



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

1 Introduction

2 Methodology

3 Results

- Impact on used observations
- Forecast scores
- Impact of RR in ARPEGE global model

4 Summary and conclusions

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Instrument Year Sat. Channels Spec. resolution

Evolution of IR sounders



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

Observations used by NWP models

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



Observations used by NWP models

analyses cut-off long ARPEGE métropole - observations conventionnelles et satellites _ 1e8 atior d'obse du nombre isuel o 2 Cumul CRIS jun déc iun déc iun déc iun déc iun déc iun dé déc iun déc iun déc iun dér 2002 2003 2013 2014 2015 2004 2005 2006 2007 2008 2010 2011 2012

. . .

	IASI	MIG-IRS
Spectral sampling	$0.25 \ { m cm}^{-1}$	$0.625 \ { m cm}^{-1}$
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)

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



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**

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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J. Andrey-Andrés et al.- Assimilation of RRs

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



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

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



Channel 1191



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

IASI channel 1191, @942.5 cm⁻¹ \Rightarrow Surface channel Weighting function

Channel 1191



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J. Andrey-Andrés et al.- Assimilation of RRs

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?



(McNally (2013))

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Météo France AROME NWP model

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	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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IASI spectrum



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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
90L	B5MJ/B5NQ	B5ML/B5OV
60L	B5MK/B5OS	B5J3/B5OX



- Period of study : 20141108 to 20141208
- B matrix from Adaptation Dynamique (P. Brousseau)
- BC from ARPEGE global model uses RAD !!!

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

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Used IASI observations

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



RR90 (exp) vs RAD90 (ref), 2014110803-2014120821 (03) ref FG departure exp FG departure ref AN departure SEVIRI BT N.Hemis exp AN departure exp-ref nobsexp 7.0 г -10 41073 7.0 6.0 -6 17688 6.0 Channel SEVIRI Channel 4.0 -5 41119 4.0 ····· 3.0 -13 84667 3.0 2.0 11 85607 2.0 0.20 0.40 0.60 0.80 1.00 1.20 1.40 0.00 0.05 0.10 0.15 0.20 Std.Dev. Bias

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] NORD20 NORD20 NORD20 24 48 72 Min=-0.23 Max=0.67 Moy= 0.17 $\stackrel{24}{Min=-0.02}$ $\stackrel{48}{Max=0.11}$ $\stackrel{72}{Moy=0.02}$ 24 48 72 Min=-0.04 Max=0.42 Moy= 0.06 TROPIQ TROPIO TROPIO Set and Attorn Alline Alline Onest 100 -500 -24 48 72 Min=-0.54 Max=0.67 Moy= 0.06 Min=-0.09 Max=0.41 Moy= 0.05 Min=-0.04 Max=0.06 Moy=0.01SUD20 SUD20 SUD20 100 -100 -200 -500 -850 -Min=-0.12 48 72 Max=1 Moy= 0.35 24 48 72 Min=-0.01 Max=0.15 Moy= 0.04 24 48 72 Min=-0.08 Max=0.37 Mov= 0.10

Impact of RR in ARPEGE global model

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Positive impact when using RR (VarBC for IASI)

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- 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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