# Assimilation of reconstructed radiances in the AROME mesoscale convection permitted model

J. Andrey-Andrés, V. Guidard and N. Fourrié
IASI conference, Antibes, 13/04/2016

# Outline

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# Evolution of IR sounders

| Instrument | Year | Sat. | Channels | Spec. resolution |
|---|---|---|---|---|

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HIRS

NASA
TIROS-N
19 IR + 1 Vis ch

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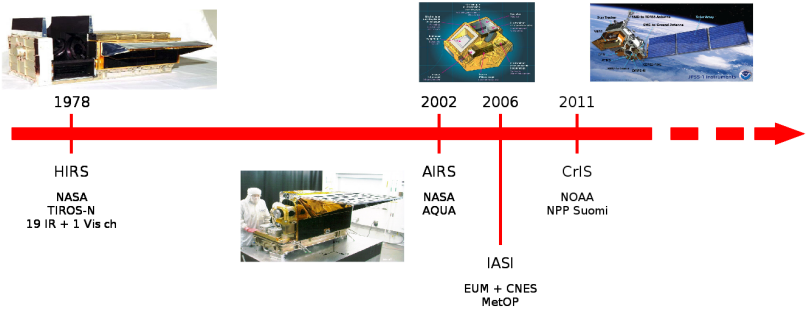


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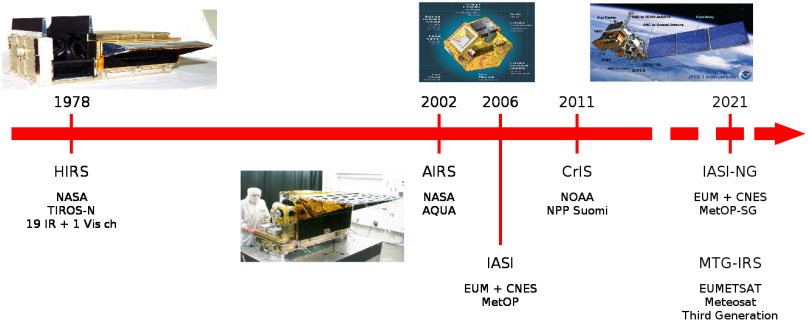


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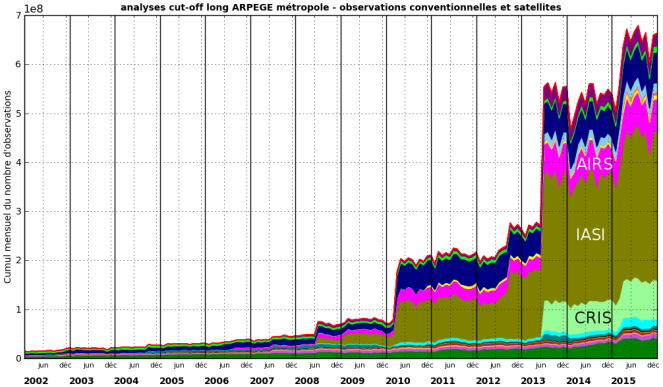
| IASI-NG | 2021 | Metop-SG | 16,921 | 0.125 $cm^{-1}$ |
| IRS | 2021 | MTG | 1,738 | 0.625 $cm^{-1}$ |

# Observations used by NWP models

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



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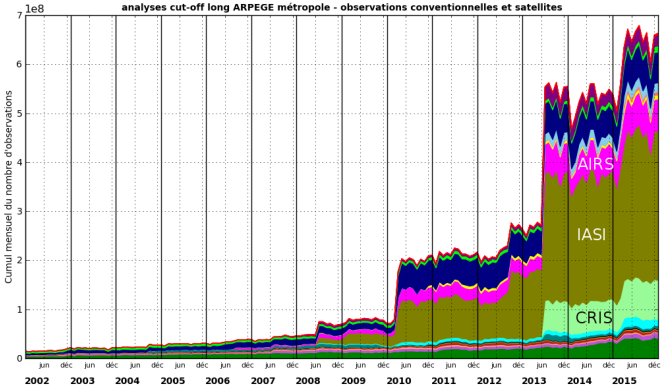


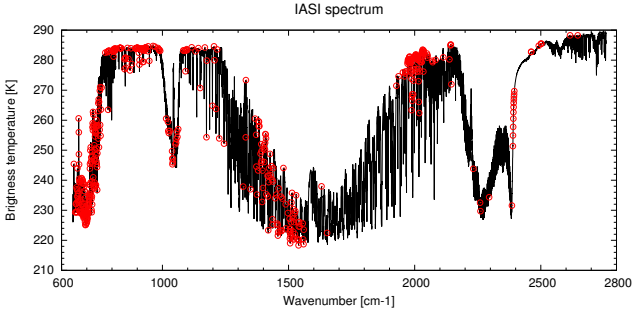

| | IASI | MTG-IRS |
|---|---|---|
| Spectral sampling | 0.25 $cm^{-1}$ | 0.625 $cm^{-1}$ |
| Samples per spectrum | 8,461 | 1,808 |
| Spatial sampling at nadir | 12 km | 4 km |
| Samples per hour | 54,000 | 8.0 $10^6$ |
| Estimation of data volume | 0.92 GB/h | 28 GB/h |

*(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 explose
- Inter-channel redundancy becomes more and more important. NWP center keep just 500 IASI channels from the 8461



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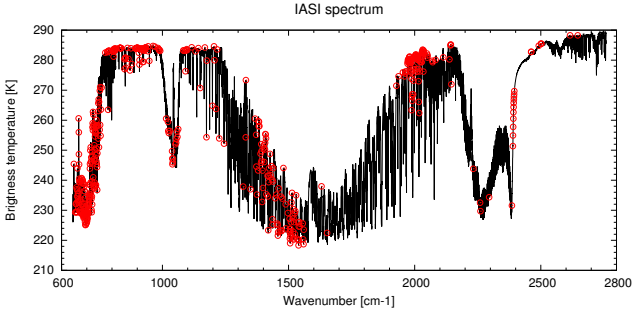


*For IASI, the best performances were obtained using* ***Principal Component Analysis (PCA)*** *plus* ***residuals quantisation***

# 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 :

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

- These new variables retain most of the information contained in the original dataset (most of the gaussian noise is filtered) :

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

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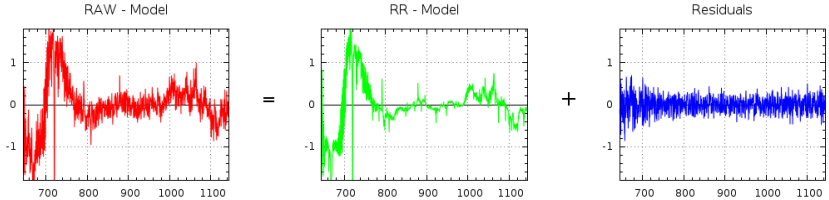
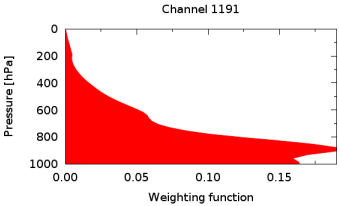


# An example of PCA compression for a single channel...

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



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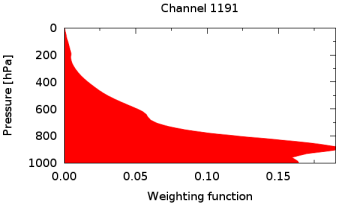
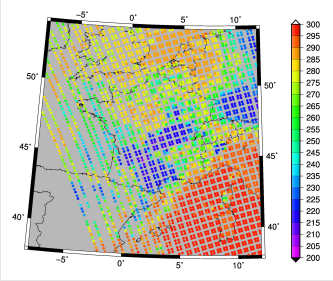
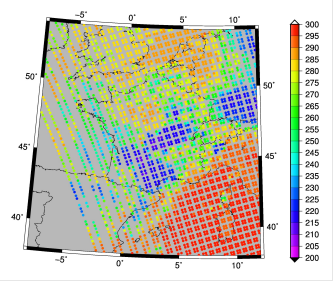



IASI
France
overpass
20130806




IASI raw radiances (RAD)




IASI reconstructed radiances (RR)

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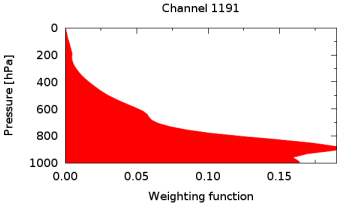


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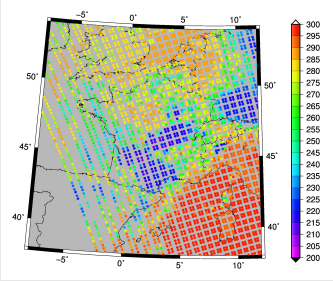


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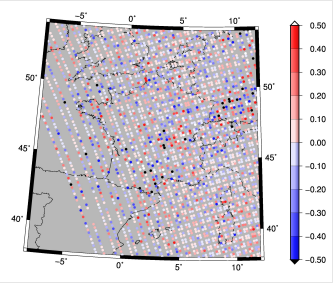
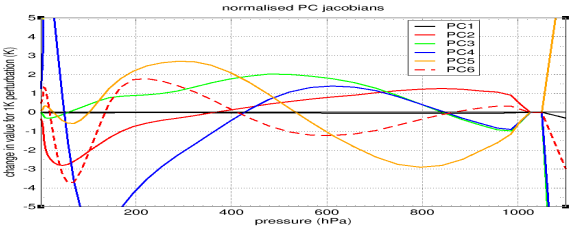



Differences in BT!!

# 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...)

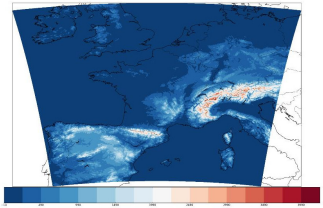
2. We can assimilate PCs directly
   - \+ We can use all the information registered in the observation
   - \- More difficult to understand. PCs are a mathematical representation
   - \- Some PCs Jacobians present structures peaking low and high in the atmosphere ⇒ What happen for low-top models ?




(McNally (2013))

# Outline

# Météo France AROME NWP model



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| Assim. cycle | 1h | 3h |
| Levels | 90 | 60/90L |
| Model top | 10 hPa | 1/10 hPa |
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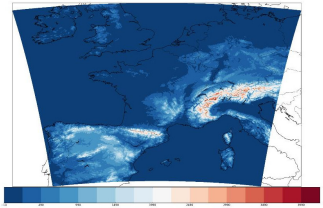

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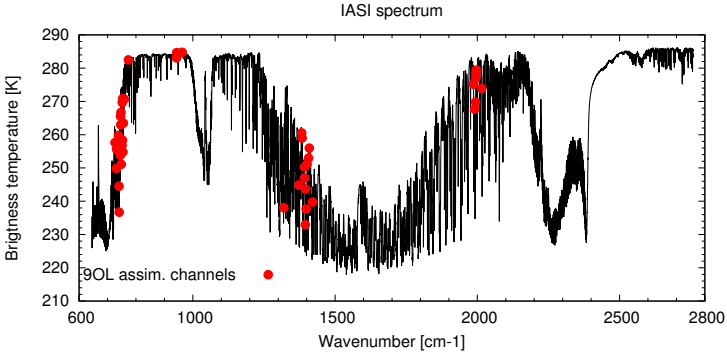

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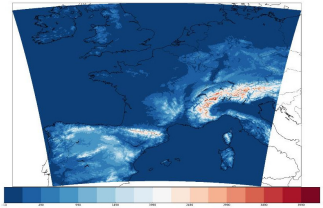

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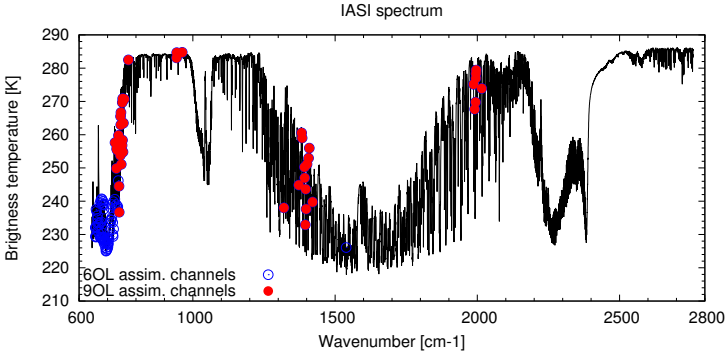

# Some more details on the experiments...

- 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

| | RR | RAD |
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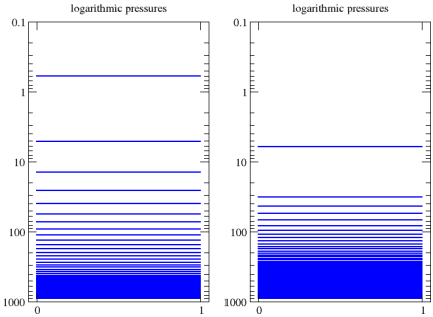


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- B matrix from *Adaptation Dynamique* (P. Brousseau)
- BC from ARPEGE global model uses RAD !!!

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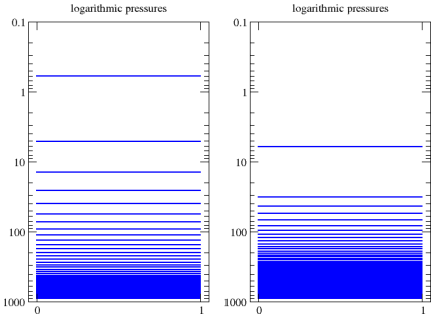


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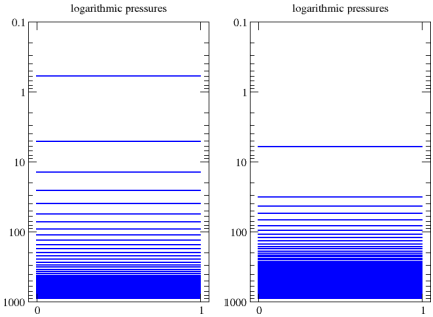


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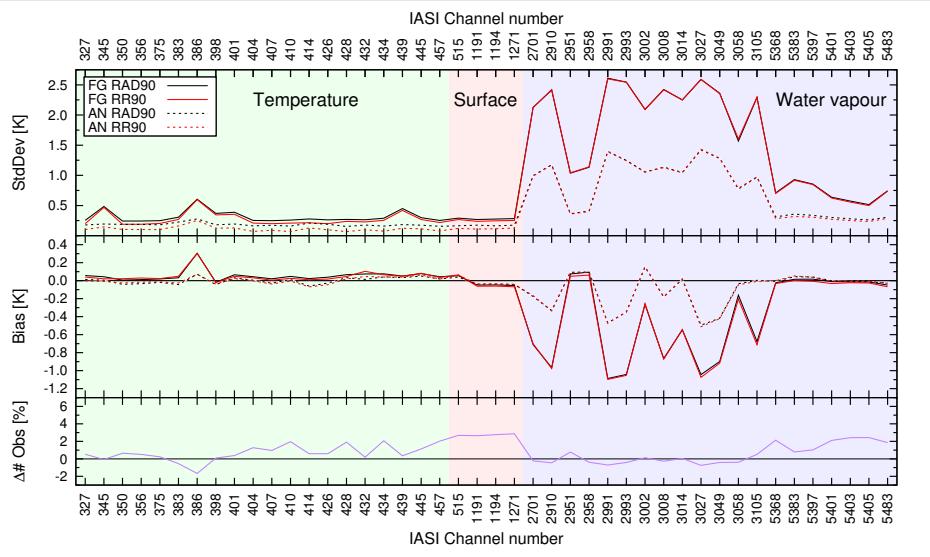
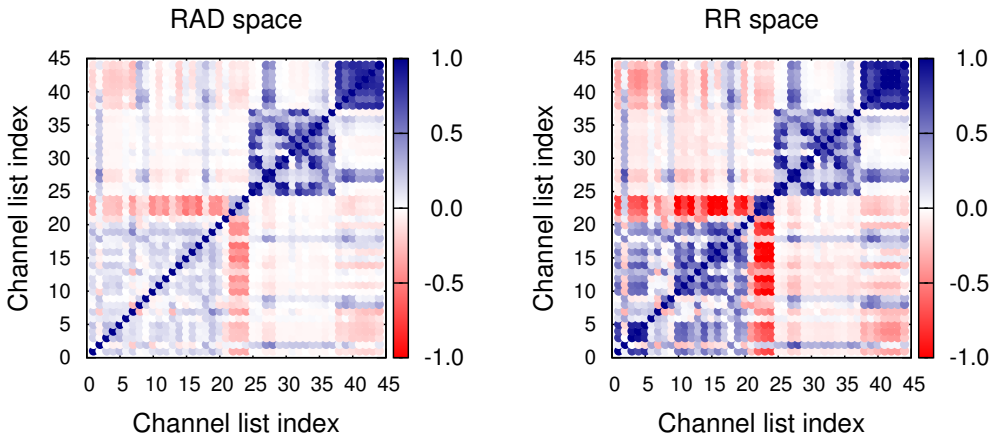
In this presentation only the impact of using RR is shown.

# Outline

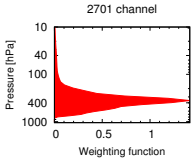
## Impact of assimilate RR instead of RAD

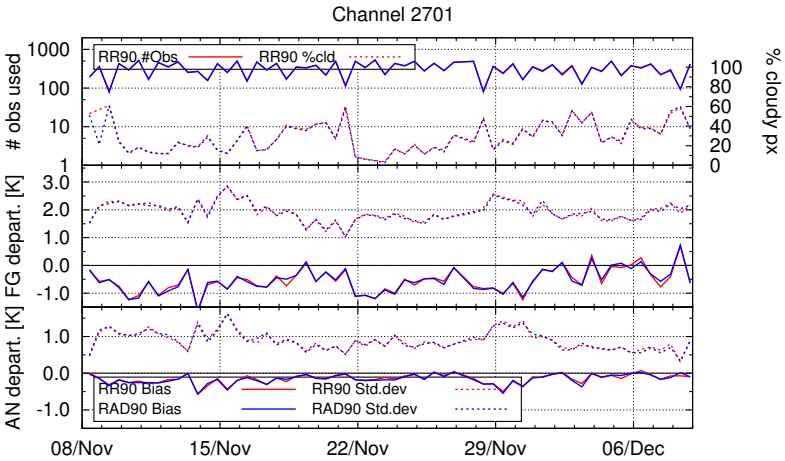


# RR and RAD observation error correlation matrices



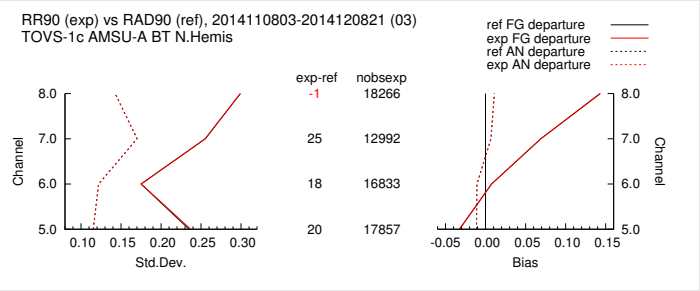
# Temporal evolution of assimilation statistics - ch 2701



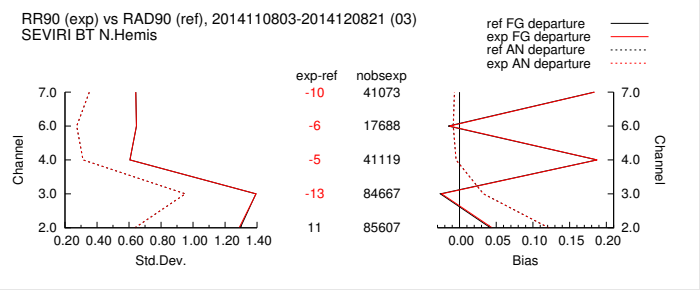



# Impact in other satellite observations

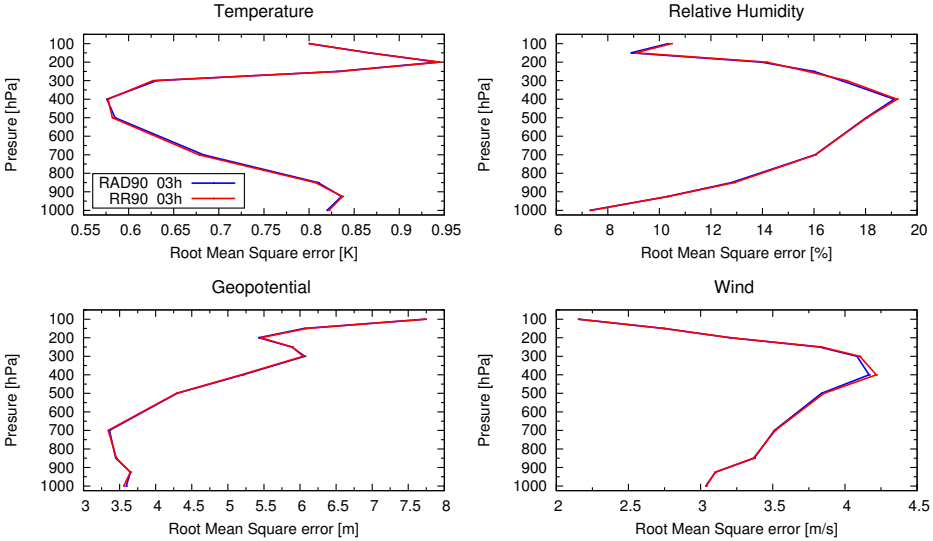
**AMSU-A**



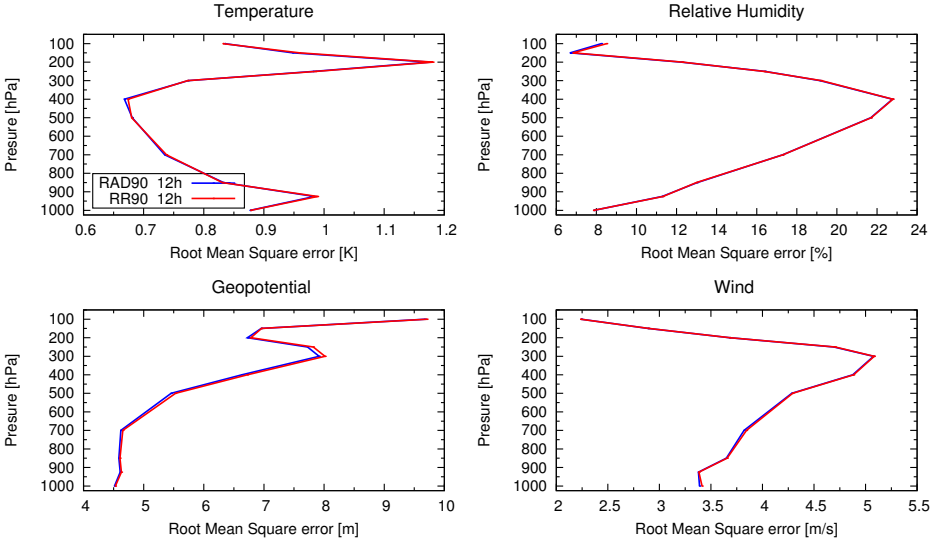

**SEVIRI**



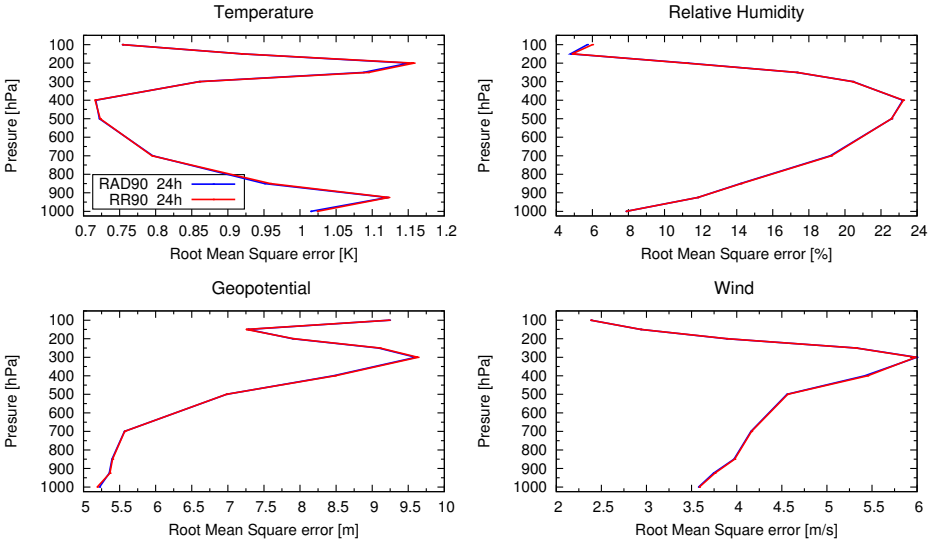
# RR vs RAD, RMS profiles, 3h forecast term



# RR vs RAD, RMS profiles, 12h forecast term



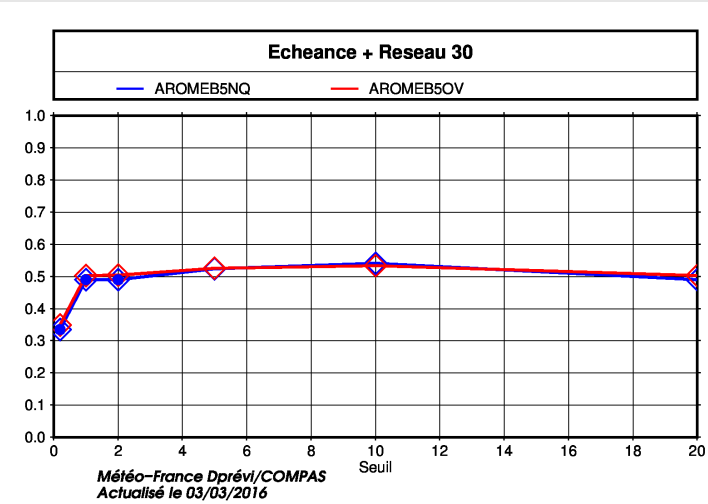
# RR vs RAD, RMS profiles, 24h forecast term



# Probabilistic control of precipitation at 24h (RR24)

**0 H forecast term,**
**1.3 km neighbourhood**

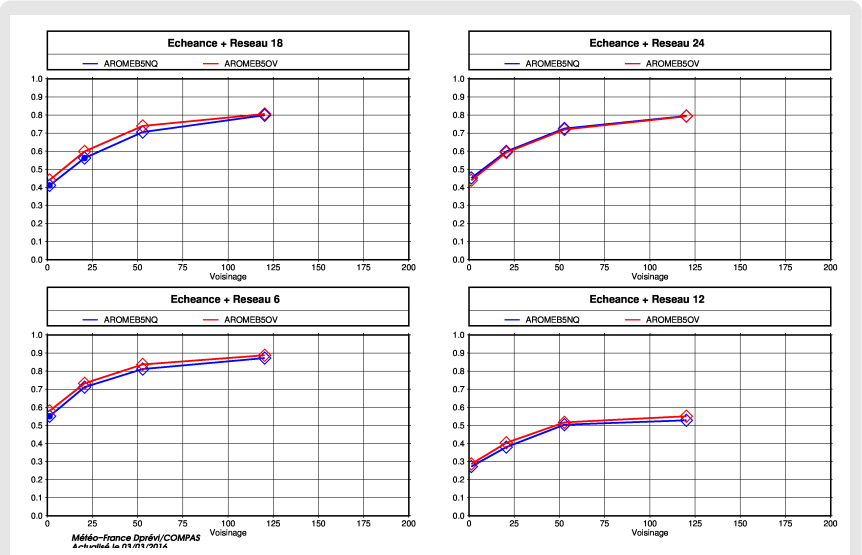
FRANGP0025 domain
BSS_NO as a function of threshold
Période 20141109 - 20141208
BDCLIMQ Reference



# Probabilistic control of precipitation at 6h (RR6)

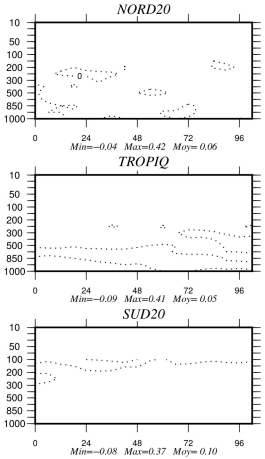
**Different forecast terms,**
**10 mm precipitation threshold**

FRANGP0025 domain
BSS_NO as a function of neighbourhood
Période 20141109 - 20141208
BDCLIMQ Reference

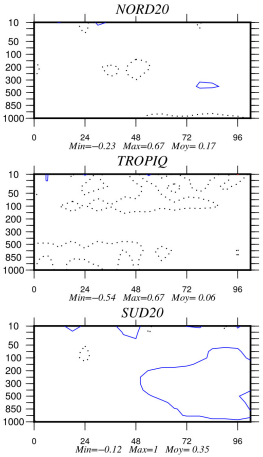


# Impact of RR in ARPEGE global model

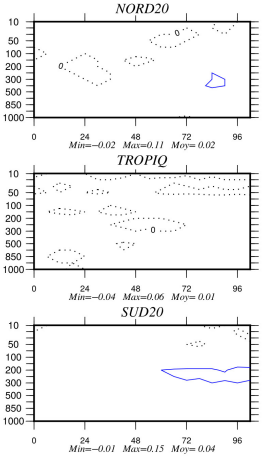
**rms RH profiles [0.5 %]**




**rms Geopotential profiles [5 m]**




**rms Wind profiles [1 m/s]**



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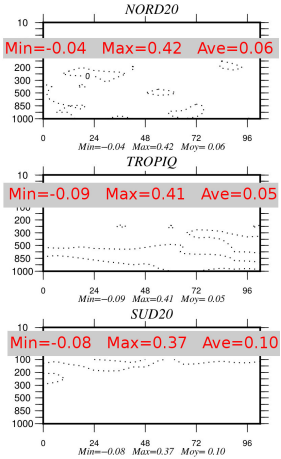
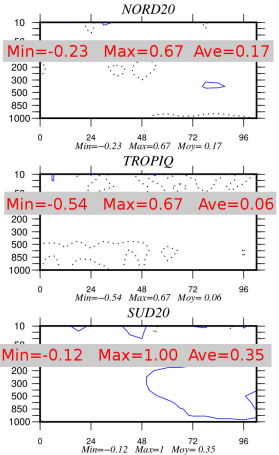
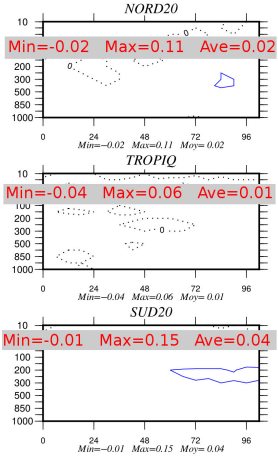



**rms Geopotential profiles [5 m]**

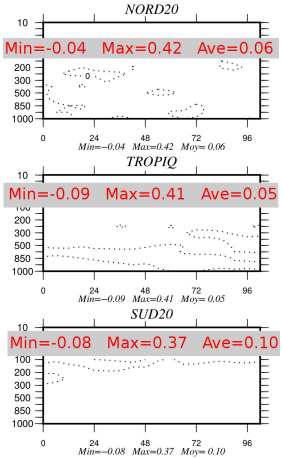



**rms Wind profiles [1 m/s]**

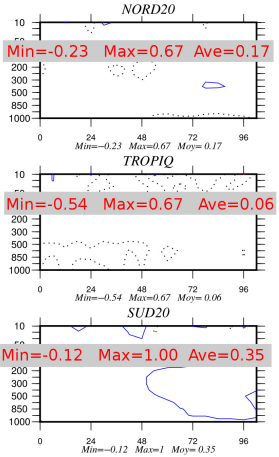


# Impact of RR in ARPEGE global model

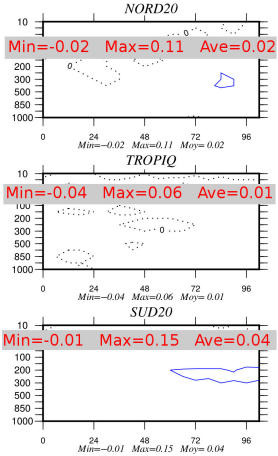
**rms RH profiles [0.5 %]**




**rms Geopotential profiles [5 m]**




**rms Wind profiles [1 m/s]**




**Positive impact when using RR (VarBC for IASI)**

# Outline

# Conclusions

- Different studies are being carried out at MF on the **assimilation of IR hyperspectral PCA compressed data** in a **low-top non-hydrostatic mesoscale model**
- There are **two possibilities to assimilate** IR hyperspectral PCA compress data : **RR and PCs**
- Assimilating **RR** is **as simple as** assimilating **RAD** but **channel noises are reduced** and **interchannel correlation is increased**
- Results present **almost non difference between RAD and RR assimilations** (Using a diagonal R-matrix, RAD bias correction from ARPEGE, and same RAD and RR channel selection)
- **Worst results in precipitation** scores but possibly caused by *a bad BC ?*
- **Positive impact** of RR in MF **ARPEGE global model**
- **Impact** of RR **in AROME** with a proper BC will be **analysed after this IASI** conference

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