LMU | LUDWIG-MAXIMILIANS-UNIVERSITÄT MÜNCHEN | MIM | EUMETSAT NWP SAF NUMERICAL WEATHER PREDICTION | Hans-Ertel-Zentrum für Wetterforschung | Deutscher Wetterdienst Wetter und Klima aus einer Hand DWD

Current issues in cloud and precipitation optical modeling: Visible

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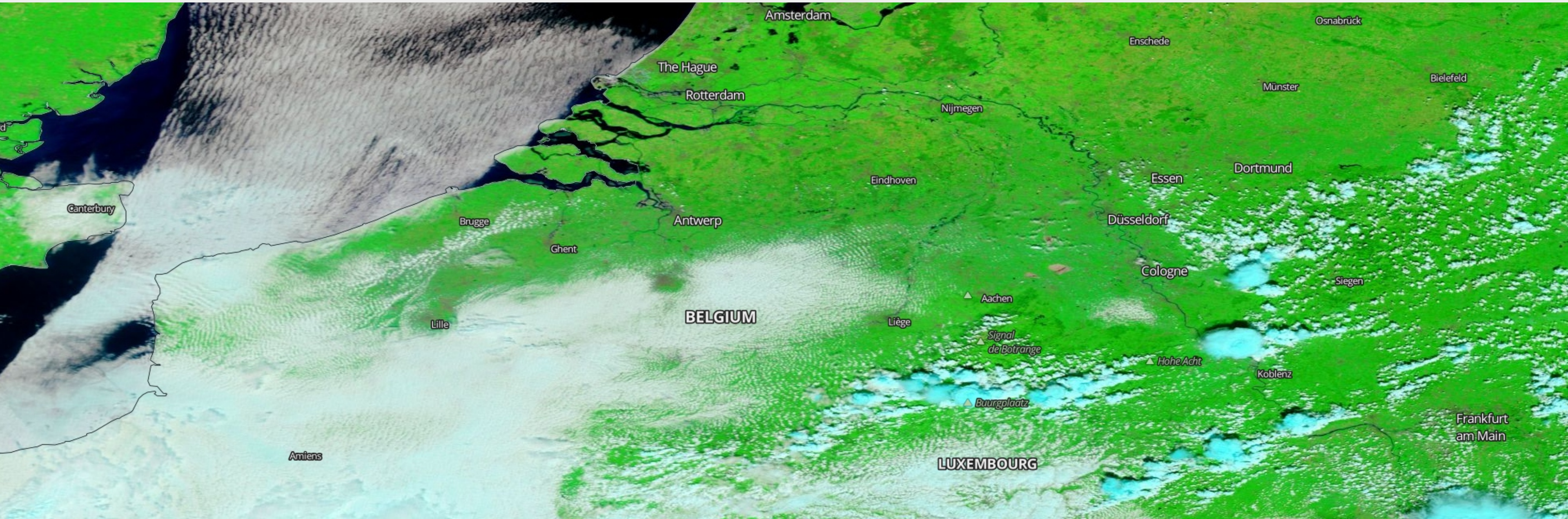

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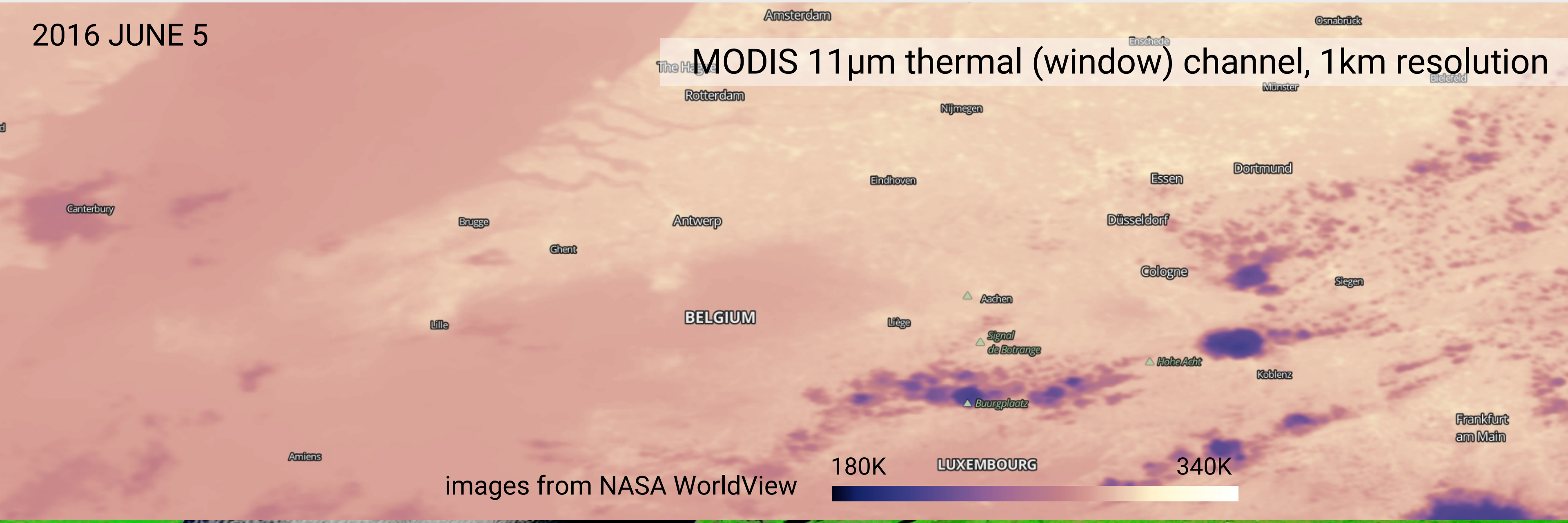
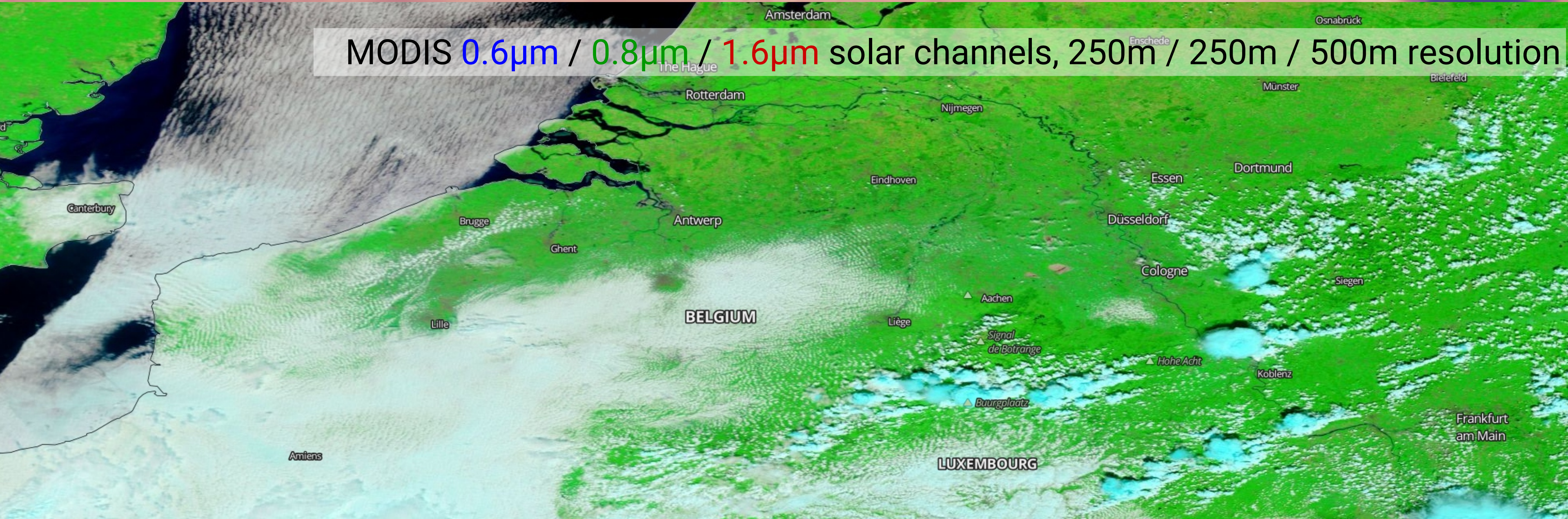
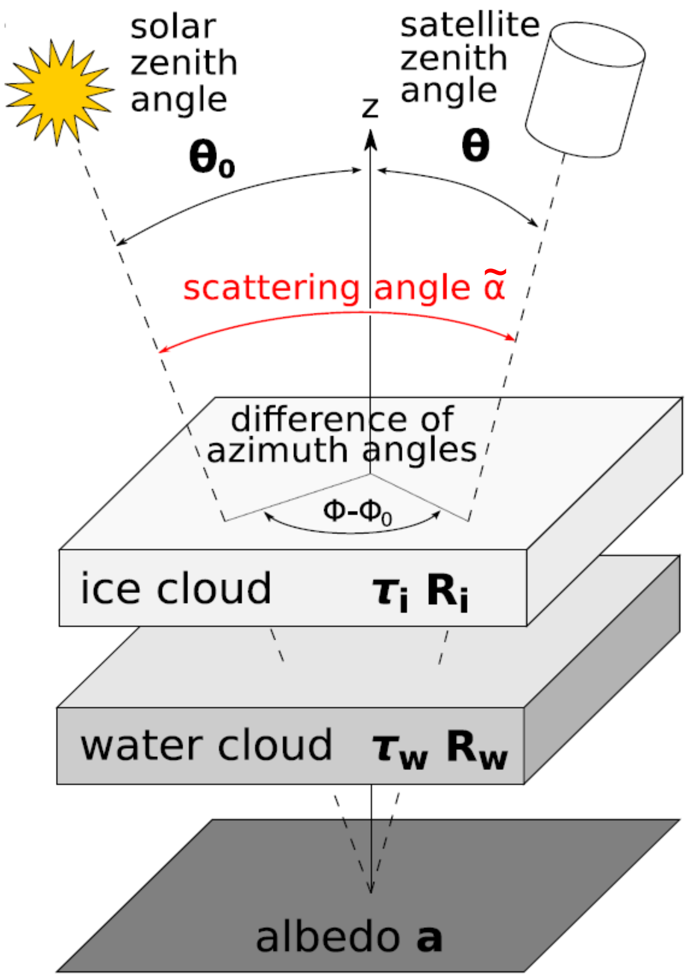
2016 JUNE 5





Strategy for fast radiative transfer method MFASIS

Method for Fast Satellite Image Synthesis



Simplifications

- Simplified Equation:
3D RT → 1D RT (tilted independent columns)
Computational effort for a SEVIRI image of Germany:
CPU-days (3D Monte Carlo) → CPU-hours (1D DISORT)

- Simplified vertical structure:
Cloud water and ice can be separated to form two two homogeneous clouds at fixed heights without changing reflectance significantly
→ only 4 parameters (optical depth, particle size)
+ 3 angles, albedo → **8 parameters per column**

Reduction of computational effort

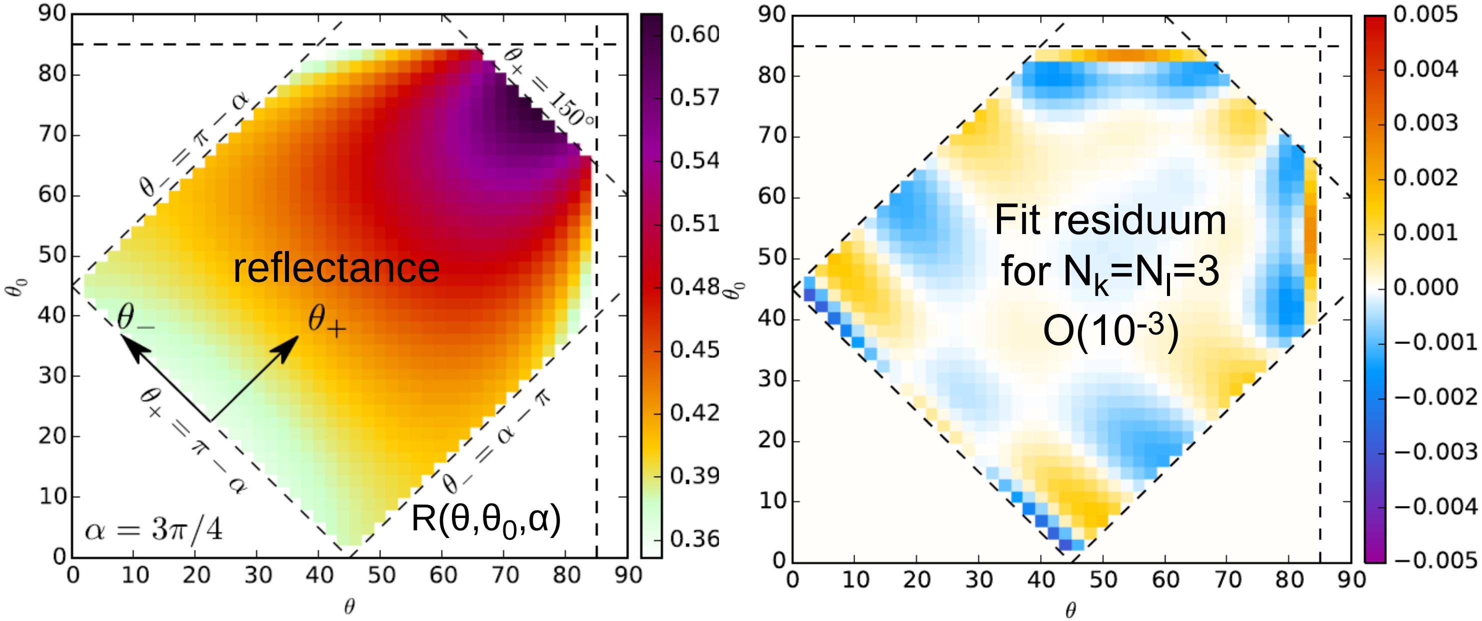
Compute **reflectance look-up table (LUT)** with discrete ordinate method (DISORT) for all parameter combinations
→ effort for looking up reflectances: CPU-minutes

Problem: Table is huge! O(10GB) → not suitable for online operator, slow interpolation → **compress table to 20MB** using truncated Fourier series → CPU-seconds

Look-up table compression in MFASIS

- **Problem:** R(θ,θ_0,Φ-Φ_0) contains a lot of rainbow-related small-scale features
- **Solution:** Consider R(θ,θ_0,α) instead : smooth function for constant scattering angle α
  → approximate by 2D Fourier series, obtain Fourier coefficients by fit to DISORT results

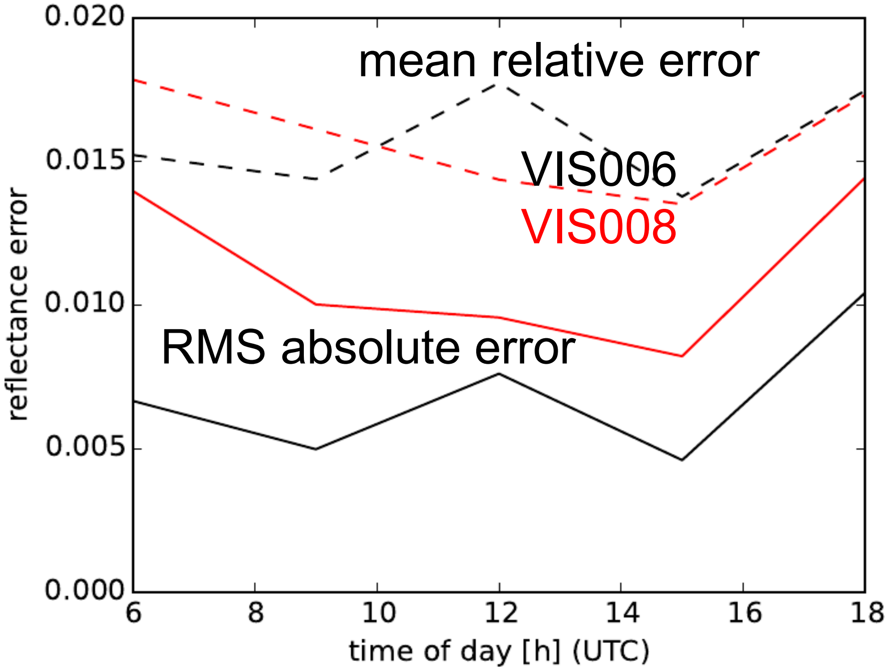
Fit function: $$R(\theta_+,\theta_-) = \sum_{k=0}^{N_k-1}\sum_{l=0}^{N_l-1}\left[C_{k,l}\cos(k\theta_+) + S_{k,l}\sin((k+1)\theta_+)\right]\cos(l\theta_-)$$ where $$\theta_+ = \theta + \theta_0 \quad \theta_- = \theta - \theta_0$$



We need to store only 18 coefficients C_{kl}, S_{kl} instead of O(1000) reflectance values (for each combination of the remaining 6 parameters) → **compression by a factor of ~O(100)**

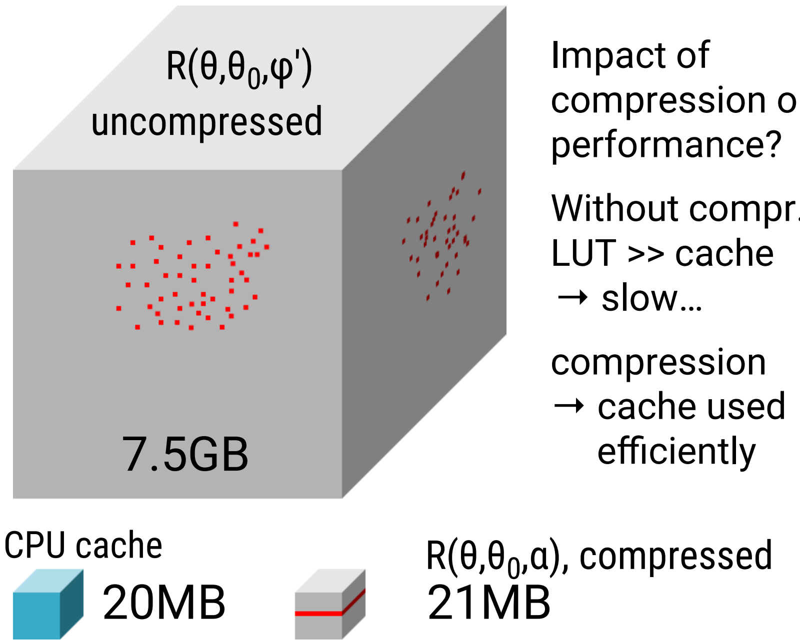
Accuracy and computational effort

Error of MFASIS (8 parameters/pixel) **with respect to DISORT** (full profiles available)
(model data: COSMO-DE fcsts for 10-28 June 2012)



Relative error < SEVIRI calibration error (~4%) for almost all pixels

Computational effort per column:
DISORT (16 streams): 2.3 x 10^{-2} CPUsec
MFASIS (21MB table): 2.5 x 10^{-6} CPUsec
(on Xeon E5-2650, for 51 level COSMO data)



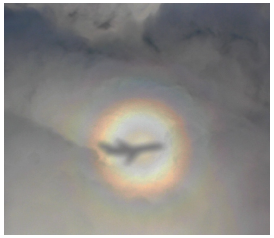
Impact of compression on performance?

Without compr.: LUT >> cache → slow...

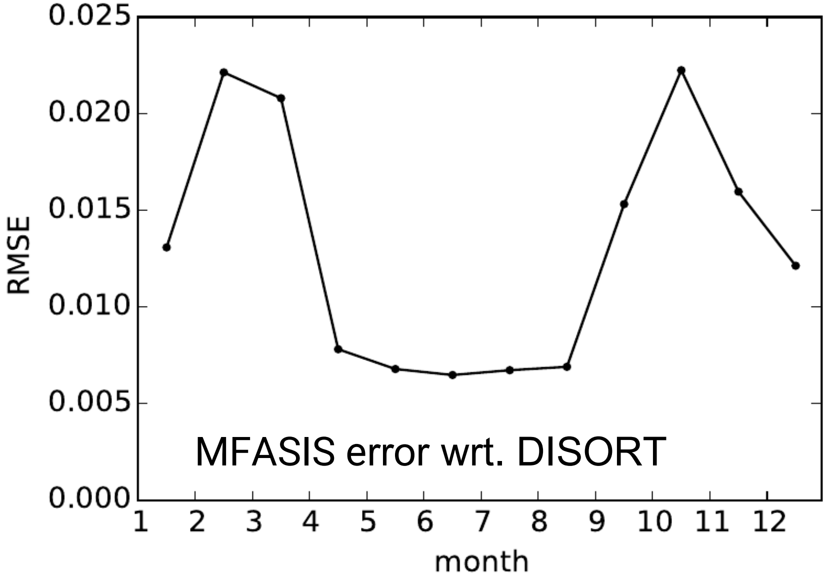
compression → cache used efficiently

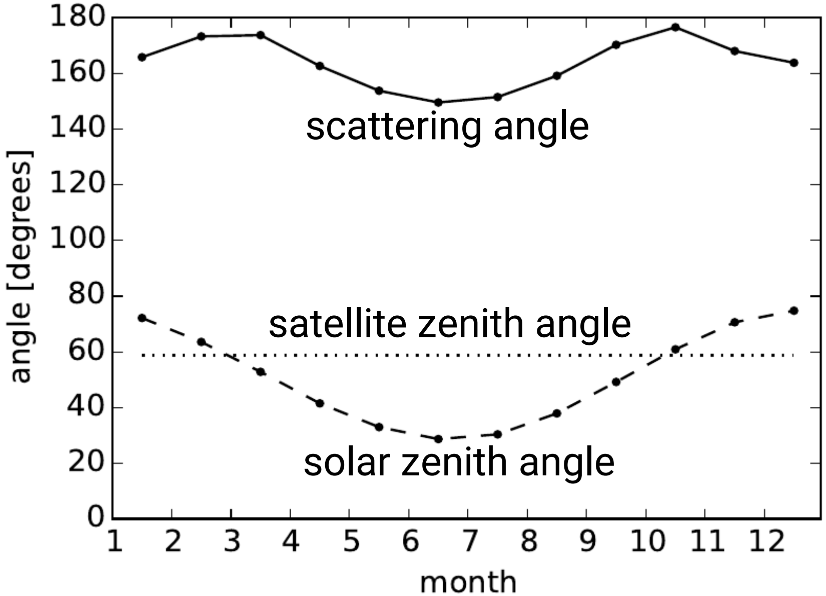
NWP-SAF → MFASIS has been included in RTTOV 12.2 by DWD + MetOffice

Backscatter glory (1D RT)



Model state from June 15, 2012, 12UTC. Sun angles from other months.



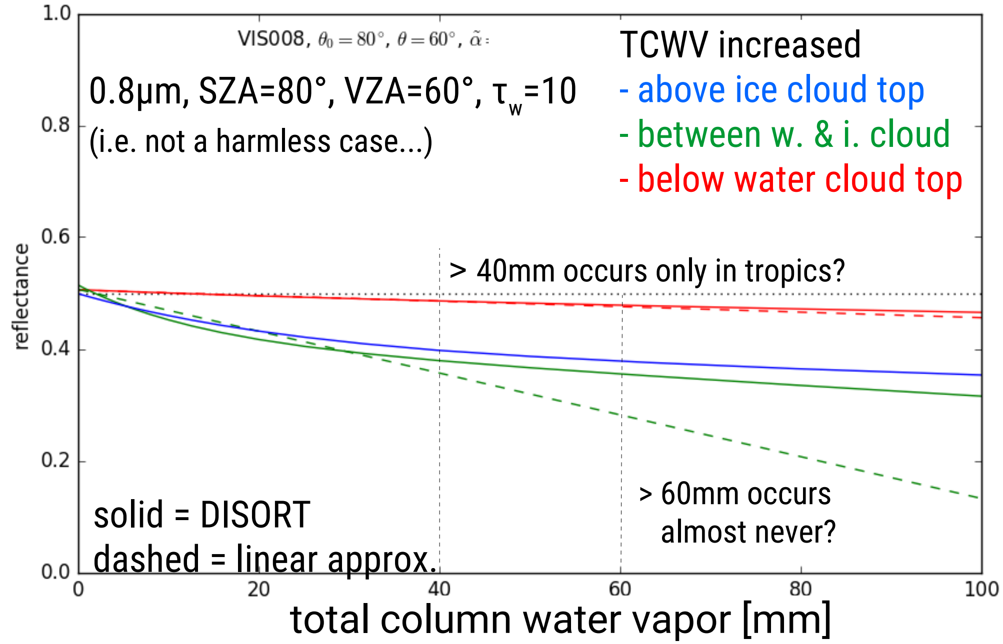


Scattering angles larger than 175° in October / March → affected by glory
From a geostationary point of view the glory is not a rare event...
Not included in the LUT → errors several times larger
Glory depends on width of droplet radius distribution → no input data available
Assimilation with higher assumed observation error should still be useful.

1D RT Improvements

Not all MFASIS assumptions are always fulfilled perfectly
→ corrections:

Non-standard water vapor profile (relevant e.g. for SEVIRI 0.8µm):
Linear correction depending on WV mass above/below cloud top
included in RTTOV 12.3

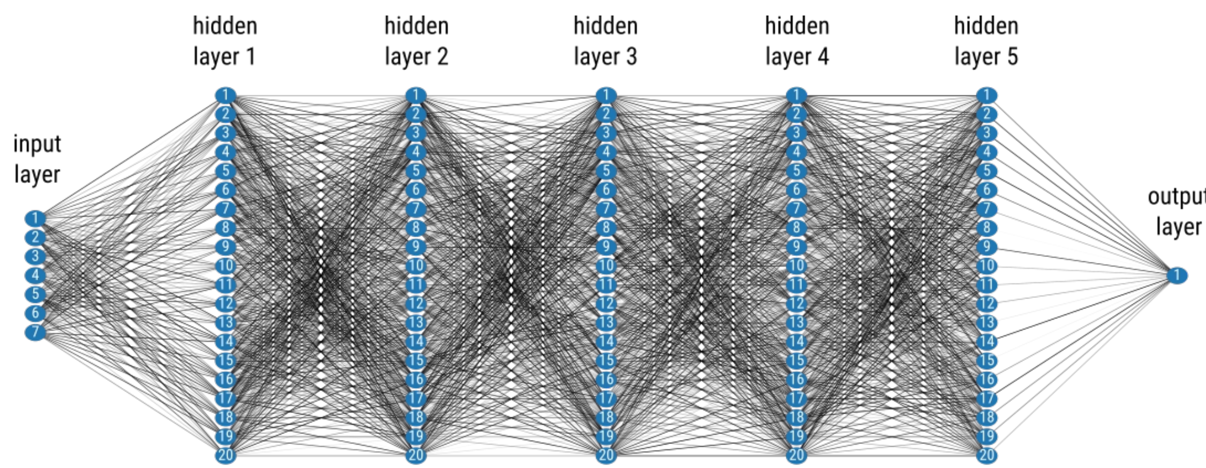


Non-standard air mass (affecting Rayleigh scattering): Should be taken into account for wavelengths < 0.5µm, for 0.6µm only important for high altitude regions with high albedo (Antarctica, Greenland).
Could be corrected similar to WV correction (to be implemented)

Mixed-phase clouds: Ice in water cloud: Single scattering signal similar to water cloud, ice contributes to multiple scattering signal.
First simple correction: Interpret non-dominant mixed-phase cloud ice content as water (included in RTTOV 12.3). More general solution under investigation...

Replace compressed LUT by a neural network?

- Motivation: There are **many reasons to increase the number of LUT dimensions** (various corrections, aerosols) → LUT size could increase strongly…
- Machine learning methods could handle more dimensions more efficiently
  Main advantage: Only a small fraction of the LUT data is required for training
- Popular choice (libraries and hardware support available): **Multilayer Perceptron = (deep) feed forward neural network**

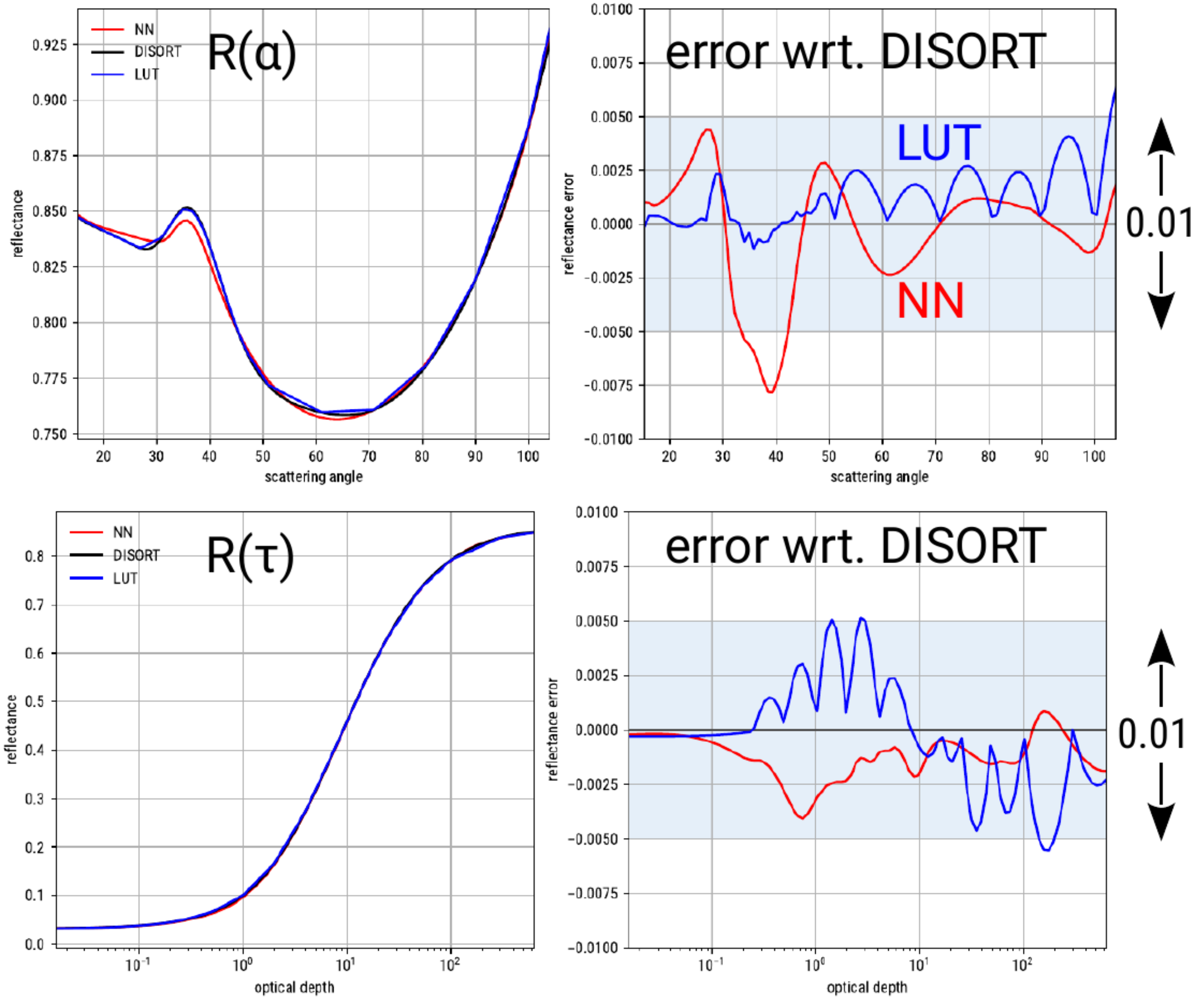


$$s_{l+1,n} = f(b_{l,n} + \sum s_{l,m} * w_{l,n,m})$$

- Additional benefits: NN much smaller than compressed LUT, hardware support, adjoint should not be a problem (I think...) and will never have to be changed
- **Is a sufficiently accurate NN as fast as the LUT-based MFASIS approach?**

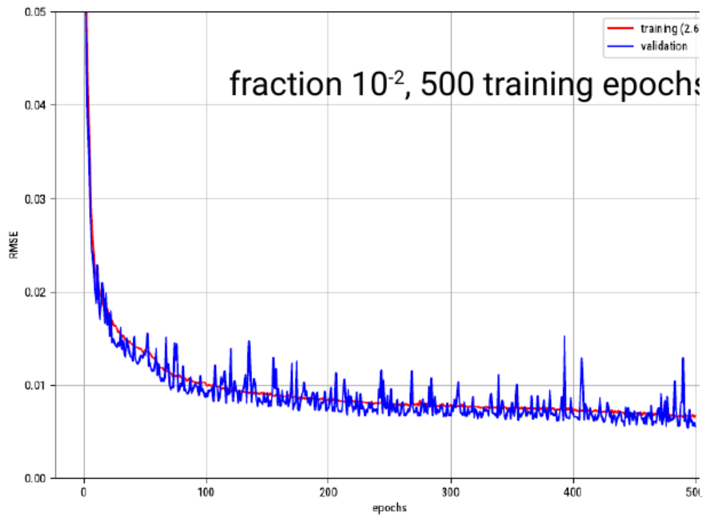
First results from a feed-forward network

- Reflectance for varying scattering angle and water cloud optical depth computed with **DISORT**, **MFASIS** and **NN**
- Neural Network:
  5 x 26 nodes (30KB) trained using 1% of the uncompressed LUT data
- Errors are in the desired range, except for rainbow. RMSE = 0.006
- NN ~3x slower than LUT
- Looks promising, optimizations are possible



Training data set requirements

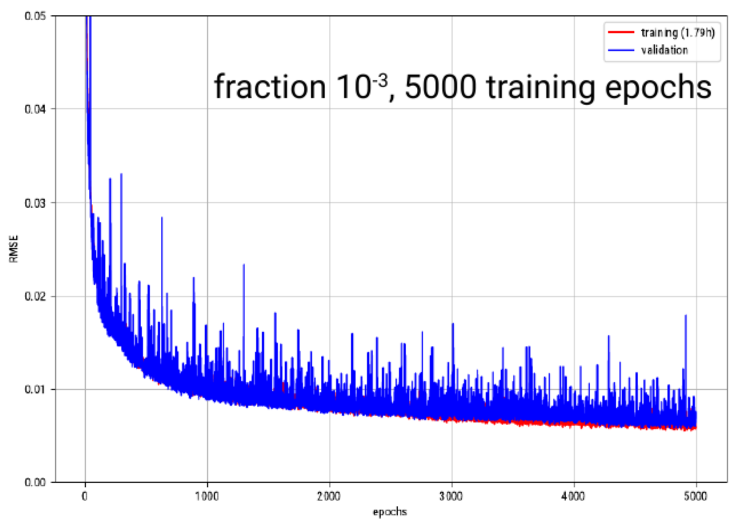
reflectance RMSE

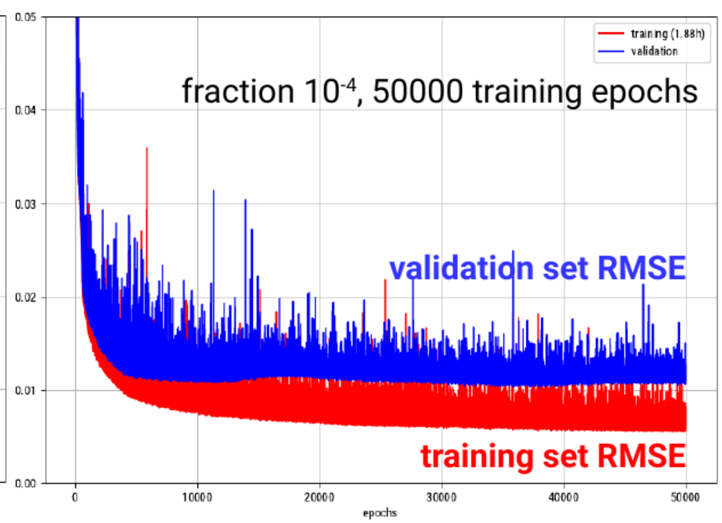


Which fraction of the full LUT data (3×10^8 samples) is required?
10^{-3} ist still ok, overfitting for 10^{-4}
Regularization methods could allow for even lower fractions…

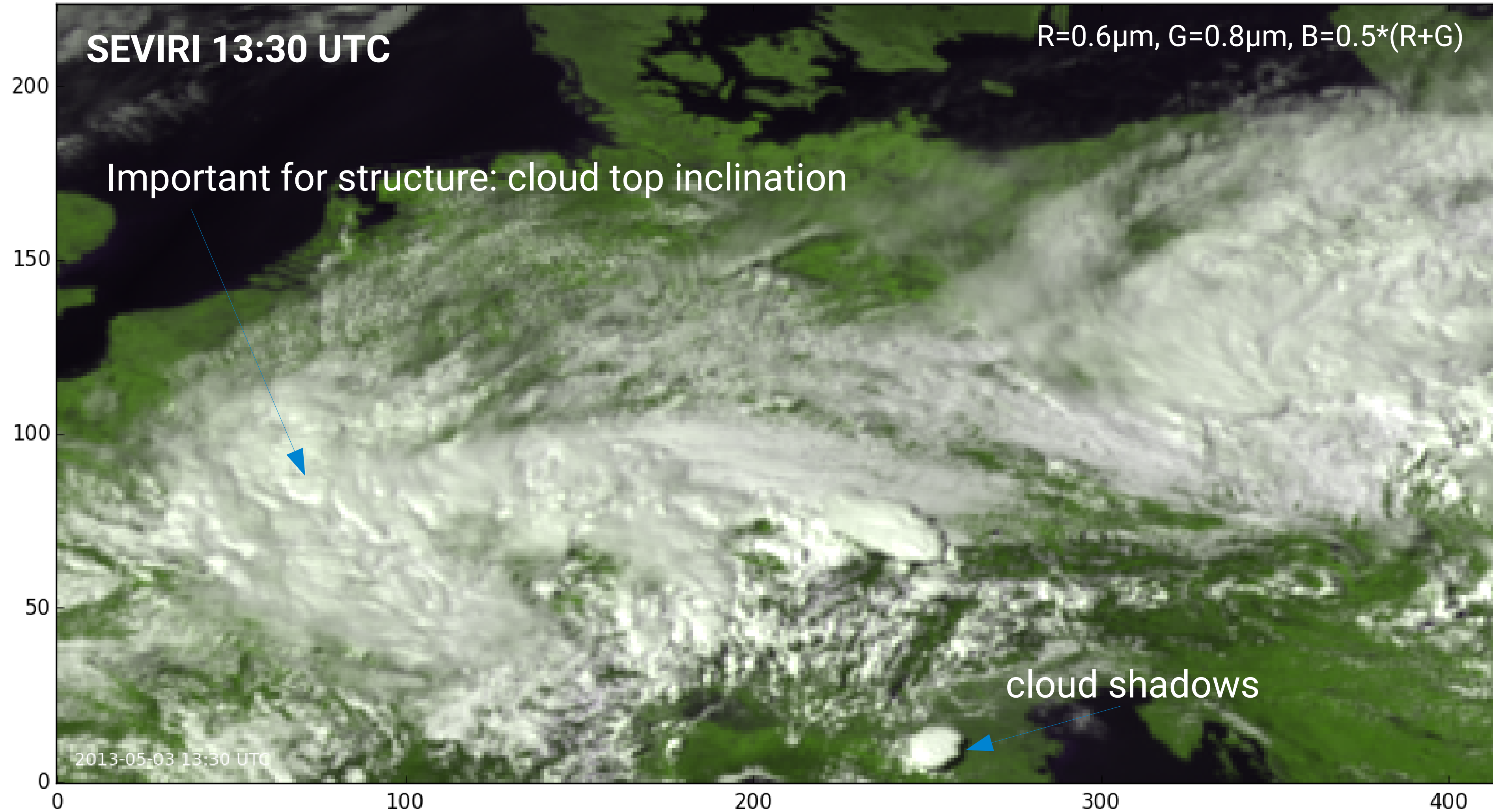
Still unclear: How reliable is the learning process?

reflectance RMSE





3D effects not accounted for in 1D radiative transfer



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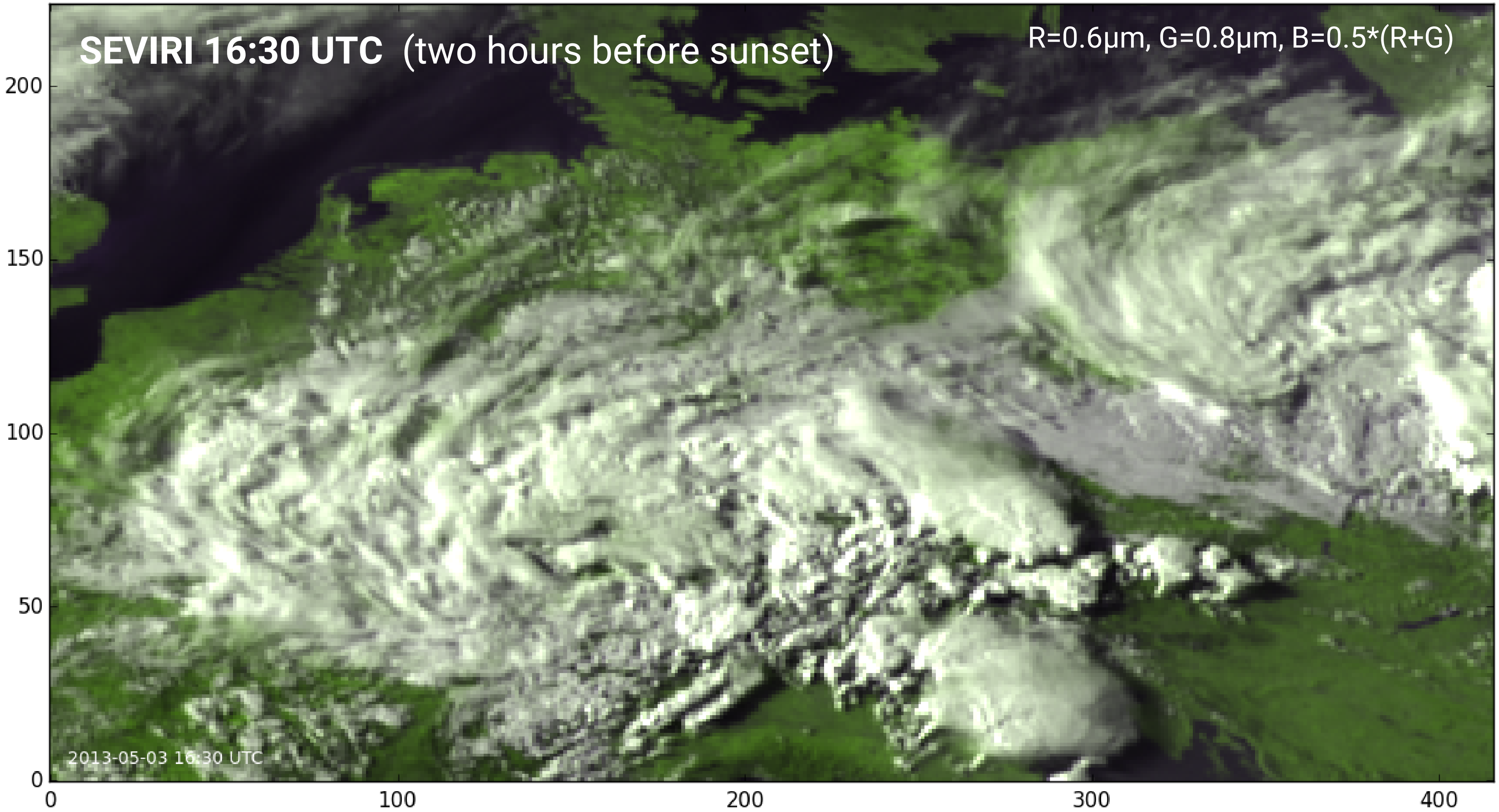
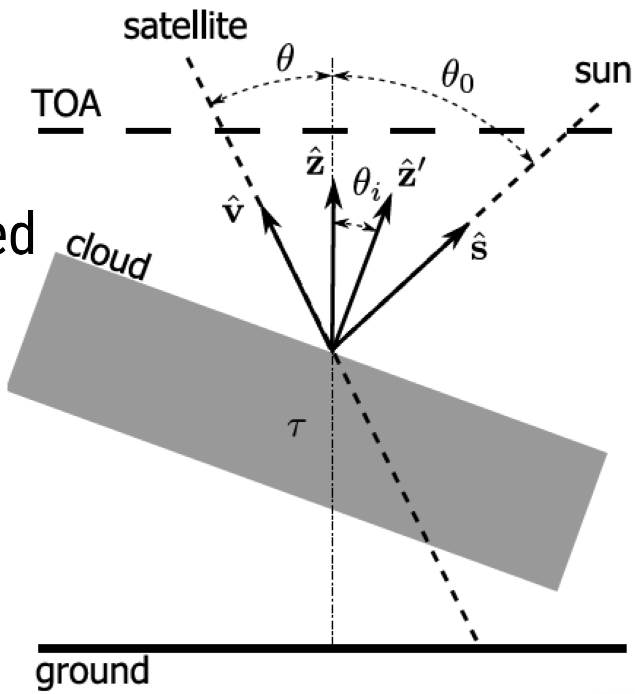
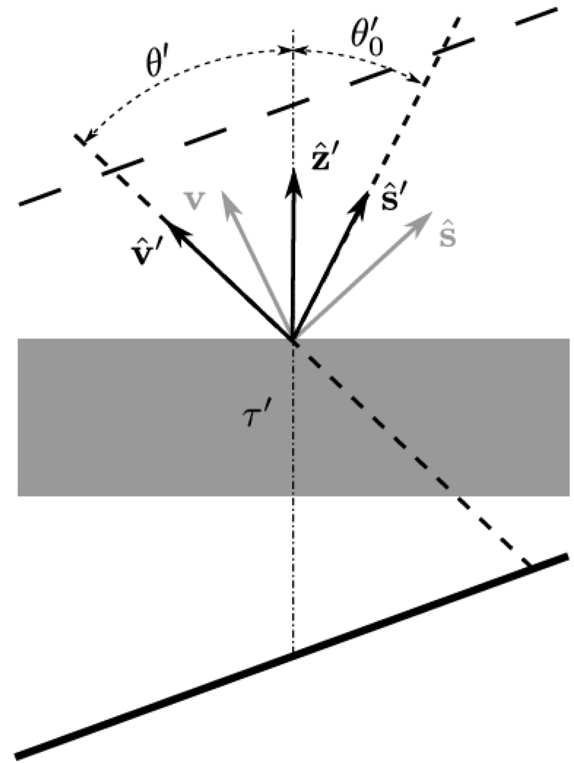


Accounting for 3D RT effects: Cloud top inclination

inclined cloud (3D)



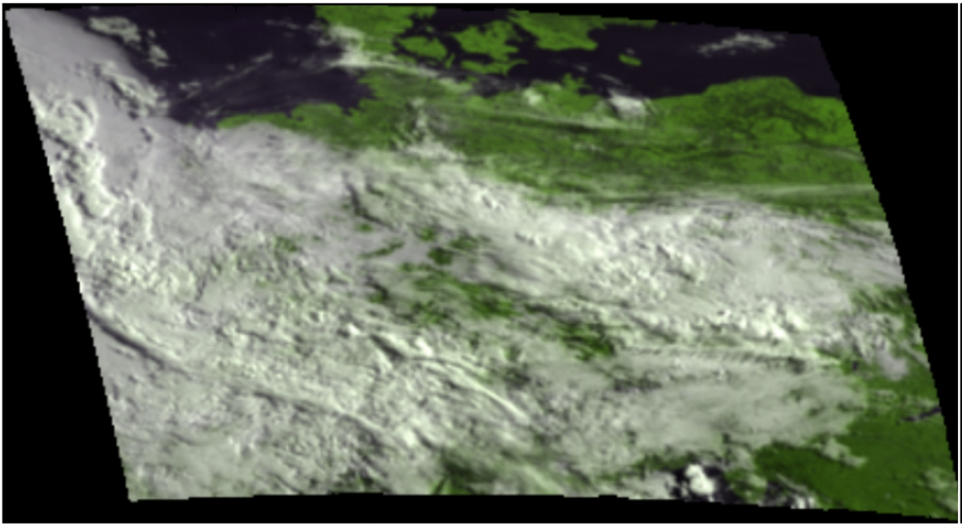


plane-parallel cloud (1D)

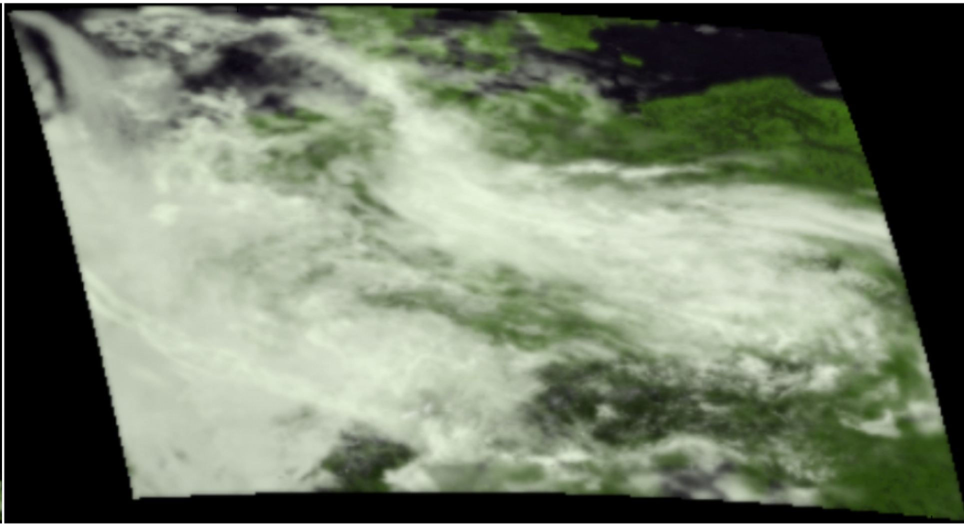
$$R_T(\theta,\theta_0,\alpha,A,\tau,\theta_i) = R(\theta',\theta'_0,\alpha,A',\tau\cos\theta_i)\,\frac{\cos\theta'_0}{\cos\theta_0}$$

Rotated frame of reference with ground-parallel cloud → nearly a 1D problem (inclined ground is taken into account by using a modified surface albedo)
→ Solve modified 1D problem, transform back to non-rotated frame.

Cloud top inclination



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

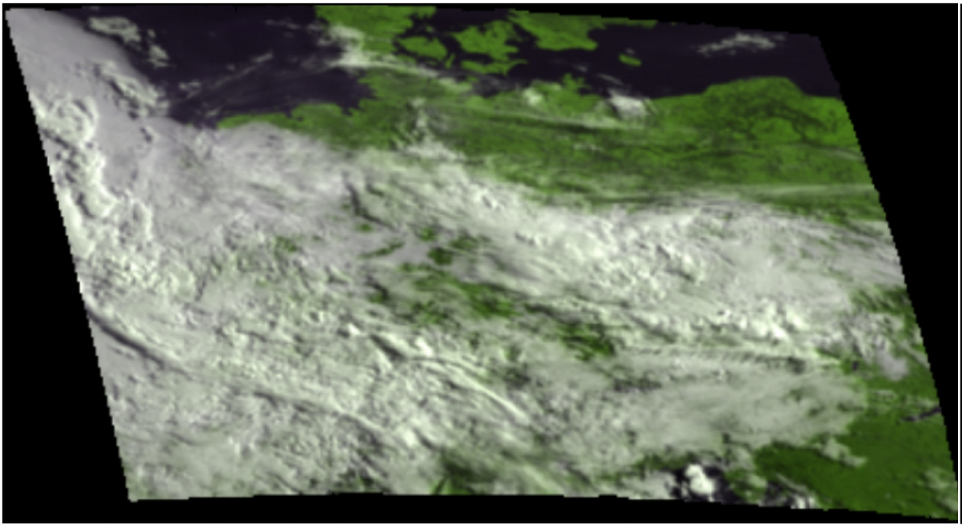


3h COSMO fcst **without 3D correction**

Cloud top definition : optical depth 1 surface
(detect tau=1 in all columns, fit plane to column and 8 neighbour columns)

Cloud top inclination correction → Increased information content
Much more cloud structure is visible, in particular for larger SZAs
For instance, one can distinguish convective from stratiform clouds

Cloud top inclination



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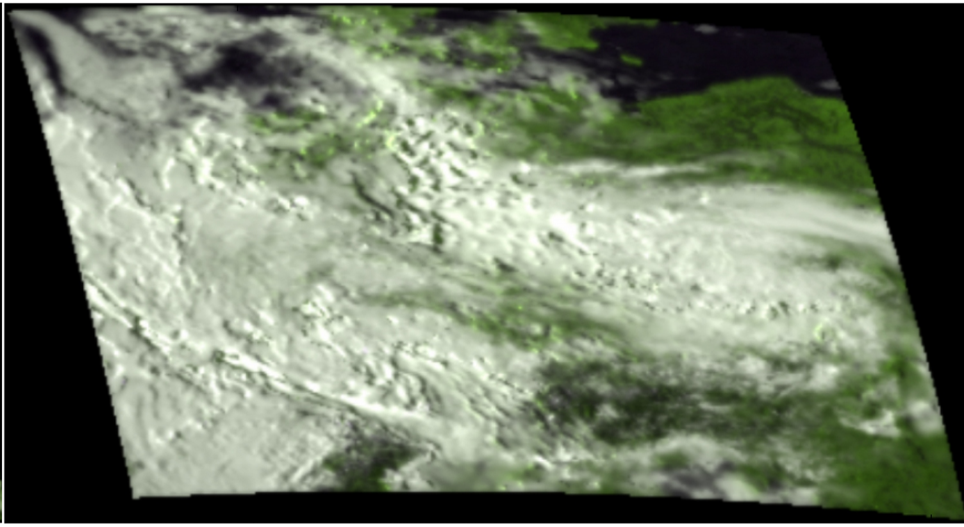

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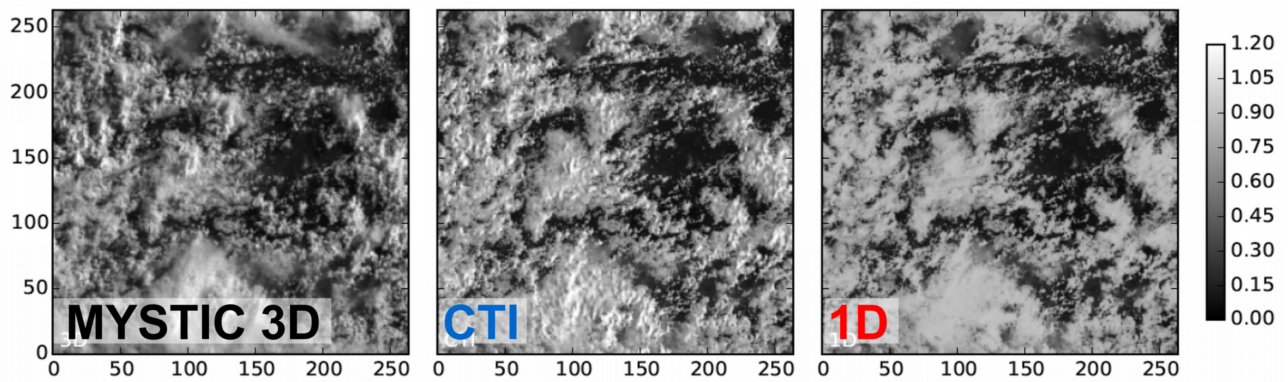
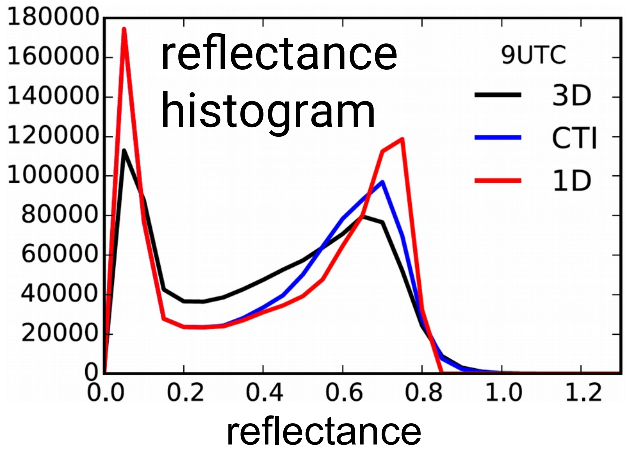
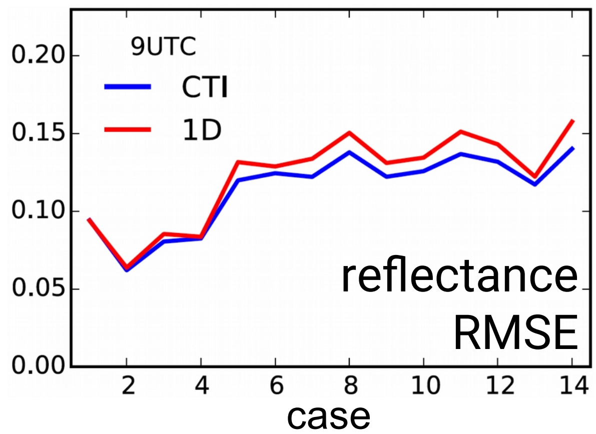
Comparison with 3D Monte Carlo RT calculations



Clean comparison (only RT errors, no model errors) based on high-res. ICON runs from the HD(CP)² project:





- RMSE is reduced
- Histogram shape is improved
- Derived empirical function to scale down 3D correction for thinner clouds

Other 3D effects are still missing (e.g. shadows, flux through cloud sides)...

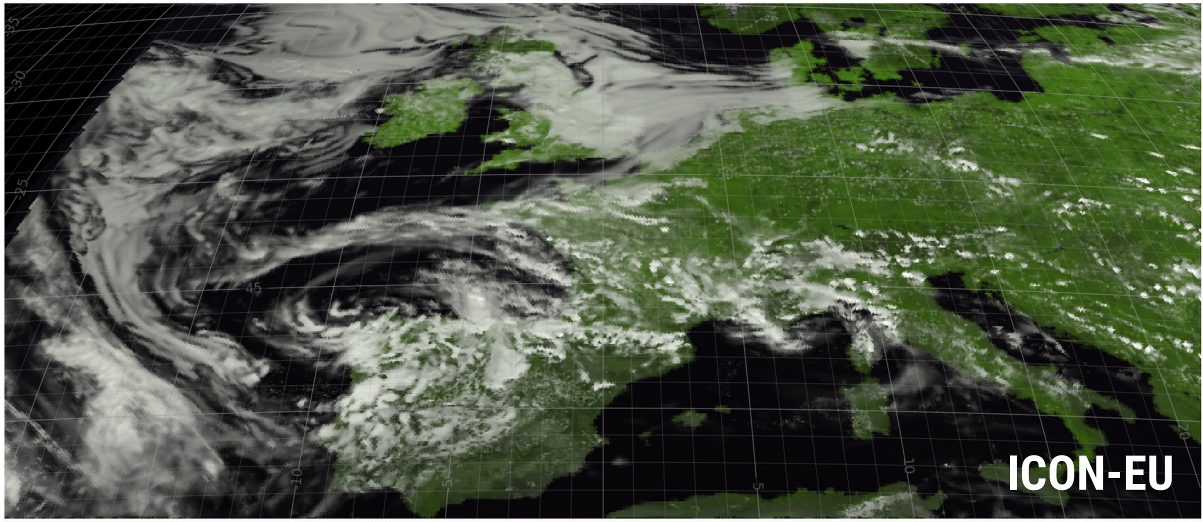
What else can be done to reduce systematic errors?

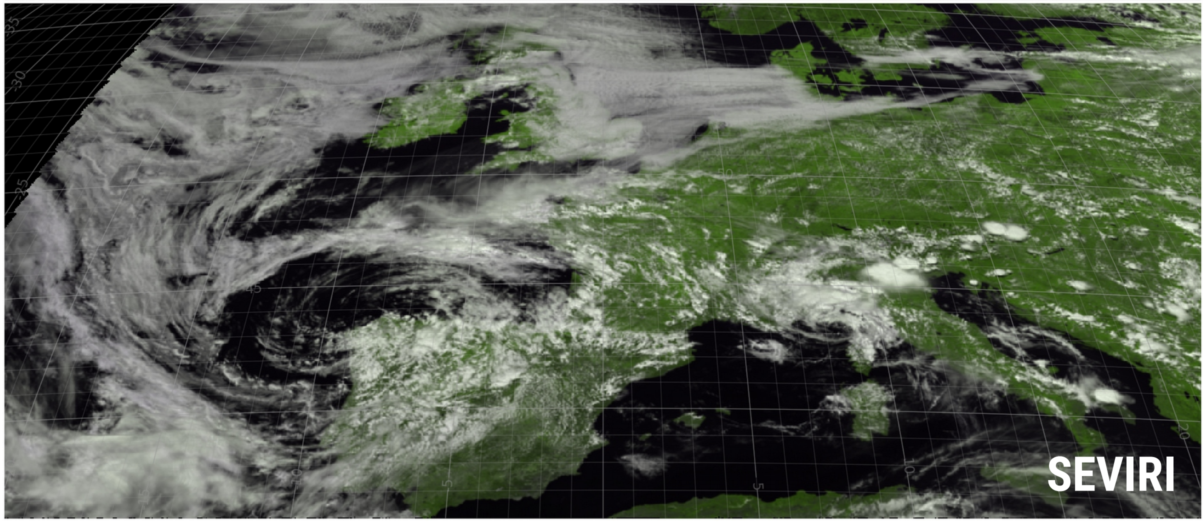
Potential error sources in the operator:

- Parameterization of effective droplet / ice particle sizes,
- ice optical properties
- subgrid cloud overlap assumption + implementation
- subgrid cloud inhomogeneity
- further 3D RT effects (e.g. cloud shadows)…

Systematic errors are already small enough for assimilation experiments

Cloud cover, precipitation and moisture are improved, impact for several hours.





Summary

- Simulating visible channels is challenging: Scattering dominates, 3D important
- MFASIS: fast 1D RT method for simulating solar channels based on a compressed look-up table (now included in RTTOV)
- 1D RT corrections (WV, airmass, mixed-phase clouds) have been / will be added
- Replacing compressed LUT by neural network could allow for additional dimensions / input variables and thus higher accuracy (work in progress)
- Cloud top inclination (3D effect) parameterization reduces the systematic error
- First data assimilation results: cloud cover, precipitation, moisture are improved

Publications:

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.

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

Heinze et al. (2017): *Large-eddy simulations over Germany using ICON: a comprehensive evaluation*, QJRMS, Vol. 143, Issue 702, p. 69-100

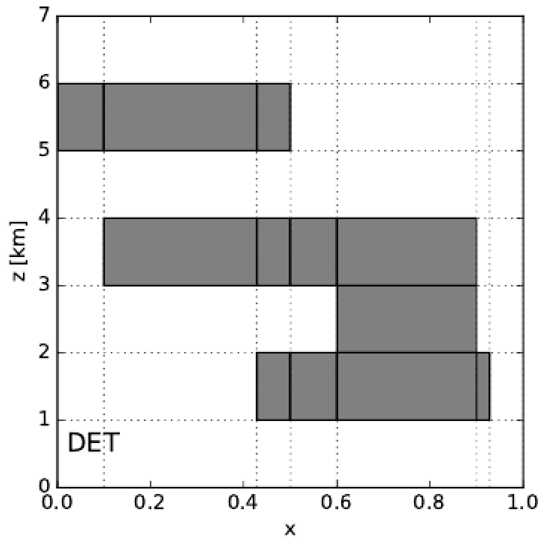
Scheck, Weissmann, Mayer (2018): *Efficient methods to account for cloud top inclination and cloud overlap in synthetic visible satellite images*, JTECH, Vol. 35, Issue: 3, p. 665-685

Subgrid cloud overlap

- Unresolved 'subgrid' clouds: Models usually provide parameterized cloud fractions and use assumptions on subgrid cloud overlap in their internal RT code.

  Most widely used assumption: *Clouds in adjacent layers overlap maximally, clouds separated by empty layers overlap randomly ("maximum-random overlap").*

  Newer assumptions often use correlation lengths (see e.g. Shonk et al. 2010).



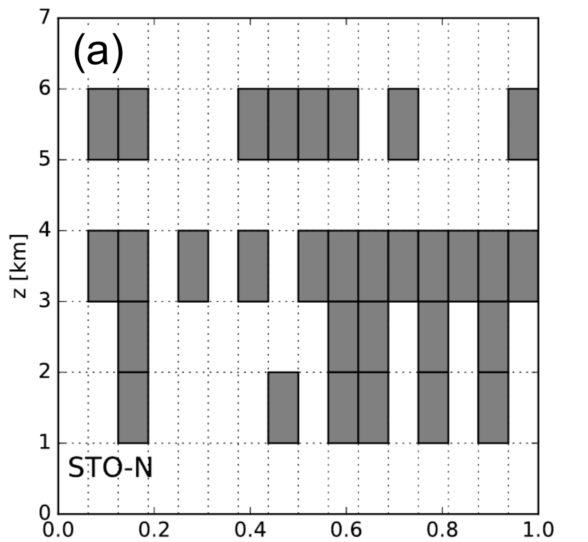
deterministic, Matricardi 2005 (RTTOV)

- How to use this information in the forward operator?
  → Overlap schemes: Distribute clouds over subcolumns, call RT for each subcolumn and compute average reflectance

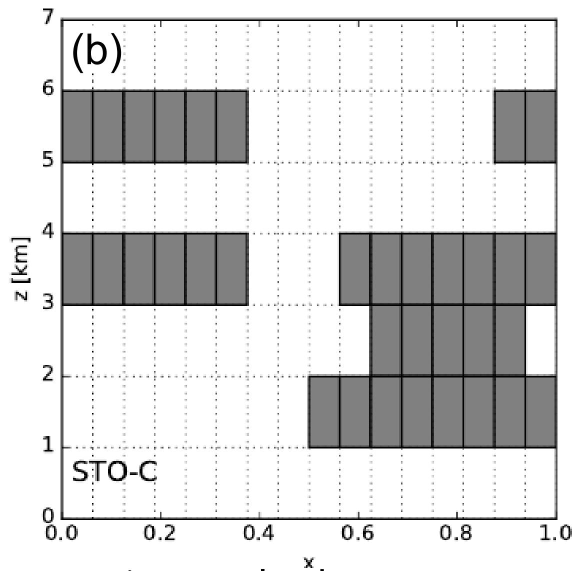
We investigated these questions:

- Is uncertainty of visible reflectances due to the unknown subgrid distribution relevant for DA? Should it be quantified by spread of stochastic scheme?
- Overlap assumptions hold for vertical direction, RT is performed along columns tilted towards the satellite – is this an important error source?

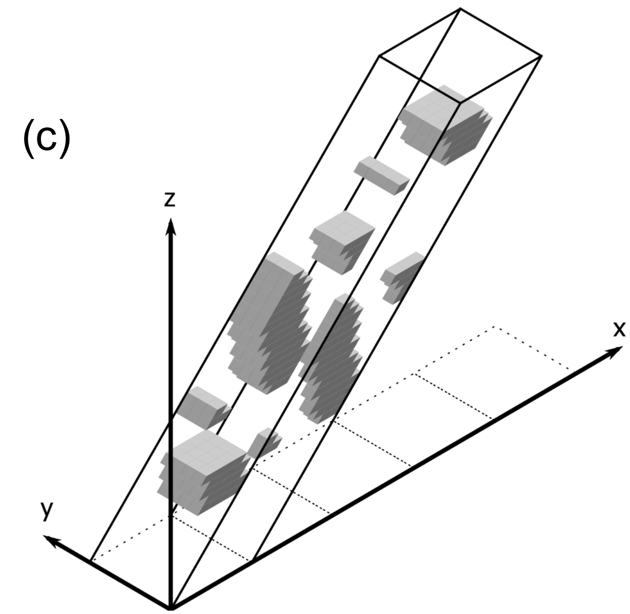
Stochastic cloud overlap schemes



independent subcolumns (Räisänen 2004, Marquart & Mayer 2001)



continuous clouds (Scheck et al. 2018)



continuous clouds in tilted subcolumns (Scheck et al. 2018)

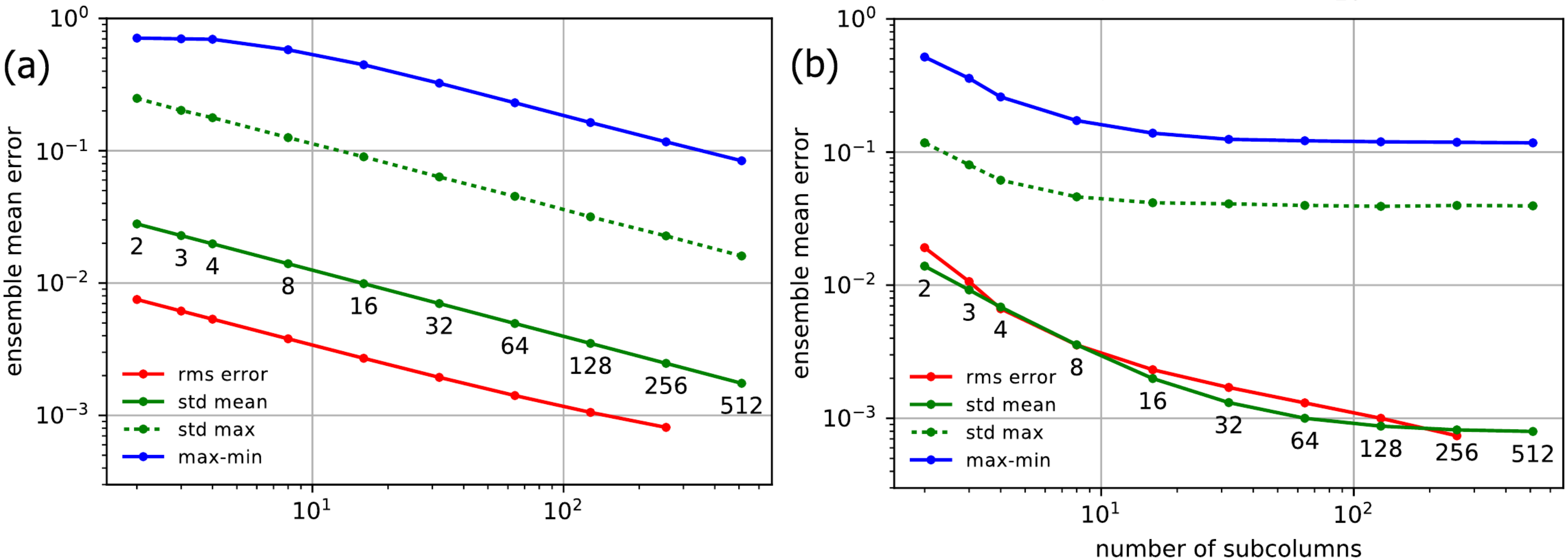
Test for COSMO-DE (Δx=2.8km) model runs for June 2016:

(a) no “physical” spread: for $N_{subcol} \rightarrow \infty$ spread → 0 (and cloud size → 0)

(b) one cloud/layer: finite spread for $N_{subcol} \rightarrow \infty$, upper limit for real spread
spread is probably too low to be useful for DA – at most a few 0.01

(c) clouds with vertical max.-rand. overlap are placed in tilted subcolumns
3d max.-rand. results are more similar to 2d random than to 2d max.-rand.

Stochastic overlap schemes: Convergence for smallest / largest cloud approach

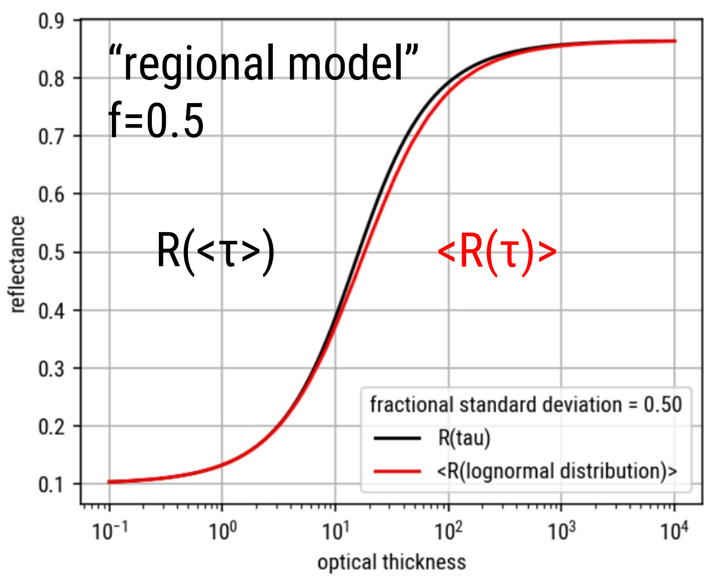


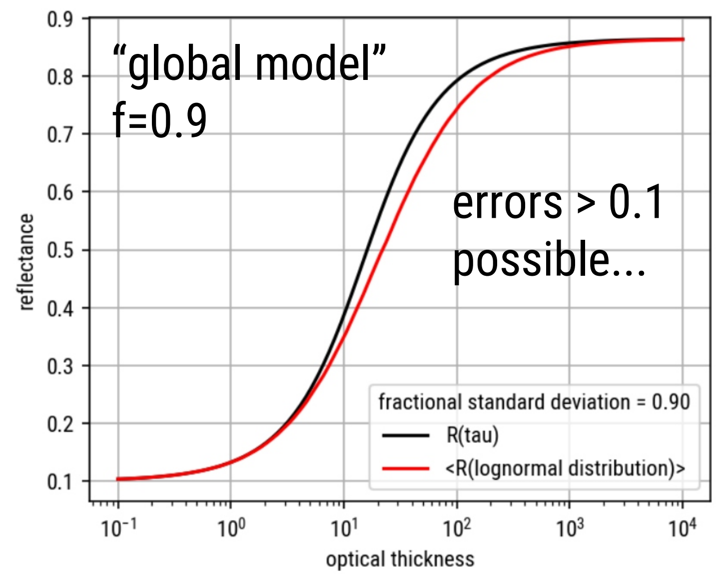
(a) Maximum deviation, 99% percentile of the deviation and root mean square deviation in ensemble mean reflectance for the stochastic maximum-random overlap method STO-N with different numbers of streams relative to the 512 stream case computed for the June 2012 test period. Ensembles with 100 members were used. (b) Like (a), but for the STO-C implementation.

Subgrid cloud inhomogeneity

Observations: Liquid and frozen cloud water content follows log-normal or gamma distributions, variability can be characterized by *fractional standard deviation* f = std(LWC) / mean(LWC), which increases with box size and is higher for partially cloudy grid cells. Parameterizations (e.g. Ahlgrimm & Forbes 2016) for f exist.

How relevant is this for visible images?





At least for global model resolutions it should be taken into account…
Could be integrated into cloud overlap scheme (work in progress).

Model state → reflectance