Data assimilation in 3D-VAR ALADIN-CZ:
data thinning and error-inflation for aircraft & satellites.

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Introduction

- Aladin/CZ: $\delta x = 4.7$ km (status presentation)
- BlendVar = DFI Blending + 3D-Var (since 2015)

$$J(\vec{x}) = \frac{1}{2}(\vec{x_b} - \vec{x})^T \mathbf{B}^{-1}(\vec{x_b} - \vec{x}) + \frac{1}{2}(\vec{y} - H(\vec{x}))^T \mathbf{R}^{-1}(\vec{y} - H(\vec{x})). \quad (1)$$

R is observation error covariance matrix:

- diagonal: $\sigma_o^2 = var(\vec{\epsilon_o})$
- non-diagonal: $cov[\vec{\epsilon_o}(\vec{\epsilon_o})^T] \rightarrow$ error correlations

R assumption

- Error correlations are neglected.

Observation error diagnostic

- using Desroziers et al. (2005) to approximate:

$$cov[\vec{d_a^o}(\vec{d_b^o})^T] \approx \tilde{\mathbf{R}} \quad (2)$$

$d_a^o = (\vec{y} - \mathbf{H}[\vec{x_a}])$ (analysis departure)

$d_b^o = (\vec{y} - \mathbf{H}[\vec{x_b}])$ (background departure)

Assumptions:

- $E[\vec{\epsilon_b}] = E[\vec{\epsilon_o}] = E[\vec{\epsilon_b}(\vec{\epsilon_o})^T] = E[\vec{\epsilon_o}(\vec{\epsilon_b})^T] = 0$
- different correlation length-scales btw background and observation errors

Simplifications:

- can be apply iteratively – good convergence (using one-iteration)

The method application

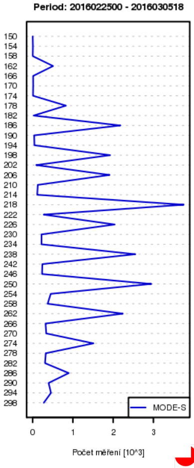
Reduction of error correlations:

- data thinning: reduction observation density so that correlations are not relevant
- error inflation: use diagonal $\mathbf{R}$ with larger σ_o than diagnostic suggest

How to set:

- Data thinning:
  1. estimate spatial error correlations by Desroziers
  2. optimal thinning distance: error correlations $\leq 0.15 - 0.2$ [3]
- Error inflation:
  1. estimate observation error by Desroziers σ_o^{der}
  2. artificial inflation of σ_o^{der} to reduce error-correlations (spatial, inter-channels,...)
  3. the error inflation is changed through sigma_coeff (SC)

- the Mode-S MRAR data (CZ domain)
- observation pairs d_a^o and d_b^o:
    - 2015-07-05/07-30 (summer)
      2016-02-25/03-25 (winter)
    - less than 1 hour apart
    - separately for each aircraft type
    - horizontal error correlations:
        - data at specific levels ±2-hPa btw 150-400 hPa (Fig)
        - separation distance 10-km
    - vertical error correlations:
        - data from 400-950 hPa
        - separation distance 4-hPa



Horizontal error correlations

- Optimal horizontal thinning btw. $25 - 35$ km ($\rho \sim 0.2$) [3]

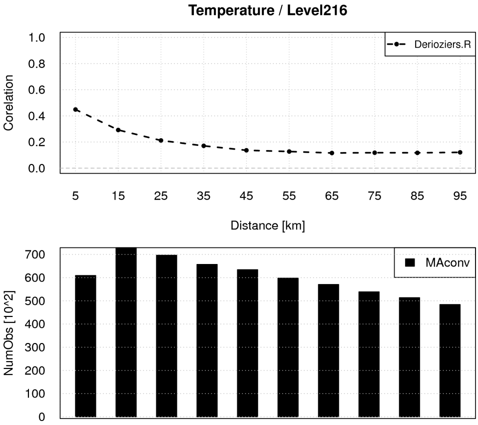


Figure : Estimates of horizontal error correlations based on Desroziers (top) and the number of a collocations (bottom) as a function of separation distance for MRAR.

Horizontal error correlations

- The 3h-forecast impact of data thinning: 5, 25, 50 and 100 km

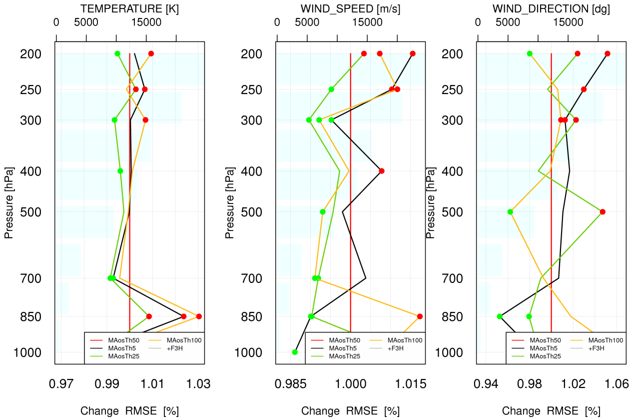


Figure : The relative change of RMSE for 3h-forecast wrt MRAR.

Vertical error correlations

- Optimal vertical thinning $\sim$ 20 hPa ($\rho \sim 0.2$) [3]

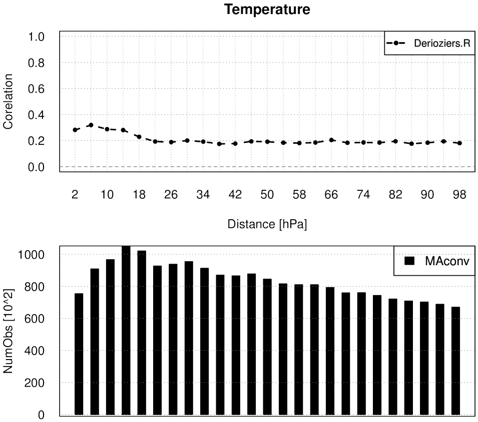


Figure : Estimates of vertical error correlations based on Desroziers (top) and the number of a collocations (bottom) as a function of separation distance for MRAR.

- The 3h-forecast impact of vertical thinning: 18 hPa

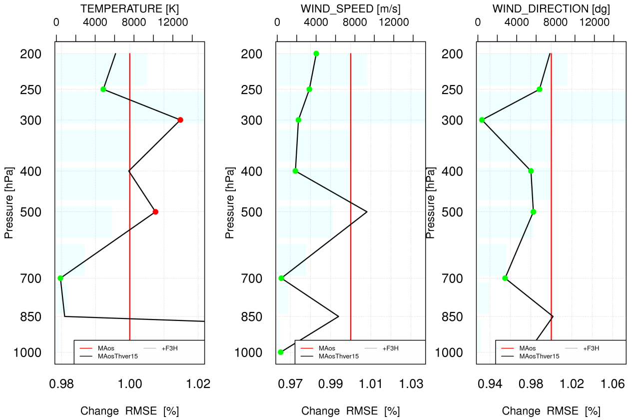


Figure : The relative change of RMSE for 3h-forecast wrt MRAR.

Observation error inflation I

- Observation errors by Desroziers for MRAR/AMDAR

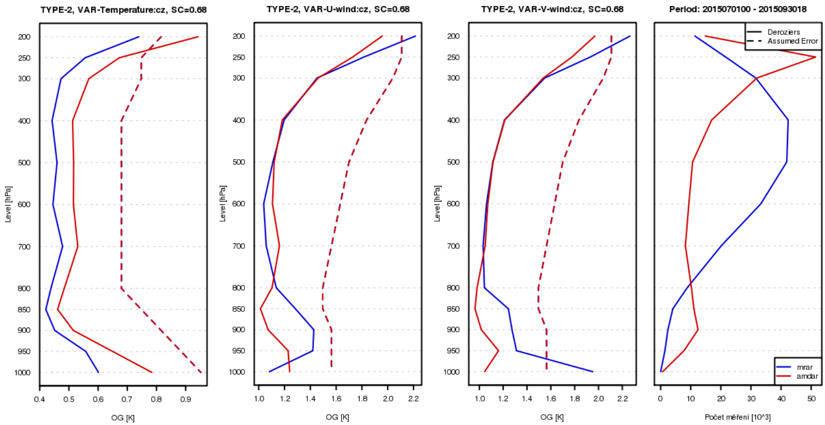


Figure : Observation error estimation for the AMDAR (red) and MRAR (blue) measurements based on Desroziers (solid) and the predefined error in the ALADIN-CZ (dotted). Scores from the period 01 Jul - 30 Sep 2015.

Observation error inflation II

- Desroziers: $SC \sim 0.6$
- Aladin/CZ: $SC \sim 0.7$
- Optimal: ?

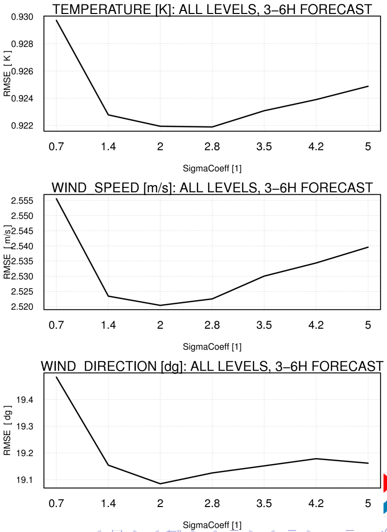


Fig: The 3-6 forecast impact of error inflation (SC) on RMSE wrt AMDAR.
Scores from the period 25 Feb - 5 Mar 2016.

Observation error inflation II

- Desroziers: $SC \sim 0.6$
- Aladin/CZ: $SC \sim 0.7$
- Optimal: $SC \sim 2.0$

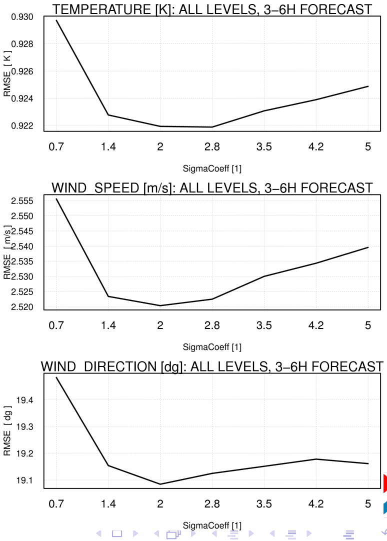
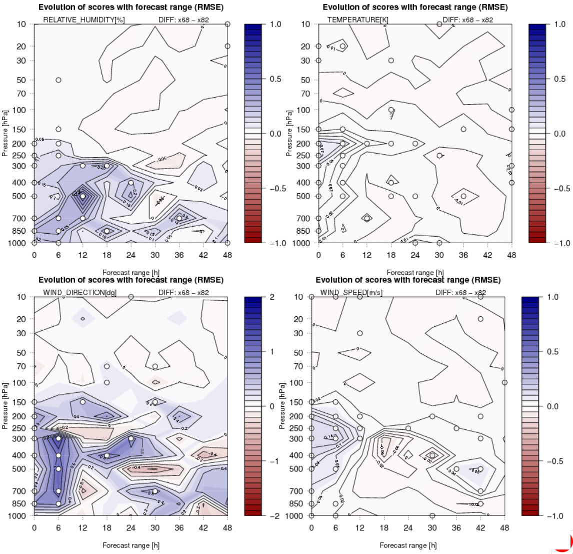


Fig: The 3-6 forecast impact of error inflation (SC) on RMSE wrt AMDAR.
Scores from the period 25 Feb - 5 Mar 2016.

Forecast Impact of NEW changes

	REF	NEW
H-Thin	50 km	25 km
V-Thin	—	18 hPa
SC	0.7	2.0

- 20 days (Feb-Mar/2016)
- production at 6, 12 UTC
- RMSE scores wrt TEMP
- positive/negative

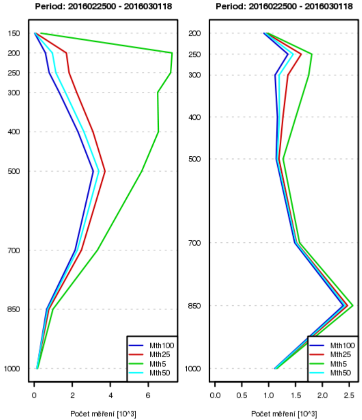


Conclusion I

- new thinning (25 km, 18 hPa) for MRAR (AMDAR) in Aladin/CZ
- similar observation errors btw MRAR and AMDAR: the same error-inflation (2.0)
- applicability of the Desroziers diagnostic for estimating observation error is questionable:
  - inconsistency btw error inflation estimated by Desroziers (~ 0.6) and based on forecast study (~ 2.0)
- should be more studied:
  - a violence of the method assumptions
  - isotropic and homogeneous B-matrix
  - ???

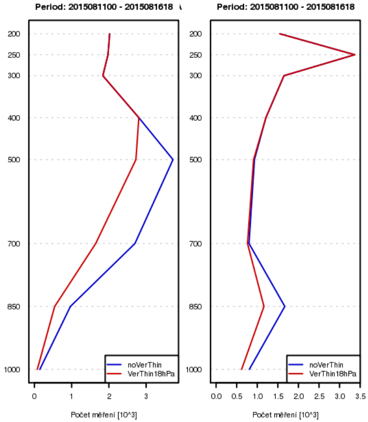
Horizontal error correlations

- The MRAR/AMDAR data reduction using 5-, 25-, 50- and 100-km horizontal thinning



Vertical error correlations

- The MRAR/AMDAR data reduction using 18-hPa vertical thinning



Satellite data

- observation error: correlations and inflation
- AMSU-A/MHS/SEVIRI on board NOAA-18,19, MetOp-A and Meteosat-10
- observation pairs d_a^o and d_b^o:
    - 2016-01-01/01-20
    - less than 1 hour apart
    - separately for each instrument and satellite
    - 20-km separation distance ($\pm$10 km)

Spatial error correlations: AMSU-A

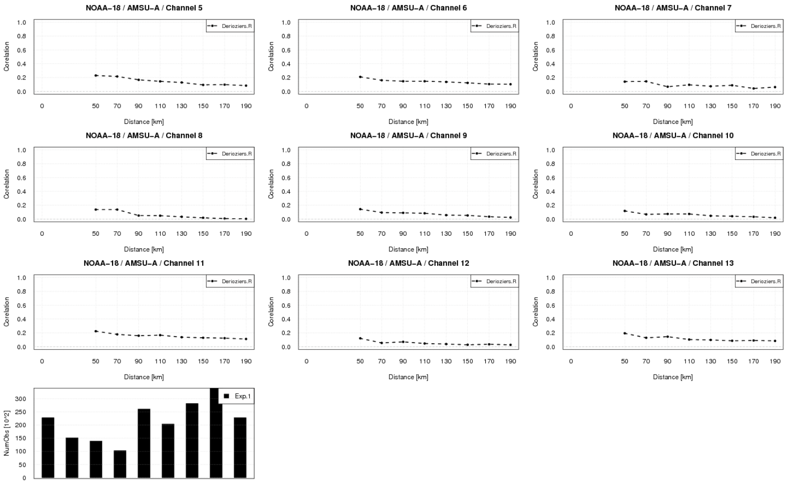


Figure : Estimates of spatial-error correlations as a function of separation distance for AMSU-A channels. Optimal thinning corresponds to AMSU-A horizontal resolution (in nadir) $\sim$ 50 km [3].

Spatial error correlations: MHS

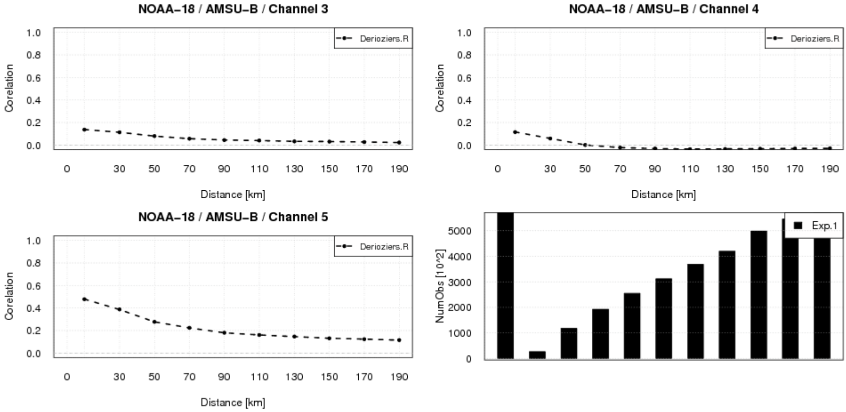


Figure : Estimates of spatial-error correlations as a function of separation distance for MHS channels. Optimal thinning corresponds to $\sim 70 - 90$ km [3].

Spatial error correlations: SEVIRI

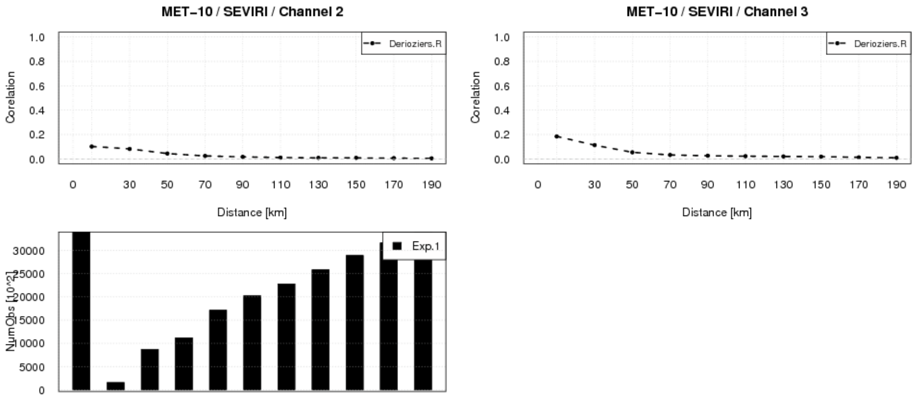


Figure : Estimates of spatial-error correlations as a function of separation distance for SEVIRI. Data are pre-thinned (every 5th pixel) in bator. Optimal thinning corresponds to $\sim$ 20 km [3].

Inter-channel error correlations: AMSU-A/MHS/SEVIRI

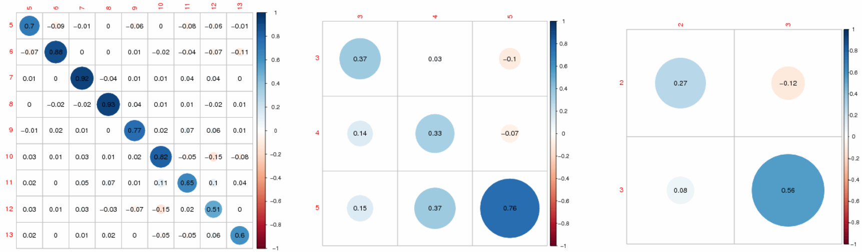


Figure : Estimates of interchannel error correlations for AMSU-A/MHS/SEVIRI (from the left) channels based on Desroziers diagnostic. The matrices have been made symetric by using $\mathbf{R} = \frac{1}{2}(\mathbf{R} + \mathbf{R}^\mathbf{T})$.

The AMSU-A error estimation

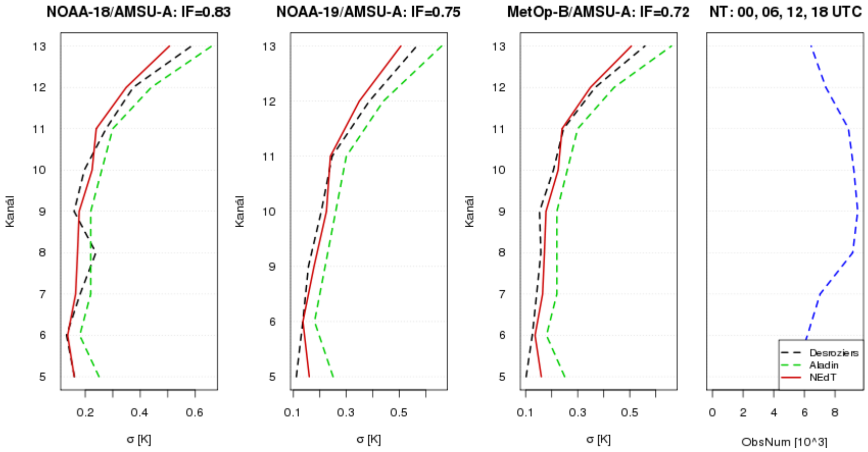


Figure : The observation error estimations by Desroziers (black), predefined in Aladin/CZ (green) and the instrument error NEdT (OSCAR-WMO) (red) of AMSU-A.

The MHS error estimation

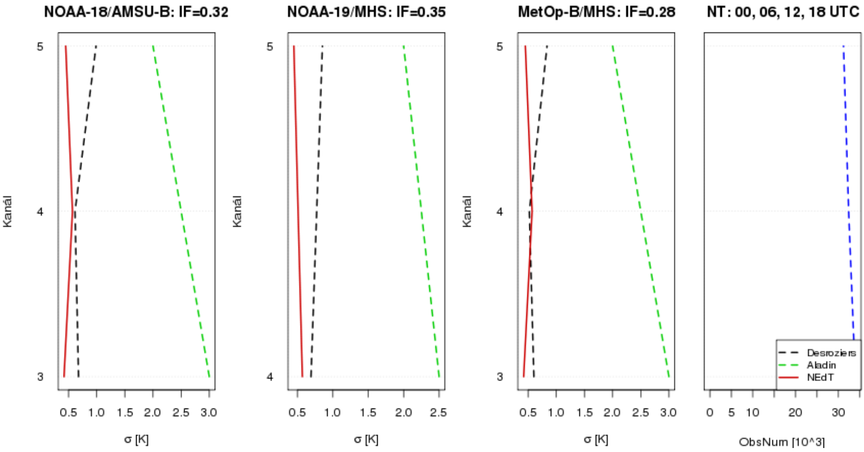


Figure : The observation error estimations by Desroziers (black), predefined in Aladin/CZ (green) and the instrument error NEdT (OSCAR-WMO) (red) of MHS.

The SEVIRI error estimation

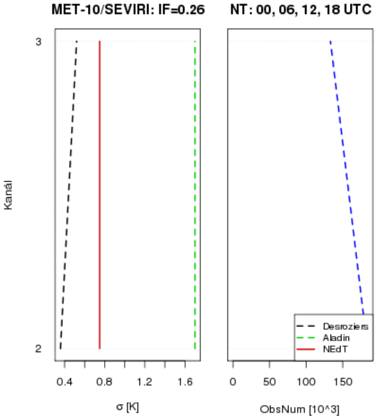


Figure : The observation error estimations by Desroziers (black), predefined in Aladin/CZ (green) and the instrument error NEdT (OSCAR-WMO) (red) of SEVIRI.

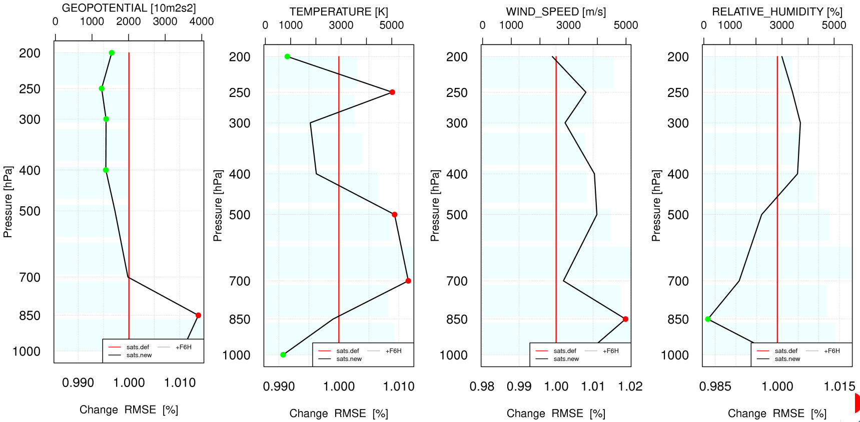
Observation error inflation

- finding optimal SC based on impact studies:
  - evaluation of the 6h-fcst impact on STD of d_b^o
  - no blending, 10-days (03/2016) at 0, 6, 12 and 18 UTC
  - wrt temp/amdar/sats (not shown)

Instrument	Thin-Old	Thin-New	SC.Ald	SC.Des	SC.Optimal
AMSU-A	70 km	50 km	1	~ 0.8	$\sim 0.8 1, 2, 3$
MHS	70 km	70 km	1	~ 0.3	$\sim 0.4, 0.6, 0.8, 1.2$
SEVIRI	70 km	20 km	1	~ 0.3	$\sim 0.5, 0.7, 0.9$

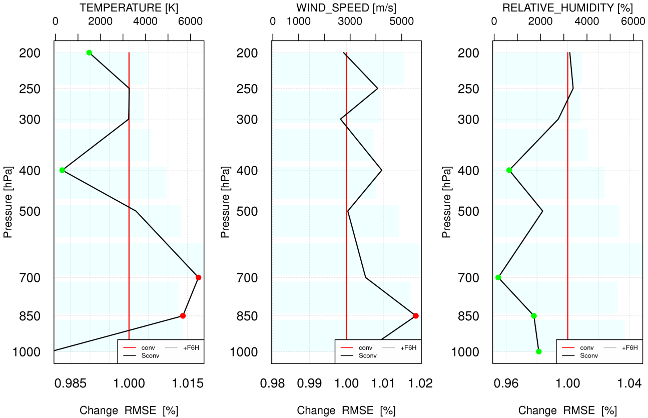
The 6h-forecast impact of NEW changes

- positive impact on humidity bias/stdv ($3 - 4\%$)
- negative impact on T700hPa bias ($\sim 1\%$)



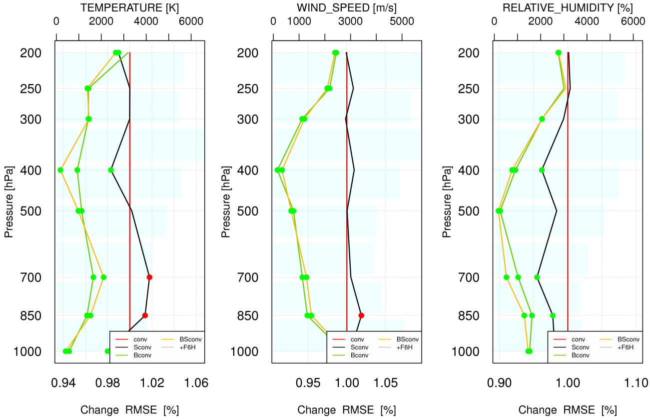
Overall satellite impact on 6h-forecast

- noBlending (conv, Sconv): RH bias/stdv (+4%); T700 bias (−1%)



Overall satellite impact on 6h-forecast

- noBlending (conv, Sconv): RH bias/stdv (+4%); T700 bias (−1%)
- Blending (Bconv,BSconv): consistent, but the impact reduction



Conclusion

- new data thinning and observation error inflation for AMSU-A/MHS/SEVIRI
- two ways of propagating satellites observations to our analysis:
  1. DFI blending with ARPEGE
  2. 3D-Var in Aladin/CZ
- blending provides sufficient information about long-scales captured by AMSU-A/MHS
- satellite DA in 3D-Var Aladin/CZ adds slight (RMSE $\sim$ 1%) improvement on the top of blending
- How beat the Blending in terms of this study:
  - high-resolution observations (IASI, radar,. . .)
  - using as much data as possible (full **R** matrix) to resolve small-scales

References

Desroziers, G., et al. 2005 **Diagnosis of observation, background and analysis tuning method in variational assimilation.**
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Liu Z-Q., and Rabier F., 2003 **The potential of high-density observations for numerical weather prediction: A study with simulated observations.**
QJRM Society 130.601, 2253-2275

Thank you for your attention.