'Balance' and Ensemble Localization

R.N. Bannister¹, L.H. Baker¹, S. Migliorini^{1,2}, A.C. Rudd^{1,3} ¹University of Reading, UK; ²ECMWF, Reading, UK; ³now CEH, Wallingford, UK

Forecast error covariance statistics, \mathbf{P}^{f} , are prominent in the Kalman Filter, e.g.

$$\mathbf{x}^{\mathrm{a}} = \mathbf{x}^{\mathrm{b}} + \mathbf{P}^{\mathrm{f}} \mathbf{H}^{\mathrm{T}} \left(\mathbf{R} + \mathbf{H} \mathbf{P}^{\mathrm{f}} \mathbf{H}^{\mathrm{T}} \right)^{-1} \left(\mathbf{y} - \mathbf{H} \mathbf{x}^{\mathrm{b}}
ight)$$

Forecast error covariance statistics can be approximated by an *N*-member ensemble for ensemble Kalman filtering:

$$\mathbf{P}^{\mathrm{f}} \to \mathbf{P}^{\mathrm{f}}_{N} = \frac{1}{N-1} \sum_{l=1}^{N} (\mathbf{x}_{l} - \bar{\mathbf{x}}) (\mathbf{x}_{l} - \bar{\mathbf{x}})^{\mathrm{T}}$$

☑ Easy to implement

☑ Flow/weather dependent

E Full rank estimate of **P**^f









Consequences of sampling error ...





Ensemble-derived forecast error correlation function

... consequences of sampling error

$$\mathbf{x}^{\mathrm{a}} = \mathbf{x}^{\mathrm{b}} + \mathbf{P}^{\mathrm{f}} \mathbf{H}^{\mathrm{T}} \left(\mathbf{R} + \mathbf{H} \mathbf{P}^{\mathrm{f}} \mathbf{H}^{\mathrm{T}} \right)^{-1} \left(\mathbf{y} - \mathbf{H} \mathbf{x}^{\mathrm{b}}
ight)$$



 $(\mathbf{H}\mathbf{P}^{\mathrm{f}}\mathbf{H}^{\mathrm{T}})_{11} = \mathbf{h}^{\mathrm{T}}\mathbf{P}_{N}^{\mathrm{f}}\mathbf{h}$ Sampling error will look like an extra obs err variance

E.g. $\left(\mathbf{H}\mathbf{P}^{\mathrm{f}}\mathbf{H}^{\mathrm{T}}\right)_{12} = \mathbf{h}_{1}^{\mathrm{T}}\mathbf{P}_{N}^{\mathrm{f}}\mathbf{h}_{2}$

Sampling error will look like an extra obs err covariance



Localization as a means of mitigating sampling error

• The error in the sample correlation between two variables *x* and *y* is:

Error in
$$\text{COR}(x, y) \sim \frac{1 - \text{COR}^2(x, y)}{\sqrt{N - 1}}$$

- Expect largest sampling error when actual correlation is small.
- Expect actual correlation to be small when separation between *x* and *y* is large.
- Introduce separation-dependent damping of the correlations and covariances.
 - → Localization

$$\mathbf{P}_{N}^{\mathrm{f}}
ightarrow \overset{\mathrm{o}}{\mathbf{P}}_{N}^{\mathrm{f}} = \mathbf{P}_{N}^{\mathrm{f}} \circ \mathbf{\Omega}$$

Localization

$$\mathbf{P}_{N}^{\mathrm{f}}
ightarrow \overset{\mathrm{o}}{\mathbf{P}}_{N}^{\mathrm{f}}=\mathbf{P}_{N}^{\mathrm{f}}\circ\mathbf{\Omega}$$

- Most applications choose $\boldsymbol{\Omega}$ to be a decreasing function of separation.
- BUT
 - Some covariances do have regions that should increase with distance.
 - Localization can remove long-range correlations, but they can destroy other important properties (e.g. balance).
 - Balance is thought to be the reason why modern data assimilation for weather forecasting is so successful, so DON'T WANT TO DESTROY THIS!

Wish list

$$\mathbf{P}_{N}^{\mathrm{f}}
ightarrow \overset{\mathrm{o}}{\mathbf{P}}_{N}^{\mathrm{f}} = \mathbf{P}_{N}^{\mathrm{f}} \circ \mathbf{\Omega}$$

• Use a finite ensemble where:

- Unphysical correlations are removed.
- Preserves physical properties like 'balance'.

• Examine five ways of modelling $\pmb{\Omega}$:

- Spectral method (static Ω).
 - Types I and II.
- SENCORP-like method (adaptive Ω Bishop et al.).
- ECORAP method (adaptive Ω Bishop et al.).
 - Types I and II.
- Remainder of this talk:
 - Describe these methods.
 - Explain the balance diagnostics.
 - Extracting balance information from the covariances.
 - Implied correlation functions and balance properties of the methods.

The localization methods

Remember ...

1. Spectral I (static, univariate *K* = No. of waves × No. of parameters)

$$\Omega_{
m spec(I)}^{n imes n} \propto \left(egin{array}{ccc} {f F} \Lambda_{p_1} {f F}^{
m T} & {f 0} & {f 0} \ {f O} & {f F} \Lambda_{p_2} {f F}^{
m T} & {f 0} \ {f 0} & {f F} \Lambda_{p_2} {f F}^{
m T} & {f 0} \ {f 0} & {f F} \Lambda_{p_2}^{n imes K} \end{array}
ight) \; {f K}_{
m spec(I)}^{n imes K} \propto \left(egin{array}{ccc} {f F} \Lambda_{p_1}^{1/2} & {f 0} & {f 0} \ {f 0} & {f F} \Lambda_{p_2}^{1/2} & {f 0} \ {f 0} & {f O} & {f F} \Lambda_{p_2}^{1/2} \end{array}
ight) \; \ {f 0} \; {f 0} \; {f O} \; {f F} \Lambda_{p_3}^{1/2} \end{array}
ight)$$

2. Spectral II (static multivariate, K = No. of waves)

$$\Omega_{\rm spec(II)}^{n \times n} \propto \begin{pmatrix} \mathbf{F} \Lambda_{p_1} \mathbf{F}^{\rm T} & \mathbf{F} \Lambda_{p_1}^{1/2} \Lambda_{p_2}^{1/2} \mathbf{F}^{\rm T} & \mathbf{F} \Lambda_{p_1}^{1/2} \Lambda_{p_3}^{1/2} \mathbf{F}^{\rm T} \\ \mathbf{F} \Lambda_{p_2}^{1/2} \Lambda_{p_1}^{1/2} \mathbf{F}^{\rm T} & \mathbf{F} \Lambda_{p_2} \mathbf{F}^{\rm T} & \mathbf{F} \Lambda_{p_2}^{1/2} \Lambda_{p_3}^{1/2} \mathbf{F}^{\rm T} \\ \mathbf{F} \Lambda_{p_3}^{1/2} \Lambda_{p_1}^{1/2} \mathbf{F}^{\rm T} & \mathbf{F} \Lambda_{p_3}^{1/2} \mathbf{F}^{\rm T} & \mathbf{F} \Lambda_{p_3} \mathbf{F}^{\rm T} \end{pmatrix} \quad \mathbf{K}_{\rm spec(II)}^{n \times K} \propto \begin{pmatrix} \mathbf{F} \Lambda_{p_1}^{1/2} & \mathbf{F} \Lambda_{p_2}^{1/2} \\ \mathbf{F} \Lambda_{p_3}^{1/2} \mathbf{F}^{\rm T} & \mathbf{F} \Lambda_{p_3}^{1/2} \mathbf{F}^{\rm T} \\ \mathbf{F} \Lambda_{p_3}^{1/2} \mathbf{F}^{\rm T} & \mathbf{F} \Lambda_{p_3}^{1/2} \mathbf{F}^{\rm T} & \mathbf{F} \Lambda_{p_3} \mathbf{F}^{\rm T} \end{pmatrix}$$

3. SENCORP (Bishop et al., $K = N^{Q}$)

$$\Omega_{\text{SENCORP}}^{n \times n} \propto \mathbf{C}^{\circ Q} = \mathbf{C} \circ \mathbf{C} \circ \cdots \circ \mathbf{C} \qquad \mathbf{K}_{\text{SENCORP}}^{n \times K} \propto \begin{pmatrix} \text{every possible} \\ \text{combination of} \\ Q \text{ smoothed members} \end{pmatrix}$$
$$\mathbf{C}^{n \times n} = \frac{1}{L} \mathbf{W}^{n \times N} \mathbf{W}^{n \times N \text{T}}$$

4. ECORAP I (Bishop et al., K = No. of waves × No. of parameters)

$$\begin{split} \Omega_{\text{ECORAP(I)}}^{n \times n} \propto \mathbf{C}^{\circ Q} \begin{pmatrix} \mathbf{F} \Lambda_{p_1} \mathbf{F}^{\text{T}} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{F} \Lambda_{p_2} \mathbf{F}^{\text{T}} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{F} \Lambda_{p_3} \mathbf{F}^{\text{T}} \end{pmatrix} \mathbf{C}^{\circ Q} \\ & \mathbf{K}_{\text{ECORAP(I)}}^{n \times K} \propto \mathbf{C}^{\circ Q} \begin{pmatrix} \mathbf{F} \Lambda_{p_1}^{1/2} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{F} \Lambda_{p_2}^{1/2} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{F} \Lambda_{p_3}^{1/2} \end{pmatrix} \\ \mathbf{5. ECORAP II (Bishop et al., K = No. of waves)} \\ \Omega_{\text{ECORAP(II)}}^{n \times n} \propto \mathbf{C}^{\circ Q} \begin{pmatrix} \mathbf{F} \Lambda_{p_1} \mathbf{F}^{\text{T}} & \mathbf{F} \Lambda_{p_1}^{1/2} \Lambda_{p_2}^{1/2} \mathbf{F}^{\text{T}} & \mathbf{F} \Lambda_{p_1}^{1/2} \Lambda_{p_3}^{1/2} \mathbf{F}^{\text{T}} \\ \mathbf{F} \Lambda_{p_2}^{1/2} \Lambda_{p_1}^{1/2} \mathbf{F}^{\text{T}} & \mathbf{F} \Lambda_{p_2} \mathbf{F}^{\text{T}} & \mathbf{F} \Lambda_{p_1}^{1/2} \Lambda_{p_3}^{1/2} \mathbf{F}^{\text{T}} \\ \mathbf{F} \Lambda_{p_3}^{1/2} \Lambda_{p_1}^{1/2} \mathbf{F}^{\text{T}} & \mathbf{F} \Lambda_{p_2} \mathbf{F}^{\text{T}} & \mathbf{F} \Lambda_{p_3} \mathbf{F}^{\text{T}} \end{pmatrix} \mathbf{C}^{\circ Q} \\ \begin{pmatrix} \mathbf{F} \Lambda_{p_1}^{1/2} \\ \mathbf{F} \Lambda_{p_3}^{1/2} \Lambda_{p_1}^{1/2} \mathbf{F}^{\text{T}} & \mathbf{F} \Lambda_{p_3}^{1/2} \mathbf{F}^{\text{T}} \\ \mathbf{K}_{\text{spec}(II)}^{n \times K} \propto \mathbf{C}^{\circ Q} \begin{pmatrix} \mathbf{F} \Lambda_{p_1}^{1/2} \\ \mathbf{F} \Lambda_{p_3}^{1/2} \\ \mathbf{F} \Lambda_{p_3}^{1/2} \end{pmatrix} \end{aligned}$$

Balance diagnostics

 $t_A + t_B = 0$

$$\rho_{AB} = \langle (t_A - \langle t_A \rangle) (t_B - \langle t_B \rangle) \rangle$$

Balanced if $\rho_{AB} \sim -1$

Examples:

	t_{A}	t _B
Geostrophic balance	Mass terms	Wind terms
Hydrostatic balance	Pressure term	Density term

Extraction of balance information

$$\mathbf{P}_{N}^{\mathrm{f}} = \frac{1}{N-1} \mathbf{X} \mathbf{X}^{\mathrm{T}}$$
$$\Omega = \frac{1}{K-1} \mathbf{K} \mathbf{K}^{\mathrm{T}}$$
$$\overset{\circ}{\mathbf{P}}_{N}^{\mathrm{f}} = \mathbf{P}_{N}^{\mathrm{f}} \circ \mathbf{\Omega}$$

$$\begin{pmatrix} \circ^{\mathbf{f}} \\ \mathbf{P}_{N} \end{pmatrix}_{ij} = \left(\mathbf{P}_{N}^{\mathbf{f}} \right)_{ij} \circ \mathbf{\Omega}_{ij}$$

$$= \frac{1}{(N-1)(K-1)} \sum_{l,k} \mathbf{X}_{il} \mathbf{X}_{jl} \mathbf{K}_{ik} \mathbf{K}_{jk}$$

$$= \frac{1}{(N-1)(K-1)} \sum_{l,k} \left(\mathbf{X}_{il} \mathbf{K}_{ik} \right) \left(\mathbf{X}_{jl} \mathbf{K}_{jk} \right)$$

Effective ensemble of NK members

Example localized correlation functions (provisional)

No localization (pressure) 1, 2. Static (types I and II)

3. SENCORP



longitude

longitude

longitude

Balance diagnostics (provisional)

