Towards the assimilation of near-infrared satellite images

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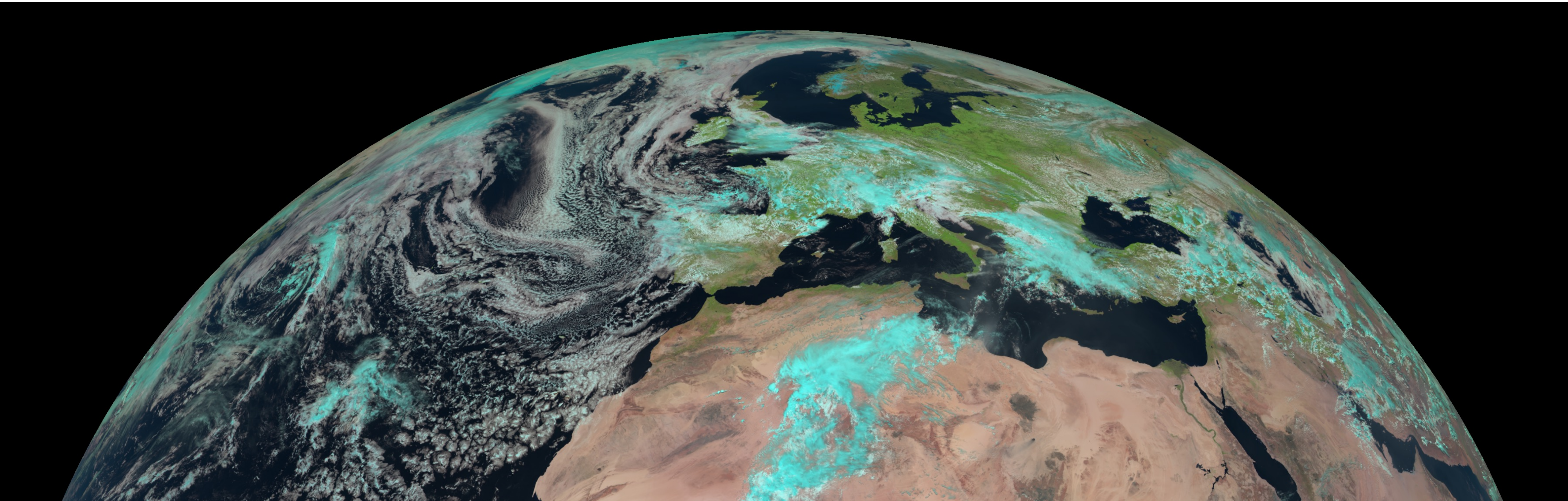
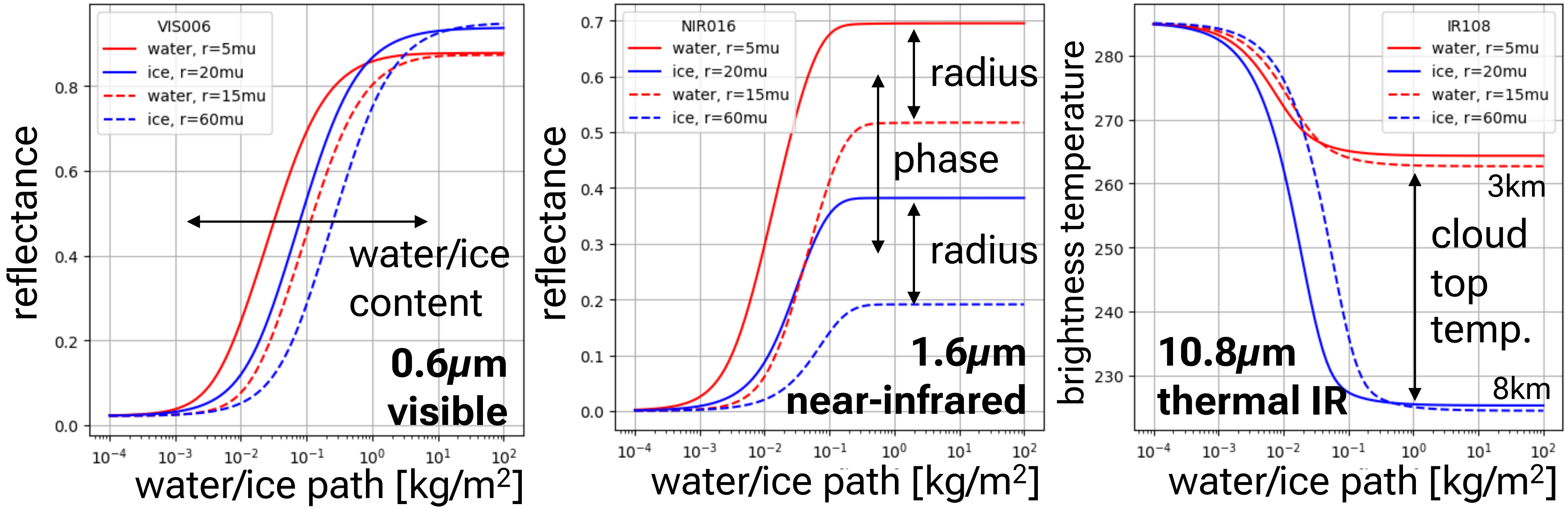


Why are we interested in near-infrared channels?

NIR channels (**λ**<4µm)**: 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 → much better information on **water/ice content** than IR
- **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**

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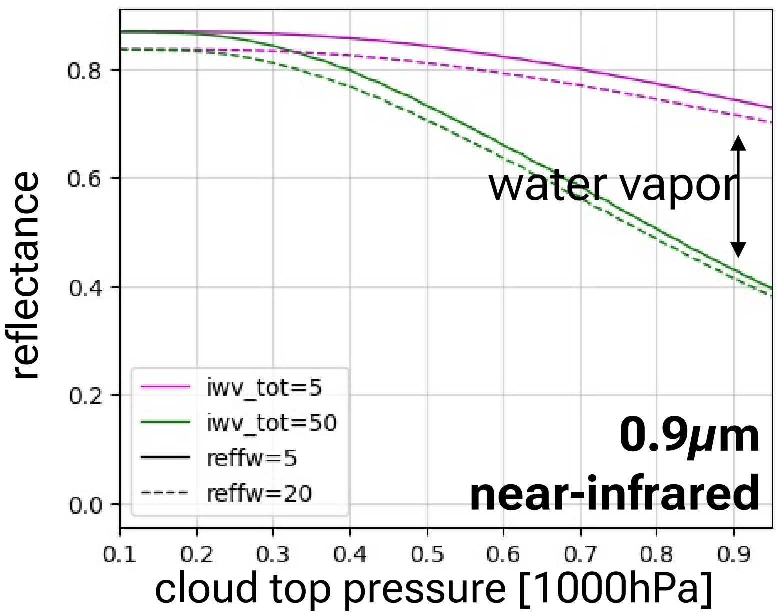
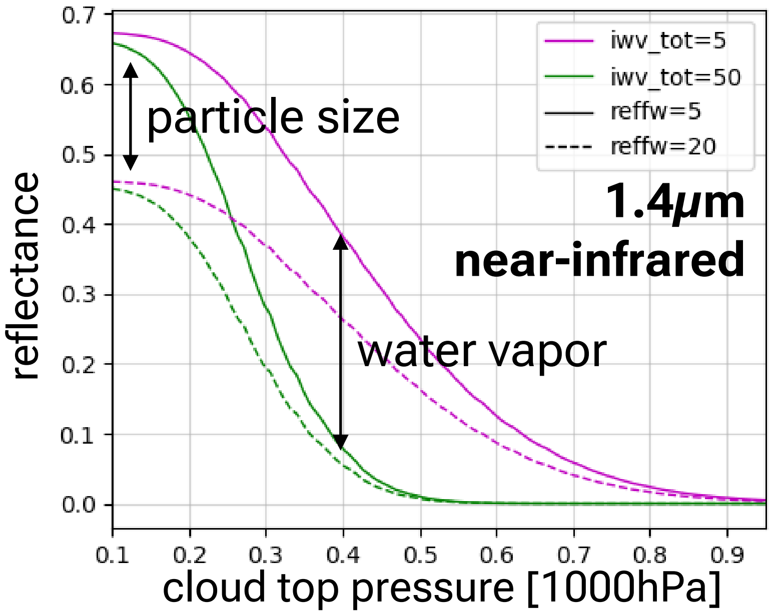




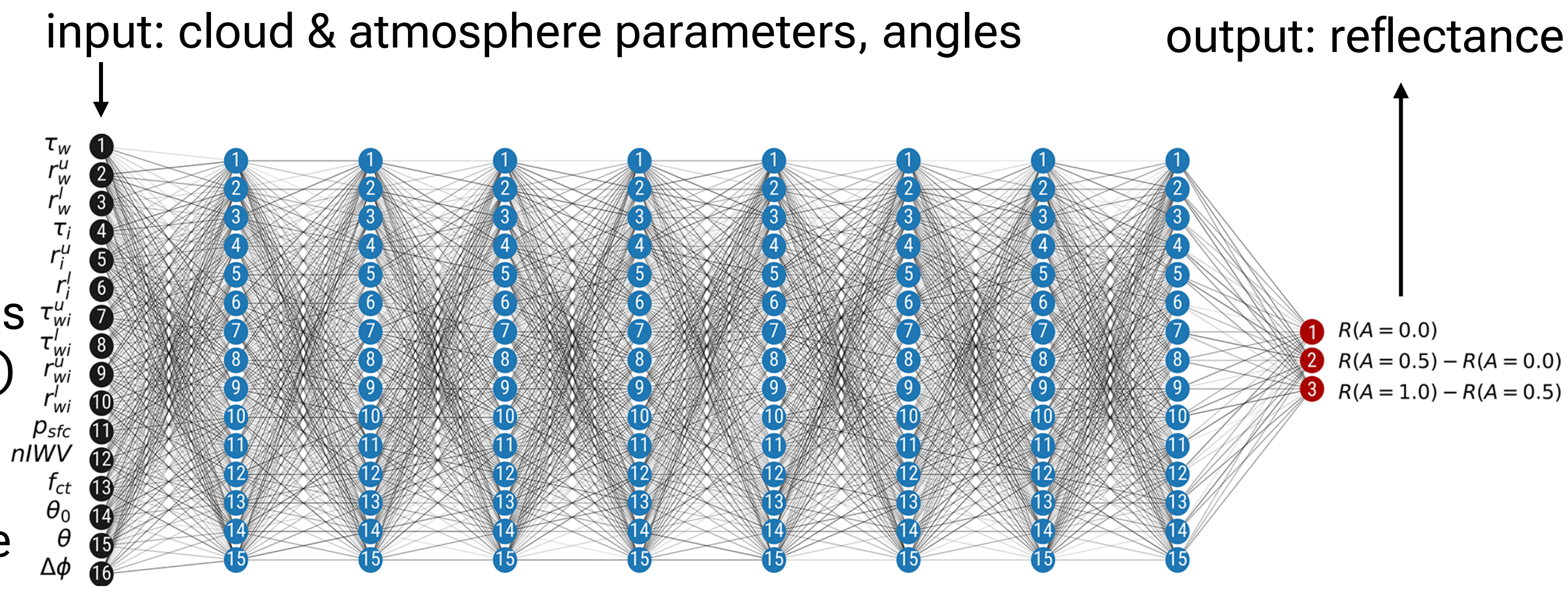
Plots: Thick water clouds (optical depth 100) with varying cloud top pressure and two different droplet sizes in a **moist atmosphere** (water vapor content 50mm) and a **dry atmosphere** (water vapor content 5mm)

Water-vapor sensitive NIR channels (e.g. on Meteosat Third Generation Flexible Combined Imager):

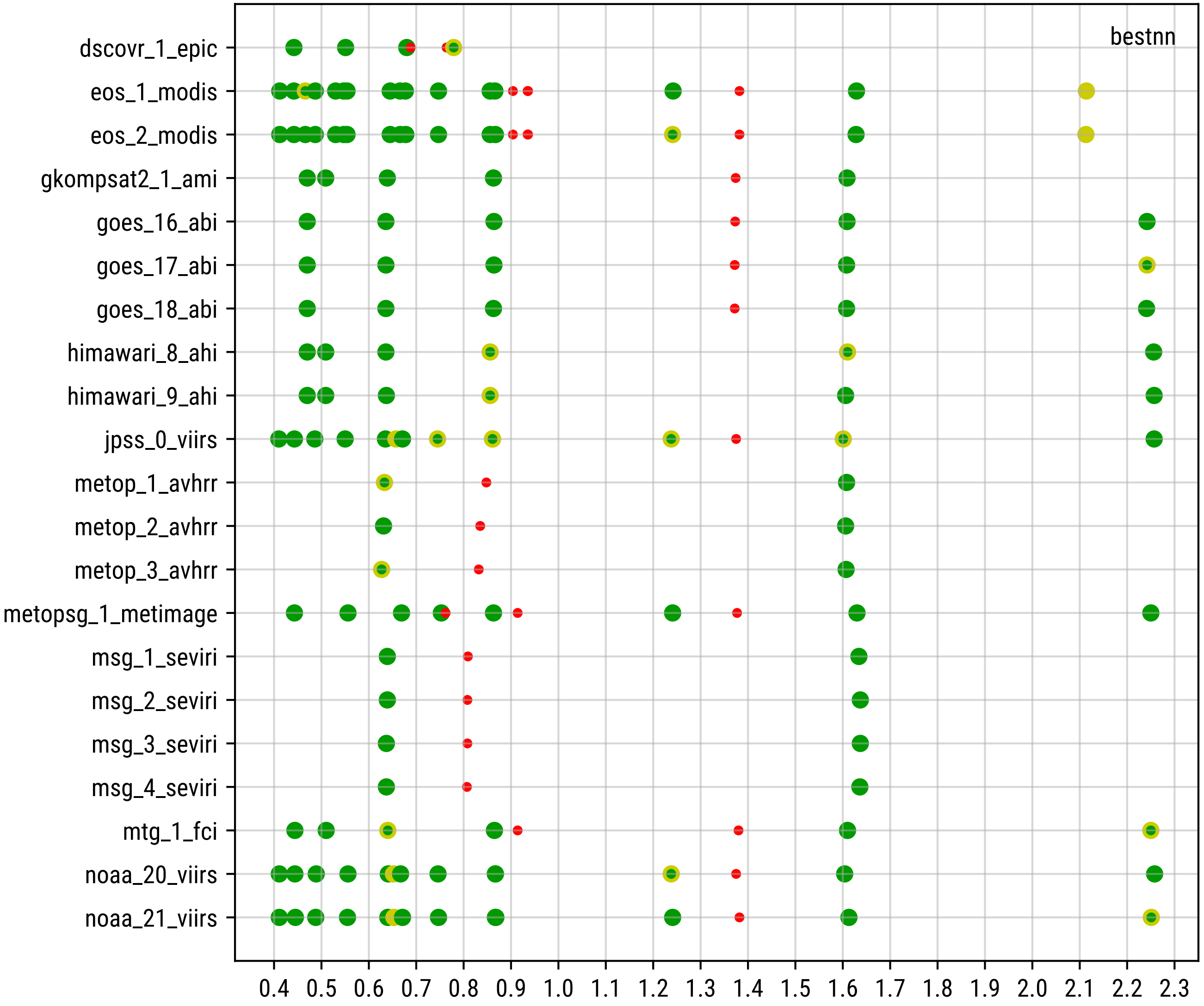
- **0.9µm**: Cloud signal similar to visible channels (weak effective radius sensitivity)
  + significant absorption by water vapor → sensitive to (mostly low-level) WV (complem. to IR-WV channels)
- **1.4µm**: Cloud signal similar to other NIR channels (stronger effective radius sensitivity)
  + strong absorption by water vapor → sensitive to moisture and clouds in upper part of troposphere

The MFASIS method for solar channels

- Making use of the information in these channels for direct assimilation (DA) & model evaluation requires a **forward operator** to compute synthetic images from numerical weather prediction (NWP) model state
  → radiative transfer (RT) problem, computationally expensive in solar spectrum: multiple scattering important
- Basic idea of **fast method MFASIS**: Characterize RT problem with few parameters (features) that describe an idealized profile, precompute solutions with standard methods and store results for full parameter space
- Current version uses a **small and therefore fast feed forward neural network** to store reflectances
- NN structure / training:
  - 15 input parameters in RTTOV 13.2
    + IWV in RTTOV 14.0 (later this year)
  - 8 hidden layers
  - 2000–5000 weight parameters
  - training with O(10^7) synthetic samples (obtained with random input params.) using Tensorflow
  - inference takes <1μs/sample on a standard CPU (3 orders of magnitude fast than discrete ordinate mthod)



Supported instruments and channels



Neural networks planned for RTTOV 14.0
(to be released later this year)

Colours: Reflectance errors are

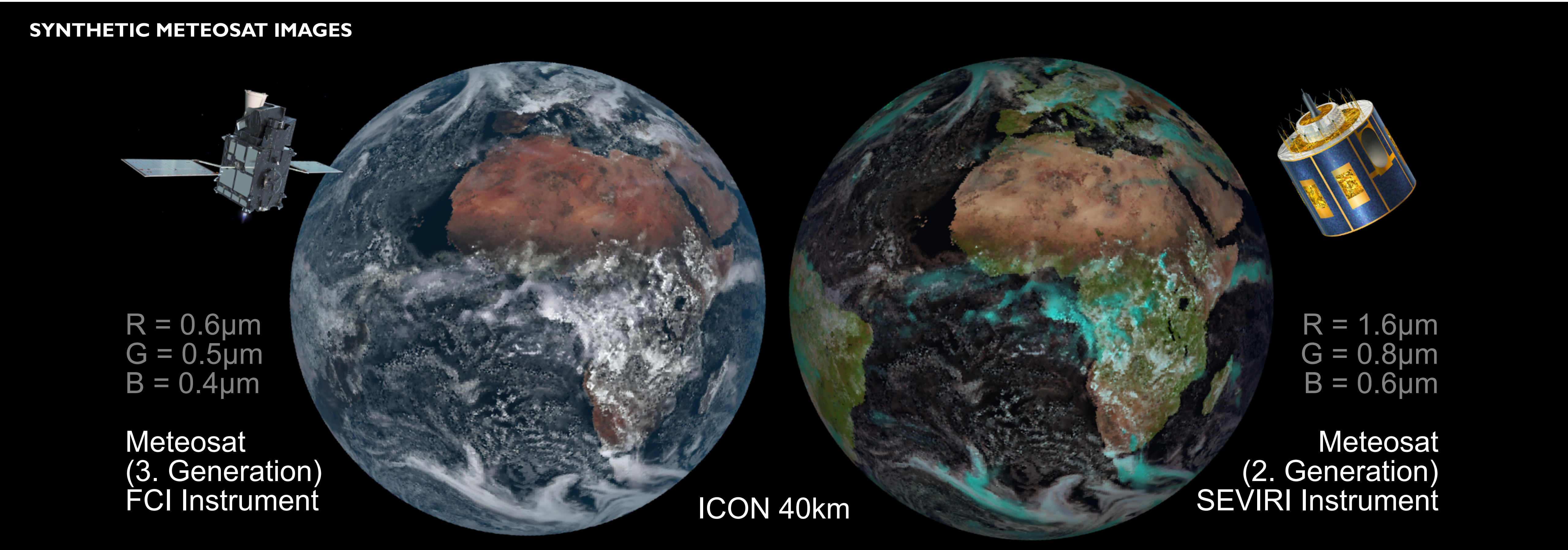
- **similar to 0.6μm channel**
  (RMSE<0.01 and 99th percentile <0.03)
- **slightly higher**
  (RMSE<0.03 and 99th percentile <0.05)
- **significantly higher**
  (RMSE>0.03 or 99th percentile >0.05)

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

NN Training at DWD is ongoing, more instruments and channels will be added...

Supported instruments and channels

- 1.2μm, 1.6μm, 2.2μm channels available on many instruments work now (e.g. for two-moment scheme eval.)
- All visible channels with wavelengths < 0.7μm work
- Many channels available for DA, model eval. and to produce synthetic versions of popular RGB composites



Water-vapor sensitive near-infrared channels

Only one water vapor input parameter in RTTOV 14.0: Not enough for new 0.9μm & 1.4μm channels
→ additional parameters or a completely new method required. We tried three approaches:

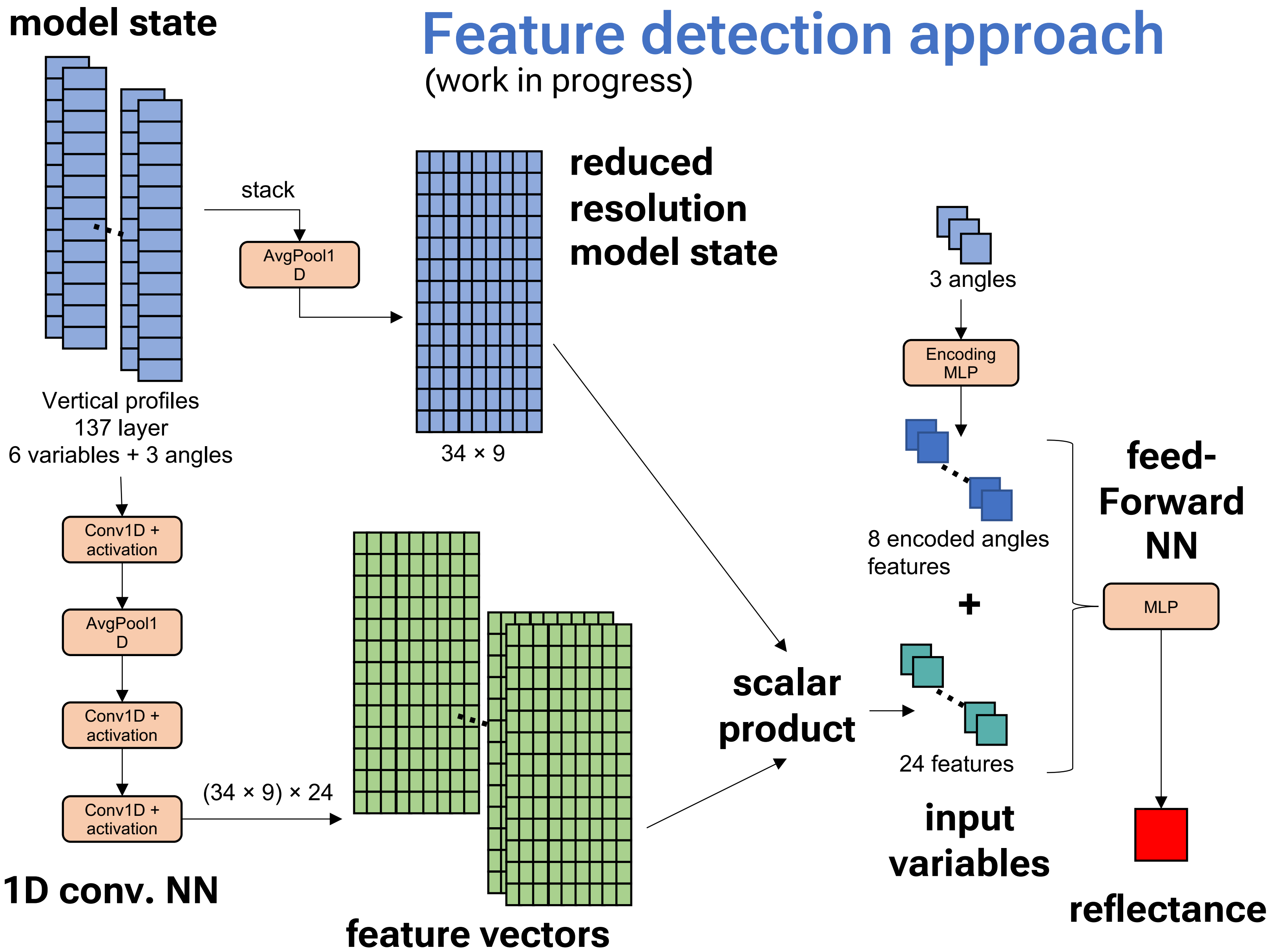
(1) Feature engineering + synthetic training data
Now 27 input variables, including WV content in and between cloud layers and information on geometrical thickness of the layers (WV absorption depends on path length)
Training data set covers full 27-dimensional parameter space

(2) Feature engineering + training data based on NWP forecasts
Same input variables, reflectances and input vars. are computed from full NWP model profiles
Training data set does not contain unrealistic parameter combinations

(3) Feature detection + training data based on NWP forecasts
New ML approach (inspired by attention concept in transformers): learns to compute input variables from full profiles and to use them for computing reflectances
No time-consuming feature engineering required

Feature detection approach

(work in progress)

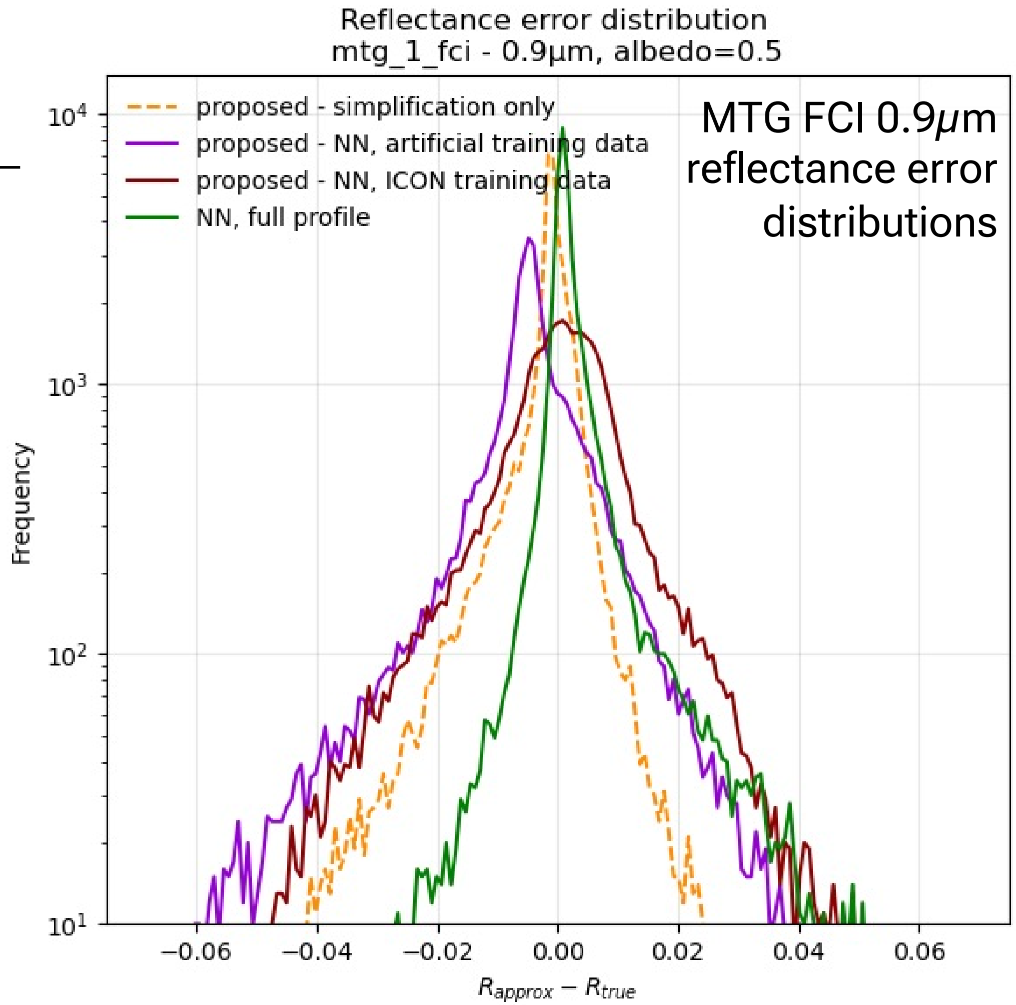


- Motivation: Most current input variables can be written as scalar product between model state vector and a constant “feature vector”
- Could we learn appropriate vectors using a 1d convolutional network?
- And then use them to compute input variables for a NN that outputs reflectance?
- Inspired by attention concept in transformers
- Current state: Proof of concept

Preliminary results for the three approaches (0.9μm channel)

Evaluation with IFS profile collection from NWP SAF

	RMSE	MAE	bias	P99	P99.9
(1) Feature engineering + synthetic training data	0.0133	0.009	-0.005	0.049	0.095
(2) Feature engineering + NWP training data	0.0123	0.008	0.0004	0.042	0.070
(3) Feature detection + NWP training data	0.0099	0.004	0.002	0.039	0.099

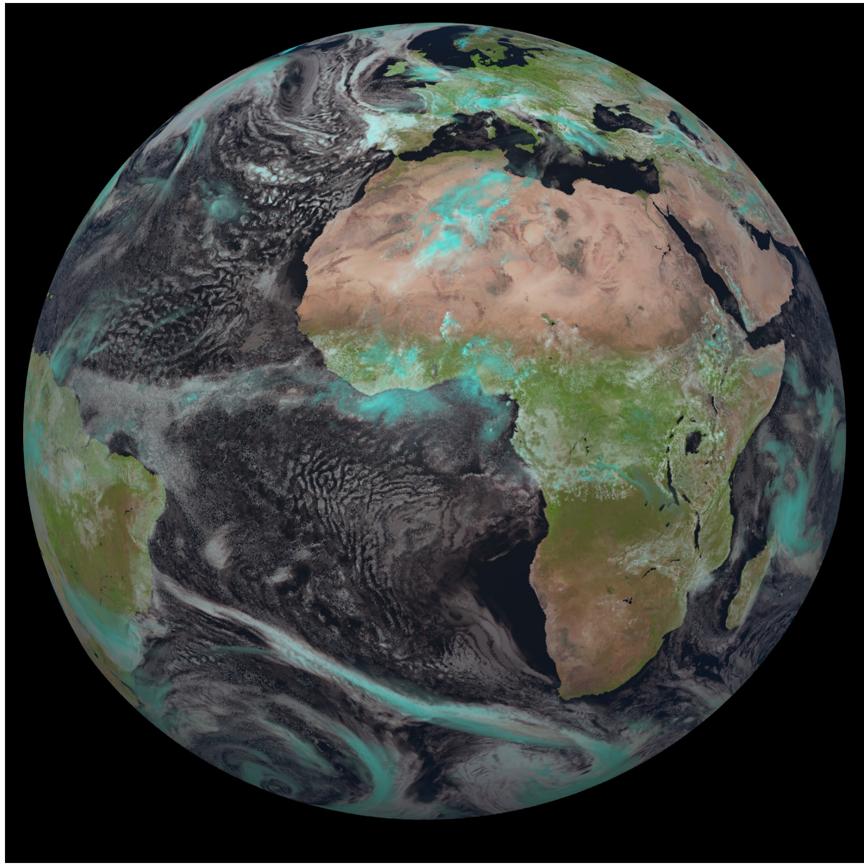


MTG FCI 0.9μm reflectance error distributions

- All approaches work! Errors are in the same range as for the visible 0.6μm channel (which is operationally assimilated in regional DWD system)
- Synthetic → NWP profiles: Factor 10 less training data required
- Feature detection looks promising! Comp. effort still to be evaluated...

Conclusions & Outlook

- Near-infrared channels can provide relevant, complementary information on clouds and water vapor
- Most solar channels are already supported by MFASIS-NN in RTTOV 13.2, some more in RTTOV 14.0 (to be released this year)
- We test three approaches for water-vapor sensitive channels, which all seem to work (including one with feature detection)
- Next steps: Finish NIR-WV developments, Aerosol version, remove model/operator subgrid cloud inconsistencies, 3D RT, perform OSSE and real DA experiments



SEVIRI RGB composite for ICON 13km

Publications

- Baur, F., Scheck, L., Stumpf, C., Köpken-Watts, C., and Potthast, R. (2023): *A neural-network-based method for generating synthetic 1.6μm near-infrared satellite images,* Atmos. Meas. Tech., 16, 5305–5326, https://doi.org/10.5194/amt-16-5305-2023.
- Scheck, L. (2021) *A neural network based forward operator for visible satellite images and its adjoint,* JQSRT, 274, 107841, ISSN 0022-4073, https://doi.org/10.1016/j.jqsrt.2021.107841
- Scheck, L., M. Weissmann, and B. Mayer (2018): *Efficient Methods to Account for Cloud-Top Inclination and Cloud Overlap in Synthetic Visible Satellite Images. J. Atmos. Oceanic Technol.*, **35**, 665–685, https://doi.org/10.1175/JTECH-D-17-0057.1.