

Objective localization of ensemble covariances: theory and applications

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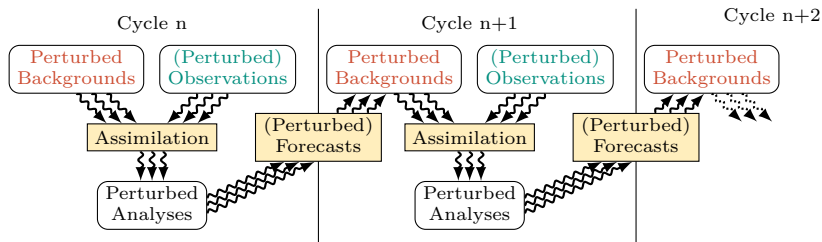
(2) NCAR, Boulder, CO, USA

25 Feb. 2015

4th International Symposium on Data Assimilation.
RIKEN AICS, Kobe, Japan.

Introduction: Ensemble data assimilation

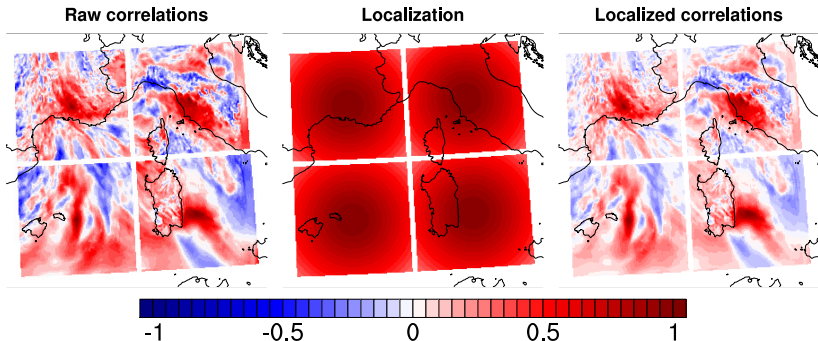
- Early days variational data assimilation considered modelled $\mathbf{B}$ estimated from NMC method.
- EnKF uses Monte Carlo sampling (ensembles) to better estimate covariances.
- We can also use ensembles in variational data assimilation, but there is sampling noise.



Introduction: Localization

Covariance localization through a Schur product:

$$\hat{\mathbf{B}} = \mathbf{L} \circ \tilde{\mathbf{B}} \quad \Leftrightarrow \quad \hat{B}_{ij} = L_{ij} \tilde{B}_{ij}$$

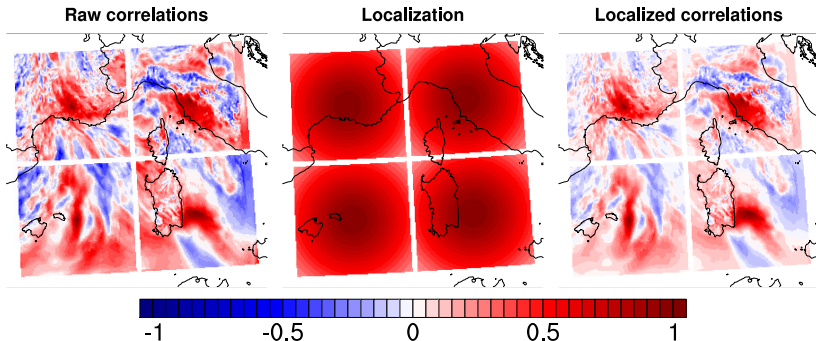


Sample correlation, localization and localized correlation
for specific humidity in the boundary layer (AROME-France - 30 members)

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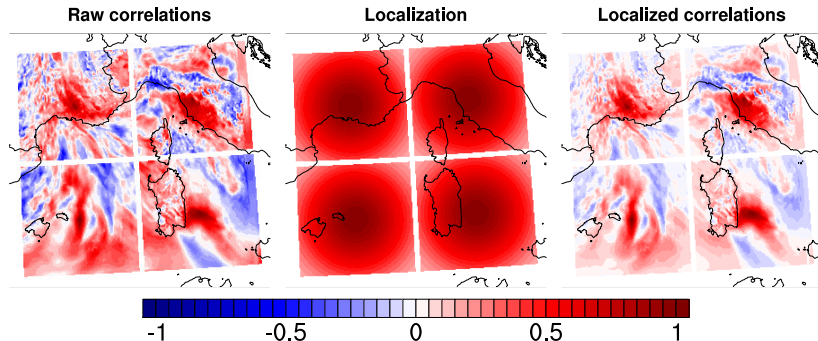


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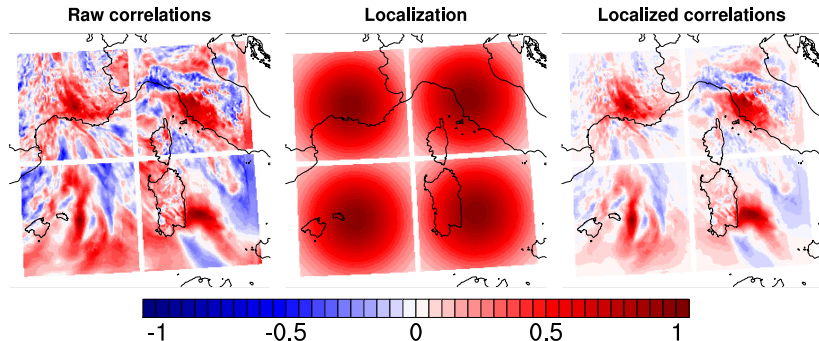


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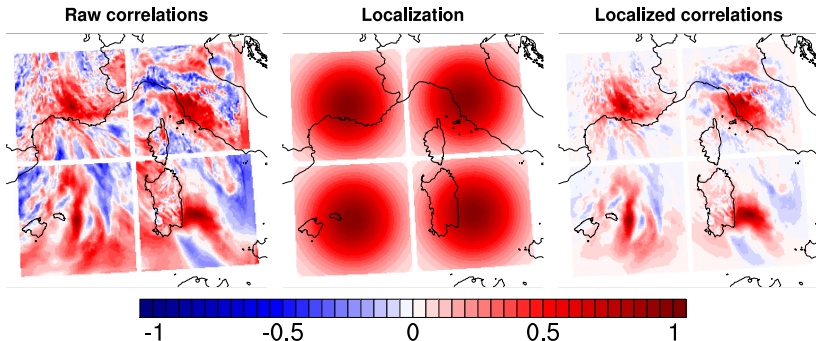


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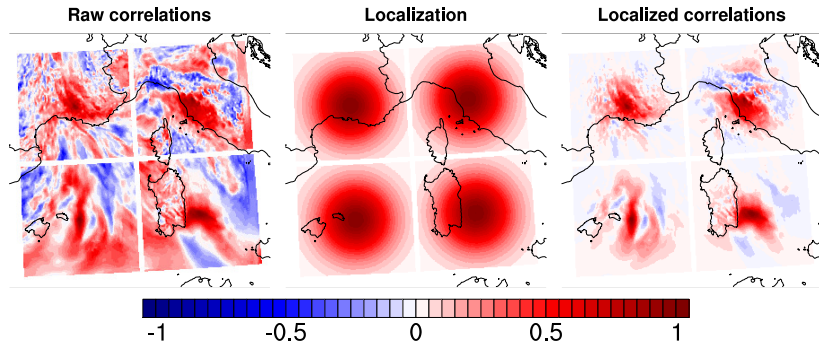


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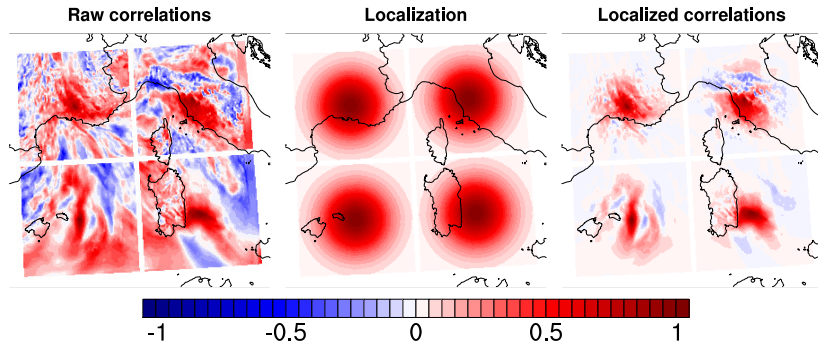


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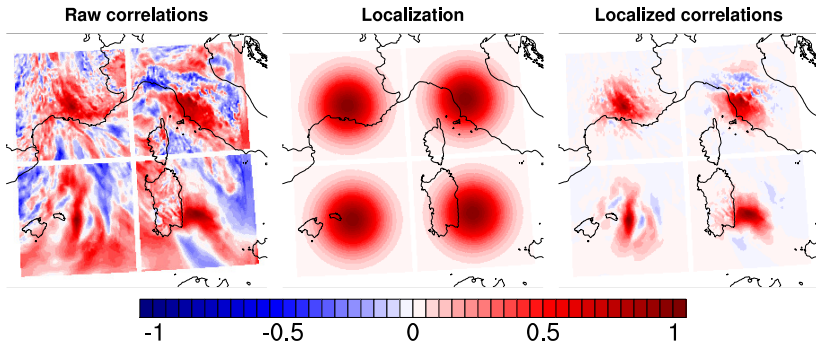


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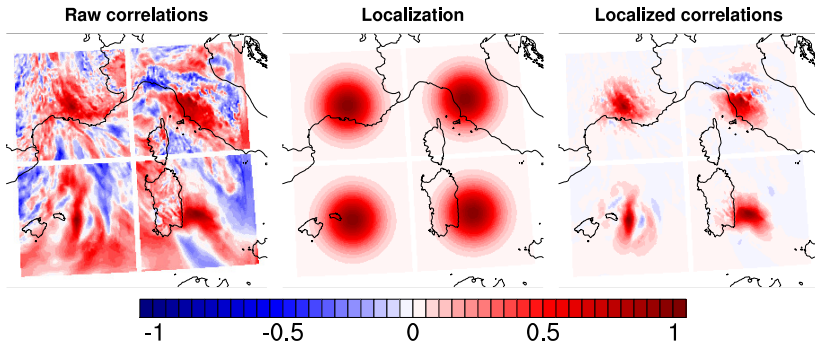


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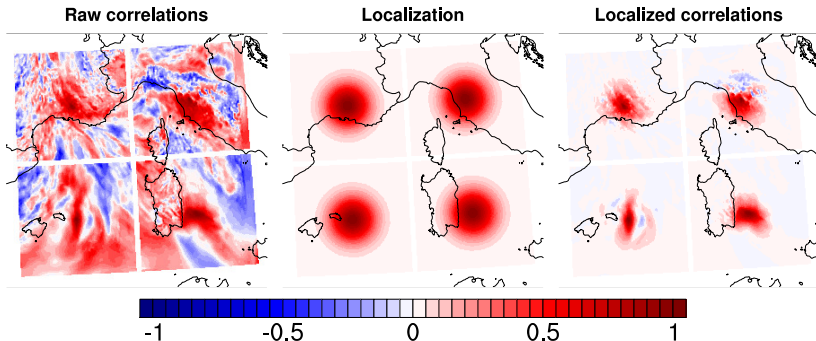


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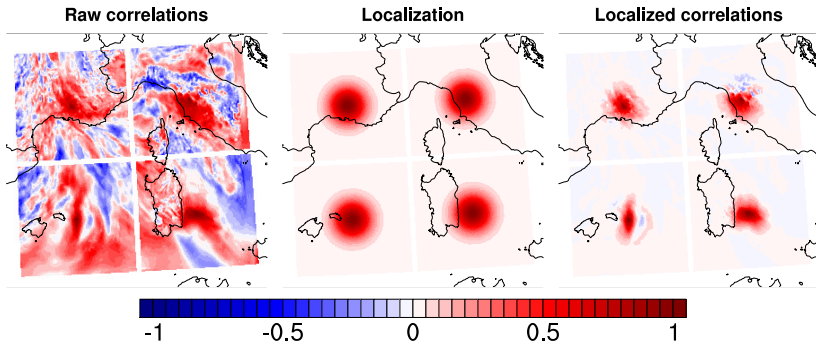


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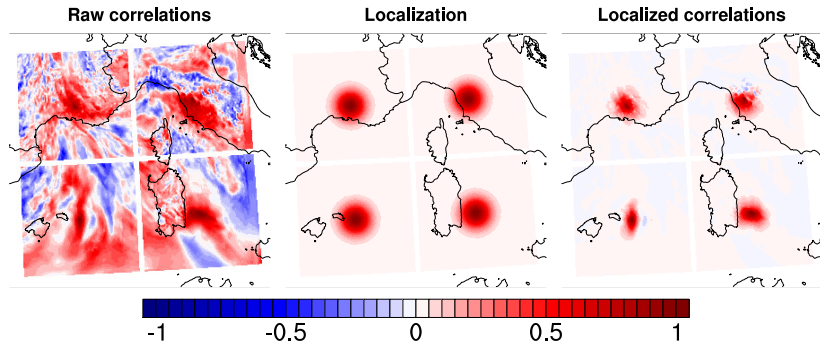


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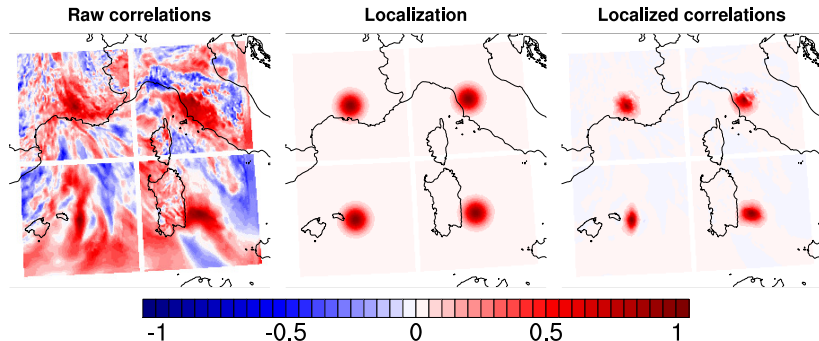


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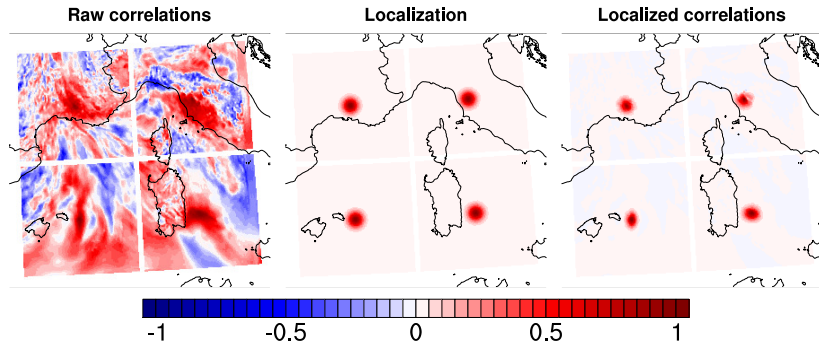


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Aim of this study:

- Development of a general theory for the linear filtering of background error sample covariances.
- (Application to the spatial filtering of variances).
- Application to the spatial localization of covariances.
- Illustration with the global ARPEGE model and the convective scale AROME model.

Main results:

- Dependency on the ensemble size;
- Dependency on the variable;
- Vertical dependency of horizontal and vertical localizations.

- 1 Introduction
- 2 Theory
- 3 Horizontal localization
- 4 Vertical localization
- 5 Conclusion and perspectives

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Theory: how to get started (I)

- The sample covariance matrix $\tilde{\mathbf{B}}$ is estimated using standard unbiased formulae:

$$\tilde{\mathbf{B}} = \frac{1}{N-1} \mathbf{X} \mathbf{X}^T$$

where $\mathbf{X}$ is the matrix of perturbations.

- Asymptotic convergence with ensemble size

$$\tilde{\mathbf{B}}^* = \lim_{N \rightarrow \infty} \tilde{\mathbf{B}}$$

- Sampling error is

$$\tilde{\mathbf{B}}^e = \tilde{\mathbf{B}} - \tilde{\mathbf{B}}^*$$

- Estimate using a linear filter is

$$\hat{\mathbf{B}} = \mathbf{F} \tilde{\mathbf{B}} + \mathbf{f}$$

- Filtering error is

$$\hat{\mathbf{B}}^e = \hat{\mathbf{B}} - \tilde{\mathbf{B}}^*$$

Theory: how to get started (II)

From our statistical knowledge

- Unbiased sampling error $\mathbb{E}[\tilde{\mathbf{B}}^e] = 0$
- Covariance of sampling error has known expression

$$\begin{aligned}\text{Cov}(\tilde{B}_{ij}^e, \tilde{B}_{kl}^e) &= \frac{1}{N} \tilde{\Xi}_{ijkl}^* - \frac{1}{N} \tilde{B}_{ij}^* \tilde{B}_{kl}^* + \frac{1}{N(N-1)} (\tilde{B}_{ik}^* \tilde{B}_{jl}^* + \tilde{B}_{il}^* \tilde{B}_{jk}^*) \\ &= \frac{1}{N-1} (\tilde{B}_{ik}^* \tilde{B}_{jl}^* + \tilde{B}_{il}^* \tilde{B}_{jk}^*)\end{aligned}$$

(under Gaussianity)

From the linear filtering theory

- Optimal filter has unbiased error $\mathbb{E}[\hat{\mathbf{B}}^e] = 0$
- Orthogonality relationship

$$\mathbb{E}[\hat{B}_{ij}^e \tilde{B}_{kl}^e] = 0$$

Theory: end result

$$L_{ij} = \frac{(N-1)^2}{N(N-3)} - \frac{N}{(N-2)(N-3)} \frac{\mathbb{E}[\widetilde{\Xi}_{ijij}]}{\mathbb{E}[\widetilde{B}_{ij}^2]} + \frac{N-1}{N(N-2)(N-3)} \frac{\mathbb{E}[\widetilde{v}_i \widetilde{v}_j]}{\mathbb{E}[\widetilde{B}_{ij}^2]}$$

$$\approx \frac{(N-1)}{(N+1)(N-2)} \left(N - 1 - \frac{\mathbb{E}[\widetilde{v}_i \widetilde{v}_j]}{\mathbb{E}[\widetilde{B}_{ij}^2]} \right)$$

(under Gaussianity)

$$\approx \frac{(N-1)}{(N+1)(N-2)} \left(N - 1 - \frac{1}{\mathbb{E}[\widetilde{C}_{ij}^2]} \right)$$

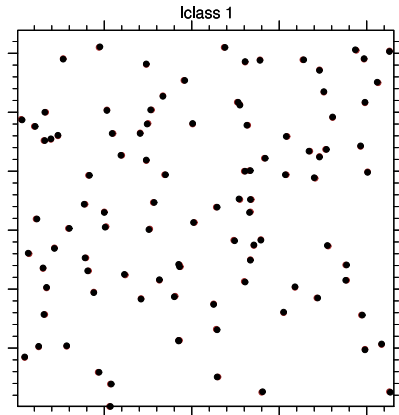
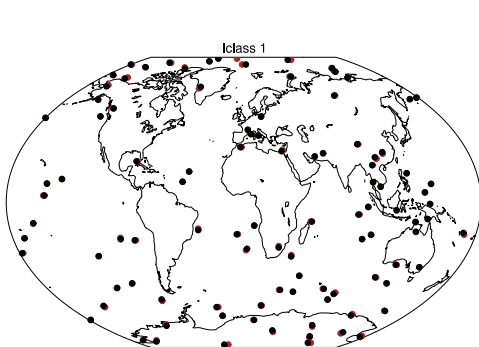
(at small separation distance)

and where:

- N is ensemble size,
- $\widetilde{\Xi}_{ijij}$ is the sample fourth order moment,
- $\widetilde{v}_j$ is the sample variance at j ,
- $\widetilde{B}_{ij}^2$ is the sample covariance squared,
- $\widetilde{C}_{ij}^2$ is the sample correlation squared.

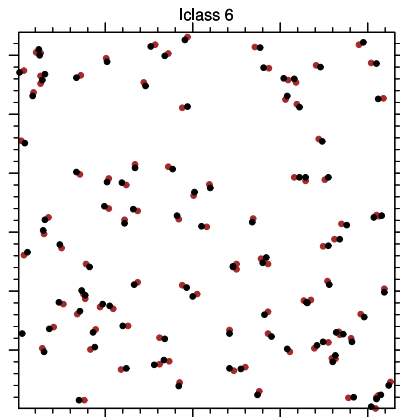
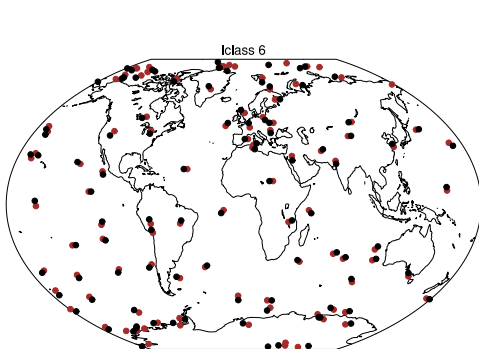
Ergodic assumptions

- $\mathbb{E}$ is replaced by averaging over sampling points.
- Sampling is randomly distributed over the domain.
- Binning is isotropic and based on distance.



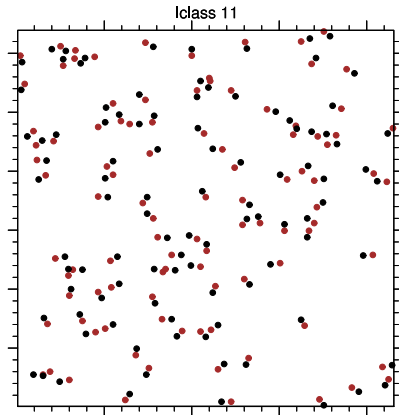
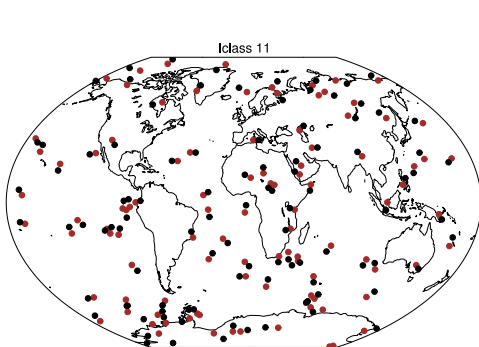
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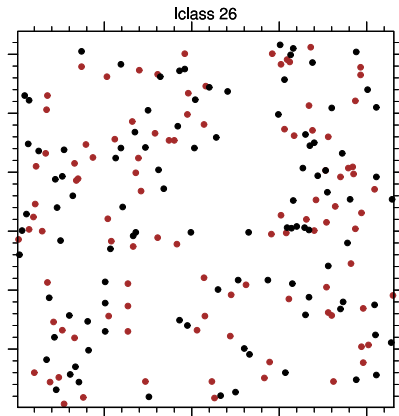
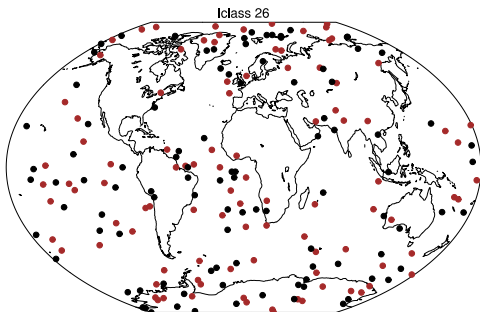
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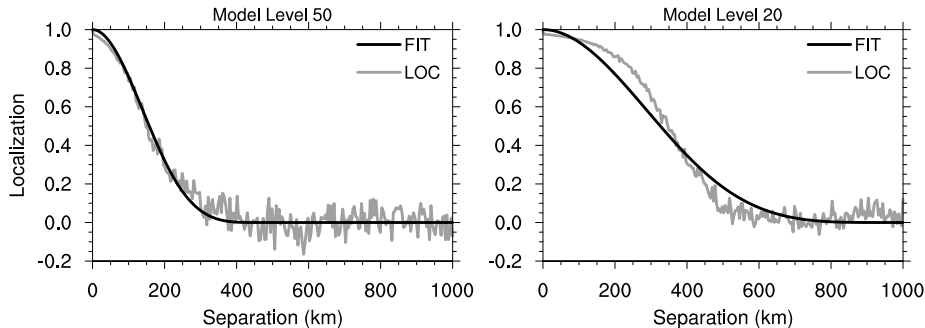
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Results: horizontal localizations

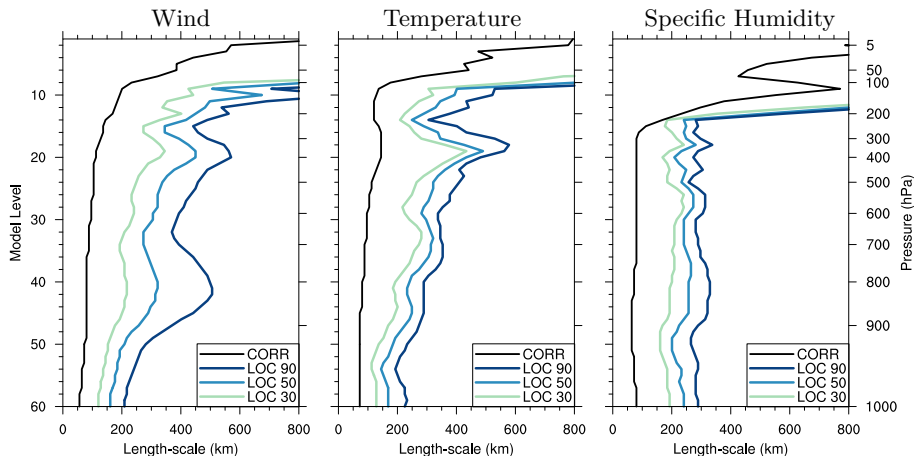
for the convective scale AROME model (I)



Raw horizontal localizations are well approximated by Gaspari and Cohn's compactly supported function.

Results: horizontal localizations length-scales

for the convective scale AROME model (II)

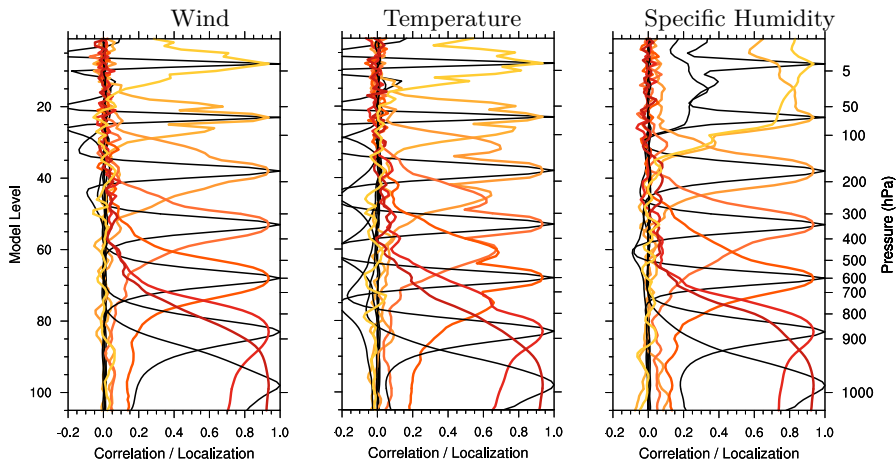


Localization length-scale increases with ensemble size. Local maxima at the top of boundary layer and at the tropopause.

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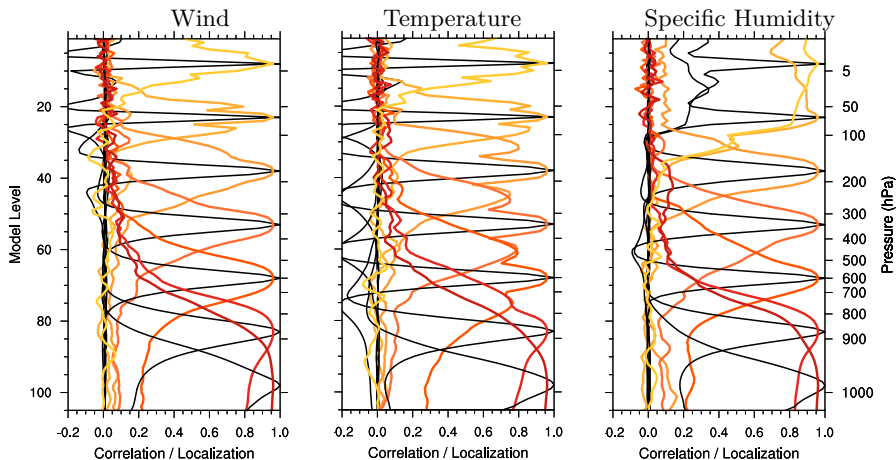
Results: vertical localizations

Comparison between variables for the global ARPEGE model (ens. size=30)



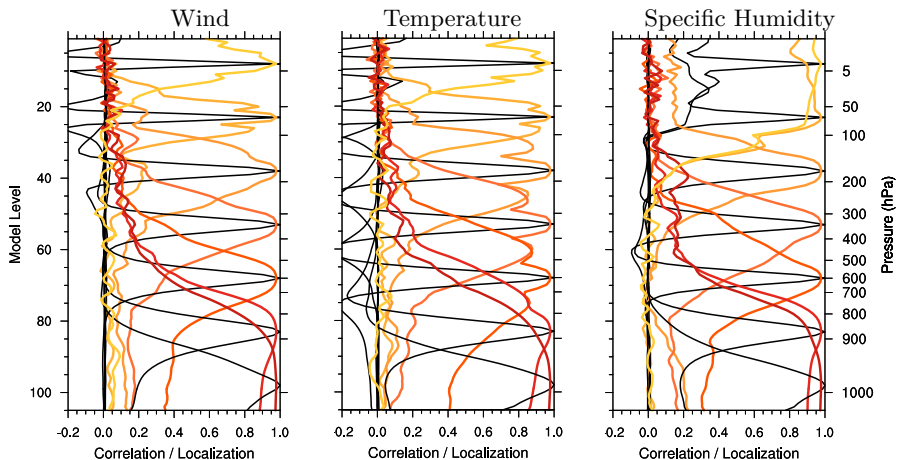
Results: vertical localizations

Comparison between variables for the global ARPEGE model (ens. size=50)



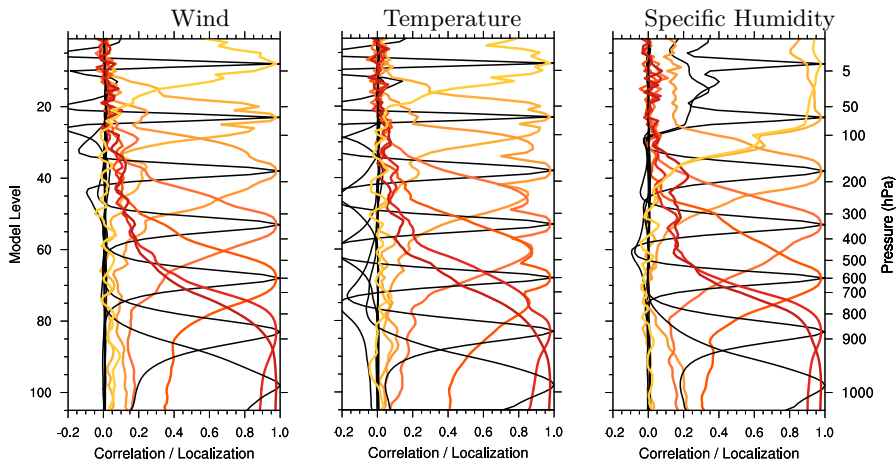
Results: vertical localizations

Comparison between variables for the global ARPEGE model (ens. size=90)



Results: vertical localizations

Comparison between variables for the global ARPEGE model (ens. size=90)



Mostly similar between variables except when there are negative correlations (*e.g.* for T) - as localization follows *squared* correlation.

Theory

- Localization is a linear filter
- Optimal (in the RMSE sense) filtering gives orthogonality relationships
- Sampling noise on covariances has known statistical structure

⇒ “Optimal” localization of background error covariances, depending only on quantities estimated over the ensemble.

Ménétrier, B., Montmerle, T., Michel, Y. and Berre, L. (2014)
Linear Filtering of Sample Covariances for Ensemble-Based Data Assimilation. Part I: Optimality Criteria and Application to Variances Filtering and Covariances Localization.
Monthly Weather Review.

Application

- Localization length-scale increases with ensemble size.
- There are differences between variables: lobes on the vertical for T , larger length-scales on the horizontal at the tropopause (T, U) and at the top of the boundary layer (U).

⇒ We will test these localizations in the 3D/4D-EnVar schemes being developed for AROME model.

Ménétrier, B., Montmerle, T., Michel, Y. and Berre, L. (2014)
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