Forecast errors at convective scale

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Outlines

- **Context:** NWP at convective scale

**Forecast errors at convective scale:**
- Specific features compared to global scale
- \( B \) modelling
  - climatological formulation
  - adding flow dependencies
    (hydrometeors)
- \( B \) deduced from ensembles

- Conclusions
Non-hydrostatic models (in the 1-3 km horizontal resolution range) allow realistic representation of convection, clouds, precipitation, turbulence, surface interactions.

**Specific features:**
- Need coupling models to provide LBCs and surface conditions
- Observations linked to clouds and precipitation can be considered (e.g. radars)
- Analyses must be performed frequently
- Forecasts are very expensive in computation time!!
The AROME NWP system

(Seity et al. 2011)

• Oper since more than 5 years, dx=2.5 km, LBCs provided by ARPEGE
• Same observations than ARPEGE with radar DOW and reflectivities

~1.3 $10^8$ variables
⇒ DA based on « real time » ensembles unaffordable for the time being

Active obs in AROME for one rainy day
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Use of an EDA based on AROME with 90 members to produce a background perturbations database

Specific features compared to Global scale

Explicit perturbation of obs: \[ y_o^* = y_o + e_o \quad (e_o \sim N(0, \sigma_o^2)) \]
Explicit perturbation of LBCs using AEARP members
Implicit perturbation of background: \[ x_b^* = M(x_a^*) + (e_m) \]

Fisher 2003; Kucukkaraca and Fisher (2006); Berre et al 2006
Specific features compared to Global scale

\( \mathbf{B} \) can be approximated using \( N \) background perturbations:

\[
\tilde{\mathbf{B}} = \frac{1}{N} \sum_{k=1}^{N} (\mathbf{x}_k - \langle \mathbf{x} \rangle)(\mathbf{x}_k - \langle \mathbf{x} \rangle)^T
\]

\( \tilde{\mathbf{B}} \) can be split in variances / correlations:

\[
\tilde{\mathbf{B}} = \tilde{\mathbf{V}}^{1/2} \tilde{\mathbf{C}} \tilde{\mathbf{V}}^{T/2}
\]

- Variances are the diagonal terms of \( \tilde{\mathbf{V}} \)
- Correlations can be approximated locally using the tensor of the Local Correlation Hessian (LCH, Weaver and Mirouze (2012)):

\[
H = -\nabla \nabla^T c(\mathbf{r})_{r=0}
\]

- \( H \) is computed using the covariances of normalized perturbation derivatives (Michel 2012)
- Local correlation lengths are then deduced in the direction of the eigen vectors of \( H \) using its eigen values:

\[
L^b = (H)^{1/2}
\]
Some features are clearly specific to convective scale processes and are reflecting the resolution differences (e.g. uncertainty of low level convergence, orographic precipitations…)

Low correlations for all variables (not shown)

⇒ Downscaling from global models seems not adapted
Total $L_b$ and ellipses of the LCH tensor
(=> correlation shapes around the origin) for q at 945 hPa

For AROME:
- Much shorter length-scales, much more anisotropic structures
- Small values over mountains and in precipitations
- Correlation function elongated along the meridional flow over Med.
- Large scale perturbations advected inside the domain due to coupling

Ménétrier et al. 2013
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B modelling

An operational NWP system at convective scale:

- Generally uses 3DVar with frequent assimilation/forecast steps to avoid the TL/AD coding of strongly non-linear parameterizations (e.g. diabatic processes) and to benefit from observations with high temporal resolutions.
- Uses a sequence of sparse operators to model $B$, that cannot be expressed at full rank ($\sim (10^8)^2$).
- Is commonly based on an incremental formulation with CVT transform:

$$x = B^{1/2}_C$$

⇒ The challenge is to capture in $B^{1/2}_c$ the known important features of $B$. 
Typical structure of $B_c^{1/2}$:

\[ B_c^{1/2} = K_P B_s^{1/2} \]

(Derber and Bouttier (1999))

- **$K_p$**: Balance operators (or parameter transform) that decorrelate multivariate relationships
- **$B_s^{1/2}$**: Spatial transforms that decorrelate univariate unbalanced variables + variance scaling

⇒ Assumes that errors in balanced variables are uncorrelated from errors in unbalanced variables
⇒ Typically transforms to variables which are assumed to be uncorrelated

Such formulation allows to get balanced analyzed fields

These operators are calibrated using ensemble of forecast differences to get climatological static values
Balance operator in AROME:

- Computed for spectral fields with an extra relationship for $\delta q$ (Berre 2000)

$$ q = QH \tilde{\omega} + R \tilde{\omega}_u + S( \tilde{T}, \tilde{P}_S)_u + q_u $$

- Analytical linear balance to ensure geostrophical balance
- Use of regression operators that adjust couplings with scales
  $\Rightarrow$ the latter balance can be relaxed for smaller scales

Balance operator at the Met-Office (similar to WRF, CMC..)

- fields in spatial representation instead of spectral
- analytical operators instead of statistical regressions (incl. NLBE, hydrostatic balance (that may be invalid at CS))

(More details can be found in Bannister (2008))
Known limitations of climatological balance operators

Strong dependencies to weather type (Brousseau et al, 2011) and to meteorological phenomena that are under-represented in the ensemble

⇒ Often high impact weather!

Normalized deviation from linear geostrophical balance for different types of rain (Carron and Fillion (2010))

Also, deviation from hydrostatic balance (Vetra-Carvalho et al. 2012)

Fraction of explained variance ratios for q (Montmerle and Berre (2010))
Improvement of climatological balance operators in deterministic VAR

For the larger scales (Fisher, 2003):

- NLBE
- Quasi-Geostrophic omega and continuity equations

A diabatic forcing of balanced vertical motion, as diagnosed by Pagé et al. (2007) could (hardly) be introduced in the latter

Use of the heterogeneous formulation with $M$ geographical masks (Ménétrier and Montmerle (2011) for fog, Montmerle (2012) for precipitation):

$$B_C = \sum_{i=1}^{M} F_i^{1/2} B_{C_i} F_i^{T/2}$$

Where $F_i$ defines the area where the ad-hoc $B_{ci}$ is applied
B modelling

Spatial transforms

\[ \mathbf{B}_S = \mathbf{C}^T \]

\( \Sigma \) : diagonal matrix of stationary grid-point \( \sigma_b \)

⇒ In areas of high uncertainties (often high impact weather!), error variances are under-estimated: the analysis is not sufficiently corrected

\( \mathbf{C} \) :
- vertical correlations represented by empirical functions (e.g. EOFs)
- horizontal correlations usually computed using the diagonal spectral hypothesis (bi-Fourier series for AROME), or in grid-point space by using recursive filters (Purser et al, 2003) (WRF, JMA…)

⇒ The resulting correlations are homogeneous and isotropic
Spatial transform

Again, strong dependencies to the meteorological phenomena of the horizontal correlation length-scales and of the vertical auto-correlations

Example for fog:

Vertical autocorrelations for $T$
(zoom in the first 500m)

Ménétrier and Montmerle (2011)
Adding anisotropies in spatial transforms

• Different length-scales corresponding to different meteorological phenomena can be imposed in specific areas using the heterogeneous VAR formulation (Montmerle and Berre, 2010) in e.g precipitating regions.

• Wavelet formulation allows to model simultaneously scale and position-dependent aspects of covariances (Fisher, 2003).

• Covariances can be stretched in recursive filters (Purser et al., 2003b).

• Isotropic correlations can be computed in an objectively distorted grid (Michel 2012).

•...
B modelling

Mesoscale Horizontal correlations modelized by wavelets
(Deckmyn and Berre (2005))
B modelling

Grid deformation for horizontal error correlations (Michel 2012)

Distorted grid (where correlations are homogeneous and isotropic)

Back to regular grid

Raw

Modeled diagonal spectral
Deformation of vertical error correlations

Adaptative mesh transform for vertical correlations that uses a monitor function that depends on the static stability \( d\theta/dz \) from the guess (Piccolo and Cullen (2012))

\[ \Rightarrow \] Mesh points are concentrated around T inversions or cloud top height

*Vertical cross sections of monitor function (top) and of the corresponding adaptative mesh (bottom)*
Use of optimally filtered error variances from small ensemble

Adaptation of Raynaud et. al (2009) work at convective scale (See B. Ménétrier poster (B-p13))

- Tests are ongoing to modulate $B_C$ by such error variances
- Potentially useful in an EnVAR context: complementary to localization as it allows to reduce the sampling noise locally

RMSE of averaged $\sigma_b^2$ for $q_u$
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In ensemble based methods, flow dependency of forecast errors is provided (entirely or partially) by ensemble perturbations $e_k = x_k - \langle x \rangle$:

$$P_e = \frac{1}{N} \sum_{k=1}^{N} e_k e_k^T$$

To avoid distant spurious correlations, to reduce the sampling noise and to increase the rank, covariance localization is applied

$$B_e = P_e \circ C \quad (Houtekamer and Mitchell (2001))$$

Where $C$ is a correlation matrix defining horizontal and vertical localization via series of transforms

$C$ is required to improve the properties of $P_e$ and can be much simpler than $B_C$, but should be modeled in a compact way for computational efficiency
Very empirical and often sub-optimal because correlation lengths depend on:

- number of samples
- resolution and model error
- observation network
- scales of the different physical processes

⇒ At convective scale, these features are even more pronounced!

Gaussian shaped-like correlation functions (e.g. Gaspari and Cohn, 1999) is commonly used in association with a Shur product

Ensemble covariances localization

Global error variance vs. relative scale of correlation for different ensemble sizes (Lorenc, 2003)
Imposing different localization lengths

- Different empirical values can be applied for different observation groups in successive analyses in SCL technique (Zhang et al. 2009)

- Bishop and Hodyss (2009) have developed a strategy to adaptively localize ensemble covariances using powers of smoothed raw correlations (for different obs. volumes in a LETKF framework)
Localization causes imbalances

• Balances are directly inherited from the ensemble covariance.
• But, when vertical or horizontal spatial gradients occur, localization implies imbalances

To alleviate this problem, Clayton et al. (2012) impose balance after localization

⇒ In EnVar methods, the balance operator in $B_C$ attenuates this problem
⇒ Damping of gravity waves is sometimes applied at global scales through digital filtering or IAU
Empirical formulations are also used vertically, even if:

- The smooth reduction of magnitude between levels is often unrealistic
- The choice of vertical coordinate is often inadequate
- Problems arise for observation of integrated contents (e.g., radiances)

⇒ Obviously, a lot of research still is needed!

Campbell et al. (2010) show that localization in model space is more efficient than in obs. space.

Analysis error vs. log of obs. error after assimilating 6 AMSU-A channels in an EnKF using different vertical localization.
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- Forecast errors at convective scale display features linked to the explicit convection, to diabatic processes, to the type of surface, to the coupling files, to the specific observation network (e.g. radars).

- Significant differences have been shown with global scale.

- Operational formulation of $B_c$ is clearly sub-optimal, especially in regions characterized by high impact weather (e.g., clouds and precipitations).

- Certain degree of flow dependencies can be added to $B_c$, whether in balance operators (NL balances) or in spatial transform using ensembles (modulation by filtered variances, compactly supported function to model horizontal correlations, grid distortion, ...)
Conclusions

Operationally, the set up of an ensemble still is difficult because:
- need of perturbed LBCs
- the computational cost
- the estimation and representation of model error
- sampling noise can be severe

⇒ Cheaper ensembles in the limit of the “grey zone” (providing that explicit convection is activated) could be an option

⇒ Improvement in localization procedures is needed: future works should consider what have been done for $B_c$

⇒ Results can eventually be validated and tuned using innovation-based diagnostics
Possible evolution of B in operational NWP systems at CS

Static $B_C$ with balance relationships and homogeneous and isotropic covariances for unbalanced variables

Static $B_C$ with variances modulated by filtered values from an ensemble

Static $B_C$ with modellized horizontal correlations deduced from an ensemble

EnVar: use of a spatially localized covariance matrix $B_e$ deduced from an ensemble, combined with $B_C$

EnVar with more optimal localizations in $B_e$

At global scale:
Desroziers et al. (2008)
Varella et al. (2011)
Thank you for your attention!
References

Clayton, A. C. Lorenc and D. M. Barker, 2012: Operational implementation of a hybrid ensemble/4D-Var global data assimilation system at the Met Office. QJMS.
Ménétrier B, Montmerle T., Berre L. and Michel Y., 2013: Estimation and diagnosis of heterogeneous flow-dependent background error covariances at convective scale using either large or small ensembles. QJMS, in press.