Modelling of flow-dependent ensemble-based background error correlations using a wavelet formulation

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1) Variational ensemble data assimilation and covariance modelling

• A variational ensemble data assimilation system is used at Météo-France to simulate the error cycling during the successive analysis and forecast steps:

$$\varepsilon^a = (I - KH)\varepsilon^b + K\varepsilon^o \qquad \varepsilon^f = M\varepsilon^a + \varepsilon^m.$$

• Background error variances are flow-dependent and are calculated from a 6-member ensemble by using objective spatial filtering techniques to reduce sampling noise effects.

• Background error correlations are currently static (averaged from few-week series of ensemble perturbations) and nearly homogeneous (except for flow-dependent effects of non-linear balances).

• A wavelet formulation (Fisher, 2003) is used at ECMWF to represent heterogeneous but static correlations.

• Since the temporal dynamics of correlations can be significant (Varella et al., 2011), a flow-dependent wavelet modelling is considered here to estimate robust flow-dependent correlations.

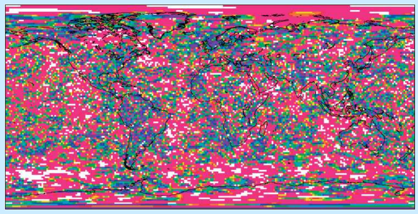
2) Wavelet formulation and sliding temporal average

• The wavelet formulation can be considered as a spatial filtering tool of ensemble-based correlations, since raw ensemble correlations are noisy.

• Wavelet functions (Fisher, 2003) allow both scale and position information to be accounted for:

$$\tilde{\varepsilon}_j^b = \varepsilon^b \otimes \psi_j \text{ , where } \psi_j \text{ are band-limited wavelet functions}$$

$$\varepsilon_w^b = \sum_j \tilde{\varepsilon}_j^b \otimes \psi_j .$$



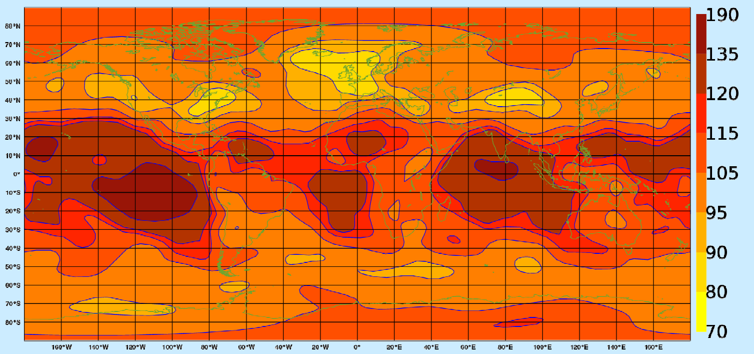
Exemple of raw correlation length-scales (Pannekoucke et al., 2007)

• A wavelet diagonal model of the correlation matrix is considered by $C^w = \mathrm{diag}\, \overline{\varepsilon_w^b (\varepsilon_w^b)^T}$, which amounts to calculate local spatial averages of correlation functions, allowing sampling noise to be reduced (Pannekoucke et al., 2007, Berre and Desroziers, 2010).

• In order to increase the sample size (for estimating robust correlations), a 4-days sliding average of correlations is calculated (instead of the usual few-week off-line static average), leading to 96-member sample.

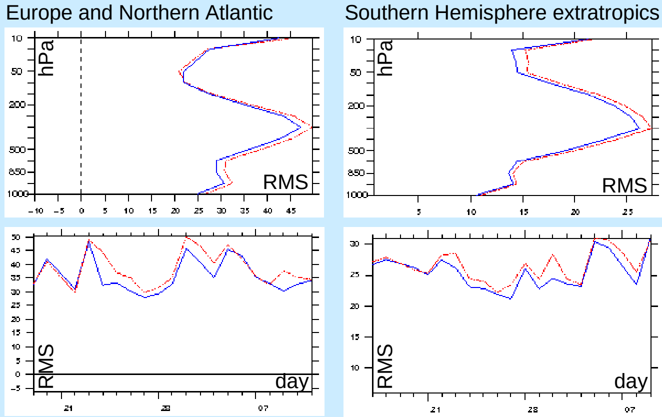
3) Diagnostic and impact results in Arpege 4D-Var

• Background error correlation length-scales of wind are diagnosed by $L(u,v) = \sqrt{\dfrac{\sigma_u^2 + \sigma_v^2}{\sigma_\zeta^2 + \sigma_\eta^2}}$, where u, v, ζ and η are zonal and meridional wind, vorticity and divergence.



Flow-dependent wavelet-implied correlation length-scales (in km) for wind near 500hPa on 28 February 2010

• Impact results are calculated in terms of RMS by running the Arpege 4D-Var system over a few-week period.



Impact of the wavelet flow-dependent correlations against spectral static correlations

4) Conclusions

• A flow-dependent wavelet modelling can be considered to represent the spatio-temporal dynamics of error correlations.

• Testing this in the Arpege 4D-Var system has a strong positive impact on forecast scores.

• Such a formulation is considered for operational implementation at Météo-France.

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