

An aerial photograph of a mountain town, likely in the Alps, is shown. The town is nestled in a valley, surrounded by steep, forested slopes. A weather map is overlaid on the image, featuring white contour lines representing pressure or temperature. The map shows a low-pressure system to the left of the town and a high-pressure system to the right. Arrows indicate wind direction and speed. The background of the slide is a deep blue gradient.

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

Javier Andrey-Andrés

CNRM, Météo-France and CNRS

March 7th, 2016



METEO FRANCE

dépasser les frontières

1 Introduction

2 Methodology

3 Results

- Used observations
 - IASI
 - Other satellite observations
- Forecast scores
 - Impact of lowering the top model
 - Impact of RR

4 Ongoing works...

5 Conclusions

Evolution of IR sounders



Instrument	Year	Sat.	Channels	Spec. resolution
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Evolution of IR sounders



1978



HIRS

NASA
TIROS-N
19 IR + 1 Vis ch

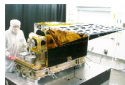
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AIRS
NASA
AQUA

Instrument	Year	Sat.	Channels	Spec. resolution
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Evolution of IR sounders



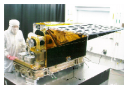
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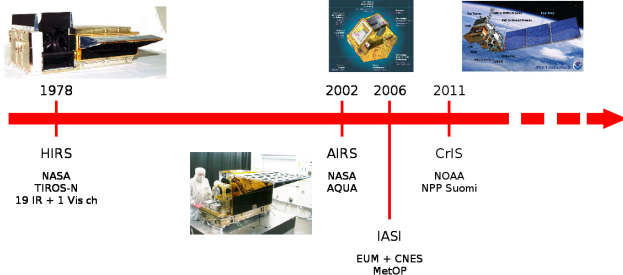
AIRS
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IASI
EUM + CNES
MetOP

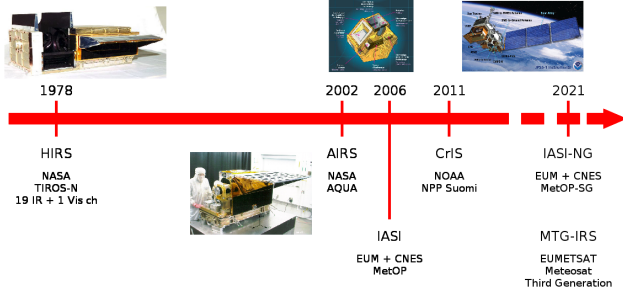
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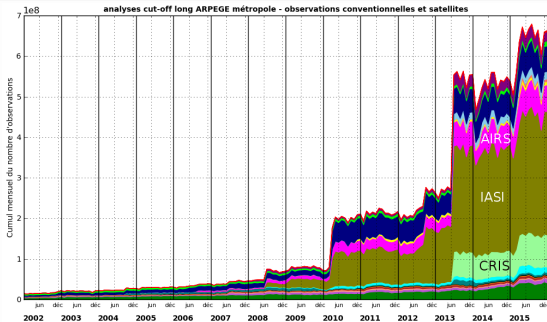
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CRIS	2011	JPSS	1,305	0.625 cm^{-1}
IASI-NG	2021	Metop-SG	16,921	0.125 cm^{-1}
IRS	2021	MTG	1,738	0.625 cm^{-1}

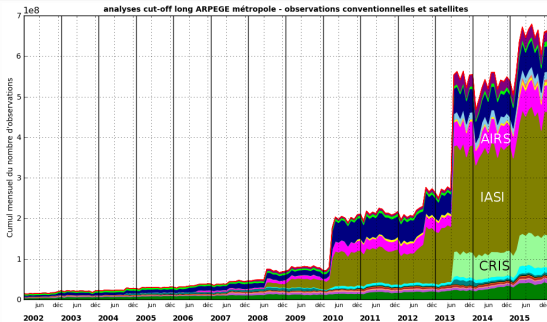
Use of IR data in NWP models

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



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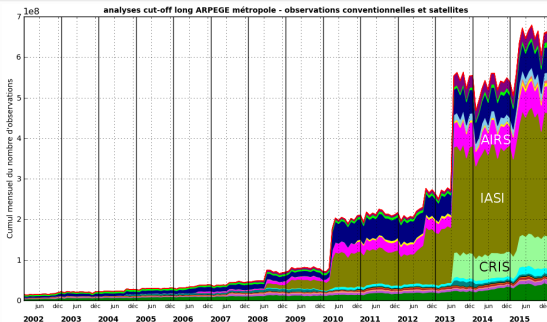
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This tendency will continue with the arrival of new hyperspectral IR sounders, above everything IRS

Use of IR data in NWP models

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



	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)

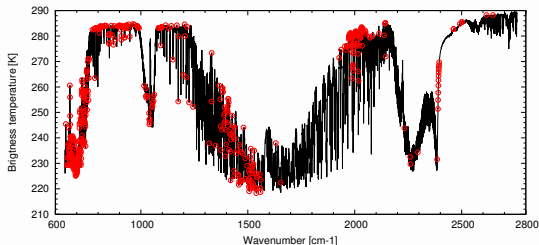
Consequences of the huge data volumes



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

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

IASI spectrum



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)
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For IASI, the best performances were obtained using PCA plus residuals quantisation

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

The PCA compression technique

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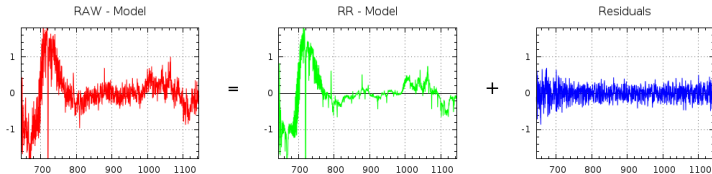
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It is a lossy compression, but most of the “loss” is noise

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

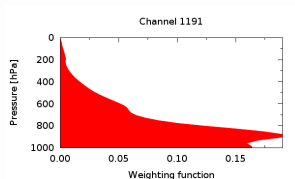
f_s Quantisation factor, typically 0.5

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

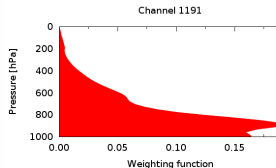
An example of PCA compression for a single channel. . .

IASI channel 1191, @942.5 cm^{-1}
⇒ Surface channel

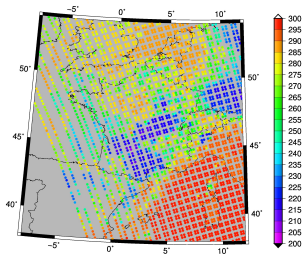


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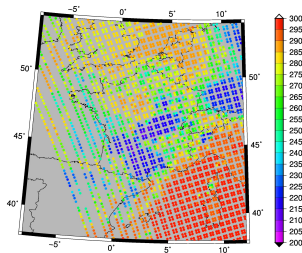
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Afternoon IASI overpass the 20130806



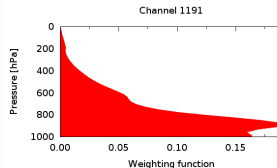
IASI raw radiances (RAD)



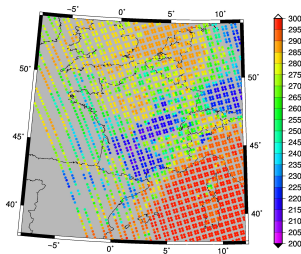
IASI reconstructed radiances (RR)

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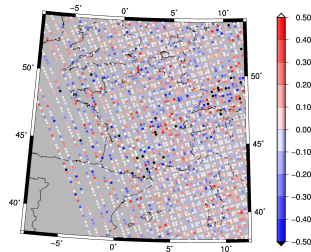
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IASI raw radiances (RAD)



Differences in BT,
Not in radiances!!!

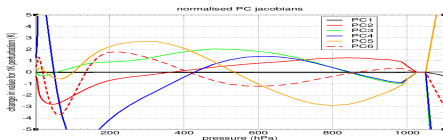
How can we assimilate PCA compressed data

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 $\Rightarrow$ What happen for low-top models?



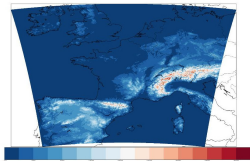
(Figure from McNally (2013))

Outline

- 1 Introduction
- 2 Methodology**
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Météo France AROME NWP model

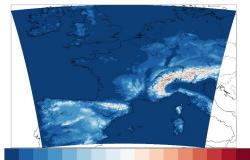
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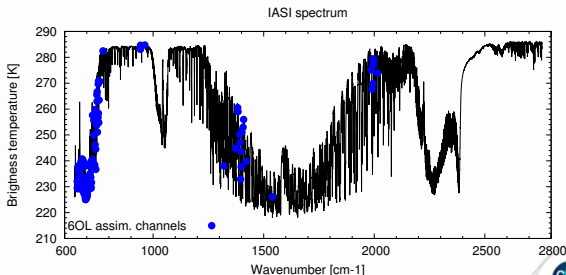
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Mesh grid	1.3 km	1.3 km
Assim. cycle	1h	3h
Levels	90	60/90L
Model top	10 hPa	1/10 hPa
IASI px assim	1/8	all
IASI ch assim	44	up to 123? / 44

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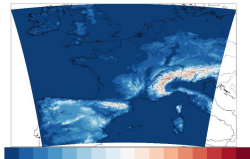


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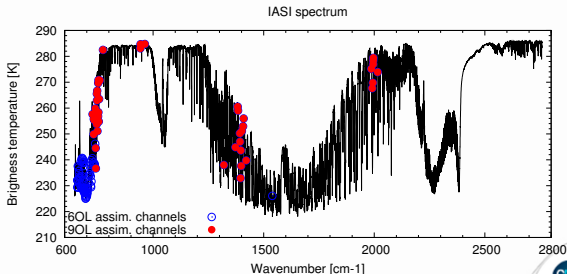


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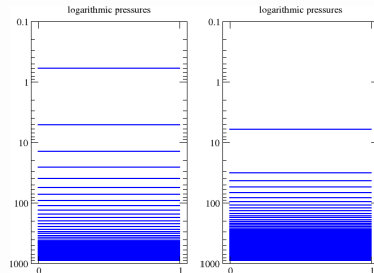
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And what have we done...

- 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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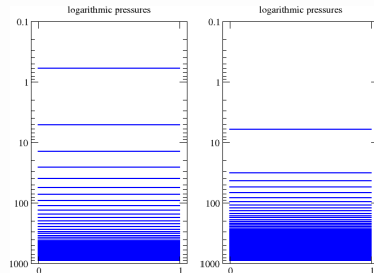


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- Preliminary analysis of this experiments (last results obtained last Thursday).
Final results will be preented in the next IASI conference (Antibes, April 2016)

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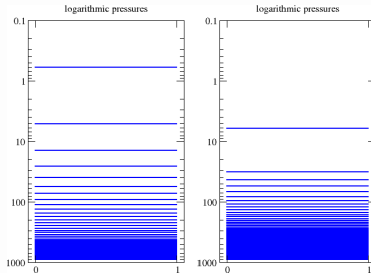


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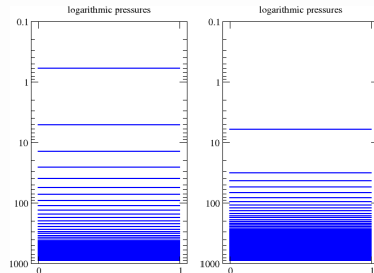


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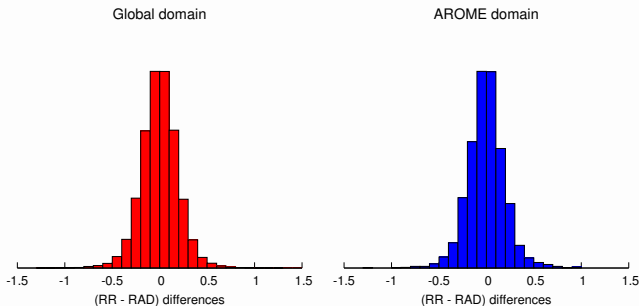


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Can we use IASI PCs product?

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

⇒ RR-RAD Differences for 1191 channel (942.5 cm⁻¹)

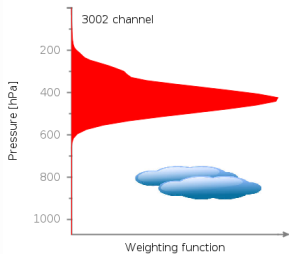


Domain	Number	Average [K]	Std.Dev. [K]	Min. [K]	Max. [K]
Global	91631	-0.001396	0.1959	-1.5433	1.5420
AROME	2665	-0.001701	0.1965	-1.2299	0.9513

NWP models assimilate IR clear channels...

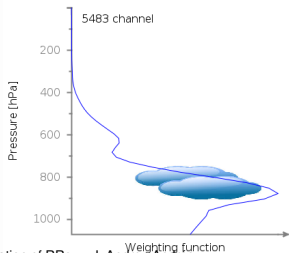
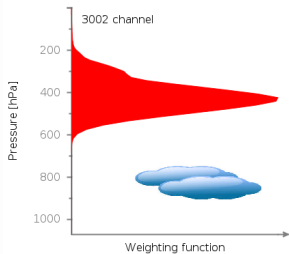
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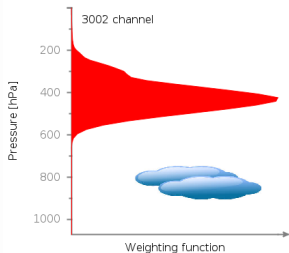
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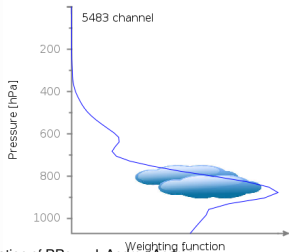


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And what is a clear channel...

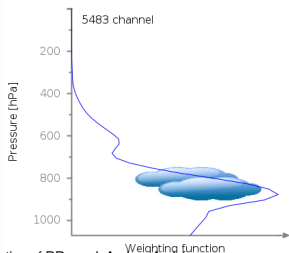
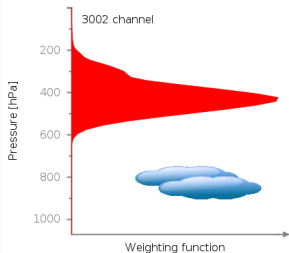


The algorithm to detect cloudy channels comes from McNally&Watts (2003)



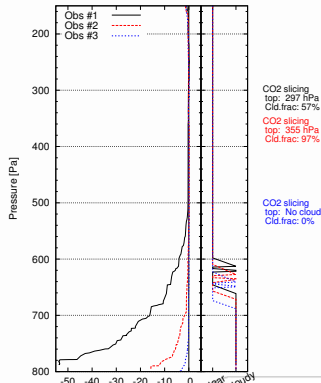
NWP models assimilate IR clear channels...

And what is a clear channel. . .



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

McNally & Watts, Band 1



1 Introduction

2 Methodology

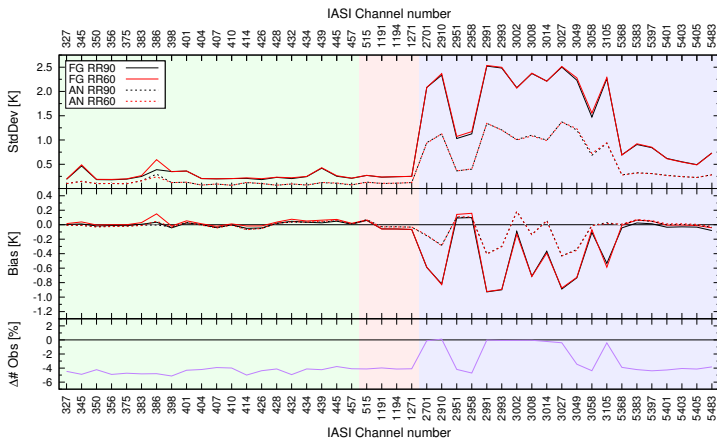
3 Results

- Used observations
- Forecast scores

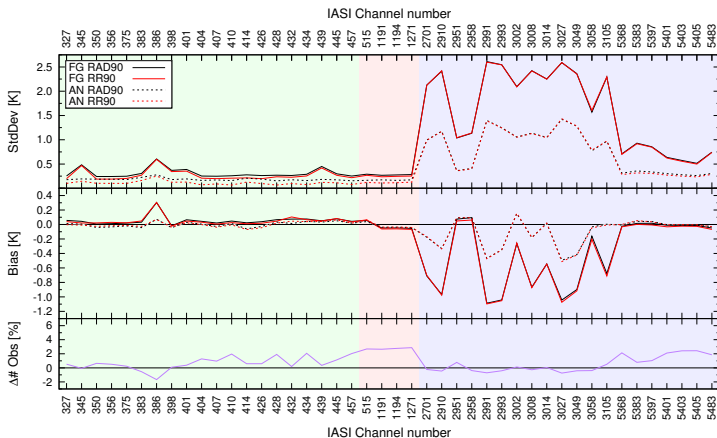
4 Ongoing works...

5 Conclusions

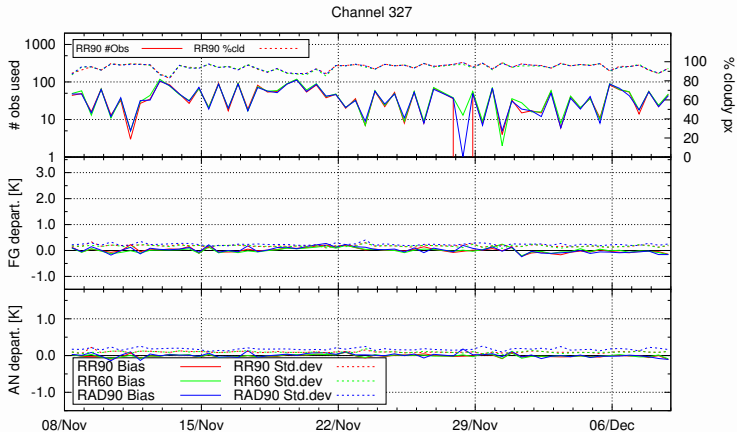
Impact of lowering the model top



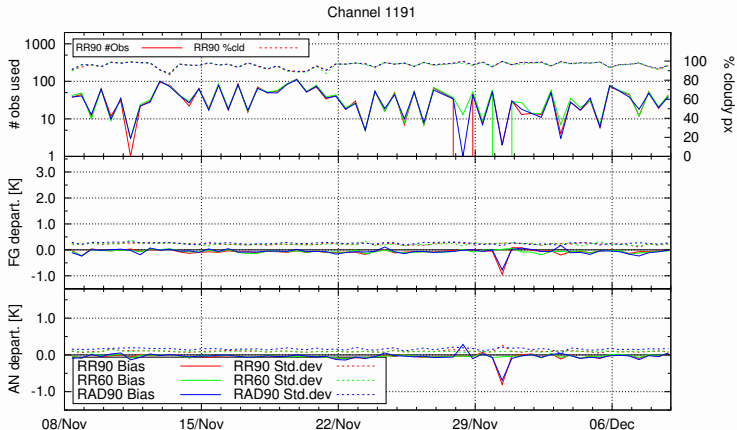
Impact of assimilate RR instead of RAD



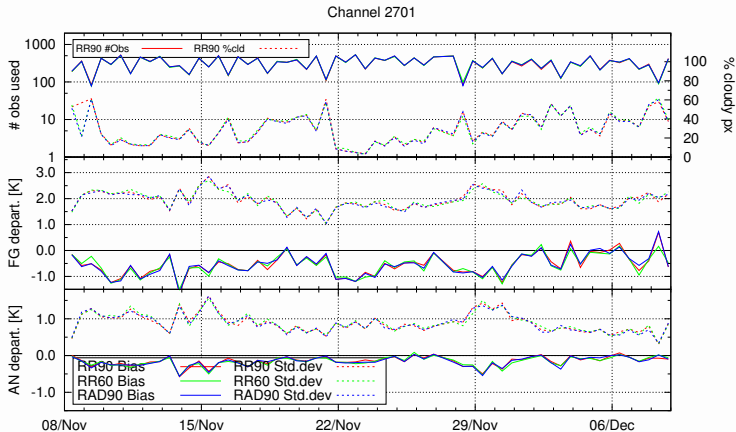
Weighting function peaking at 825 hPa



Surface channel

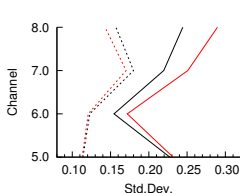


Weighting function peaking at 440 hPa

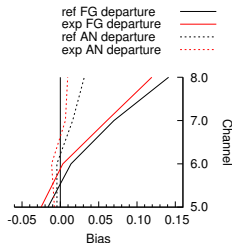


AMSU-A

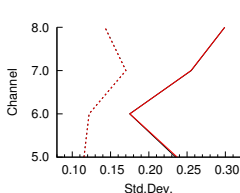
RR90 (exp) vs RR60 (ref), 2014110803-2014120821 (03)
TOVS-1c AMSU-A BT N.Hemis



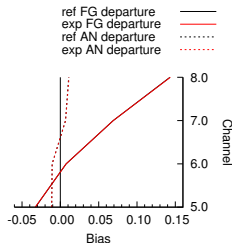
exp-ref	nobsexp
-1533	24280
-473	16686
-9	21801
30	23141



RR90 (exp) vs RAD90 (ref), 2014110803-2014120821 (03)
TOVS-1c AMSU-A BT N.Hemis

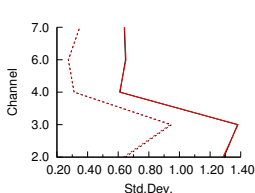


exp-ref	nobsexp
-1	18266
25	12992
18	16833
20	17857

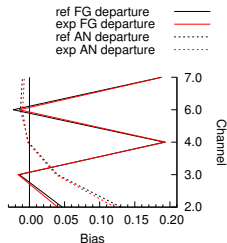


SEVIRI

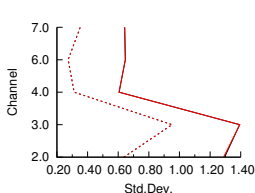
RR90 (exp) vs RR60 (ref), 2014110803-2014120821 (03)
SEVIRI BT N.Hemis



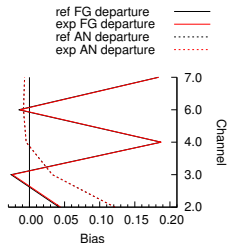
exp-ref	nobsexp
1	44033
3	18627
-1	44081
-27	92917
83	93853



RR90 (exp) vs RAD90 (ref), 2014110803-2014120821 (03)
SEVIRI BT N.Hemis

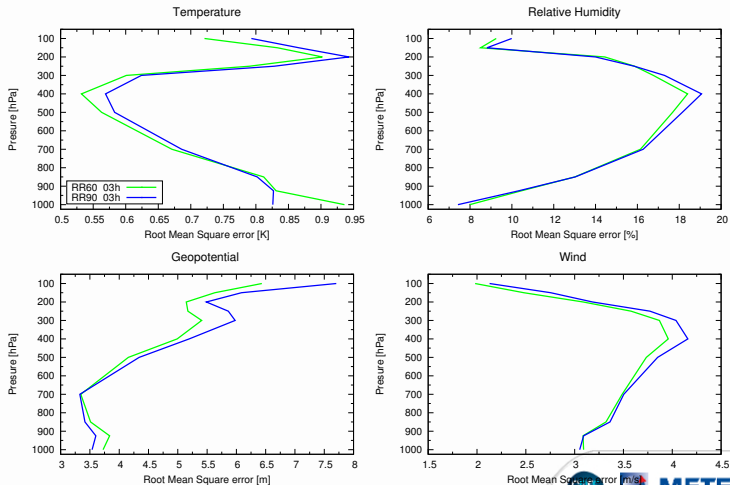


exp-ref	nobsexp
-10	41073
-6	17688
-5	41119
-13	84667
11	85607



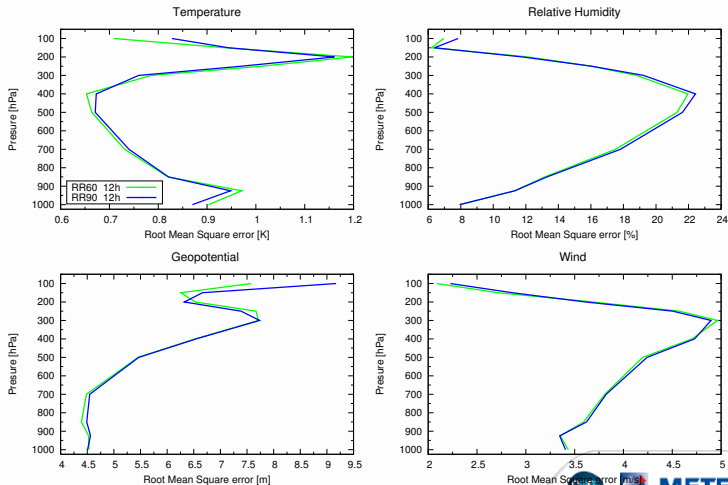
Scores: low-top impact (RR90 vs RR60), 3h terms

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



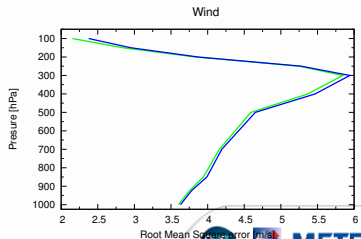
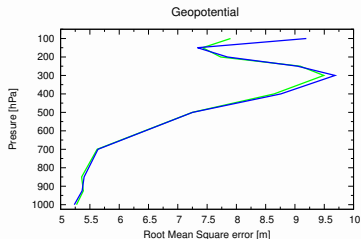
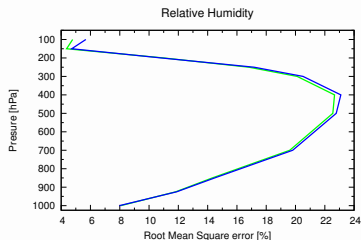
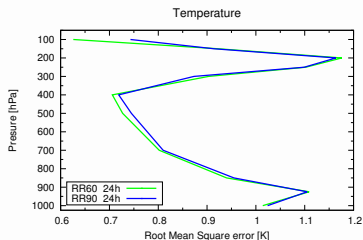
Scores: low-top impact (RR90 vs RR60), 12h terms

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



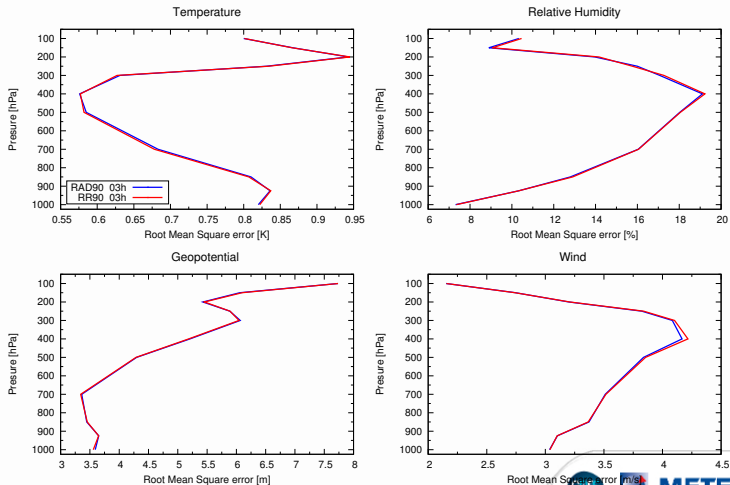
Scores: low-top impact (RR90 vs RR60), 24h terms

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



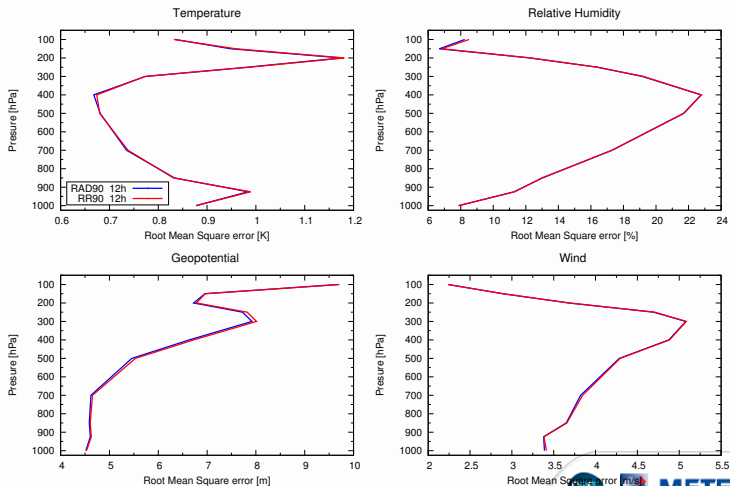
Scores: RR impact (RR90 vs RAD90), 3h terms

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



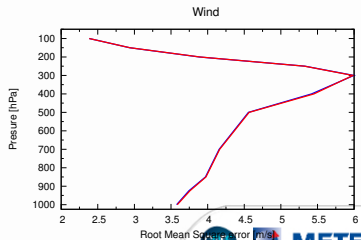
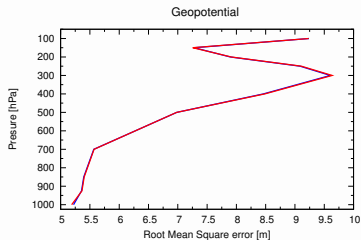
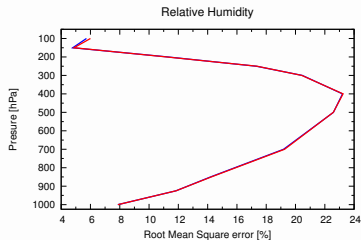
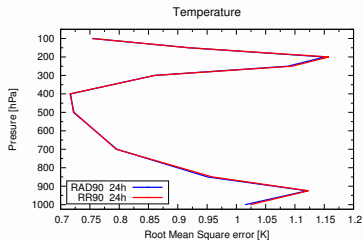
Scores: RR impact (RR90 vs RAD90), 12h terms

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Scores: RR impact (RR90 vs RAD90), 24h terms

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



Outline

- 1 Introduction
- 2 Methodology
- 3 Results
- 4 Ongoing works...**
- 5 Conclusions

- ▶ 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
⇒ 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
⇒ A few days at ECMWF (wih M. Matricardi) are programmed to integrate PCs assimilation scheme in AROME

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- ▶ 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
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An aerial photograph of a mountain town, likely in the Alps, with a weather map overlay. The map shows contour lines, isobars, and wind vectors. The town is nestled in a valley, surrounded by steep, forested slopes. The weather map overlay includes contour lines with values such as 1015, 1020, 1025, 1030, 1035, 1040, 1045, 1050, 1055, 1060, 1065, 1070, 1075, 1080, 1085, 1090, 1095, 1100, 1105, 1110, 1115, 1120, 1125, 1130, 1135, 1140, 1145, 1150, 1155, 1160, 1165, 1170, 1175, 1180, 1185, 1190, 1195, 1200, 1205, 1210, 1215, 1220, 1225, 1230, 1235, 1240, 1245, 1250, 1255, 1260, 1265, 1270, 1275, 1280, 1285, 1290, 1295, 1300, 1305, 1310, 1315, 1320, 1325, 1330, 1335, 1340, 1345, 1350, 1355, 1360, 1365, 1370, 1375, 1380, 1385, 1390, 1395, 1400, 1405, 1410, 1415, 1420, 1425, 1430, 1435, 1440, 1445, 1450, 1455, 1460, 1465, 1470, 1475, 1480, 1485, 1490, 1495, 1500, 1505, 1510, 1515, 1520, 1525, 1530, 1535, 1540, 1545, 1550, 1555, 1560, 1565, 1570, 1575, 1580, 1585, 1590, 1595, 1600, 1605, 1610, 1615, 1620, 1625, 1630, 1635, 1640, 1645, 1650, 1655, 1660, 1665, 1670, 1675, 1680, 1685, 1690, 1695, 1700, 1705, 1710, 1715, 1720, 1725, 1730, 1735, 1740, 1745, 1750, 1755, 1760, 1765, 1770, 1775, 1780, 1785, 1790, 1795, 1800, 1805, 1810, 1815, 1820, 1825, 1830, 1835, 1840, 1845, 1850, 1855, 1860, 1865, 1870, 1875, 1880, 1885, 1890, 1895, 1900, 1905, 1910, 1915, 1920, 1925, 1930, 1935, 1940, 1945, 1950, 1955, 1960, 1965, 1970, 1975, 1980, 1985, 1990, 1995, 2000, 2005, 2010, 2015, 2020, 2025, 2030, 2035, 2040, 2045, 2050, 2055, 2060, 2065, 2070, 2075, 2080, 2085, 2090, 2095, 2100, 2105, 2110, 2115, 2120, 2125, 2130, 2135, 2140, 2145, 2150, 2155, 2160, 2165, 2170, 2175, 2180, 2185, 2190, 2195, 2200, 2205, 2210, 2215, 2220, 2225, 2230, 2235, 2240, 2245, 2250, 2255, 2260, 2265, 2270, 2275, 2280, 2285, 2290, 2295, 2300, 2305, 2310, 2315, 2320, 2325, 2330, 2335, 2340, 2345, 2350, 2355, 2360, 2365, 2370, 2375, 2380, 2385, 2390, 2395, 2400, 2405, 2410, 2415, 2420, 2425, 2430, 2435, 2440, 2445, 2450, 2455, 2460, 2465, 2470, 2475, 2480, 2485, 2490, 2495, 2500, 2505, 2510, 2515, 2520, 2525, 2530, 2535, 2540, 2545, 2550, 2555, 2560, 2565, 2570, 2575, 2580, 2585, 2590, 2595, 2600, 2605, 2610, 2615, 2620, 2625, 2630, 2635, 2640, 2645, 2650, 2655, 2660, 2665, 2670, 2675, 2680, 2685, 2690, 2695, 2700, 2705, 2710, 2715, 2720, 2725, 2730, 2735, 2740, 2745, 2750, 2755, 2760, 2765, 2770, 2775, 2780, 2785, 2790, 2795, 2800, 2805, 2810, 2815, 2820, 2825, 2830, 2835, 2840, 2845, 2850, 2855, 2860, 2865, 2870, 2875, 2880, 2885, 2890, 2895, 2900, 2905, 2910, 2915, 2920, 2925, 2930, 2935, 2940, 2945, 2950, 2955, 2960, 2965, 2970, 2975, 2980, 2985, 2990, 2995, 3000, 3005, 3010, 3015, 3020, 3025, 3030, 3035, 3040, 3045, 3050, 3055, 3060, 3065, 3070, 3075, 3080, 3085, 3090, 3095, 3100, 3105, 3110, 3115, 3120, 3125, 3130, 3135, 3140, 3145, 3150, 3155, 3160, 3165, 3170, 3175, 3180, 3185, 3190, 3195, 3200, 3205, 3210, 3215, 3220, 3225, 3230, 3235, 3240, 3245, 3250, 3255, 3260, 3265, 3270, 3275, 3280, 3285, 3290, 3295, 3300, 3305, 3310, 3315, 3320, 3325, 3330, 3335, 3340, 3345, 3350, 3355, 3360, 3365, 3370, 3375, 3380, 3385, 3390, 3395, 3400, 3405, 3410, 3415, 3420, 3425, 3430, 3435, 3440, 3445, 3450, 3455, 3460, 3465, 3470, 3475, 3480, 3485, 3490, 3495, 3500, 3505, 3510, 3515, 3520, 3525, 3530, 3535, 3540, 3545, 3550, 3555, 3560, 3565, 3570, 3575, 3580, 3585, 3590, 3595, 3600, 3605, 3610, 3615, 3620, 3625, 3630, 3635, 3640, 3645, 3650, 3655, 3660, 3665, 3670, 3675, 3680, 3685, 3690, 3695, 3700, 3705, 3710, 3715, 3720, 3725, 3730, 3735, 3740, 3745, 3750, 3755, 3760, 3765, 3770, 3775, 3780, 3785, 3790, 3795, 3800, 3805, 3810, 3815, 3820, 3825, 3830, 3835, 3840, 3845, 3850, 3855, 3860, 3865, 3870, 3875, 3880, 3885, 3890, 3895, 3900, 3905, 3910, 3915, 3920, 3925, 3930, 3935, 3940, 3945, 3950, 3955, 3960, 3965, 3970, 3975, 3980, 3985, 3990, 3995, 4000, 4005, 4010, 4015, 4020, 4025, 4030, 4035, 4040, 4045, 4050, 4055, 4060, 4065, 4070, 4075, 4080, 4085, 4090, 4095, 4100, 4105, 4110, 4115, 4120, 4125, 4130, 4135, 4140, 4145, 4150, 4155, 4160, 4165, 4170, 4175, 4180, 4185, 4190, 4195, 4200, 4205, 4210, 4215, 4220, 4225, 4230, 4235, 4240, 4245, 4250, 4255, 4260, 4265, 4270, 4275, 4280, 4285, 4290, 4295, 4300, 4305, 4310, 4315, 4320, 4325, 4330, 4335, 4340, 4345, 4350, 4355, 4360

Main « IASI » updates in Météo-France global model

