Deutscher Wetterdienst
Wetter und Klima aus einer Hand

Assimilating visible channels of SEVIRI on the convective scale

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1) Overview

- Our goal is to assimilate the 0.6 µm channel of SEVIRI / MSG (0°/0°)
  - with a pixel resolution of ~ 6km x 3km
  - in the ICON-D2 model @ limited-area mode (Δx=2km)
  - using a local ensemble transform Kalman filter (KENDA [1]) + incremental analysis update + latent heat nudging
  - and forward operator MFASIS (RTTOV13) [2]
  - additionally to conv. obs, 3D radar reflectivities, radial winds
- In the framework of the development of a seamless prediction system (SINFONY) with Rapid Update Cycle (RUC) for the very short-range with lead times +0h to +12h
- Development is now technically mature & tested with many different models & model versions in different weather regimes, i.e. we target pre-operational DA in 2021

Figure 1: *Synthetic satellite image simulated by the forward operator MFASIS.*

2) Ingredients of data assimilation

Forward operator MFASIS (RTTOV-13.0)

- Read preprocessed satellite data after some basic quality control
- Assign model grid points to satellite pixels by nearest neighbor to avoid interpolation of cloud quantities

Micro- and macro-physical assumptions:

1. Cloud properties based on parameterization of effective radii (Reff):
   - Deff-scheme: Martin et. al 1994 (cloud water)
   - Baum-scheme: Mc Farquhar et. al 2003 (cloud ice)
   - Under testing: use of Reff from ICON microphysics & radiation
2. Cloud overlap: maximum random overlap, no horizontal inhomogeneity

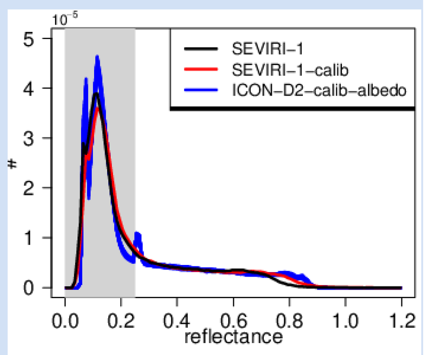

Figure 2: *Histograms of reflectance for observations(black), calibrated observations (red), simulated from ICON+MFASIS (blue). Calibration enhances agreement of distributions.*

Calibration of observations and bias correction (BC, see 4)

- SEVIRI visible channels are ~ 8 % to 10 % too dark compared to MODIS (Meirink et. al, 2013) , we scale them accordingly (see Fig. 2)

Quality control

Flag observations / model equivalents (see Fig. 3) if:

- Sun zenith angle > 75 ° : darkness, miss. 3D-effects
- REFL (obs) > 1.5 : missing 3D-effects
- MFASIS flag is set : effective radius < 10 µm
- NWCSAF cloud mask: exclusion of pixels with snow, aerosols, volcanic ash

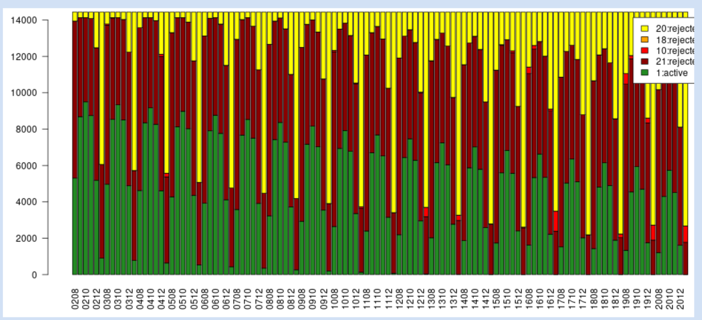

Figure 3: *Example distribution of active and rejected REFL obs during experimental period in November 2020 with Saharan dust outbreaks. Active (green), rejected: 21 (Saharan dust, dark red), 20 (SZA, yellow), 10 (MFASIS, red).*
REFL assimilated daily from 10 to 14 UTC.

Data reduction

- Pure superobbing, i,e, averaging of satellite pixels (2 x 4 ~ 12 km x 12 km to extract small-scale information)
- Same method for observations and model equivalents residing on satellite grid (after nearest neighbor interpolation)

Observation error model

- Desroziers statistics stratified by first guess departures of ensemble mean suggest a quadratic error model (Fig. 4, eq. I)

$$(I)\ eo = \sqrt{\max\left(ec^2, \left(y - \overline{H(x)}\right)^2\right)}$$

If the quadratic first guess departure exceeds prescribed obs error *ec* it is used for observation error estimation

- Prevents large analysis increments causing introduction of strong imbalance to the model state due to cloud displacement error / large first guess departures

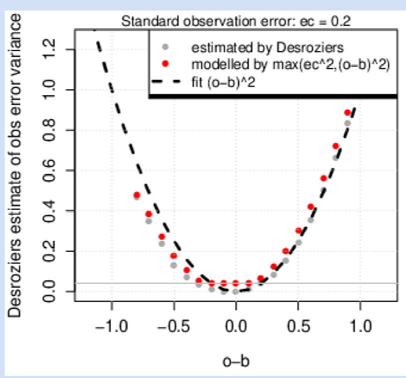

Figure 4: *Desroziers estimation of observation error variance stratified by first guess departure. Grey points: Desroziers estimate, black: fit ~ (o-b)^2. Red points: mean modelled obs error in bin. Grey horizontal line: prescribed minimum observation error.*

Model-to-satellite

- Goal: first guess departures free of conditional bias (additional to BC)
- Improve model via tuning against SEVIRI data (using hindcasts)
- Improve forward operator (see poster by Stumpf et. al)
- Improve consistency in microphysical assumptions in forward operators and NWP model, e.g. by using effective radii parameterized in ICON model within MFASIS

5) Literature

[1] Schraff, C. et. al. (2016), Kilometre-scale ensemble data assimilation for the COSMO model (KENDA). Q.J.R. Meteorol. Soc., 142: 1453-1472.
[2] Scheck, L. et. al (2016), A fast radiative transfer method for the simulation of visible satellite imagery. Elsevier, 175:10.1016
[3] Scheck, L, et. al (2020) Assimilating visible satellite images for convective-scale numerical weather prediction: A case-study. QJR Meteorol Soc.; 146: 3165– 3186.

3) Sensitivities and impact

What is reflectance?

- Proportion of incoming sun light reflected by clouds + the earth's surface (~albedo)
- REFL depends and (partially) constrains cloud properties: water mass, effective particle radius, number concentration, optical depth, cloud overlap, horizontal inhomogeneity

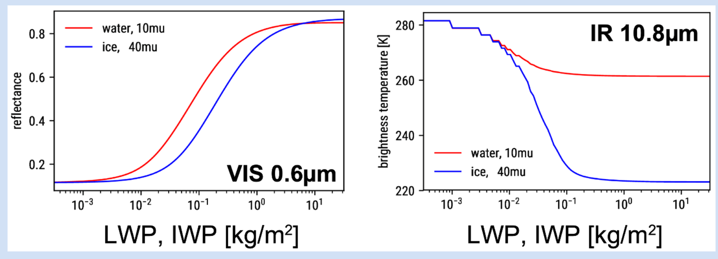

Figure 6: *reflectance (0.6 µm) and brightness temperature (10.8µm) as a function of liquid water path (LWP) and ice water path (IWP) for cloud water (red) and cloud ice (blue). In combination VIS and IR span the whole range of LWP / IWP up to 10^8 kg/m². IR saturates at very small water paths.*

Why assimilate?

- Low clouds visible (low stratus, convective initiation)
- Different from IR channels, reflectance is sensitive to a wide range of IWP, LWP
- We aim to improve cloud optical depth, cloud positions, precipitation, radiation and dependent processes

Experimental settings

- ICON-D2 (ecRAD) + LETKF
- Obs: conventional, radar reflectivities and radial winds, reflectance
- Latent heat nudging
- Hourly cycling
- Superobbing scale 12km
- MFASIS standard effective radii
- Prescribed observation error 0.2
- Horizontal localization 35 km
- No vertical localization
- Explicit update of cloud water in IAU
- 1- or 2-moment microphysics
- Forecast horizon 12-14 hours

1. Results from DA cycle

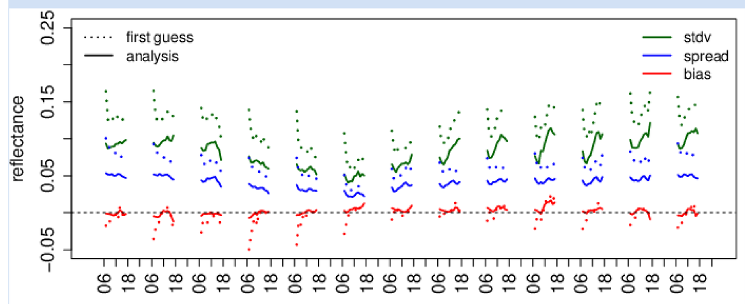

Figure 7: Evolution of first guess and (linear) analysis error in cycled DA experiment (hourly cycle) in terms of reflectance. Standard deviation (green), spread (blue), bias (red). First guess is depicted as dotted line, analysis as solid line.

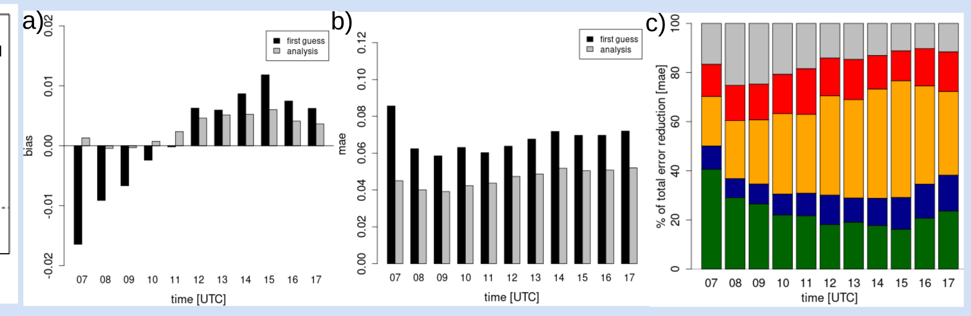

Figure 8: Error measures in reflectance space for first guess (black) and (linear) analysis (grey) depending on the time of day. a)bias, b) mean absolute error, c) percentage of error total reduction in terms of mean absolute error for correction of false alarms (green), misses (blue), too reflective clouds (orange), too dark clouds (red), grey (albedo). If a threshold of 0.25 is exceeded by reflectance, a cloud is detected. Experimental period: 4 weeks August 2020.

2. Results from forecasts

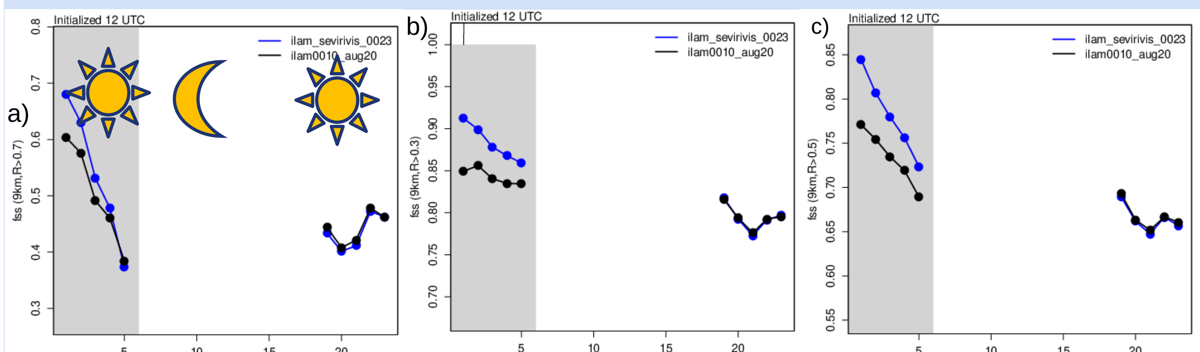

Figure 9: *Fraction Skill Score as a function of threshold and forecast lead time. Spatial scale: 3 satellite pixels. a) REFL > 0.3 (all clouds), b) REFL > 0.5 (optically medium thick and thick clouds), c) REFL > 0.7 (optically thick clouds).*
Blue: CONV + RADAR + REFL. Black: CONV + RADAR.
Forecasts initialized at 12 UTC, experimental period 02/08/2020 to 30/08/2020. Grey area marks the target forecast time for the seamless prediction system for the very-short range (SINFONY).

1. Results from DA cycle

- REFL error is strongly reduced by DA (Fig 7,8); strongest in the first step in the morning (07 UTC)
- Error reduction of mean absolute error dominated by correcting false alarm clouds and too reflective ones (Fig. 8c)
- In the first half of the day, the model is too reflective, from 12 UTC onwards it is too little reflective (Fig. 8a)
- On average strong error growth during first guess run (Fig. 8b)

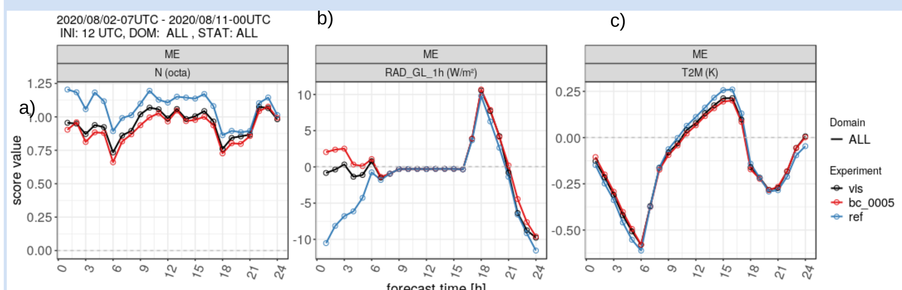

Figure 10: *Bias as a function of lead time for 24-hour-forecasts of a) global radiation, b)cloud cover, c) 2m temperature. Black: CONV + REFL, red: CONV + REFL + BC, blue: CONV*
Forecasts initialized at 12 UTC, experimental period 02/08/2020 to 16/08/2020

2. Results from forecasts

- FSS of reflectance is improved for all thresholds during the first 6 hours of lead time (Fig. 9)
- FSS of precipitation is similarly improved (not shown)
- Radiation bias (too little radiation) is improved by reducing overestimated cloud cover / reflectance (Fig. 10 a,b)
- Even though reflectance bias is positive at 12 UTC (Fig. 8b), there is still too little radiation in ICON (inconsistency between radiation (ecRAD), microphysics, MFASIS)
- T2M bias is improved (Fig. 10 c))
- Upper air verification (TEMP & AIREP) is neutral except for reduction of moist bias in middle troposphere (not shown)

4) Bias correction (BC)

What bias?

- Histograms of reflectances are non-Gaussian / asymmetric, their shape depends on seasonal / diurnal cycle, current weather situation
- Histogram bias can be due to model, observation or observation operator

How to correct it?

- Use an adaptive algorithm to estimate a non-linear BC function to tackle these biases

Results

- Improves histogram shapes, reduce REFL bias
- Stable against changes of the weather situation
- Preserves positive impact from experiments w/o BC

Bias correction inside the data assimilation cycle

1. before analysis: apply BC to reflectances r, i.e.
$$f(r, \theta) = \sum_{ij} c_{ij} T_i(r) U_j(\theta),$$
θ: physical predictor, c_{ij}: coefficients from last cycle, T_i, U_j: polynomials
2. after analysis: estimate coefficients c^a by minimizing
$$J[c^a] = \alpha \left\|c^a - c^b\right\|^2_{B_1^{-1}} + \beta \left\|c^a - c^0\right\|^2_{B_2^{-1}} + \left\|hist(corr) - hist(obs)\right\|^2_{R^{-1}},$$
c^b, c^0: background / climatological coefficients, $hist$: histogram of observed / corrected reflectances

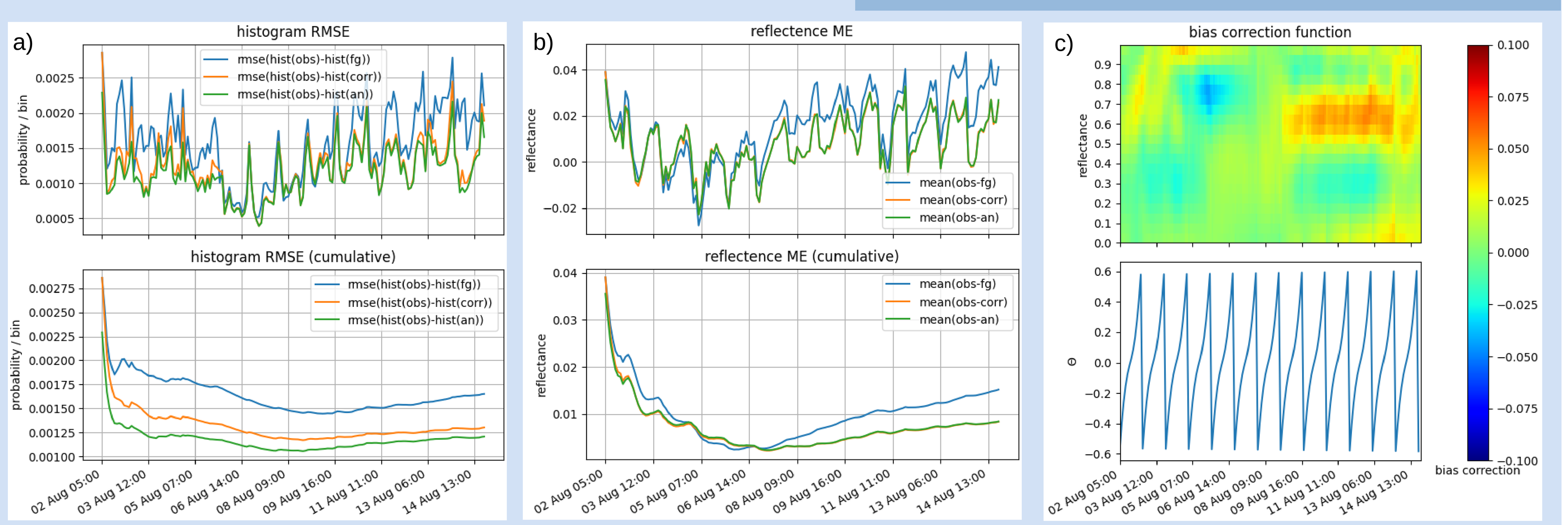

Figure 11: *a) RMSE comparing histograms before BC / after BC / after coefficient update with observations: histogram RMSE significantly reduced through BC.*
b) ME comparing reflectances before BC / after BC / after coefficient update with observations: smaller ME and less variance in ME with BC.
c) Upper panel: bias correction as a function of time (positive value: reflectance is increased). Lower panel: predictor θ depends on SZA and local time.
'Cumulative' scores include all past data.

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