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USING MACHINE LEARNING TO ACCELERATE A FORWARD OPERATOR FOR SOLAR SATELLITE IMAGES

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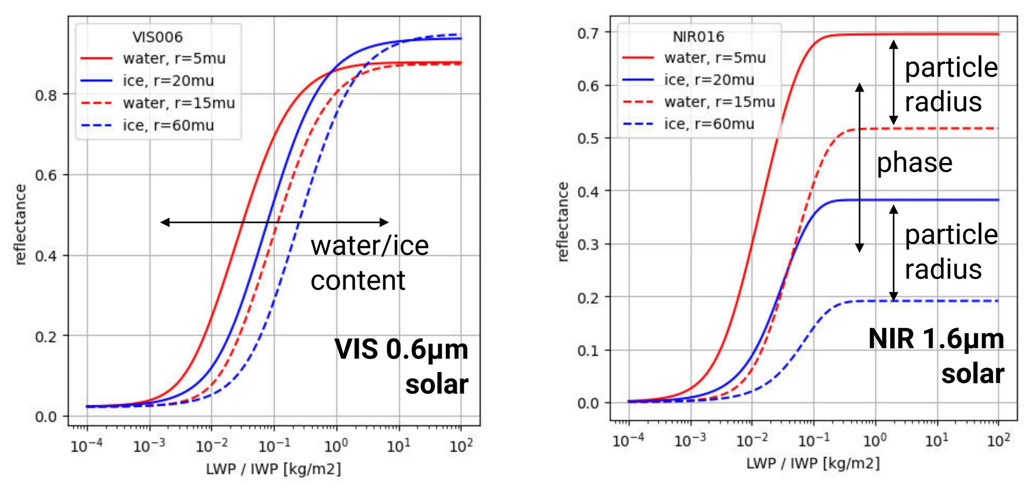
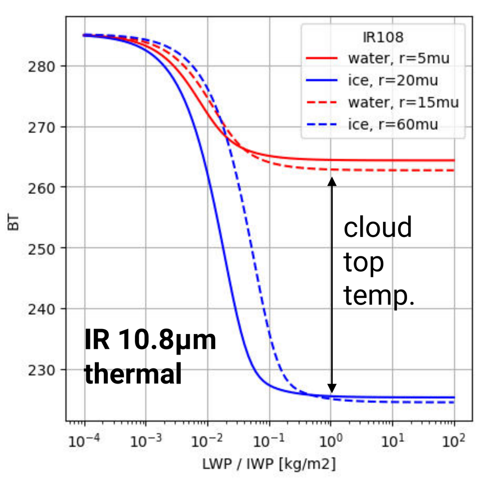
MOTIVATION

- **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), which can provide **high-resolution information on clouds and aerosols**

SOLAR CHANNELS

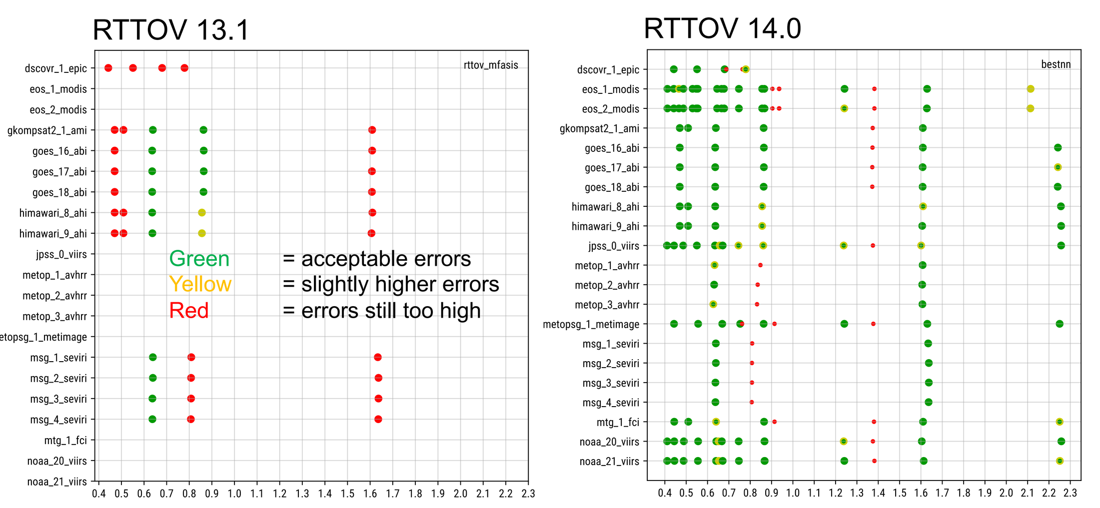


Signals in different SEVIRI channels for uniform water or ice clouds at fixed heights with varying water path.
The **cloud information** in solar (visible or near-infrared) channels is complementary to the information available from thermal channels.



RTTOV INTEGRATION

MFASIS-NN and its look-up table-based predecessor MFASIS have been **implemented in the RTTOV satellite forward operator package** (developed by EUMETSATs numerical weather prediction satellite application facility, including DWD), which is used in many operational centres. The **number of supported instruments was increased significantly** with the new versions 13.2 and 14.0 (the latter will be released later this year).

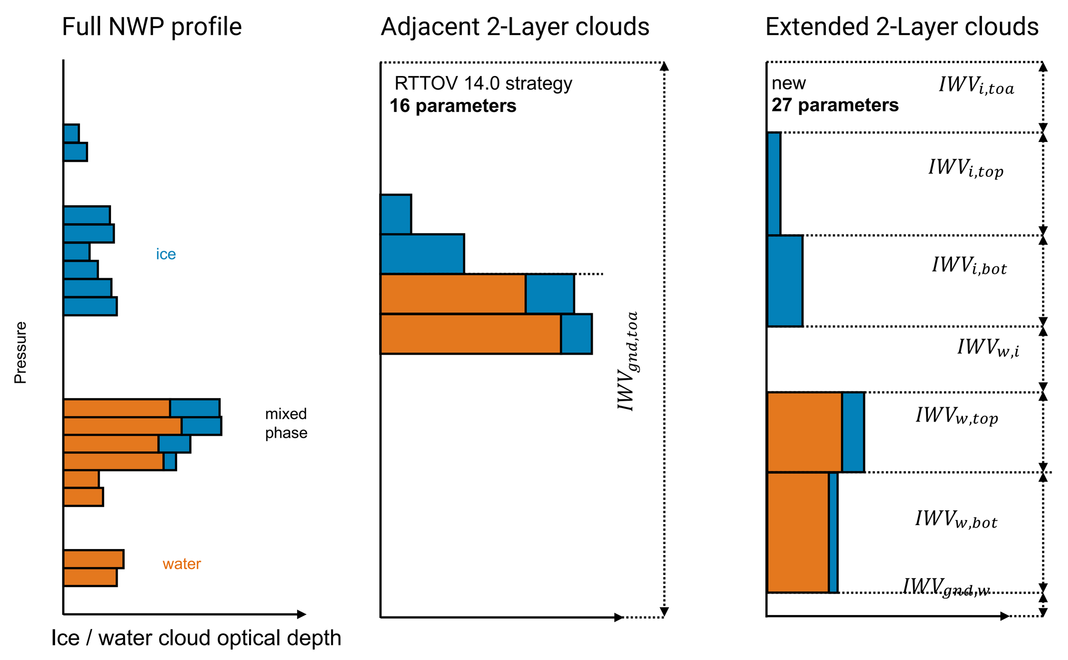


FEATURE ENGINEERING

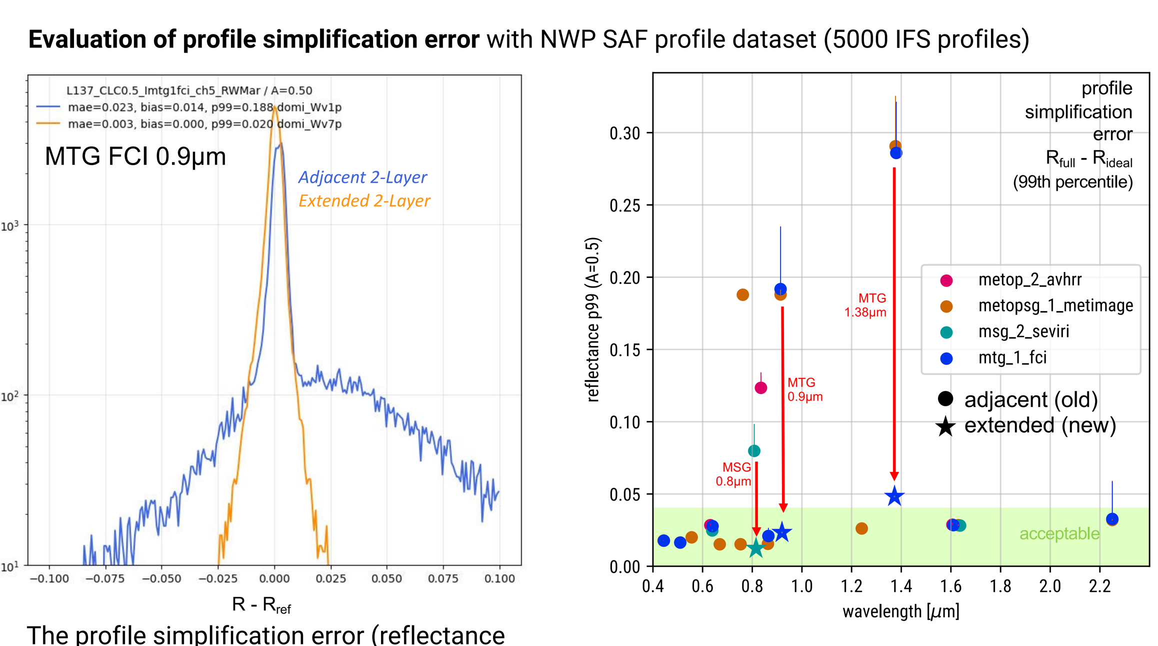
Basic approach for MFASIS-NN:
(1) Replace complex NWP model profiles by idealised profiles, which can be described by few parameters (features)
(2) Compute reflectances (using RTTOV DOM) for these idealised profiles for random parameter combinations
(3) Train a deep neural network that estimates the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

Constructing suitable idealised profiles (which lead to nearly the same reflectances as the original profiles) = **"feature engineering".** For "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.

Current work in progress: Adapting the idealised profiles for **strongly water-vapor sensitive channels** (e.g. MTG FCI 0.9µm and 1.38µm)



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.



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.

For most solar channels the "adjacent 2-layer clouds" approach from RTTOV 14.0 is working well already. The strongly WV-sensitive channels should become usable with the new approach.

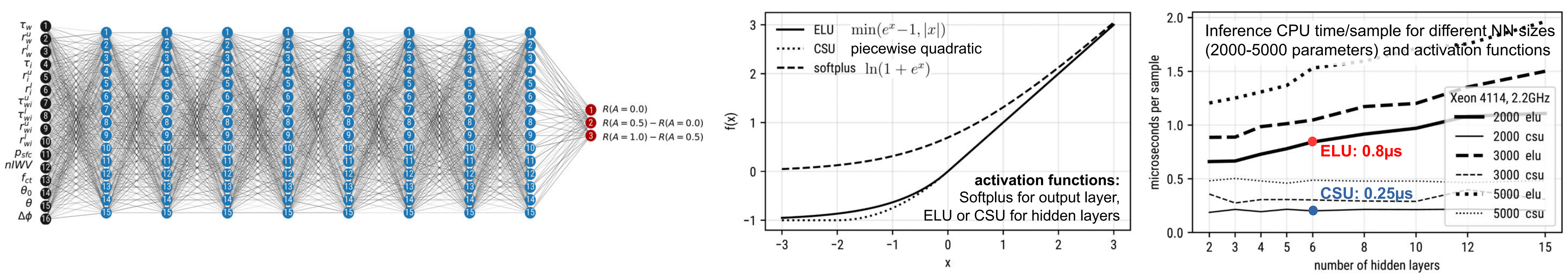
NETWORK TRAINING AND INFERENCE

Small (=fast), deep feed-forward neural networks (with several 1000 parameters, 4-10 hidden layers) are trained with synthetic training data (typ. several 10^7 samples) based on idealized profiles using standard methods like the Adam optimizer.

Input parameters: Normalized features describing the idealized profiles (see box above) + sun and satellite angles
Output parameters: Reflectances R for three albedo values. R for arbitrary albedo values can be computed from these three reflectances.

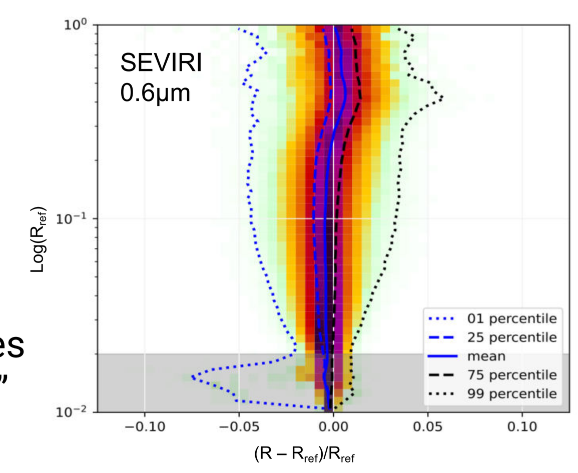
A FORTRAN code optimized for small networks and including adjoint and tangent linear versions is used for inference. The exp()-free CSU activation function used in the hidden layers leads to improved performance, compared to the standard ELU function (exp() is expensive and hampers vectorization).

MFASIS-NN is sufficiently fast (< 1µsec/column) **and accurate** (mean reflectance errors < 0.01) **for operational data assimilation.**



NEXT STEPS

- **Aerosol version:** A version for aerosol-affected reflectances is in preparation. It will generate reflectances for arbitrary combinations of the nine CAMS aerosol species for which optical properties are available in RTTOV. Like the cloud ersion it will be based on idealised profiles, in this case containing two aerosol layers. Preliminary results look promising (see plot to the right).
- **Feature extraction instead of feature engineering:** As an alternative to the feature engineering and synthetic training data approach followed so far we will investigate the feature extraction capabilities of neural networks using full global ICON model profiles as input. Networks with a "bottleneck layer" we will allow us to identify important features.
- **3D radiative transfer effects and uncertainty quantification:** With increasing resolution 3D radiative transfer effects (e.g. due to inclined cloud tops, cloud sides, cloud shadows) become more important and have to be taken into account. In contrast to earlier developments for specific effects (see Scheck et al. 2018), neural networks trained with 3D Monte Carlo RT results have the potential to take all relevant effects into account and may allow also to quantify the uncertainty related to inclomplete knowledge of the state (subgrid uncertainty).

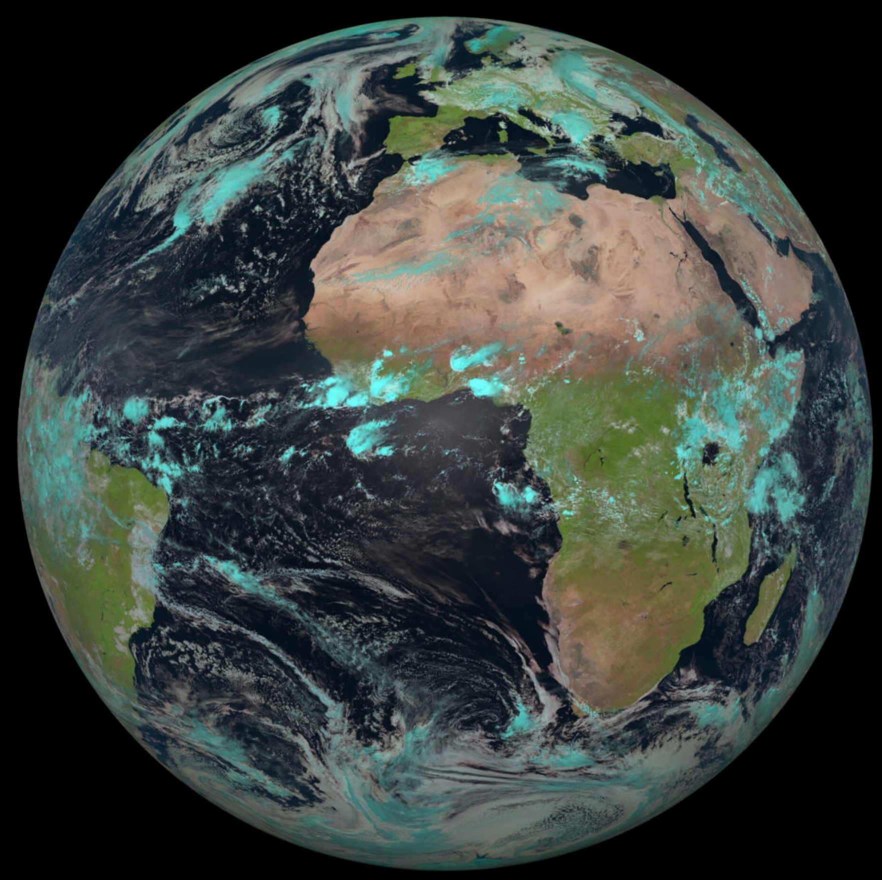


Aerosol profile simplification error evaluated with MACC dataset (5x4000 CAMS profiles). Each line is the PDF for the relative error for samples in the reflectance bin given by the vertical axis.

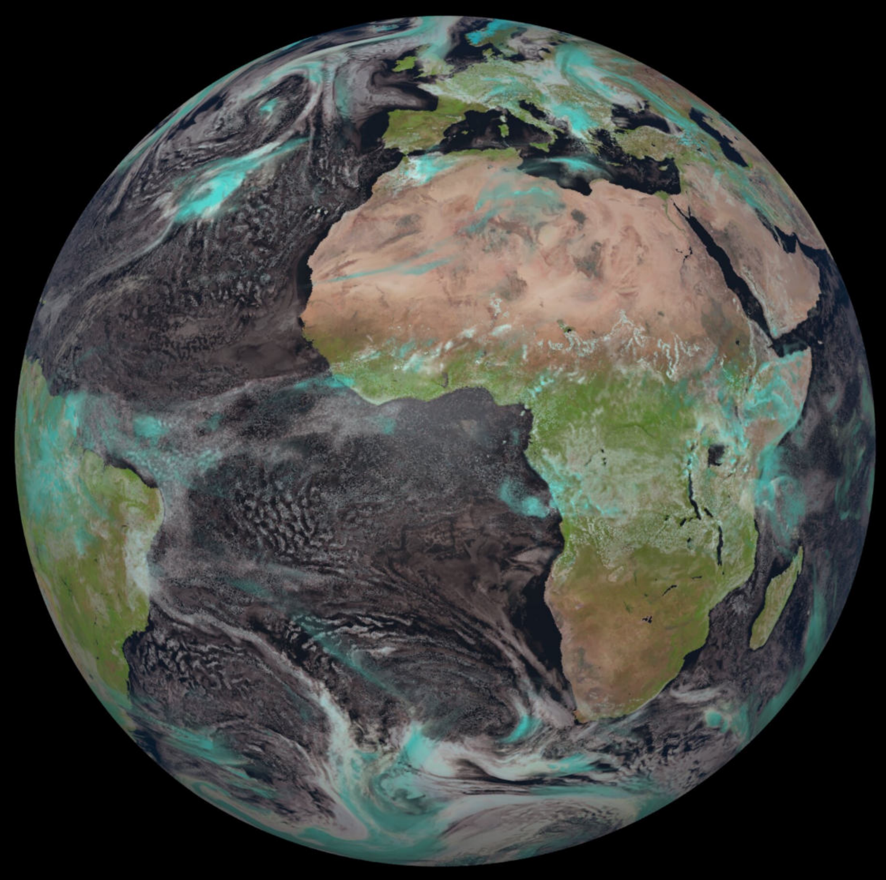
PUBLICATIONS: Baur, F., Scheck, L., Stumpf, C., Köpken-Watts, C., and Potthast, R. (2023): *A neural-network-based method for generating synthetic 1.6 µm near-infrared satellite images,* Atmos. Meas. Tech., 16, 5305–5326, https://doi.org/10.5194/amt-16-5305-2023.
Scheck, L. (2021) *A neural network based forward operator for visible satellite images and its adjoint,* JQSRT, 274, 107841, ISSN 0022-4073, https://doi.org/10.1016/j.jqsrt.2021.107841
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.

FULL DISK EXAMPLES

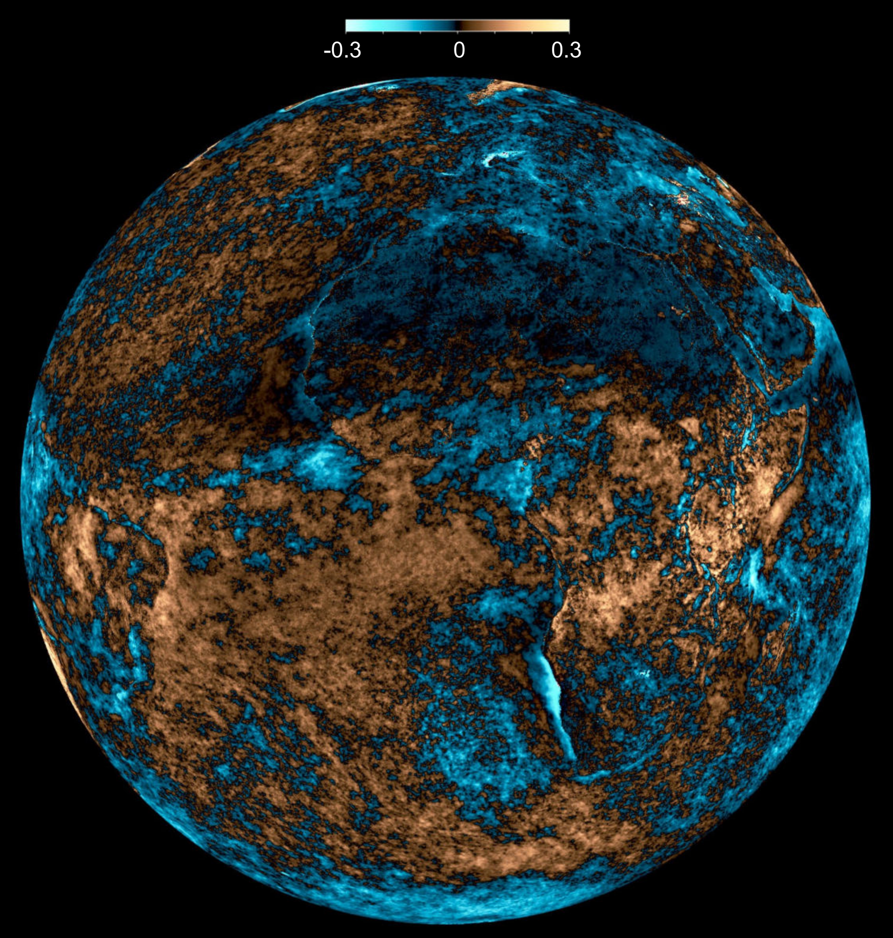
Meteosat Second Generation SEVIRI image
RGB composite for 2024 / 04 / 26, 12 UTC
R=1.6µm, G=0.8µm, B=0.6µm



Synthetic image computed with MFASIS-NN
for operational deterministic ICON 3h-forecast
(grid resolution 13 km)



Synthetic minus obsered 0.6µm image
averaged over 1 month (only 12 UTC images)



Almost a **synthetic MTG FCI image**
(Geometry from SEVIRI, channels from FCI)
R=0.6µm, G=0.5µm, B=0.4µm