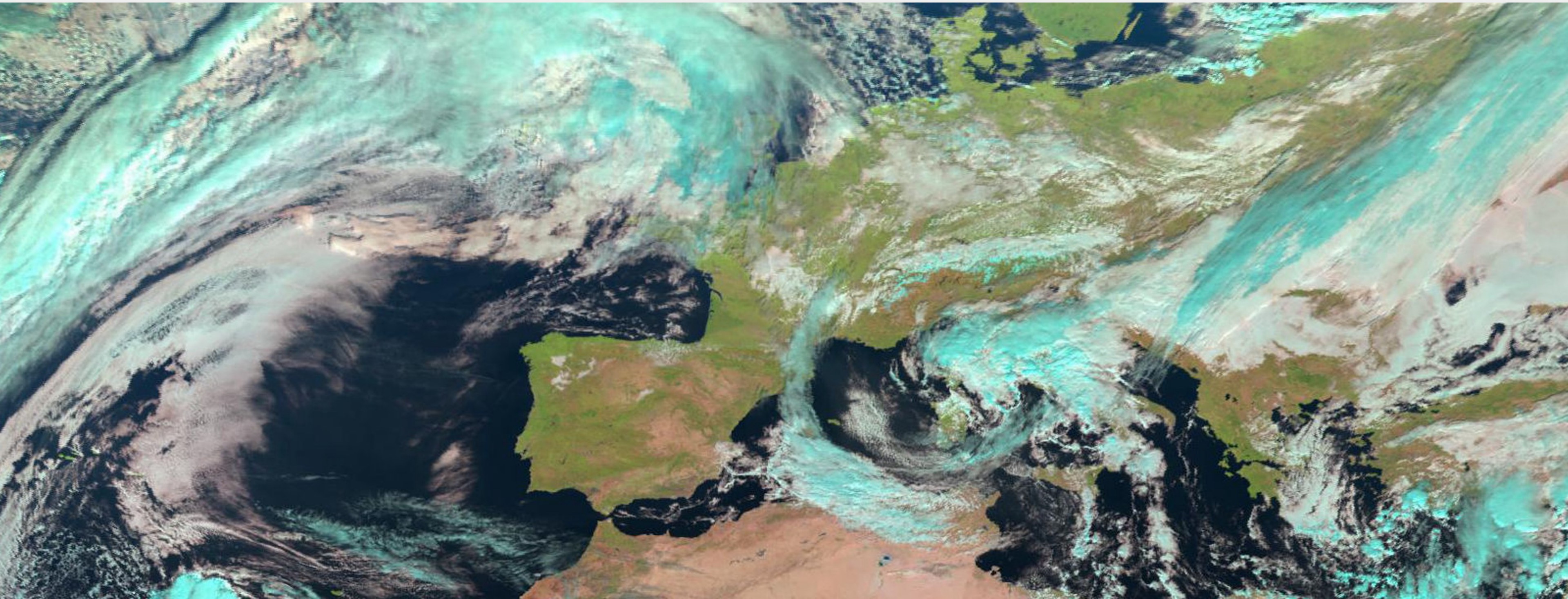
A neural network-based forward operator for assimilating near-infrared satellite images

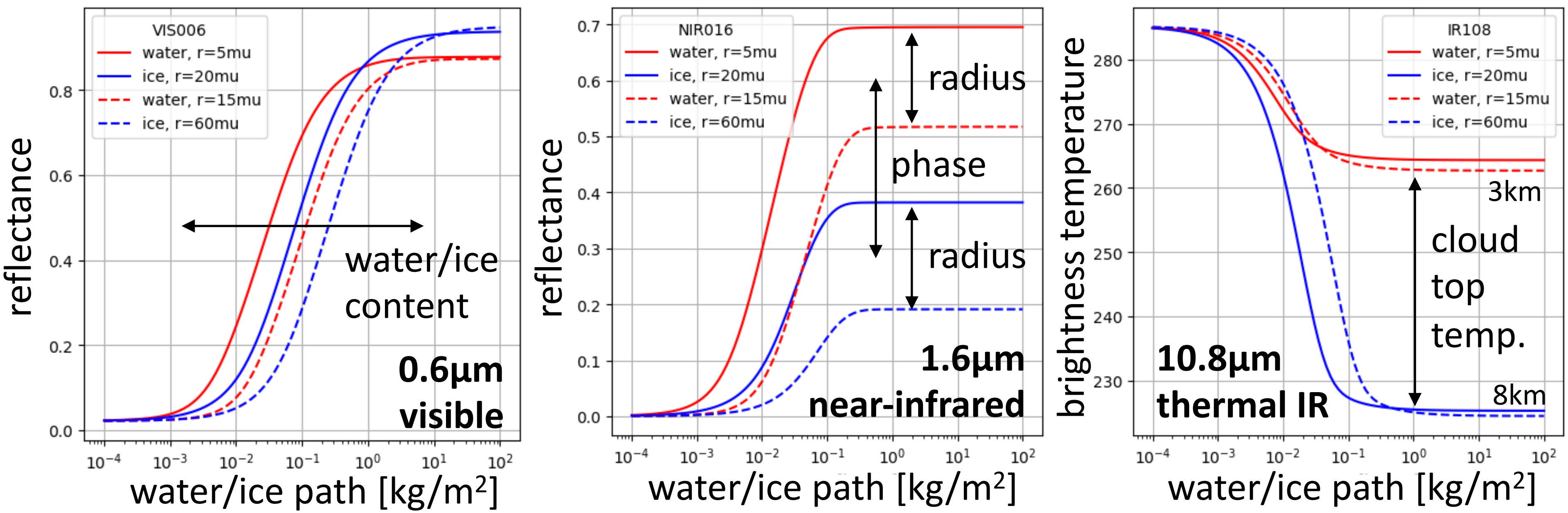
Leonhard Scheck[1,2], Florian Baur[1,2], Olaf Stiller[2], Christina Stumpf[2], Christina Köpken-Watts[2], Roland Potthast[2]

1) Hans-Ertel-Center for Weather Research / LMU Munich, Germany
2) Deutscher Wetterdienst, Offenbach, Germany



LMU LUDWIG-MAXIMILIANS-UNIVERSITÄT MÜNCHEN MIM EUMETSAT NWP SAF NUMERICAL WEATHER PREDICTION Hans-Ertel-Zentrum für Wetterforschung Deutscher Wetterdienst Wetter und Klima aus einer Hand DWD

Why are we interested in near-infrared channels?



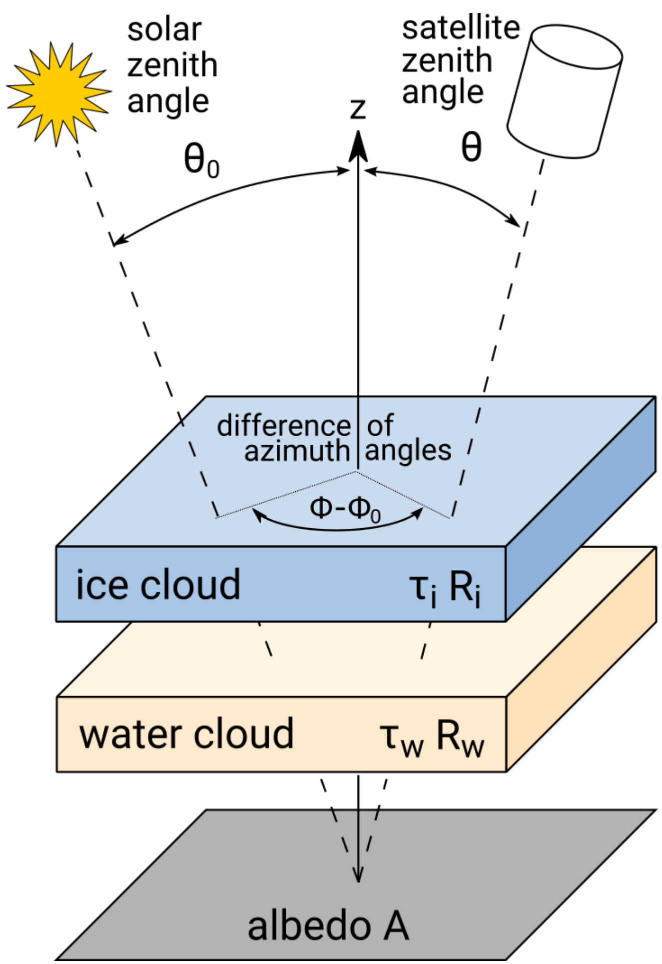
NIR: High-resolution cloud information (complementary to thermal and visible channels)

- Thermal infrared: signal saturates early, provides information on cloud top temperature
- Visible: signal saturates only for rather thick clouds → information on water/ice content
- Near-infrared: saturates early but is sensitive to effective radii even in saturated state
- Special case 1.6µm: Signal depends on phase, ice clouds darker than water clouds

VIS, NIR operators: Multiple scattering important → Radiative transfer complicated…

MFASIS for cloud-affected visible channels (LUT-based)

Method for Fast Satellite Image Synthesis



The fast "conventional" (no machine learning) method (used for operational DA at DWD)

- **Simplify vertical cloud structure:** Complex structure can be replaced by two homogeneous clouds with same optical depth without changing reflectance significantly

  → only 4 parameters (optical depth, particle size)

  + 3 angles, albedo → **8 parameters per column**
- **Compute 8-dimensional reflectance look-up table** (LUT) with discrete ordinate method (DOM) for all parameter combinations → **8GB,** use **lossy compression** → **21MB** = O(CPU cache)
- Determine parameters from profile, interpolate in LUT

fast (O(μsec/column)), mean reflectance error < 0.01
Implem. in RTTOV 12.2 by DWD in collab. with MetOffice

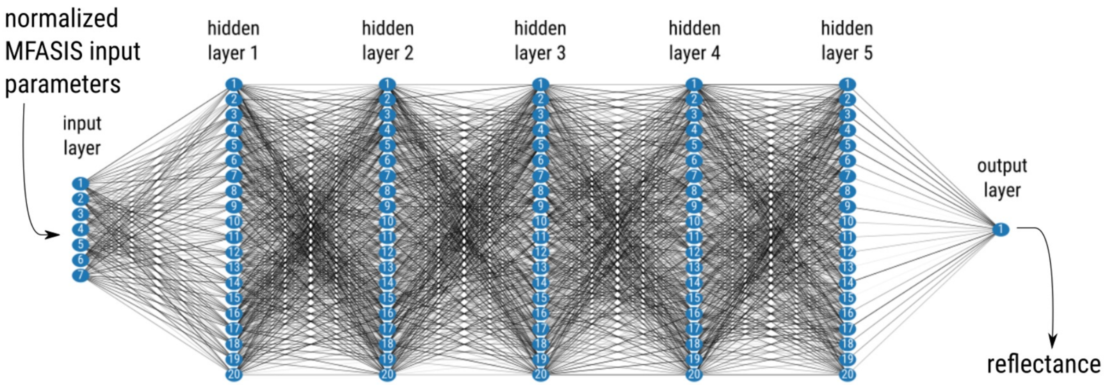
- Simple corrections for mixed-phase clouds and weakly water vapor sensitive channels (0.8μm SEVIRI)
- Preliminary correction for 1.6μm channels

Could we replace the LUT by a neural network (NN)?

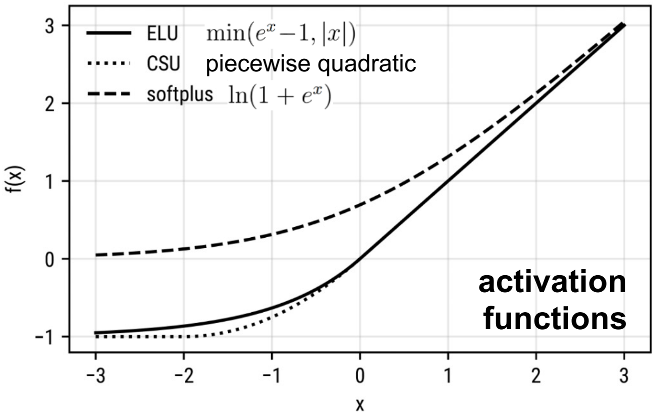
Motivation: Absorbing channels (water vapor, trace gases, clouds) and aerosols (many different species) require additional input variables → LUT size would explode…

Approach: Keep idealized profile strategy (low number of input parameters) but use relatively small (= fast) feed-forward neural network (several 1000 params.) instead of LUT

First goal: Replace LUT by NN for the visible 0.6µm channel (no additional inputs)



$$s_{l+1,n} = f(b_{l,n} + \sum s_{l,m} * w_{l,n,m})$$



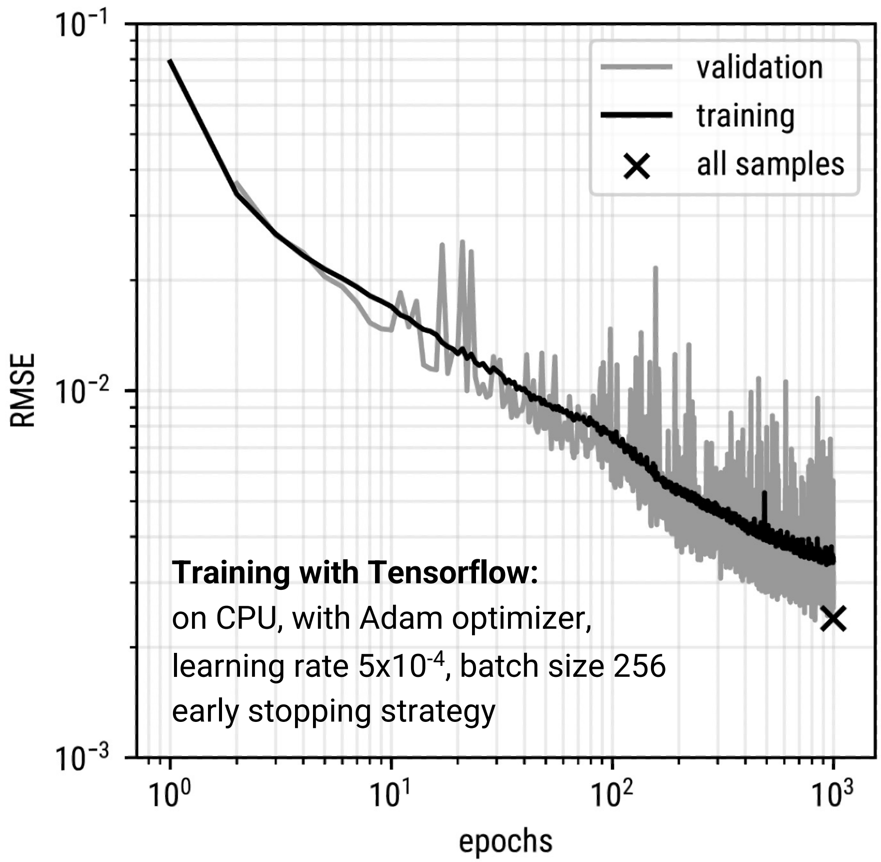
NN structure: best results for 4 – 8 hidden layers ("deep"), CSU activation function

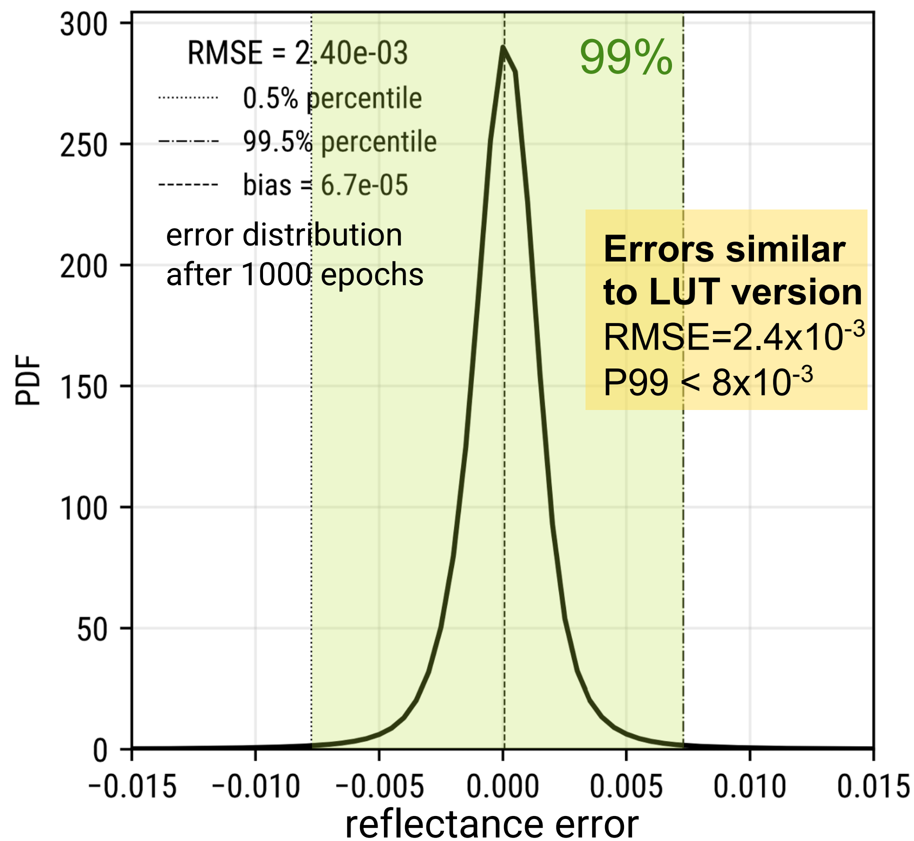
Training data: Synthetic (random numbers for input params., reflectance computed with DOM) → produce as much data as is required, cover full parameter space with constant density

Training process: Tensorflow standard methods (Adam optimizer, early stopping strategy)

Error evolution during training for an example

3000 parameters, 6 hidden layers, 23 nodes/layer, 3.4×10^6 samples, trained for 13h





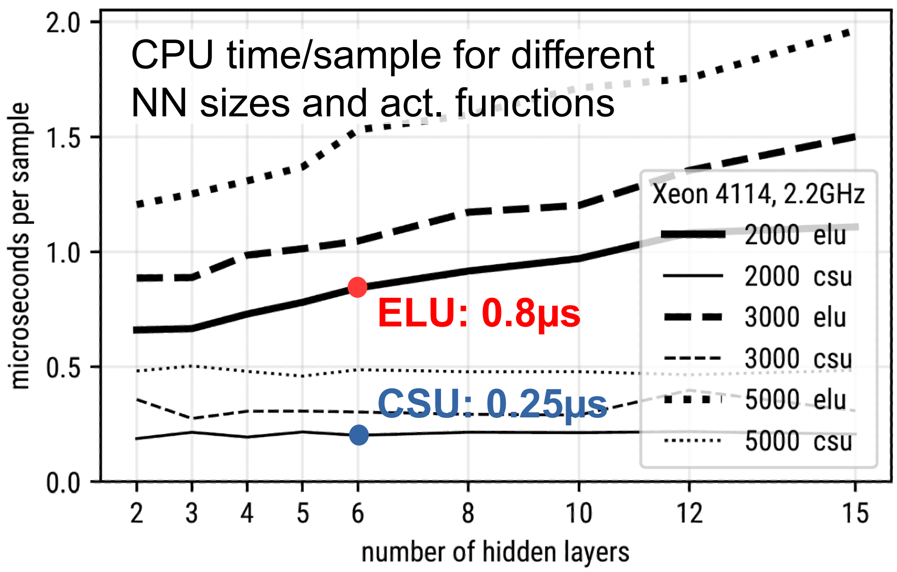
DOM-generated training data can be several 100 times smaller than DOM-generated LUT

Performance

- Development of **Fortran inference code optimized for small NNs** (<100 nodes/layer) (vectorized, much faster than Tensorflow)
- Using a **activation function without exp()** (CSU, piecewise linear/quadratic)
  → inference 3-4 times faster for small NNs

→ Final version for SEVIRI 0.6µm channel 11 x faster than MFASIS-LUT, similar errors

(and MFASIS-LUT is ~200 x faster than DOM)

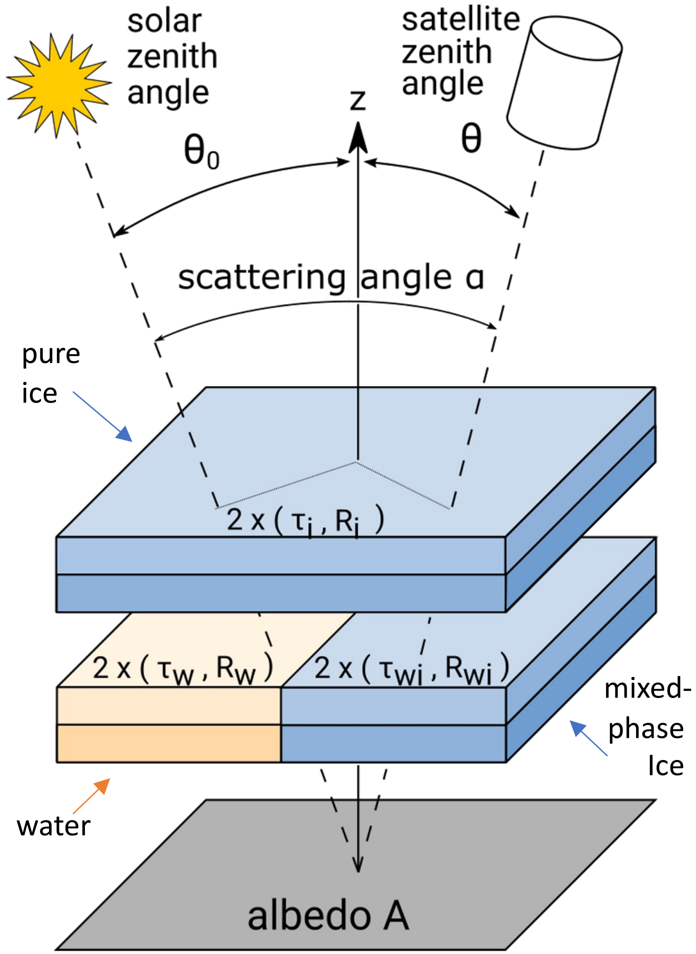


Adjoint / tangent linear codes

- Adjoint (AD) + tangent linear (TL) versions of the nonlinear NN inference code (NL) are required for variational and hybrid DA methods. → AD+TL implemented for Fortran code
- Advantage of neural networks: **AD/TL codes easy to derive, do not have to be modified** when training data or network structure is changed.

For more details see Scheck, L., 2021: *A neural network based forward operator for visible satellite images and its adjoint,* Journal of Quantitative Spectroscopy and Radiative Transfer, DOI:10.1016/j.jqsrt.2021.107841

Additional input parameters for the 1.6µm channel



Errors too high with standard MFASIS → need to consider:

- Sensitivity to effective radius profiles
  → use **two-layer clouds** to provide information on vertical effective radius gradients
- (Dark) ice in mixed-phase clouds is often below water
  → add a two-layer **mixed-phase ice cloud** in the same location as the water cloud
- Weak absorption by CO2, CH4
  → use **surface pressure and cloud top pressure** as input parameters to quantify influences
- Weak absorption by water vapor
  → use **integrated water vapor** as input parameter

→ In total **16 input parameters**

NN learns more complex function → 2.5 times larger NN and 4 times more training data required than for 0.6µm.

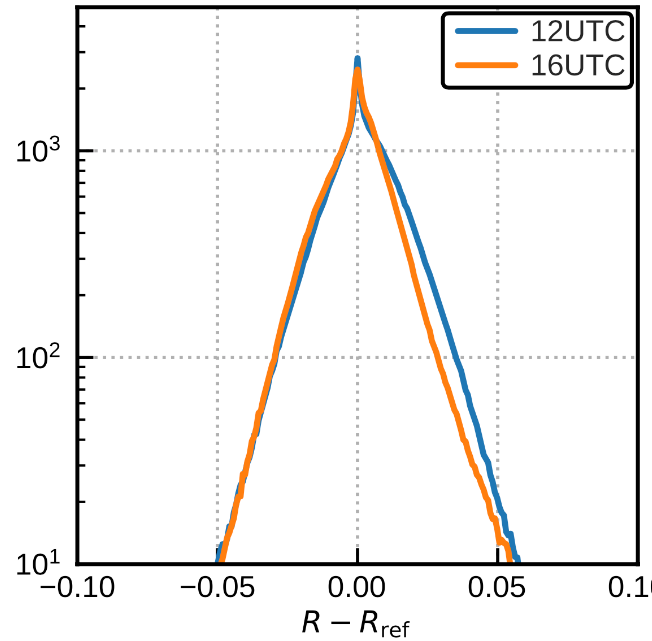
Implemented in RTTOV 13.2 (except for WV input variable and vectorization → RTTOV 14 next year)

Evaluation MFASIS-NN vs. RTTOV-DOM for SEVIRI 1.6µm

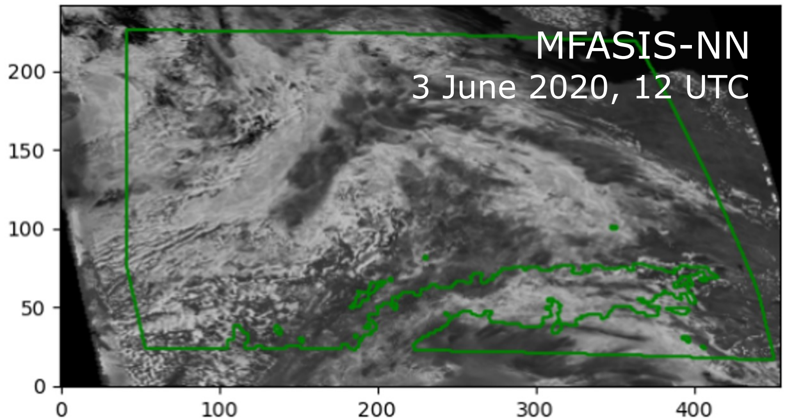
- Data set 1: IFS profile collection available from NWP SAF (5000 profiles, effective radii parameterized)
- Data set 2: Regional model hindcasts (ICON-D2, 30 days, effective radii from 2-moment microphysics scheme)

	Mean absolute error	99th percentile
5000 IFS profiles	0.010	0.035
ICON-D2 (12UTC)	0.011	0.046
ICON-D2 (16UTC)	0.013	0.056

Summary: 1.6µm works -- errors are similar to 0.6µm errors



Reflectance error (compared to RTTOV DOM) distribution for 30 days of ICON-D2 hindcasts

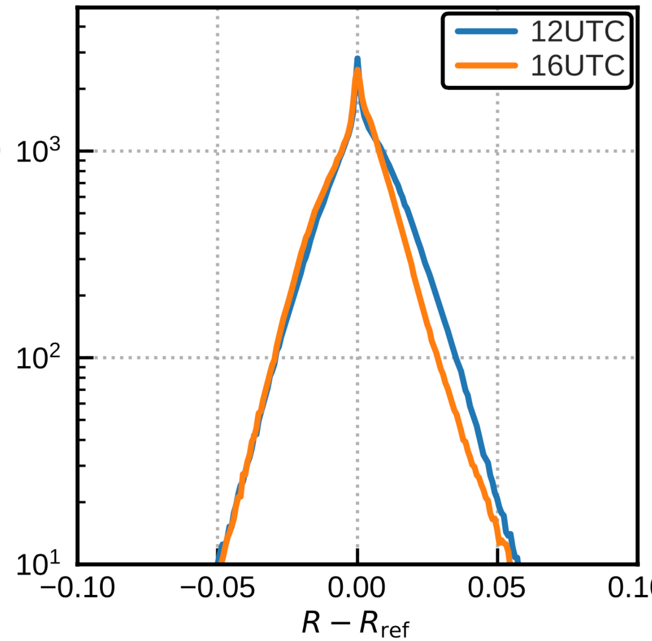


For more details see Baur F. et al., 2023: *A neural-network-based method for generating synthetic 1.6µm near-infrared satellite images* (accepted, AMT)

Evaluation MFASIS-NN vs. RTTOV-DOM for SEVIRI 1.6µm

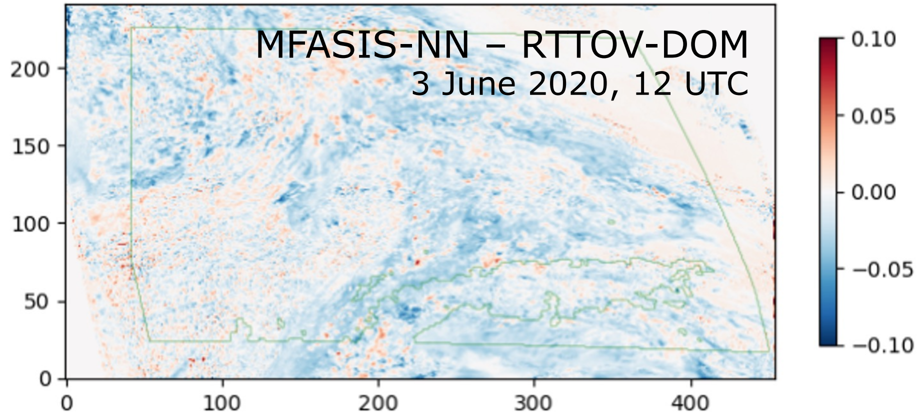
- Data set 1: IFS profile collection available from NWP SAF (5000 profiles, effective radii parameterized)
- Data set 2: Regional model hindcasts (ICON-D2, 30 days, effective radii from 2-moment microphysics scheme)

	Mean absolute error	99th percentile
5000 IFS profiles	0.010	0.035
ICON-D2 (12UTC)	0.011	0.046
ICON-D2 (16UTC)	0.013	0.056



Summary: 1.6µm works -- errors are similar to 0.6µm errors

Reflectance error (compared to RTTOV DOM) distribution for 30 days of ICON-D2 hindcasts

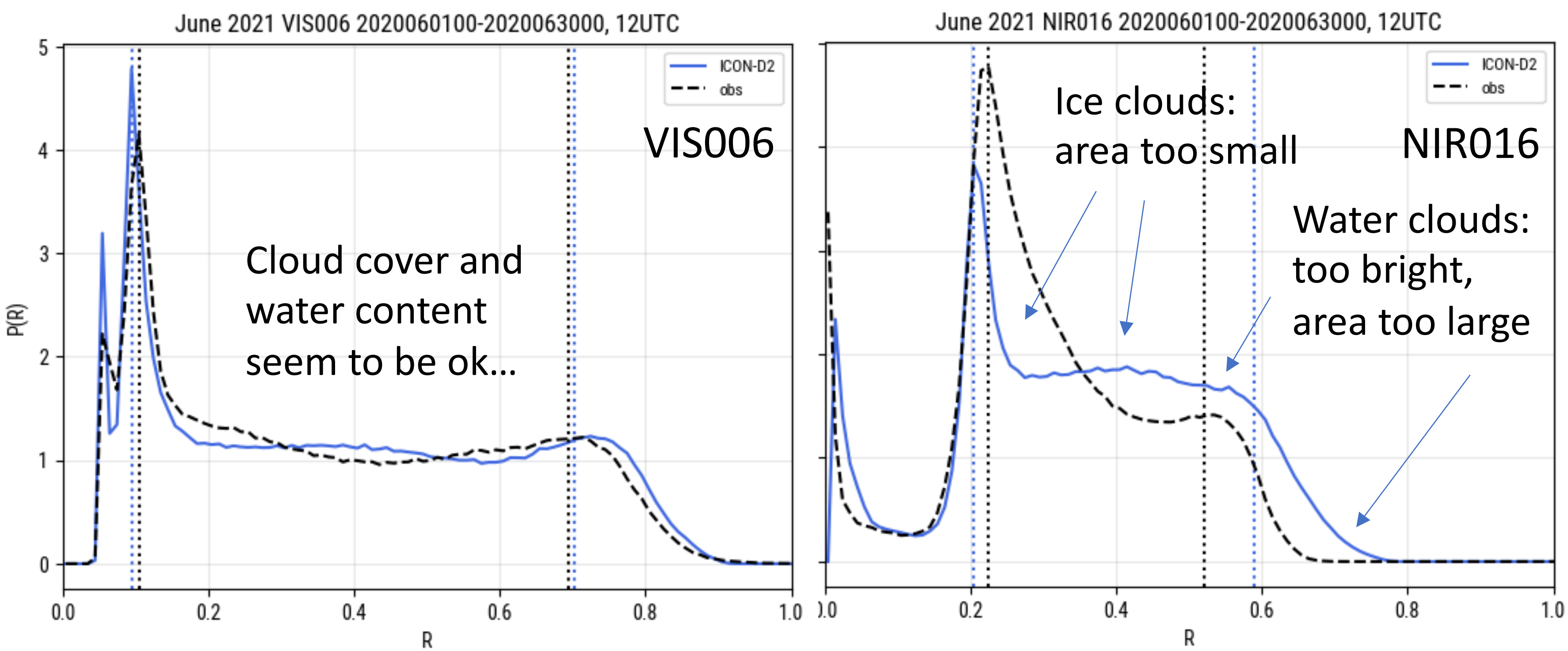


For more details see Baur F. et al., 2023: *A neural-network-based method for generating synthetic 1.6µm near-infrared satellite images* (accepted, AMT)

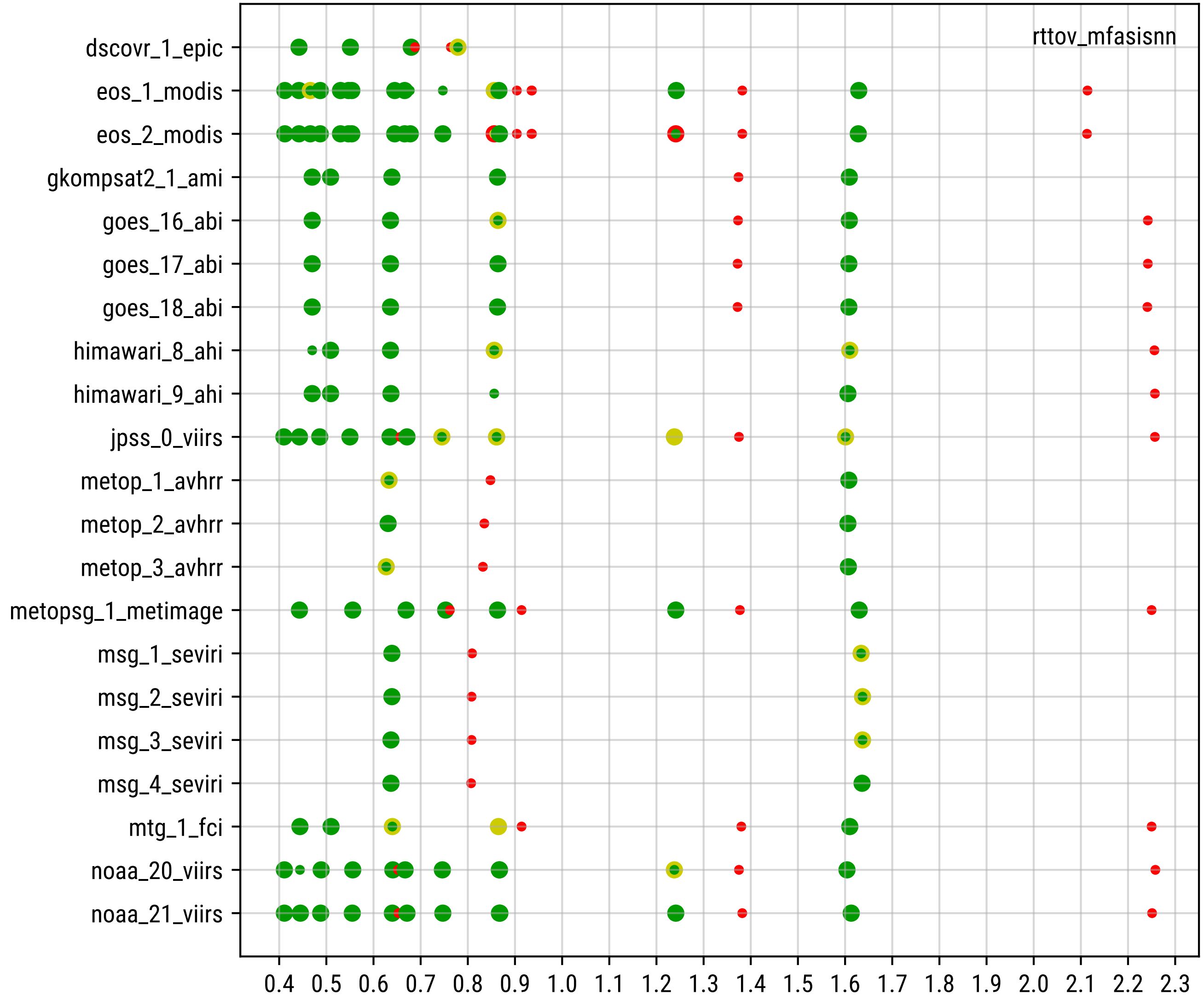
LMU LUDWIG-MAXIMILIANS-UNIVERSITÄT MÜNCHEN MIM EUMETSAT NWP SAF NUMERICAL WEATHER PREDICTION Hans-Ertel-Zentrum für Wetterforschung Deutscher Wetterdienst Wetter und Klima aus einer Hand DWD

First model – observation comparison based on ICON-D2

- Synthetic 0.6µm and 1.6µm SEVIRI images based on ICON-D2 hindcasts (30 days) using 2-moment microphysics scheme (provides prognostic information on radii)
- ICON-D2 was tuned based on visible and thermal infrared SEVIRI channels (Geiss et al. 2021) → histograms look good… (SEVIRI 0.6 µm images operationally assimilated since March 2023)
- 1.6µm histogram should allow for detecting and reducing further model cloud deficiencies…



Supported instruments and channels



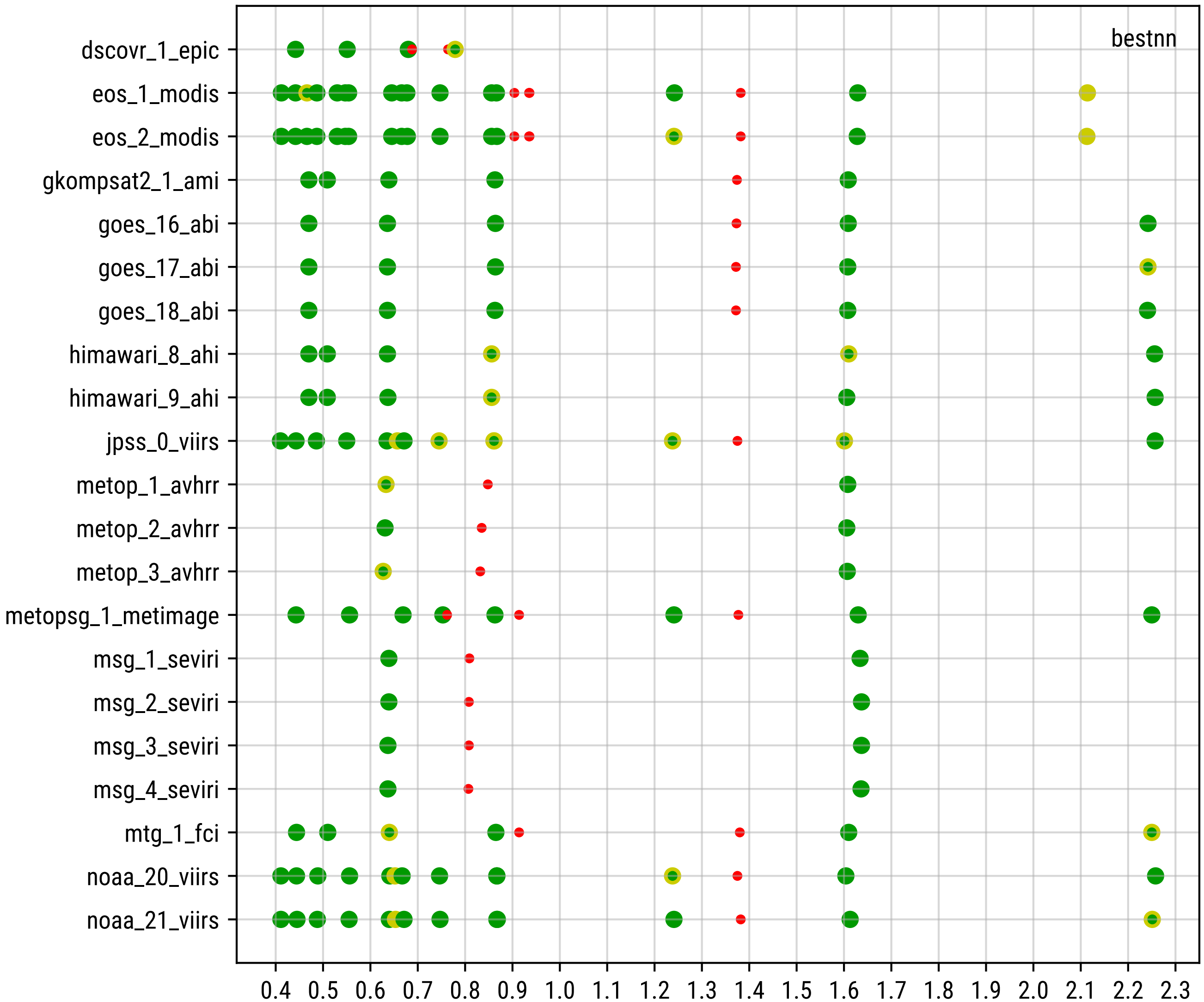
Available neural networks for MFASIS-NN (RTTOV 13.2)

Colors: Reflectance errors are

- **similar to 0.6µm channel** (RMSE<0.01 and 99th percentile <0.03)
- **slightly higher** (RMSE<0.03 and 99th percentile <0.05)
- **significantly higher** (RMSE>0.03 or 99th percentile >0.05)

Small red dots: NN not available, errors still too high

Supported instruments and channels



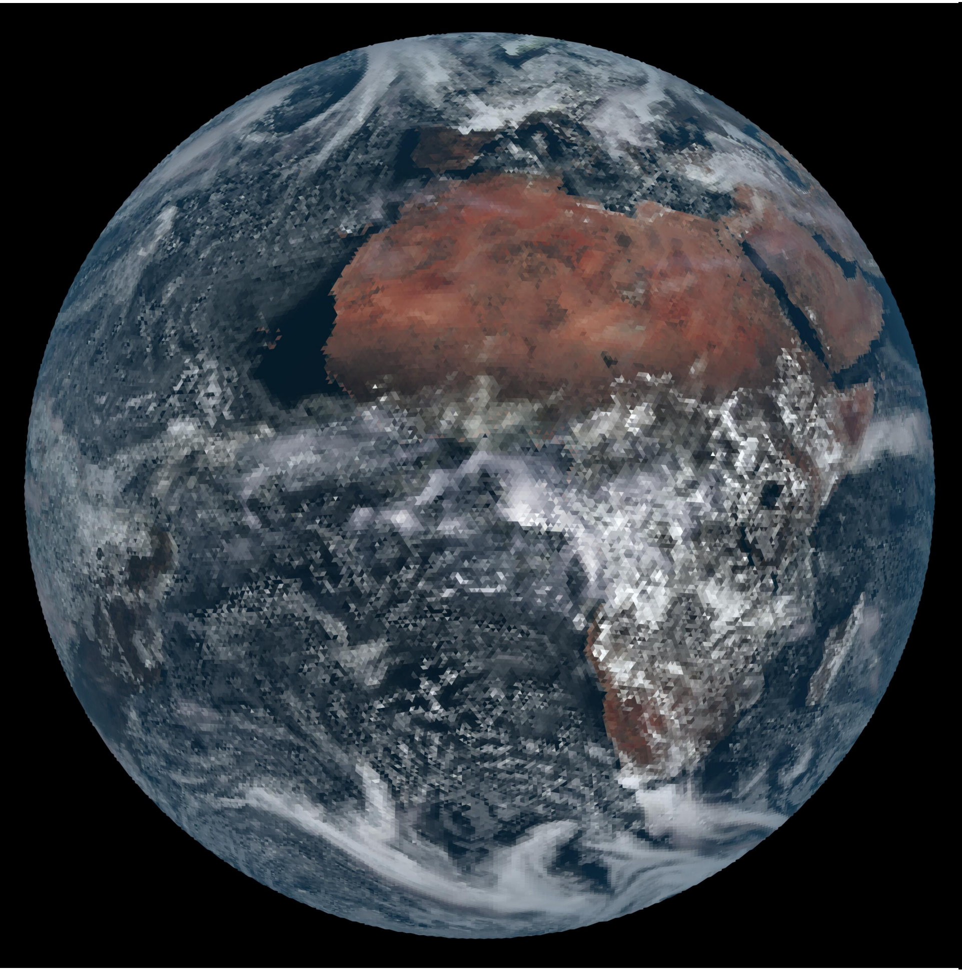
Neural networks planned for next RTTOV 14 release

Colors: Reflectance errors are

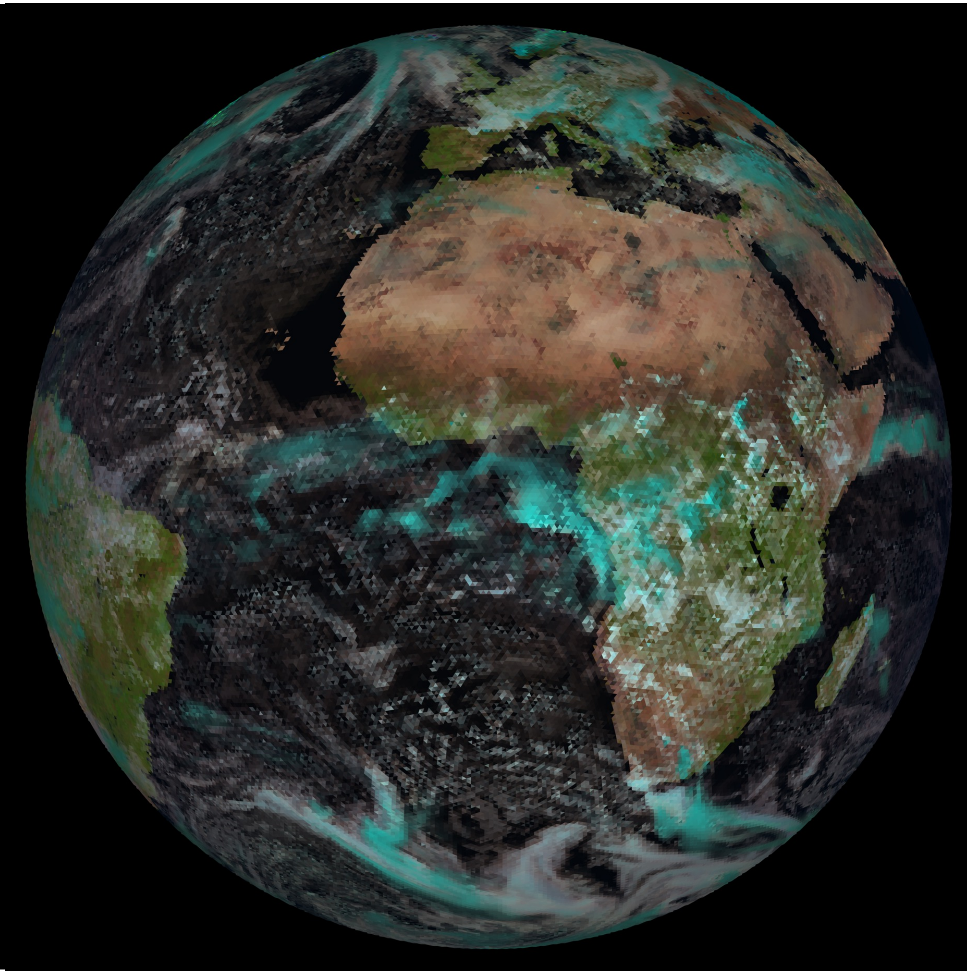
- **similar to 0.6µm channel** (RMSE<0.01 and 99th percentile <0.03)
- **slightly higher** (RMSE<0.03 and 99th percentile <0.05)
- **significantly higher** (RMSE>0.03 or 99th percentile >0.05)

Small red dots: NN not available, errors still too high

RGB composites



ICON 40km / MTG FCI
R=0.6µm, G=0.5µm, B=0.4µm

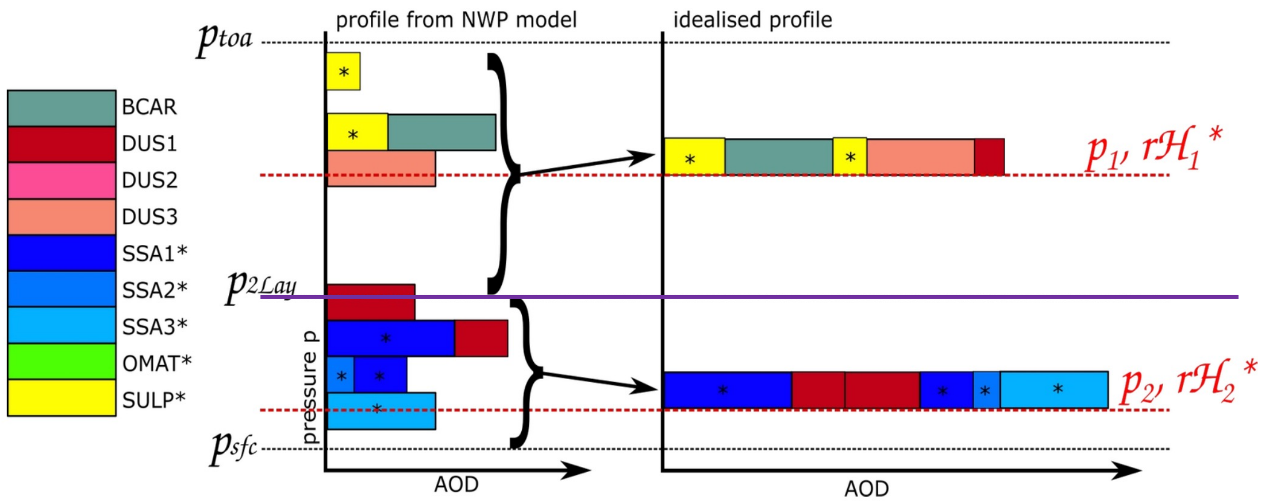


ICON 40km / MSG SEVIRI
R=1.6µm, G=0.8µm, B=0.6µm

First results for aerosols (preliminary)

A prototype based on CAMS aerosols

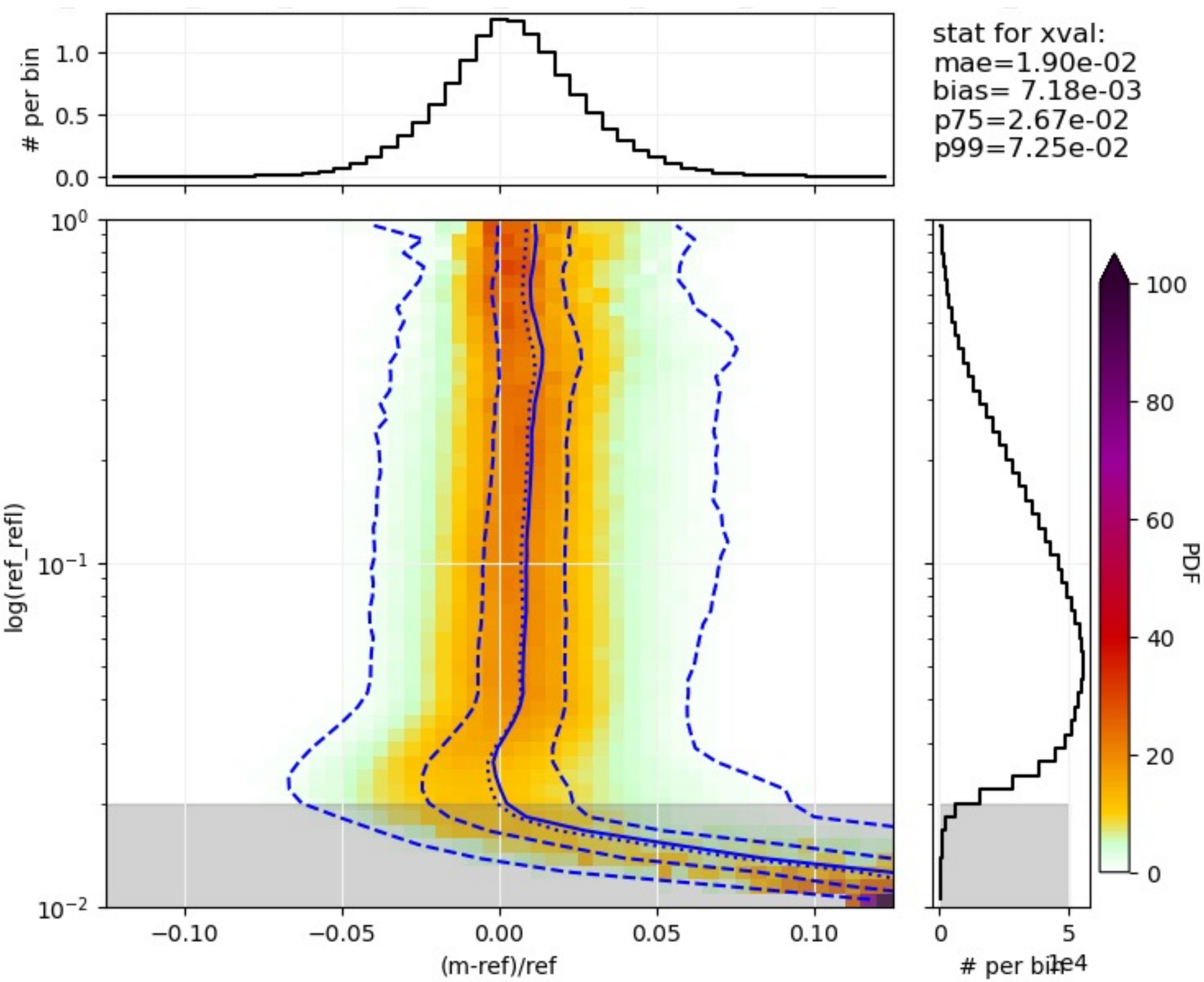
- Can we generate reflectances for arbitrary combinations of many aerosols species with one NN and still have sufficiently small errors? Species A may be above B or vice versa…
- Same strategy as for clouds: **Replace complex aerosol profile by simplified version** with same AOD and approximately same relative humidity and air mass above/below aerosols



Split atmosphere in upper and lower part

- Prototype with **23 input variables** (incl. AOD in upper and lower layer for 9 CAMS species) for SEVIRI 0.6µm channel

First results for aerosols (preliminary)



Relative reflectance error distribution as a function of the reflectance

Evaluation with MACC-60L data set (5 x 4000 IFS profiles optimized for different species)

- relative error < 5% for almost all cases
- relative error < 2% in 50% of cases
- NN larger than for clouds (several 10^4 params.)
- Further improvements should be possible

→ **looks promising…**

Summary

- Replacing a compressed look-up table by a **neural network** in a forward operator for solar satellite channels **has significant advantages** in terms of speed, memory consumption, number of input parameters and time required to generate training data
- **MFASIS-NN for clouds** with additional input parameters **yields good results** for the 1.6µm channels and many other channels. The new developments have been implemented in RTTOV 13.2 (except for WV input variable and code vectorization)
- A prototype of **MFASIS-NN for CAMS aerosols looks promising**
- **Next steps:**
  - finish first aerosol version, support further channels (in particular WV sensitive)
  - use feature extraction capabilities of neural networks for more complex channels
  - include 3D radiative transfer effects and polarization in neural network

Publications

- Baur F. et al., (2023): A neural network-based method for generating synthetic 1.6µm near-infrared satellite images (AMT, accepted)
- Scheck, L., (2021): *A neural network based forward operator for visible satellite images and its adjoint,* Journal of Quantitative Spectroscopy and Radiative Transfer, DOI:10.1016/j.jqsrt.2021.107841
- Scheck, Weissmann, Mayer (2018): *Efficient methods to account for cloud top inclination and cloud overlap in synthetic visible satellite images*, JTECH, Vol. 35, Issue: 3, p. 665-685.
- Scheck, Frerebeau, Buras-Schnell, Mayer (2016): *A fast radiative transfer method for the simulation of visible satellite imagery*, Journal of Quantitative Spectroscopy and Radiative Transfer, 175, p. 54-67.