Generating synthetic visible satellite images with RTTOV

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PRESENTER

Visible satellte images provide high-resolution information about the cloud distribution and cloud microphysical properties. This information is often complementary to the one that can be obtained from thermal infrared channels. Visible satellite images would thus be a promising type of observation for data assimilation (DA) and model evaluation. However, the importance of scattering and 3D effects in the visible spectral range hampered the development of a suffienctly fast and accurate forward operators. Only recently MFASIS, a fast radiative transfer (RT) method based on a look-up table (LUT) was implemented in RTTOV. The LUT is computed using the discrete ordinate method (DOM), an accurate 1D RT solver. Here we discuss MFASIS and a 3D extensions, report on experiments to replace the LUT by a neuronal network and show first DA results for the SEVIRI 0.6μm channel.

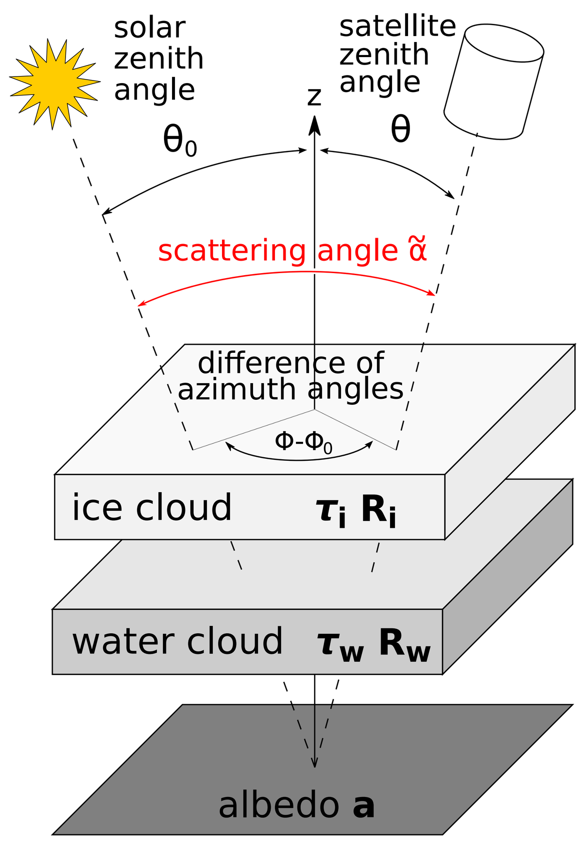
MFASIS: A FAST, LOOK-UP TABLE BASED METHOD FOR GENERATING VISIBLE SATELLITE IMAGES

Standard 1D RT solvers: too slow for operational DA and high-resolution model evaluation. → MFASIS (Method for FAst Satellite Image Simulation): fast, look-up table based RT method

Basic strategy
- Describe relevant atmospheric properties and geometry by a minimal parameter set
- Compute look-up tables (LUTs) with DISORT for all parameter value combinations
- Compress LUT using Fourier series representation
- Compute reflectance = calculate parameters from model output, interpolate in tables

Reflectance table generation
- DOM 1D RT calculations for idealised scenes: Two homogeneous clouds at fixed heights, defined by only 4 parameters per column: optical depths and effective particle radii for water and ice clouds
- Vertical structure of clouds (e.g. cloud top height) has only weak influence on VIS/NIR reflectances
- 4 more parameters for albedo and geometry

→ 8-dimensional LUT with a size of about 8GB

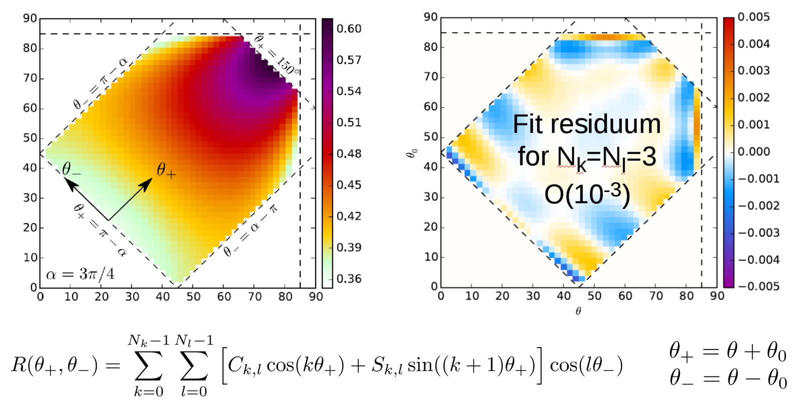


Large LUT is problematic for online operator, causes cache misses

→ **lossy compression of LUT**

Small scale features in R(θ_0, θ, Φ-Φ_0) make compression difficult → use scattering angle α

→ R(θ_0, θ, α) is smooth function for α=const



$$R(\theta_+,\theta_-) = \sum_{k=0}^{N_k-1}\sum_{l=0}^{N_l-1}\left[C_{k,l}\cos(k\theta_+) + S_{k,l}\sin((k+1)\theta_+)\right]\cos(l\theta_-) \qquad \theta_+ = \theta+\theta_0,\ \theta_- = \theta-\theta_0$$

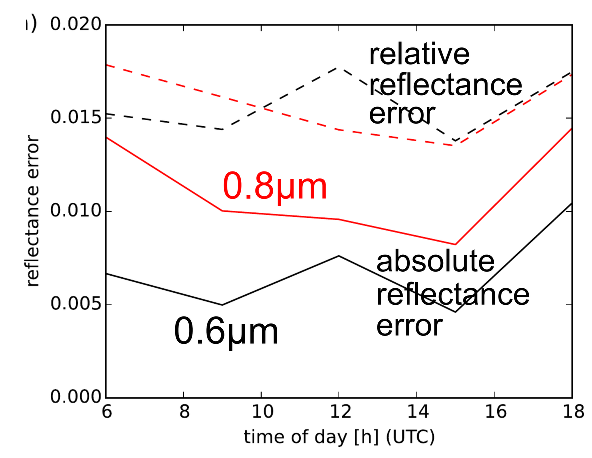
18 Fourier terms describe R(θ_0, θ, α) well

→ LUT reduced to 21MB LUT (factor 390)

Accuracy & Speed
- Error with respect to DOM < SEVIRI calibration error
- This error does not include 3D effects (see below) and assumed a fixed water vapor profile
- MFASIS is 4 orders of magnitude faster (only RT), total run time (including e.g. computation of optical properties) is reduced by 2 orders of magnitude

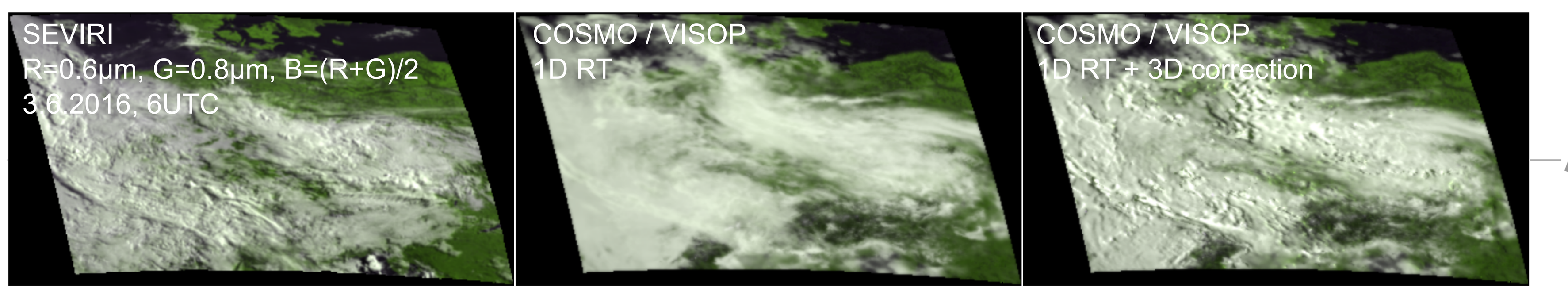
Mean error with respect to DOM for a 19-day period in June 2012.

See Poster 11p.03 by C. Stumpf et al. for a more detailed evaluation



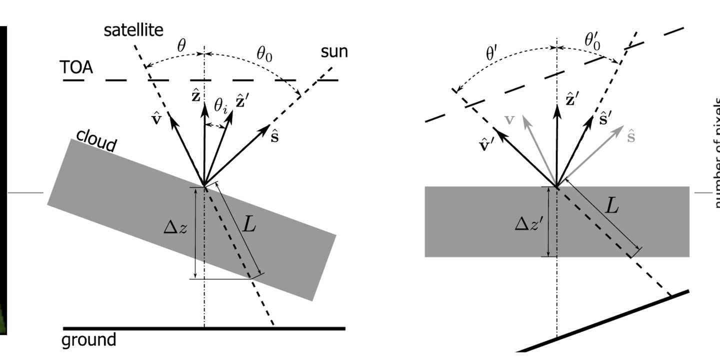
3D RADIATIVE TRANSFER EFFECTS: CLOUD TOP INCLINATION

Most important 3D RT effect: Cloud top inclination (→increased information content).

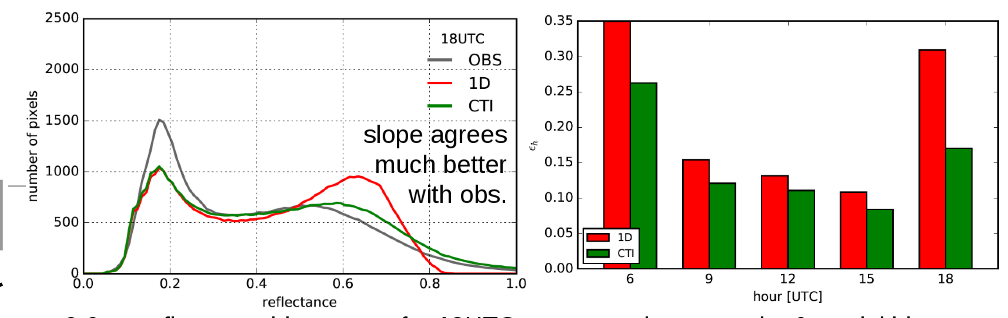


Efficient approximation: Solve quasi-1D problem in rotated frame of reference, transform back.

Cloud top definition: optical depth 1



Systematic errors are reduced...



0.6mu reflectance histograms for 18UTC

area between obs.& model histogram

$$R_{3D}(\alpha,\theta,\theta_0,A,\tau,\theta_i,\phi_i) \approx R_{1D}(\alpha,\theta',\theta_0',A\sigma^{-1},\tau\sigma)\times\sigma_0 \quad \theta' \text{ and } \theta_0'\text{: functions of } \alpha,\theta,\theta_0,\theta_i,\phi_i; \quad \sigma=\frac{\cos\theta'}{\cos\theta},\quad \sigma_0=\frac{\cos\theta_0'}{\cos\theta_0}$$

REPLACING THE LOOK-UP TABLE BY A NEURONAL NETWORK

Main motivation: Adding more dimensions to the LUT to take more RT effects or more particle species (aerosols) into account

→ LUT size will explode, generating the LUT (uncompressed now already 8GB) will become too expensive

Machine learning approaches: It could be sufficient to compute only a small fraction of the data required for the LUT approach

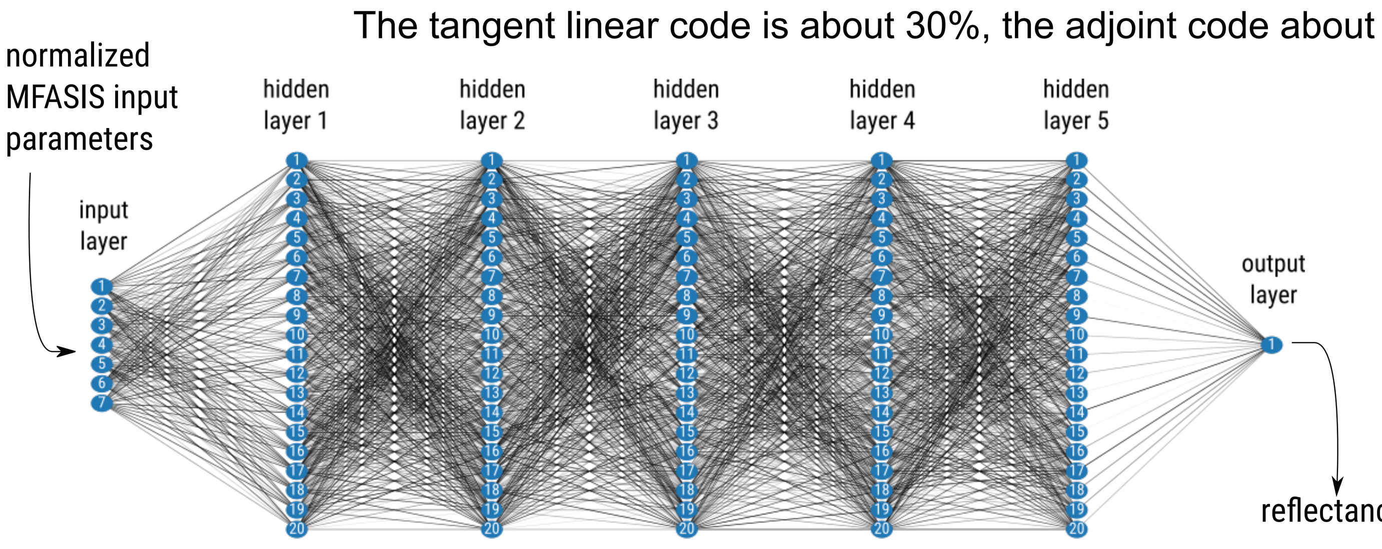
Popular choice (libraries and hardware support available): **Multilayer Perceptron = (deep) feed forward neural network (NN)**

Additional benefits: **NN much smaller** than compressed LUT, **adjoint is continuous** (in contrast to MFASIS), was easy to develop.

Key issue: Is a sufficiently accurate NN as fast as the LUT-based MFASIS?

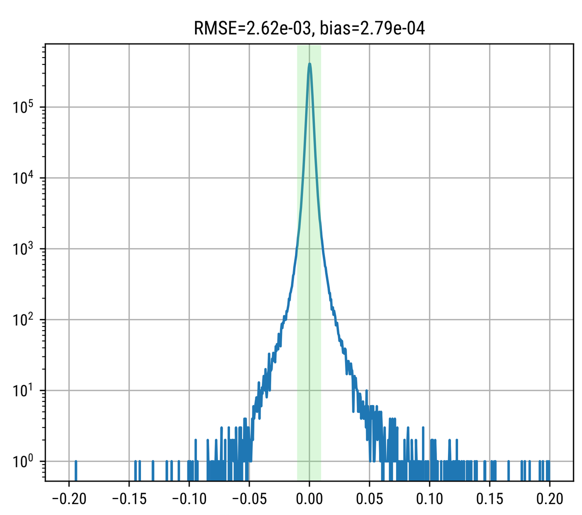
Preliminary result: A NN with 5 x 26 nodes (35KB parameters) trained for 10h with 1% of the uncompressed 8BG LUT is sufficently accurate and the computational effort for its evaluation is comparable to the one of MFASIS.

The tangent linear code is about 30%, the adjoint code about 60% slower than the nonlinear code.

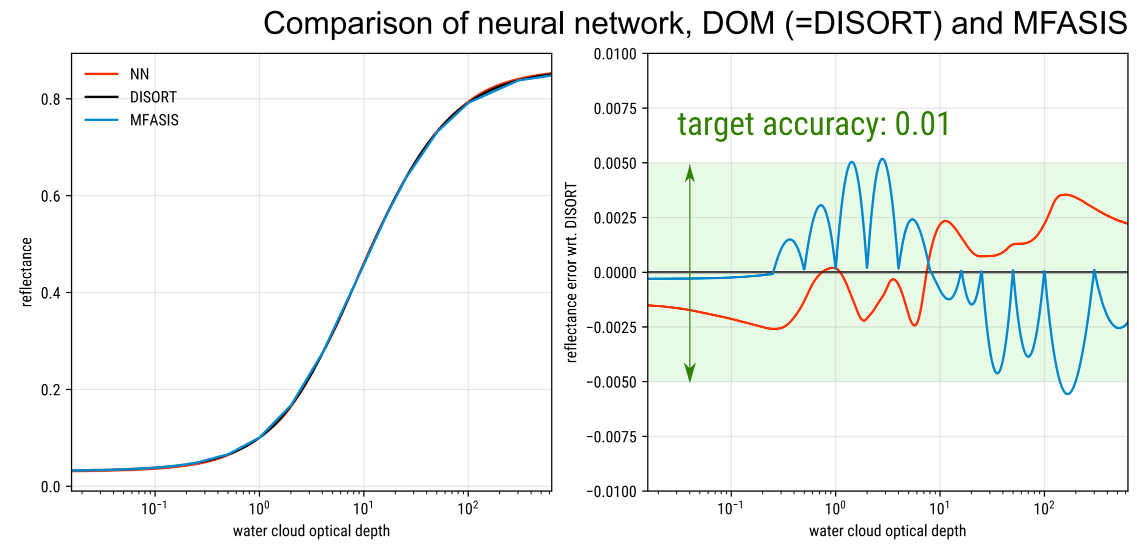


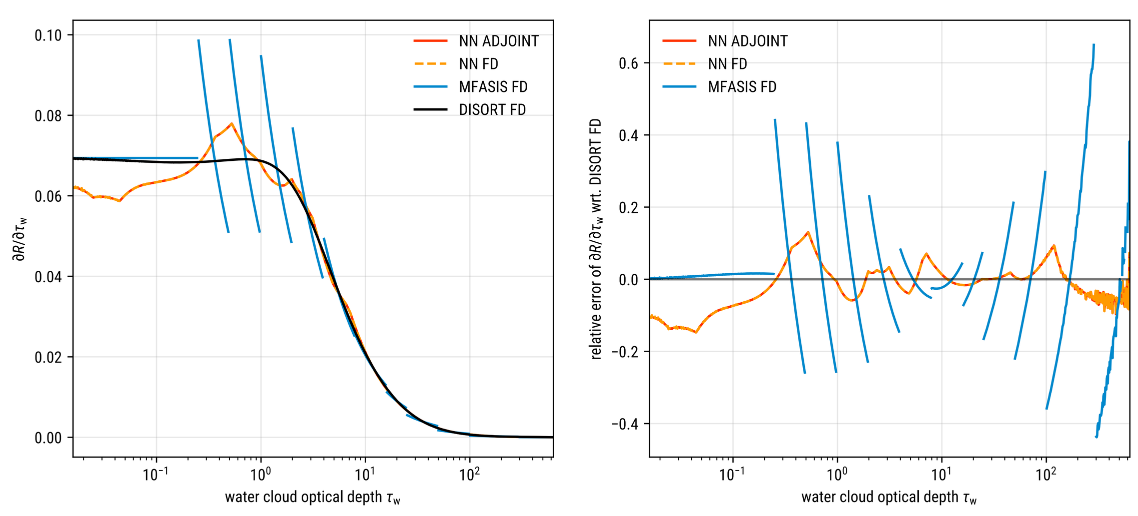
$$s_{l+1,n} = f(b_{l,n} + \sum s_{l,m} * w_{l,n,m})$$

validation with 1% of the 8GB LUT data (different from the 1% used for training)



Reflectance as a function of optical depth: Comparison of neural network, DOM (=DISORT) and MFASIS





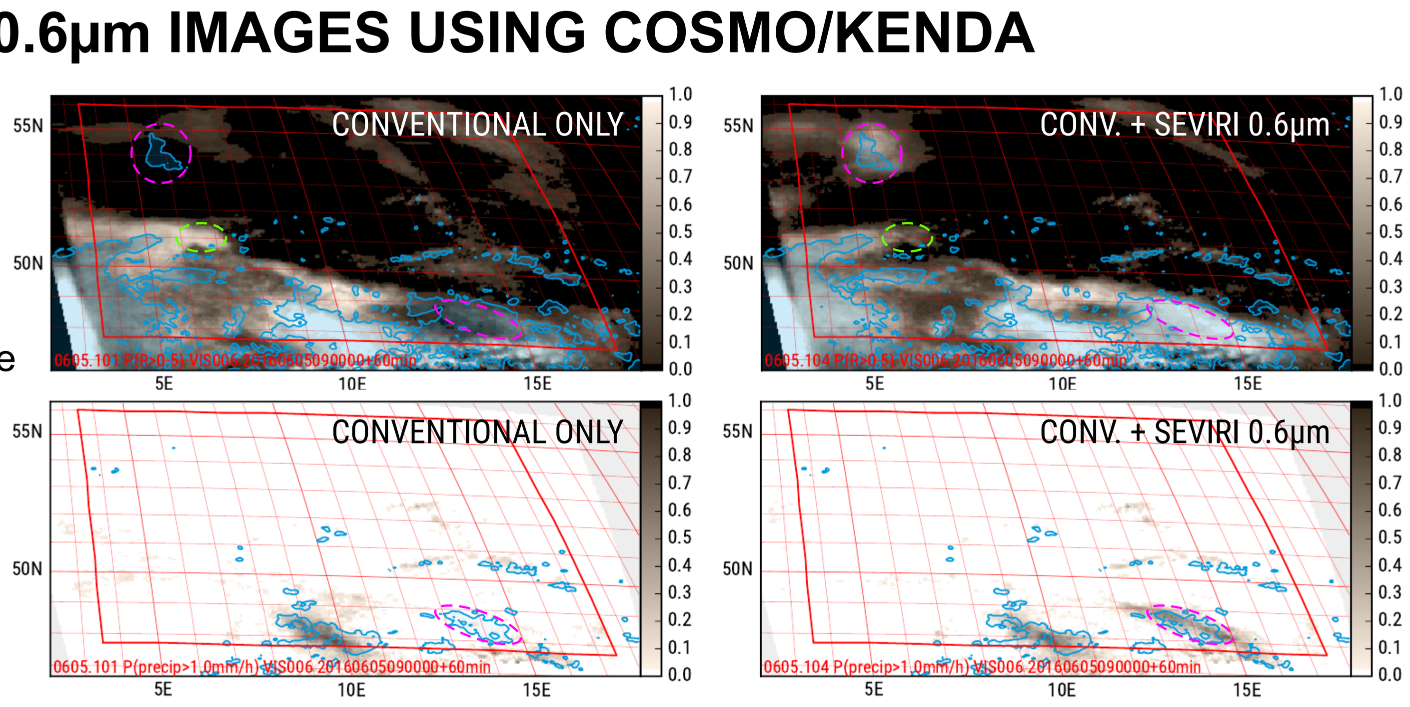
Reflectance derivative with respect to optical depth: Comparison of finite difference results with adjoint code results

APPLICATION: ASSIMILATING SEVIRI 0.6μm IMAGES USING COSMO/KENDA

Assimilation experiments with the local ensemble transform Kalman filter (**LETKF**) implemented in DWDs Kilometre-scale ensemble data assimilation system (**KENDA**) and the **COSMO** model (Δx=2.8km, domain covering Germany) for two strongly convective summer days in 2016.

Settings: Near-operational (40 members, multiplicat. & additive inflation + RTPP), but no latent-heat nudging, no MODE-S, assimilation window 1h. Experiments with conventional obs. compared to conv. obs. + SEVIRI 0.6μm images.

Main results: Cloud cover is strongly improved, beneficial impact on precipitation and humidity. Impact lasts for > 3h (we did not yet perform longer forecasts).



Example: 1-h forecast valid at 10 UTC, 5 June 2016

Left column: Only conventional observations assimilated

Right column: Conventional obs. + SEVIRI 0.6μm assimilated

Upper panels: Probability of cloudiness P(R>0.5) = Fraction of ensemble members exceeding reflectance 0.5

Blue contours: Reflectance > 0.5 in the observation

Lower panels: Probability of precipitation P(precip>1mm/h) = Fraction of ens. members with a precip. rate exceeding 1mm/h

Blue contours: Observed precip. rate > 1mm/h (radar product)

See talk 9.04 by L. Bach et al. and poster 3p.02 by C. Köpken-Watts et al.!

PUBLICATIONS:

Scheck, Frerebeau, Buras-Schnell, Mayer (2016): *A fast radiative transfer method for the simulation of visible satellite imagery,* JQSRT, 175, 54-67.

Scheck, Hocking, Saunders (2016): *A comparison of MFASIS and RTTOV-DOM, NWP-SAF visiting scientist report,* http://www.nwpsaf.eu/vs_reports/nwpsaf-mo-vs-054.pdf

Scheck, Weissmann, Mayer (2018): *Efficient methods to account for cloud top inclination and cloud overlap in synthetic visible satellite images,* JQSRT, 35, 665–685.

Scheck, Weissmann, Bach: *Assimilating visible satellite images for convective scale weather prediction: A case study,* in preparation

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