Challenges and potential benefits of assimilation of space-borne radar and lidar observations in a global numerical weather prediction system

Marta Janisková and Mark Fielding
ECMWF

Thanks to:
P. Lopez, R. Hogan

7th International WMO Symposium on Data Assimilation
11-15 September 2017
Improvements in cloud parametrization

CloudNet project data at Chilbolton

Observed cloud fraction

ECMWF model cloud fraction

Météo-France model cl. fraction

June 2003

August 2012
Introduction

• 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
• Assimilation of vertically resolved cloud information in a global numerical weather system brings a lot of challenges to succeed.

• There are several **important requirements**:
  
  – availability of sufficiently accurate observation operators
  
  – linearity and regularity of the observation operator used in the variational assimilation framework
  
  – appropriate quality control strategy and bias correction scheme
  
  – observation error definition accounting for the spatial representativity of space-borne observations with narrow field of view
Requirements for cloud radar and lidar data assimilation (1)

Accurate enough observation operators:

- Observations
- Model not accurate enough
- ECMWF model used for 1D+4D-Var

Reflectivity in dBZ
The numbers indicate different steps in operator computations.
ECMWF cloud radar & lidar obs. operator - performance

- ECMWF’s radar and lidar observation operators now show
great agreement with CloudSat and Calipso measurements

cloud radar reflectivity (at 94 GHz, CloudSat)
cloud lidar backscatter (at 532 nm, Calipso)
Linearity of physical parametrization/observation operator:

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

finite difference (FD)

Tangent-linear (TL) integration

Cloud scheme with linearity/threshold problems

u-wind increments: fc t+12, ~700 hPa
Linearity of physical parametrization/observation operator:

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Requirements for cloud radar and lidar data assimilation (3)

• Appropriate screening and quality control

• Well-defined bias correction scheme

• Observation error definition accounting for spatial representativeness of space-borne observations
Observation processing, initial screening and quality control

- **Observation processing** – averaging observations to the model scale to:
  - smooth observation field
  - improve representativity
  - reduce error correlations

- **Screening & quality control** – providing balance between including as much information from observations as possible whilst preventing ‘bad’ ones from degrading the analysis/forecast.
  - It is important to ensure measurements are not assimilated where:
    - they are of poor quality
    - the forward model is not capable of representing the observations
    - there is an excessive non-linear relationship between perturbations in the control variables and the corresponding simulated parameters

- Observation points must pass initial screening based on **screening threshold** for:
  - height of observations
  - cloud fraction given by model and observations
  - plausible bounds for radar/lidar (observation & model equivalent to observations)
  - first guess departures
  - avoiding radar multiple scattering and lidar excessive attenuation
Bias correction scheme

• Data assimilation systems combine a model background and observations given the errors that are inherent in both. However, any biases in either will likely degrade the subsequent analysis and forecasts.

• A bias correction scheme aims to remove systematic biases, whilst retaining random errors.

• A good bias correction scheme can also help identify any model weaknesses or forward model deficiencies.

• Indicators are required to subset the data so that different biases can be accounted for. Selected bias correction indicators:
  – height
  – temperature
  – model hydrometeor type
  – mean radar reflectivity/lidar backscatter
Bias correction for CloudSat radar (September 2007)

Before bias correction

bias = -2.0834 dB, std = 10.5464 dB

After bias correction

bias = 0.10147 dB, std = 9.4894 dB
Bias correction for Calipso lidar (September 2007)

Before bias correction

After bias correction

bias = 2.1818 dB, std = 7.5915 dB

bias = -0.048232 dB, std = 6.7431 dB
Observation error definition (1)

- Observation errors are a crucial component of a data assimilation system as, coupled with the background error, control the weight each obs. is given.
- Often assumed to have no correlation & used for tuning data assim. system
- Can be estimated directly or inferred through a statistical evaluation of FG departures and/or analysis increments

**Selected approach** – defining the observation error explicitly based on physical understanding because:
- Owing to the profiling nature of the observations, the true obs. error likely to be highly situation dependent
- At the time EarthCARE becoming operational, no availability of long history of observations to generate a climatological obs. error covariance matrix

- Under the hypothesis of uncorrelated errors, obs. error is defined as a combination of **instrument** error, **obs. operator** error and **representativity** error:

\[
2^{\text{obs}} = 2^{\text{ins}} + 2^{\text{oper}} + 2^{\text{rep}}
\]
**Instrument error:**

- The random error in the measurement due to noise
- Typically small compared to other errors, but straightforward to estimate

**Observation operator error:**

- To convert model hydrometeor content into radar reflectivity/lidar backscatter, many assumptions made with the potential to introduce error in:
  - Radiative transfer of scattering models
  - Hydrometeor shape
  - Particle size distribution
  - Multiple scattering
  - Subgrid assumptions (overlap, inhomogeneity & convective precip.fraction)

- To characterize errors:
  - perturbing parameters with plausible bounds
  - using Monte Carlo simulation – PSD uncertainty is st.dev. of reflectivity/ backscatter given a set of random realisations of PSD variables / densities / particle shapes

- Errors are function of hydrometeor type, LWC and temperature
**Observation error definition (3)**

**Representatvity error:**

- Expected error due to mismatch between the model and the observational spatial and/or temporal scales.

- Difficult to characterize analytically as the observations are correlated and non-gaussian.

- Use ‘sampling approach’ based upon the assumption that:
  - the local variability of measurements along the satellite track is representative of the gridbox variability
  - the spatial variability can be approximated using a climatological correlation

- Representatvity error is a function of:
  - standard deviation of obs within superob (obs averaged to model scale)
  - latitude
  - longitude,
  - height
  - month
Error components for radar

Observed radar reflectivity (dBZ)

Model radar reflectivity (dBZ)

Obs. Operator error (dB)

Representativity error (dB)

Measurement error (dB)

Total observation error (dB)

Cloudsat

FG

Obs. operator error

Repres. error

Instrum. error

Total error

Representativity error dominates total error
Error components for lidar

Observed lidar backscatter (dB)$\beta$

Model lidar backscatter (dB)$\beta$

Obs. Operator error (dB)

Representativity error (dB)

Measurement error (dB)

Total observation error (dB)

Obs. operator error tends to dominate total error
Investigation of potential for assimilation of cloud observations from space-borne radar and lidar using observations from CloudSat and Calipso in global model (Janisková et al 2012, Janisková 2015)

Impact of the new observations on 4D-Var analyses and subsequent forecasts studied using a 1D+4D-Var technique:

- Information on T and q retrieved from 1D-Var of cloud radar/lidar data and used as pseudo-observations in 4D-Var

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)

Performance of 1D-Var verified using independent observations:

- cloud optical depth (MODIS, at 0.55 μm)
- radar reflectivity or lidar backscatter when not assimilated
Improvement from assimilation of cloud radar and lidar observations

**RMS (OBS – FG) – RMS (OBS – AN)**

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 of $T,q$ pseudo-observations - impact on subsequent forecast

Specific humidity [g/kg] $T+24$

Negative values (blue colours): 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

RMS (FCexp – AN) – RMS (FCref – AN)
Summary & perspectives

• Assimilation studies using observations providing 3D-information on clouds from space-borne active instruments on board of CloudSat & CALIPSO in order to prepare for the EarthCARE mission

• Impact of the new observations on 4D-Var analyses and subsequent forecasts studied using a 1D+4D-Var technique
  — Information on T and q retrieved from 1D-Var of cloud radar/lidar data and used as pseudo-observations in 4D-Var can lead to improve initial conditions & better forecast

• The feasibility of assimilating space-borne radar & lidar cloud observations demonstrated:
  — The achieved results triggered the desirability to use these new types of cloud observations for assimilation.

• At ECMWF, direct 4D-Var assimilation of cloud radar/lidar observations being developed: (1D+4D-Var too expensive for operational application)

• ESA funded study “Operational Assimilation of Spaceborne Radar and Lidar cloud Profile Observations”:
  — Development of an assimilation system for the monitoring the data quality of the EarthCARE radar & lidar profiles and assimilating them into an operational global weather prediction model