TOWARDS THE ASSIMILATION OF SOLAR SATELLITE CHANNELS: NEW FORWARD OPERATOR DEVELOPMENTS

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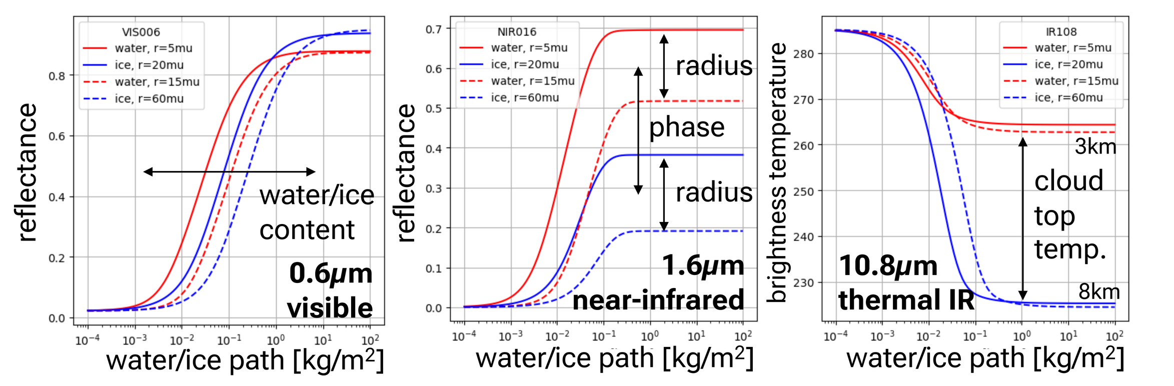
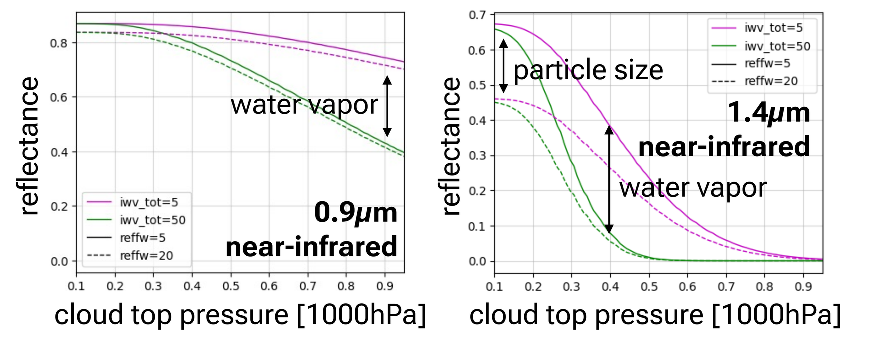
INFORMATION CONTENT OF SOLAR CHANNELS

Solar channels (measuring reflected sun light with wavelengths < 4μm) of imagers on geostationary and polar orbiting satellites provide **high-resolution information on clouds, aerosols and humidity** that could be valuable for model evaluation and data assimilation (DA). Up to now only the 0.6μm visible channel of Meteosat SEVIRI is being assimilated operationally (in DWDs regional DA system).



← Signals in different SEVIRI channels for uniform water or ice clouds at fixed heights with varying water path.

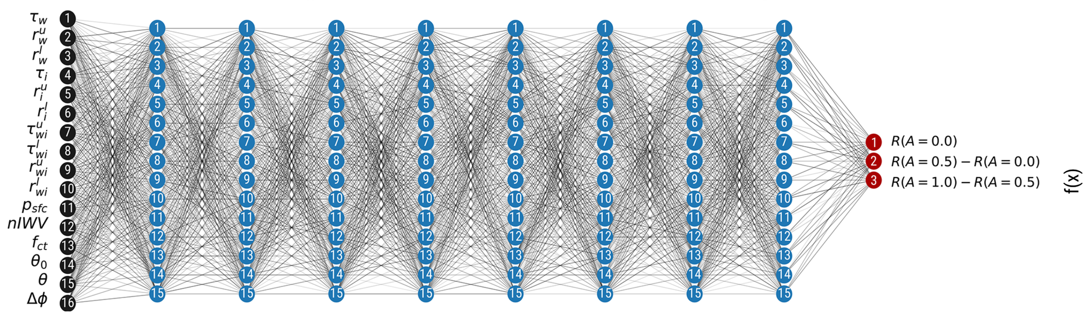
The **cloud information** in solar channels is complementary to the information available from thermal channels.



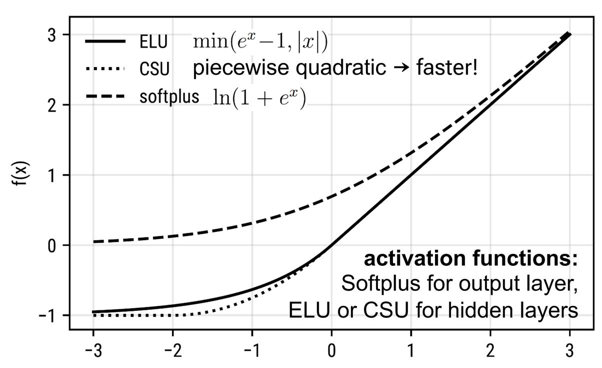
← Water vapor (WV) sensitive solar channels Reflectance in MTG FCI channels for thick water clouds (optical depth 100) with varying cloud top pressure and two different droplet sizes in a **moist atmosphere** (WV content 50mm) and a **dry atmosphere** (WV content 5mm)

FORWARD OPERATOR RTTOV-MFASIS

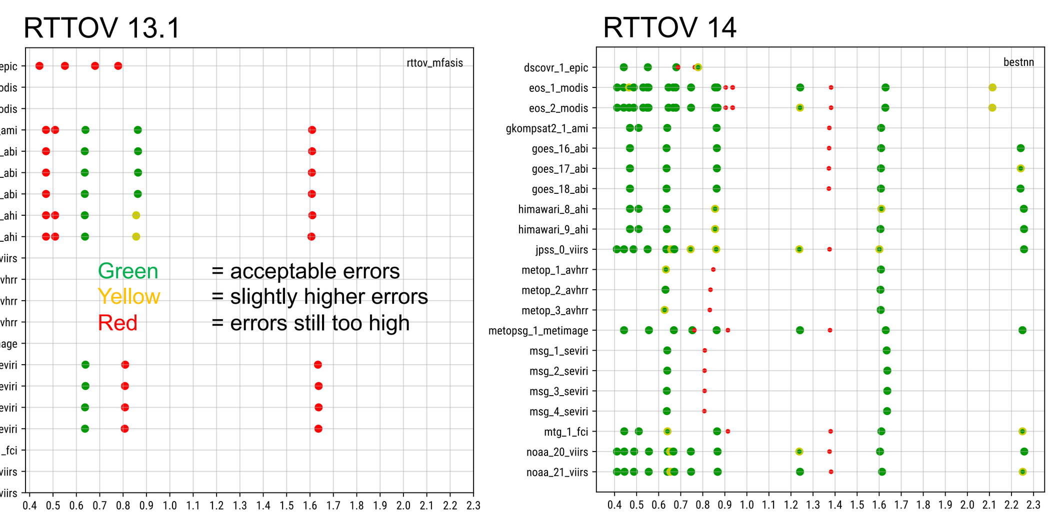
- **Exploiting information content requires forward operator**, which generates synthetic images from numerical weather prediction (NWP) model state by solving a radiative transfer (RT) problem
- Solar channels: Multiple scattering complicates solution, **standard methods are too slow** for DA
- **MFASIS** (method for fast satellite image synthesis): Sufficiently **fast and accurate**
- Strategy: (1) Complex NWP model profiles can be replaced by idealised profiles (see box to the right) defined by few parameters without changing the reflectance significantly
  (2) Compute reflectances for idealised profiles based on random parameter combinations using standard RT solver (discrete ordinate method)
  (3) Train a deep feed forward neural network (aka multi-layer perceptron MPL) to generate reflectances from parameters



MFASIS network with 16 input nodes, 8 hidden layers and 2000 parameters



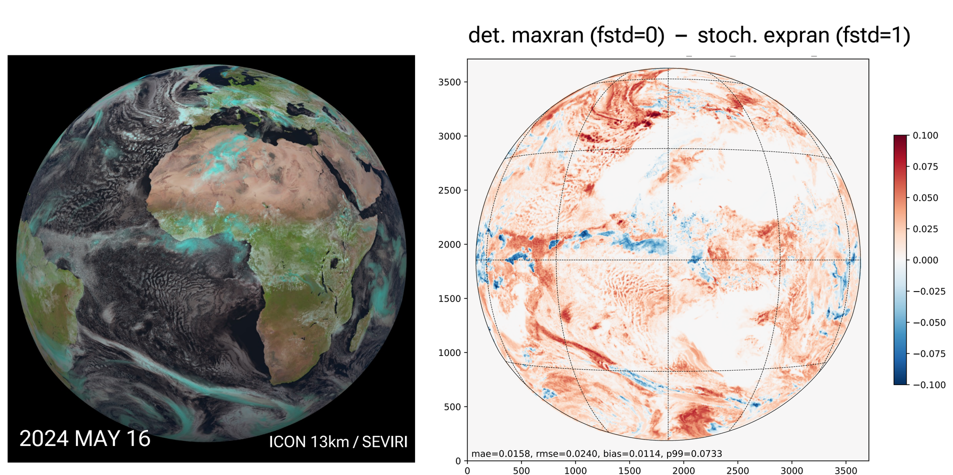
- **Neural networks** (NNs): Small (typ. 2000-5000 parameters) → fast (<1μsec/column), trained with Tensorflow using O(10^7) samples. Mean reflectance errors in most cases smaller than 0.01.
- **Inference**: Vectorized Fortran code including tangent linear and adjoint versions
- MFASIS has been **implemented in RTTOV** satellite forward operator package (developed by EUMETSATs numerical weather prediction satellite application facility). The number of supported instruments was increased significantly with version 14 (released in February 2025).



CONSISTENCY WITH ECRAD

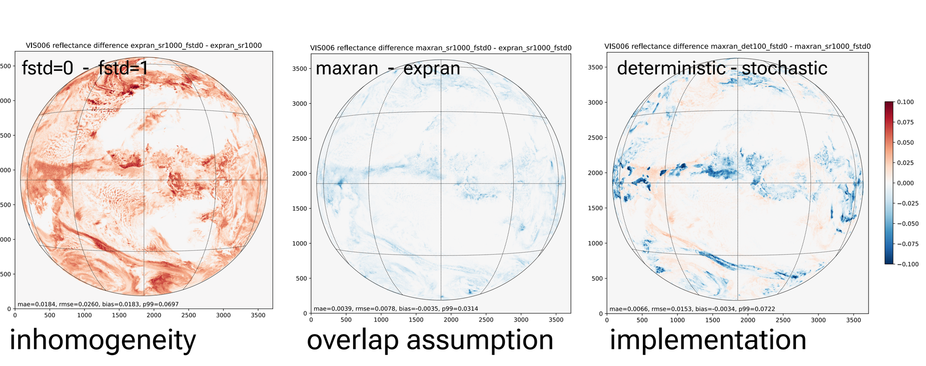
in collaboration with **Robin Hogan (ECMWF)**

- Assumptions made on overlap and inhomogeneity of **unresolved clouds in RTTOV should be consistent** with assumptions in the internal RT code in the NWP model (ICON and IFS: ecRad)
- At the moment this is not yet the case, **RTTOV assumes homogeneous clouds** with maximum-random overlap, **ecRad inhomogeneous clouds** with exponential-random overlap
- Inhomogeneity is quantified by fractional standard deviation fstd = std(LWC) / mean(LWC)
- A slow but fully ecRad-consistent stochastic cloud overlap/inhomogeneity implementation (based on ecRad code) was used to investigate the **reflectance errors arising from the inconsistencies**
- These Reflectance **errors often exceed 0.05 in denser clouds** (larger than typical MFASIS errors, not much smaller than the the observation errors of 0.1-0.15 assumed in DA)



Example: Synthetic SEVIRI RGB image generated from ICON forecast using RTTOV (left) and 0.6μm reflectance difference (right) between

- maximum-random overlap without inhomogeneity (deterministic implementation as in RTTOV) and
- stochastic method with exponential-random overlap and inhomogeneity (ecRAD-consistent)



Contributions to the reflectance difference related to inhomogeneity, different overlap assumptions and different implementations.

In development: "optimal columns", a fast and consistent method.

MFASIS FOR WATER VAPOR SENSITIVE CHANNELS

- MFASIS in RTTOV 14.0: Too large errors for water-vapor sensitive channels (e.g. MTG 0.9μm)
- Reason: Not enough information on WV impact available from the 16 NN input parameters
- WV absorption depends on photon path length and WV concentration
- Clouds: Path length is increased by multiple scattering, depends on geometric thickness of cloud

→ We need additional parameters describing WV content in / between clouds & cloud geometry

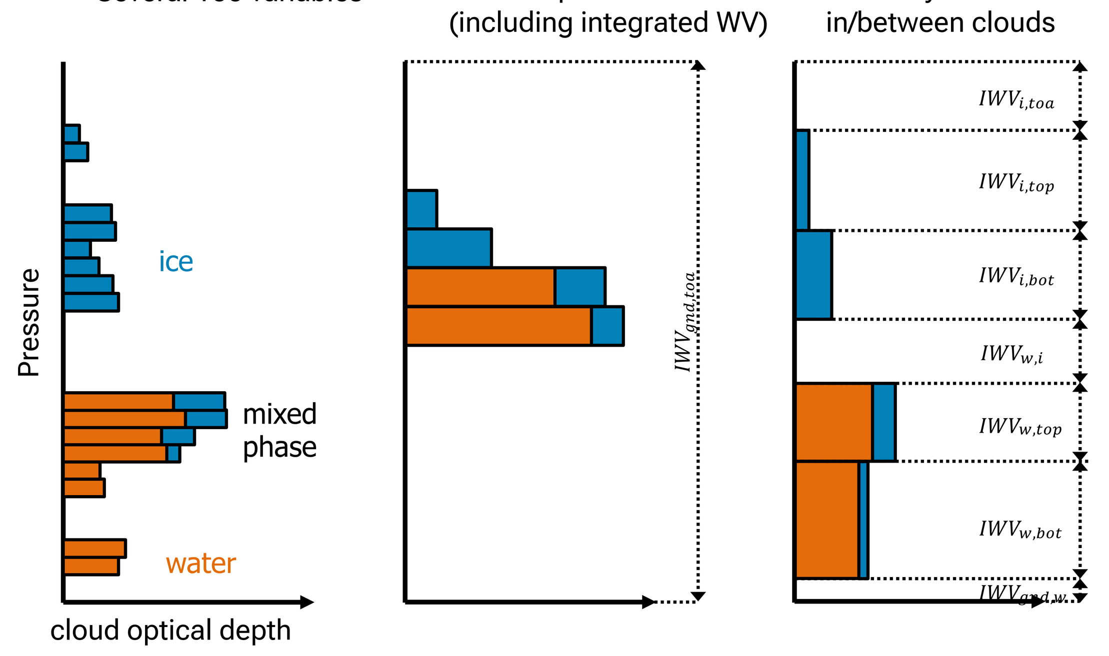
→ New set of 27 input parameters defining more detailed idealized profiles ("extended 2-layer clouds")

Idealized profiles used within MFASIS

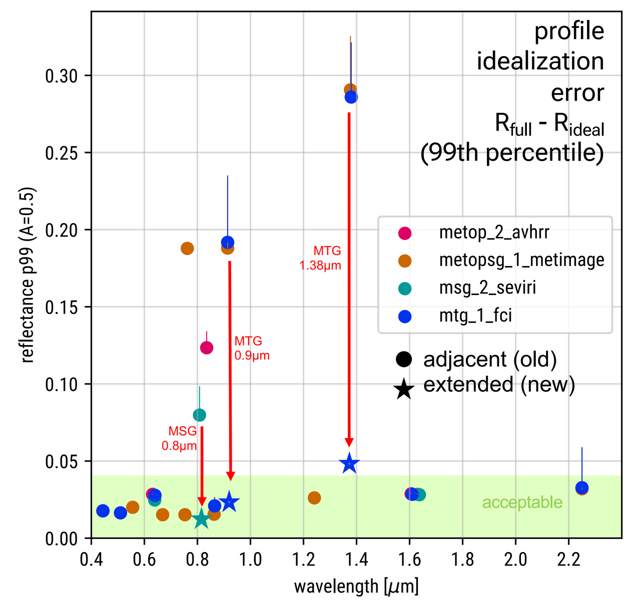
Full NWP profile
- WV and cloud variables per layer
- Several 100 variables

Adjacent 2-Layer clouds
- Developed for 1.6μm channel (Baur et al. 2023)
- 16 NN input features (including integrated WV)

Extended 2-layer clouds
- 27 features describing geometrical thickness of cloud layers and WV in/between clouds

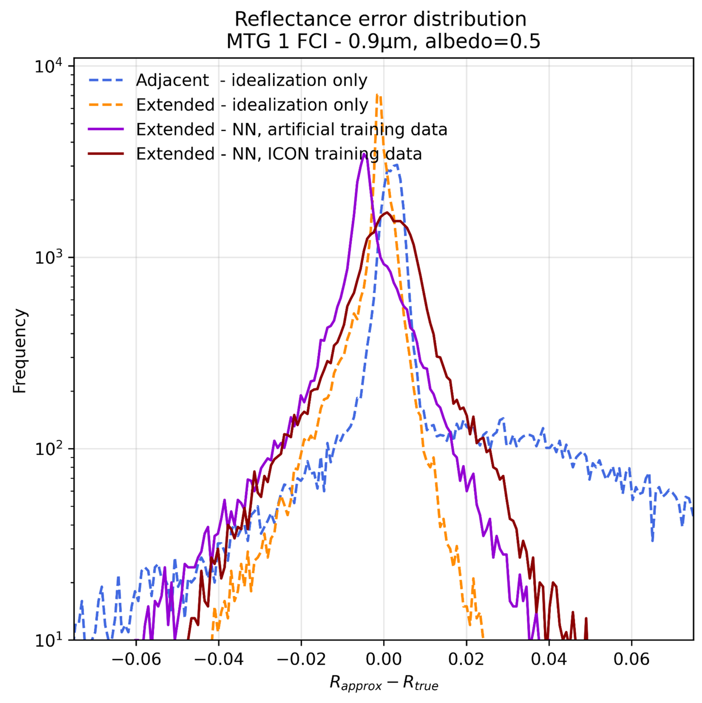


Errors caused by idealized instead of full NWP model profiles.
● = Adjacent 2-Layer clouds
★ = Extended 2-Layer clouds



Neural network training / errors

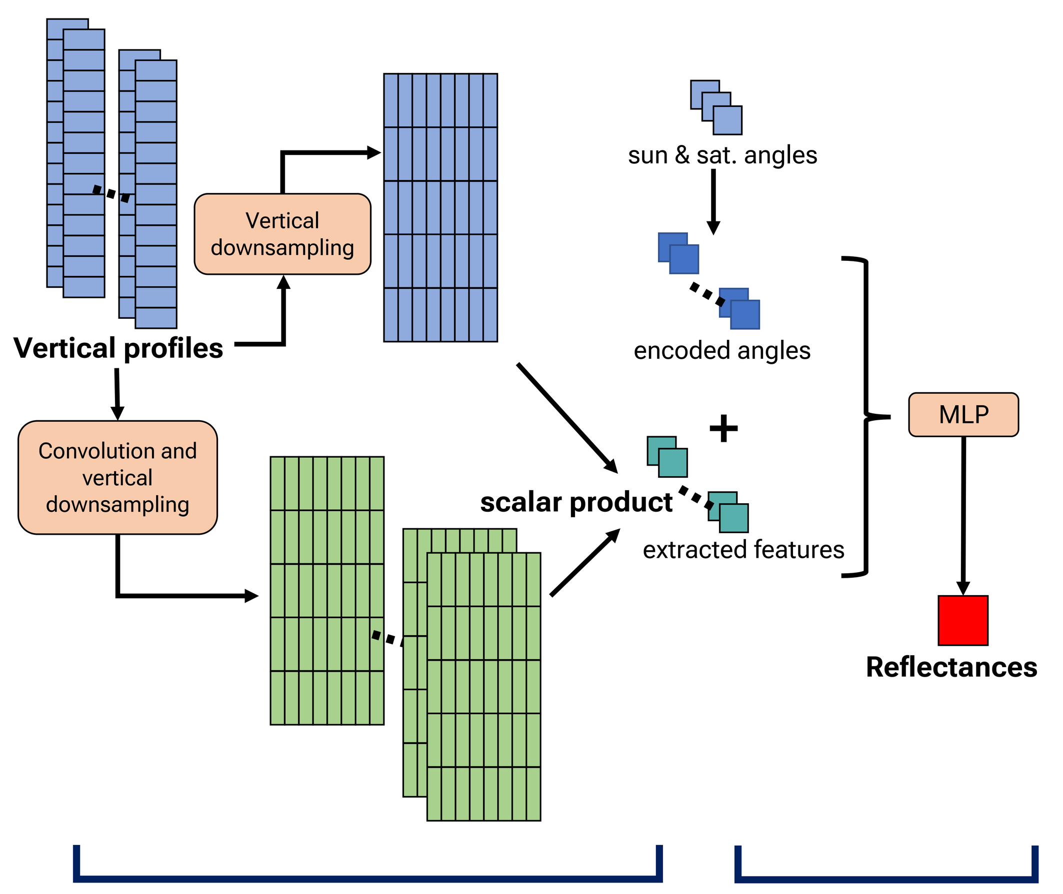
- Increased number and complexity of input features → larger NN required: ~31k parameters
- Inference is still fast (< 2μsec / profile)
- Artificial training data covers full parameter space evenly (good) but may contain many unrealistic cases (problem becomes worse with increasing number of dimensions) → we compare two approaches for the training data set:
  (1) $2.8{\times}10^7$ samples of artificial data (the 27 input features are chosen randomly)
  (2) $2.7{\times}10^6$ samples extracted from ICON profiles
- Validation with set of 5000 diverse IFS NWP profiles: Both approaches work well (errors comparable to 0.6μm), smaller bias for ICON profile training data set



MTG 1 FCI 0.9μm - albedo 0.5	RMSE	MAE	bias	P99	P99.9
Adjacent – idealization only	0.0461	0.0225	0.0144	0.1883	0.3027
Extended – idealization only	0.0079	0.0040	-0.0019	0.0332	0.0635
Extended – NN, artificial training data	0.0133	0.0087	-0.0048	0.0494	0.0954
Extended – NN, ICON training data	0.0123	0.0083	0.0004	0.0426	0.0700

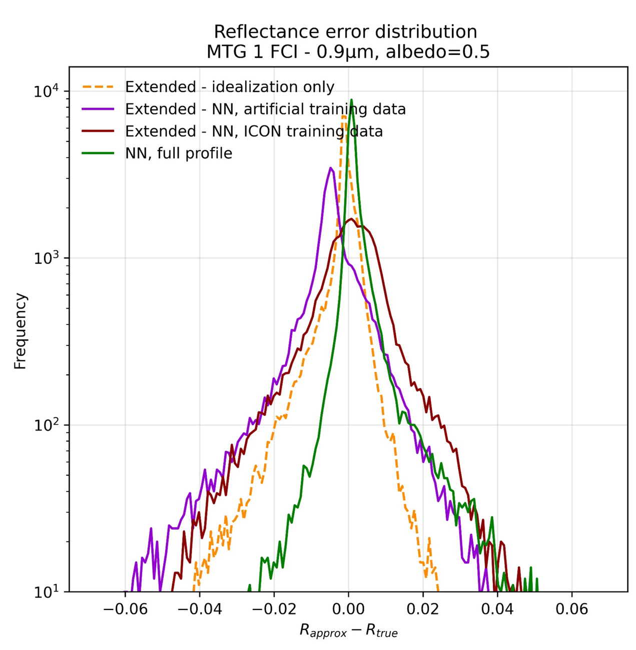
NEW NN ARCHITECTURE FOR FULL PROFILE INPUT

Identifying suitable input features for new satellite channels ("**feature engineering**") **is complex** and time-consuming → Design (transformer-inspired) network to use full atmospheric profiles as input and train it to **learn features automatically** ("feature extraction") and compute reflectance in one network.



Learned "feature vectors" (attention maps) are multiplied with profiles to obtain features

Reflectances are generated from features using MLP (as before)



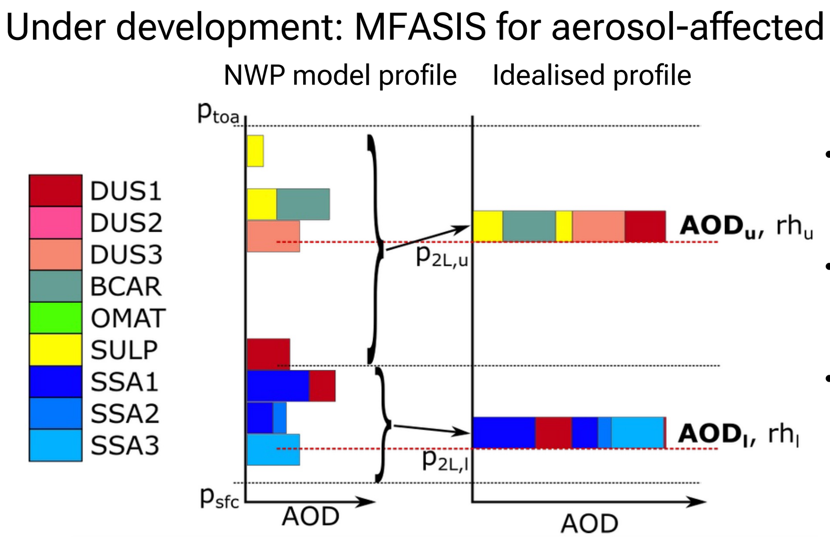
Preliminary results for MTG FCI 0.9μm channel, Full-profile-NN trained with $3{\times}10^6$ ERA5 profiles: Slightly better than for the old approach

RMSE	MAE	bias	P99	P99.9
0.0099	0.0040	0.0024	0.0390	0.0993

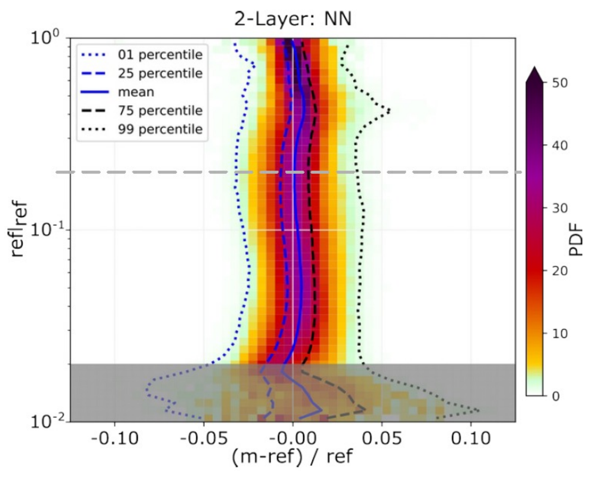
→ Promising approach!

MFASIS FOR AEROSOLS

- Under development: MFASIS for aerosol-affected reflectances



- Idealised profiles: Two layers, 27 NN input parameters
- Atmosphere split where total AOD exceeds 50%
- Upper & lower layer can contain arbitrary species combinations



Prototype for CAMS aerosol species:
NN with 80k parameters → relative errors of a few percent (optimization in progress...)