Prospects for radar and lidar cloud assimilation

Marta Janisková, ECMWF

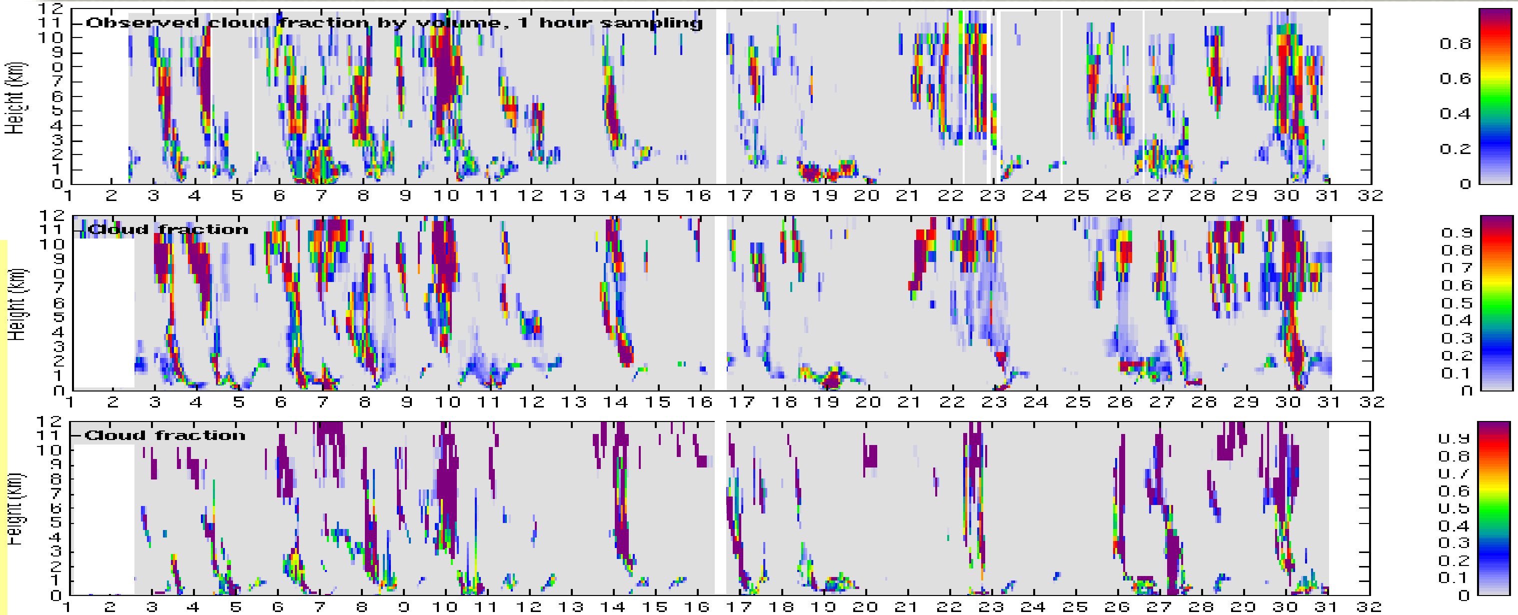
Thanks to: S. Di Michele, E. Martins,
A. Beljaars, S. English, P. Lopez, P. Bauer

ECMWF Seminar on the Use of Satellite Observations in NWP
10 September 2014

Improvements in cloud parametrization

CloudNet project data at Chilbolton

June 2003

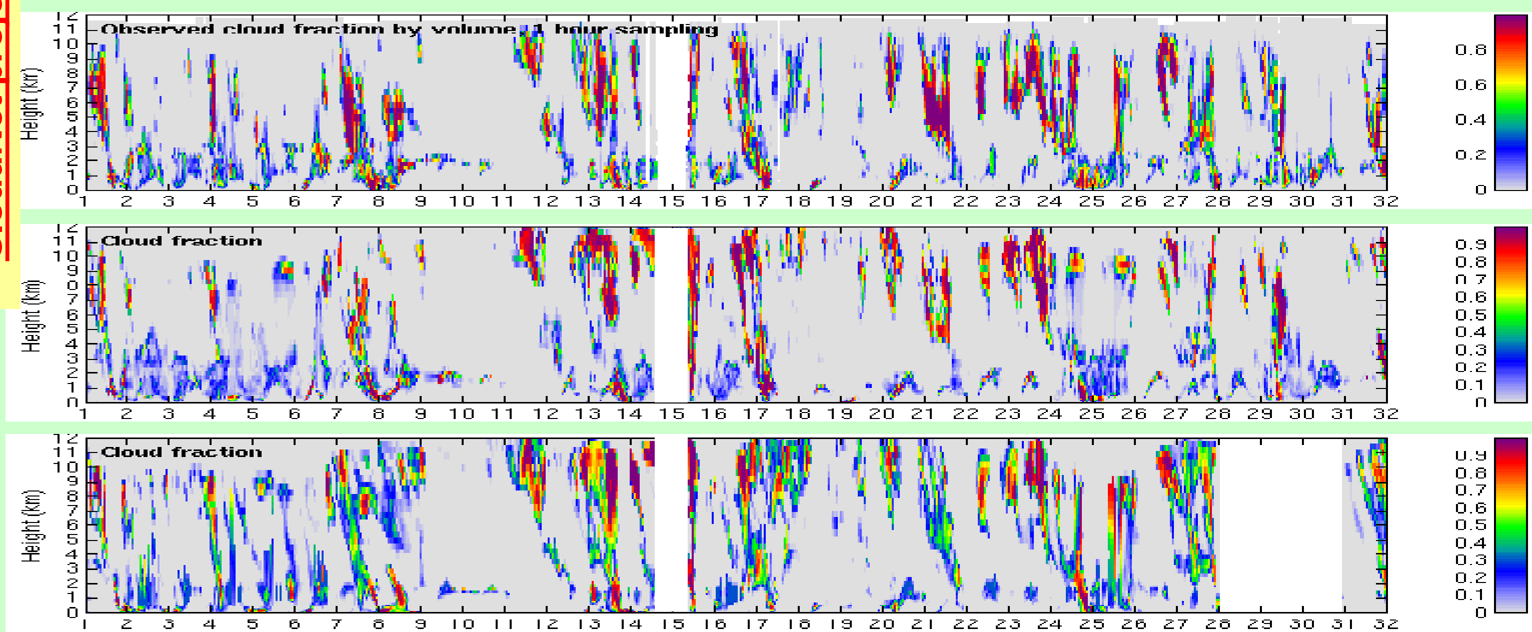


Observed cloud fraction

ECMWF model cloud fraction

Météo-France model cl. fraction

August 2012



Observed cloud fraction

ECMWF model cloud fraction

Météo-France model cl. fraction

Cloud related observations and their assimilation (1)

- New possibilities for model improvement to be explored through assimilation of data related to clouds from active and passive sensors.

- Observations providing 3D-information on clouds from space-borne active instruments on board of CloudSat & CALIPSO already available and new ones, such as EarthCARE should appear in the near future.

- Despite the major influence of clouds and precipitation on atmospheric water and energy balance, most cloud-affected observations are discarded in current data assimilation systems mainly because of:
  - discontinuous nature (in time and space) of clouds and precipitation
  - need to use linearized versions of these nonlinear processes (for variational assimilation)
  - spatial representativeness of satellite observations, especially from active instruments
  - non-Gaussian error characteristics of the cloud models

CALIPSO – Cloud Aerosol Lidar and Infrared Pathfinder Satellite Observations
EarthCARE – Earth Clouds, Aerosols and Radiation Explorer

Cloud related observations and their assimilation (2)

In global models :

- Operational assimilation of:
  - satellite infrared radiances in overcast conditions at ECMWF *(McNally 2009)*
  - microwave radiances in all sky conditions *(Bauer et al. 2010, Geer et al. 2010)*
- Experimental assimilation of :
  - cloud-affected infrared radiances from AIRS in 4D-Var *(Chevallier et al. 2004)*
  - cloud optical depth from MODIS in 4D-Var *(Benedetti and Janisková 2008)*

In mesoscale models :

- Cloud analyses based on nudging technique *(Macpherson et al. 1996, Lipton and Modica 1999, Bayer et al. 2000)*
- Exploiting visible & infrared cloudy satellite radiances in 4D-Var *(Vukicevic et al. 2004)*

AIRS – Advanced Infrared Sounder
MODIS – Moderate Resolution Imaging Spectroradiometer

Cloud related observations and their assimilation (3)

Experiments with observations from cloud radar:

- 1D-Var experiments using cloud retrievals from ARM cloud radar

  (Janisková et al. 2002, Benedetti et al 2003, Benedetti and Janisková 2004)

- 2D-Var technique for ARM cloud radar observations combined with the ground-based precipitation measurements and GPS total column water-vapour retrievals

  (Lopez et al. 2010)

- Experimental assimilation of cloud fraction (considered as binary occurences) from CloudSat in limited-area 3D-Var through the use of humidity pseudo-observations derived from 1D Bayesian analysis *(Storto and Tveter 2009)*

- Experimental 1D+4D-Var assimilation of CloudSat observations where information on temperature and specific humidity retrieved from 1D-Var using cloud radar reflectivity or liquid and ice water contents used as pseudo-observations in 4D-Var

  (Janisková et al. 2012)

1D-Var/4D-Var – One/Four-Dimensional Variational assimilation
ARM – Atmospheric Radiation Measurement programme

- To study the impact of the new observations on 4D-Var analyses and subsequent forecasts, a 1D+4D-Var technique has been selected.

Methodology:

– 1D-Var + 4D-Var approach built on experience of using such technique for formally operational assimilation of precipitation related observations. *(Bauer et al. 2006 a, b)*

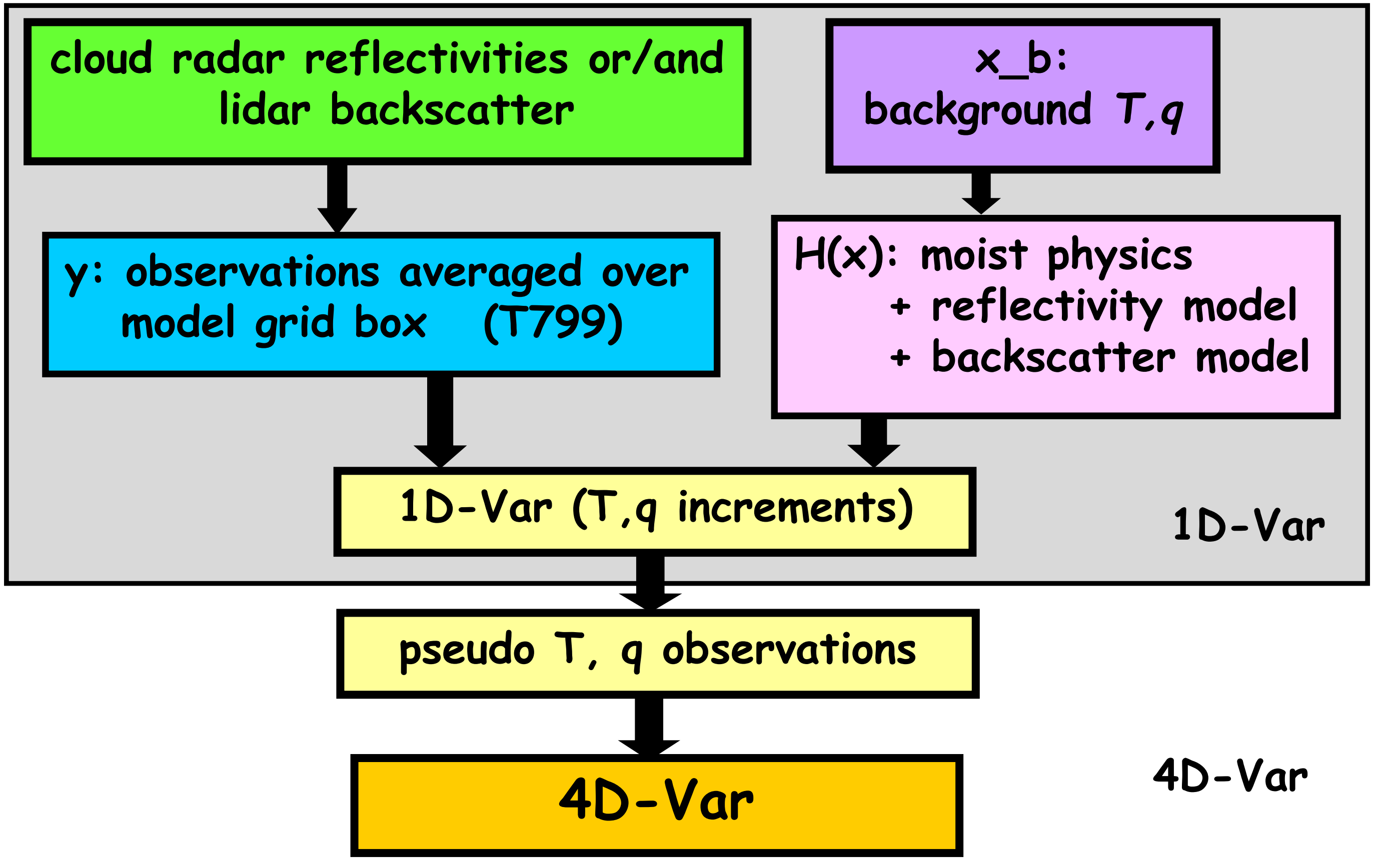
– In 2-step 1D-Var + 4D-Var approach used for cloud radar reflectivity *(Janisková et al. 2012)* or/and lidar backscatter:

  – 1D-Var retrieval first run on the set of observations to produce pseudo-observations of temperature *T* and specific humidity *q* (*based on evaluation of T and q* increments *both variables are modified by the assimilation of cloud related observations)*,

  – modified *T* and *q* profiles then assimilated in the ECMWF 4D-Var system.

Schematic description of 1D+4D-Var for CloudSat & CALIPSO observations

Flowchart describing 1D+4D-Var technique:



1D-Var assimilation

- For a given observation y^o, 1D-Var searches for the model state $x=(T,q_v)$ that minimizes the cost function:

$$J(\mathbf{x}) = \underbrace{\frac{1}{2}(\mathbf{x}-\mathbf{x}^b)^{\mathrm{T}}\mathbf{B}^{-1}(\mathbf{x}-\mathbf{x}^b)}_{\text{Background term}} + \underbrace{\frac{1}{2}(H(\mathbf{x})-\mathbf{y}^o)^{\mathrm{T}}\mathbf{R}^{-1}(H(\mathbf{x})-\mathbf{y}^o)}_{\text{Observation term}}$$

B = **background error covariance matrix**

R = **observation and representativeness error covariance matrix**

H = **nonlinear observation operator (model space → observation space)**

(physical parametrization schemes, radiative transfer model, reflectivity model, …)

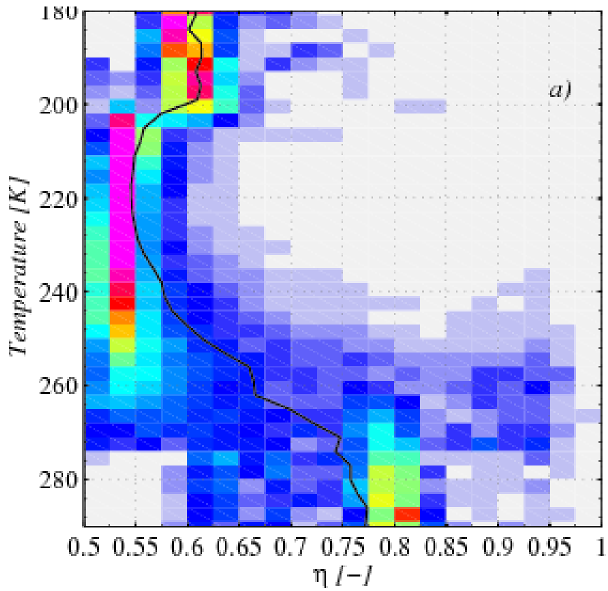
- The minimization requires an estimation of the gradient of the cost function:

$$\boxed{\nabla J(\mathbf{x}) = \mathbf{B}^{-1}(\mathbf{x}-\mathbf{x}^b) + \mathbf{H}^{\mathrm{T}}\mathbf{R}^{-1}(H(\mathbf{x})-\mathbf{y}^o)}$$

- The operator $\mathbf{H}^{\mathrm{T}}$ can be obtained:
  - explicitly (Jacobian matrix)
  - **<u>using the adjoint technique</u>**

1D-Var observation operators

- Moist physics (cloud&convection schemes) – simplified schemes with their adjoint versions already used in 4D-Var *(Janisková and Lopez 2012)*
- ZMVAR radar reflectivity operator:
  - using pre-calculated lookup table of hydrometeor optical properties (extinction and backscattering coefficients) – *Di Michele et al. 2012*
  - multiple scattering not considered for assimilation studies
- ZMVAR lidar backscatter operator:
  - operator extended to simulate the lidar signal in clouds – *Di Michele et al. 2013*
  - simple parametrization of multiple scattering for assimilation to decrease computational cost



Frequency distribution of small-angle correction factor η across a range of temperature

Data selection tools

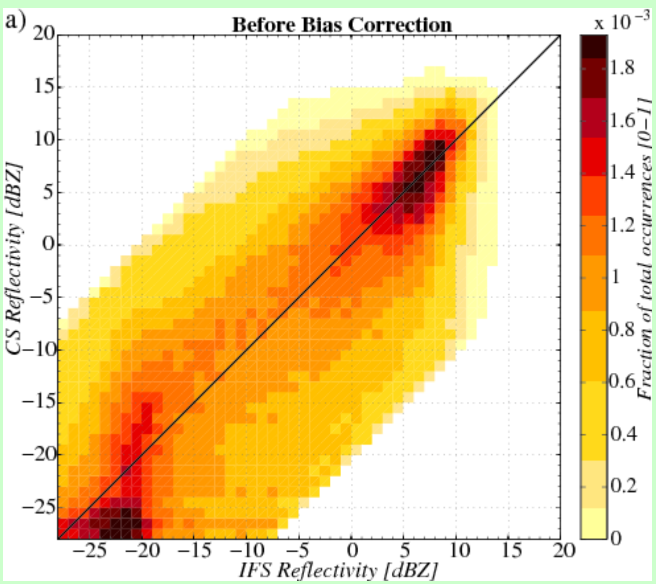
Quality control :

- excluding situations when discrepancies between observations and model equivalents are large → *based on statistics of first-guess (FG) departures*

Bias correction:

- Statistics based on the comparison of model FG with observations

  → *temperature and altitude used as predictors, separately over seasons and geographical regions*
- Applying correction → to obtain more Gaussian distribution of FG departures

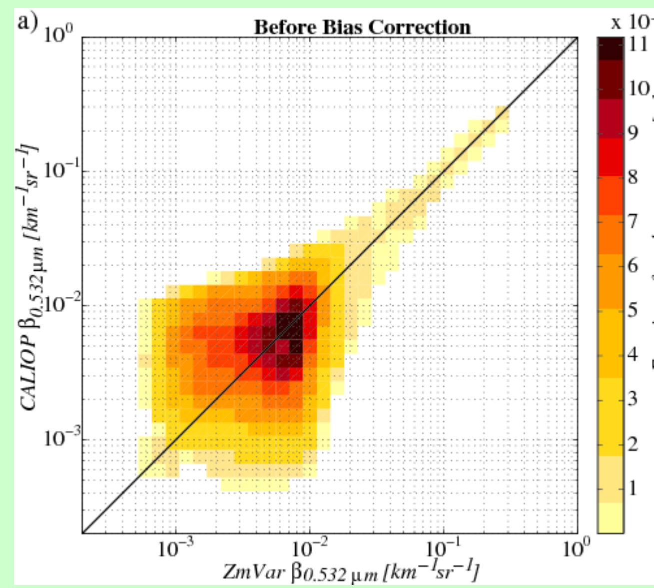


EXAMPLE

(Mid-latitudes South)

before bias correction

Radar **Lidar**



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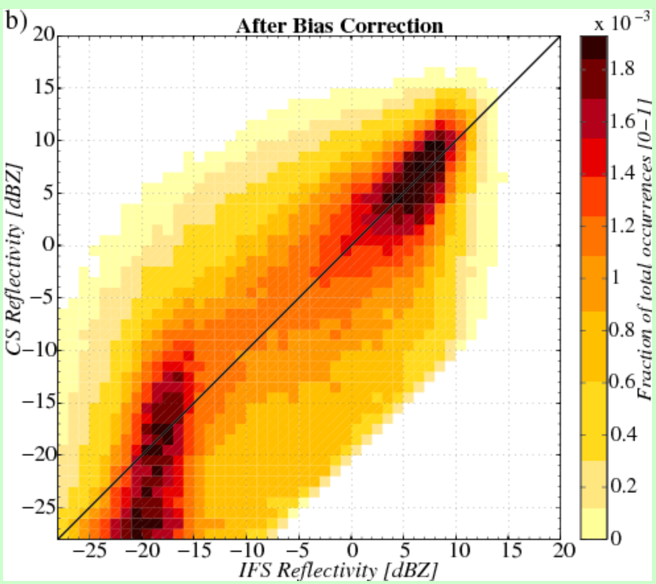

EXAMPLE
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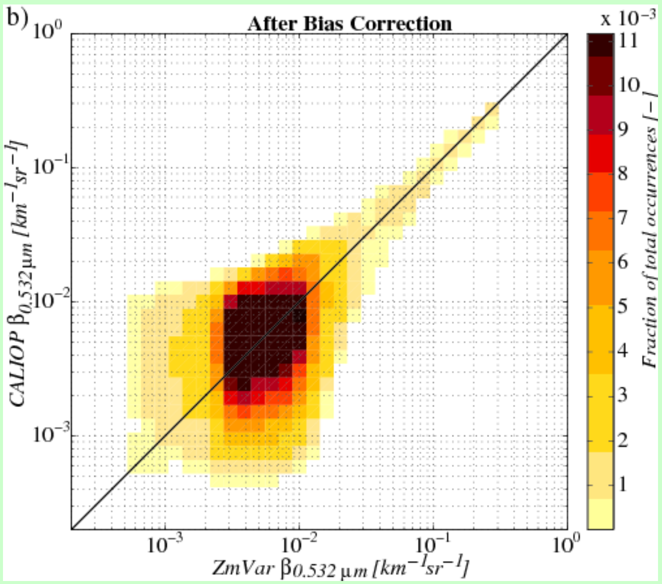


Observation errors (1)

Observation error = instrument error + forward modelling error + representativity error

Instrument error:

- CloudSat instrument random error $$\Delta Z_{dB} = \frac{4.343}{\sqrt{M}}\left(1 + \frac{1}{SNR}\right)$$

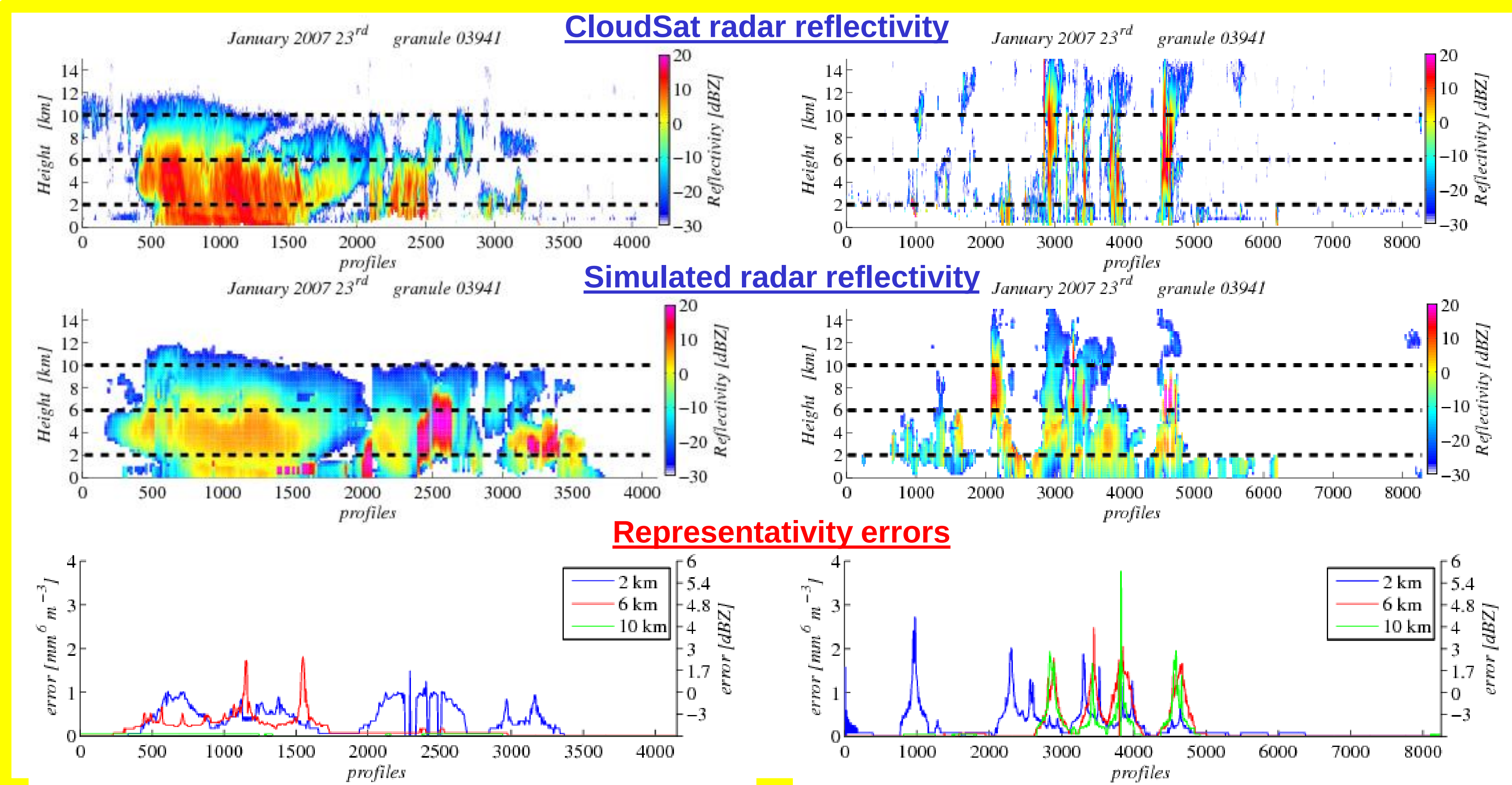
- CALIOP instrument errors evaluated from Level-1 data (background signal power st.dev. and NoiseScaleFactor) according to Liu *et al.* (2006).

Forward modelling error:

- Approach: – error expressing uncertainty in microphysical assumption
  – evaluation through differences between perturbed state and reference configuration
- Reflectivity/backscatter standard deviation expressed as percentage of the simulated radar reflectivity/backscatter separately for different ranges of temperature *(Di Michele et al. 2013)*

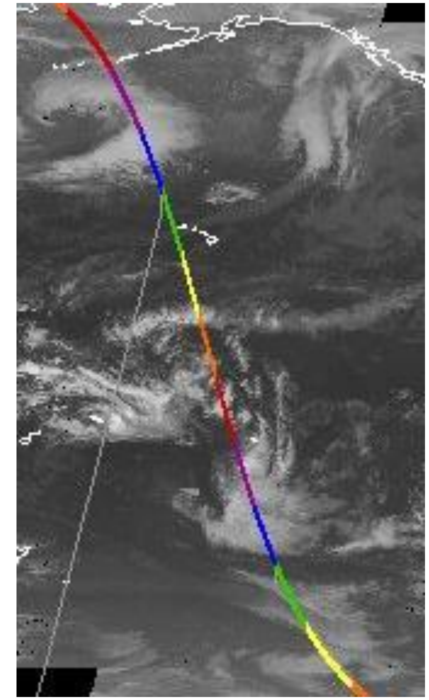
Representativity error:

- Flow dependent error estimated based on statistical approach using the Structure Function Maximum (SFM) defined for different altitudes and geographical regions *(Stiller 2010)*



1D-Var assimilation experiments

- Assimilating different observations:
  - *cloud radar reflectivity* *(at 94 GHz, CloudSat)* *(R)*
  - *cloud lidar backscatter* *(at 532 nm, CALIPSO)* *(L)*
  - *cloud radar reflectivity + lidar backscatter* *(C)*

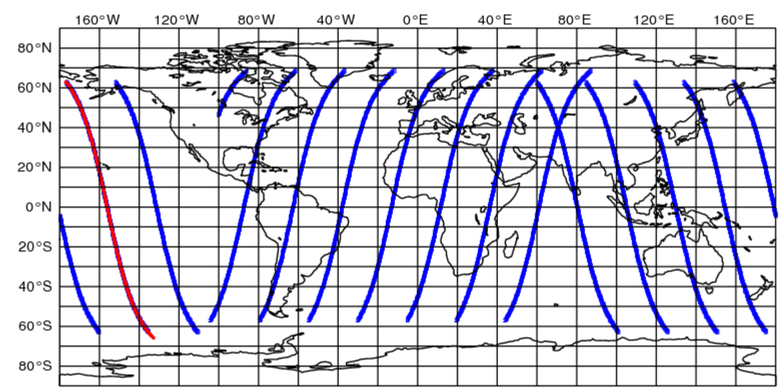


2007012400 over Pacific

- Observations averaged in the grid-box using:
  - *full error definition*
  - *quality control and bias correction*

- Performance of 1D-Var verified using independent observations:
  - *cloud optical depth (MODIS, at 0.55 μm)*
  - *radar reflectivity or lidar backscatter when not assimilated*

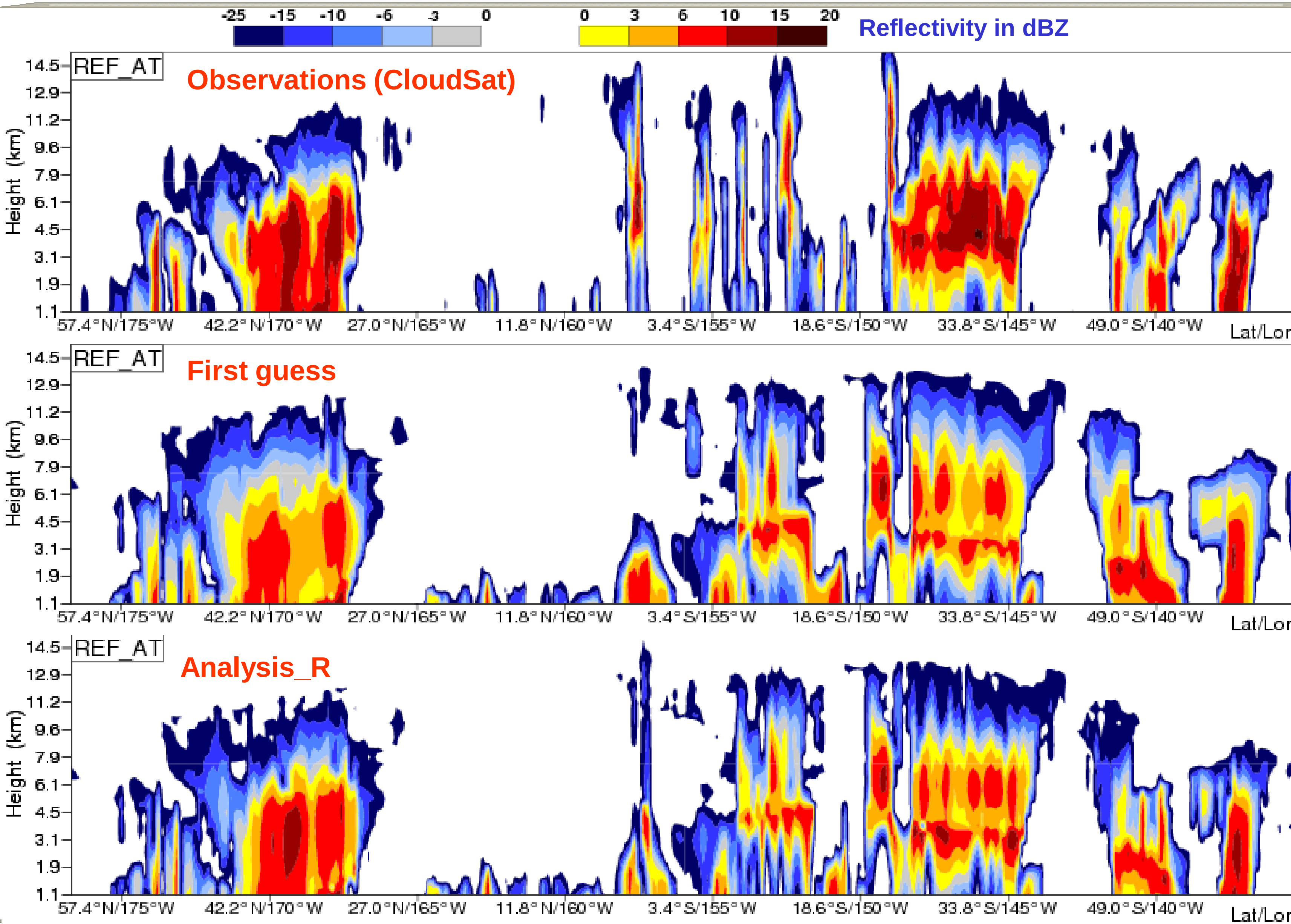
- Checking increments of system control variables (temperature *T* and specific humidity *q*)



20070123 21UTC – 20070124 09UTC

(Janisková , 2014)

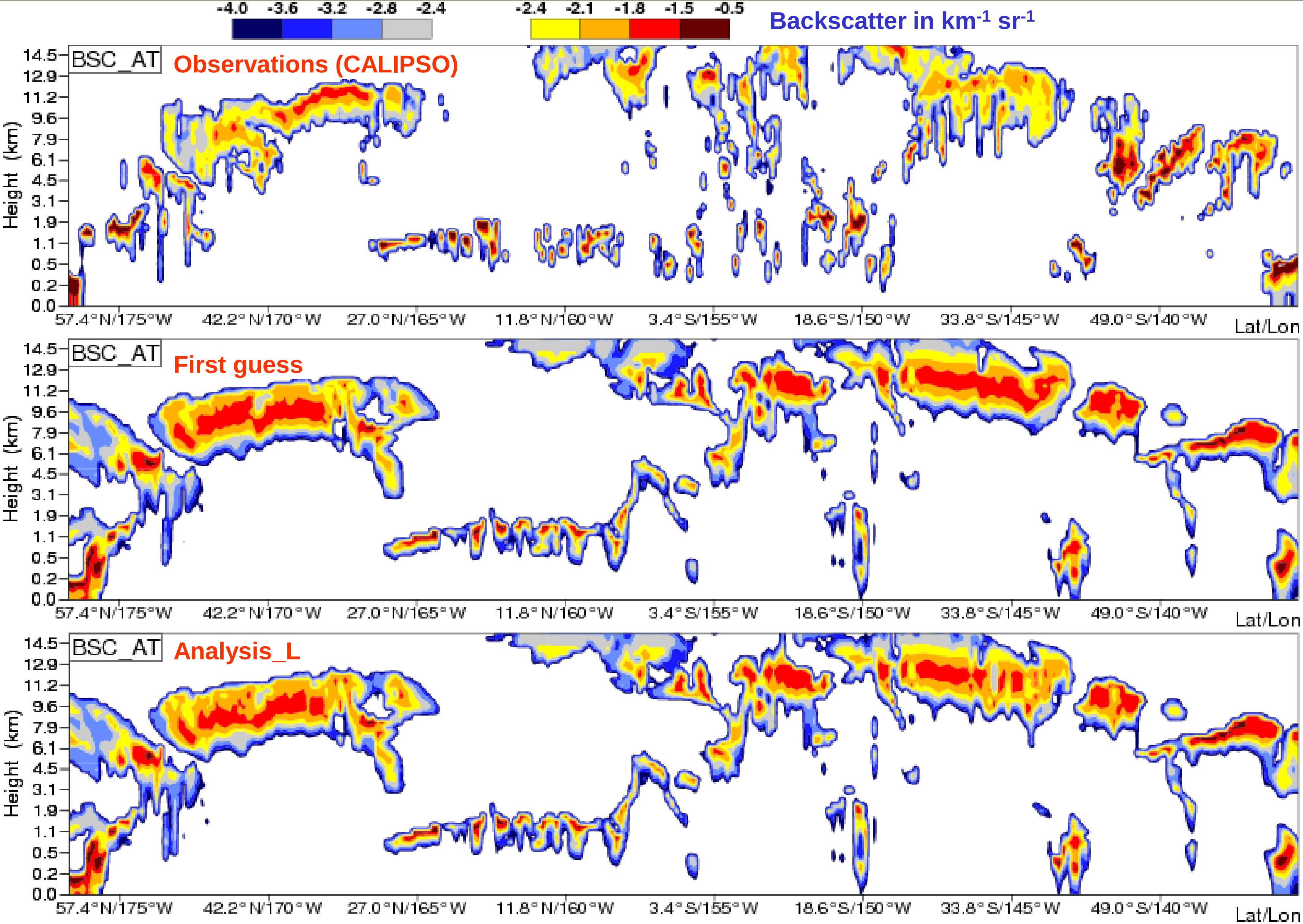
1D-Var of cloud radar reflectivity



Reading, UK

2007012400 over Pacific

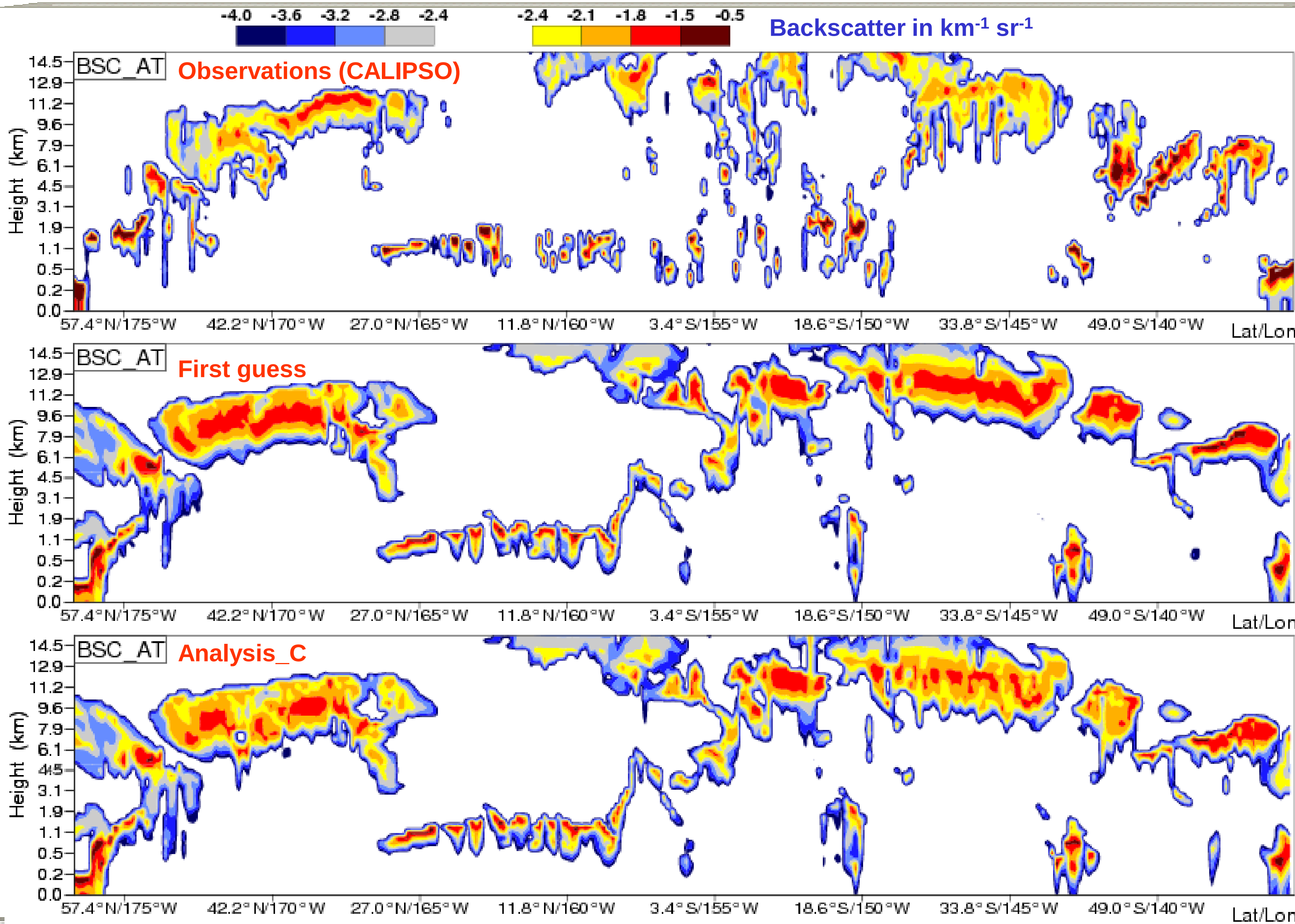
1D-Var of cloud lidar backscatter



ECMWF Reading, UK

2007012400 over Pacific

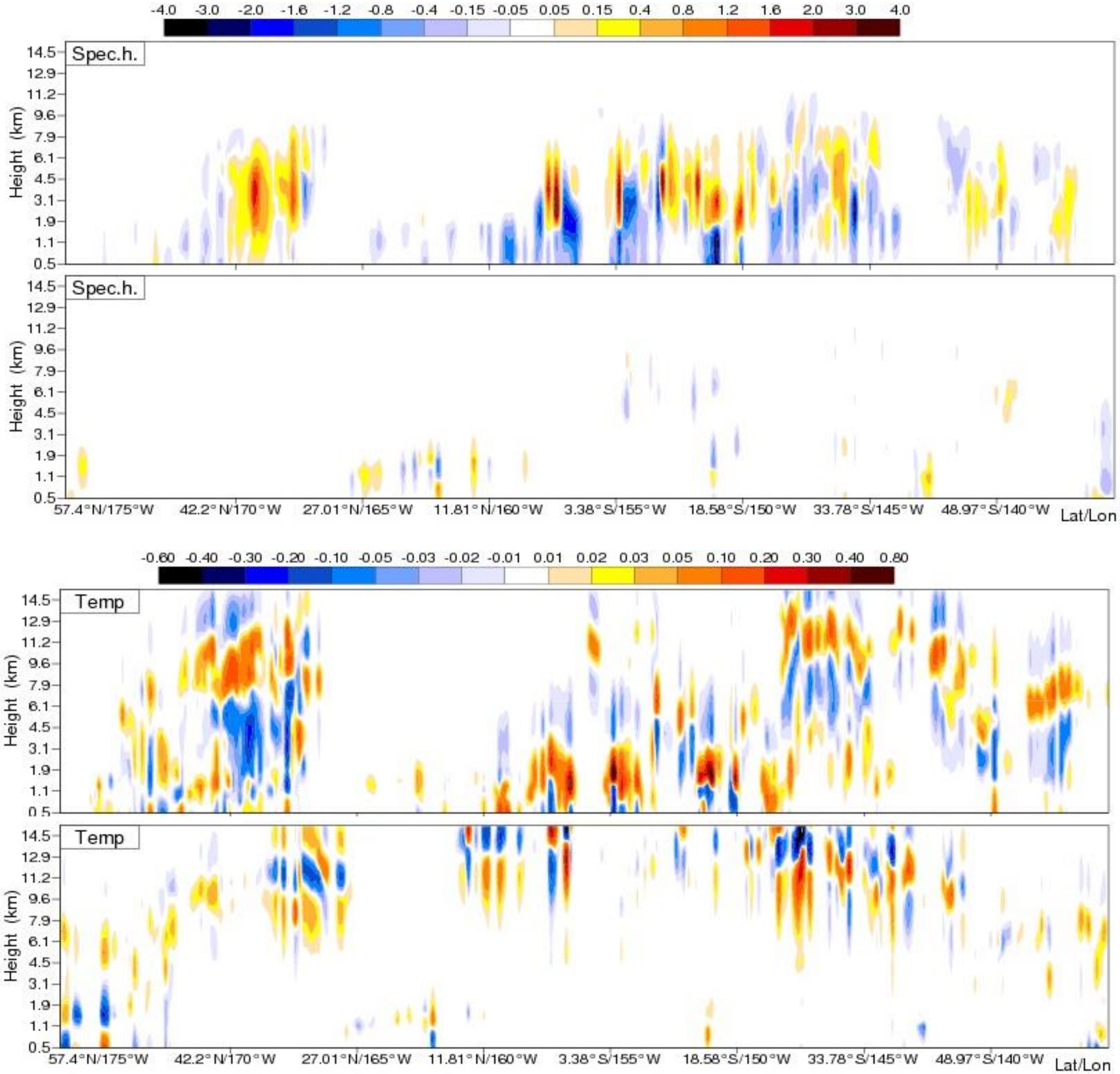
1D-Var of cloud lidar backscatter + radar reflectivity



ECMWF Reading, UK

2007012400 over Pacific

Increments of T and q from 1D-Var



Specific humidity [g/kg]

1D-Var - radar

1D-Var - lidar

Temperature [K]

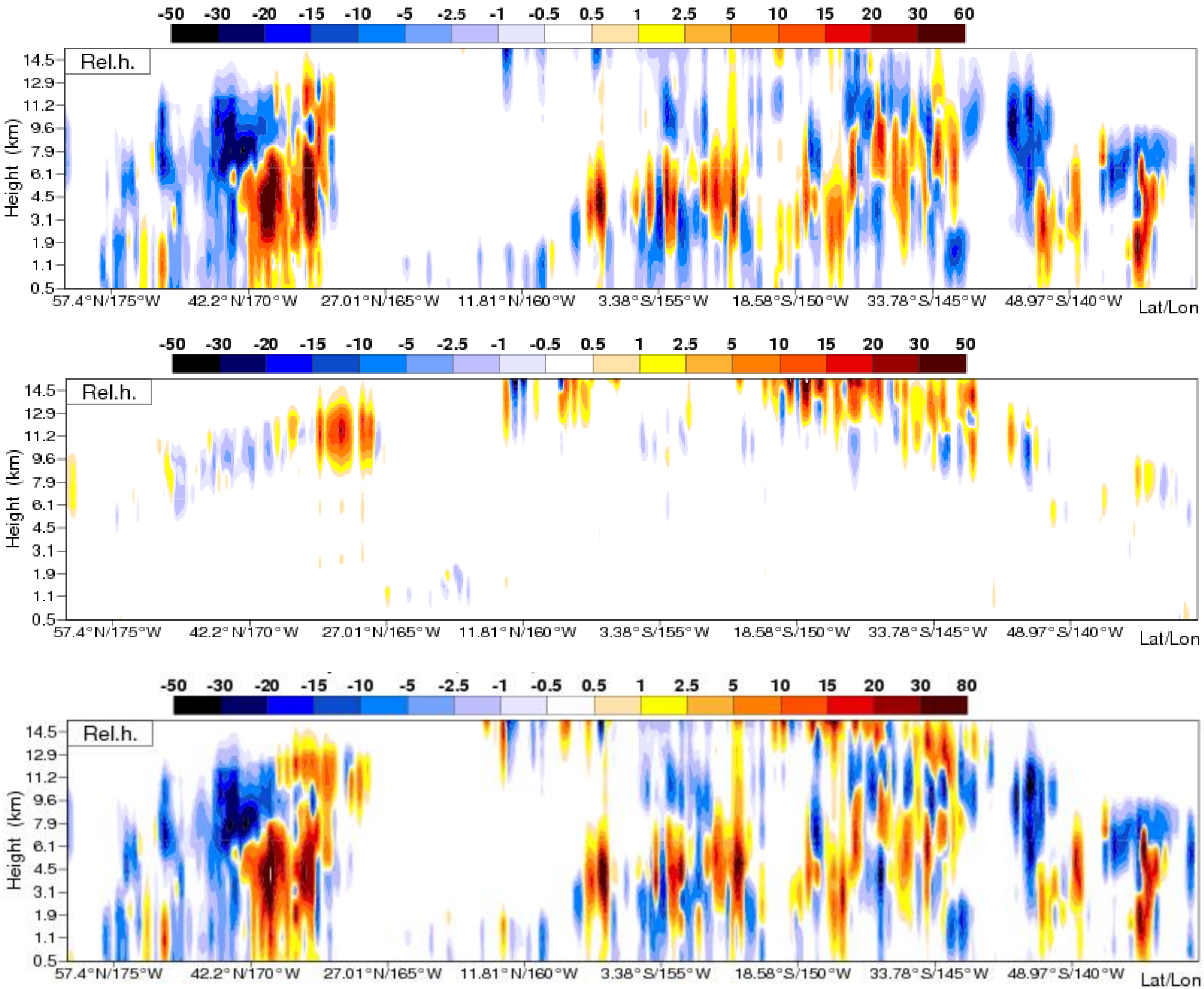
1D-Var - radar

1D-Var - lidar

2007012400
over Pacific

Lidar increments: smaller than radar ones at higher altitudes

Increments of RH (derived from T and q) from 1D-Var



Relative humidity [%]

1D-Var radar

1D-Var lidar

1D-Var radar+lidar

2007012400 over Pacific

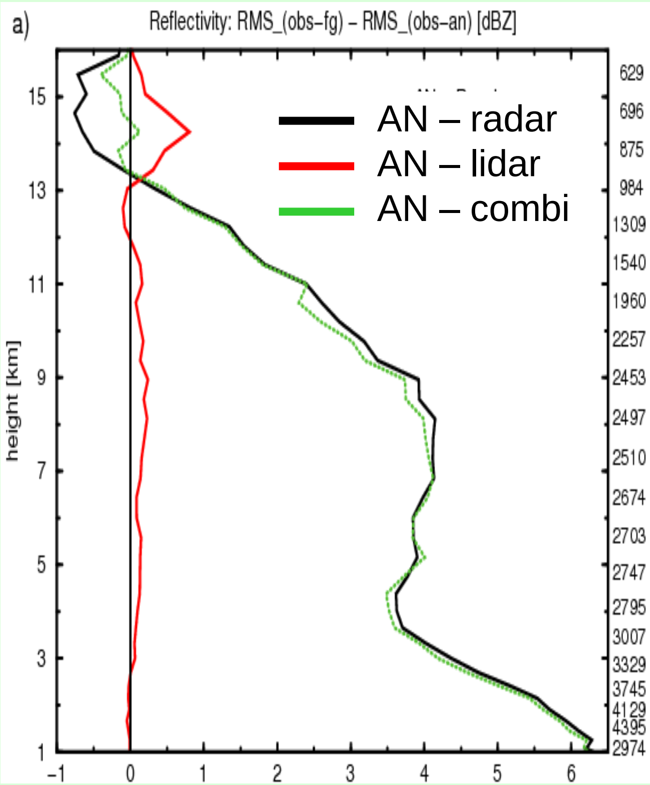
Lidar and radar increments are complimentary

Improvement from assimilation of cloud radar and lidar observations

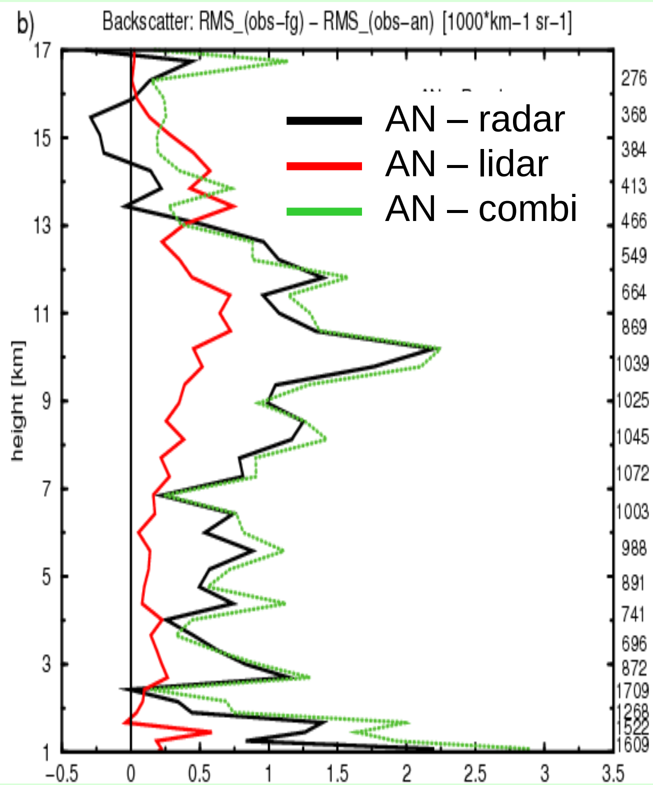
RMS (OBS – FG) – RMS (OBS – AN)

20070123 21UTC – 20070124 09UTC

Cloud radar reflectivity



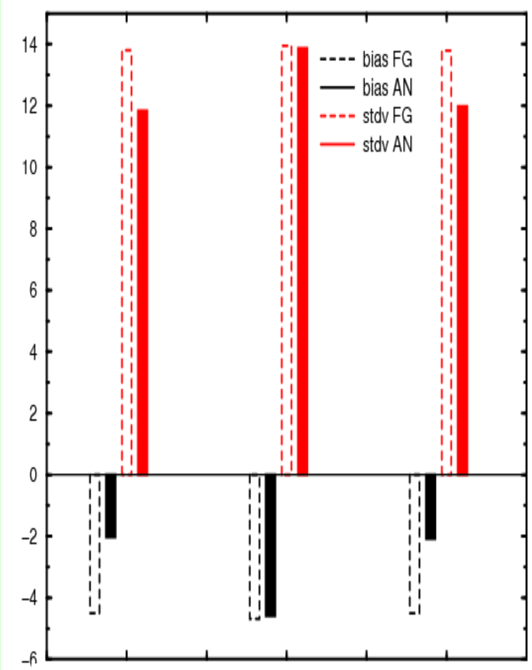
Cloud lidar backscatter



Positive values → improvement

Comparison for:
FG, AN and OBS ≤ 50

Cloud optical depth
(independent OBS)



– 1D-Var analysis gets closer to assimilated and also independent observations:
impact of cloud radar reflectivity larger than of lidar backscatter

1D+4D-Var for CloudSat and CALIPSO observations

Observations :

- modified profiles of *T* and *q* from 1D-Var retrievals used as pseudo-observations in 4D-Var

Observation errors :

- Observation errors for *T* and *q* pseudo-observations:
  - derived from 1D-Var analysis error covariance matrix

$$\mathbf{A} = \left[\mathbf{B}^{-1} + \mathbf{K}^{T}(\mathbf{x})\ \mathbf{R}^{-1}\,\mathbf{K}(\mathbf{x})\right]^{-1} \quad \text{where} \quad \mathbf{K} = \left[\frac{\partial H(\mathbf{x})}{\partial \mathbf{x}}\right]$$

  - or twice *(2err)* as large as computed

    (i.e. closer to the errors for radiosonde T and q)

Experimental setup :

- assimilation cycle of 12 hours, adding the new observations to the full system of regularly assimilated observations
- 10-day forecast run from the analyses

(Janisková , 2014)

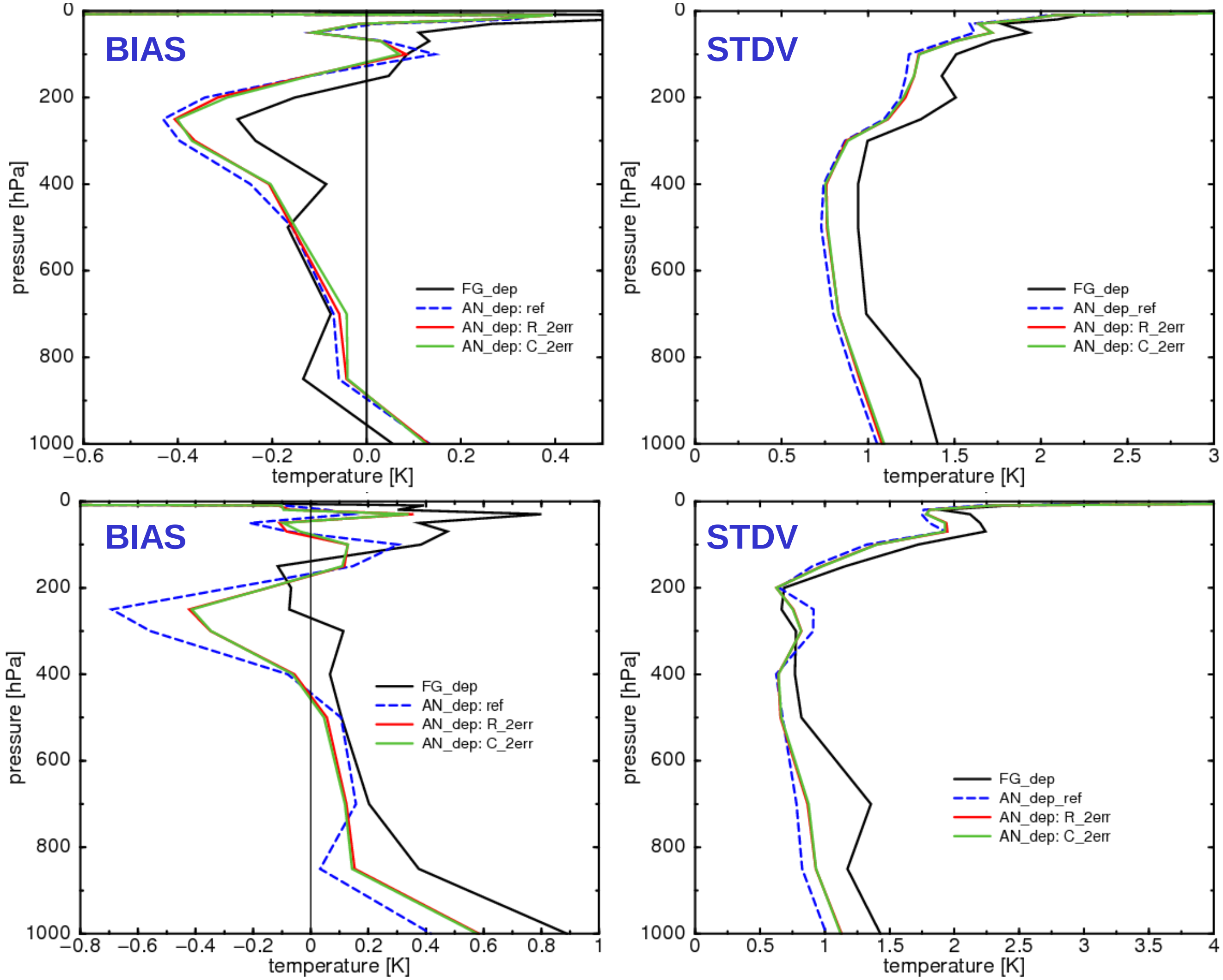
Verification of assimilation runs against other assimilated observations

4D-Var assimilating *T*, *q* pseudo-obs from 1D-Var with radar alone and combined with lidar

TEMP – T NH

FG_dep
AN_dep_ref
AN_dep_R_2err
AN_dep_C_2err

TEMP – T Tropics

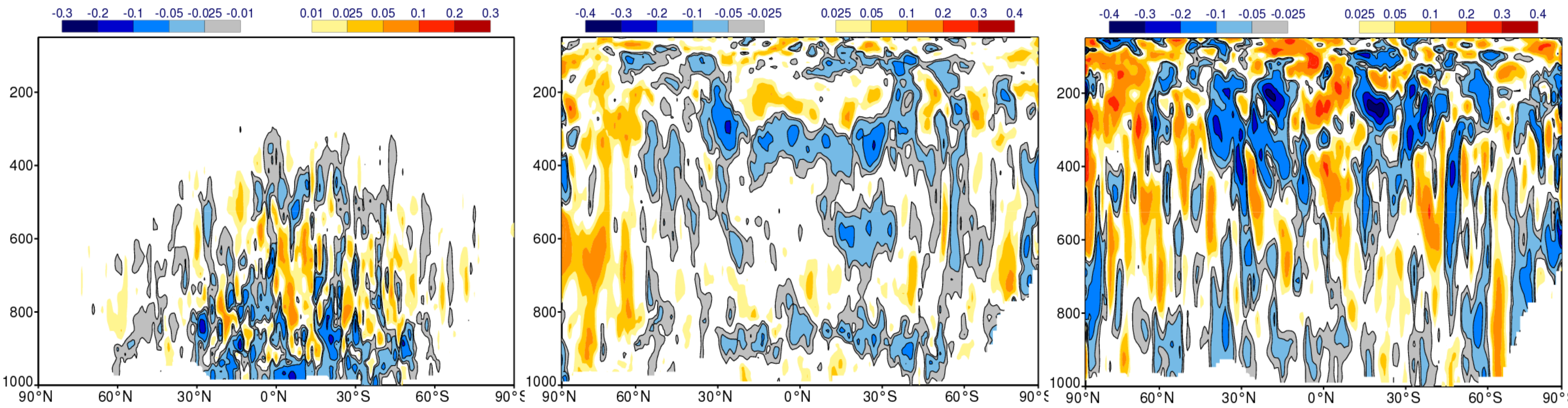


20070123 21UTC – 20070124 09UTC

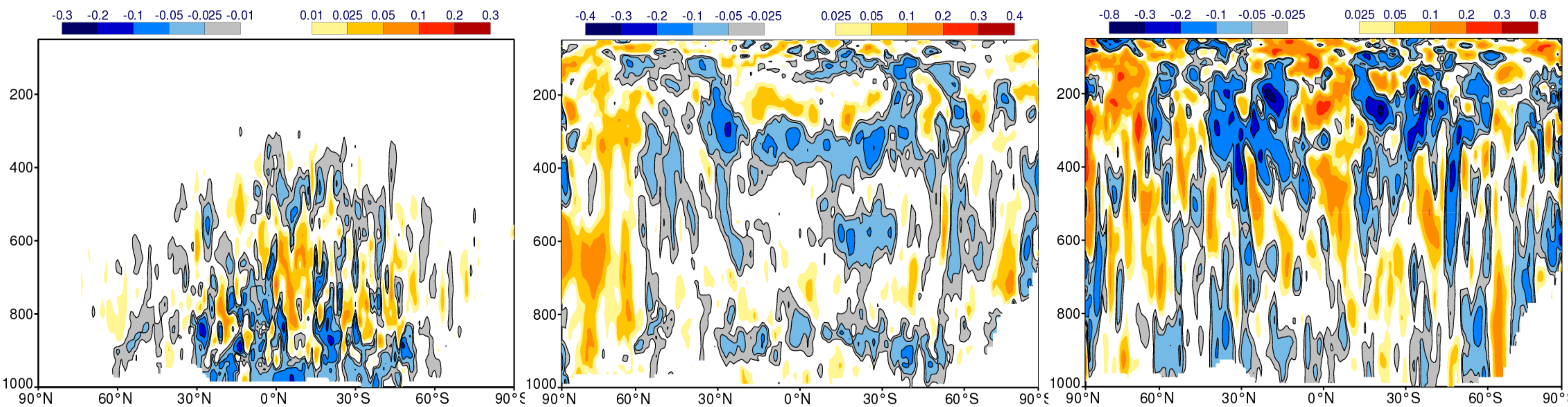
– impact of the new observations when verified against other assimilated observations in 4D-Var rather small: *small, but systematic improvements coming from the lidar observations when combined with the radar*

1D+4D-Var of T,q pseudo-observations – impact on subsequent forecast (1)

T, q pseudo-observations from 1D-Var of radar



T, q pseudo-observations from 1D-Var of radar + lidar

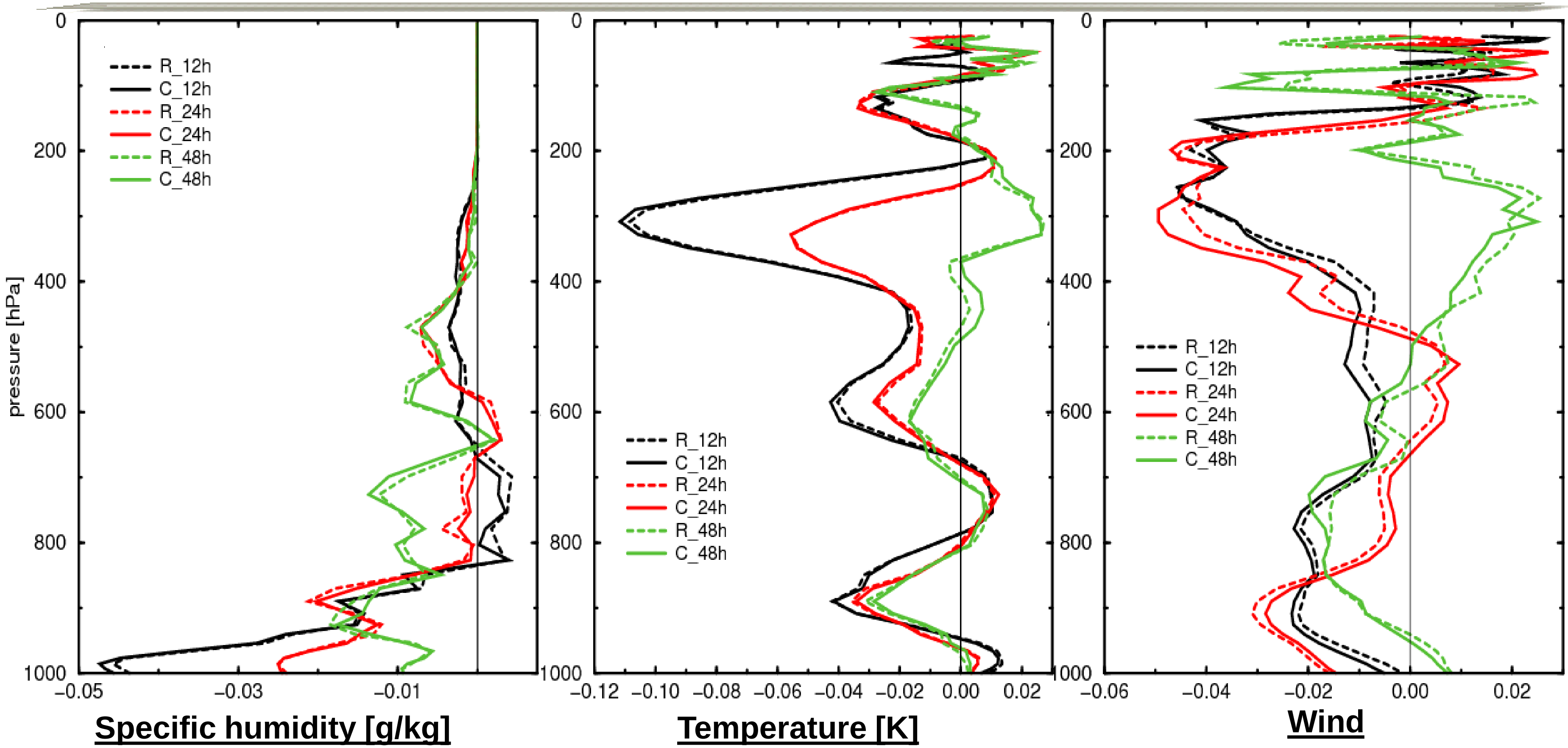


Specific humidity [g/kg] T+24 **Temperature [K] T+24** **Wind T+24**

RMS (FCexp – AN) – RMS (FCref – AN)

Negative values (blue colours): rms of EXP smaller than REF

1D+4D-Var of T,q pseudo-observations – impact on subsequent forecast (2)



RMS (FCexp – AN) – RMS (FCref – AN)

Negative values:
rms of EXP smaller than REF

– generally, a positive impact of the new observations on the subsequent forecast:
  + *even though it decreases in time, it is still noticeable up to 48-hour forecasts*
  + *small additional improvement when the radar and lidar observations combined*

Conclusions

- The feasibility of assimilating space-borne radar and lidar cloud observations has been demonstrated.

↓

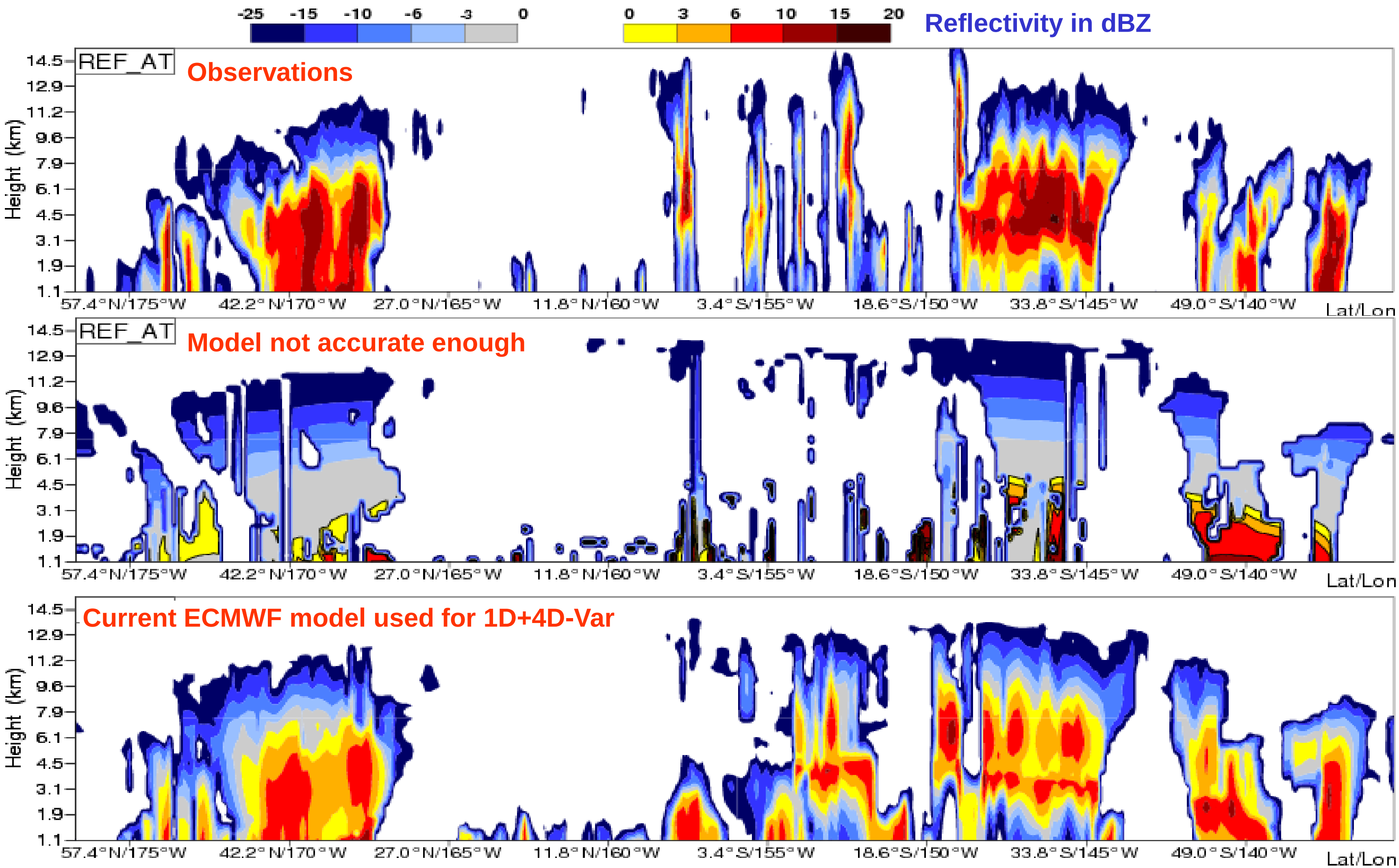
The achieved results triggered the desirability to use these new types of cloud observations for assimilation.

BUT

To achieve that there are certain requirements/constraints.

Requirements for cloud radar and lidar data assimilation (1)

Accurate enough observation operators:



Requirements for cloud radar and lidar data assimilation (2)

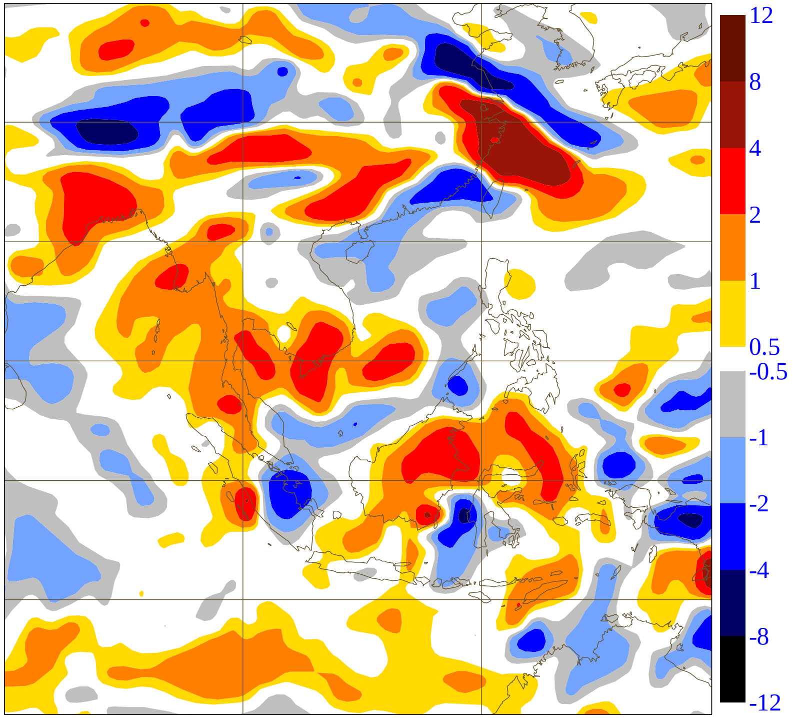
Linearity of physical parametrization/observation operator:

- Variational assimilation is based on the strong assumption that the analysis is performed in quasi-linear framework.

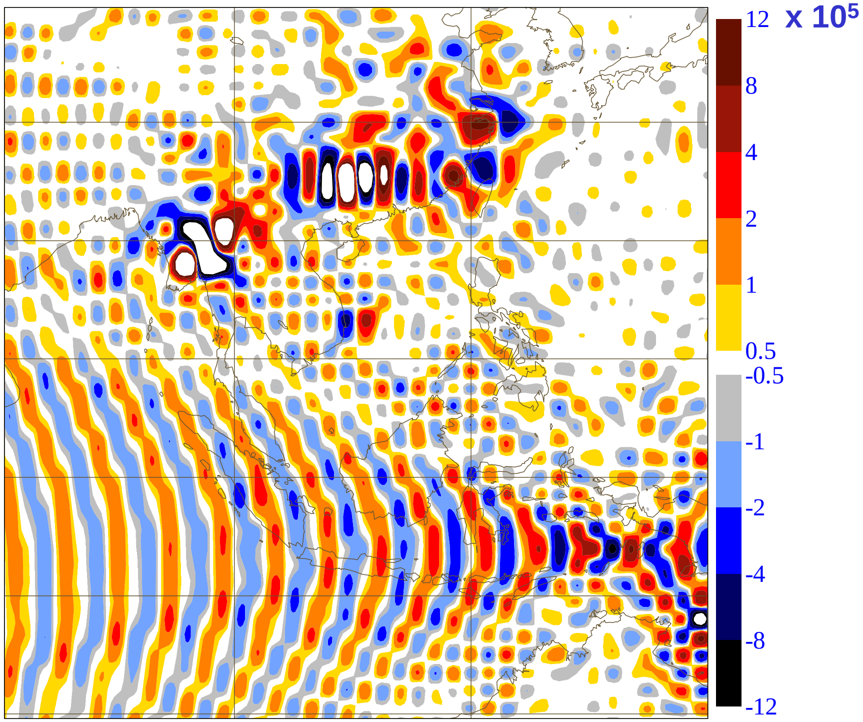
cloud scheme with linearity/threshold problems

u-wind increments: fc t+12, ~700 hPa

finite difference (FD)



Tangent-linear (TL) integration



Requirements for cloud radar and lidar data assimilation (2)

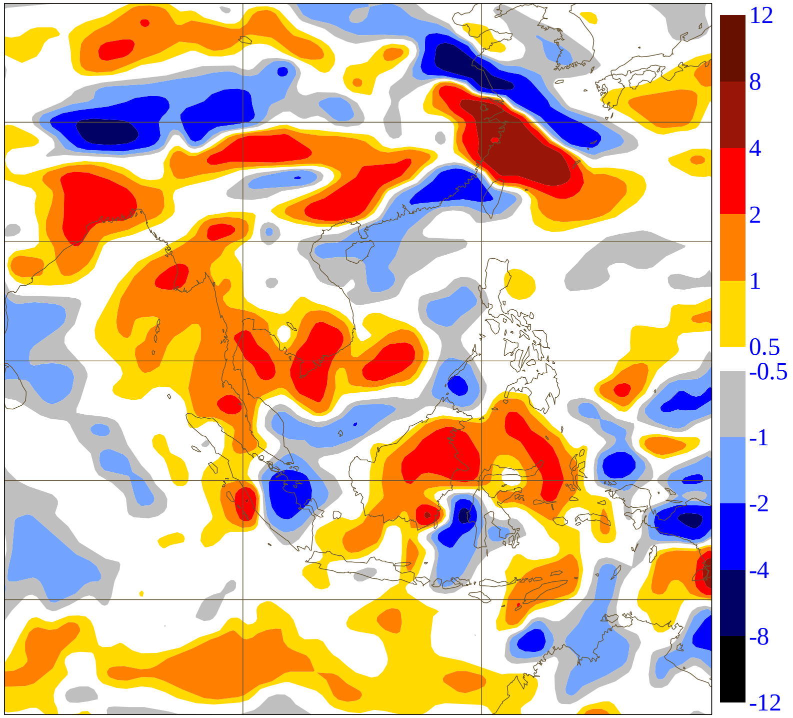
Linearity of physical parametrization/observation operator:

- Variational assimilation is based on the strong assumption that the analysis is performed in quasi-linear framework.

cloud scheme after solving linearity/threshold problems

u-wind increments: fc t+12, ~700 hPa

finite difference (FD)



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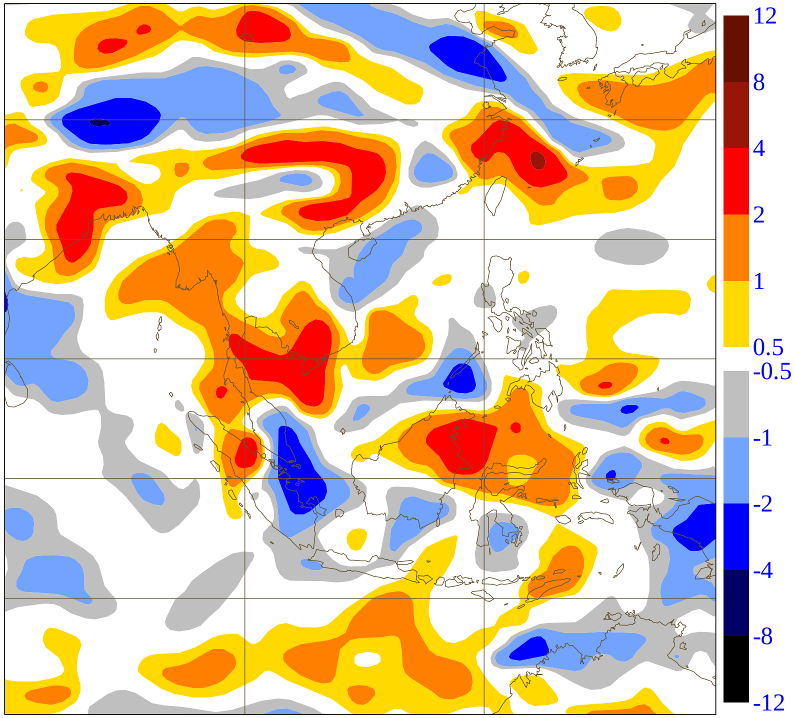
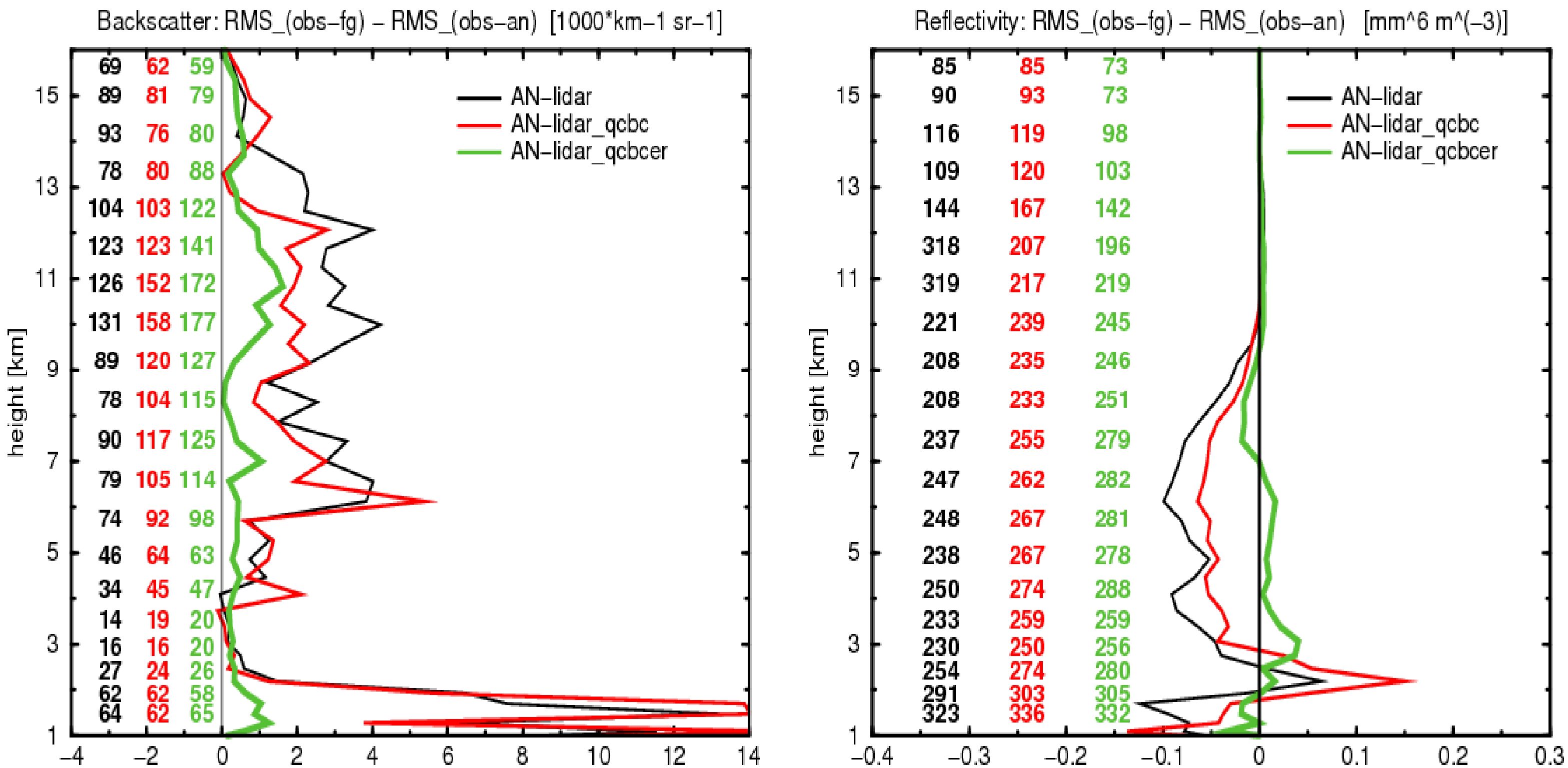


Requirements for cloud radar and lidar data assimilation (3)

- **Appropriate quality control and bias correction scheme**
- **Observation error definition accounting for spatial representativeness of space-borne observations**



RMS (OBS – FG) – RMS (OBS – AN)

Positive values → AN closer to OBS than FG

qcbc – quality control + bias correction
qcbcer – qcbc + observation error improved

Perspectives

- In the future, direct 4D-Var assimilation of cloud radar/lidar observations should be considered at ECMWF.

  (1D+4D-Var too expensive to be used for operational application)

- An additional beneficial activity would be a quality monitoring system against a global NWP model

  (important step before any observations are assimilated into 4D-Var)

- To achieve that requires:
  - adjustments of assimilation related tools previously developed, such as quality control, data screening, bias correction and observation error definitions

- Based on experimental results, it would be highly desirable for NWP applications to have space-borne radar and lidar observations in near-real time *(such as those from the future EarthCARE mission)*