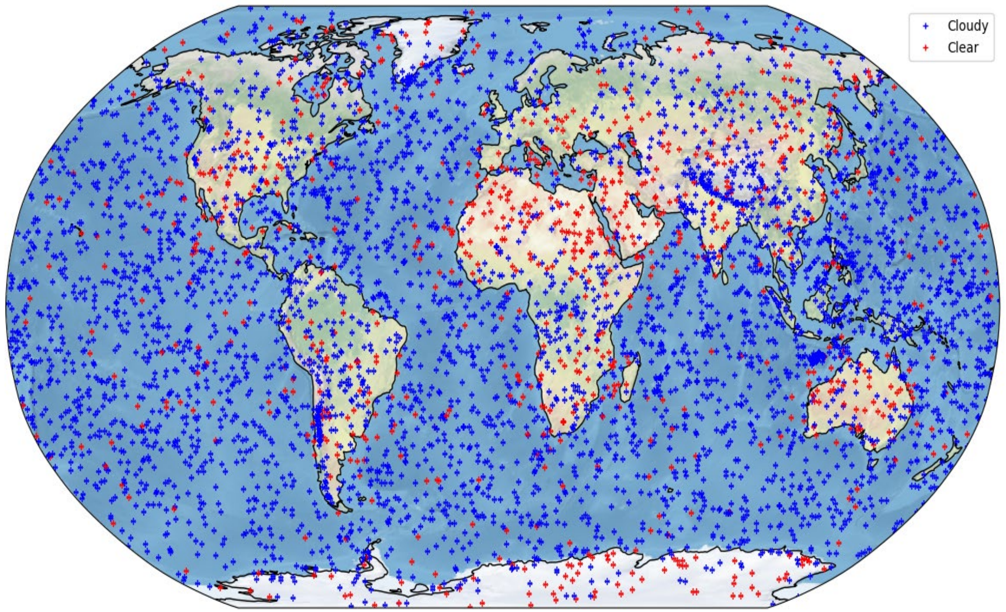
- A **2028 satellite mission** will carry a dedicated instrument for Earth radiation measurement.
- The goal of the FORUM mission is to collect measurements in **the spectral range** $[\mathbf{100, 1600}]\ \boldsymbol{cm^{-1}}$.
- The **Far-infrared** (100–667 cm^{-1}) accounts for ~50% of Earth's outgoing longwave radiation yet has never been observed from space before.



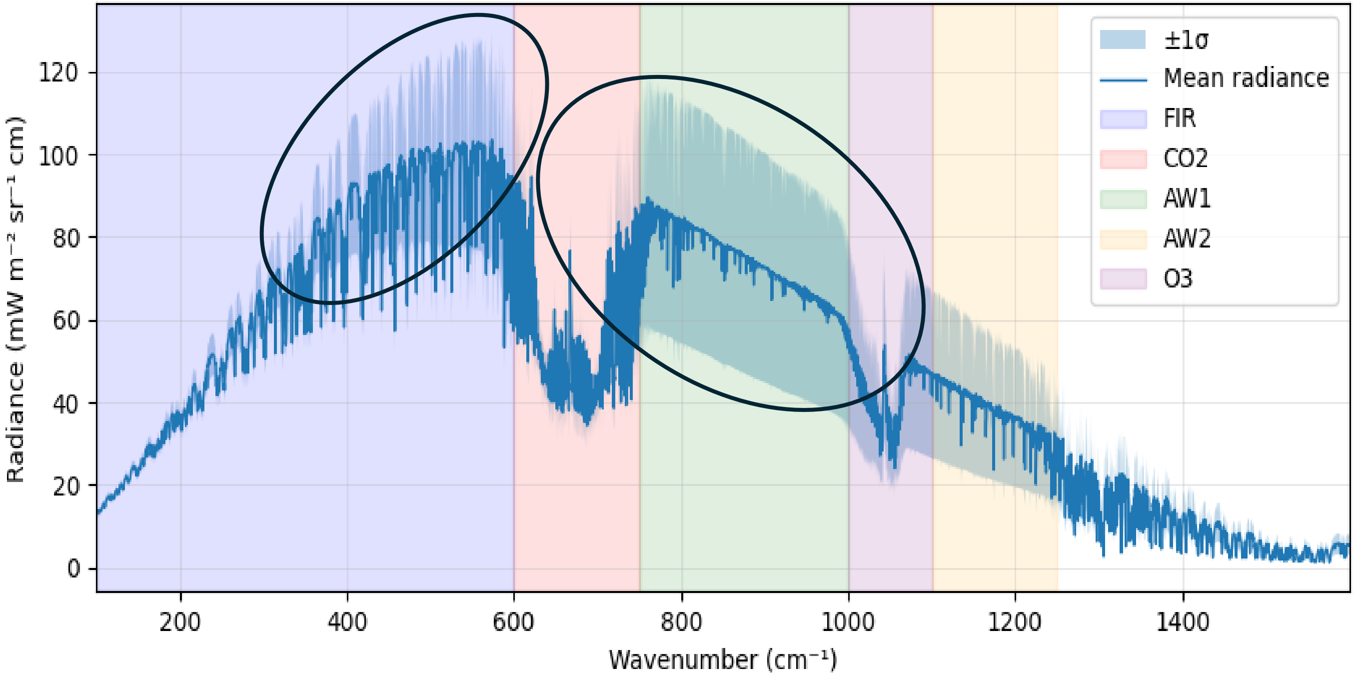
Source: "Unique Far-Infrared Satellite Observations to Better Understand How Earth Radiates Energy to Space", Palchetti et al. 2019.

Dataset: *less samples for less redundancy*

- Atmospheric profiles data from the EUMETSAT NWP SAF 2025 *[Turner, 2025]*.
- Radiances target simulated by the $\sigma - FORUM$ model in the FORUM spectral range.
- Dataset counts **35k scenarios.**



Synthetic data: Mean and Variance

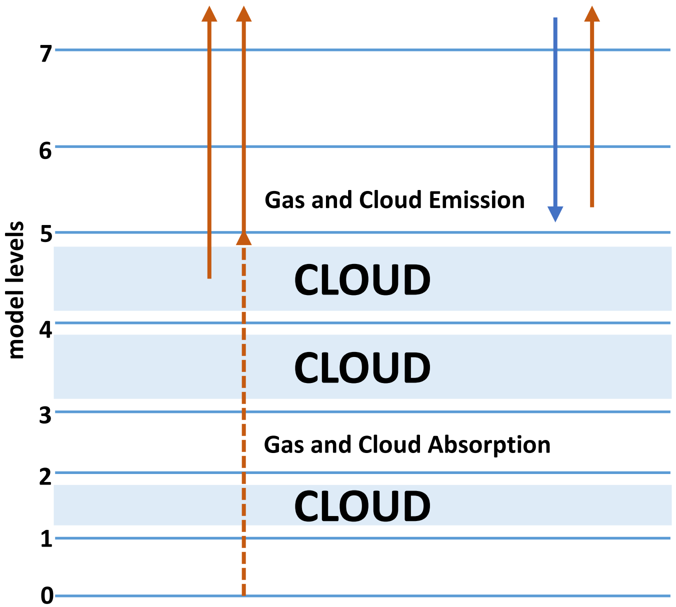


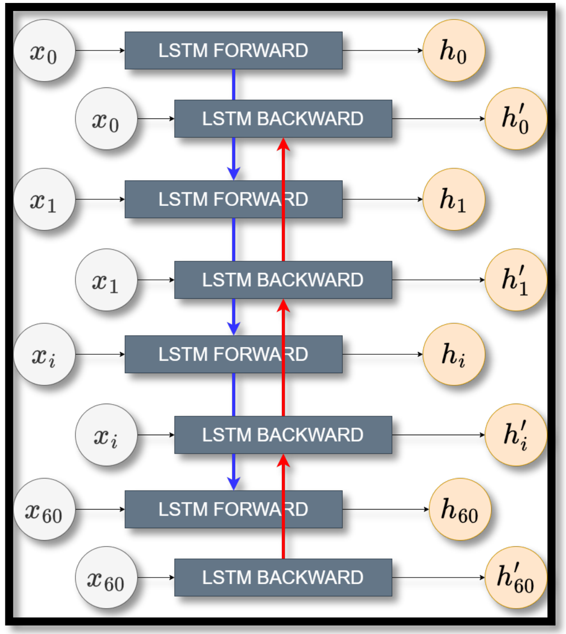
Our architecture: *Mirroring the two-stream radiative transfer*

Assumption: *Sequential nature of radiative transfer*

Radiation propagates **layer by layer** through the atmosphere (surface → TOA). Physics is described by *Radiative Transfer Equation:*

$$I_\lambda(s_1) = I_\lambda(0)e^{-\tau_\lambda(s_1,0)} + \int_0^{s_1} B_\lambda[T(s)]e^{-\tau_\lambda(s_1,s)}k_\lambda \rho ds + \textit{scattering terms}$$





Partitioning

- Dataset split in 5k scenarios of test and 30k of training (80 % train and 20 % validation).

Early Stopping

- Validation loss monitoring to avoid overfitting.

Mean Squared Error and L2 Regularization

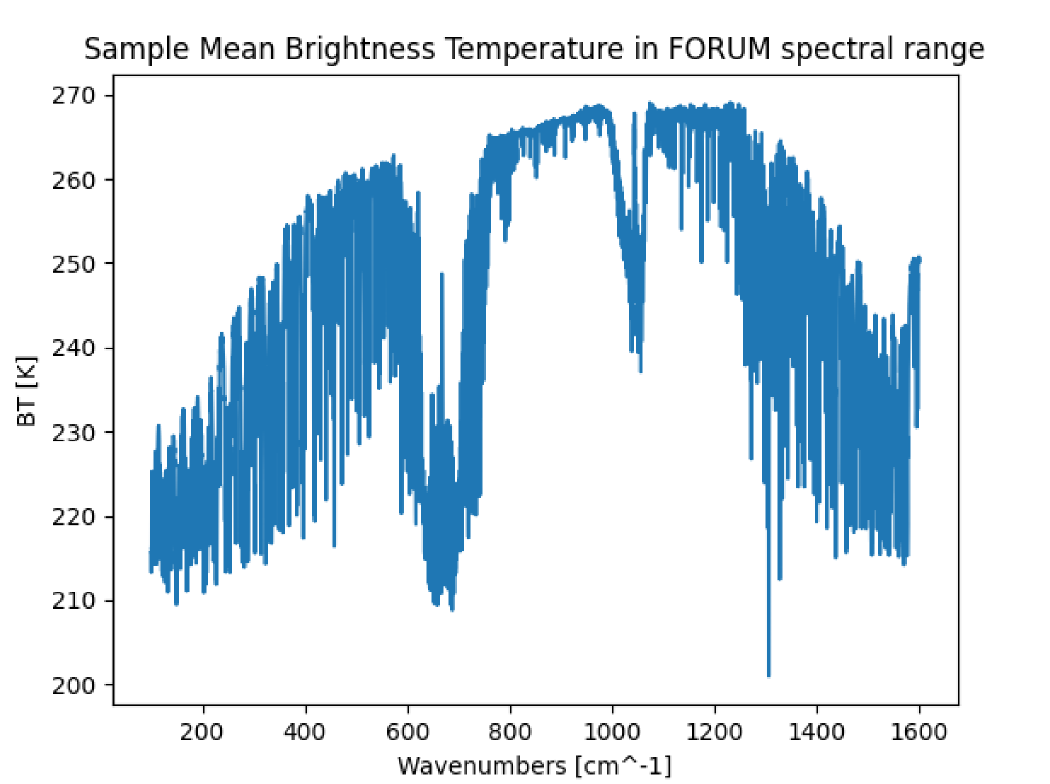
- A Tikhonov regularization applied, to select only small parameter.

Normalization

- Min-Max and Layer Normalization was applied.

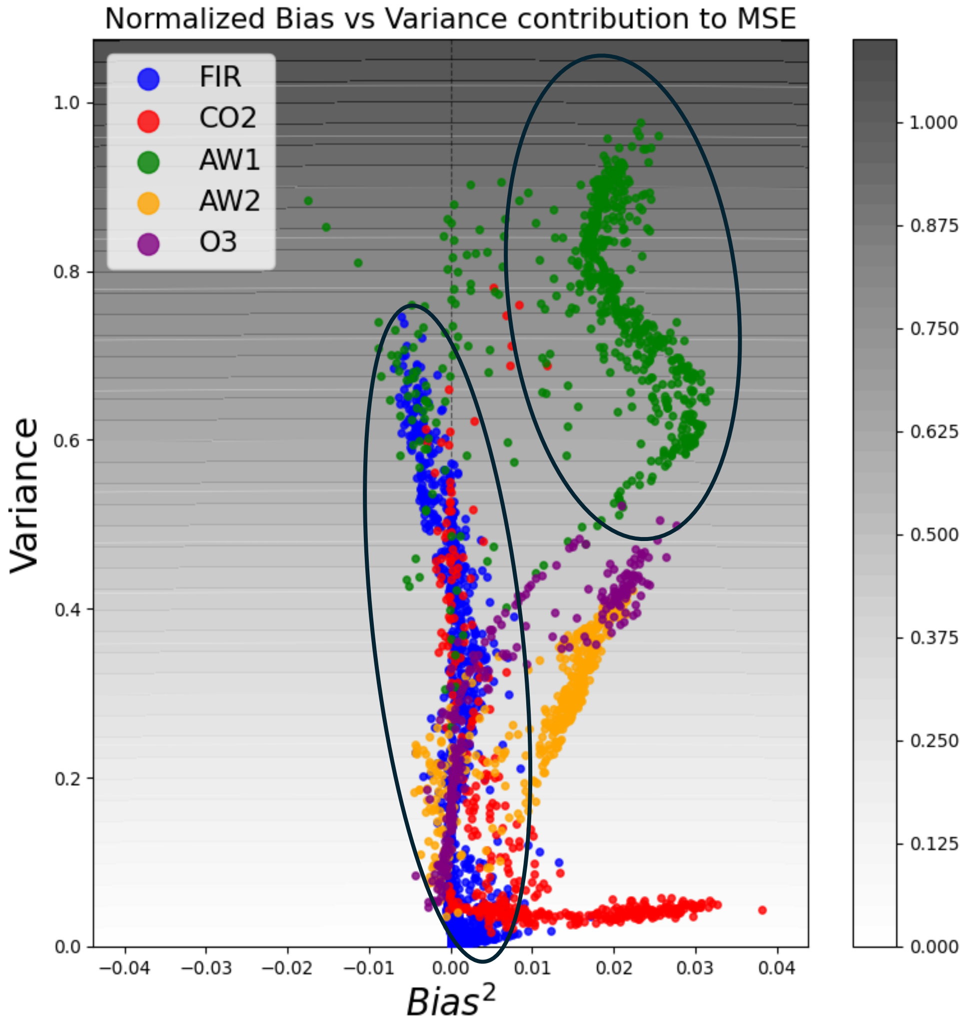
Brightness Temperature as target values

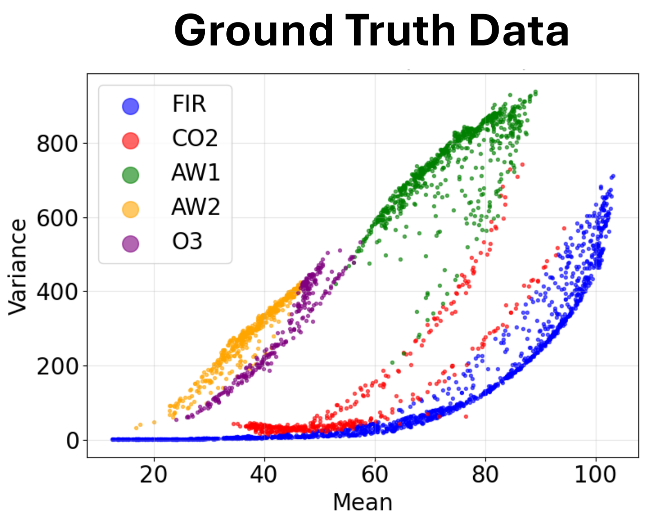
- Brightness Temperature shrinks the range of training values.
- Reduce by one order the degree of nonlinearity.

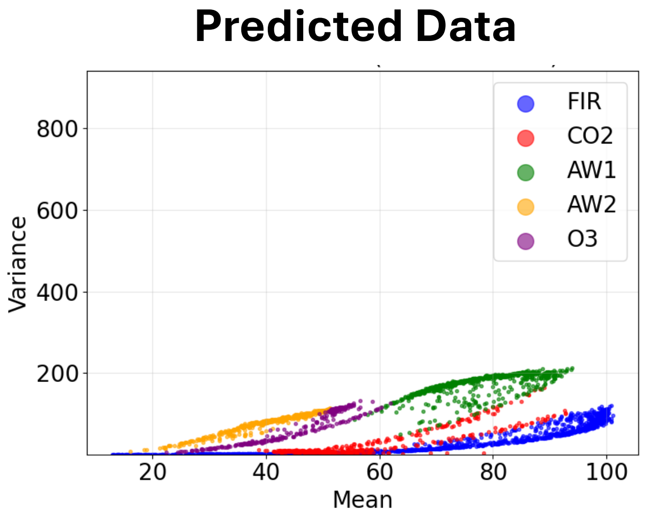


Network Training & Validation: *Issue of reducing bias and variance*

$$MSE = Var[y - h(x)] + (y - h(x))^2.$$



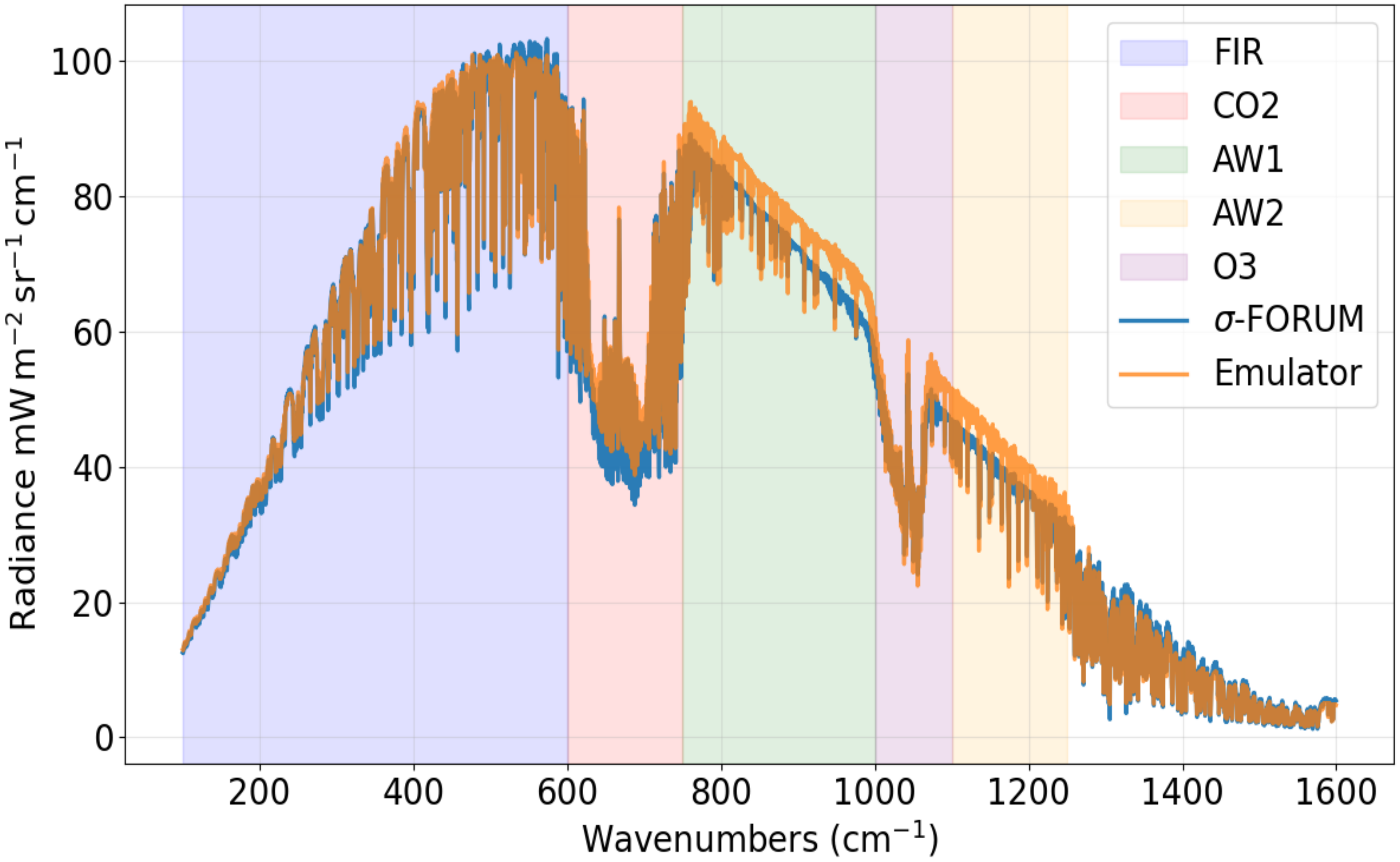




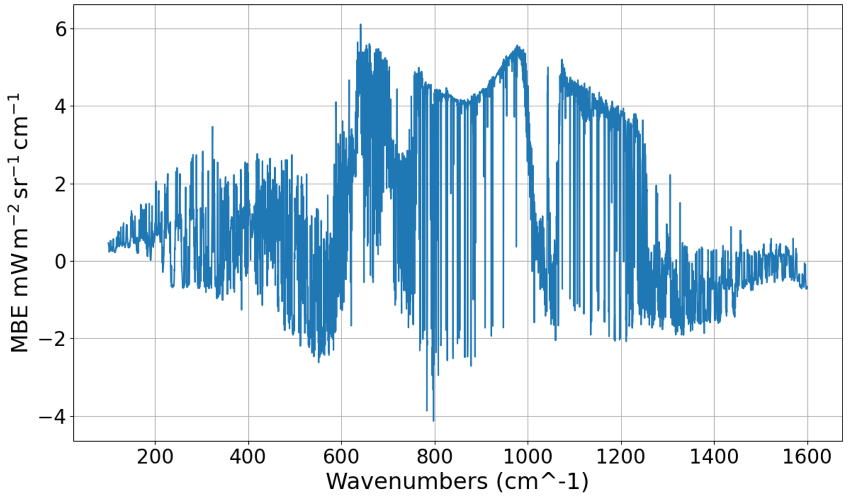
Emulator has minimized ***residual bias****, but not the* ***residual variance****.*

Reconstructed Spectra: *Sample Means*

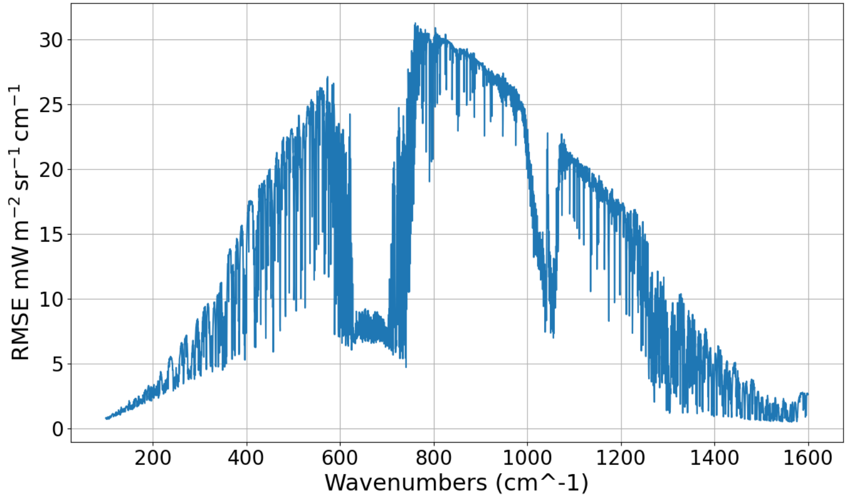
Sample mean radiances



Mean Bias Error (MBE)

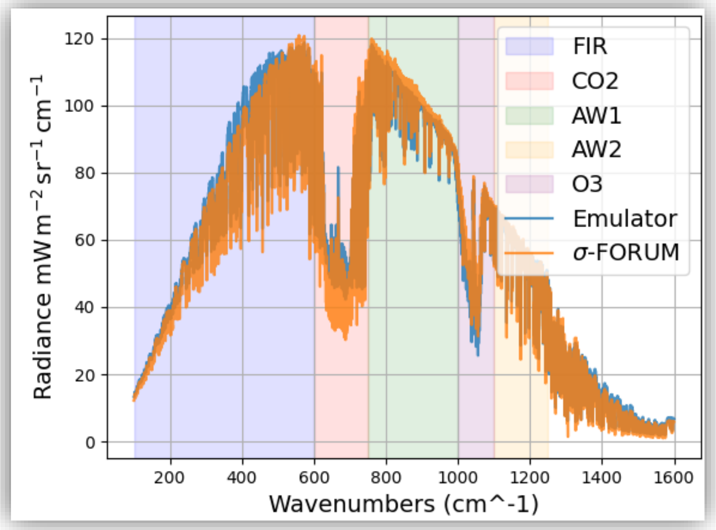


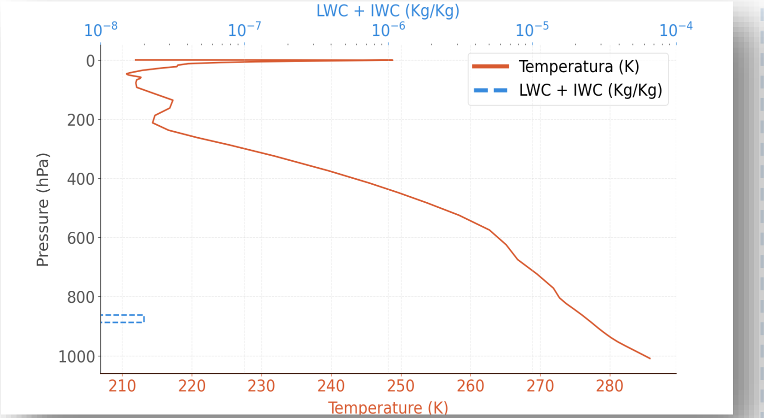
Root Mean Square Error (RMSE)



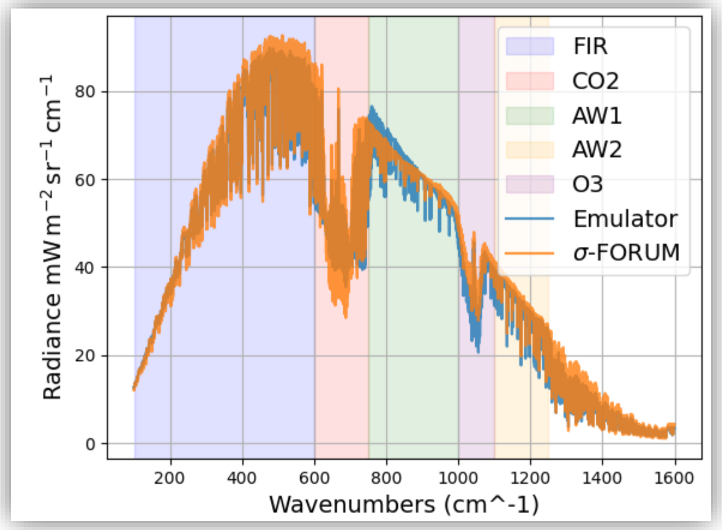
Reconstructed Spectra: *Single scenario*

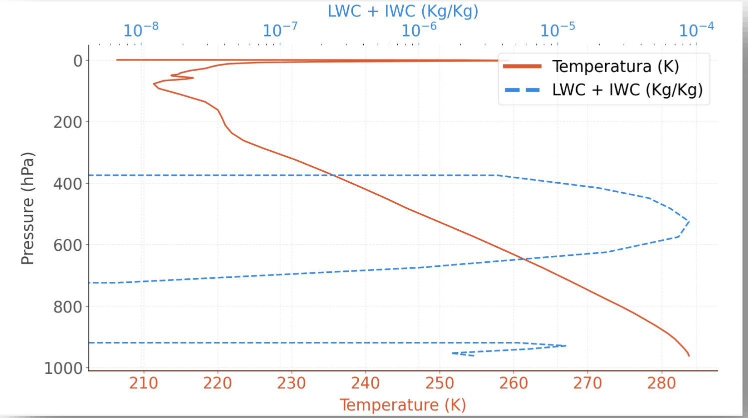
Case 1: Ocean + Clear sky



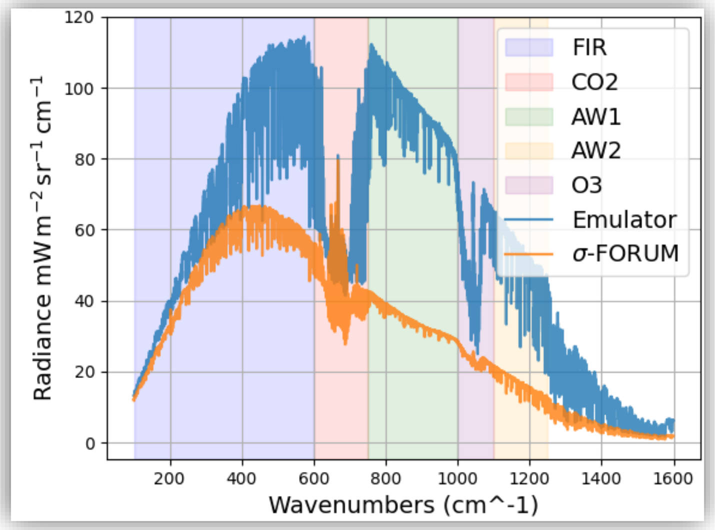


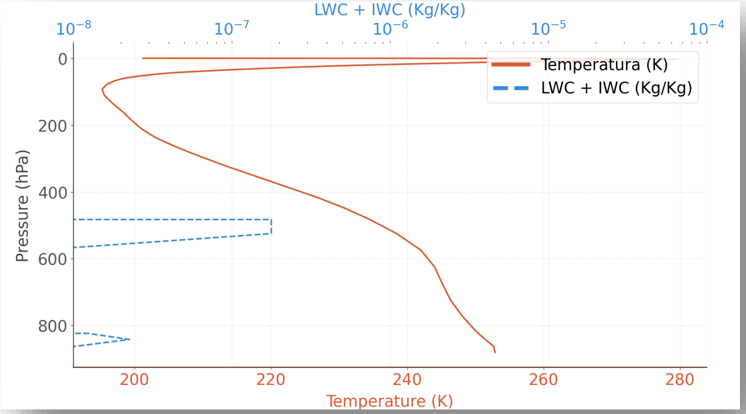
Case 2: Ocean + Thick Cloud





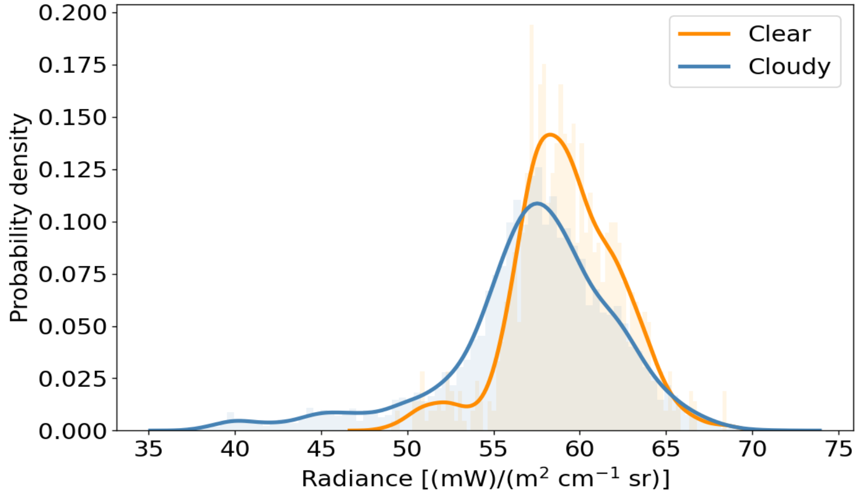
Case 3: Ice surface + Clear Sky





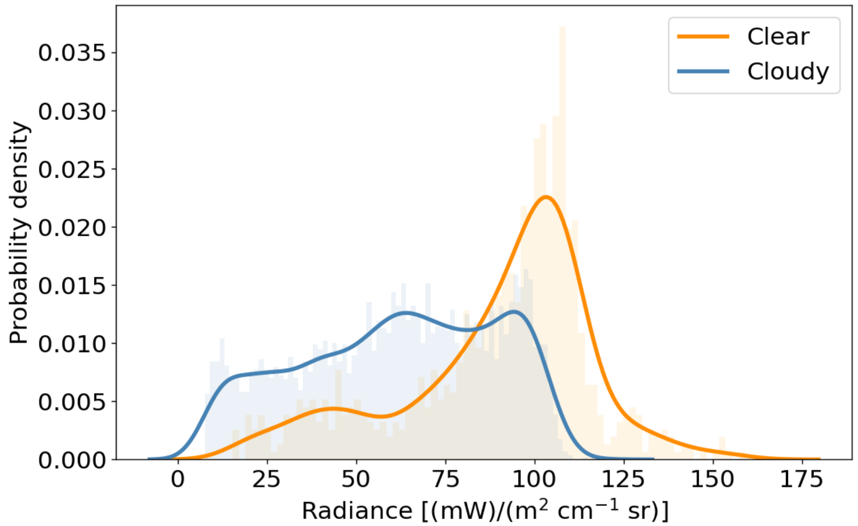
SAF Statistical Characterization: *Does Clear and Cloudy sky differs?*

Water absorption channel 370 cm^{-1}



- **Same support**
  - **Same shape**
    - **Overlap**

Atmospheric window channel 910 cm^{-1}

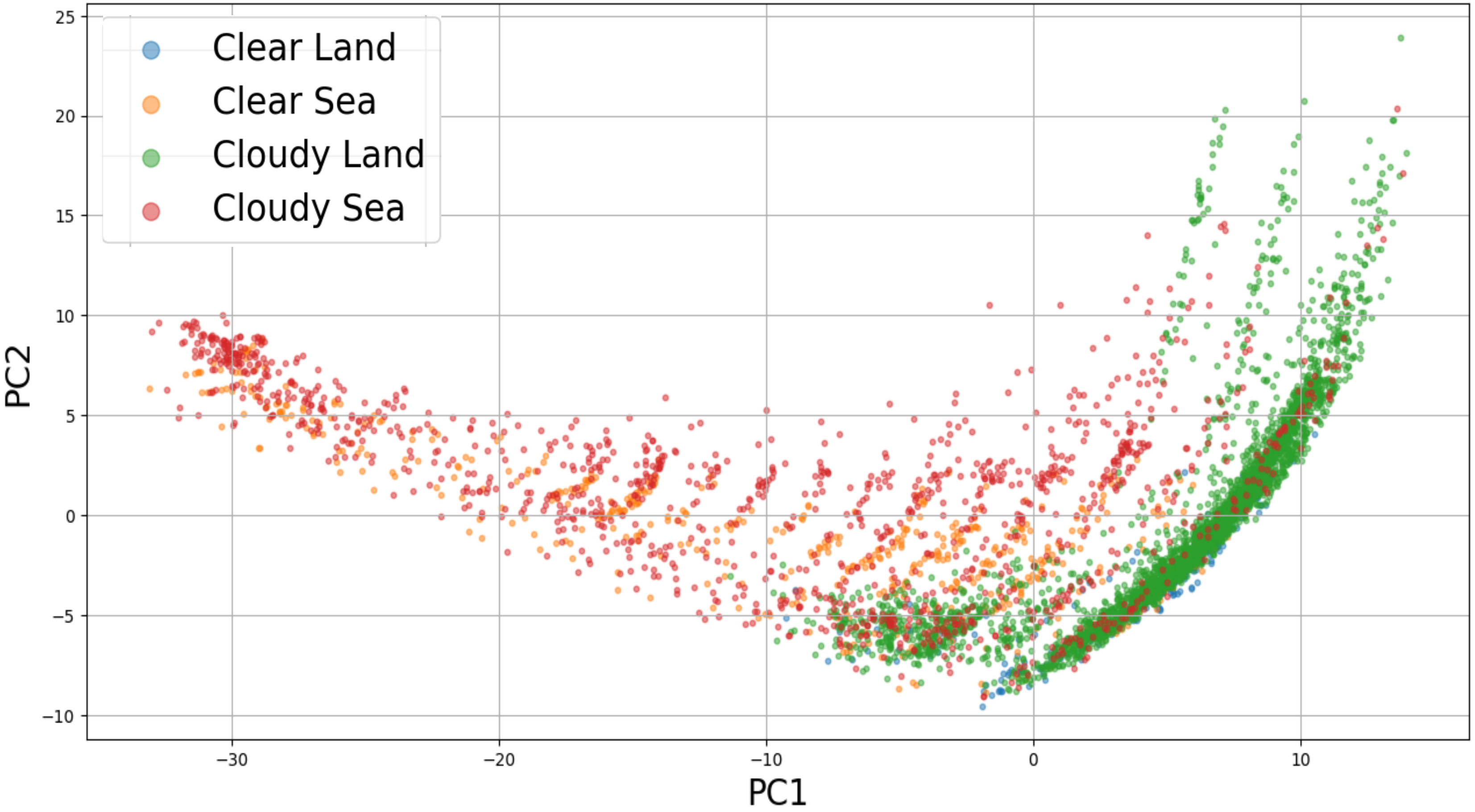


- **Almost same support**
  - **Different shape**
    - **Overlap**

*This promotes an emulator trained **without an explicity distinction** between scenarios.*

SAF Statistical Characterization: *Does Land and Sea differs?*

- A Principal Component Analysis (PCA) was performed to the variables: **P, T, H_2O, IWC and LWC**.



- Projected data on the subspace generated by *PC1 and PC2.*
- Different structures related on *land* and *ocean*.

This promotes a surface-aware emulator.

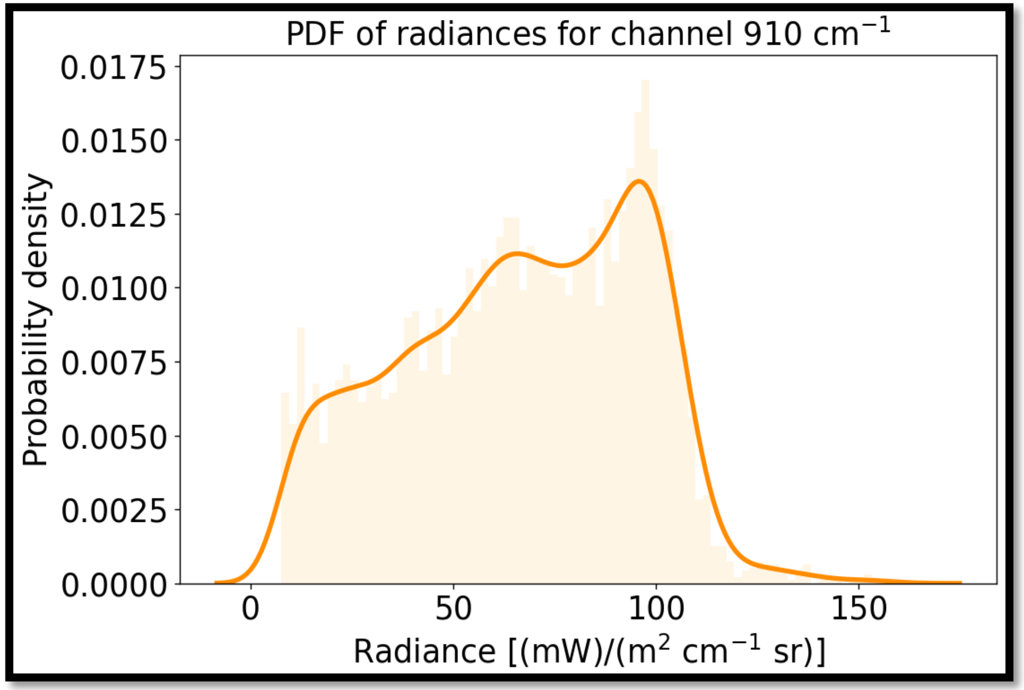
Only latitude and longitude matter!

Limitations: *the challenge of the atmospheric windows*

- **Variance reconstruction** error
- **Multimodality of PDF** in some spectral ranges

Shouldn't we move away from point estimator loss function to PDF generator?

Atmospheric window channel



Conclusions

- Computational performance: 10^{-3} ***seconds for each*** profile.
- Good qualitative **full reconstruction of the spectrum**.
- But performance **depends on the spectral range**
- Ranges with **high variance and/or multimodality** are very challenging.

TOWARDS

What's next?

- Spectrum-aware or surface-aware emulator.
- Switch to a **distribution estimator model,** using a PDF-based cost function (e.g. *Wasserstein* distance, *KL-divergence* etc).
- Change or modify architecture(e.g. Encoder-Decoder model).
- Implement emulator in data assimilation algorithm like **EnKF.**

Thank you for the Attention!