Background errors and control variables for clouds and precipitation

Thibaut MONTMERLE

With inputs from Yann Michel, Benjamin Ménétrier, Mayeul Destouches, Jean-François Caron and Raphaël Legrand*

CNRM, Toulouse, France
* ECCC

2020/02/05
ECMWF Clds and Precip DA Workshop

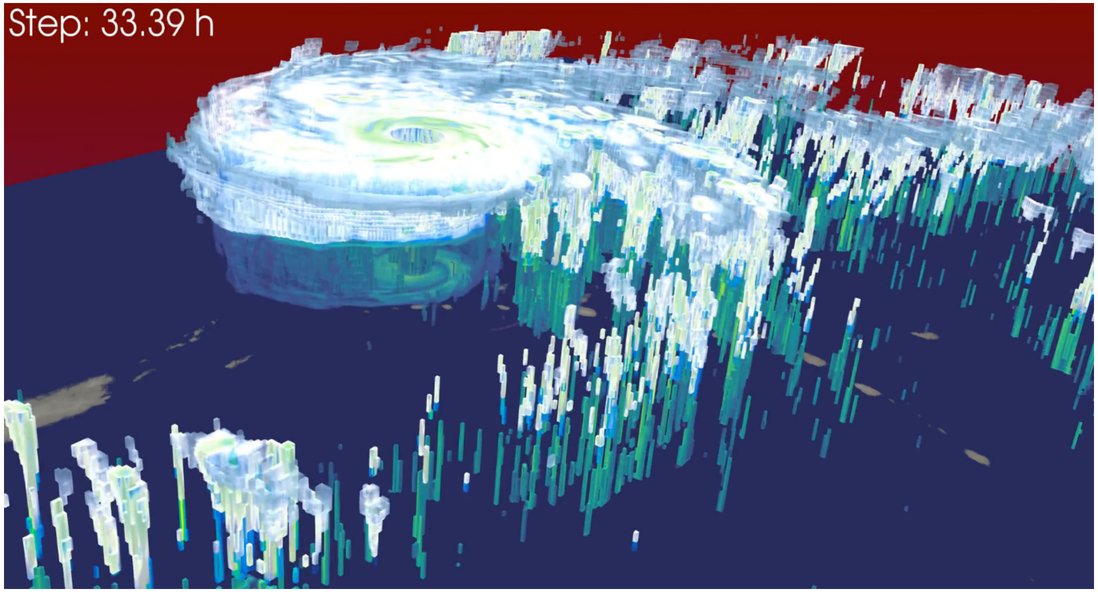
Outlines

1. Introduction
2. Diagnosing and modelling forecast errors in clouds and precipitation
3. CV in clouds and precipitation
4. Accounting for hydrometeors in VAR DA
5. Conclusions

Introduction

Motivations :

- Association with high-impact weather : Thunderstorms, flash floods, fog
- Strong radiative impacts of clouds in NWP
- Availability of new observations related to clouds and precipitations (e.g MW/IR radiances, DPOL Radar, lightning activity …)
- Explicit representation of hydrometeors in NWP at convective scale leading to realistic simulated observations



Ice cloud and liquid rain simulated by AROME for cyclone IRMA
© G. Faure

Introduction

Accounting for hydrometeors in DA may allow to :

- Simulate observations more realistically
- Have a positive feedback on the linear/NL forecasts within the assimilation window
- Retrieve realistic analyses of clouds and precipitations (instead of e.g cycling values from the guess)
- Improve the analyses of classical variables through the use of background error cross-covariances, and thus improve initial balances
- Improve the resulting forecasts !

Diagnosing and modelling forecast errors in clouds and precipitation

Methodology

1. Raw covariances $\widetilde{\mathrm{B}}$

Sample forecast errors following a Monte-Carlo approach with an ensemble of L background perturbations :

$$\widetilde{\mathrm{B}} = \frac{1}{L-1}\sum_{p=1}^{L}\left(\widetilde{\mathbf{x}}_p^b - \langle\widetilde{\mathbf{x}}^b\rangle\right)\left(\widetilde{\mathbf{x}}_p^b - \langle\widetilde{\mathbf{x}}^b\rangle\right)^{\mathbf{T}}$$

Here, background fields x^b are provided by different Ensemble Data Assimilation systems (EDA) based on AROME-France.

Usable in EnVar (or EnKF) after localization.

2. Modelled covariances B_c

Use the same background perturbations to calibrate balance operators and spatial transforms used in e.g VAR DA systems (see rev. by Bannister (2008)):

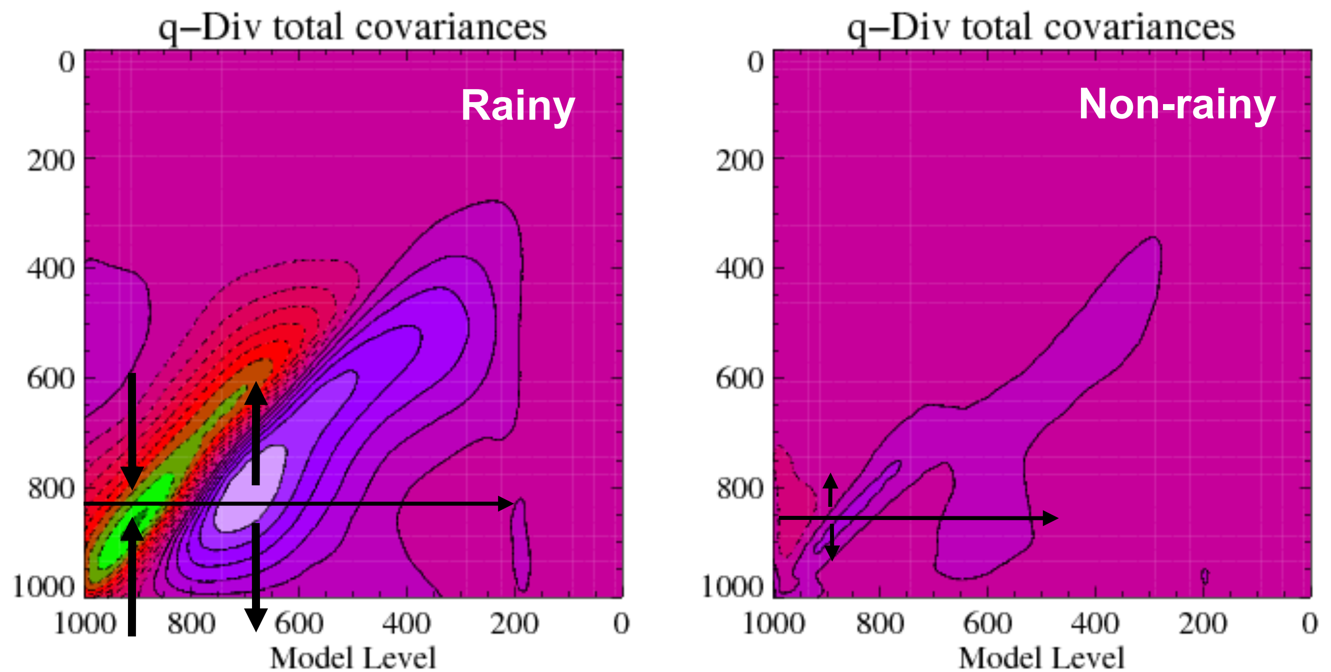
$$\mathrm{B}_c = \mathrm{K}_p \mathrm{B}_s \mathrm{K}_p^T$$

$\Rightarrow$ Allow to model full rank covariances and balance relationships between control variables

Forecast errors in clouds and precipitation

Modelling multivariate B_c in precipitation using geographical masks (Montmerle and Berre, 2010)

(q,div) Vertical covariances



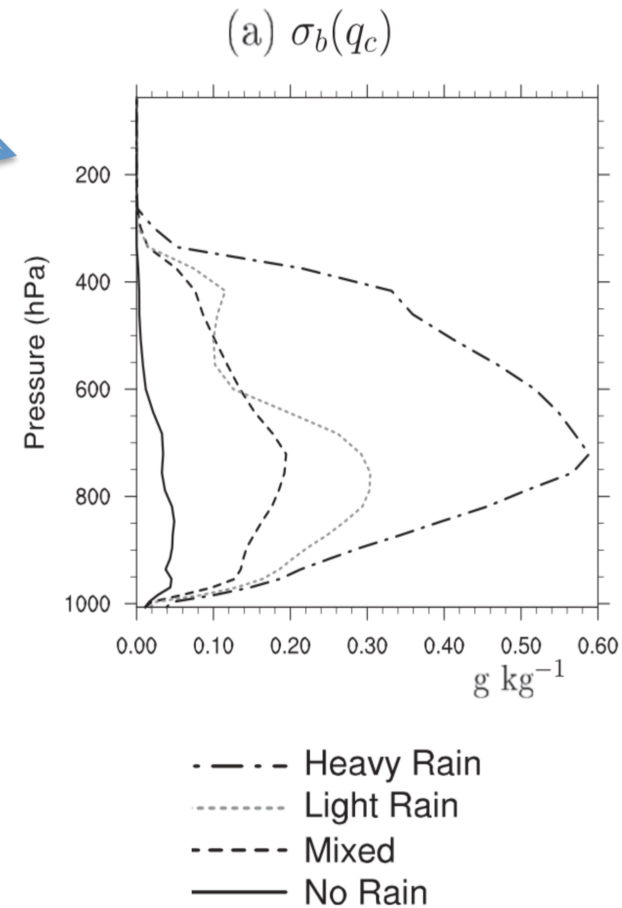
Also :

- Vertical covariances clearly linked to diabatic processes
- Shorter correlation lengths for q and T
- Larger standard deviations for vorticity and divergence

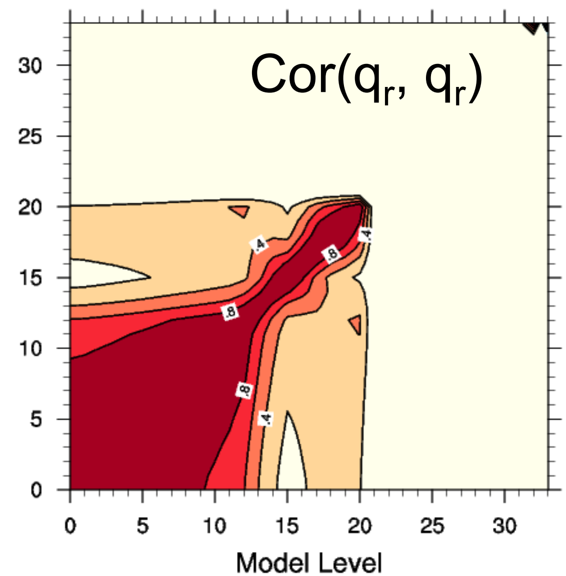
Forecast errors in clouds and precipitation

Modelling multivariate B_c in precipitation using geographical masks
Extension to q_c and q_r (Michel, Montmerle and Auligné (2011))

- Error variances depend on rain intensity
- Shorter horizontal correlation lengths
- Strong coupling with *q* (which is also largely coupled with div_u)



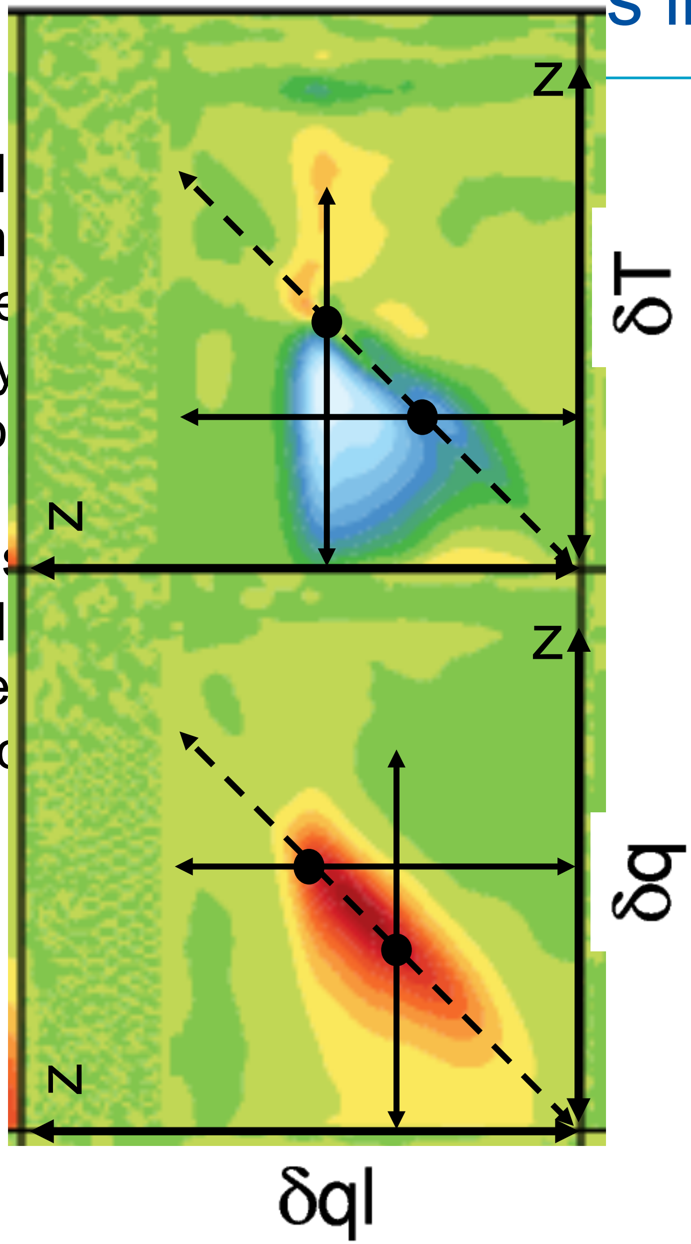
- Vertical correlations reflect the averaged vertical structure of precipitating systems and sedimentation processes

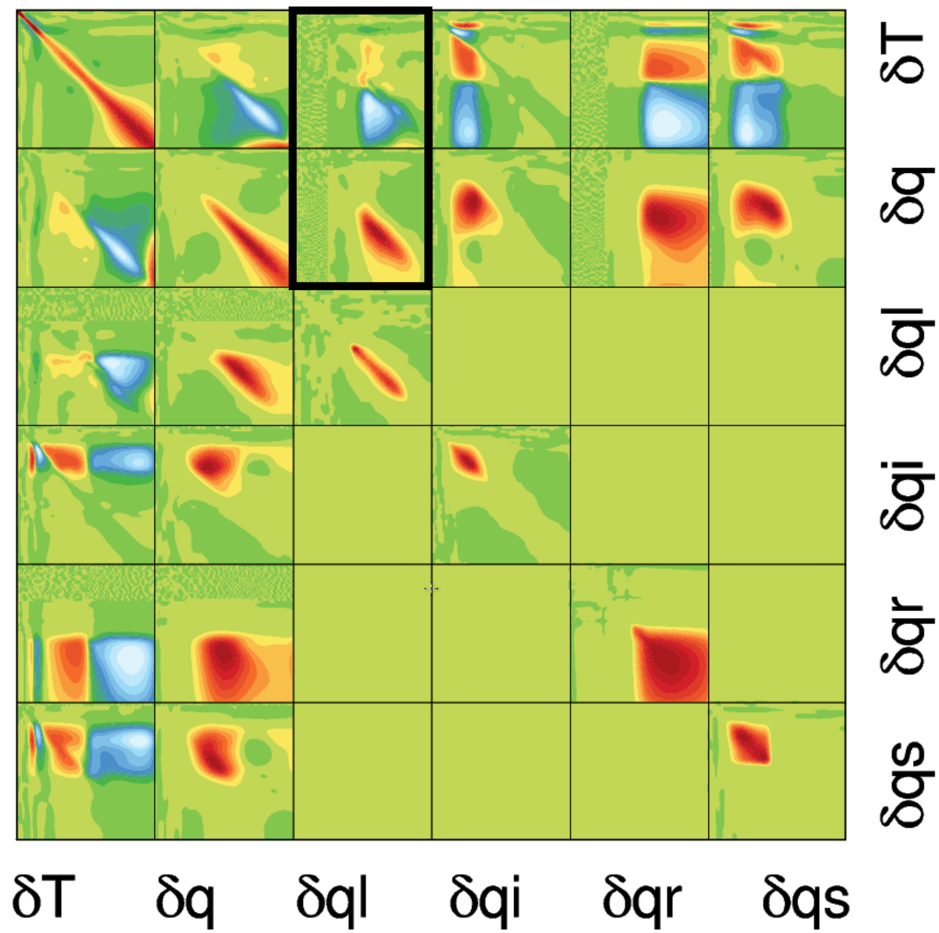


s in clouds and precipitation

M
m
be
hy
fo

Us
M
re
fr

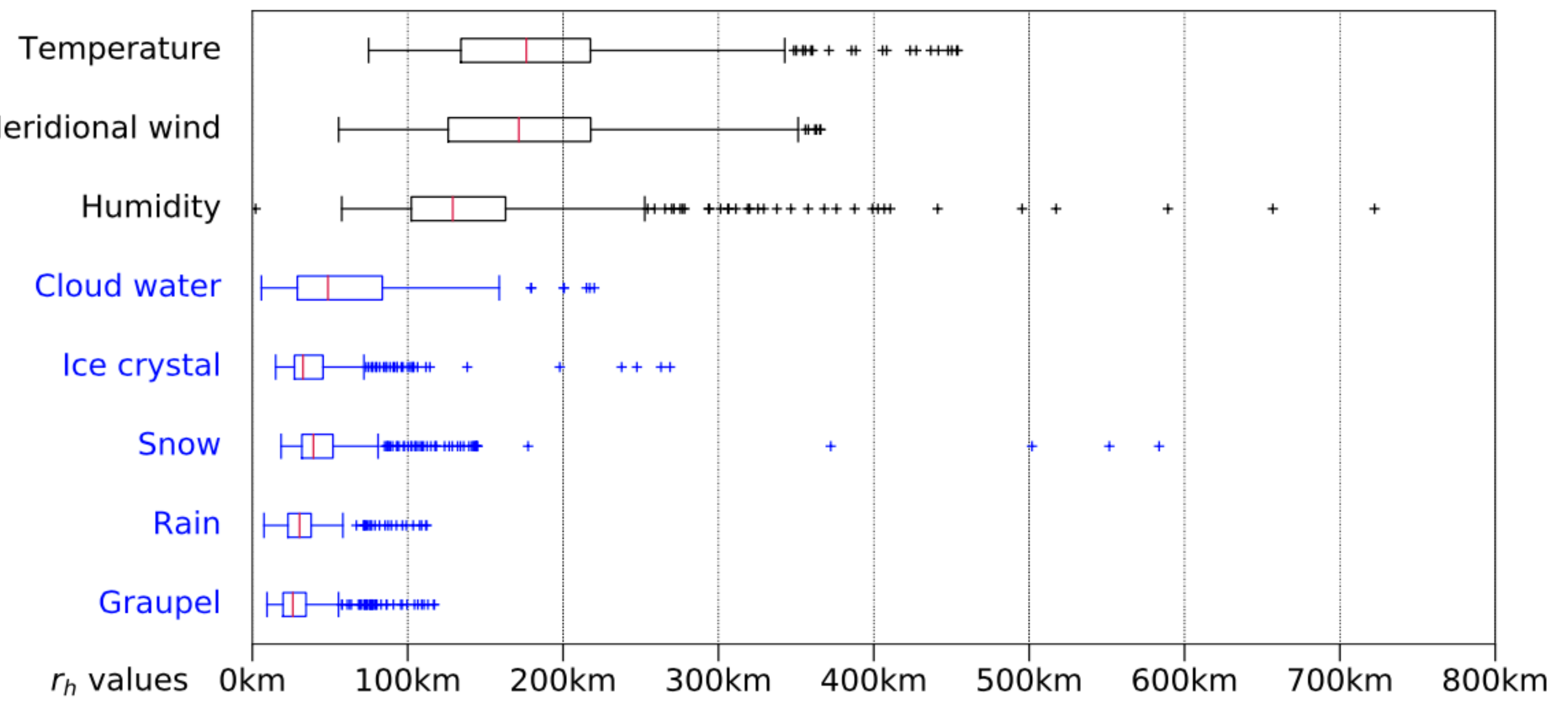




Normalized total vertical covariances

Forecast errors in clouds and precipitation

Localization lengths have been objectively diagnosed for hydrometeors using Ménétrier et al (2015) (here results for 8 summer and winter cases)



Localization lengths can be relied to background error correlation lengths
$\Rightarrow$ One has to keep those results in mind when modeling $\mathbf{B_c}$ / localizing $\widetilde{\mathrm{B}}$ / thinning data within clouds and precipitation

CV in clouds and precipitation

CV in clouds and precipitation

The diagnostic approach : total water

Use of simplified version of the moist phases in or out the assimilation window (e.g $q_T = q + q_c$) together with a partition operator (e.g Migliorini (2018))

+ Only error covariances of δq_T need to be modelled

+ Those covariances may be smoother that of separated quantities

- Partition operator with closure assumption
- Zero-gradient problem if the background is clear

The explicit approach : separate hydrometeors

Consider each hydrometeor (and q) separately

+ No partionning operator, can create condensate increments in dry areas

- Need to linearize the microphysics
- Need to model ad-hoc multivariate background error covariances

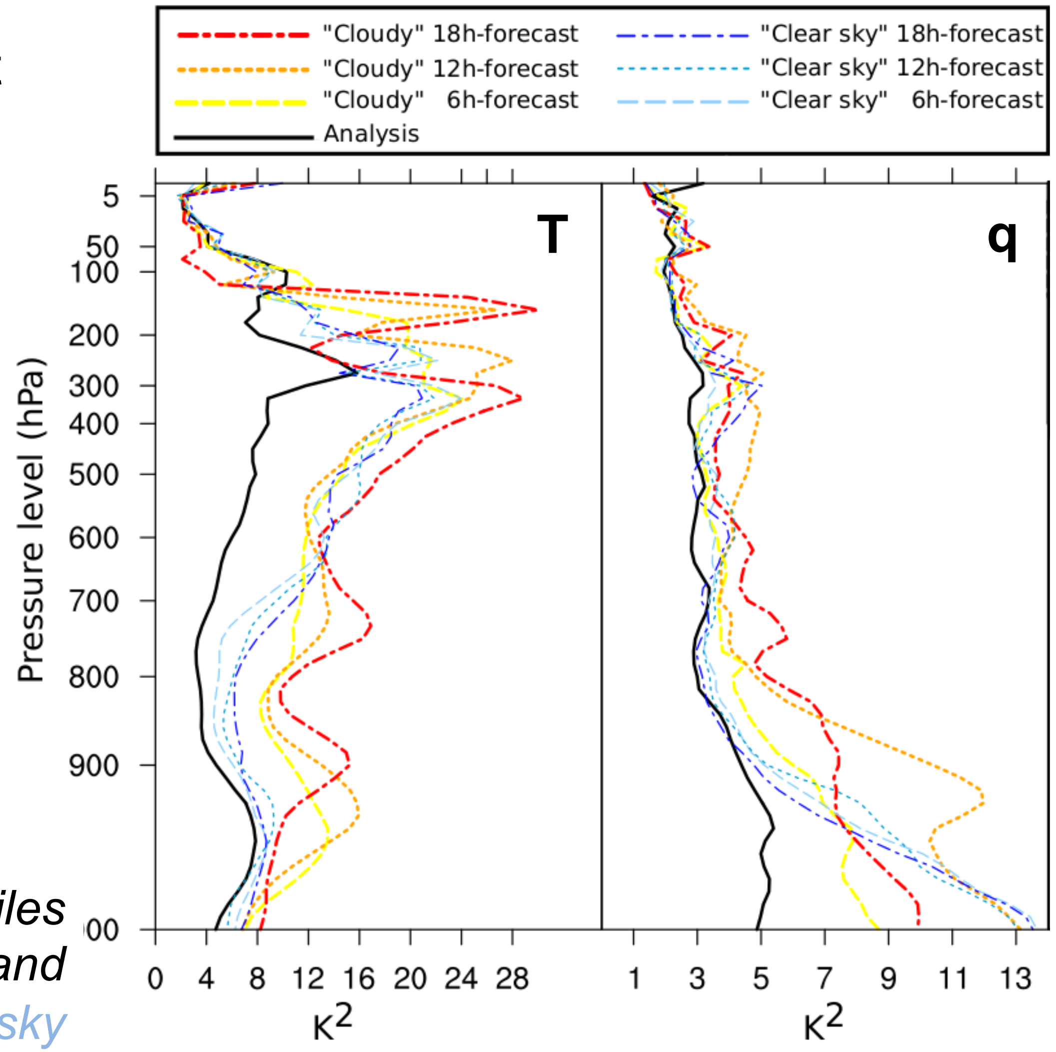
$\Rightarrow$ Not the case in Ensemble DA (but with other issues)

CV in clouds and precipitation

Non-Gaussianity:

As q and RH are bounded at saturation, their PDFs are clearly NG, especially in clouds and precipitation

K^2 statistics from the D'Agostino test performed on profiles extracted from a 90 members AROME EDA (Legrand et al. 2016)



Time evolution of K^2 profiles averaged in clouds and clear-sky

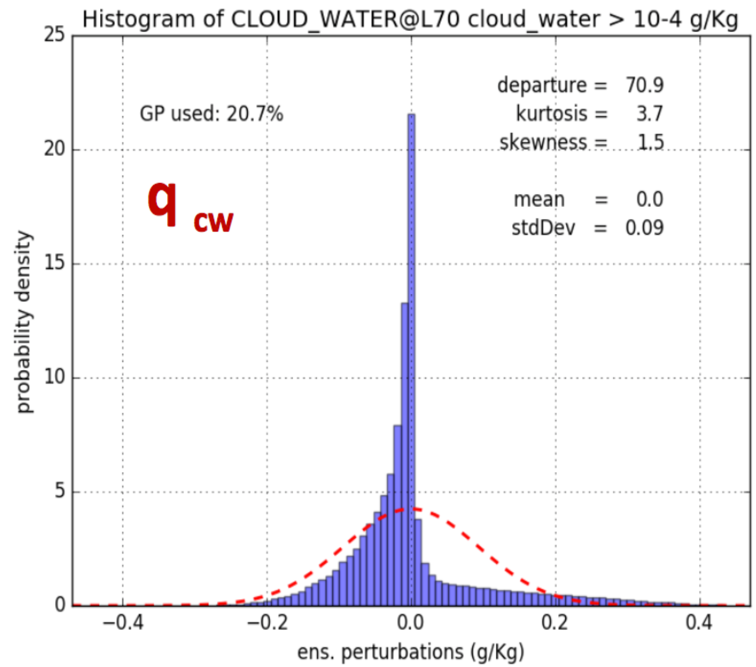
CV in clouds and precipitation

Hydrometeors are even more NG because of NL in the microphysical parameterization, physical bounds, displacement errors

How to become more Gaussian ?

- **NL change of variable** (e.g Bocquet et al 2010) : Gaussian anamorphosis, Log-normal…

⇒ Suitability to hydrometeors questionable : multiplicative nature of errors, difficult to use in VAR because of different mean, median and mode (Fletcher and Zupanski 2006)



PDF of Cld Water around 800 hPa deduced from a 50 members AROME EDA
© J.-F. Caron

- **Normalization** of variable by information from the background to get more symmetric PDF (Holm 2002). Used in many centres for humidity

Accounting for hydrometeors in VAR DA

Accounting for hydrometeors in VAR DA

Pre-assimilation retrievals

- In case of **1D-Var**, only needs to compute background error vertical covariances

⇒ Allow typically to retrieve TCLW or (T,q) profiles (Janiskova 2015), or to explicitly retrieve profiles of cloud related information from MW or IR radiances in cloudy areas (e.g Pavelin (2008), Geer (2008), Martinet (2013)).

- **Non-Var method** such as basic 1D PF are also used to retrieve RH profiles from radar reflectivities (Caumont 2010) or MW radiances (Duruisseau (2019), see poster by M. Barreyat): no need for **B** (but retrieved profiles potentially correlated with the background)

⇒ Allows however for correcting displacement errors at some point

Accounting for hydrometeors in VAR DA

3D/4D VAR

- **To consider hydrometeors in the CV**, Michel (2011) approach can be used to model $\mathbf{B_c}$, but with frequent updates

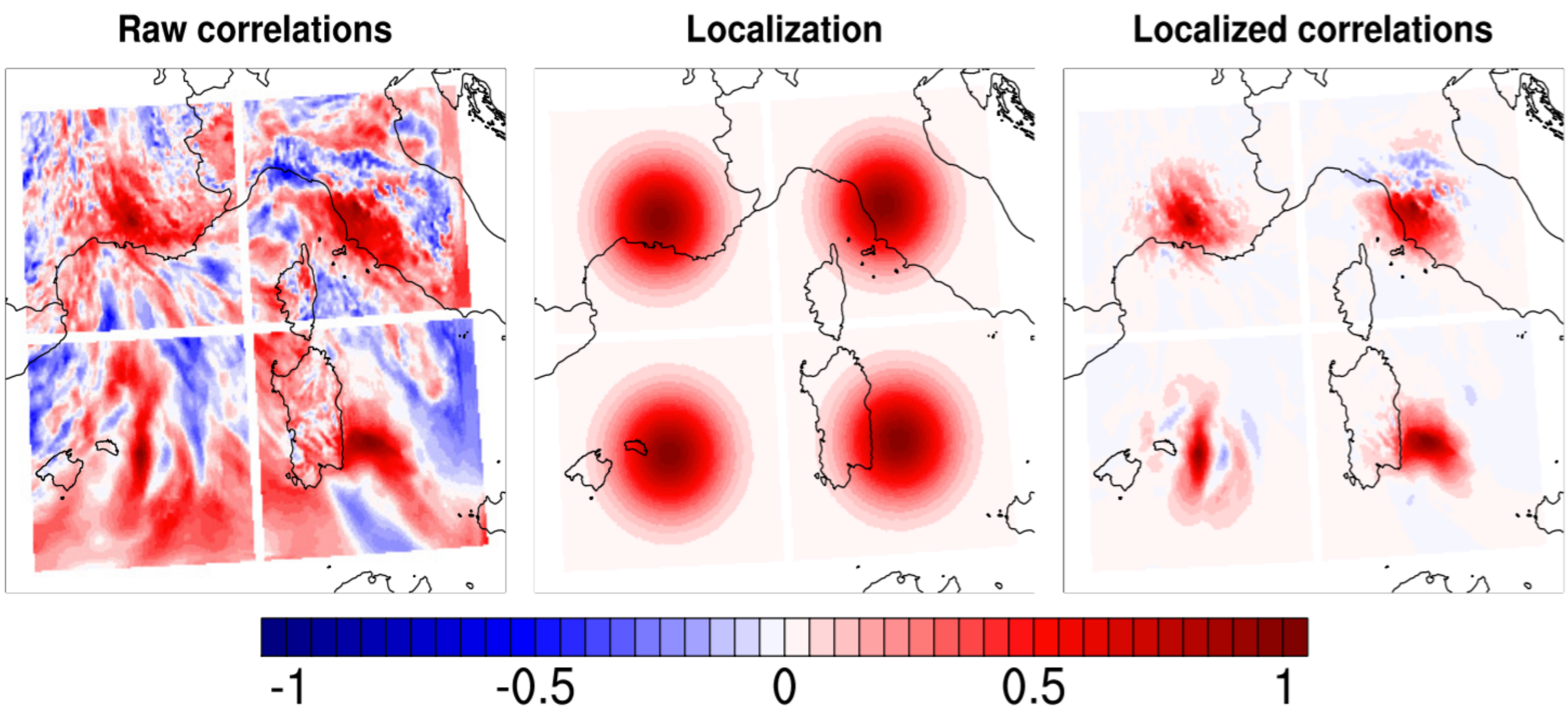
⇒ The needed level of flow dependency is however beyond the capabilities of $\mathbf{B_c}$ with daily update of variances and wavelet correlations used at MF and ECMWF. Unrealistic smoothings and couplings may occur

⇒ May work only for LAM and for rather homogeneous meteorological situations.

- **4DVar requires TL/AD models** : may need incremental technique and very short assimilation window to stay close to the microphysic's linear regime

Accounting for hydrometeors in VAR DA

Pure EnVar (1/2) : Considering new CV and their errors is more straightforward
$\widetilde{B}$ is flow dependent, but rank-deficient and affected by sampling noise : localization step is needed (Houtekamer and Mitchell, 2001)



Accounting for hydrometeors in VAR DA

Pure EnVar (2/2)

- In 4D, the temporal evolution of forecast errors is simulated by a linear combination of perturbations (instead of TL/AD)

$\Rightarrow$ Allows to avoid the complex linearisation of microphysics

- **The main science relies on localization :** how to limit the induced imbalances ? How to localize cross-covariances ? (+Efficiency issues when considering variable dependent localization lengths)

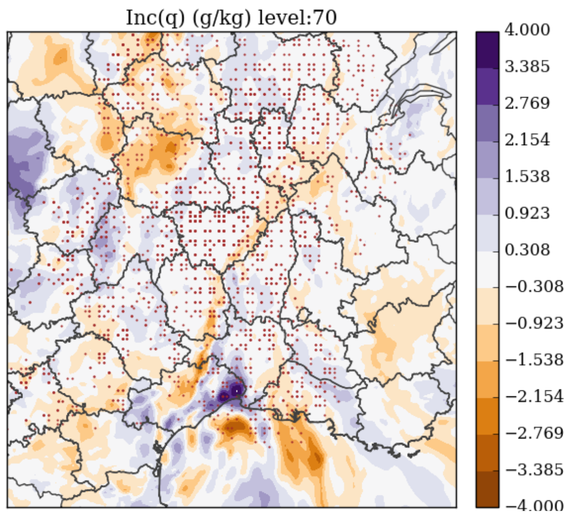
Requirements :

- Ensemble of forecasts is needed at each assimilation step
- **Performances are clearly linked to the level of sampling noise** in the resulting covariances, which depends on the ensemble size and on the localization procedure

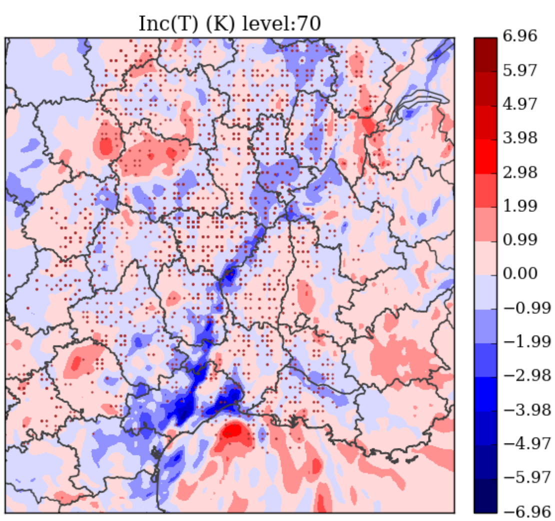
Accounting for hydrometeors in VAR DA

Increments retrieved from the AROME 3DEnVar with hydrometeors :
(25th of April 2019)

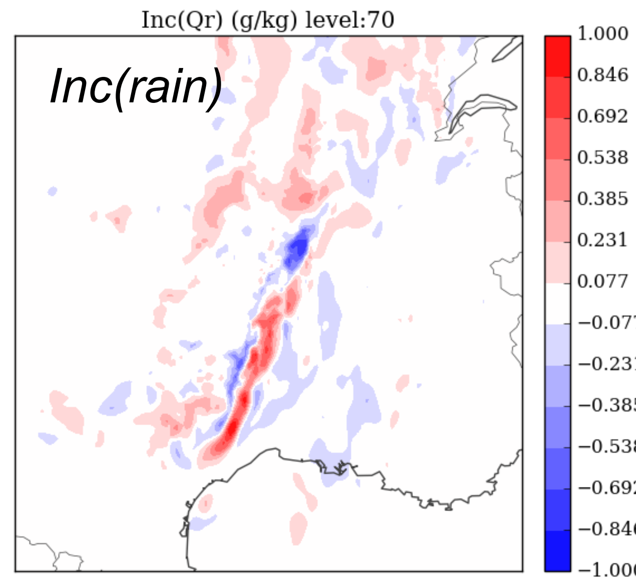
Inc(q) @800hPa + active radar profiles



Inc(T) @800hPa



Cross-covariances allow the projection of (q,T) increments on hydrometeor increments, i.e clouds and precipitation can be created/ removed without any direct observation

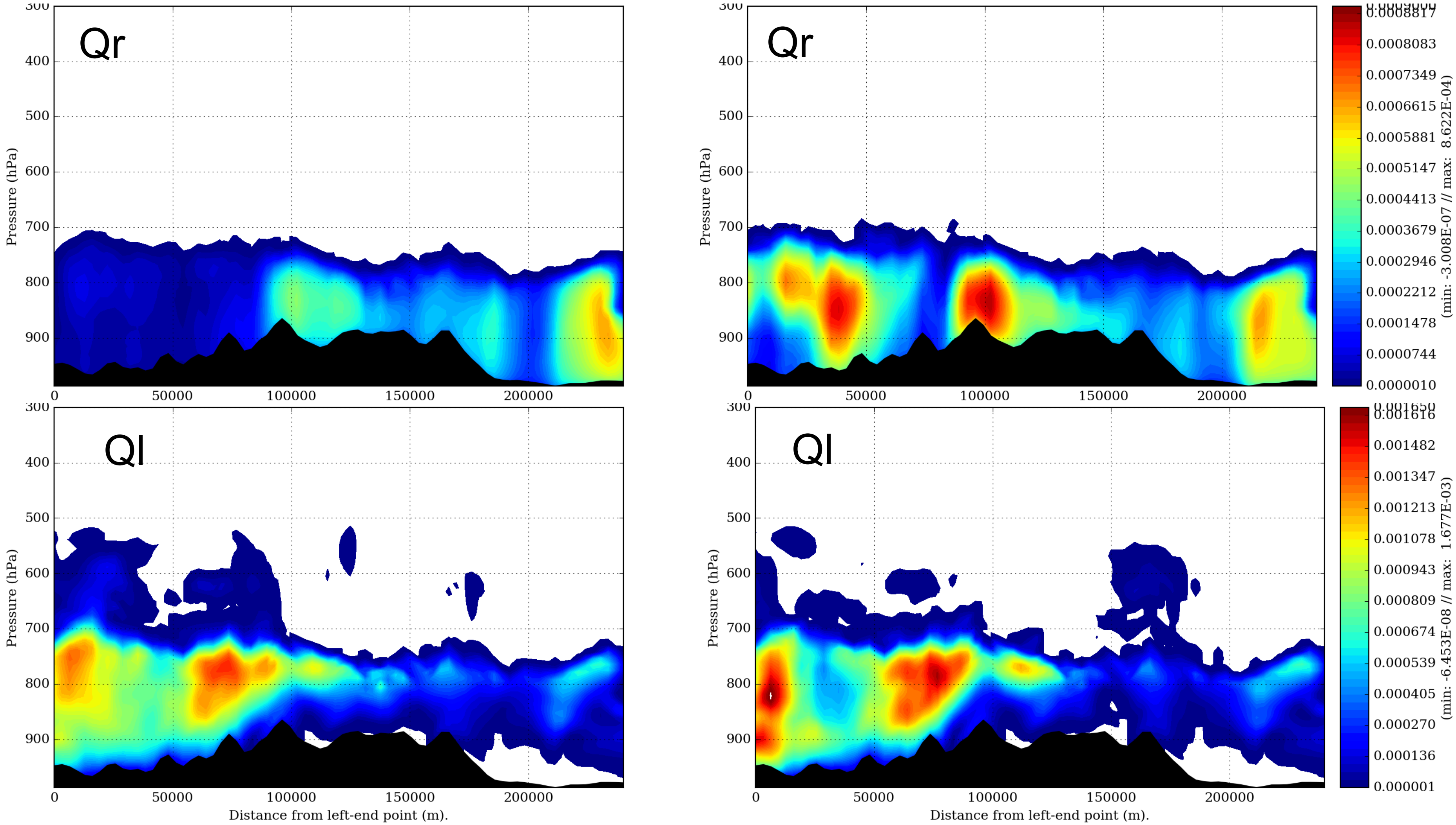


⇒ Significant positive scores on short-term forecast of cloud cover and accumulated precipitations (cf M. Destouches's poster)

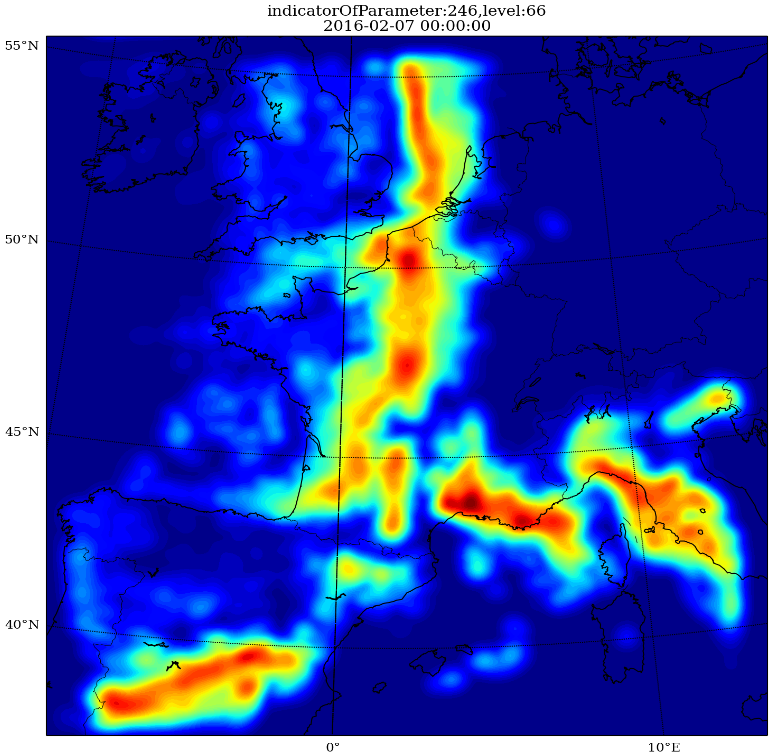
Accounting for hydrometeors in VAR DA

Vertical cross sections along the main convective line :

CNTRL HYMNCy



Accounting for hydrometeors in VAR DA



Ql variances @700 hPa , deduced from a 25 m AROME EDA (7th of Feb. 2016)

Handling zero spread of hydrometeors in the ensemble :

- Perform local additive inflation, eventually combined with σ_o deflation
- Use modeled $\mathbf{B_c}$ (with hydros) in a hybrid formulation
- Derive information from the ensemble in surrounding areas (poster by K. Aonashi)

Conclusions

Because of the positive and discontinuous nature of hydrometeors, **acounting for these variables in DA pushes « traditional »VAR systems to its limit** :

- **NG Pdfs** of innovations and forecast errors
- **Strongly flow-dependent forecast errors** with cross-correlations important to account for
- **Non-linearities** to handle in the assimilation window

⇒ The use of ensembles may be the solution, but more work on localization and on the zero-spread issue is needed.

On the forecast side, **DA can create imbalances** (spin up/spin down effects), and negatively analyzed quantities may generate biases once removed by the microphysicals.

⇒ Initial balances and forecast impacts (e.g. radiation/precipitations) must be carefully checked

Thank you for your attention !

References

Bannister, R.N. (2008b) A review of forecast error covariance statis- tics in atmospheric variational data assimilation. II: Modelling the forecast error covariance statistics. *Quarterly Journal of the Royal Meteorological Society*, 134, 1971–1996.

Bocquet, M., Pires, C.A. and Wu, L. (2010) Beyond Gaussian statisti- cal modeling in geophysical data assimilation. *Monthly Weather Review*, 138, 2997–3023.

Caumont, O., Ducrocq, V., Wattrelot, É., Jaubert, G. and Pradier-Vabre, S. (2010) 1D+3DVar assimilation of radar reflectivity data: a proof of concept. *Tellus A*, 62, 173–187

Derber, J., and F. Bouttier, 1999: A reformulation of the background error covariance in the ECMWF global data assimilation system. Tellus, 51A, 195–221.

Duruisseau, F., Chambon, P., Wattrelot, E., Barreyat, M. and Mah- fouf, J.-F. (2019) Assimilating cloudy and rainy microwave obser- vations from SAPHIR on board Megha Tropiques within the ARPEGE global model. *Quarterly Journal of the Royal Meteoro- logical Society*, 145(719), 620–641.

Fletcher, S. and Zupanski, M. (2006) A data assimilation method for log-normally distributed observational errors. *Quarterly Journal of the Royal Meteorological Society*, 132, 2505–2519.

Geer, A.J., Bauer, P. and Lopez, P. (2008) Lessons learnt from the operational 1D+ 4D-Var assimilation of rain-and cloud-affected SSM/ I observations at ECMWF. *Quarterly Journal of the Royal Meteorological Society*, 134, 1513–1525.

Hólm, E., Andersson, E., Beljaars, A., Lopez, P., Mahfouf, J., Sim- mons, A. and Thépaut, J. (2002) *Assimilation and modelling of the hydrological cycle: ECMWF's status and plans*. ECMWF Technical Memorandum 383.

Houtekamer, P. L. and Mitchell, H. L., 2011:A sequential ensemble Kalman lter for atmospheric data assimilation. Mon. Weather Rev., 129, 123–137

Janiskova, M. (2015) Assimilation of cloud information from space- borne radar and lidar: experimental study using a 1D+4D-Var technique. *Quarterly Journal of the Royal Meteorological Society*, 141, 2708–2725.

covariances at convective scale using either large or small ensembles. QJRMS, in press.

Ménétrier, B., Montmerle, T., Michel, Y. and Berre, L. (2015b) Linear filtering of sample covariances for ensemble-based data assim- ilation. Part II: Application to a convective-scale NWP model. *Monthly Weather Review*, 143, 1644–1664.

Michel, Y., Auligné T. and T. Montmerle, 2011 : Diagnosis of heterogeneous convective-scale Background Error Covariances with the inclusion of hydrometeor variables. Mon.Wea Rev., 138(1), 101–120.

Migliorini, S., Lorenc, A.C. and Bell, W. (2018) A moisture- incrementing operator for the assimilation of humidity- and cloud-sensitive observations. *QJRMS*, 144(711), 443–457.

Montmerle T. and L. Berre, 2010: Diagnosis and formulation of heterogeneous background error covariances at mesoscale. Quart. J. Roy. Meteor. Soc., 136, 1408–1420.

Montmerle T., 2012: Optimization of the assimilation of radar data at convective scale using specific background error covariances in precipitations. Mon. Wea Rev., 140, 3495-3506.

Pavelin, E., English, S. and Eyre, J. (2008) The assimilation of cloud-affected infrared satellite radiances for numerical weather prediction. *Quarterly Journal of the Royal Meteorological Society*, 134, 737–749.

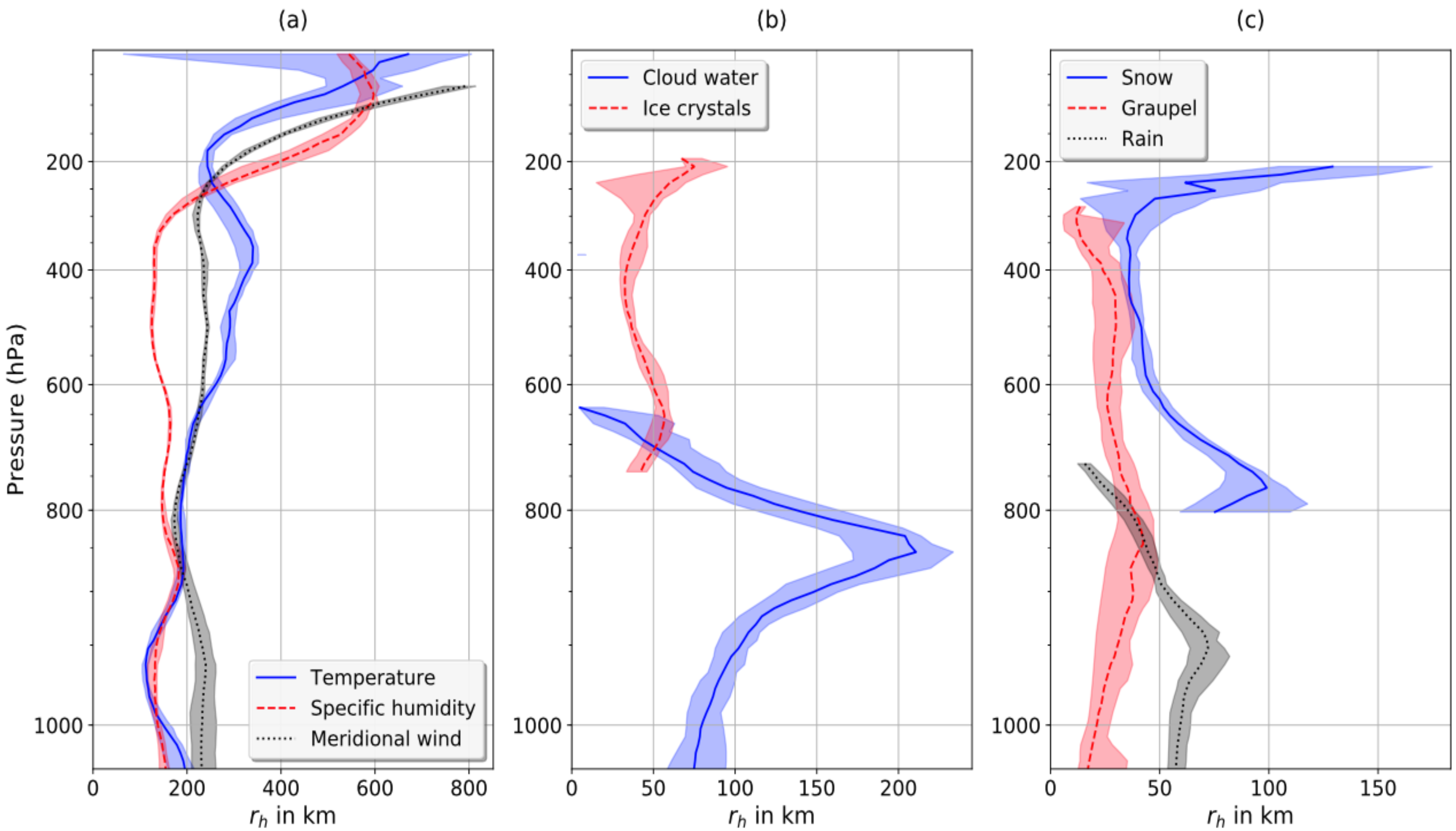
.

METEO FRANCE

Forecast errors in clouds and precipitation

Localization lengths have been objectively diagnosed for hydrometeors using Ménétrier et al (2015) :

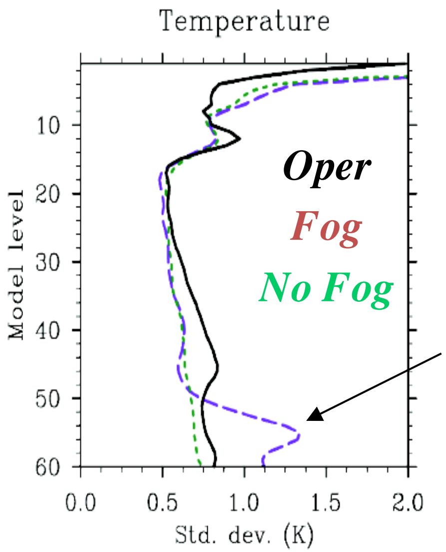
Vertical profiles of horizontal length-scales (15^{th} of Nov 2018)
© M.Destouches



Here again strong flow dependency, and much shorter values that of classical variables on the horizontal

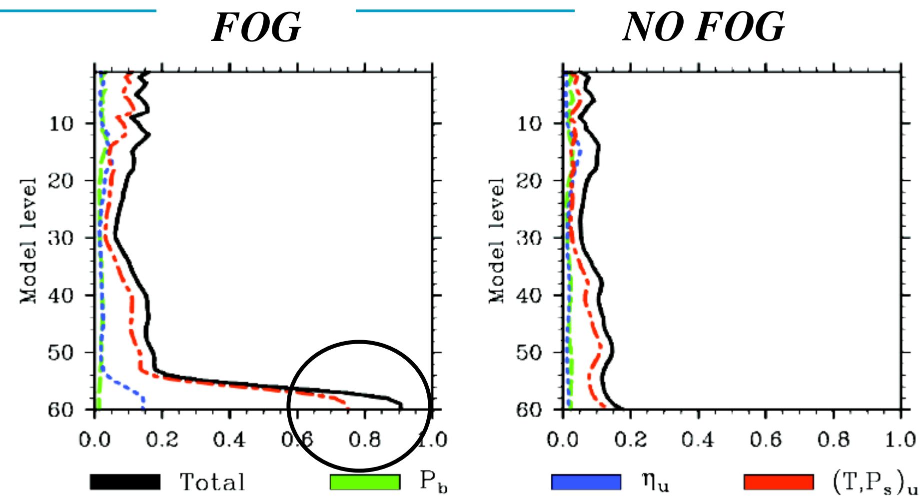
Diagnostics of covariances in clouds and precipitation

Same approach has been recently applied for fog:



$\sigma_b(T)$

Maximum reflecting T inversion above fog



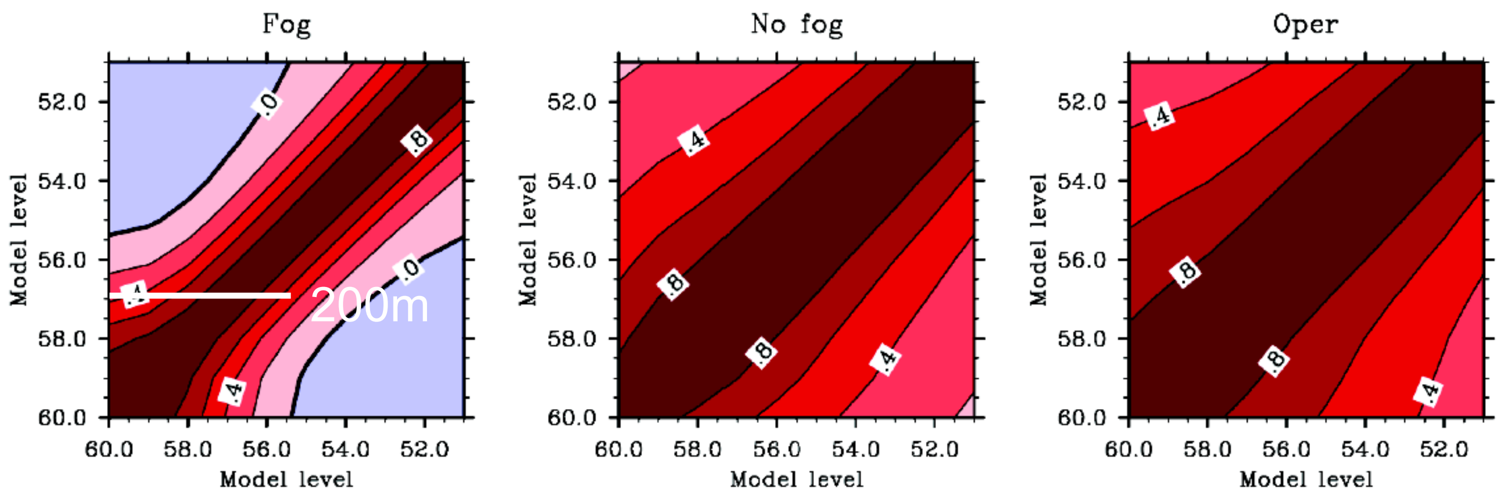
Fraction of explained q variance ratios

Very strong coupling between q and T in fog due to saturation

Vertical correlations for T

(zoom in the first 500m)

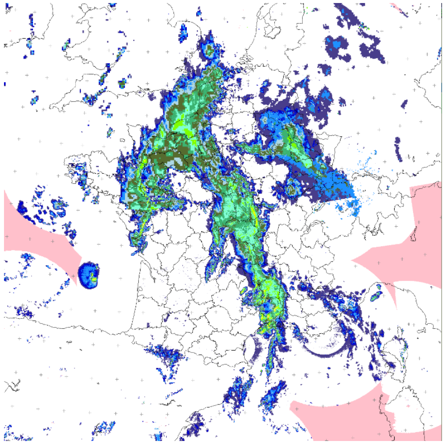
Vertical stability of fog



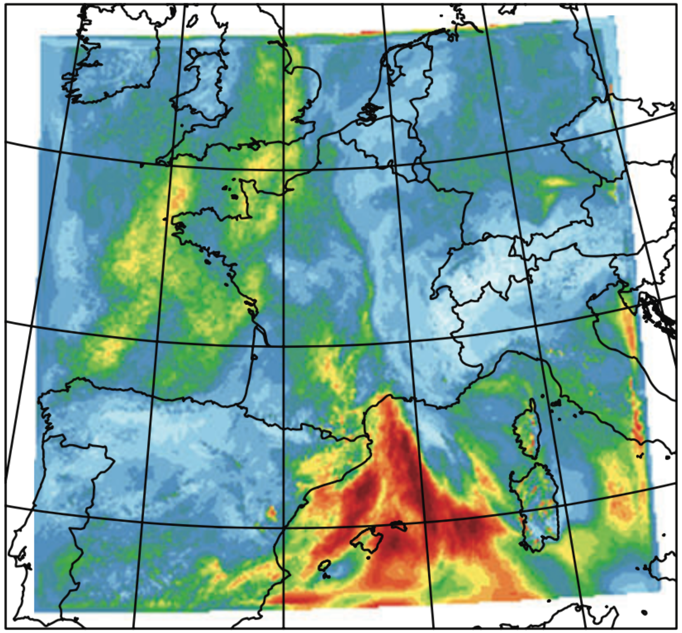
B. Ménétrier

Diagnosing forecast errors in clouds and precipitation

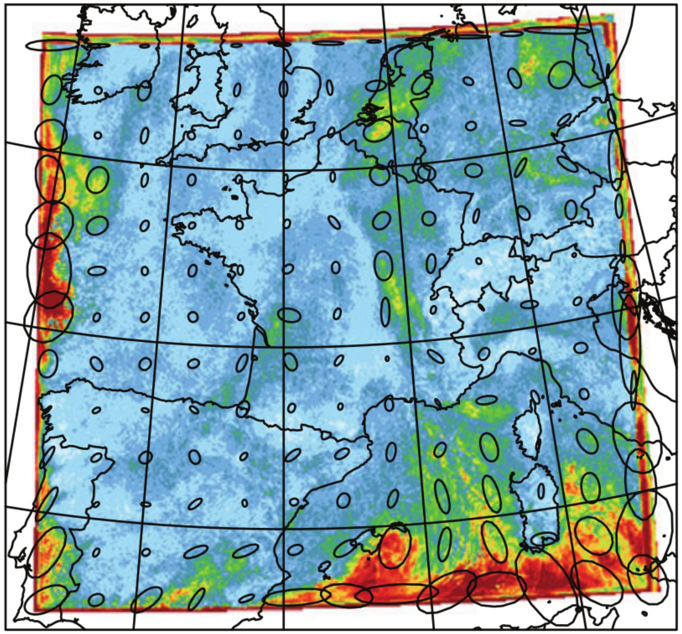
Specific humidity (q) in the BL retrieved from an EDA of 84 members
(3h fcst, Ménétrier et al. 2014)



Radar



Standard deviation



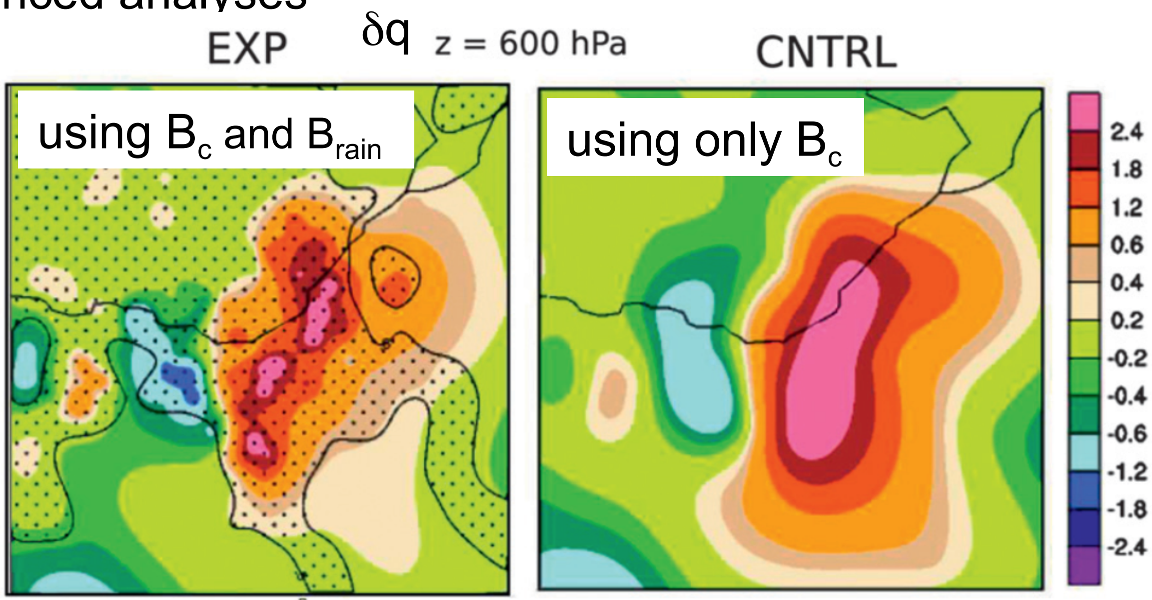
Correlation : Local tensor and total length-scales

- Strongly flow-dependent structures that are mainly linked to diabatic processes, LBCs, orography and assimilated observations
- Results differ with scale (e.g with EDA at global scale)

Accounting for hydrometeors in VAR DA

3D/4D VAR

- **To consider hydrometeors in the CV**, ad-hoc forecast errors must be frequently computed following e.g Michel (2011) approach. May work only for LAM and for rather homogeneous meteorological situations.
- The $\mathbf{B_c}$ matrix is at full rank, but flow dependencies in clouds and precipitation may still be limited, leading to unrealistic smoothings and couplings that can result in unphysical/unbalanced analyses
- Improvements may be obtained while applying simultaneously different (and frequently updated) $\mathbf{B_c}$ matrices in clear sky and in precip. regions (Montmerle 2012)



- 4DVar requires TL/AD models : may need incremental technique and very short assimilation window to stay close to the microphysic’s linear regime