A Latent Twin Architecture for Robust Clear-Sky Retrieval from IASI Acquisitions

Michele Martinazzo[1], Cristina Sgattoni[2,4], Marco Menarini[3], Chiara Zugarini[5,6], Luca Sgheri[5], Tiziano Maestri[1]

michele.martinazzo2@unibo.it

1- Department of Physics and Astronomy Augusto Righi, University of Bologna, via Irnerio 46, Bologna, 40126, Italy
2 - Institute of BioEconomy (IBE), National Research Council (CNR), Via Madonna del Piano, 10, Sesto Fiorentino, 50019, Firenze, Italy.
3 - Institute of Atmospheric Sciences and Climate, Italian National Research Council, Bologna (CNR-ISAC) - Bologna, Italy
4 - INdAM Research Group GNCS, P.le Aldo Moro, 5, 00185 Roma, Italy.
5 - Institute for Applied Mathematics (IAC - CNR), Via Madonna del Piano, Sesto Fiorentino-Firenze, 50019, Italy.
6 - Department of Information Engineering, University of Florence, Via di Santa Marta n. 3, Firenze, 50139, Italy

Introduction

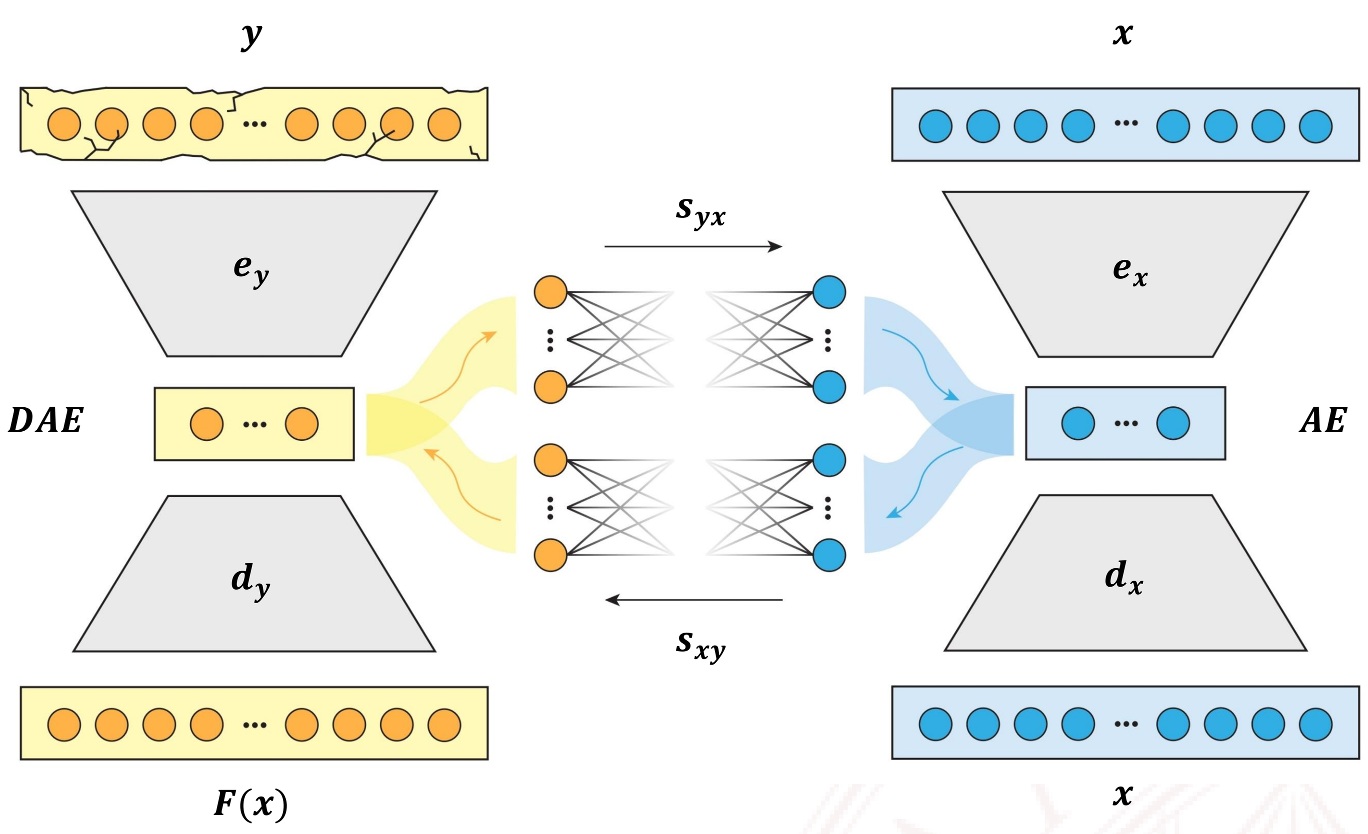
In recent years, data-driven approaches have emerged as powerful alternatives to traditional physics-based retrievals. These methods take advantage of machine learning techniques such as learnable pseudoinverse or deep learning architectures to extract relations and patterns hidden in the observed data. In this work, a deep learning architecture, based on latent twin approach (originally introduced in theoretical works as Chung et al., 2025), is applied to IASI spectra, with the goal to assess the robustness of this method for retrieving atmospheric profiles, including temperature, water vapor, ozone, surface emissivity, and surface temperature, in real-world clear-sky conditions. The algorithm is first applied on synthetic radiances derived from the NWP SAF database using the fast radiative transfer code sigma-IASI/F2N (Masiello et al, 2024). The algorithm is then applied to IASI Level 1C observations, along with their corresponding Level 2 products which serve as reference to evaluate the reconstruction accuracy of the autoencoder-based retrieval.

1. Architecture

Given the forward problem

$$y = F(x) + \epsilon$$

The Latent twin architecture is a data-driven yet physics-aware approach introduced by Chung et al. (2025), optimized to solve a given inverse problem. The main architecture is presented here:



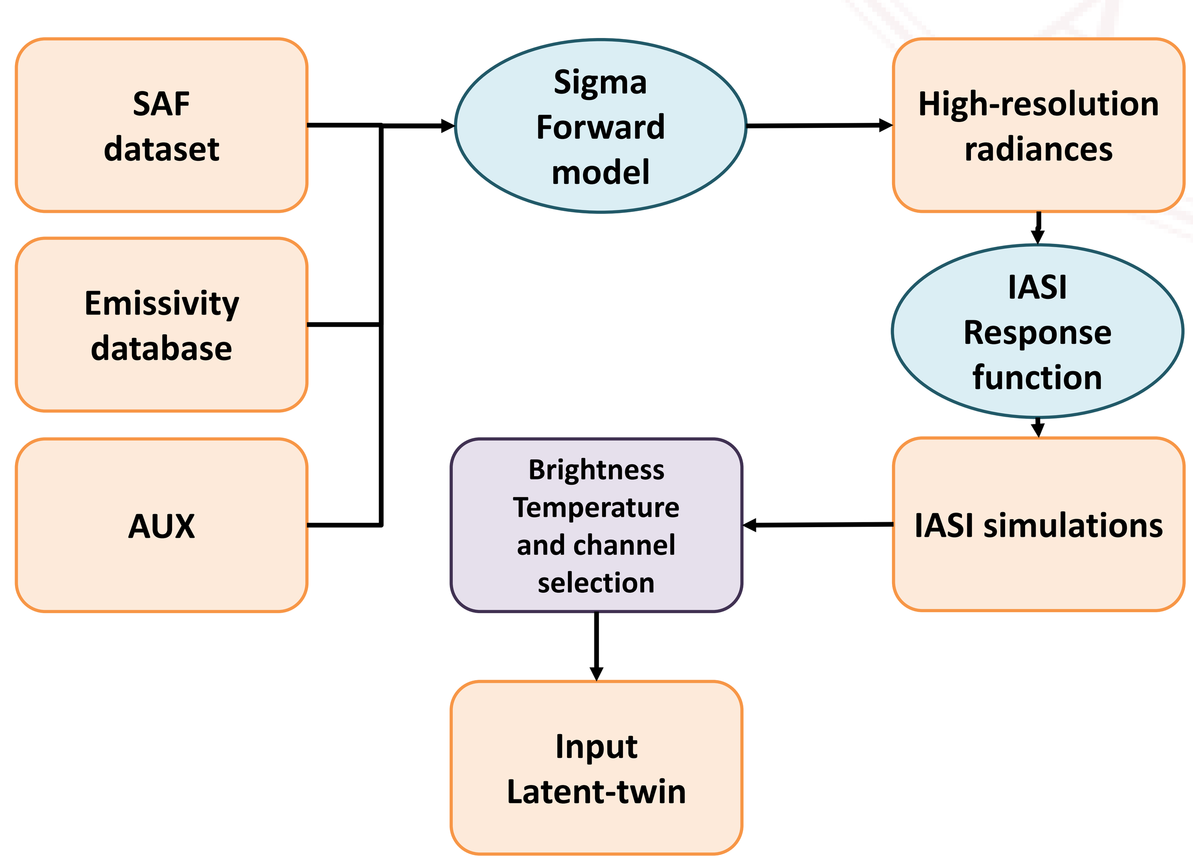
Physics-awareness stems from restricting solutions to a learned physically plausible manifold and from additional model-consistency corrections.
During the training phase all components are jointly optimized by minimizing a weighted combination of reconstruction and surrogate losses.

$$\min_{\theta} \frac{1}{N} \sum_i \alpha_x D_x(d_x \circ e_x(x_i), x_i) + \alpha_y D_y(d_y \circ e_y(y_i), F(x_i)) +$$
$$+\alpha_{xy} D_{xy}(d_y \circ s_{xy} \circ e_x(x_i), F(x_i)) + \alpha_{yx} D_{yx}(d_x \circ \overset{x}{s}_{yx} \circ e_y(y_i), x_i)$$

Where θ collects all trainable parameters, and D is a distance metric.
A fine-tuning procedure is performed to achieve better score in the surface temperature and humidity reconstruction.

2. Dataset and Preprocessing

The training, validation and test sets are generated starting from the NWP SAF atmospheric database using the sigma fast radiative transfer model (Masiello et al., 2024), for a total of 25'000 clear sky scenarios.



The state vector contains the atmospheric state, where the profiles are stretched to maintain a total of 60 layers per profile.

$$x = [T, H_2O, O_3, EM, TS] \in \mathbb{R}^{231}$$

On the other hand, the measurement vector is created starting from a channel selection of the IASI acquisition and auxiliary data such as the geolocation, the pressure grid and surface pressure.

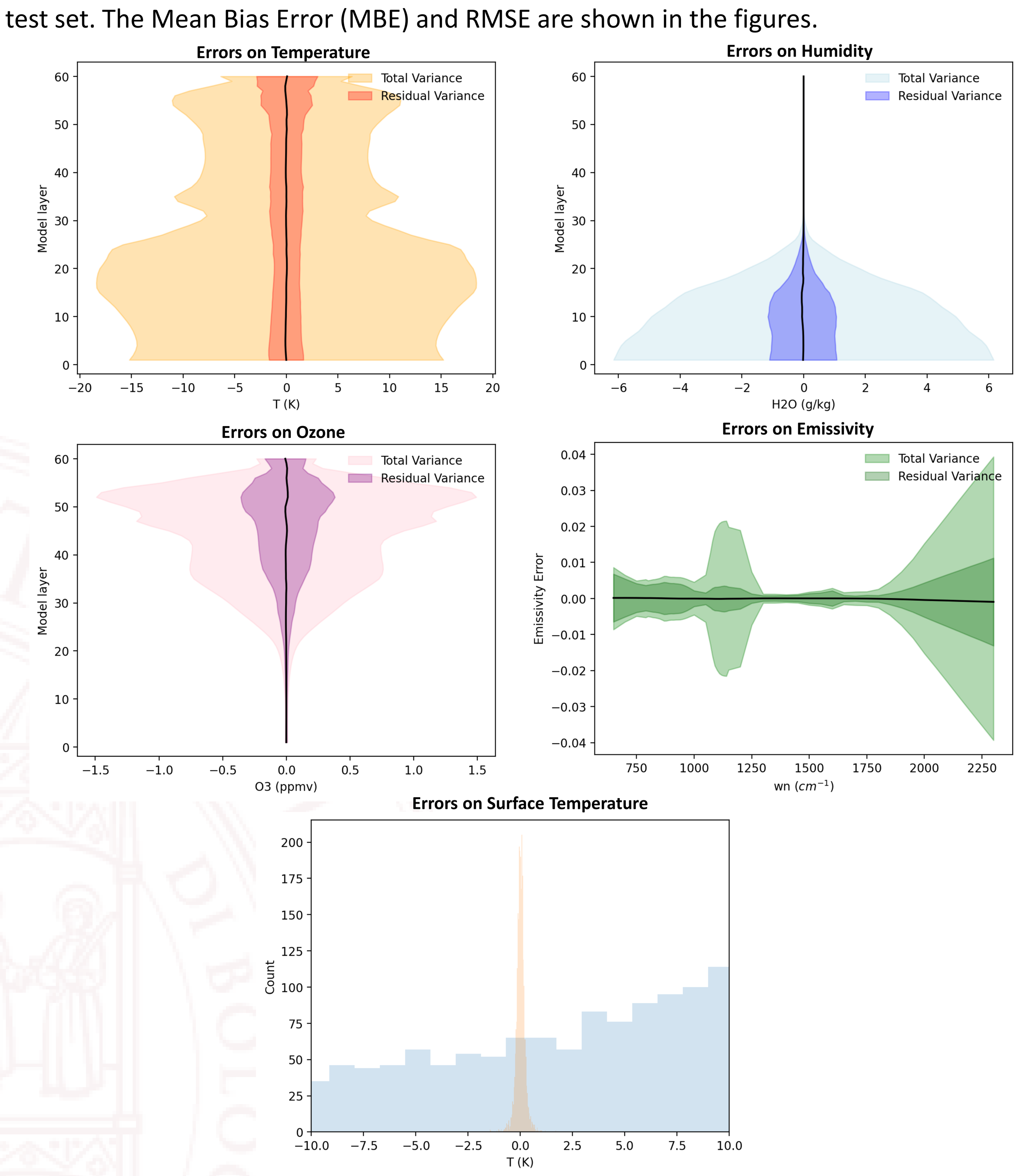
$$y = [I_{ch}, lat, lon, Month, PS, P] \in \mathbb{R}^{864}$$

Min-Max normalization is applied for each independent physical quantity. Humidity and ozone profiles are transformed using the soft-max inverse transformation.

3. Results

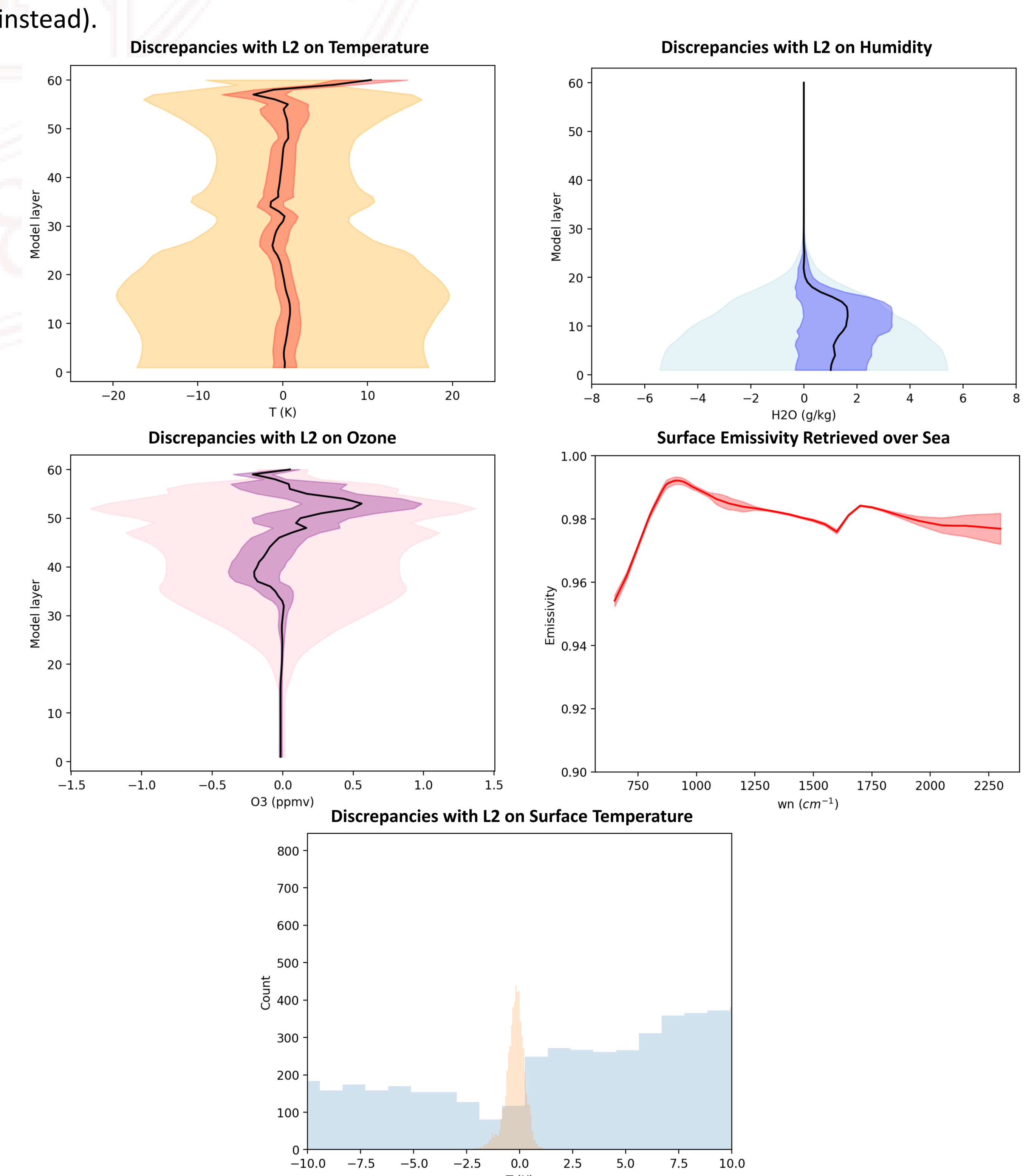
3.1. Application to synthetic data

The residuals between the predicted profiles and the target profiles are computed for the entire test set. The Mean Bias Error (MBE) and RMSE are shown in the figures.



3.2. Application to measured data and comparison with IASI L2 data

Residuals between the predicted and IASI L2 profiles are computed for different orbits for a total of almost 20'000 acquisitions (nadir-like). The MBE and RMSE are shown here for acquisitions over the sea (since L2 emissivity is not retrieved over the ocean, the Latent Twin retrieval is shown instead).



Biases with respect to IASI L2 retrievals in humidity and ozone profiles can be related with **different assumptions in the spectroscopic database**.

Conclusion

The framework provides a viable basis for retrieving atmospheric properties under clear-sky conditions. In particular, it allows the retrieval of **temperature, water vapor, ozone, surface temperature, and surface emissivity**. The retrieved profiles yield low chi-square values ($\langle \chi^2 \rangle \cong 1.7$), indicating **good radiance consistency**. A key strength of the proposed approach is its computational efficiency. Once trained, the latent twin model can perform **around 440'000 retrievals per minute** on a standard laptop. Several important extensions remain for future work, such as the introduction of aerosol scattering layers or the retrieval of trace gases. The possibility of retrieving water and ice clouds is explored in Sgattoni et al. (2025).