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MACHINE LEARNING-BASED FORWARD OPERATORS FOR VISIBLE AND NEAR-INFRARED SATELLITE IMAGES

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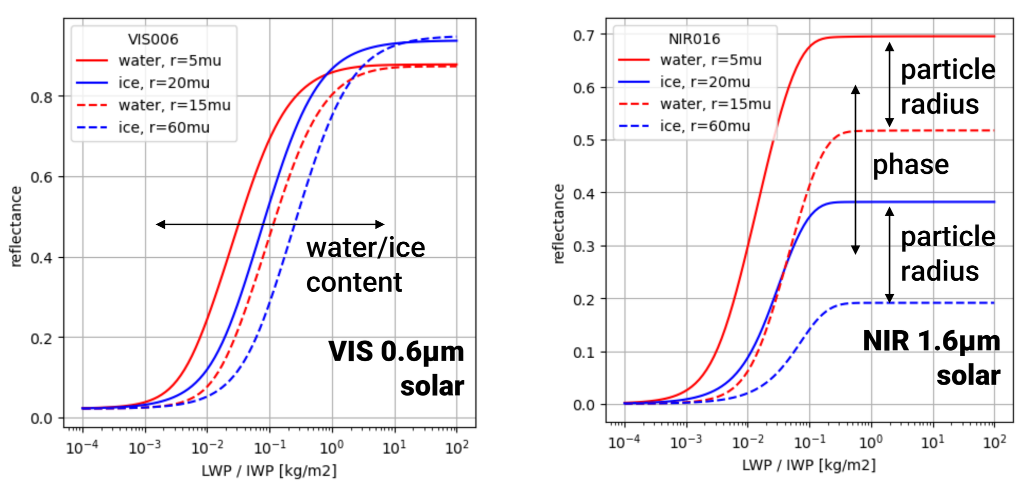
MOTIVATION

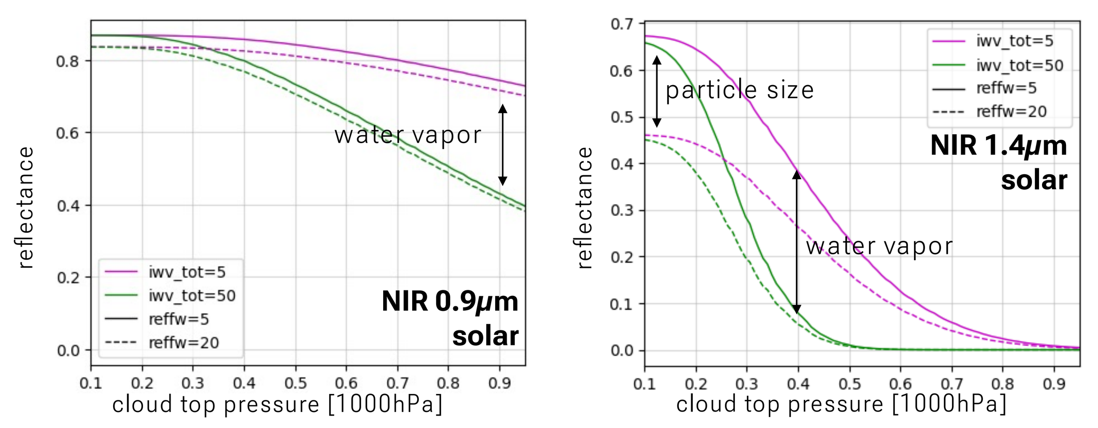
- **Forward operators** compute synthetic observation from the numerical weather prediction / earth system model state
- They are essential for using real observations to improve predictions, either by reducing errors in the initial state (**data assimilation**) or by reducing model errors (**model evaluation and improvement**)
- Generating synthetic observations with standard methods can require **high computational effort**, in particular when radiative transfer (RT) problems have to be solved
- **Machine learning approaches** can be used to reduce to computation effort for forward operators by orders of magnitude, and can thereby **allow us to exploit so far unused or underused observation types**
- Here we report on **MFASIS-NN**, a **neural network-based forward operator for solar satellite channels** (with wavelengths < 4µm, where multiple scattering makes RT particularly complicated and expensive) that has been **integrated in NWP SAFs RTTOV** package.

SOLAR CHANNELS

Standard visible and near-infrared channels: Reflectance for water / ice clouds (fixed height) with varying water / ice paths.



Water vapour sensitive solar channels (e.g. on MTG FCI): Reflectance for 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)

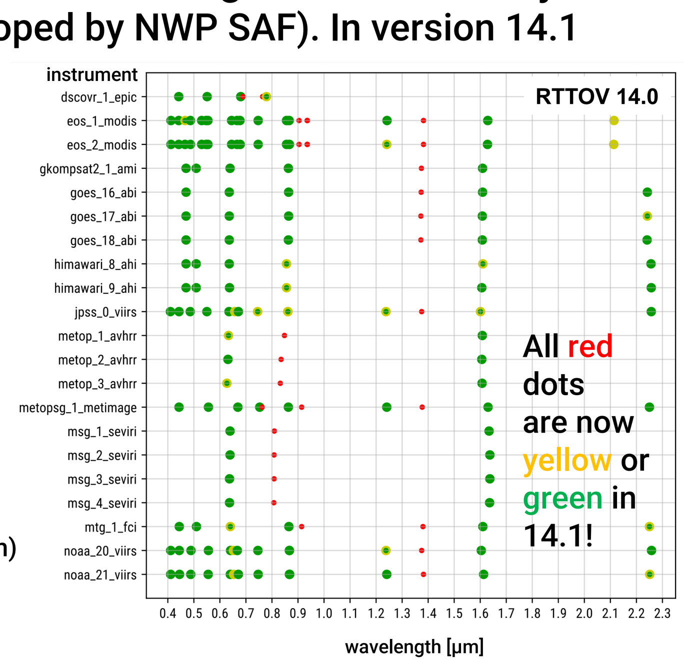


- **0.9µm:** significant wv absorption → sensitive to (mostly low-level) WV
- **1.4µm:** Stronger effective radius sensitivity + very strong absorption by water vapor → sensitive to moisture and clouds in upper part of troposphere only

RTTOV INTEGRATION

MFASIS-NN for clouds has been **integrated in the widely used RTTOV package** (developed by NWP SAF). In version 14.1 (released in February) nearly all channels with λ < 2.5µm are now supported.

Since version 14.1 also an aerosol version is included (supporting only a few channels at the moment).



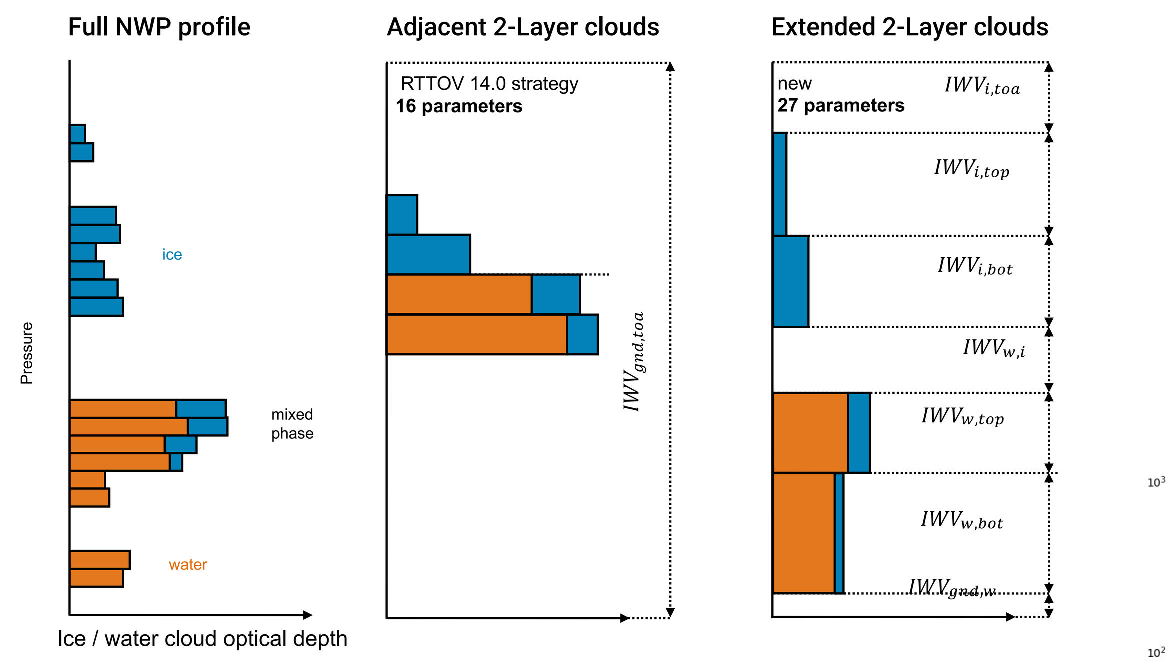
Green = small errors (like 0.6µm)
Yellow = acceptable errors
Red = errors too high

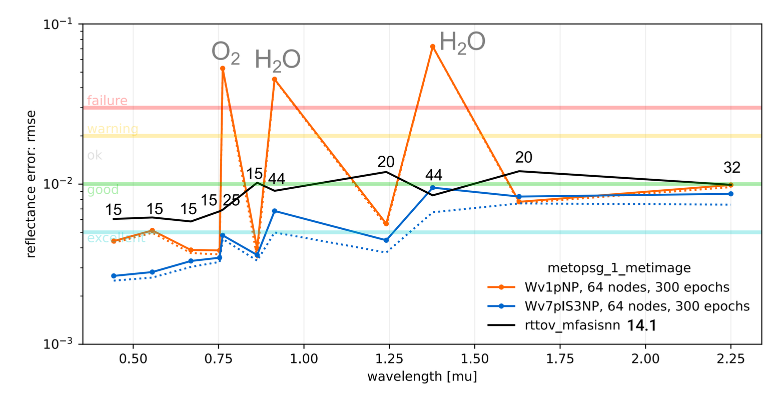
MFASIS-NN WITH NEW WATER VAPOUR INPUT VARIABLES

Basic approach for MFASIS-NN:
(1) Replace complex NWP model profiles by idealised profiles, which can be described by few parameters (features)
(2) Compute reflectances (using RTTOV DOM) for these idealised profiles for random parameter combinations
(3) Train a deep neural network that estimates the reflectances from the idealised profile parameters / features

Constructing suitable idealised profiles (which lead to nearly the same reflectances as the original profiles) = **"feature engineering"**. "Harmless" channels (e.g. 0.6µm visible, see Scheck, 2021) only four cloud parameters (optical depths and effective particle radii) are sufficient. For channels with more complicated dependencies (e.g. 1.6µm NIR, see Baur et al. 2023) additional parameters are required.

NEW: Idealised profiles with additional parameters for **strongly water-vapor sensitive channels** (e.g. MTG FCI 0.9µm and 1.38µm)

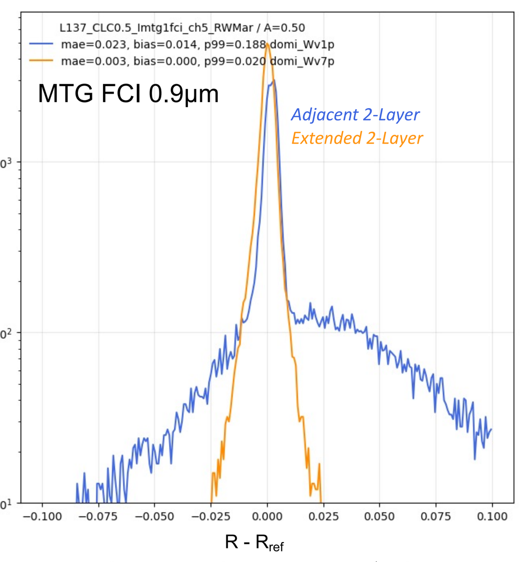




Left: Total errors for all channels of the Metimage instrument on MetOpSG using the old adjacent layers (orange) and the new extended layers approach (blue) and a NN with 64 nodes per layer. For the black line NNs with the indicated number of nodes per layer were used to balance accuracy & effort.

Left: Profile simplification/idealization strategies. For strongly WV-sensitive channels not only the optical but also the geometric thickness of the clouds must be taken into account and the WV contents of all layers in and between the clouds are required as input parameters.

Evaluation of profile simplification error with NWP SAF dataset (5000 IFS profiles)



The profile simplification error (reflectance computed for idealized profile minus reflectance computed for original profile) distribution for the strongly WV-sensitive MTG FCI 0.9µm channel is significantly improved with the new approach

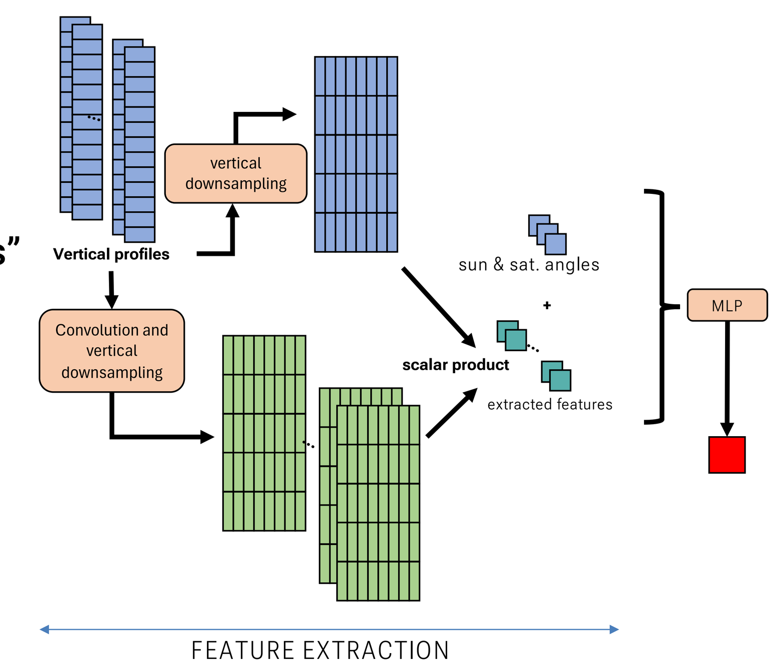
Networks: Training & Inference

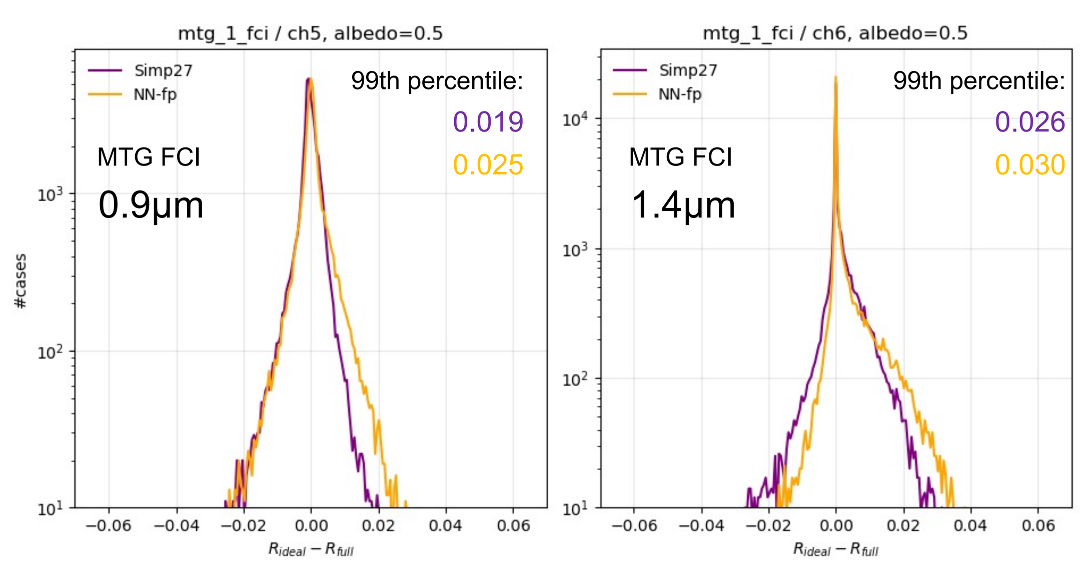
- Small (=fast) deep feed forward NNs are trained with synthetic training data using Tensorflow
- Typically, 8 hidden layers and 15 – 50 nodes per layer are used (depending on channel)
- A vectorized Fortran code (Including an adjoint version) requires less than 1µsec per sample for most channels on standard CPUs, which is about three orders of magnitude faster than the discrete ordinate method used to generate the training data
- The total reflectance error (simplification and imperfect training) is typically < 0.01

AUTOMATIC FEATURE EXTRACTION

"Feature engineering" = Identifying suitable NN inputs **is complex** and time-consuming
Can we let the NN do this automatically? → **New transformer-inspired approach:**

- 1D convolutional layers produce 24 feature vectors from full model state profiles
- Scalar product of feature vectors (attention maps) with model state → "extracted features"
- Feature and angles are fed into a MLP to generate reflectances (as before)





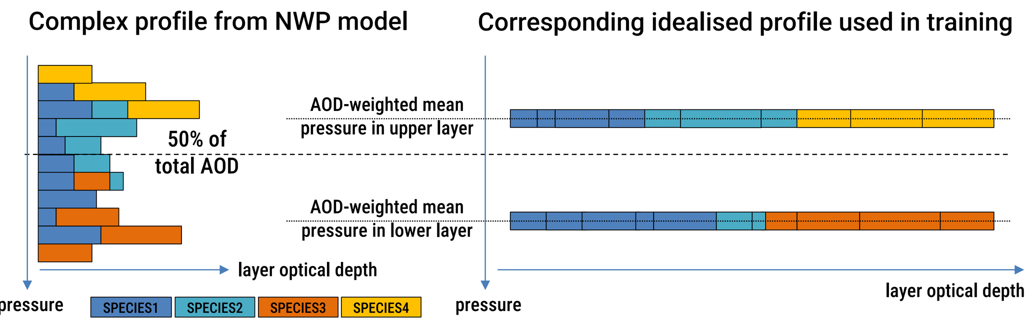
Left: Full error distribution of „feature extraction" approach is close to simplification error of 27 parameter version

→ We successfully emulated the feature engineering process

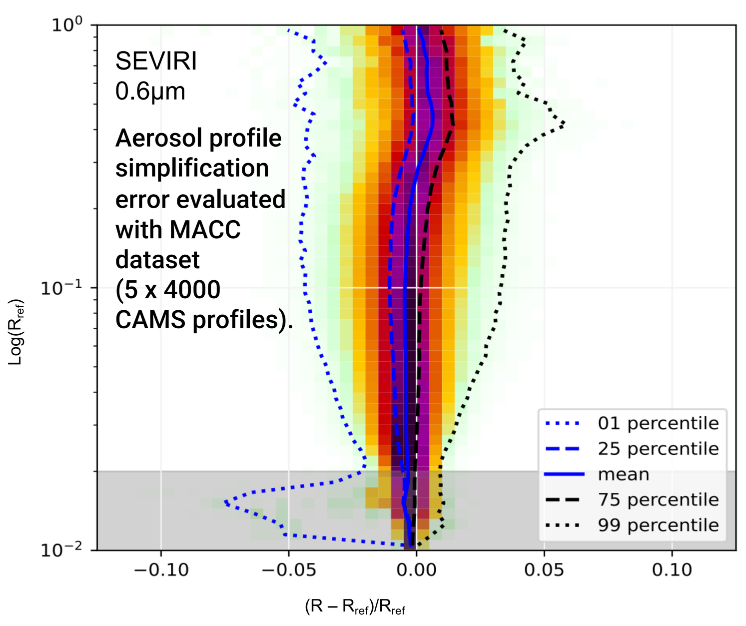
- Errors are already smaller than for the 27-parameter approach
- This comes at a cost: Number of floating-point operations for inference is factor ~20 higher (feature detection dominates)
- Proof of concept, many improvements are possible

AEROSOL VERSION

A version for aerosol-affected reflectances uses similar techniq ues as the cloud version (topmost box) and generates reflectances for arbitrary combinations of the nine CAMS aerosol species for which optical properties are available in RTTOV 14.1. In this case the idealised profiles contain two aerosol layers and each of them can contain all species, allowing for different overlap situations. Relative errors are only a few percent.



- Lower and upper aerosol layer are placed at pressures such that Rayleigh scattering contribution to reflectance is approximately correct
- Relative humidity in the lower/upper layer is set to the AOD-weighted average in the layer → approximately correct optical properties for hydrophilic species

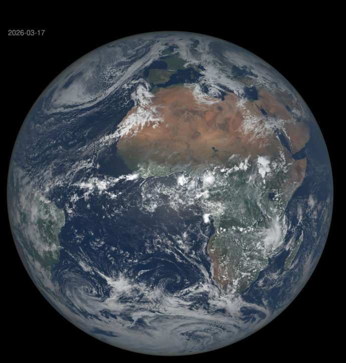


PUBLICATIONS: Baur, F., Scheck, L., Stumpf, C., Köpken-Watts, C., and Potthast, R. (2023): *A neural-network-based method for generating synthetic 1.6 µm near-infrared satellite images,* Atmos. Meas. Tech., 16, 5305–5326, https://doi.org/10.5194/amt-16-5305-2023.
Scheck, L. (2021) *A neural network based forward operator for visible satellite images and its adjoint,* JQSRT, 274, 107841, ISSN 0022-4073, https://doi.org/10.1016/j.jqsrt.2021.107841
Geiss, S., Scheck, L., de Lozar, A., and Weissmann, M. (2021): *Understanding the model representation of clouds based on visible and infrared satellite observations*, Atmos. Chem. Phys., 21, 12273–12290, https://doi.org/10.5194/acp-21-12273-2021.
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.

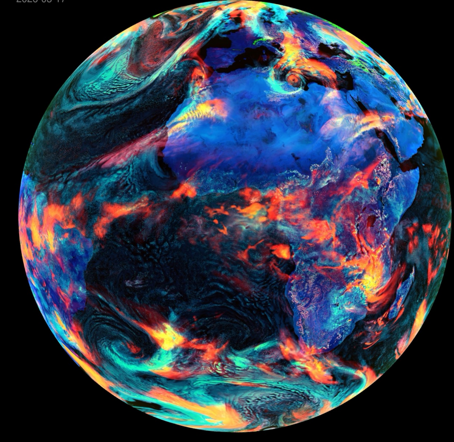
MODEL EVALUATION / METEOSAT FCI RGB COMPOSITES

- Solar satellite channels provide high-resolution information on clouds, aerosols and humidity
- MFASIS for clouds supports now all of these channels → they can be used for model evaluation
- Comparing observed and synthetic RGB composites (see full disk FCI examples to the right) is often the first step in the evaluation
- The "cloud phase" composite can already be generated with RTTOV 14.0 and contains also information on effective radii
- The "cloud type" composite uses the 1.38µm now available in 14.1

FCI observation

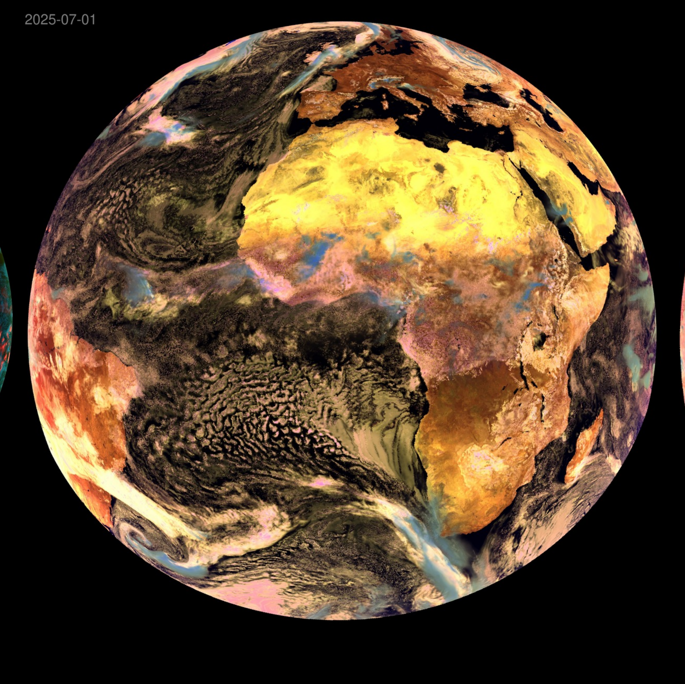


"True colour" RGB composite (R=0.6µm, G=85% 0.5µm + 15% 0.8µm, B=0.4µm)

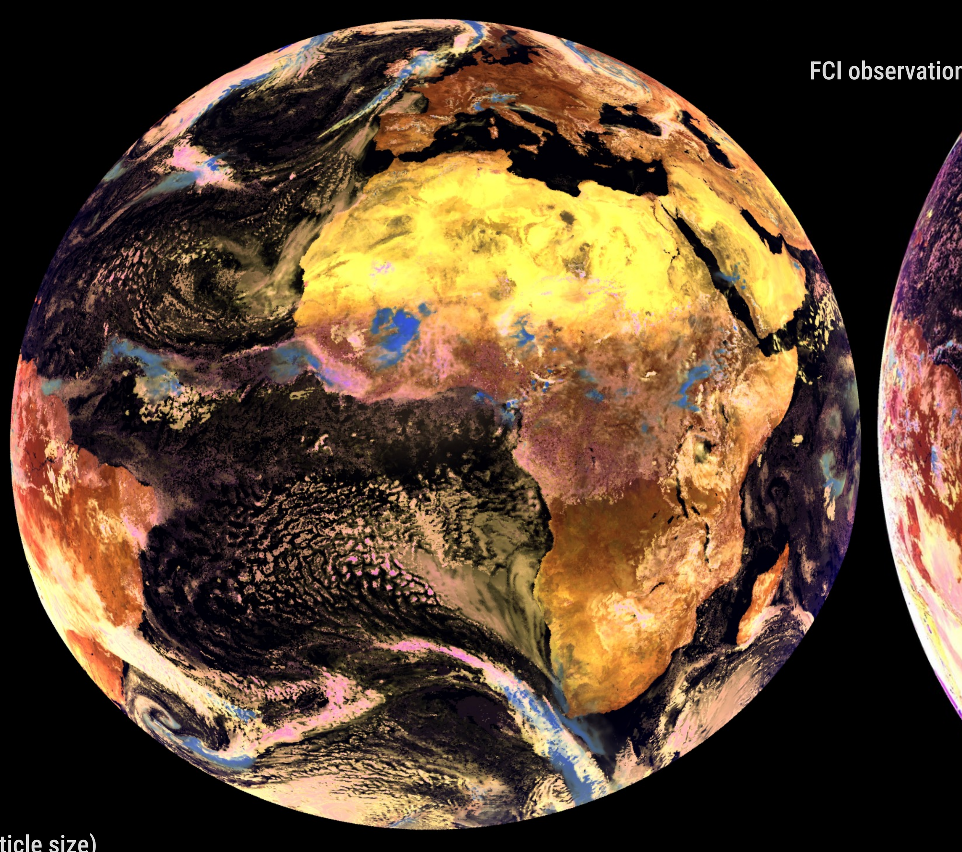


EUMETSAT cloud type RGB composite (R=1.3µm, G=0.6µm, B=1.6µm) High clouds are red to yellow

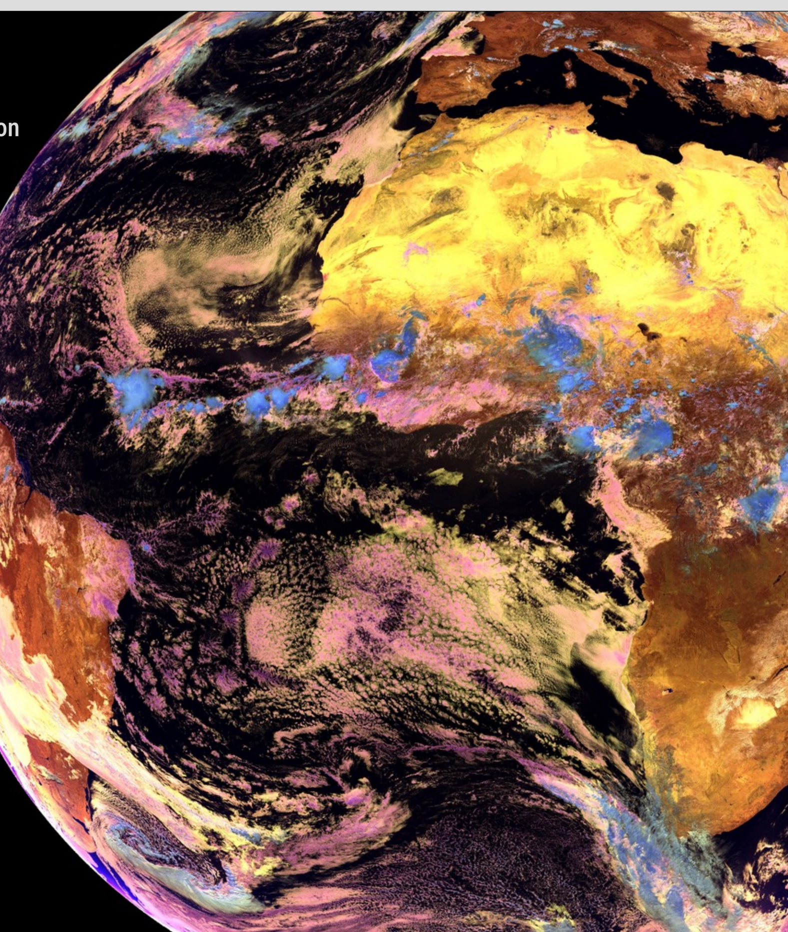
Operational 13km ICON forecast (1-moment scheme)



13km ICON forecast with 2-moment scheme, modified cloud cover settings



FCI observation



EUMETSAT cloud phase RGB composite (R=1.6µm, G=2.2µm, B=0.6µm)
Water clouds are pink to yellow, ice clouds are blue to turquoise (depending on particle size)