











# Using visible and near-infrared satellite channels in NWP

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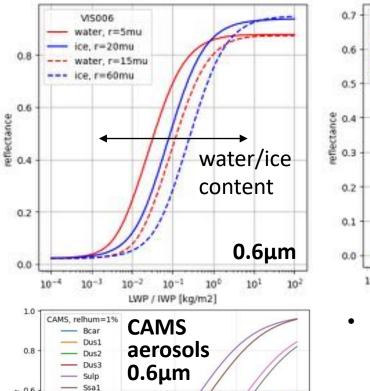


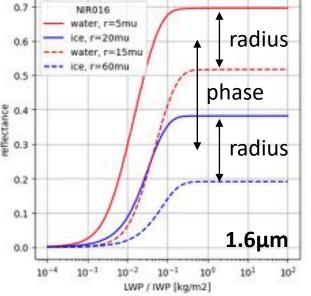


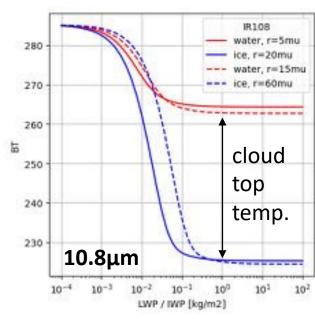




### Why are we interested in solar channels?







- High-res. cloud information (also for low clouds, complementary to thermal channels) for improving forecasts (including radiation)
- Aerosols (optical properties differ significantly)
- Channels sensitive to water vapor, O2, ...

#### Challenges: Multiple scattering, 3D effects

→ Standard radiative transfer methods too slow for DA

10-1

100

101

0.2

10-2







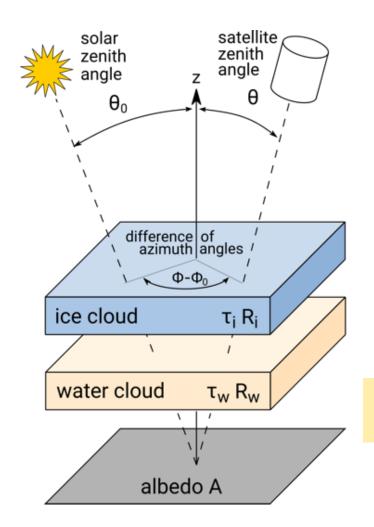






#### A forward operator for visible channels: MFASIS

Method for Fast Satellite Image Synthesis



- 1D RT method (tilted, independent columns)
- 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
- Compress LUT to 21MB using truncated Fourier series (lossy compression, similar to JPEG graphics format)
- Linear interpolation in compressed LUT is fast...

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

 Corrections for mixed-phase clouds and weakly water vapor sensitive channels (0.8µm SEVIRI)





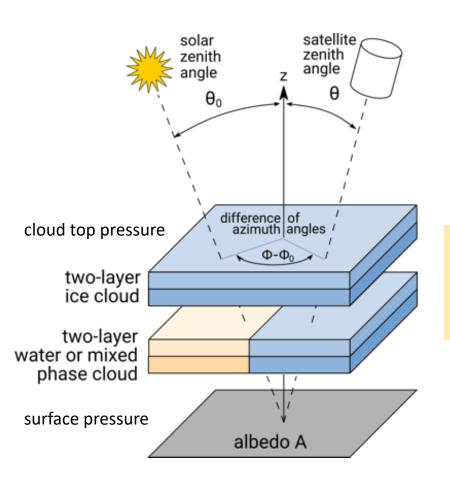








### Idealised cloud structure for the 1.6µm channel



Compared to the 0.6µm visible channel:

- Stronger dependence on effective radii
  Single scattering signal from upper cloud layers
  and multiple scattering contribution from rest of
  cloud depend on effective radii
- stronger absorption in ice clouds
- slight absorption by trace gases (CO2)
- → more detailed cloud description is required:
   two-layer clouds, separate input variables for ice in mixed phase cloud, surface & cloud top pressure
   → after some optimizations 14 input variables
- 14-dimensional LUT for storing reflectances? Not feasible, LUT size explodes...
- Similar problems with aerosols: AOD and scale height for 11 CAMS species → 22 dimensions...
- → Replace LUT by neural network!











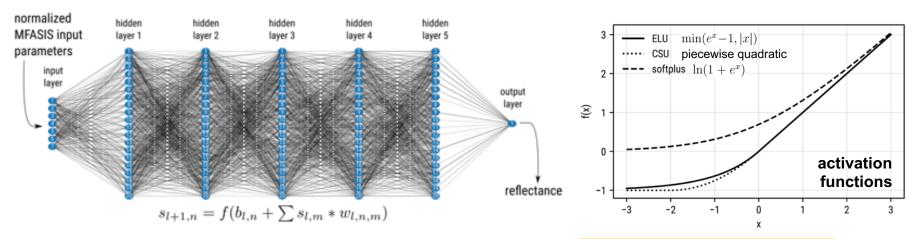


# Could we replace the LUT by a neural network (NN)?

**Approach:** Use relatively small (= fast) feed-forward neural network (several 1000 parameters),

train with Tensorflow standard methods (Adam optimizer, early stopping strategy)

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



NN structure: best results for 4 – 8 hidden layers ("deep"), needs only O(10KB) RAM

**Training data:** Synthetic (random numbers for input params., reflectance computed with DOM) NN learns functions, not data → factor 1000 less data required than for LUT (8MB, not 8GB)

Inference code: Vectorized Fortran (much faster than TF for small networks) includes adjoint & tangent linear versions (no effort for keeping in sync with nonlinear version). Optimized activation function (without exp()) → ~10 times faster than LUT version for VIS006





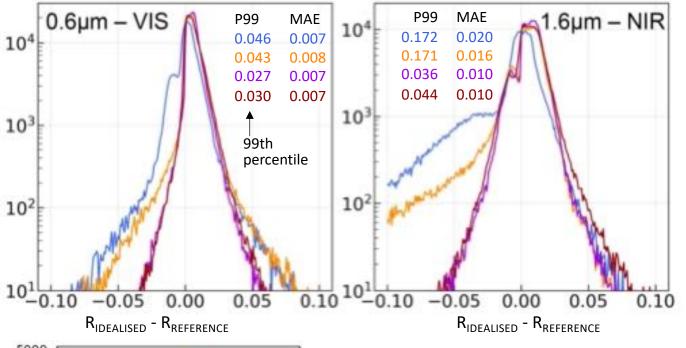








#### Lastest neural network results (preliminary)



#### Clouds:

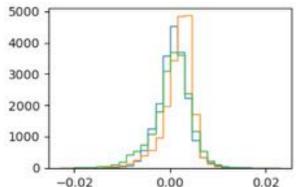
Evaluation with NWP SAF diverse IFS profile data set

Errors with respect to DOM for full profiles

DOM for simplified profiles:

1-layer water & ice clouds 2-layer water & ice clouds 2-layer + mixed-phase Neural network (14 inputs)

NIR errors now similar to VIS errors, neural network works well



**Aerosols:** Many species with one network?

Prototype with 9 CAMS aerosol species (AOD + scale height)

+ relative humidity + angles = 26 input variables

MACC-60L profiles: RMSE < 0.01, relative error < 5%

looks promising...





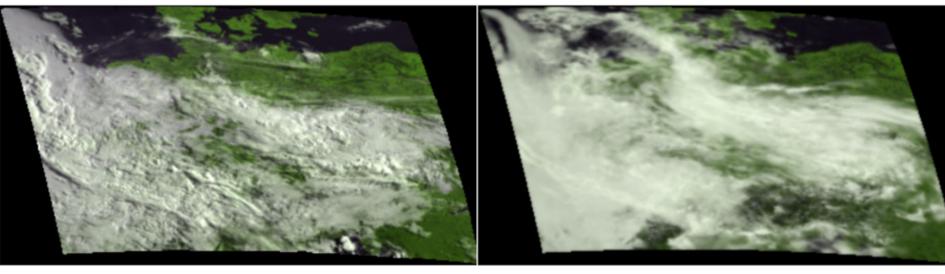








#### Taking cloud top inclination into account (3D RT effect)



SEVIRI 0.6mu+0.8mu, 3 June 2016, 6UTC

3h COSMO fcst without 3D correction

#### Cloud top tilted away from/towards sun → reflectance lower / higher

**Fast approximation:** Find optical depth 1 surface, determine inclination angles Compute 1D RT solution in rotated frame of reference (in which inclination is zero), transform reflectance back to non-rotated frame

Cloud top inclination correction → Reduced errors, increased information content Much more cloud structure is visible, in particular for larger SZAs





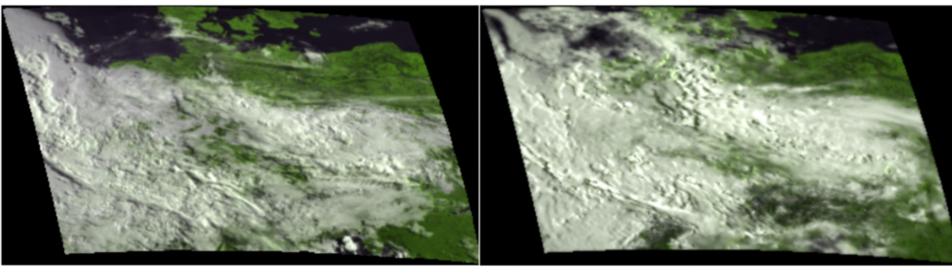








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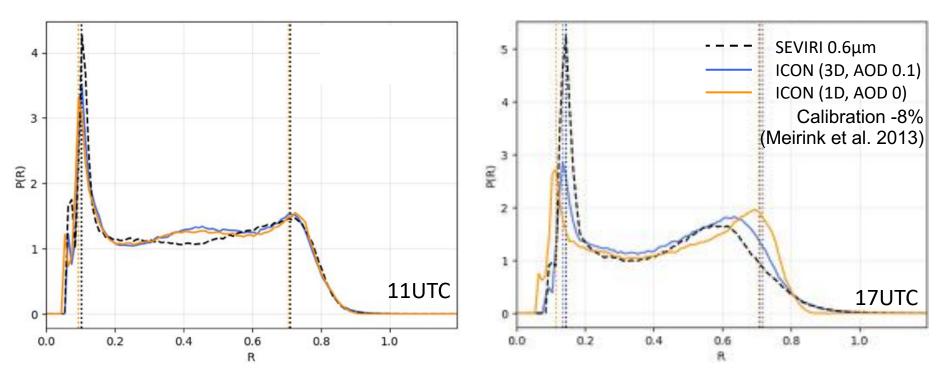








### Observation vs. Model: regional ICON-D2 model



30 day free ICON-D2 run (June 2020), effective radii from two-moment microphysics After some model tuning (guided by 0.6µm + 10.8µm channels, mostly subgrid clouds, see Geiss et al. 2021) **histograms agree well during the day**, larger deviations for low sun (cloud top inclination and aerosol background helps)







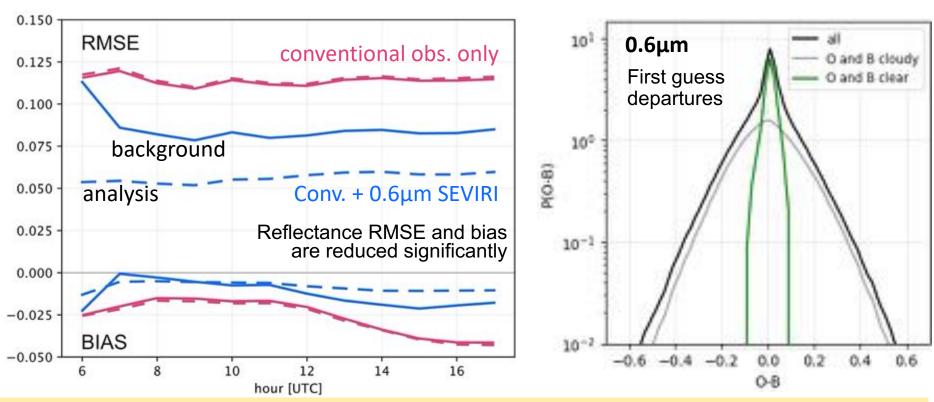






### **ICON-D2** assimilation experiments

Near-operational, 40 mem. LETKF, 1h cycles, conventional + 0.6µm SEVIRI obs. one-moment microphysics (paramet. eff. radii), 12km superobbing, obs. error 0.15



Location and thickness of clouds (and therefore also radiation) strongly improved for several hours, some impact is left after the night.





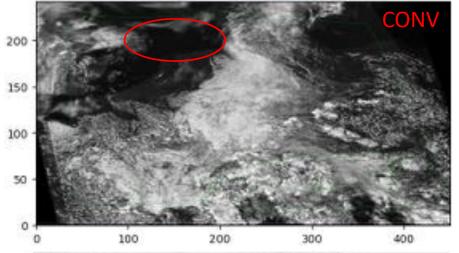






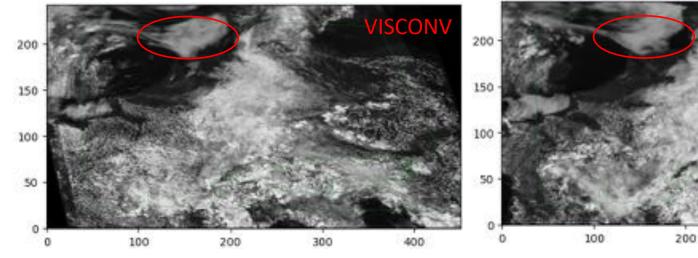


### **ICON-D2** assimilation experiments



#### Example:

Cloud is missing in first guess (deterministic member) when only conventional observations are assimilated.
Cloud is present when in addition 0.6µm SEVIRI images are assimilated.



300

**OBS** 









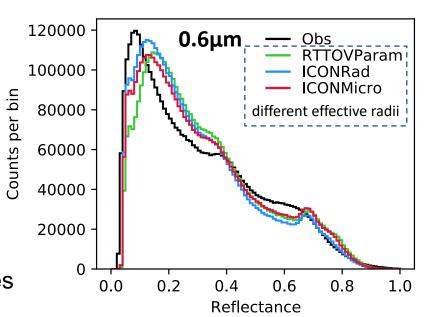


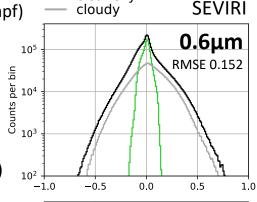


MSG4

### Results for global ICON model (by Christina Stumpf)

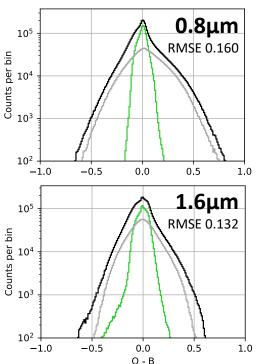
- 3h ICON forecasts (40km) for 15-21 November 2020 and 15-21 March 2021 valid at 6, 9, 12, 15, 18 UTC
- Zenith angles > 75° and sunglint area are excluded
- RTTOV13-MFASIS (no aerosol background, no 3D effects)
- Different choices for effective radii → cannot explain all differences between observed and synthetic histograms
- Subgrid clouds: more important than for ICON-D2
- Still not clear: importance of cloud inhomogen.
- Departures more gaussian for cloudy-cloudy cases





all profiles

clear-sky















## **Summary**

- Solar satellite channels are interesting for NWP: water content, microphysics, aerosols, ...
- Forward operator: Neural network approach reduces computational effort significantly, allows for including absorbing channels (e.g. 1.6µm) and aerosols (works in progress)
- Regional model results: Good agreement of O & B reflectance histograms with effective radii from two-moment microphysics scheme
  - Assimilating visible satellite images strongly improves location and thickness of clouds
- Preliminary results for global ICON model: Somewhat larger errors (work in progress)
   (also at ECMWF monitoring studies for visible channels are in progress)

#### **Publications**

- Geiss, S., L. Scheck, A. de Lozar, M. Weissmann, 2021, *Understanding the model representation of clouds based on visible and infrared satellite observations*, ACP, DOI:10.5194/acp-21-12273-2021
- 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
- Saunders et al., 2020, RTTOV-13 Science and vaildation report,
   https://nwp-saf.eumetsat.int/site/download/documentation/rtm/docs\_rttov13/rttov13\_svr.pdf
- Scheck, L., M. Weissmann, L. Bach, 2020, Assimilating visible satellite images for convective-scale numerical weather prediction: A case study, Q. J. R. Meteorol. Soc., 146: 3165–3186.
- 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.