Pre- and Post-Processing in Data Assimilation

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Introduction

- Data assimilation : art of combining model and observations

- It relies on a set of equations with a solid statistical basis

- Theoretical studies :
  - how to define optimally the various quantities
  - how to combine all the flow-dependent information

- In practice, a lot of attention has to be paid to details in
  - handling observations
  - possible filtering of the resulting analysis

Outline

Transforming the raw data
- Transforming into a different space
- Averaging the data
- Filtering the observations

Comparing model and observations
- Monitoring and choice of observations
- Bias correction
- Removing wrong data

Thinning the data
- Reducing data quantity and error correlation
- Choosing the most relevant local data
- Selective thinning depending on the flow

Filtering the analysis
- Initialisation methods
- Influence on the analysis

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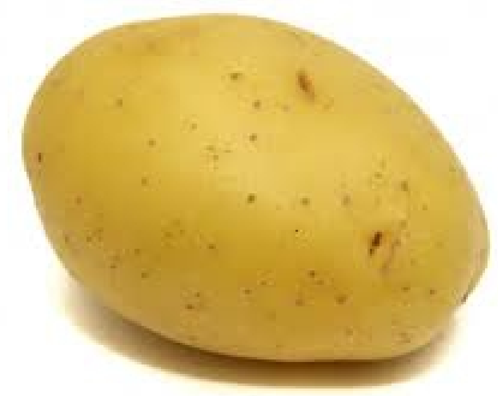

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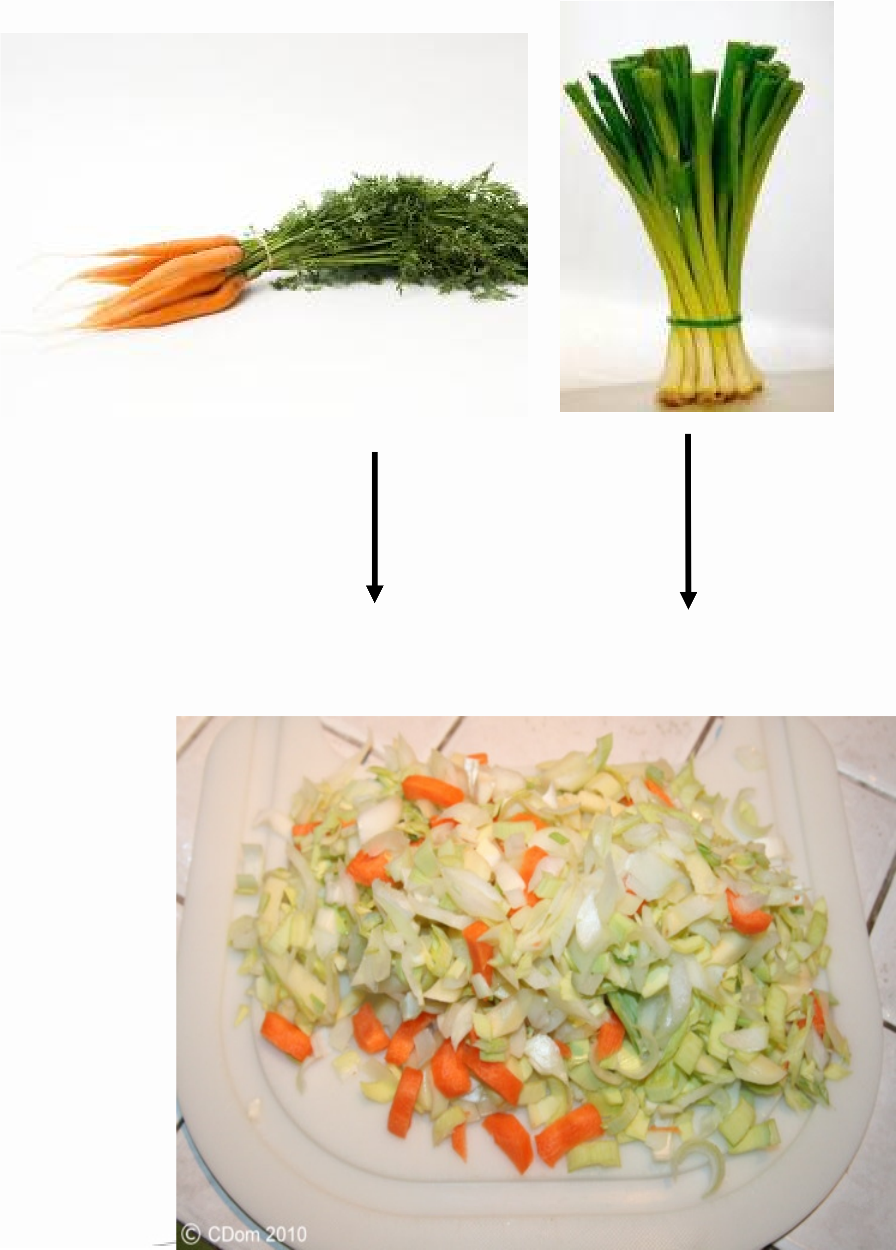

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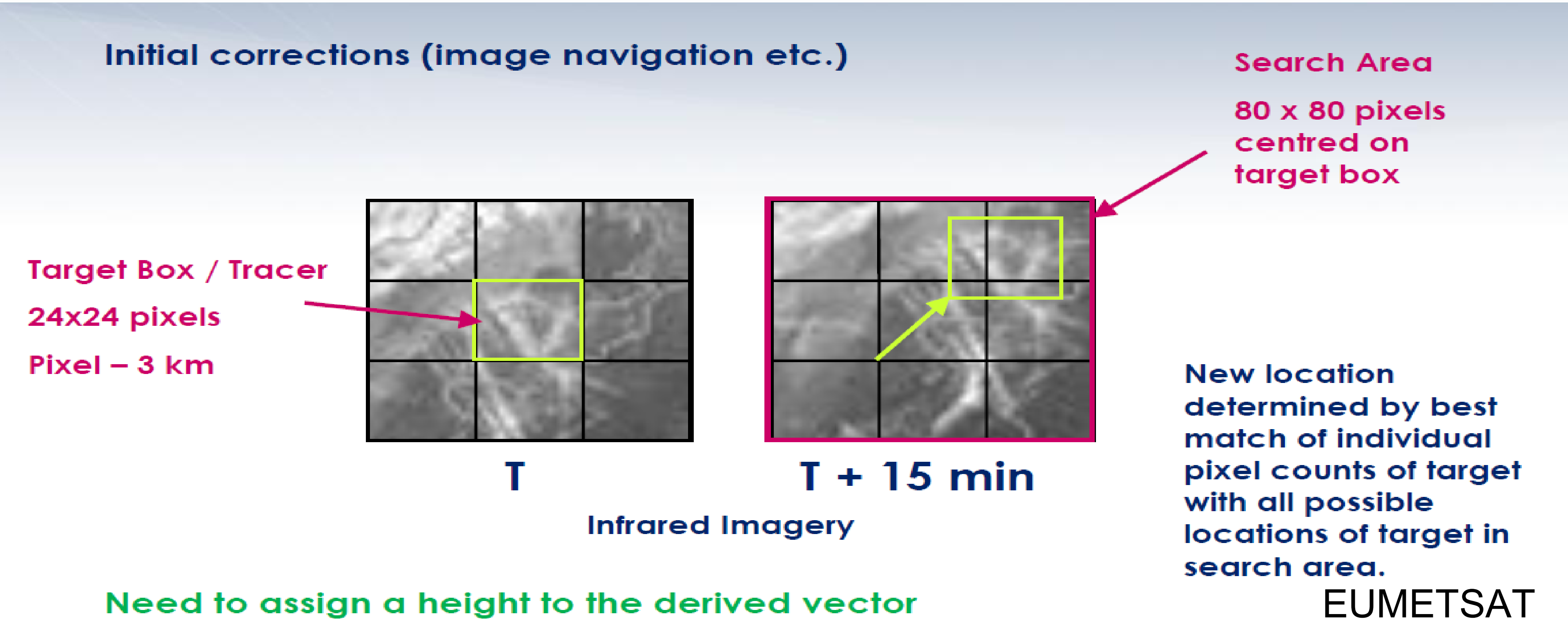
From the raw data to observations

- Some observations are simple measurements: radiosondes
- Other observations are very indirect measurements:
  - Series of images from satellites to derive atmospheric motion vectors

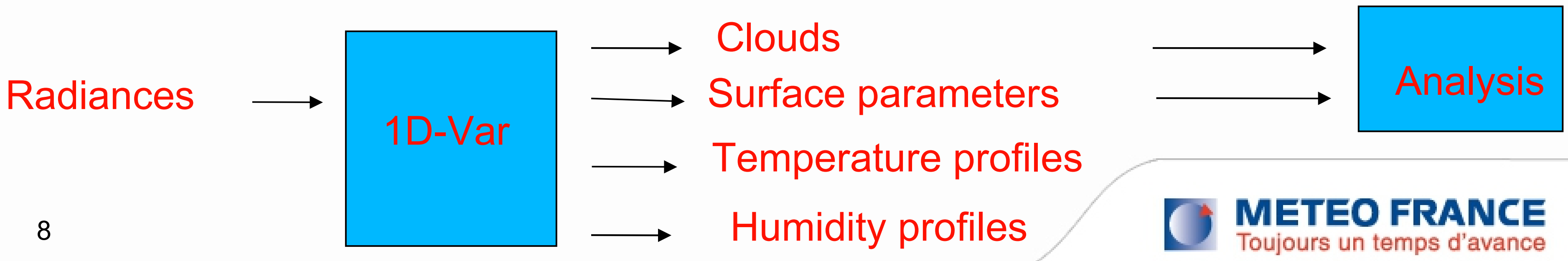


From the raw data to observations

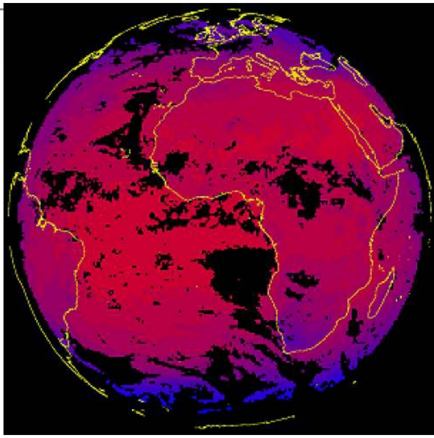
Pre-processing the data to data easier to assimilate

- Radiances measure the electromagnetic spectrum
- Provide indirect information on temperature, humidity, surface, ozone…
- Can be used directly in data assimilation schemes

  (John Derber's talk)
- or via retrievals,
- or a mix, for some parameters and quality control



Averaging the data : spatially



Horizontal averaging performed by data producers

CSR= Clear-Sky radiances, averaged in boxes

typically 16*16 pixels for SEVIRI

Some averaging can be done at the user's level

- All-sky radiances at ECMWF : averaging observations
  to create AMSR-E superob (at 80km scale, Geer and Bauer, 2010)

- NRL produces superobs from satellite winds with a complex algorithm
  - Averaging in boxes (prisms of about 2° side)
  - Prism-quartering when high degree of variability
  - U and V obs have to agree within a certain range
  - … (Pauley, 2003)

  and get more positive results than other centres

Averaging the data: spatially

Radar winds in the HIRLAM 3D-Var and at NCAR for WRF

(Lindskog et al, MWR, 2004) (Zhang et al, MWR, 2009)

Horizontal averaging to create super-obs from radial winds

Quality control steps

* At least 4 or 5 data in an bin
* Accepted only for low variance of the Vr values

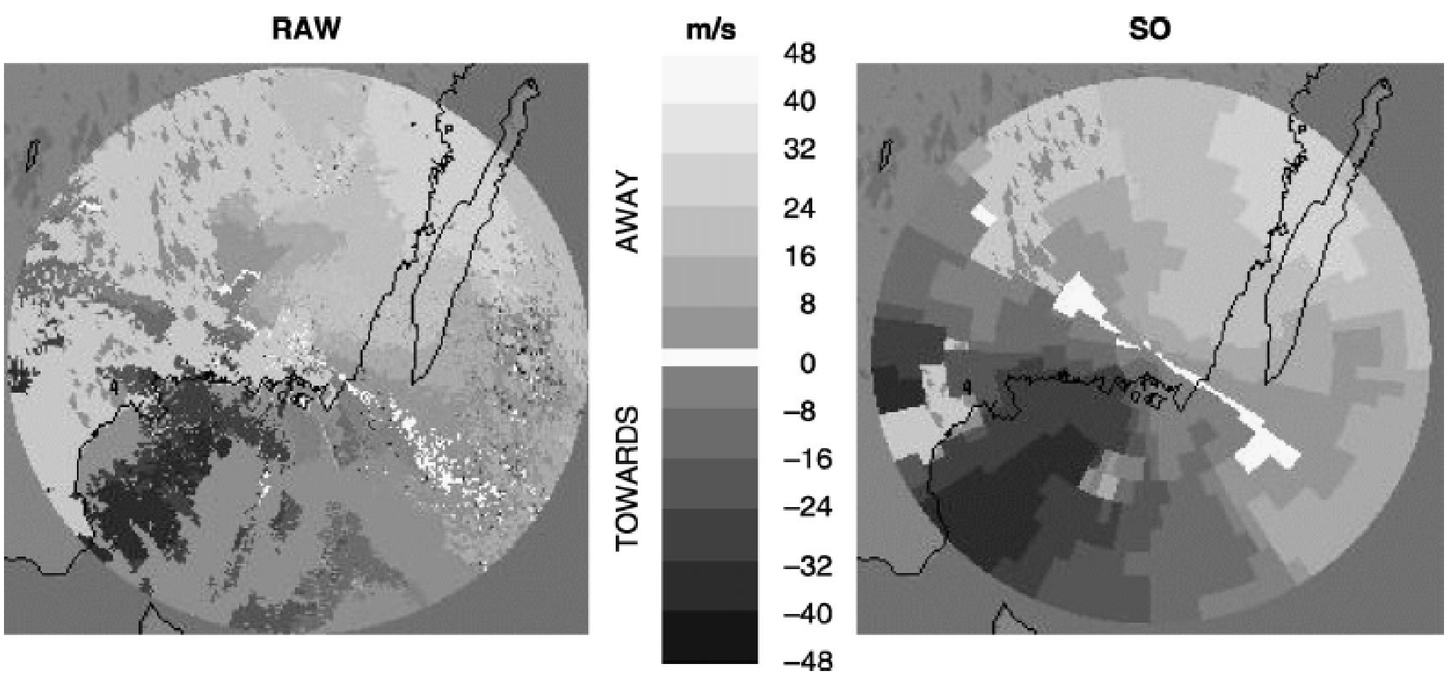


FIG. 1. (left) Doppler radar radial wind raw data and (right) SOs generated through horizontal averaging.

Lindskog, Salonen, Järvinen, Michelson, MWR, 2004

Averaging the data: spatially

With a median concept

(Montmerle and Faccani, MWR, 2009)

* Median filter on boxes of 5*5 pixels
Replace value by the median
of neighouring points

* and a « cleaner » filter, removing pixels
when large inconsistencies within boxes

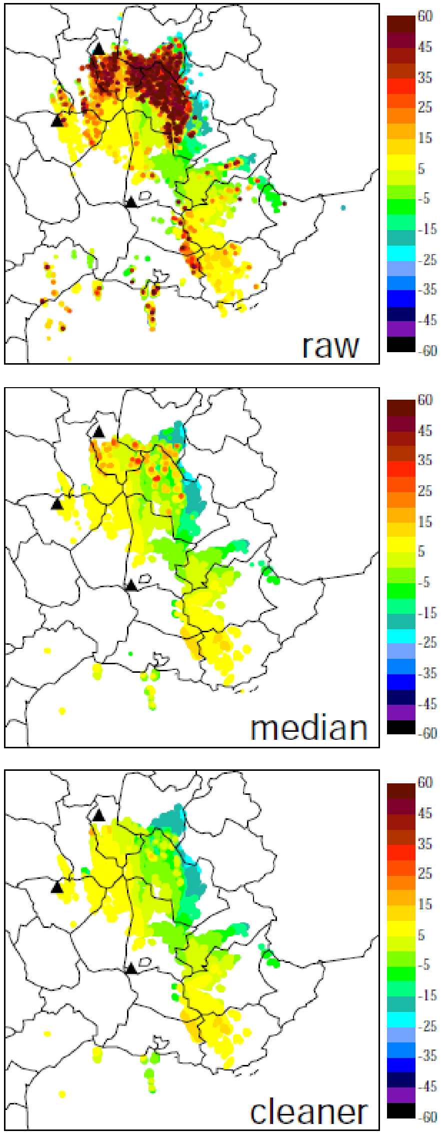


FIG. 2. Example of radial velocities from the first elevation performed by the BOLL radar (Fig. 1): raw data (top) and after the application of median (middle) and cleaner filters (bottom). Positive velocities point towards the radar.

Averaging the data: temporally

Ground-based GPS

- Time-averaging of observations, 30 to 60 minutes.
  - Poli et al (JGR, 2007),
  - McPherson, Deblonde, Aparicio (MWR, 2008)

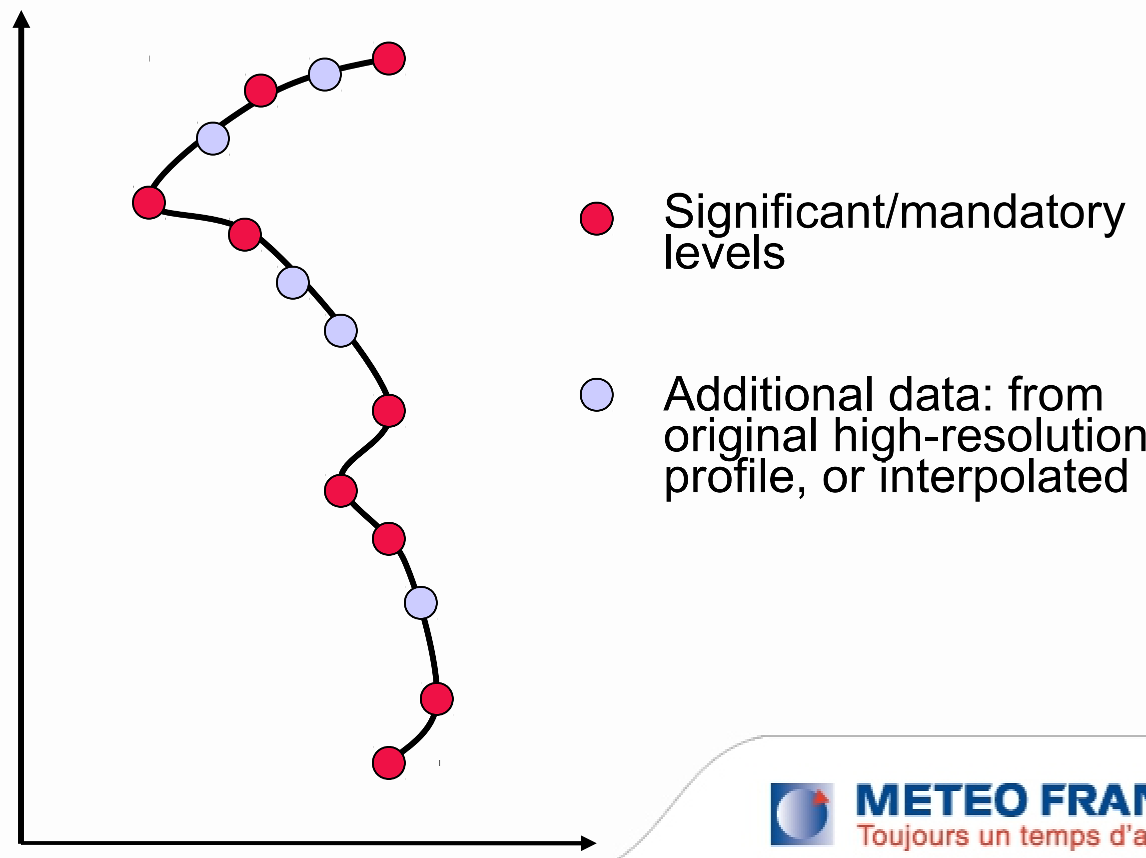
Radar data

- NCEP Stage IV radar and gauge precipitation data at ECMWF
  - Hourly data, but 6-hourly accumulations perform better
  - Correlation between departure computed in full trajectory (T799, full physics) and in first minimisation (T95, simplified physics): 0.2 to 0.7
  - 6-hour = compromise between linearity and observation usage over the 4D-Var 12-hour window (Lopez, MWR, 2011)

From the raw data to observations

Vertical choice of data for conventional observations: radiosondes

- Usually selecting all levels
- Interpolating between significant and mandatory levels (Benjamin et al, MWR, 2004)
- In the future, vertical averaging for radiosonde high-resolution profiles ?



From the raw data to observations

- New challenges: transforming hyperspectral sounder data
- Channel selection for IASI (Collard, QJRMS, 2007)

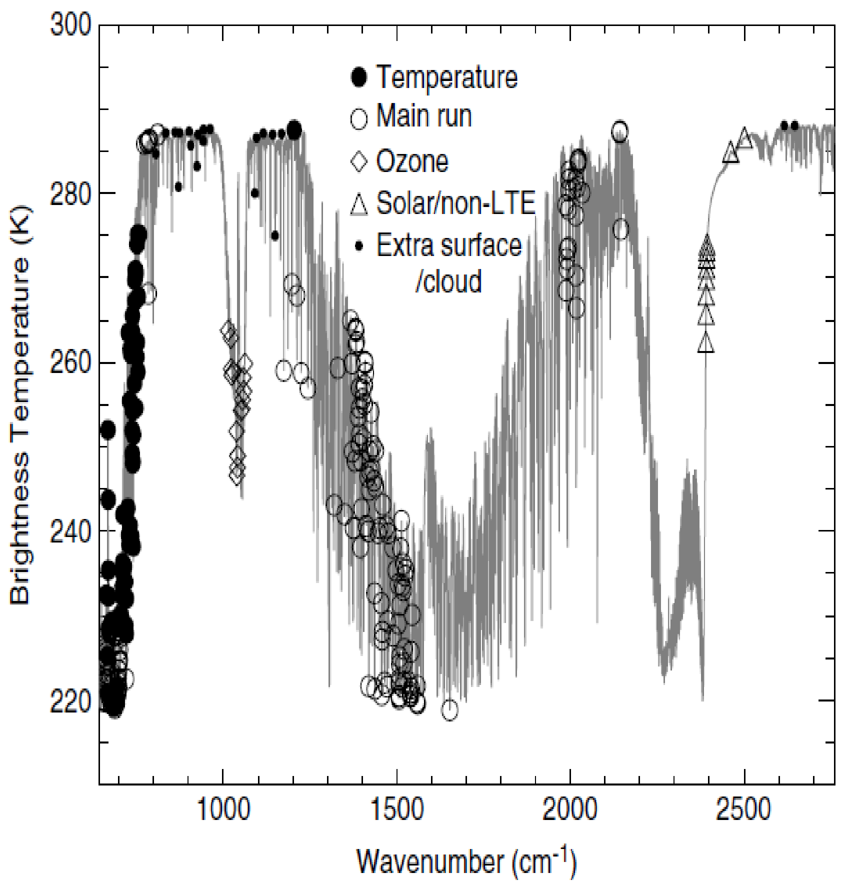


Figure 5. The 300 channels chosen with the methodology described in the text.

Based on the information content

- Test which channel most improves DFS= $tr(I-AB^{-1})$
- Update the optimal A matrix
- Choose the next best channel
- ….

From the raw data to observations

Principal component compression (Collard et al, QJRMS, 2010)

PCs computed from a large set of spectra $C = 1/n\, XX^T = L \Lambda L^T$

Principal component amplitudes related to observed radiances $p = L^T y$

Around 200 PCs required to represent signal, rest is noise

Using leading PCs efficient for Data transfer and noise filtering

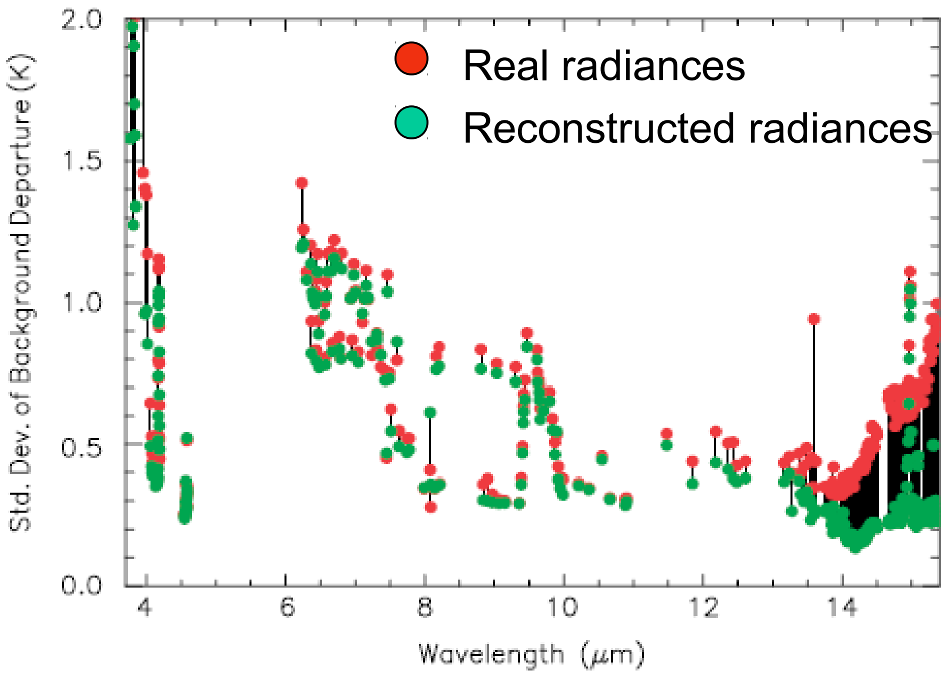


Figure 8. A comparison of the standard deviations of clear-sky departures from the same model background for real (dark/red) and reconstructed (light/green) radiances. Significant 'denoising' is seen in the 15 μm band where instrument noise is dominant over model error. One channel, at 8.07 μm, has an apparent increase in departure standard deviation, but this is an artifact arising from the cloud detection scheme. This figure is available in colour online at wileyonlinelibrary.com/journal/qj

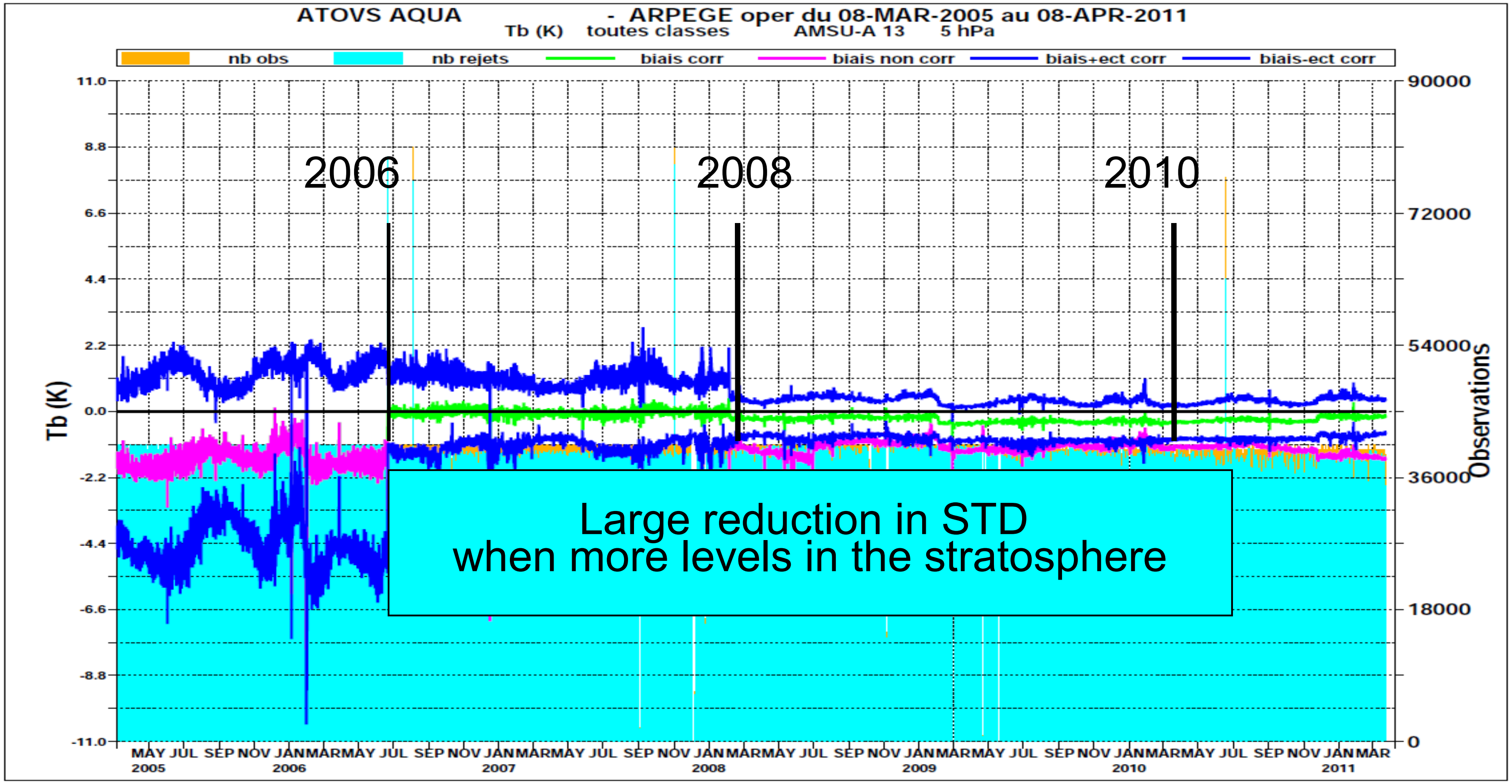
Monitoring and choice of relevant obervations

Change in vertical resolution: better fit to high-peaking channels,AMSU-A ch 13

2006: Change from 41 to 46 levels: 5 more channels up to 0.05hPa

2008: Change from 46 to 60 levels: more channels in stratosphere.

2010: Change from 60 to 70 levels: more channels in troposphere



Bénichou pers comm

Monitoring and choice of relevant obervations

Choice of relevant observation: example of precipitation threshold at JMA

In Honda and Yamada (SOLA, 2007):

Radar rain-gauge data assimilated in 4D-Var with simplified cloud microphysics

Exp A: no radar Rain-gauge data

Exp B: 1-hour rain > 0.5mm

ExpC: 1-hour rain > 0mm

Including more data can remove spurious precipitation

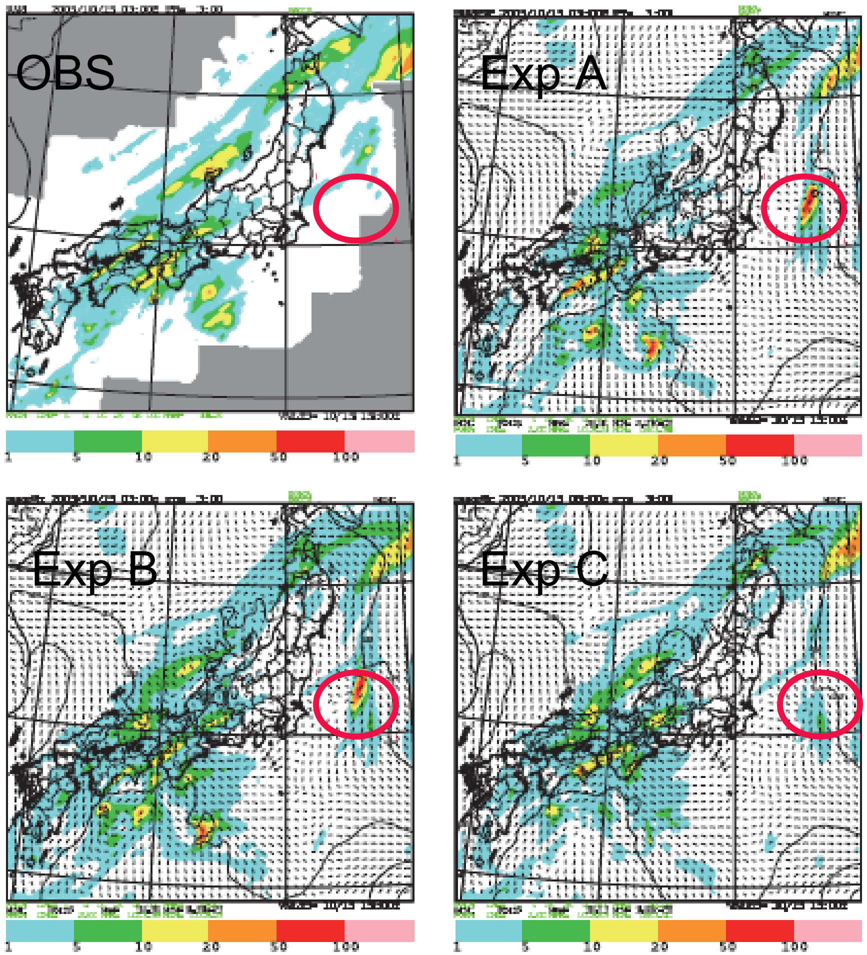


Fig. 3. The 3 hourly precipitation from 03 UTC to 06 UTC on 2005/10/15. (left top) R/A precipitation data, (right top) analysis of Exp A, (left bottom) analysis of Exp B and (right bottom) analysis of Exp C.

Monitoring and bias correction

Part of the biases seen in monitoring is attributed to observations

Bias correction scheme: from simple to elaborate

GPS data: Bias correction simply based on averaged deviation from model

(Poli et al, JGR 2007), or on a 10-day running mean (McPherson et al, MWR, 2008)

Radiosondes: bias depends on a few factors

- Sonde type: Vaisala RS-80, RS-92, MODEM… sonde age
- Solar elevation: causes solar heating of the sensor
- Pressure level: the amount of solar radiation varies with pressure level
- Wetting of the radiosonde sensor in cloud can cause a wet bias at higher levels …

Nuret et al, JAOT, 2008: scattered sampling at Niamey during AMMA,

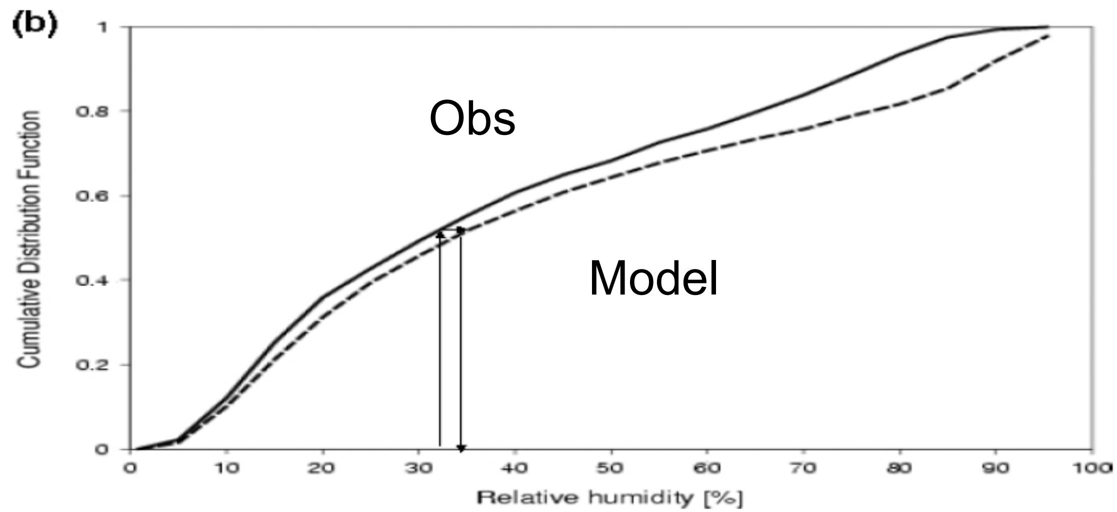
for RS-80A and RS-92. Bias correction of RS-80 based on RS-92

Monitoring and bias correction

Agusti-Panareda et al, QJRMS, 2009: bias-correction assuming the night-time RS-92 is bias-free, using the model as an intermediate

Refined correction takes into account the dependence of the bias on the observed humidity.

CDF matching, then fitting four-sine wave components of a Fourier series



$$
\begin{aligned}
BIAS(R_{\text{obs}}, P, \theta, s) = {} & \alpha_1 \sin[\frac{\pi}{100} R_{\text{obs}}(P, \theta, s)] \\
& + \alpha_2 \sin[\frac{2\pi}{100} R_{\text{obs}}(P, \theta, s)] \\
& + \alpha_3 \sin[\frac{3\pi}{100} R_{\text{obs}}(P, \theta, s)] \\
& + \alpha_4 \sin[\frac{4\pi}{100} R_{\text{obs}}(P, \theta, s)]. \quad (1)
\end{aligned}
$$

The bias correction is computed using Equation (1) by subtracting the bias function of the reference sonde (sonde type BUFR code $s = 79$) from the bias function of the sonde to be corrected. The corrected RH (R_{corr}) for an observed RH value (R_{obs}) is given by:

$$
\begin{aligned}
R_{\text{corr}}(p, \theta, s) = R_{\text{obs}}(p, \theta, s) - [& BIAS(R_{\text{obs}}, p, \theta, s) \\
& - BIAS(R_{\text{obs}}, p, \theta < 0, s = 79)]. \quad (2)
\end{aligned}
$$

Monitoring and bias correction

Radiances: a priori knowledge about the parameters affecting obs bias

Harris and Kelly (QJRMS, 2001) use scan-dependence and air-mass predictors

- Model thicknesses (1000-300hPa, 200-50hPa,…)
- Model surface temperature
- Model TCWV…

Regression coefficients are computed over a long time-series.

Can be adapted before each analysis off-line, or inside the assimilation (VarBC, see talk from John Derber)

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Removing wrong data

Each observation is subject to a variety of errors

- biases from calibration…
- random errors
- representativeness errors
- gross errors: instrument malfunction, transmission error…

Data with gross errors are useless

Need for a quality control step

Removing wrong data

Blacklist

based on monthly monitoring generally,

can also be dynamically updated, based on gross-error statistics from the previous analyses (De Pondeca et al, WAF, 2011)

Check for observation consistency

« **Buddy checks** »

Check with observation consistent with neighbours (Benjamin et al, MWR, 2004)

Estimate of the innovation at the observation point from the innovations of a group of nearby observations

If the difference between the estimated and observed innovations exceeds a threshold, the observation is discarded

Removing wrong data

Check with model « **First-guess check** »

Gross check tests based on the comparison of departures with error estimates

$(O-G)^2 < a\ (sigmao^2)$ (De Pondeca et al, WAF, 2007)

$(O-G)^2 < a\ (sigmab^2)$ (Benjamin et al, MWR, 2004)

$(O-G)^2 < a\ (sigmao^2 + sigmab^2)$ (Lorenc and Hammon, QJRMS, 1988)

$(sigmao^2 + sigmab^2)$ from accumulated statistics of departures (Cucurull et al, MWR, 2007),

or from the values used in the assimilation

Lorenc and Hammon. 1988

Gaussian

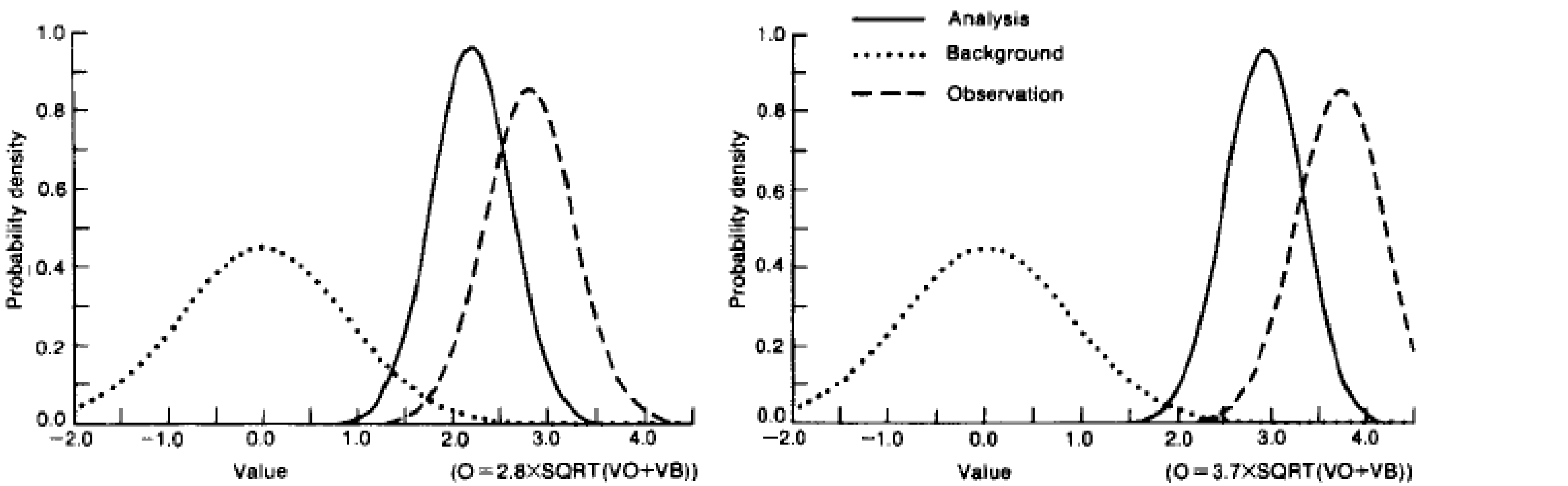


Figure 1. Probability density functions for background, observation, and Bayesian analysis, for four different observed values and a Gaussian observational error distribution.

Gaussian + Small constant

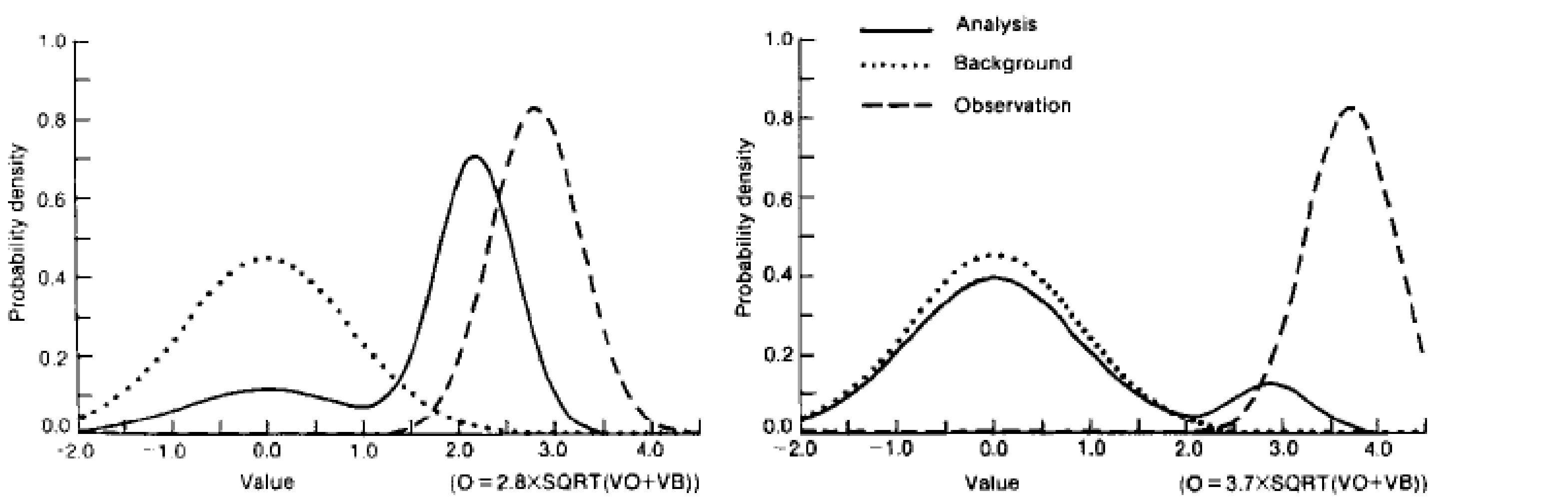


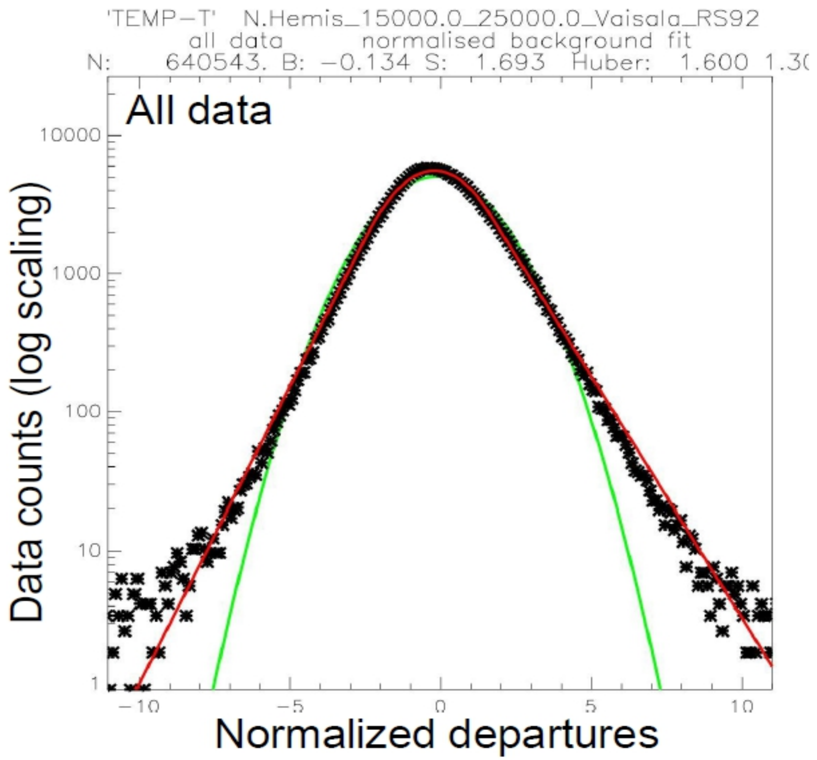
Figure 2. As Fig. 1 for an observational error distribution equal to a Gaussian plus a small constant.

Removing wrong data: combination of tests

Different norms can be used (ex : Huber norm at ECMWF)

to represent departure statistics inside the assimilation

and adapt the prior FG-check

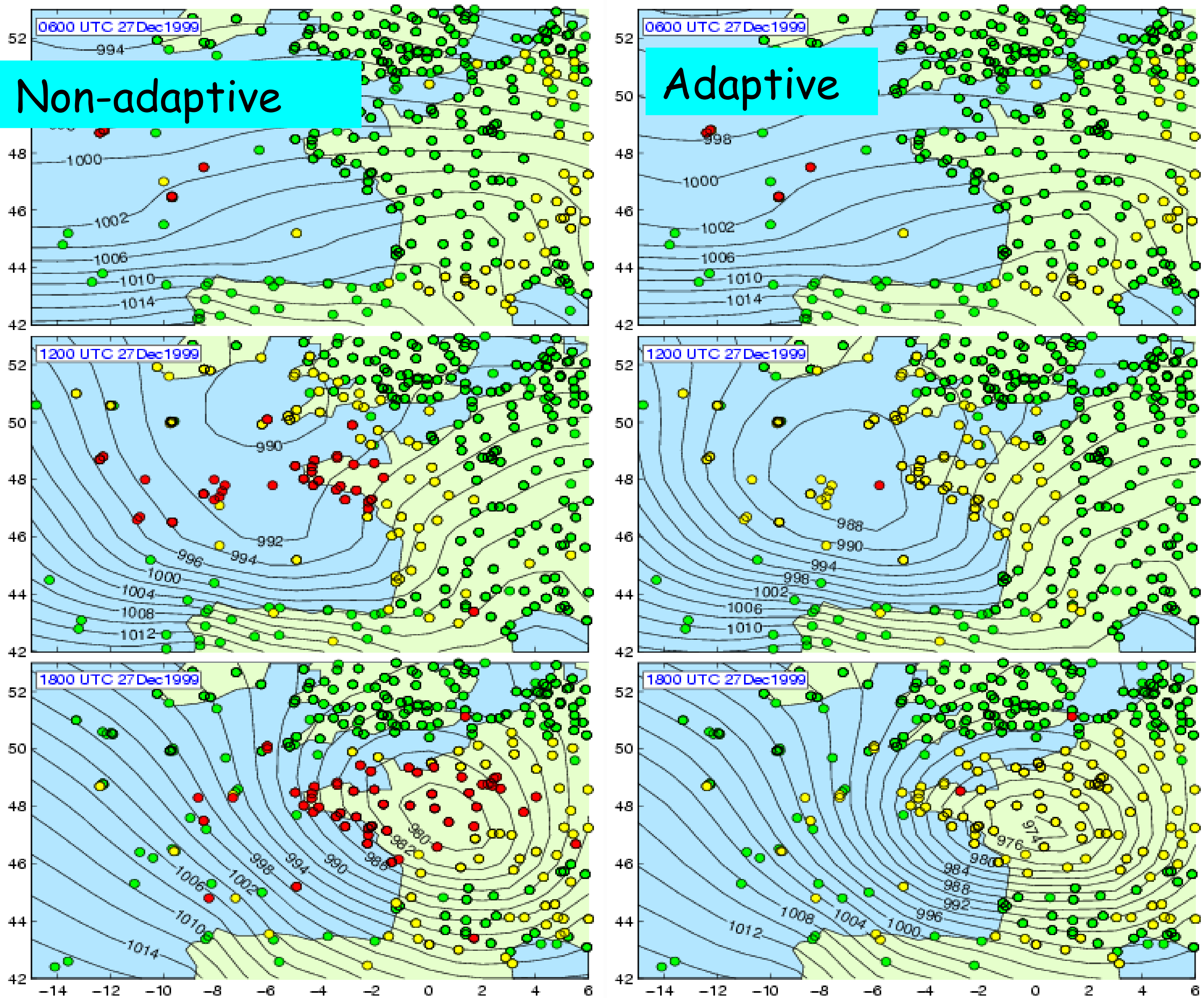


The pdf for the Huber norm is:

$$p(y\mid x)=\begin{cases}\dfrac{1}{\sigma_o\sqrt{2\pi}}\exp\left(\dfrac{a^2}{2}-\left|a\delta\right|\right) & \text{if } a<\delta\\[2ex] \dfrac{1}{\sigma_o\sqrt{2\pi}}\exp\left[-\dfrac{1}{2}\delta^2\right] & a\le\delta\le b\\[2ex] \dfrac{1}{\sigma_o\sqrt{2\pi}}\exp\left(\dfrac{b^2}{2}-\left|b\delta\right|\right) & \text{if } \delta>b\end{cases}$$

$$\text{where } \delta=\frac{y-H(x)}{\sigma_o}$$

Removing wrong data: combination of checks



Adaptive buddy check

flow- dependent tolerances for outlier observations

(Dee et al, QJRMS, 2001)

Dec 1999 storm

rejected by buddy check

passed buddy check

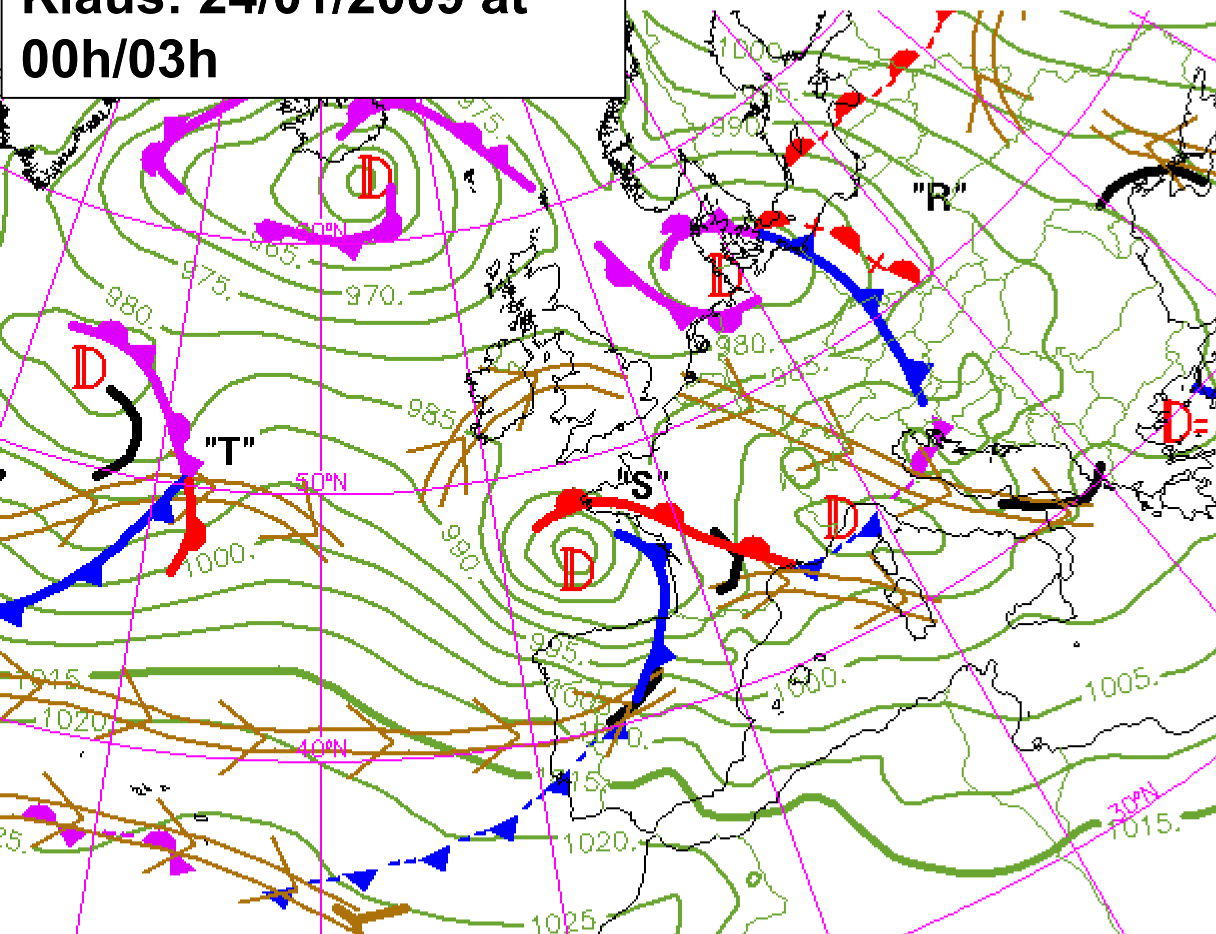
passed FG check

Removing wrong data Dependance on the errors of the day

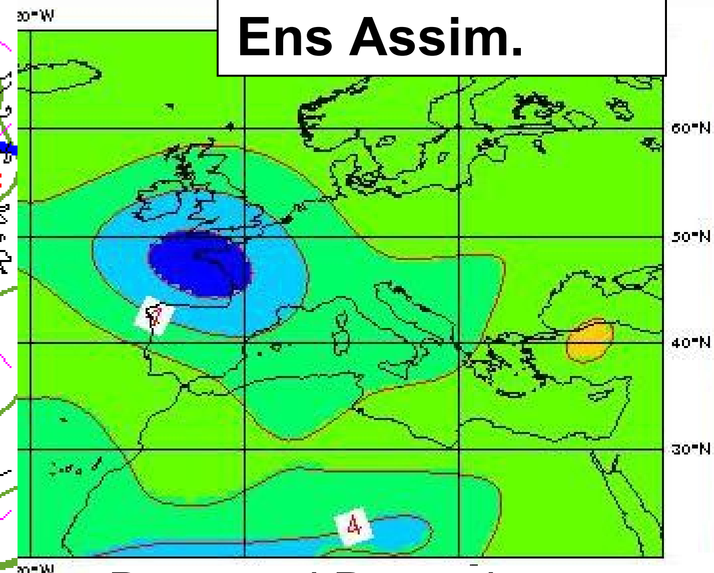
Errors of the day provided by the Ensemble Data Assimilation.

New operational applications (in 2008 at Meteo-France for example)

Klaus: 24/01/2009 at 00h/03h



Errors for 3-hr fcst from the Ens Assim.



Berre and Desroziers, pers comm

Thinning: Time thinning

Different analysis schemes use different temporal thinning of data

In 4D-Var, one groups observations in 30 or 60 minute time-slots and thin observations within each time-slot

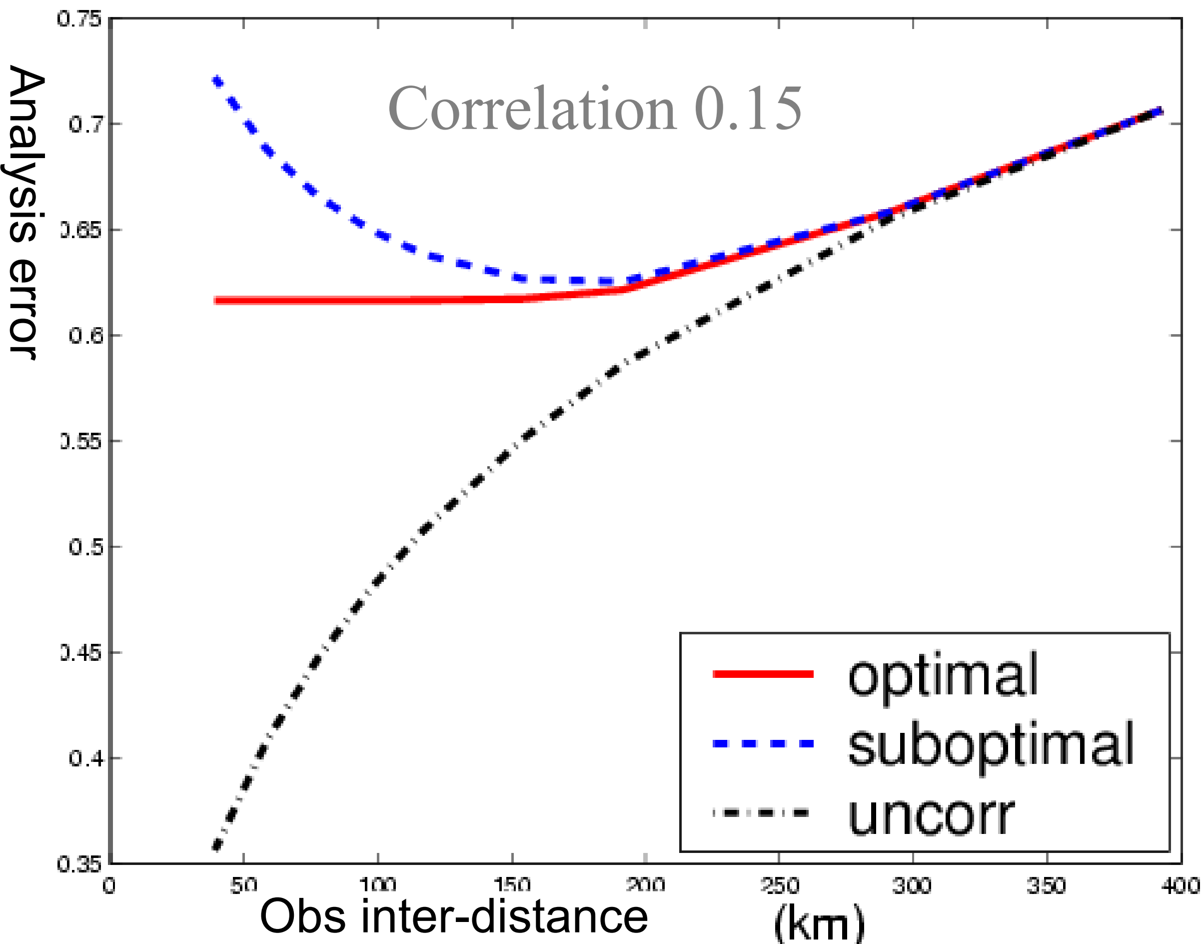
In 3D-Var, select data closer to central analysis time (ex: +/- 1.5 hour for aircraft data)

In non-cycled schemes, choice of data really representative of analysis time

ex for the hourly Real-time Mesoscale Analysis (De Pondeca et al, WAF, 2011), time window of –12 to +12 minutes

Horizontal thinning

For practical reasons, and avoiding obs error correlations not accounted for



Liu, 2002

Δx=100km, $\sigma_b=\sigma_o=1$

L_b=208km, L_o=100km

Optimal distance can be found

Evidence of error correlation exist in AMVs, radiances (Bormann et al, QJRMS 2003; Bormann and Bauer, QJRMS, 2010)

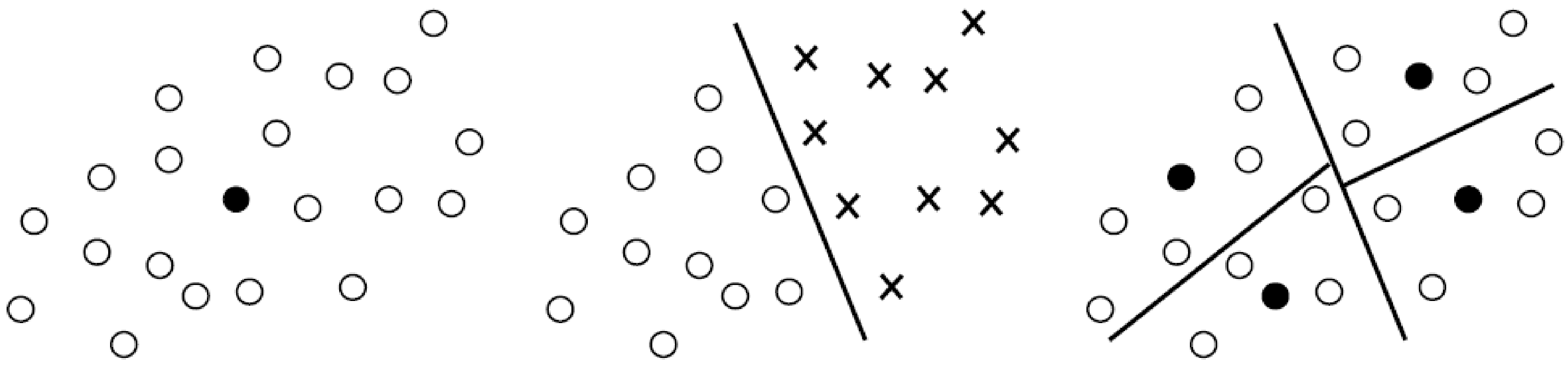
Horizontal thinning

Generally, simple thinning by lat-lon boxes, with choice by quality criteria

(distance to guess, Quality Indicator, small value of radial wind variance in the superobs, ma
number of elevations which pass QC in radar profiles…).

Adaptive thinning : Ochotta et al, QJRMS, 2005

- Observations representative of clusters are inserted iteratively
- Or, removal of the observations from the full set, by removing redundant data



(a) (b) (c)

Figure 1. Concept of top-down clustering. (a) Observations are grouped to a cluster with a cluster centre (filled dot); (b) when the associated cluster error is too large, the cluster is split up by Principal Component Analysis, providing two new clusters; (c) this procedure is repeated until all cluster errors are below a given threshold, $t > 0$. The set of centroids is the reduced observation set.

Horizontal thinning

Optimal thinning distance investigated in the Met Office NWP system

(Dando, Thorpe and Eyre, QJRMS, 2007)

Control: thinning distance of 308km. Optimal distances found : 100-150km.

Detrimental to use thinning at 40-km distance, especially in Tropics (weak gradients in the fields)

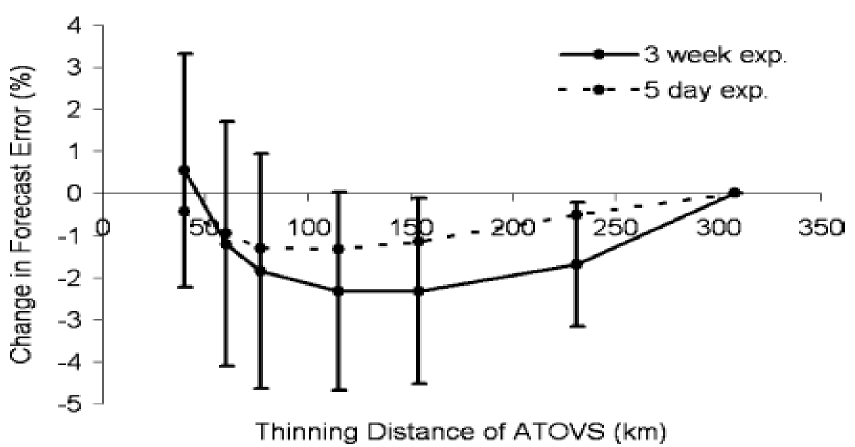


Figure 2. Change in the global average of the absolute forecast error, shown as a percentage of the control forecast error, versus the thinning distance of ATOVS. The percentage change is shown as an average over 3 weeks (solid line) and an average over 5 days (dashed line). The error bars are the standard deviations for the 3-week experiment.

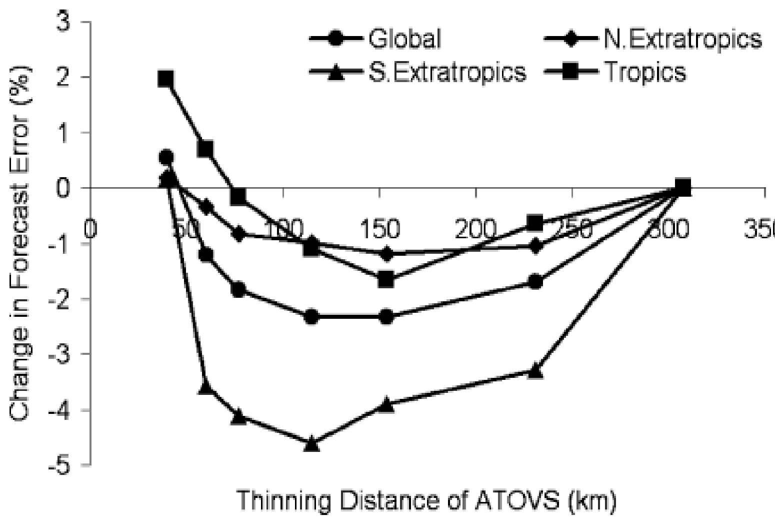


Figure 3. Change in the average absolute forecast error for different regions, shown as a percentage of the control forecast error, versus the thinning distance of ATOVS.

Horizontal thinning

Optimal thinning using Singular vector information in Southern Hemisphere at ECMWF (Bauer et al, QJRMS, 2010). Different configurations, two seasons (JAS, DJF):

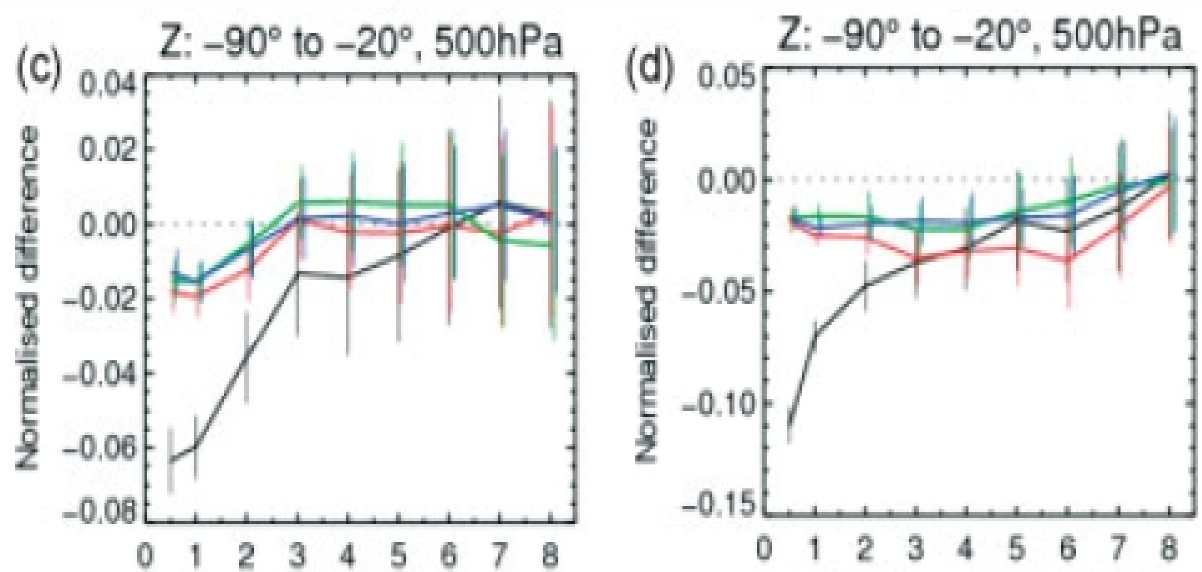
EXP: global density of 1.25°

EXP-HI: Global High-density 0.625°

EXP-SV: High-density only in SV areas

EXP-CLI: High-density in SV-based climatological regions

EXP-RND: High-density in random areas



Horizontal thinning

Radius of Influence in EnKF, Zhang et al, MWR, 2009

Radar data assimilation, 3 domains D1 (40km) to D3 (4.5km)

FIX1: ROI = 1215km for D1, D2, D3

FIX2: ROI = 405km for D1, D2, D3

FIX3: ROI = 135km for D1, D2, D3

CNTL:

ROI of 1215km for 10% of data in D1, D2, D3

Then ROI of 405km for 20% of data in D2, D3

Then ROI of 135km for 60% of data in D3

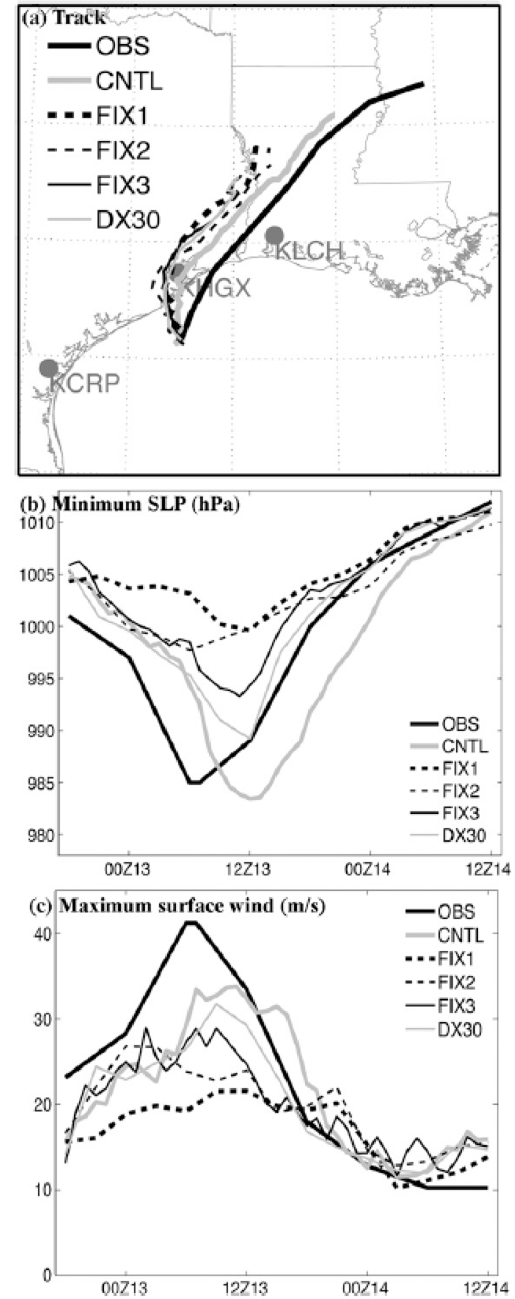
DX30:

ROI of 1215km in D1

Then ROI of 405km in D2

Then ROI of 135km in D3

Better performance of **CNTL and DX30**



Hurricane Humberto,

Forecast from 18UTC 12 Sep 2007

Post-processing: Filtering

The model can take time to adjust initial fields with respect to model equations. Dynamical adjustment by inertia-gravity waves, diabatic adjustment.

Ideally, balanced increments in the analysis (through B). There is also a possibility to include constraint terms inside the analysis (Gauthier and Thépaut, MWR, 2001).

Posterior filtering of the analysis is frequently performed.

Forces the initial state not to generate model tendencies that project onto high-frequencies model solutions

Different methods can be used:

DFI: Digital Filter Initialization (Lynch and Huang, MWR, 1990; Huang and Lynch, MWR, 1993)

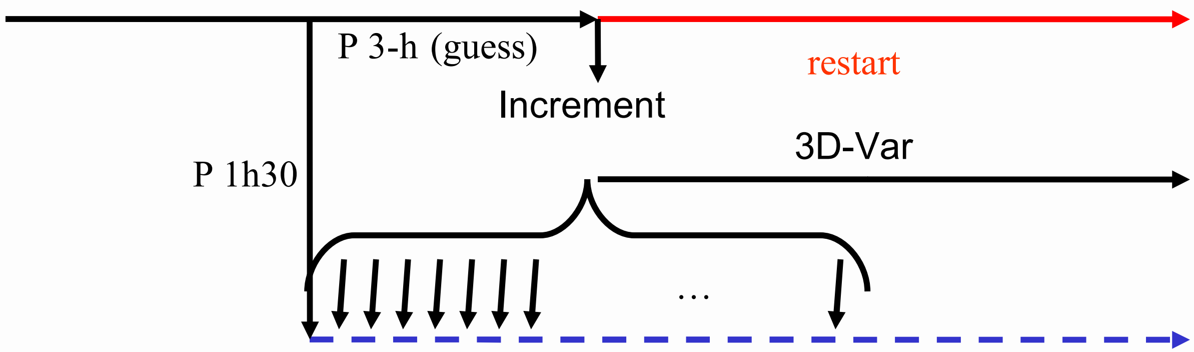
IAU: Incremental Analysis Update (Lorenc et al, QJRMS, 1991; Bloom et al, MWR, 1996)

Initialization methods

- DFI :
  - Backward integration in time by Ndt, then forward integration by 2Ndt
  - Time series X(n) is then filtered removing high frequencies
  - X*= sum h(-n)X(n) where h(n) are the filter coefficients
  - $h(n) = \{ \sin(n\Pi/(N+1)) / (n\Pi/(N+1)) \} * \{ \sin(n\theta_c) / n\Pi \}$
  - θ_c is the cutoff frequency

- IAU :

  3D-Var increment added gradually in the assimilation window



Incremental Analysis Update

Filtering

Imbalance depends on the quality of the analysis.

DFI applied to MM5 using either Cressman or 3D-Var analysis in Chen and Huang, MWR, 2006

DFI applied to both OI and 3D-Var versions of the RUC (Benjamin et al,MWR, 2004)

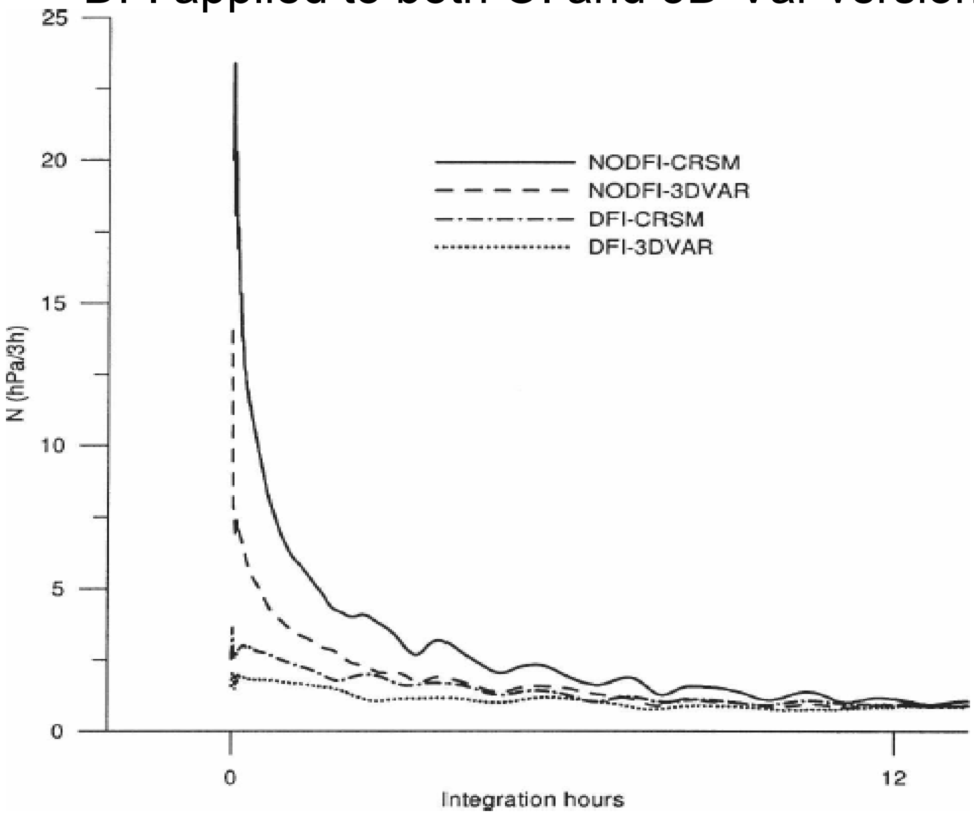


FIG. 8. The evolution of the mean absolute surface pressure tendency N [hPa (3 h)$^{-1}$] in the first 12-h forecasts averaged from 14 cycles from 0000 UTC 21 Aug to 1200 UTC 27 Aug 2002.

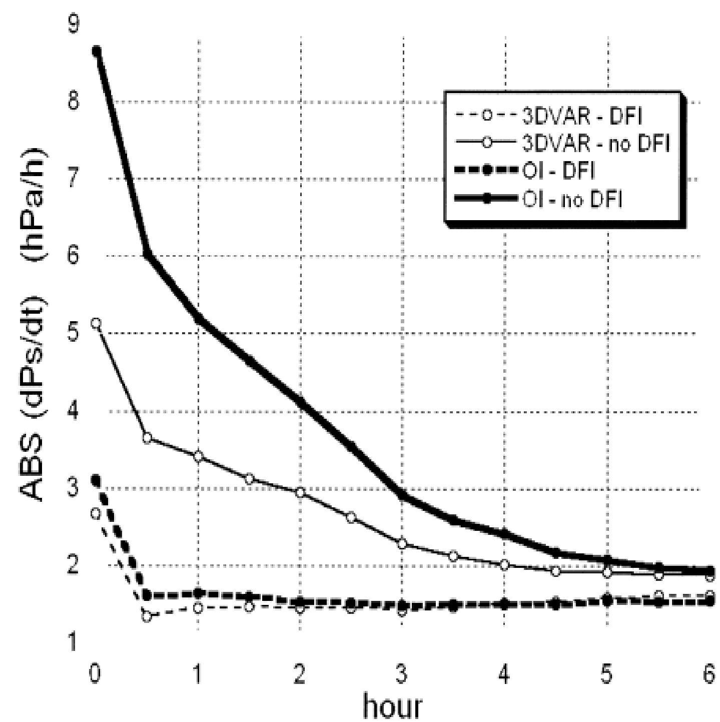


FIG. 2. Noise parameter over a single time step (30 s) in the RUC model with 3DVAR or OI analysis, both with and without application of DFI. For the case with initial conditions at 1200 UTC 19 Nov 2002, data points taken every 30 min of integration.

Filtering

Various flavours of DFI : diabatic versus adiabatic (Huang and Lynch, MWR, 1993), incremental versus non-incremental (Fischer and Auger, MWR, 2011)

Standard DFI: $X_a^* = DFI(X_a)$

Total increment for standard DFI is

$DFI(X_a) - X_b =$

$DFI(X_a) - DFI(X_b) - (X_b - DFI(X_b))$

The total increment is the sum of

a balanced increment and a

removal of the high frequencies in x_b

Incremental DFI:

$X_a^* = X_b + \{ DFI(X_a) - DFI(X_b) \}$

Total increment is $DFI(X_a) - DFI(X_b)$

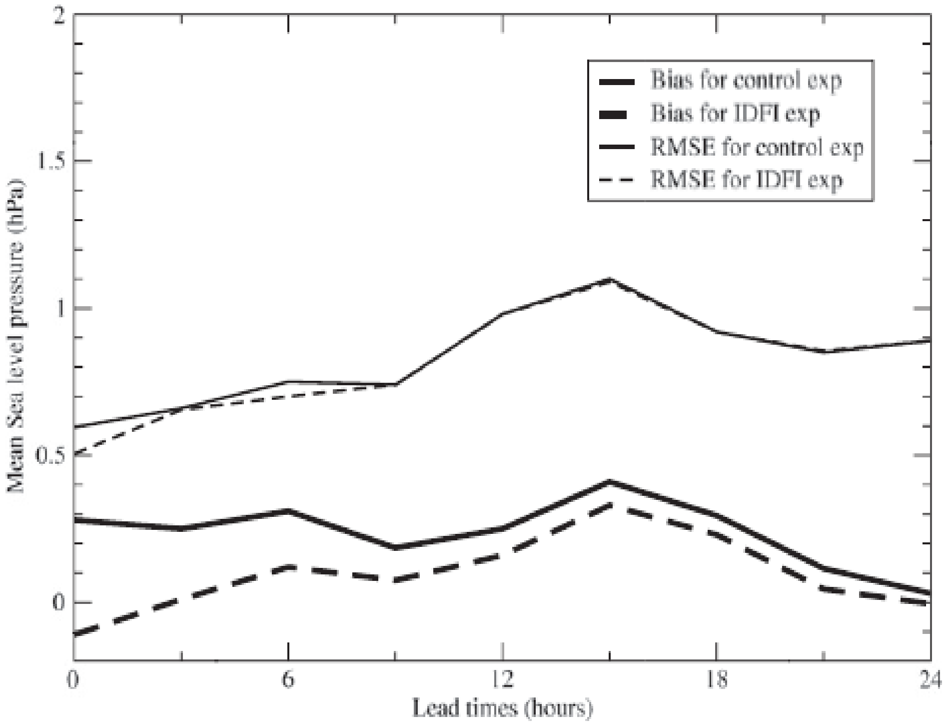
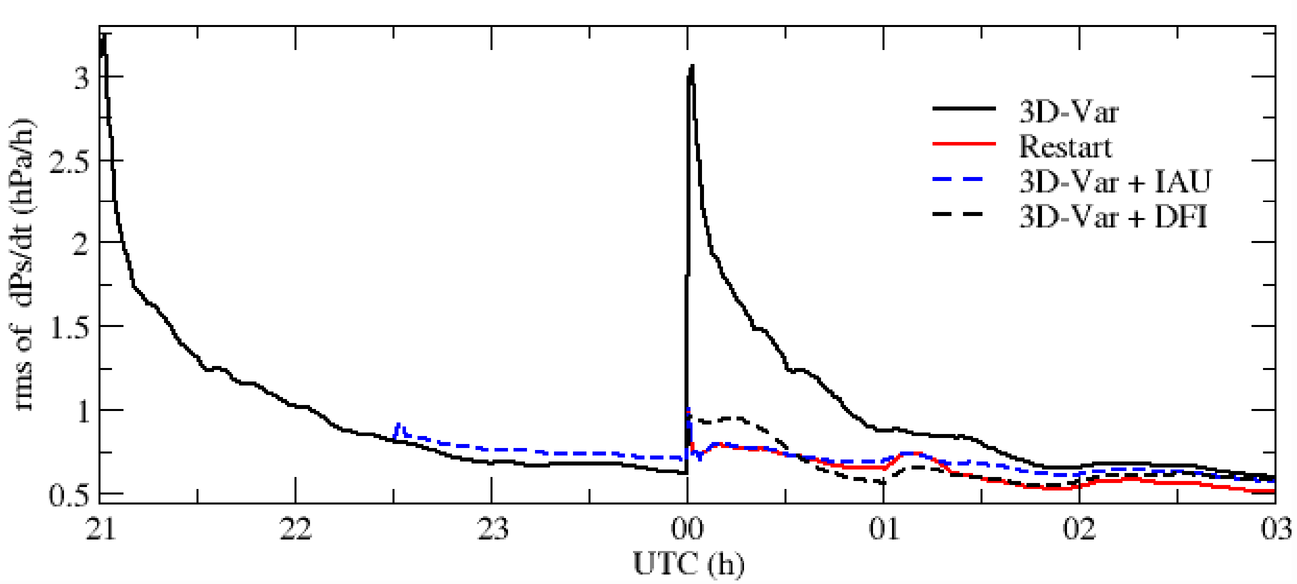


FIG. 3. Scores of biases (thick curves) and RMSEs (thin curves) of MSLP with respect to the French surface station network, for the operational ALADIN-France model (nonincremental DFI, solid lines) and for the test model (incremental DFI, dashed lines). Units are model lead times from 0 to 24 h, every 3 h (horizontal axis), and hPa (vertical axis). Note that lead time 0 corresponds to the initialized analysis.

Filtering for the assimilation cycle

Filtering not only for forecasts, but also for assimilation.

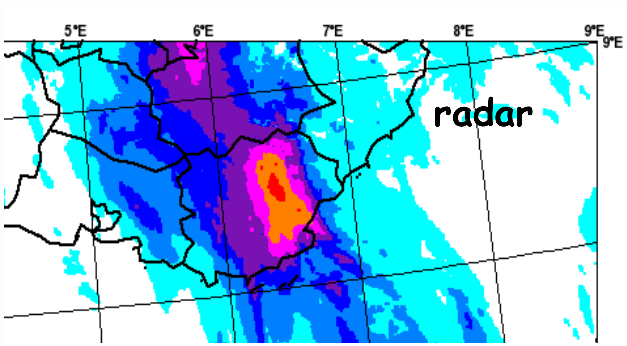
For rapid cycles, the assimilation cycle could be adversely affected by spurious waves



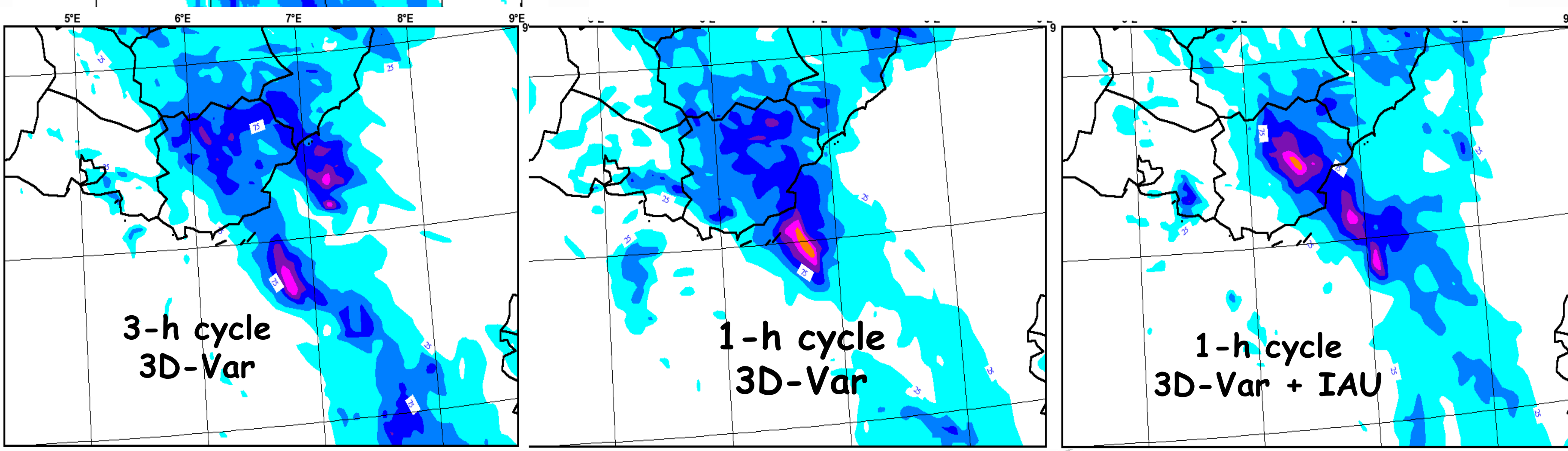
Brousseau, pers comm

Impact of initialization in AROME

Example of one precipitating event over SE France (Brousseau, pers comm)



- Date 15/06/2010 :
  - 3-h and 1-h cycling perform similarly
  - IAU improves location



Conclusion

Le Bon Dieu est dans le détail, Gustave Flaubert, 1821-1880

Or

The devil is in the details

METEO FRANCE
Toujours un temps d'avance