Impact of PCA on the assimilation of hyperspestral infrared sounder data in the frame of the AROME mesoscale convection-permitted NWP model

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CNRM, Météo-France and CNRS

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dépasser les frontières

Outline

CNRS dépasser les frontières METEO FRANCE

Evolution of IR sounders

Instrument	Year	Sat.	Channels	Spec. resolution

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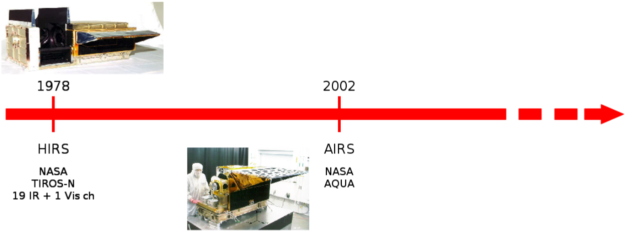

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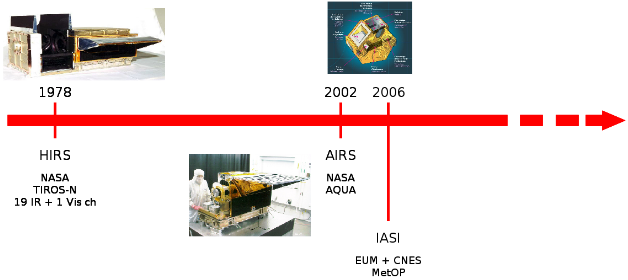

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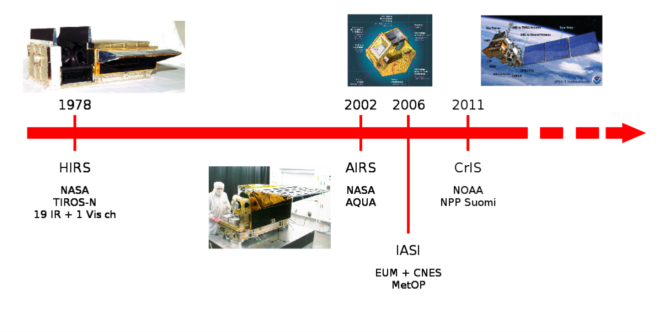

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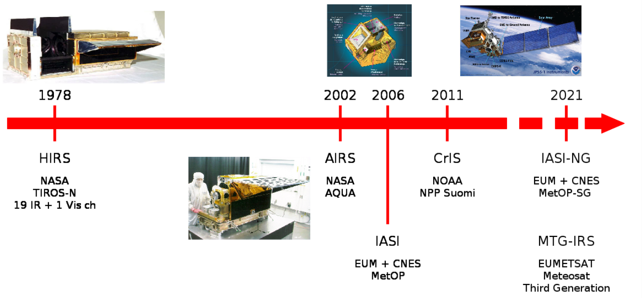

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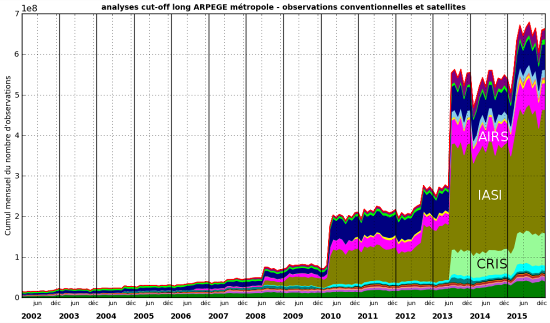
IASI-NG	2021	Metop-SG	16,921	0.125 cm^{-1}
IRS	2021	MTG	1,738	0.625 cm^{-1}

Use of IR data in NWP models

Data from IR sounders are the most used by NWP models in terms of number



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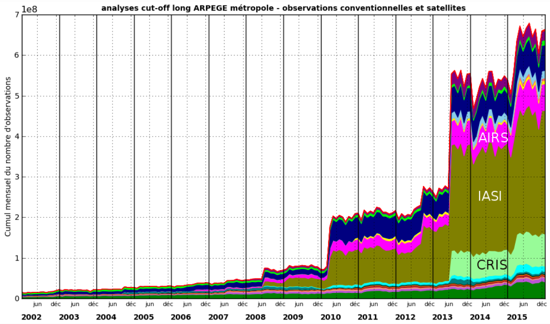

This tendency will continue with the arrival of new hyperspectral IR sounders, above everything IRS

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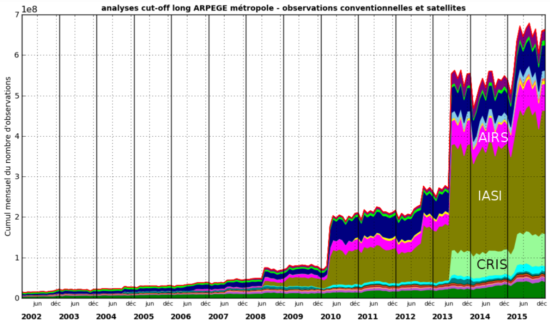


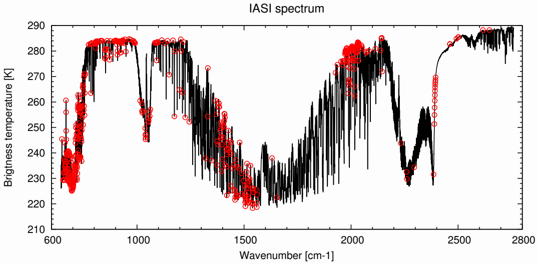
	IASI	MTG-IRS
Spectral sampling	$0.25\ \text{cm}^{-1}$	$0.625\ \text{cm}^{-1}$
Samples per spectrum	8,461	1,808
Spatial sampling at nadir	12 km	4 km
Samples per hour	54,000	$8.0\ 10^{6}$
Estimation of data volume	0.92 GB/h	28 GB/h

(Atkinson, 2013)

Consequences of the huge data volumes

- Atmospheric profiling errors are improved
- More chemical compounds can be profiled

- Data dissemination becomes impossible (costs) and data storage needs explode
- Inter-channel redundancy becomes more and more important. NWP center keep just 500 IASI channels from the 8461



There is a need to reduce the data volume...

Why not to compress the data?

Compression types definitions (from Atkinson, 2013):

- Lossless
  - Exact reconstruction of the input (with machine precision)
- Near-lossless
  - Input reconstruction with a maximum defined error
  - Error typically a defined (small) fraction of instrument noise
  - Example: digitisation error (or quantisation error)
- Lossy
  - e.g. compression algorithms for images (jpeg, etcetera)
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For IASI, the best performances were obtained using PCA plus residuals quantisation

The PCA compression technique

PCA definition

PCA allows the reduction of the dimensionality of a problem by examining the linear relationship between all the variables contained in a multivariate dataset

- The original set of correlated variables, y^{obs}, is replaced by a smaller number of uncorrelated variables called principal component scores (PCS, x^{pcs}). A corresponds with the eigenvectors matrix:

$$x^{pcs} = A * y^{obs}$$

- To return to the original space it is only need to make the following multiplication:

$$y^{pcs} = A^T * x^{pcs}$$

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$$y^{obs} = A * x^{pcs} + residuals = y^{pcs} + residuals$$

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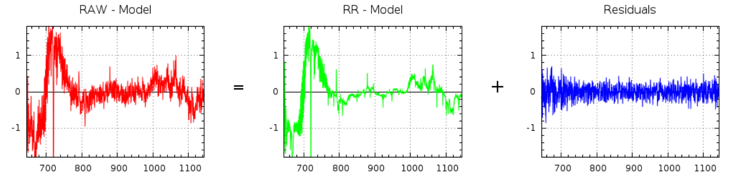


PC scores and quantised residuals

proposed by Tony Lee and Steve Bedford (2004), slide from Atkinson (2013)

It is a lossy compression, but most of the "loss" is noise

1. Noise-normalised radiance: $y = \frac{r - y_0}{n}$

   y Normalised radiance
   r Observed spectrum
   n Noise
   y_0 Mean

2. PC Score (integer): $s = NINT(\frac{E^T y}{f_s})$

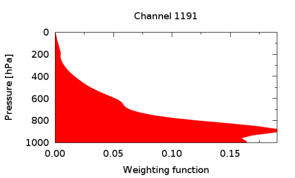
   s PC score
   E^T Eigenvectors matrix transposed
   f_s Quantisation factor, typically 0.5

3. Residual (integer): $\Delta y = NINT(\frac{y - f_s \, E \, s}{f_r})$

   f_r Noise quantisation factor, typically 0.5. Gives 1% noise increase

An example of PCA compression for a single channel. . .

IASI channel 1191, @942.5 cm^{-1}
$\Rightarrow$ Surface channel



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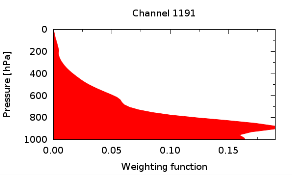
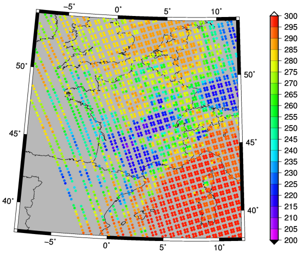
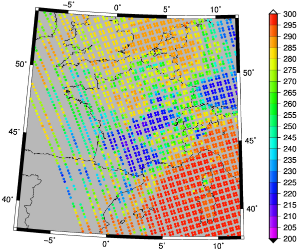


Afternoon IASI overpass the 20130806



IASI raw radiances (RAD)



IASI reconstructed radiances (RR)

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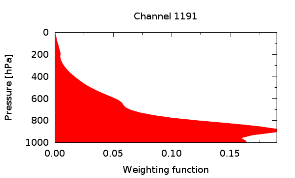

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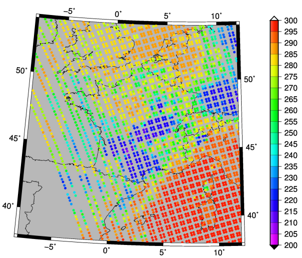

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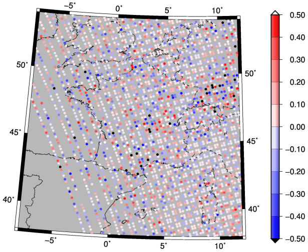
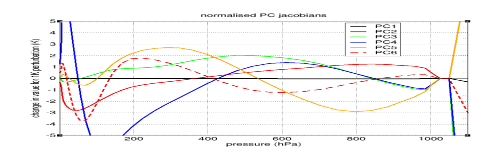


Differences in BT,
Not in radiances!!!

How can we assimilate PCA compressed data

1. We can use reconstructed radiances from PCs. . .
   - + No much work to adapt current assimilation systems
   - + Channel noises are filtered by PCA
   - - Interchannel correlations are heavily increased (and we use a diagonal R matrix. . .)

2. We can assimilate PCs directly
   - + We can use all the information registered in the observation
   - - More difficult to understand. PCs are a mathematical representation
   - - Some PCs Jacobians present structures peaking low and high in the atmosphere ⇒ What happen for low-top models?



(Figure from McNally (2013))

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Outline

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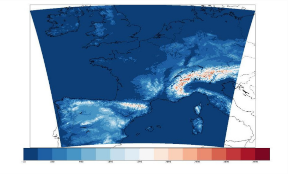
AROME is the operational convective scale non-hydrostatic limited area Numerical Weather Prediction (NWP) model used at Météo France



	AROME-OPER	AROME-EXP
Mesh grid	1.3 km	1.3 km
Assim. cycle	1h	3h
Levels	90	60/90L
Model top	10 hPa	1/10 hPa
IASI px assim	1/8	all
IASI ch assim	44	up to 123? / 44

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METEO FRANCE

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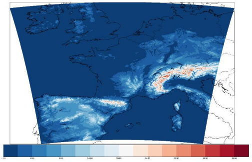

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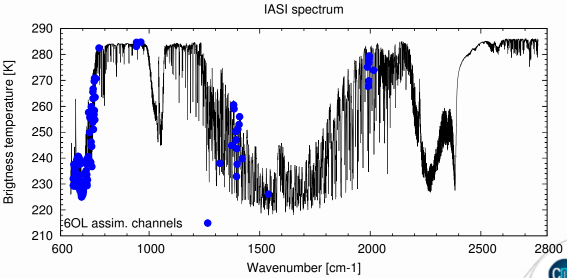

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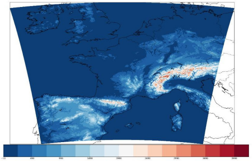

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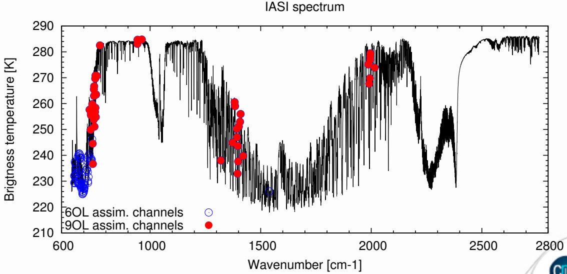

And what have we done...

- Impact on a low-top model: Old and New AROME vertical resolutions have been chosen to test
- Assimilation of both RAD and RR IASI EUMETSAT data

Lvls. / Obs.	RR	RAD
90L	B5MJ	B5ML
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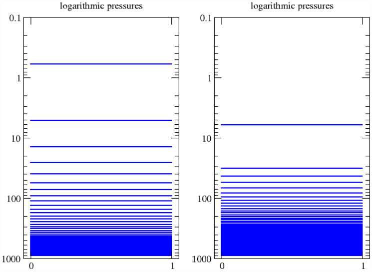

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- Preliminary analysis of this experiments (last results obtained last Thursday). Final results will be preented in the next IASI conference (Antibes, April 2016)

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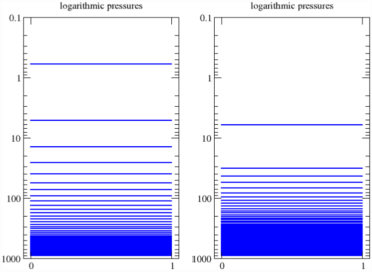

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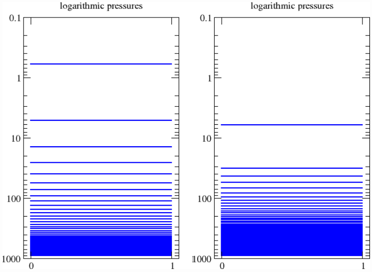

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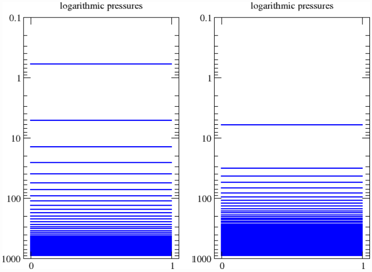

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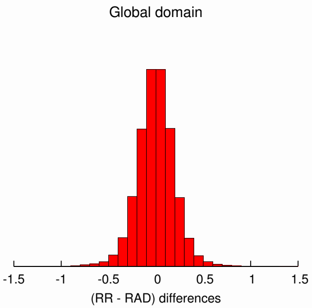
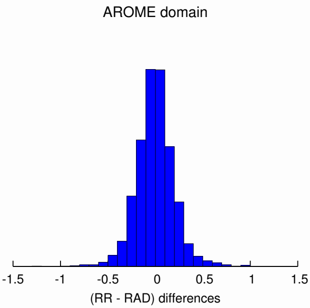
Can we use IASI PCs product?

EUMETSAT IASI PCs product was generated using a global domain. Is this product valid for a regional model?

$\Rightarrow$ RR-RAD Differences for 1191 channel (942.5 cm-1)





Domain	Number	Average [K]	Std.Dev. [K]	Min. [K]	Max. [K]
Global	91631	-0.001396	0.1959	-1.5433	1.5420
AROME	2665	-0.001701	0.1965	-1.2299	0.9513

NWP models assimilate IR clear channels...

And what is a clear channel. . .

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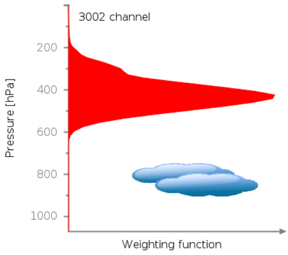

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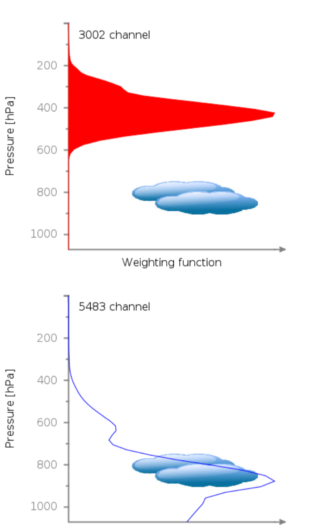

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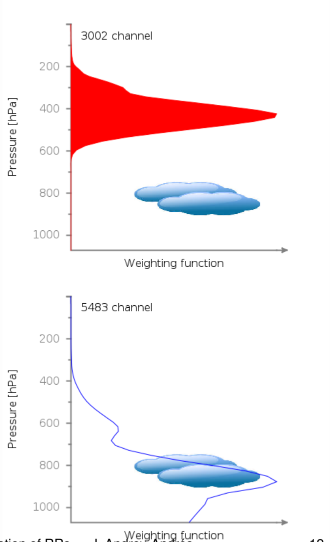

The algorithm to detect cloudy channels comes from McNally&Watts (2003)

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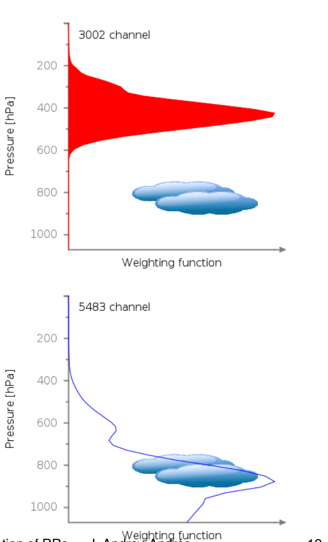

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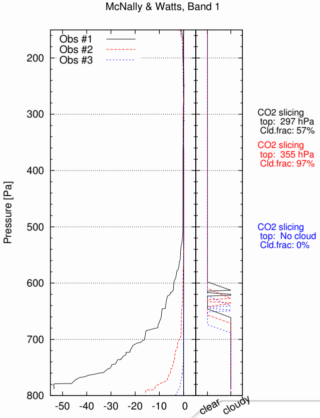
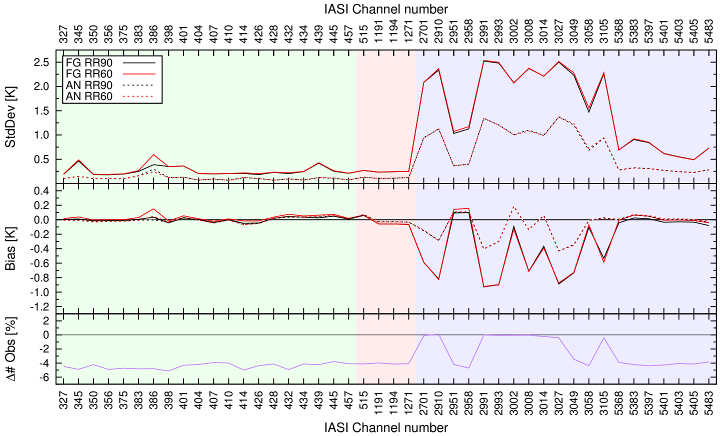


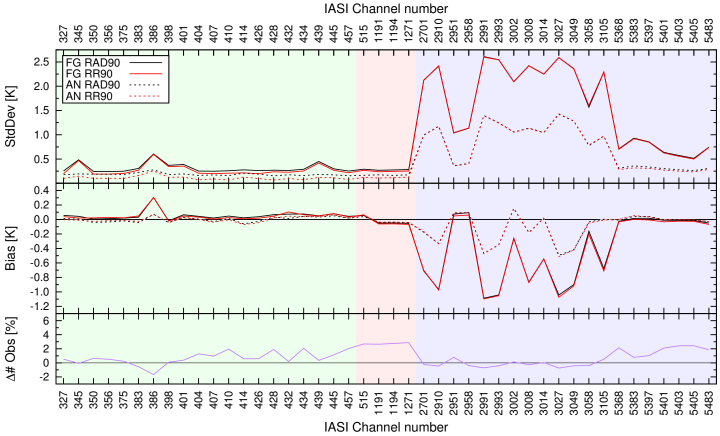
Outline

Used IASI observations

Impact of lowering the model top

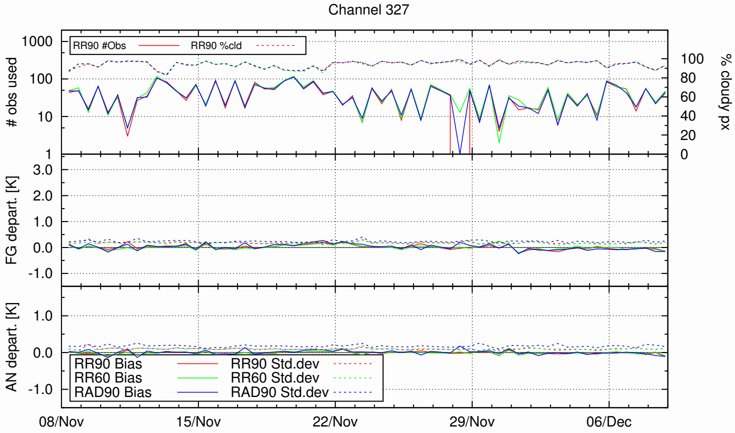


Impact of assimilate RR instead of RAD



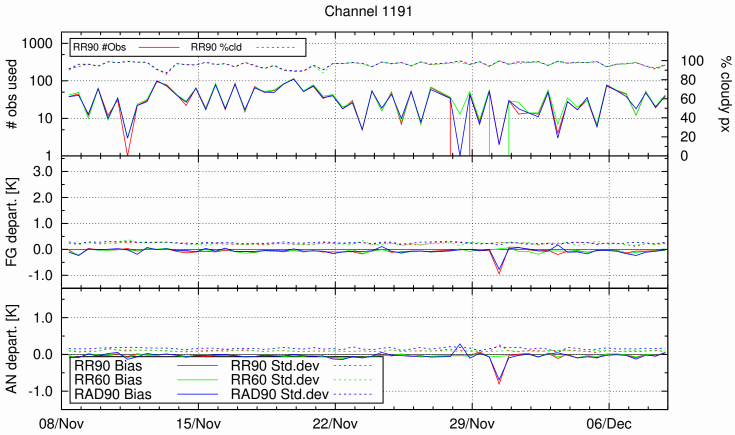
Temporal evolution of assimilation statistics - ch 327

Weighting function peaking at 825 hPa



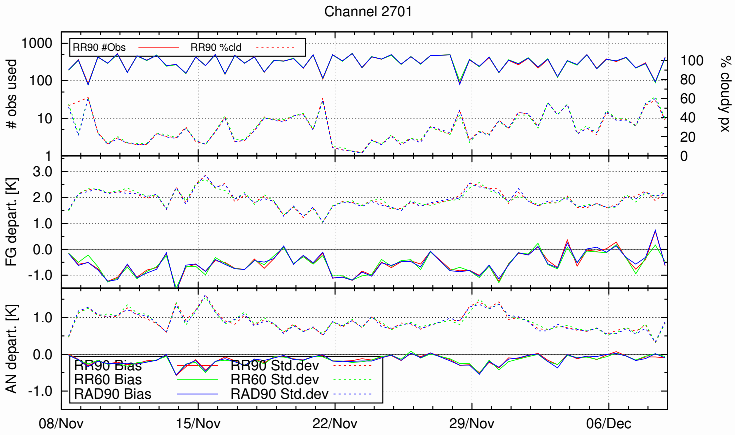
Temporal evolution of assimilation statistics - ch 1191

Surface channel



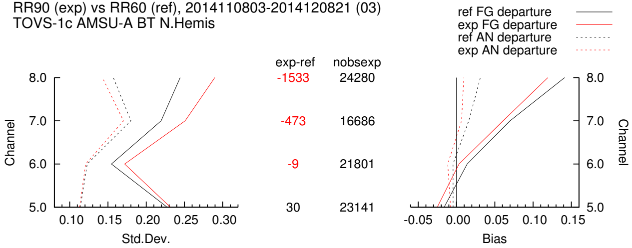
Temporal evolution of assimilation statistics - ch 2701

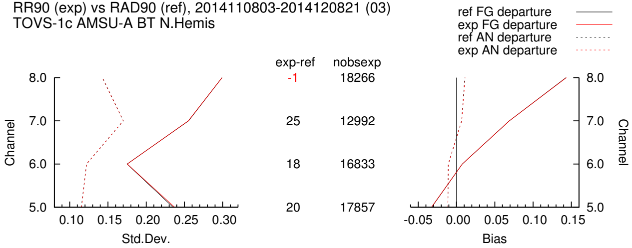
Weighting function peaking at 440 hPa



Impact in other satellite observations (I)

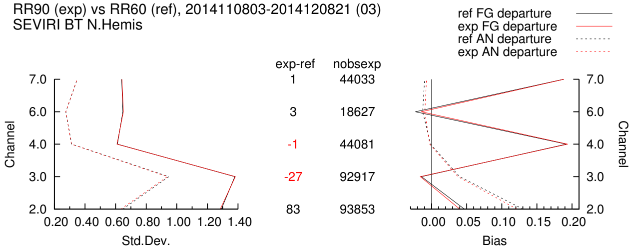
AMSU-A

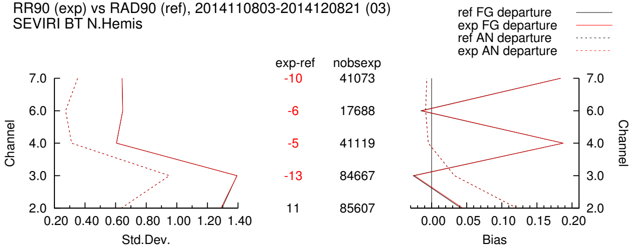




Impact in other satellite observations (II)

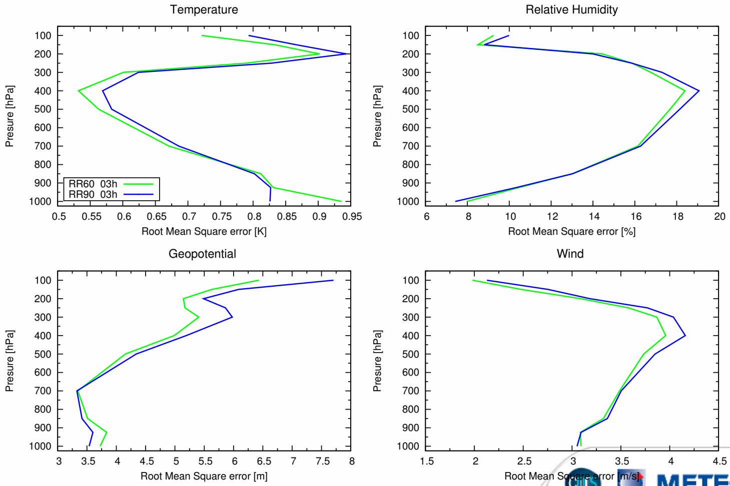
SEVIRI





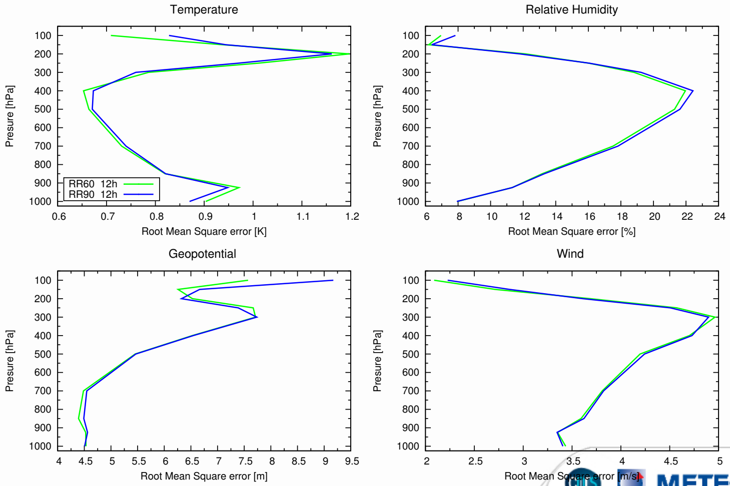
Scores: low-top impact (RR90 vs RR60), 3h terms

RMS of forecasted vertical profiles against a reference (PAROME) at different forecast terms



Scores: low-top impact (RR90 vs RR60), 12h terms

RMS of forecasted vertical profiles against a reference (PAROME) at different forecast terms



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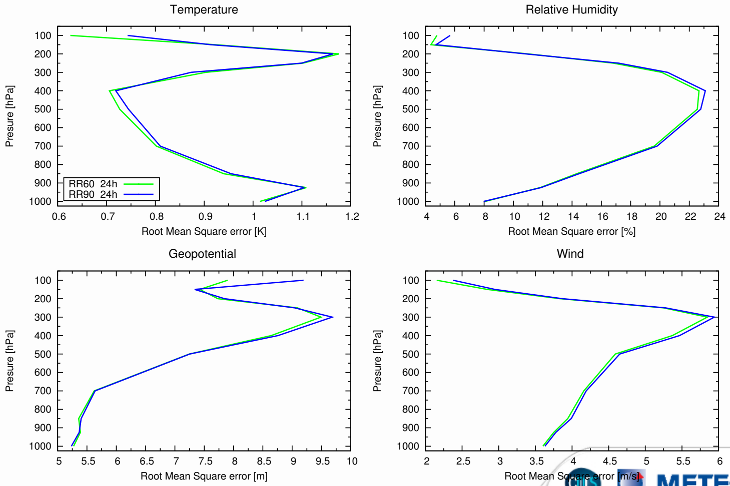
Scores: low-top impact (RR90 vs RR60), 24h terms

RMS of forecasted vertical profiles against a reference (PAROME) at different forecast terms



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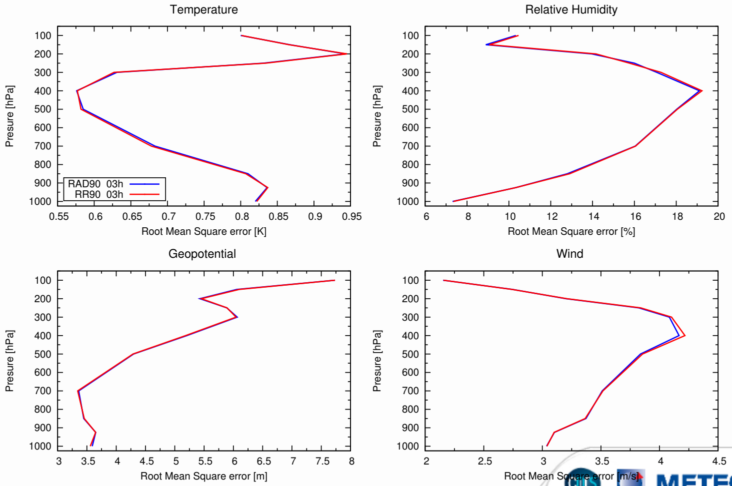
Scores: RR impact (RR90 vs RAD90), 3h terms

RMS of forecasted vertical profiles against a reference (PAROME) at different forecast terms



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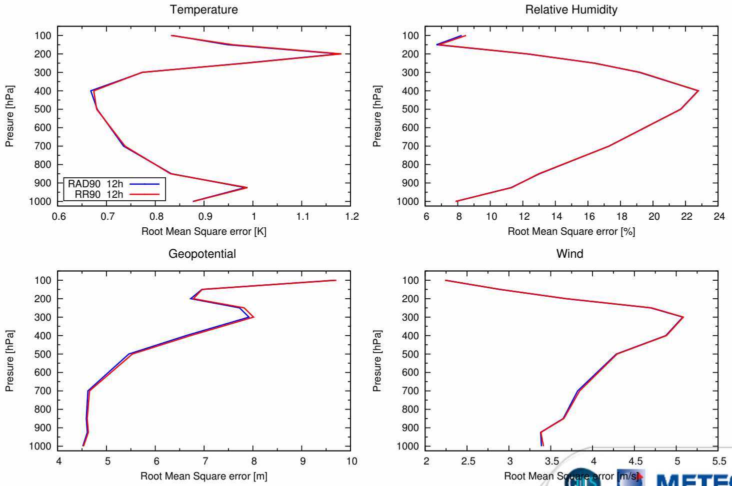

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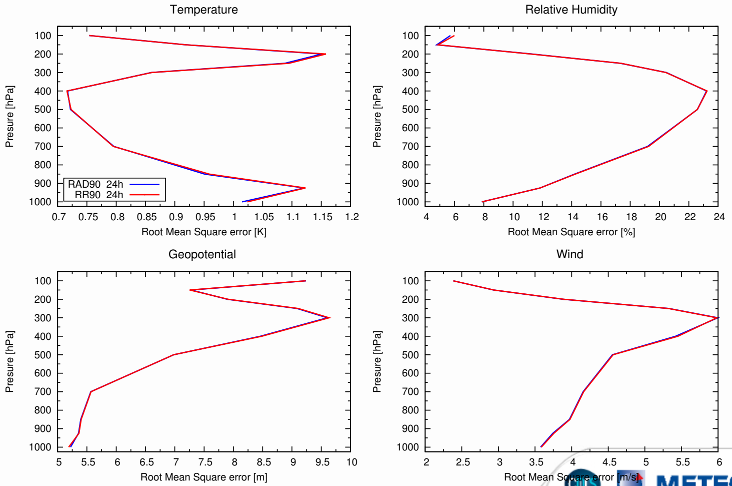

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Outline

Direct assimilation of PCs

- A new dataset of full IASI spectra is being grabbed at MF
- A PCs dataset will be generated using RTTOV eigenvectors (need of an adapted-to-PCs RT model)
- Preliminary 1D-VAR experiments will be carried out to asses the impact of having a low-top model
  $\Rightarrow$ A few days at MetOffice (wih P. Weston) for NWPSAF 1D-Var software modification
- Modification of AROME *bias correction*, *screening* and *minimization* steps to work with PCs instead of RAD
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Conclusions

- Different studies are being carried out at MF to work in the assimilation of IR hyperspectral PCA compress data in a low-top non-hydrostatic mesoscale model
- Impact of having lowered the AROME model top has been also investigated
- There are two different possibilities to assimilate IR hyperspectral PCA compress data: RR and PCs
- Assimilating RR is as simple as assimilating RAD but meanwhile channel noise is reduced interchannel correlation is increased
- Preliminary results present almost non differences between two assimilations (Using a diagonal R-matrix RAD bias correction from ARPEGE, and same channel selection!!!)
- To assimilate PCs requires an adapted RT model
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Thank you for your attention

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Main « IASI » updates in Météo-France global model