New error covariances & DA formulations at Météo-France with OOPS

Loïk Berre, Etienne Arbogast, Camille Birman,
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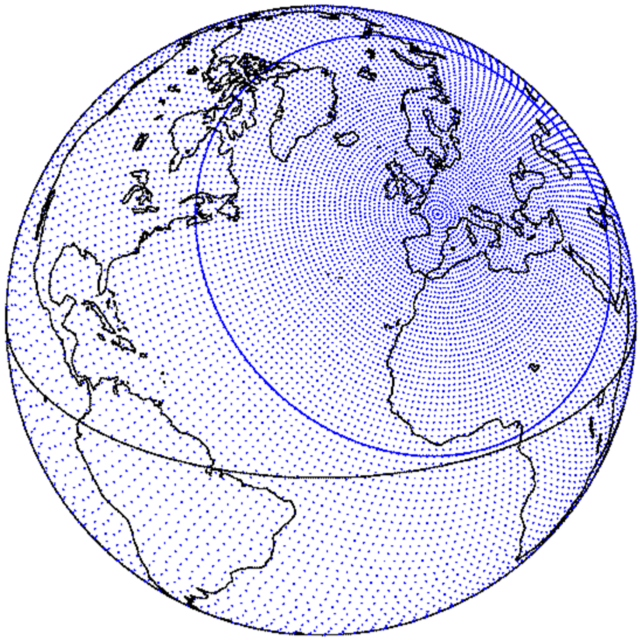
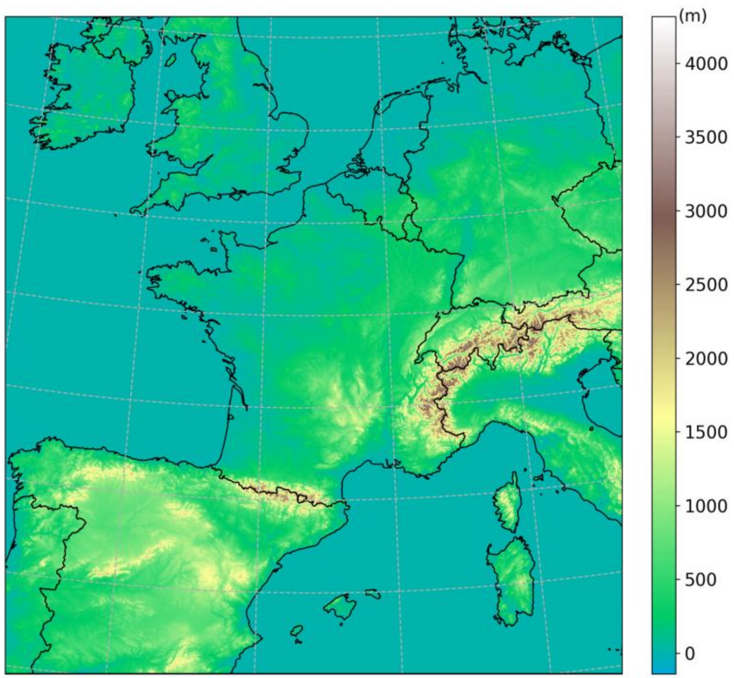
Mayeul Destouches, Nicole Girardot, Sophie Marimbordes,
Maud Martet, Argan Purcell, Valérie Vogt

9 April 2025, ECMWF workshop

Global and mesoscale DA at Météo-France



Lateral Boundary Conditions



ARPEGE (5 km - 30 km)
Hybrid 4D-Var (6h cycle)
with 50-member EDA

AROME (1.3 km)
3DEnVar (1h cycle)
with 50-member EDA

=> Emphasis on research with **EDA** & **EnVar** approaches,
using **OOPS** (developed in collaboration with ECMWF and ACCORD)

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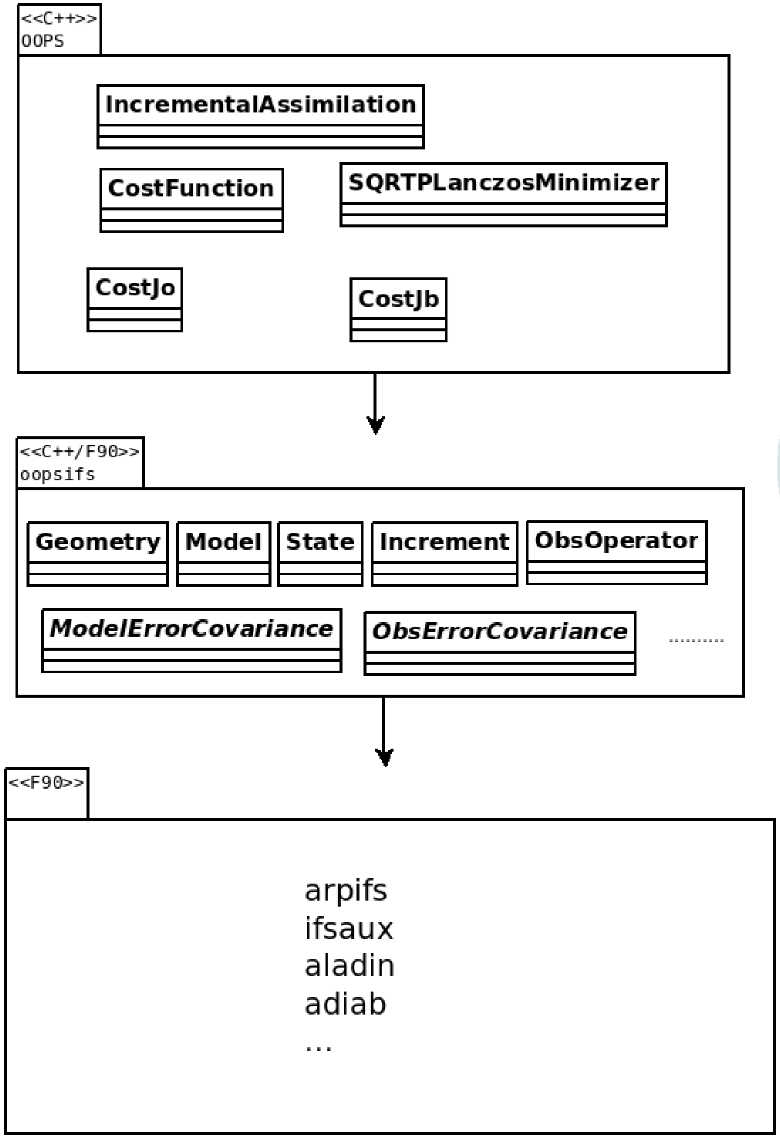
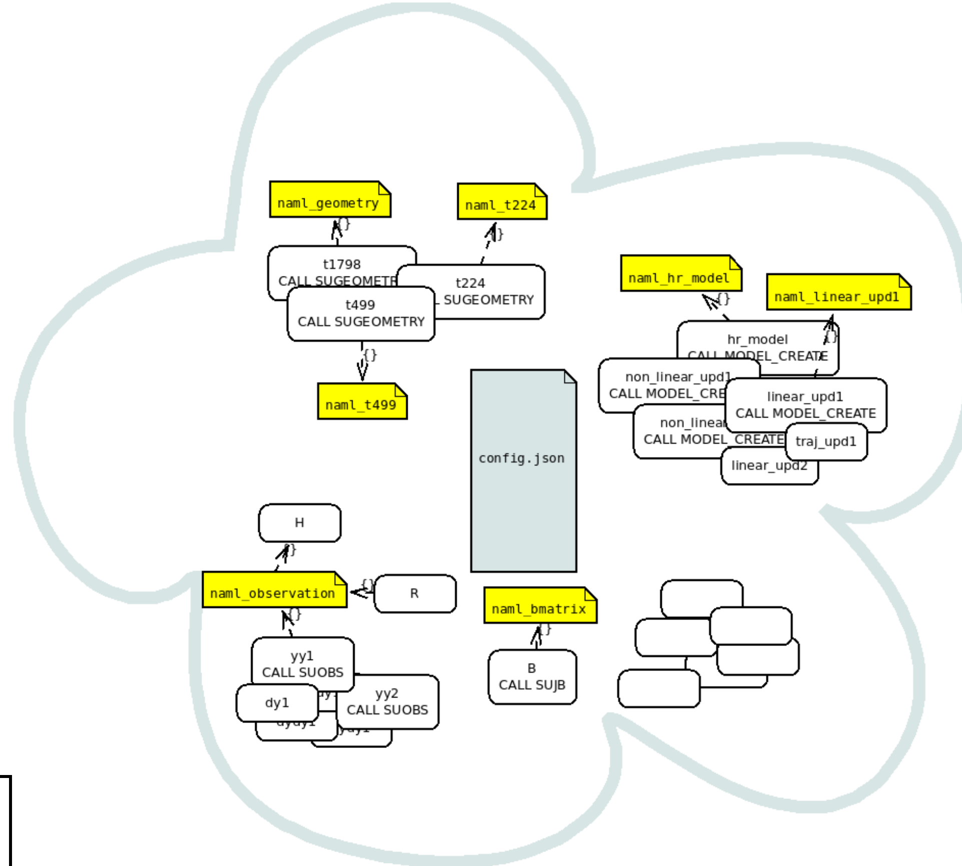
OOPS for research, development and maintenance of DA algorithms



OOPS structure



One OOPS application

Combining building blocks in a flexible way
easens R&D on EnVar and maintenance of DA software

Outline

- **Flow-dependent error covariances** for global DA

- Implementation of **3DEnVar** for convective-scale DA

- Implementation of **4DEnVar** for convective-scale DA

- **Extensions** to surface DA and coupled DA; observation error correlations

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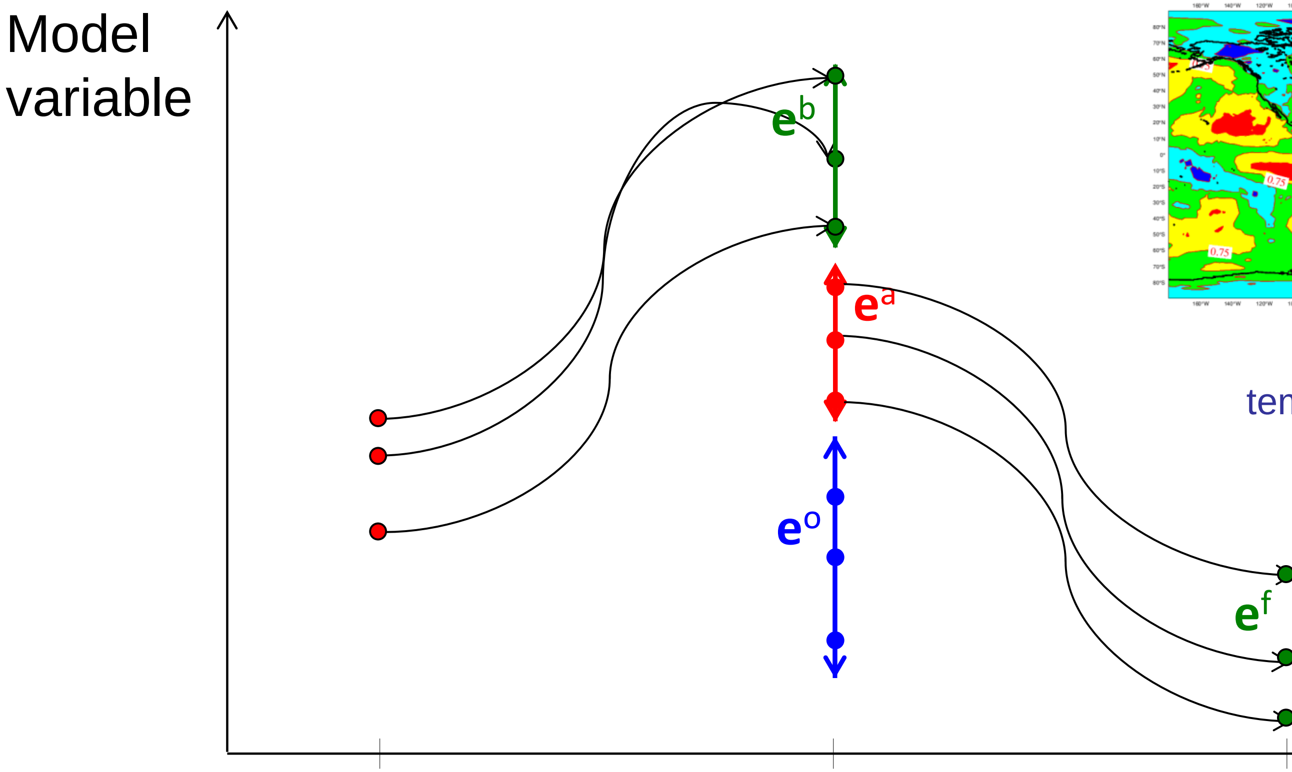
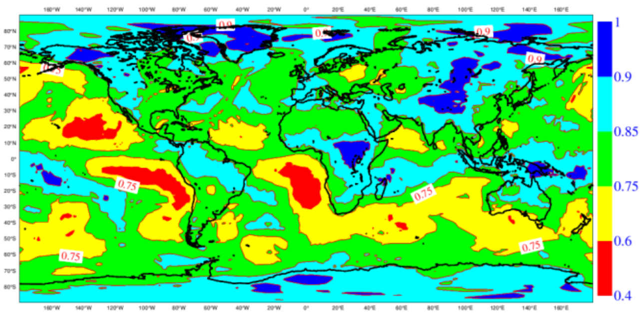
Ensemble (of) Data Assimilations (EDA) : simulation of error propagation during DA cycling





Vertical correlations of temperature background errors between 850 & 870 hPa

$$\mathbf{e}^a = (\mathbf{I}-\mathbf{KH})\mathbf{e}^b + \mathbf{K}\mathbf{e}^o$$

$$\mathbf{e}^f = \mathbf{M}\mathbf{e}^a + \mathbf{e}^m$$

with $\mathbf{e}^b = \mathbf{e}^{f-}$

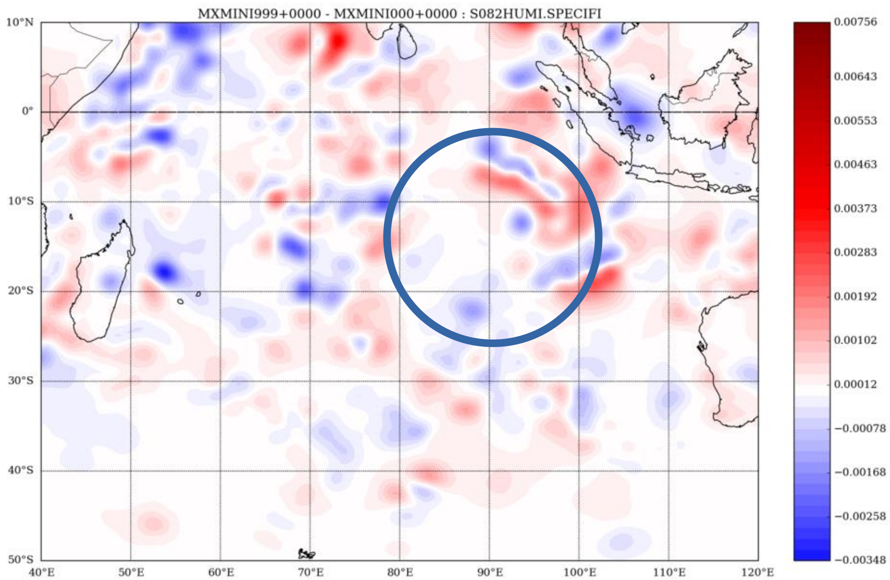
and $\mathbf{e}^o = \mathbf{R}^{1/2}\,\eta$ (random draws of **R**)

(e.g. Berre et al 2015 for ARPEGE ; Brousseau et al 2011 for AROME)

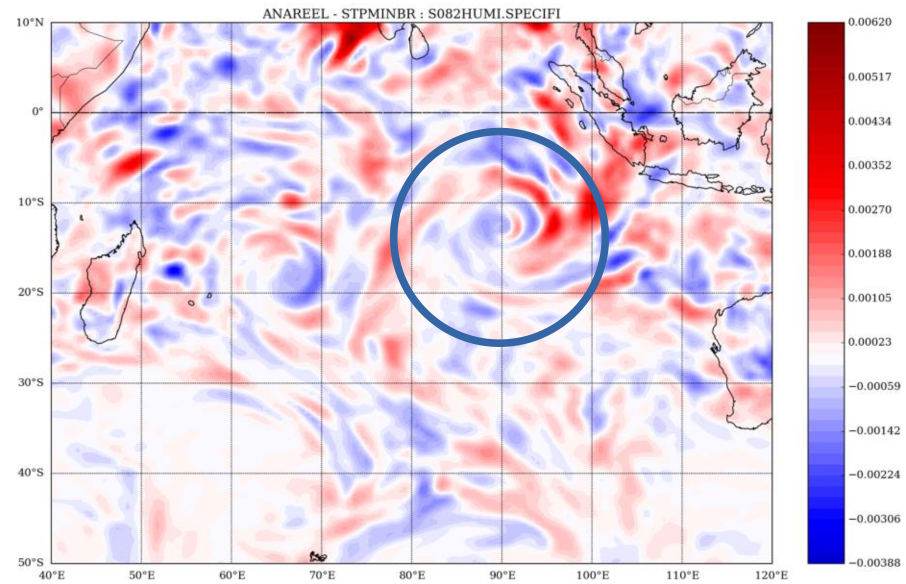
Synergy with R&D on **R**, model perturbations, EPS, innovation-based estimates...

Use of localised flow-dependent 3D covariances in ARPEGE 4D-Var with OOPS

Moisture analysis increments at 850 hPa

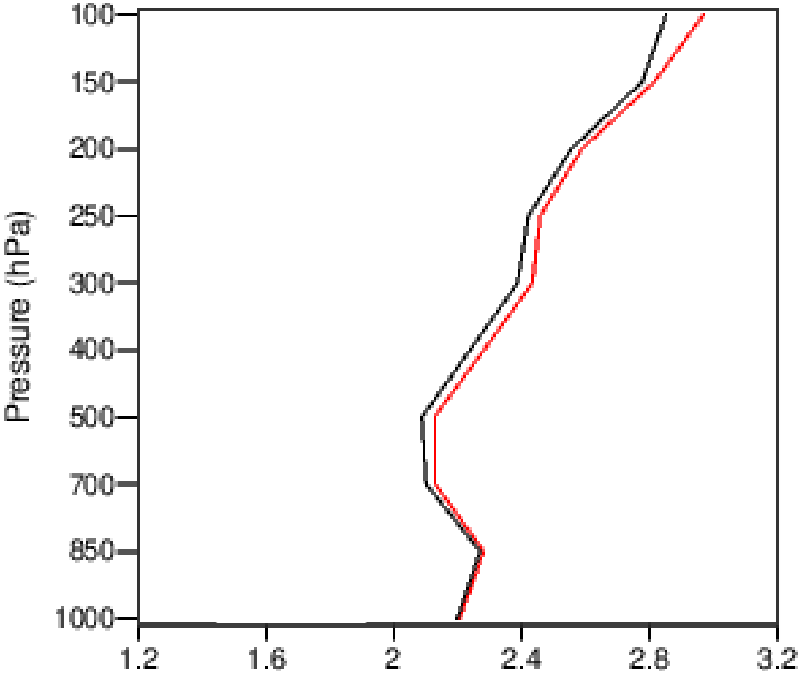


Using isotropic covariances

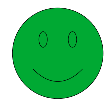


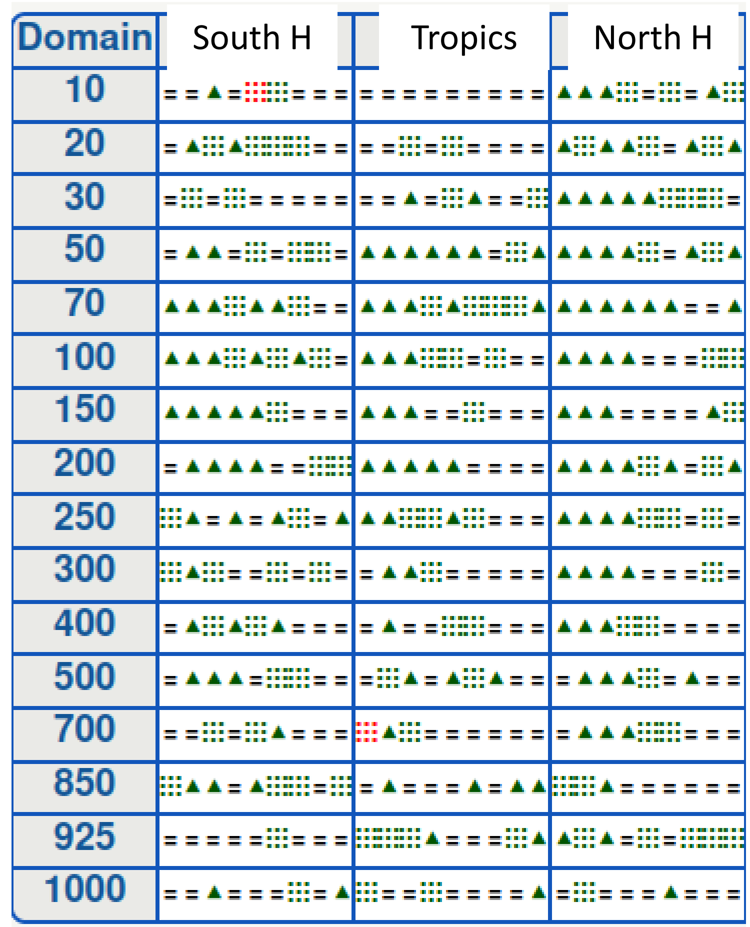
Using anisotropic ensemble covariances filtered by localisation

Impact of localised flow-dependent 3D covariances in ARPEGE 4D-Var with OOPS



RMS(wind) North Hemisphere :
obs(airep)-guess
(2 months)

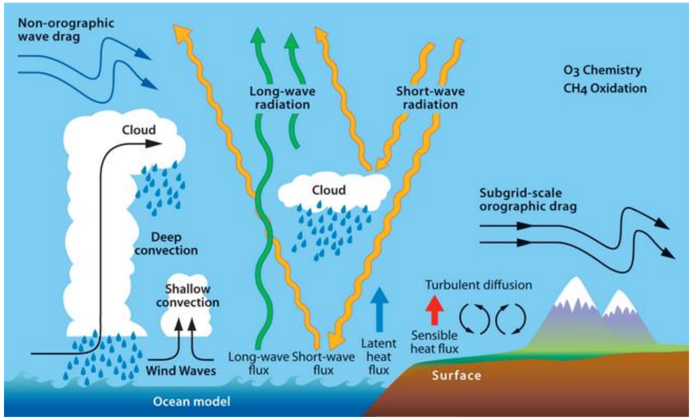




Wind forecast RMSE score cards
as function of height & fc range
(radiosonde verification)
(2 months)
(Berre and Arbogast 2024, QJRMS)

Such flow-dependent anisotropic covariances became operational in October 2024.

Revised model & obs perturbations in ARPEGE EDA



Revised representation of model errors (N. Girardot)

- Model parameters are uncertain
  => apply **Random model Parameter (RP) perturbations**.

- Set of perturbed model parameters for deep convection, turbulence, microphysics, gravity wave drag, radiation, surface and shallow convection, as in ARPEGE-EPS (L. Descamps).

- Modest increase of EDA spread, more pronounced in the Boundary Layer.

- Smoother EDA cycling compared with previous approach (inflation of cycled forecast perturbations).

- Innovation-based diagnostics (Desroziers et al 2005) to tune global amplitude of specified sigmab's.

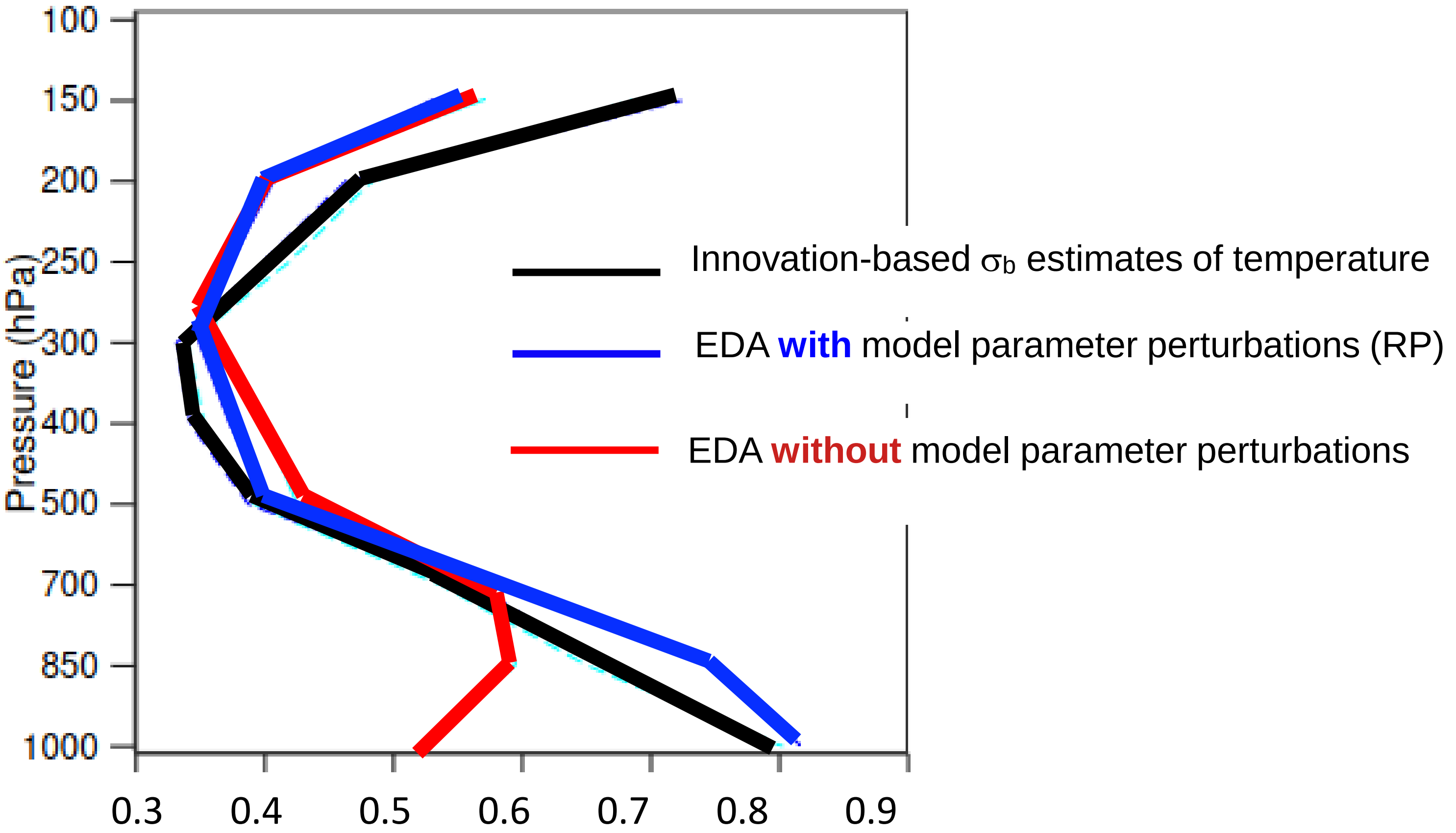
Extended representation of observation uncertainties (M. Borderies, P. Chambon)

- **Uncertainties on hydrometeor shape & distribution**, specified in observation operator.

- Use different Mie table versions for allsky microwave observations.

- Modest increase of EDA spread, more pronounced in the South Hemisphere.

Impact of Random Parameters (RP) on EDA (model perturbations)

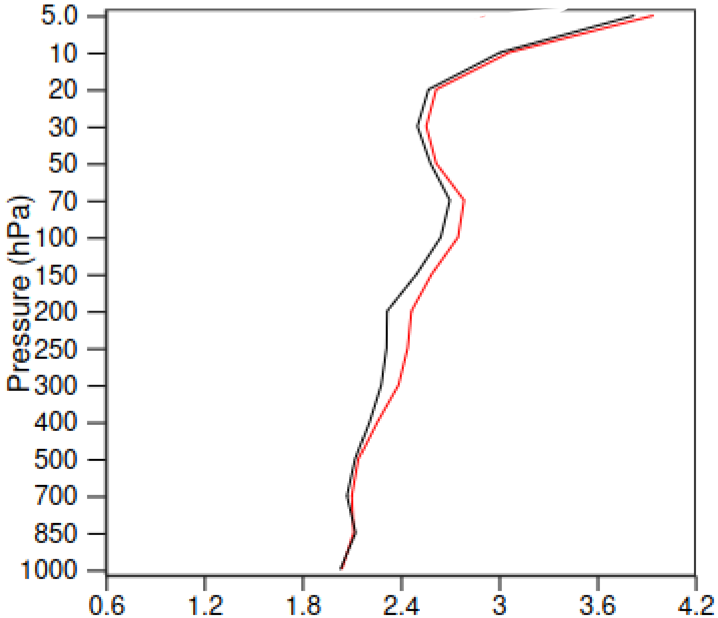


Estimates of ***background error standard deviations***
in observation space (AIREP)
(temperature, in K)

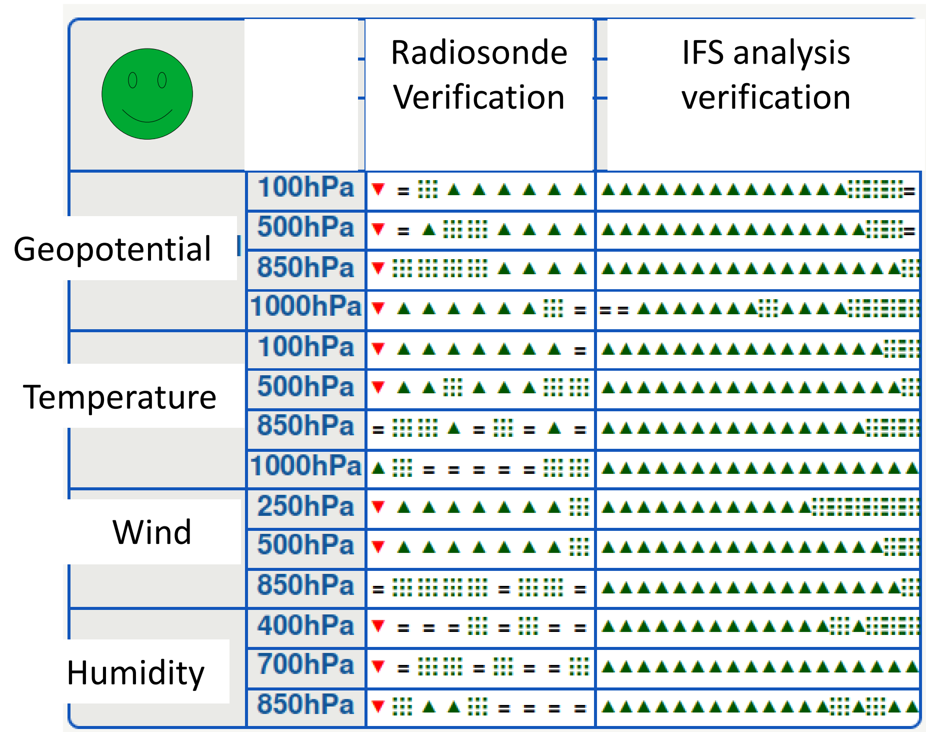
With model parameter perturbations,
EDA spread is more realistic in the Boundary Layer

(N. Girardot)

Impact of new covariances (EDA-RP) on hybrid 4D-Var



Observation-guess wind RMS of 4D-Var based on EDA **with**/without RP



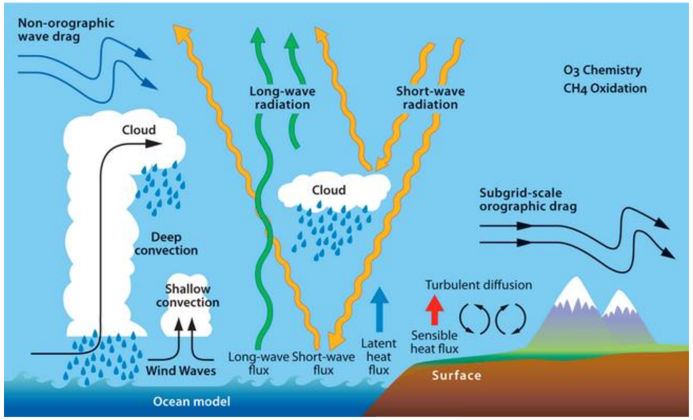
Forecast RMSE score cards (51 cases, North Hemisphere)

Improved flow-dependent B : better guess & forecast quality

(N. Girardot)

=> EDA-RP is included in current E-suite.

A few prospects for global DA



Extended representation of model errors in EDA

- Need to pursue & improve **physical parameter perturbations** (e.g. list of parameters, ranges & structures of perturbations (SPP)).

- Extend model parameter perturbations to uncertain components in **model dynamics** (ex : departure points of SL trajectories).

- Comparison with **innovation-based estimates** of model errors (e.g. Berre 2019) and with **multi-physics** approach (e.g. Hubans et al 2022).

From large-scale 4D-Var to 4DEnVar at high resolution

- Severe **simplifications in TL/AD physics** become more prominent at high resolution; **scalability issues** of TL/AD model integrations.

- **4DEnVar** allows 4D error covariances to be derived at **high resolution** without TL/AD models; it also easens extension to **hydrometeors, surface DA and coupled DA.**

- Possible 4D-hybrid approach (Berre and Arbogast 2024) for a progressive transition towards 4DEnVar at high resolution.

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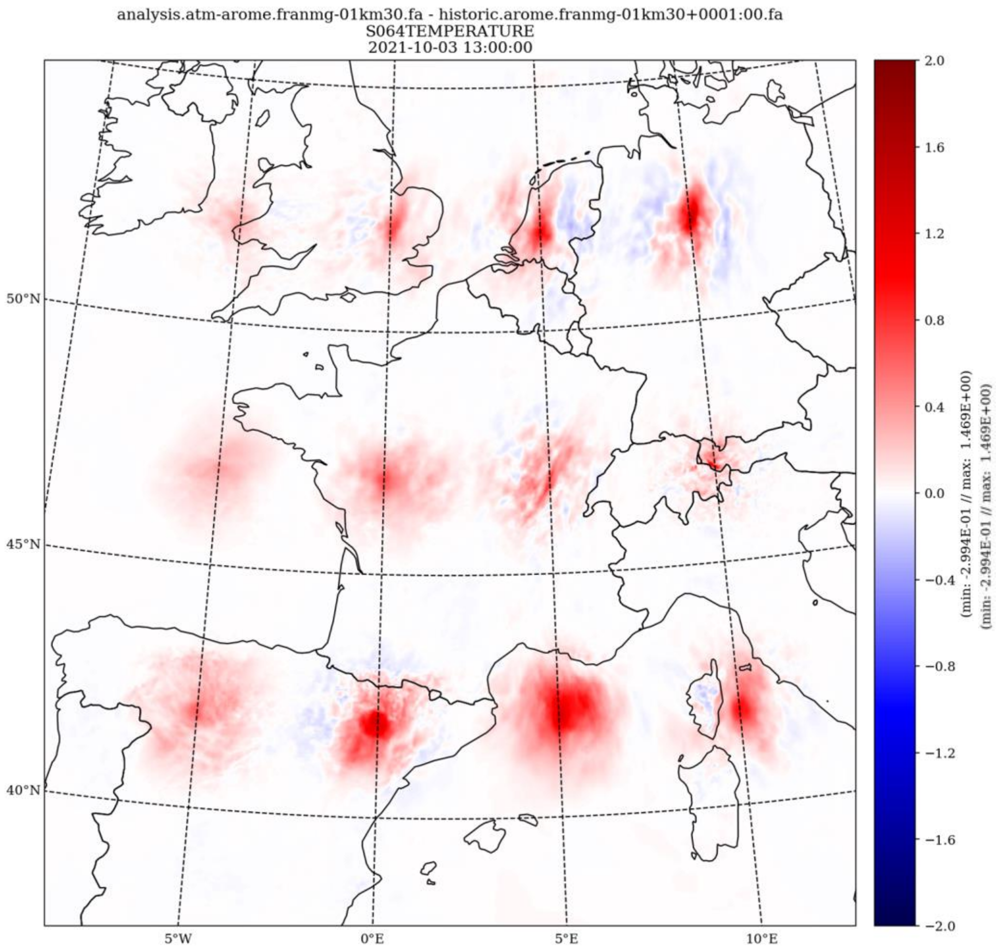
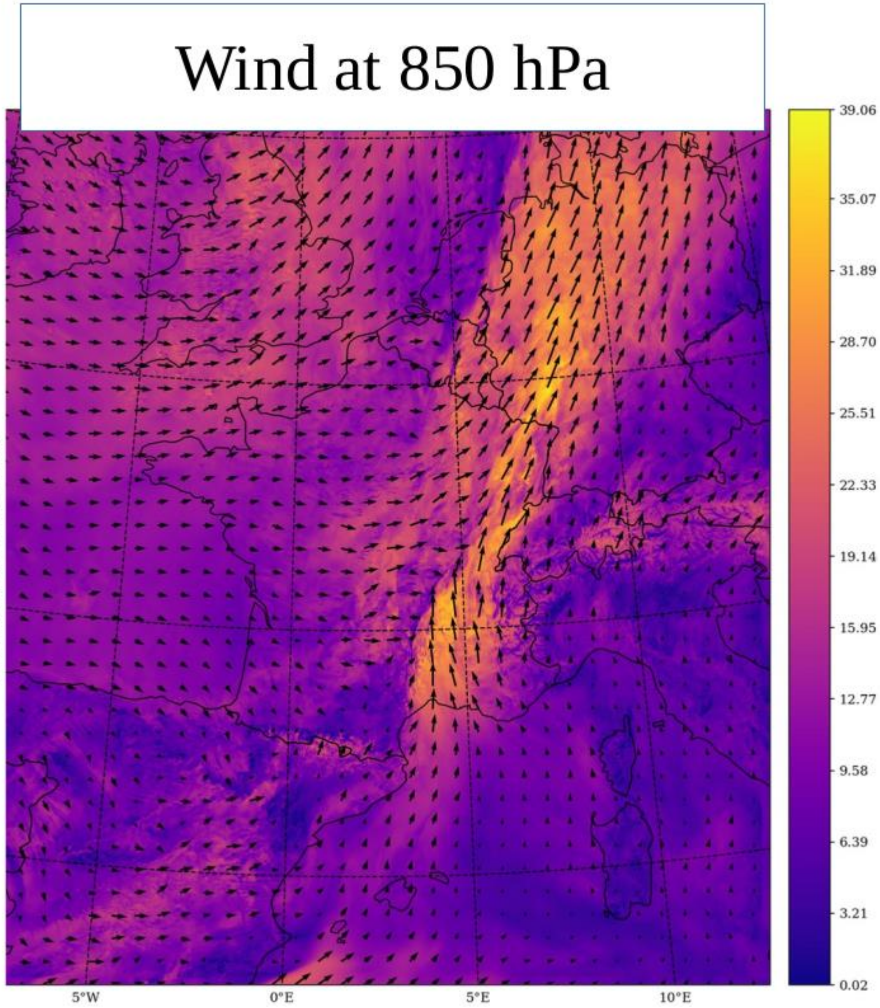
Flow-dependent 3D covariances in AROME 3DEnVar





Local covariances at 850 hPa for T
derived from 50 ensemble members + localisation

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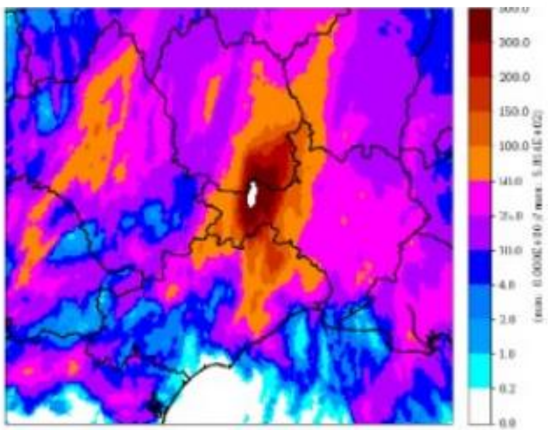
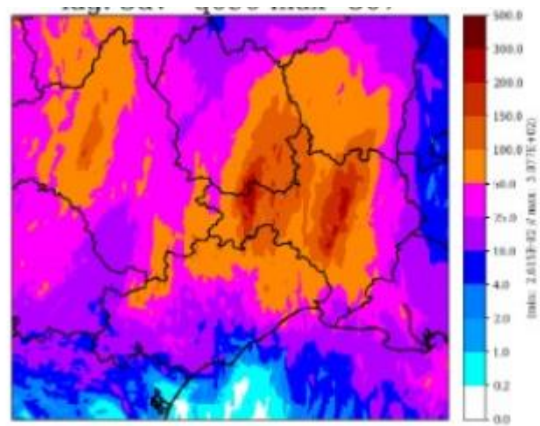
(V. Vogt, P. Brousseau)

Impact of 3DEnVar in AROME 1.3 km (with EDA 50mb 3.2 km)

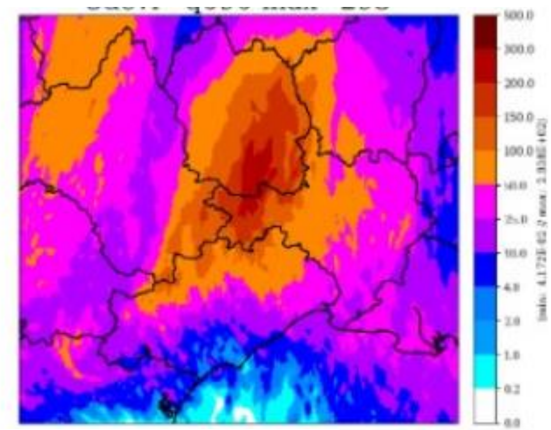
REF = SYNOP precip



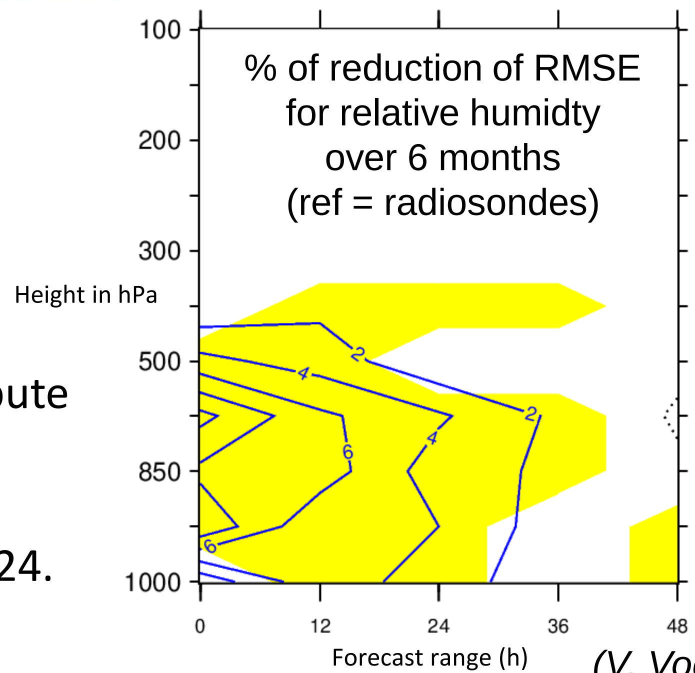
3D-Var fc quantile 90%



3DEnVar fc quantile 90%



Heavy Precipitation Event
on 19 September 2020



Flow-dependent covariances in AROME contribute to major positive impacts on HR forecasts (fc).

3DEnVar operational for AROME in October 2024.

(V. Vogt, P. Brousseau)

Adding new control variables in EnVar with SDL

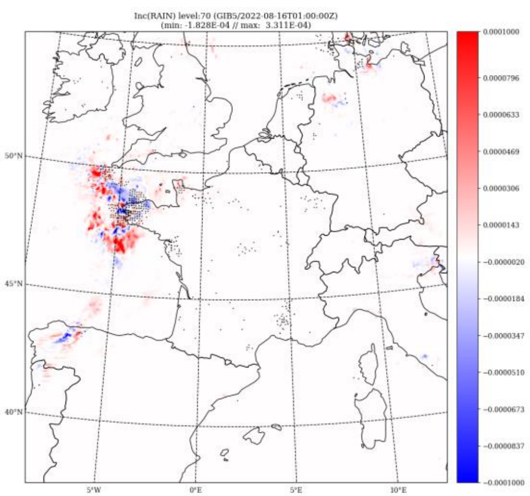
(M. Martet,

V. Vogt)

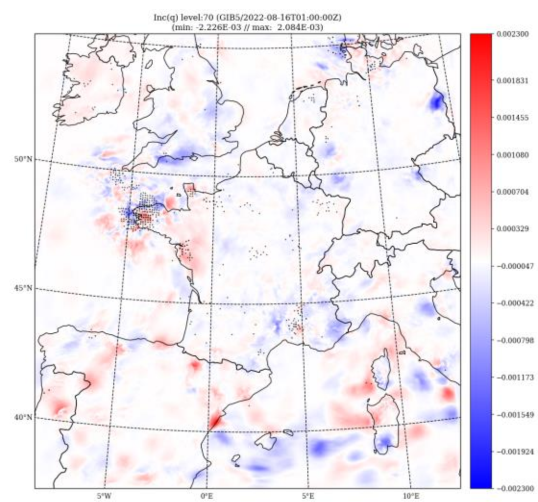
- Adding new control variables such as **hydrometeors & NH variables**
- becomes straightforward in EnVar with extended covariances.

- **Scale Dependent Localisation** (e.g. Caron et al 2019) allows localisation
- to be adapted to both small scale variables such as hydrometeors
- and large scale variables such as surface pressure.

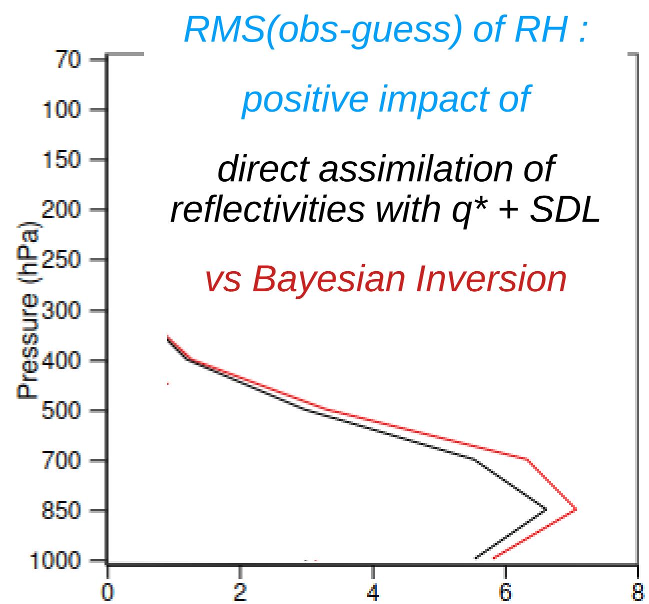
- With hydrometeors in the control variable of EnVar, it is
- possible to **assimilate radar reflectivities directly** (instead of Bayesian inversion),
- with rain increments providing humidity increments through cross-covariances.



Rain increment



Water vapor increment



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4DEnVar for high resolution (HR) DA

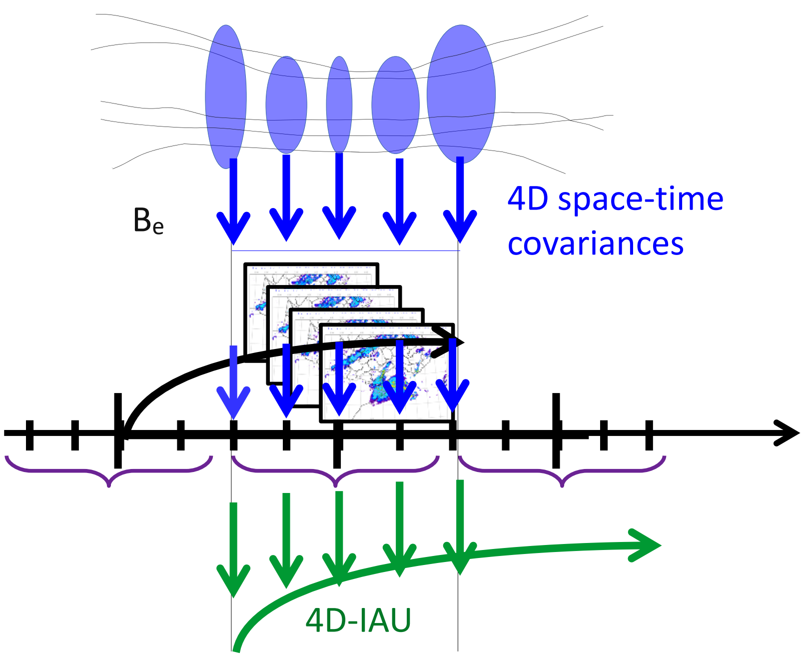
4DEnVar :

$$J(\underline{\delta\mathbf{x}}) = \frac{1}{2}(\underline{\delta\mathbf{x}})^T\underline{\mathbf{B}}^{-1}(\underline{\delta\mathbf{x}}) + \frac{1}{2}(\underline{\mathbf{d}} - \underline{\mathbf{H}}\underline{\delta\mathbf{x}})^T\underline{\mathbf{R}}^{-1}(\underline{\mathbf{d}} - \underline{\mathbf{H}}\underline{\delta\mathbf{x}})$$

$$\underline{\delta\mathbf{x}} = \begin{pmatrix} \delta\mathbf{x}_0 \\ \delta\mathbf{x}_1 \\ \vdots \\ \delta\mathbf{x}_K \end{pmatrix} \qquad \underline{\mathbf{B}} = \underline{\widetilde{\mathbf{B}}^e} = \begin{pmatrix} \widetilde{\boldsymbol{B}}^e_{0,0} & \widetilde{\boldsymbol{B}}^e_{0,1} & \cdots & \widetilde{\boldsymbol{B}}^e_{0,K} \\ \widetilde{\boldsymbol{B}}^e_{1,0} & \widetilde{\boldsymbol{B}}^e_{1,1} & & \widetilde{\boldsymbol{B}}^e_{1,K} \\ \vdots & & \ddots & \\ \widetilde{\boldsymbol{B}}^e_{K,0} & \cdots & & \widetilde{\boldsymbol{B}}^e_{K,K} \end{pmatrix}$$

(e.g. Desroziers et al 2014)

EDA



- Use of 4D covariances from ensemble of NL trajectories allov

… without having to handle the difficult derivation & mainter

- Assimilation of frequent observations (15 min.), such as radar

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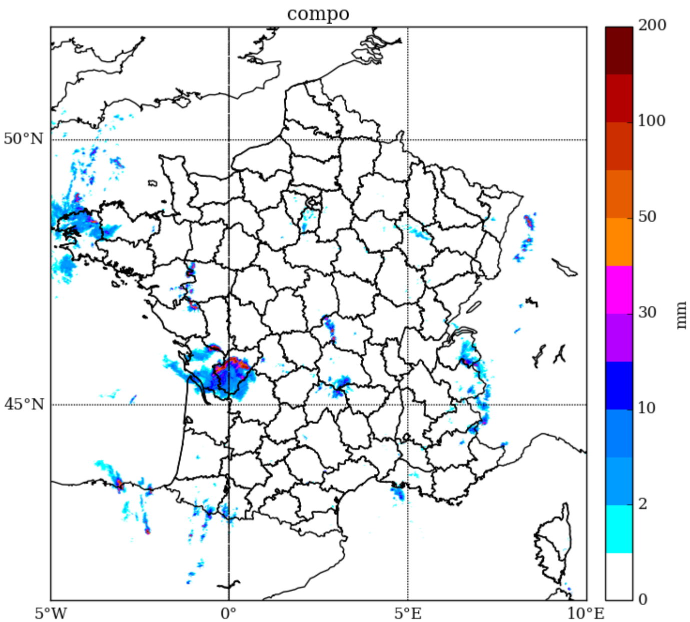
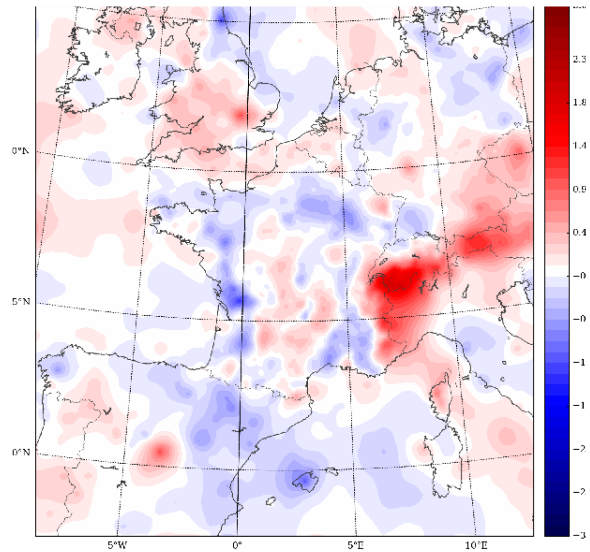
(P. Brousseau)

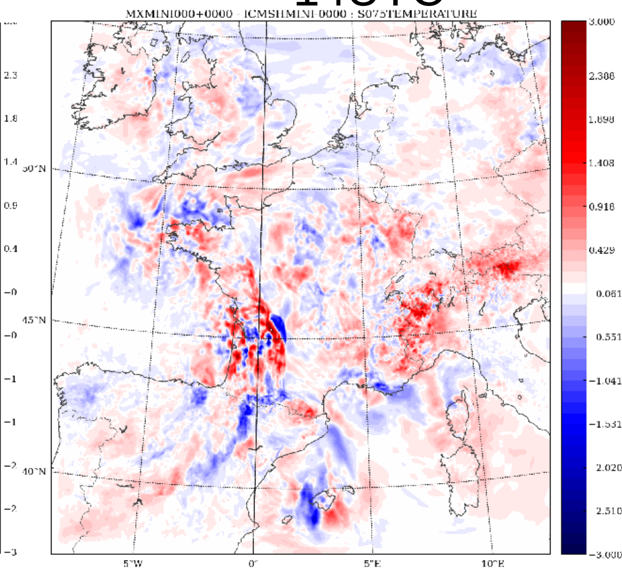
4D Temperature increment at 850 hPa



3DVar increment
14UTC

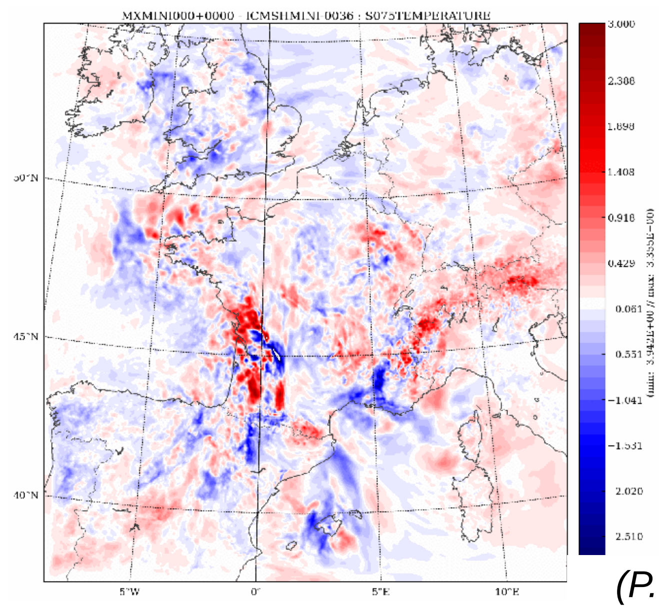


3DEnVar increment
14UTC



4DEnVar allows 4D analysis increments to be provided consistently at different times,

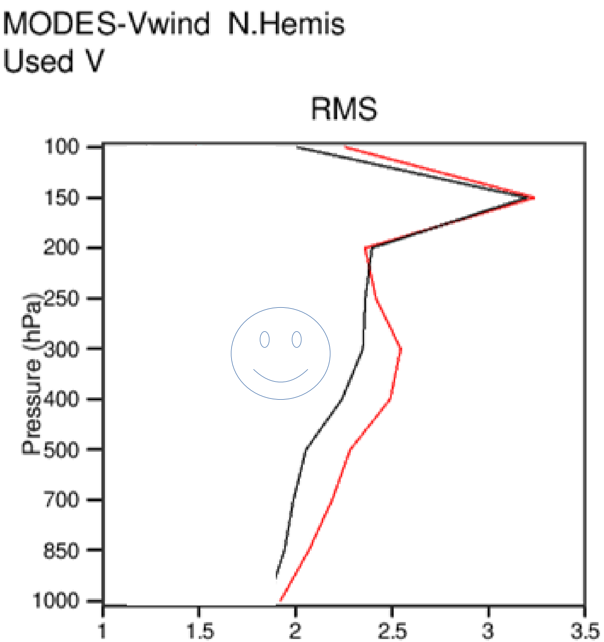
in accordance with ongoing processes
in such a convective situation at HR.



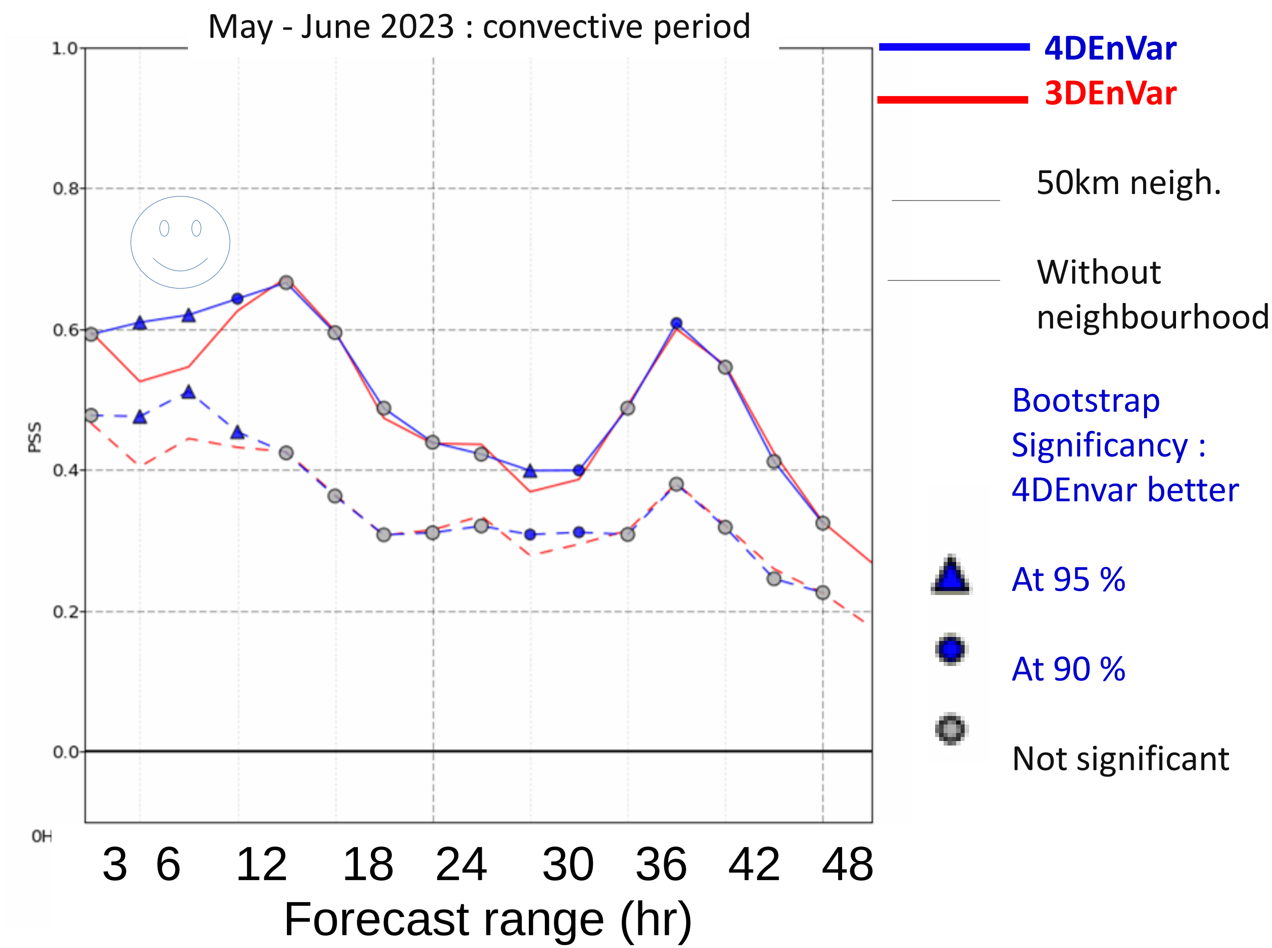
4DEnV
increme
13h30-1

(P. Brousseau)

Impact of 4DEnVar on average scores



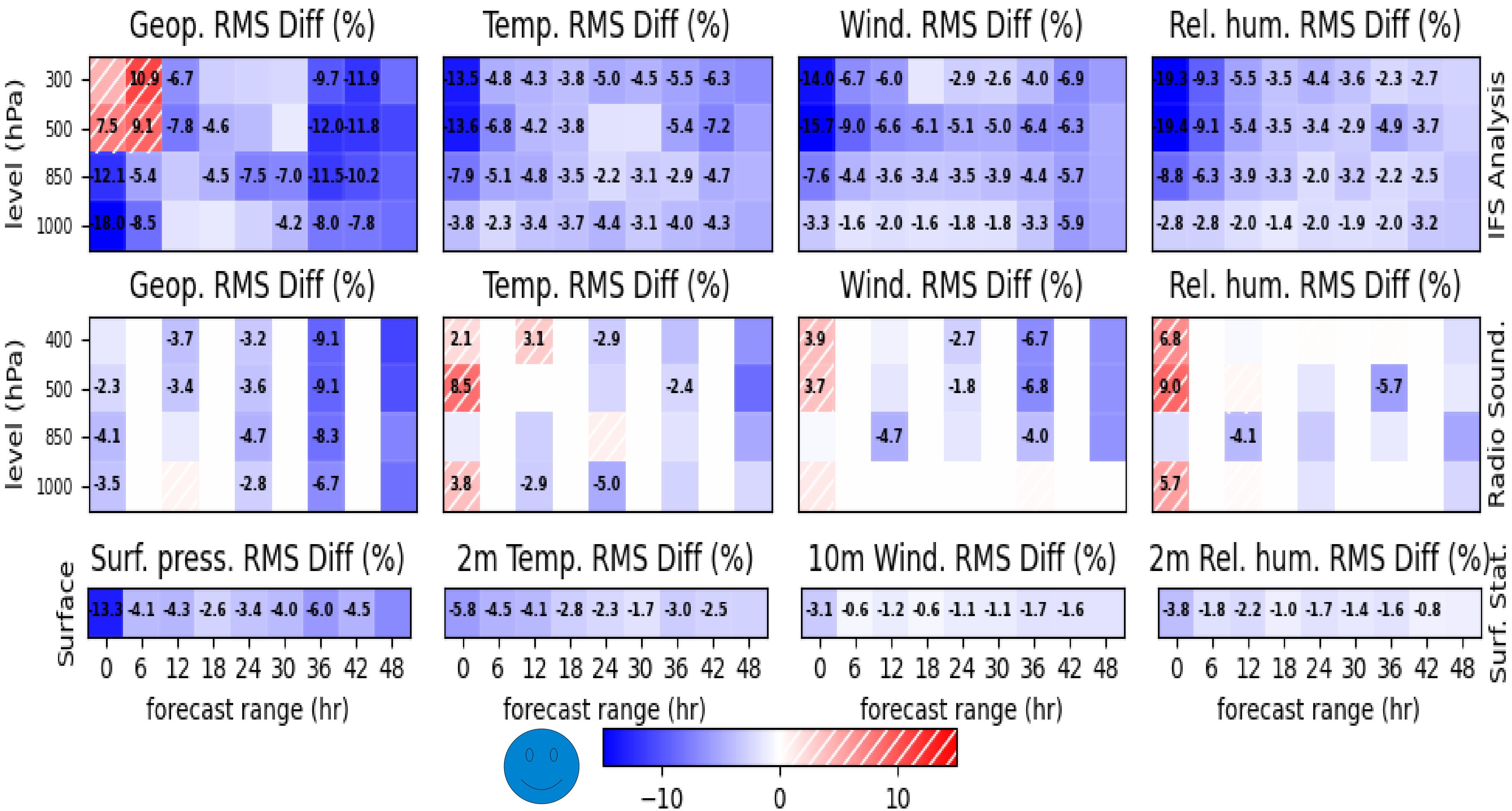
Improved obs-guess RMS of **4DEnVar** vs **3DEnVar**



Improved precipitation forecasts

(P. Brousseau)

AROME E-suite : impact of 4DEnVar+SDL+reflZ + ARPEGE_LBCs_withEDA-RP (scorecard 14 Oct - 24 Dec 2024)



Relative RMSE differences against IFS analysis (top), radiosondes (middle) and surface stations (bottom), for different parameters, depending on forecast range :

- blue boxes : E-suite better than oper
- numerical values in boxes : difference is statistically significant at 95 % confidence (bootstrap test)

It has been verified that each component (4DEnVar, SDL, reflZ, new_ARPEGE) contributes positively to this impact, with good synergies leading to this total positive impact.

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4DEnVar

20220817

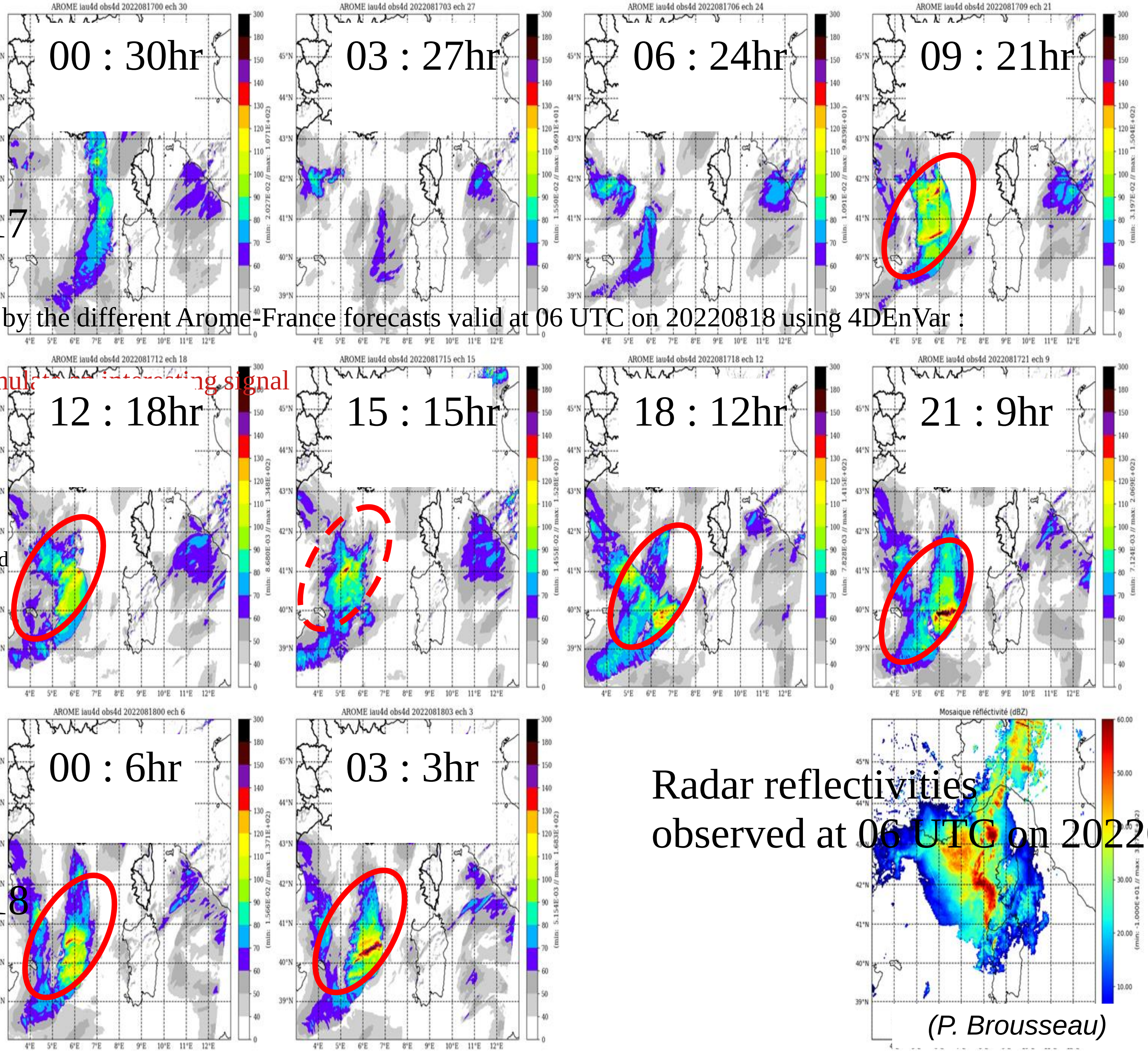
Wind gusts simulated by the different Arome-France forecasts valid at 06 UTC on 20220818 using 4DEnVar :

the last 7 forecasts simulate an interesting signal

(Yellow > 110 Km/h)

(versus
3 forecasts with 3D-Var, and
5 forecasts with 3DEnVar)

20220818



Radar reflectivities
observed at 06 UTC on 2022

(P. Brousseau)

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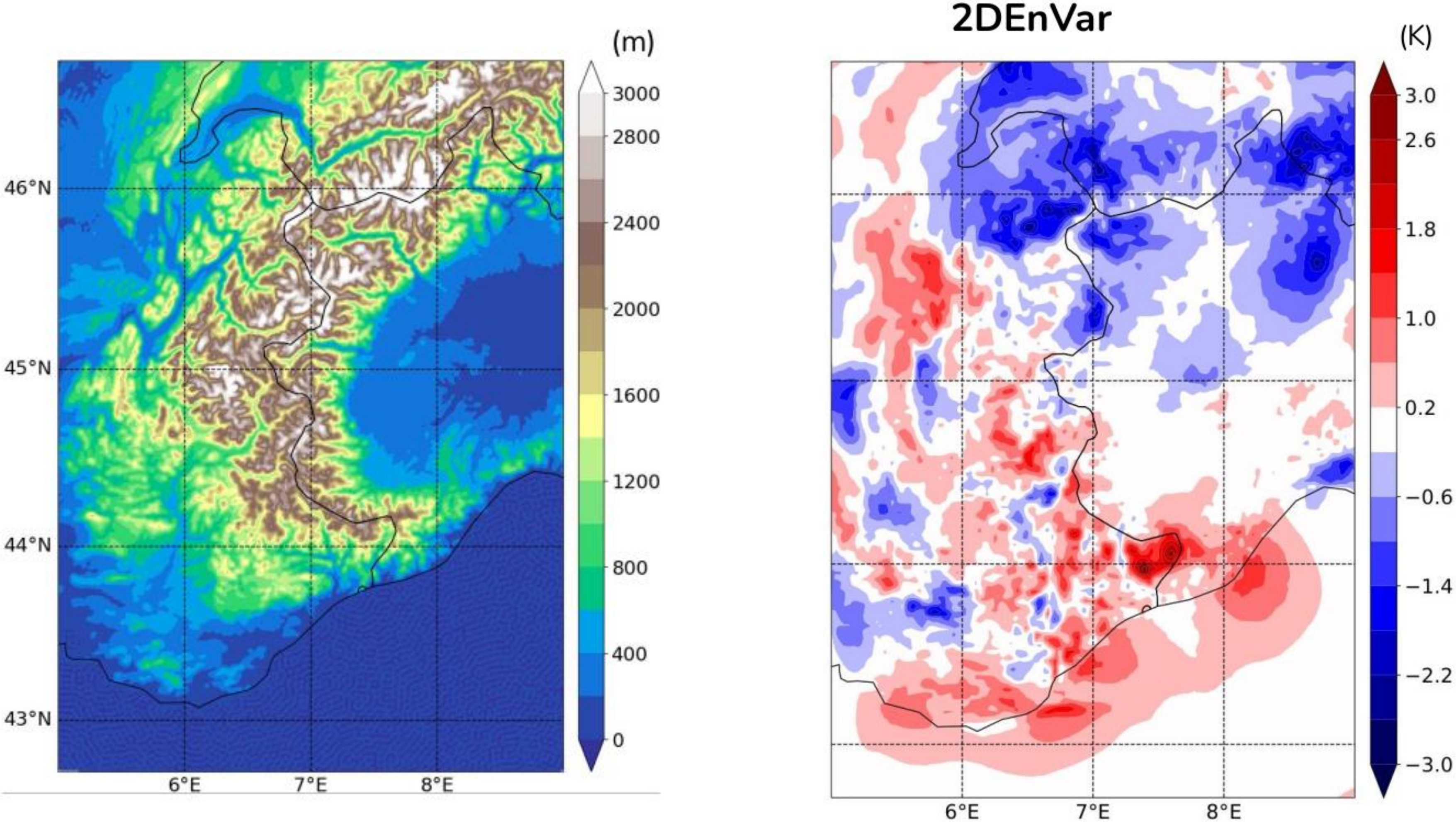
2DEnVar analysis of T2m with OOPS (+ RH2m, LST, snow, precipitation, ...)

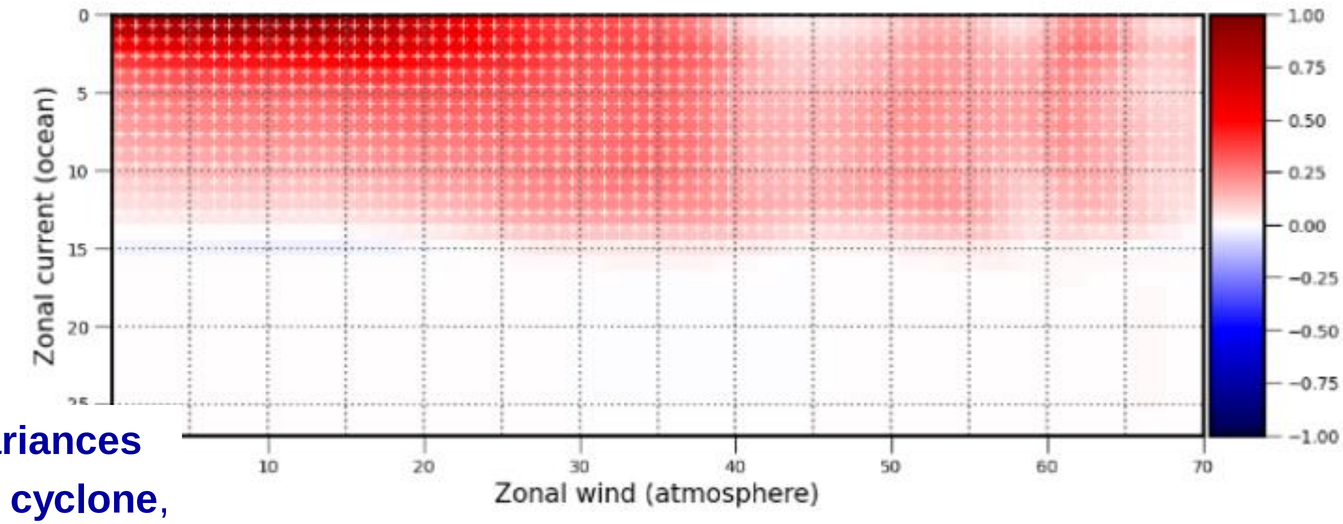


OOPS allows EnVar to be extended to 2D-surface analyses

(S. Marimbordes, C. Birman, E. Arbogast, N. Fourrié)

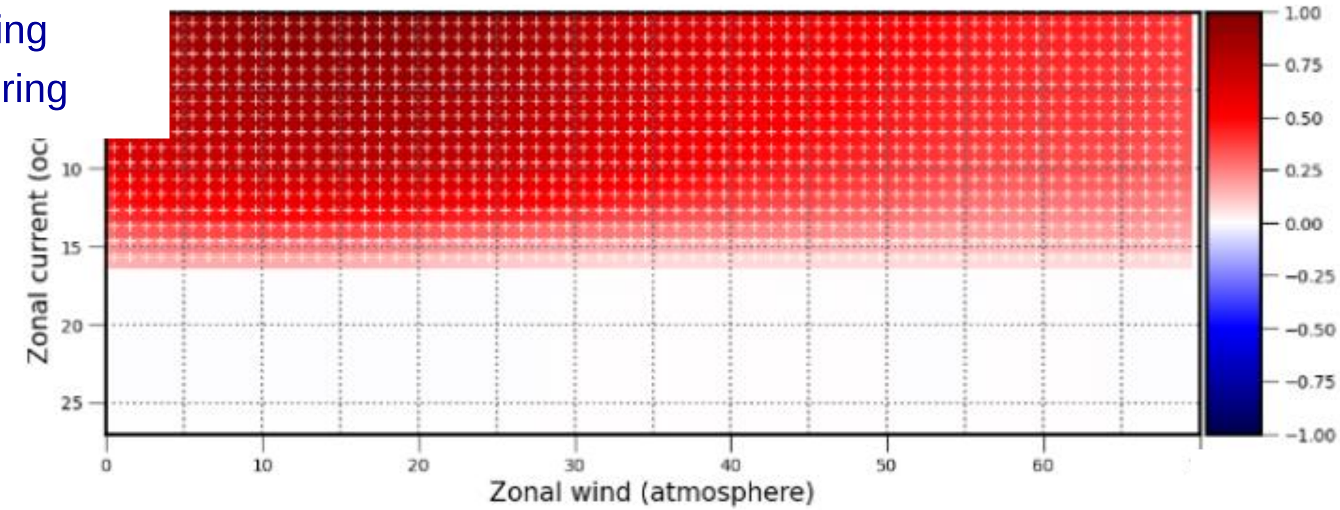
Ocean/atmosphere cross-covariances : tropical cyclone case (Arome EDA coupled with 1D mixed ocean layer)

Outside the cyclone



Ocean/atm cross-covariances are increased under the cyclone, due to turbulent mixing and thermocline lowering

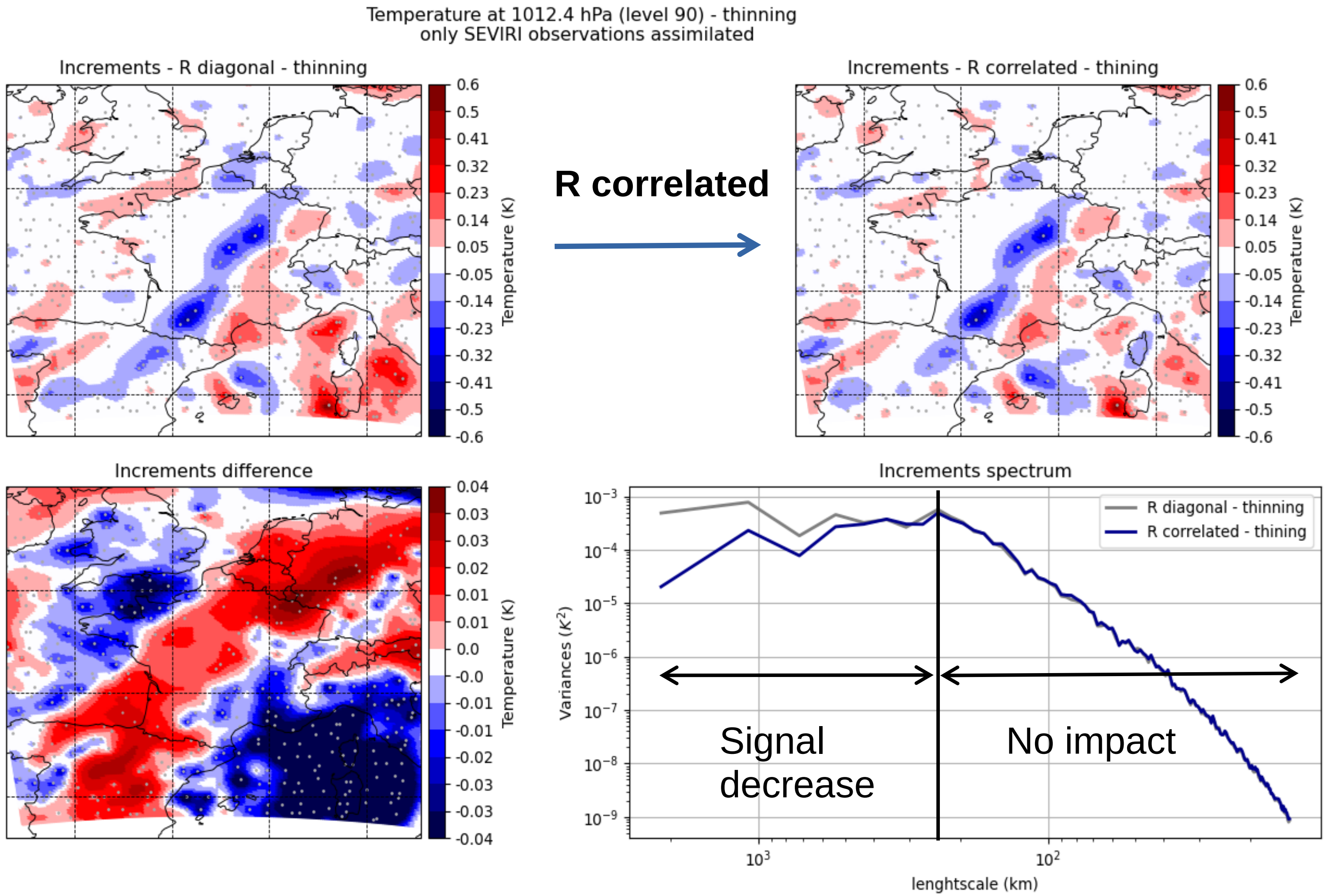
Under the cyclone



To be experimented in ocean/atm coupled 4DEnVar

(A. Purcell, P. Brousseau, S. Malardel)

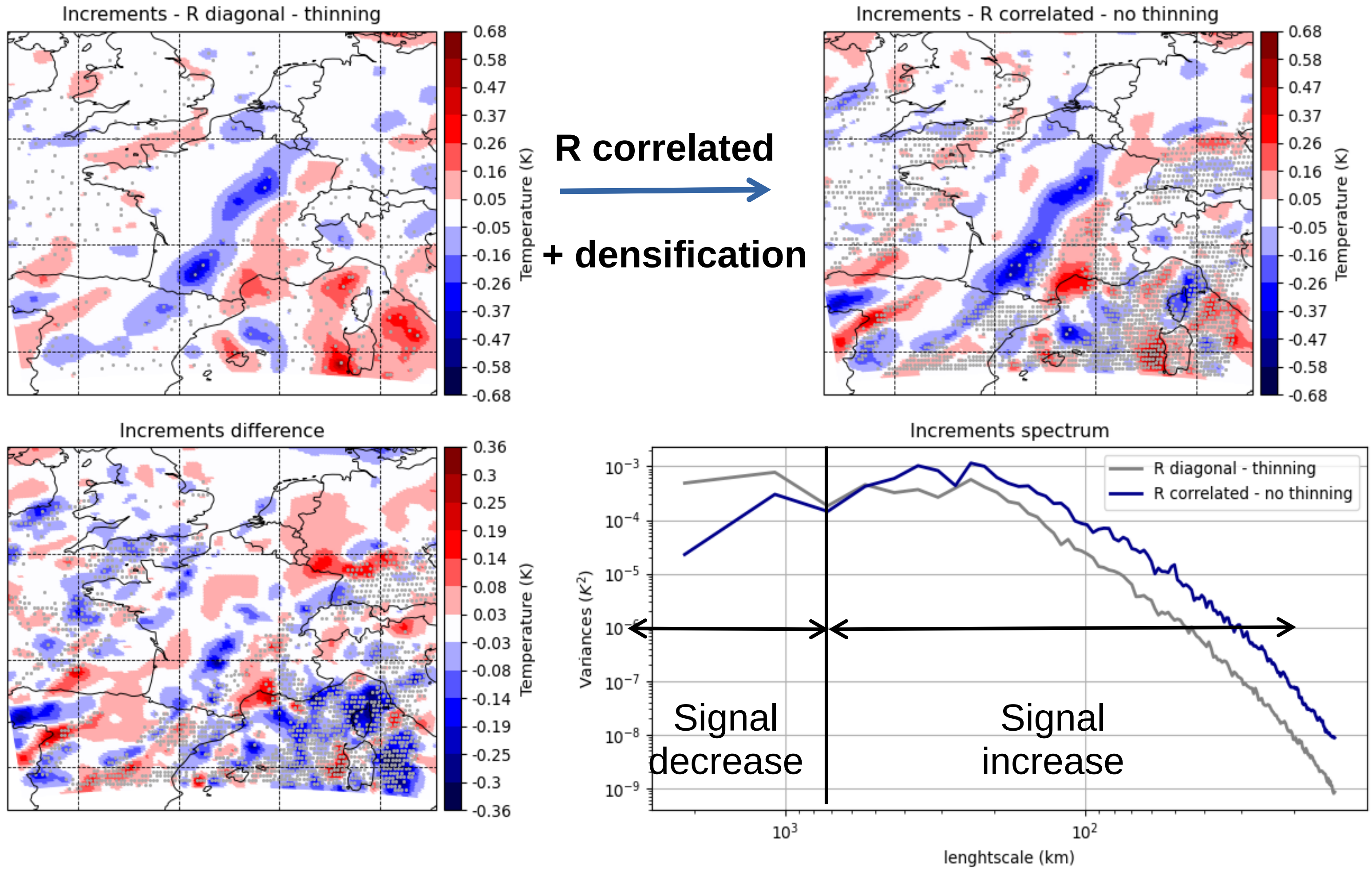
Impact of modeling observation error correlations (SEVIRI, 70 km thinning ; temperature, 1012 hPa)



Representing observation error correlations leads to larger relative emphasis on small scale features

(T. Buey, O. Guillet, N. Fourrié, O. Audouin)

Impact of modeling observation error correlations & reduced thinning (15 km ; SEVIRI ; temperature, 1012 hPa)



Combining non-diagonal R with increased observation density allows more small scale information to be extracted from observations

(T. Buey, O. Guillet, N. Fourrié, O. Audouin)

Conclusions & perspectives

- **Central role of EDA** : propagation of observation errors and model errors in DA cycling can be simulated, for both covariance estimation and initialisation of EPS.

- Importance of **model perturbations** & observation perturbations in EDA ; synergy with **innovation-based estimates**, in order to validate & tune ensemble covariances.

- **EnVar formulations** easen evolution towards :
  - flow-dependent 4D assimilation (4DEnVar) at **high resolution, with complex non linear physics**,
  - new variables such as **hydrometeors**, NH variables,
  - extensions to **surface DA**, couplings with ocean & soil DA, with different scales handled through **SDL.**

- Importance of EnVar with hydrometeors is growing with the **direct assimilation of radar reflectivities, allsky radiances and lightning data** (MTG/LI).

- Progress on **observation error correlations**, in order to better assimilate high resolution information brought by **dense observations**.

- An **object-oriented software approach (OOPS)** facilitates research and maintenance of such algorithmic developments at high resolution.

- See also ***Vincent Chabot's talk*** for emulation of DA components at Météo-France.

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Thanks for listening