



Representing Ensemble Covariances in Variational Assimilation with a Diffusion Operator

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Context

- We consider the problem of estimating the $N \times N$ background-error covariance matrix (\mathbf{B}) from an ensemble of $N_e \ll N$ error realizations.
- We consider localized, ensemble-based \mathbf{B} models suitable for application with conjugate gradient (CG) algorithms in variational data assimilation.

Definitions

- Let $\{\epsilon_p = \mathbf{x}_p - \mathbf{x}_0\}$ denote an ensemble of $p = 1, \dots, N_e$ state error realizations with respect to an unperturbed control member \mathbf{x}_0 .
- Let $\epsilon'_p = \epsilon_p - \bar{\epsilon}$ where $\bar{\epsilon} = \sum_{p=1}^{N_e} \epsilon_p / N_e$, and $\mathbf{B}_{\text{sam}} = \mathbf{X}' \mathbf{X}'^T$ where $\mathbf{X}' = (\epsilon'_1, \dots, \epsilon'_{N_e}) / \sqrt{N_e - 1}$.
- We define the *sample correlation matrix*

$$\mathbf{C}_{\text{sam}} = \mathbf{D}^{-1/2} \mathbf{X}' \mathbf{X}'^T \mathbf{D}^{-1/2} = \hat{\mathbf{X}}' (\hat{\mathbf{X}}')^T \quad (1)$$

where $\mathbf{D} = \mathbf{D}^{1/2} \mathbf{D}^{1/2} = \text{diag}(\mathbf{B}_{\text{sam}})$ and $\hat{\mathbf{X}}' = \mathbf{D}^{-1/2} \mathbf{X}' = (\hat{\epsilon}'_1, \dots, \hat{\epsilon}'_{N_e})$.

Correlation Operators based on Implicit Diffusion

- Consider the operator $\hat{\psi} \xrightarrow{C_{\text{dif}}} \psi$ on \mathbb{R}^d defined by the solution of an M -step implicitly-formulated diffusion equation:

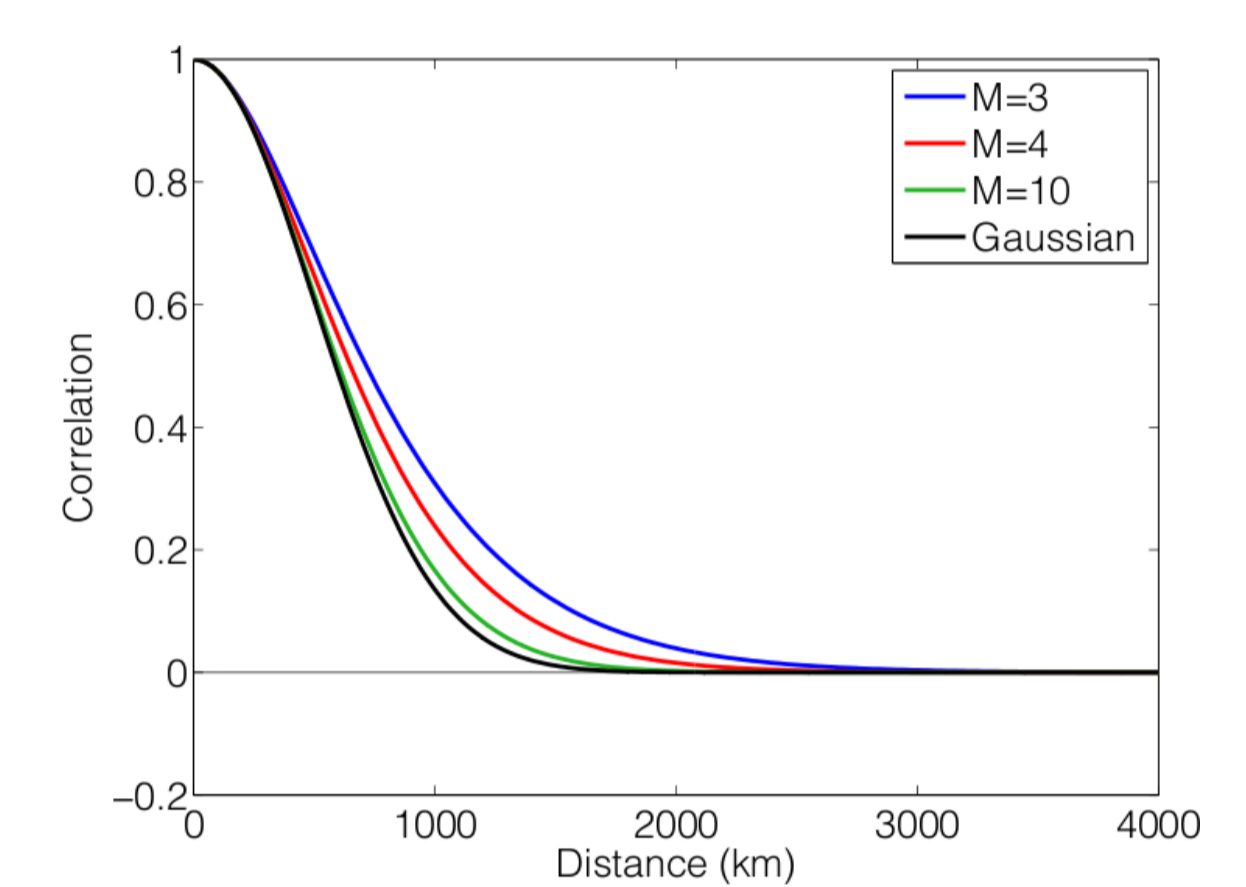
$$(1 - \nabla \cdot \boldsymbol{\kappa} \nabla)^M \psi(\mathbf{x}) = \hat{\psi}(\mathbf{x}) \quad (2)$$

- For constant $\boldsymbol{\kappa}$, the solution is a convolution of $\hat{\psi}(\mathbf{x})$ with a covariance function from the Whittle-Matérn family ([3], [7]):

$$c_d(r) \sim r^{M-d/2} K_{M-d/2}(r)$$

where $K_{M-d/2}(r)$ is the modified Bessel function of the second kind, and

$$r = \sqrt{(\mathbf{x} - \mathbf{x}')^T \boldsymbol{\kappa}^{-1} (\mathbf{x} - \mathbf{x}')}$$



Method 1: Covariance modelling using Diffusion

- Represent the covariance matrix of the analysis variables as

$$\mathbf{B}_1 = \mathbf{D}^{1/2} \mathbf{C}_{\text{dif}} \mathbf{D}^{1/2}$$

where \mathbf{C}_{dif} is a *full-rank* correlation matrix.

- Represent the correlation matrix as ([6])

$$\mathbf{C}_{\text{dif}} = \mathbf{N}^{1/2} \mathbf{L} \mathbf{W}^{-1} \mathbf{N}^{1/2}$$

where \mathbf{L} is the solution operator of Eq. (2), $\mathbf{W} = \text{diag}(\text{metric coefficients})$ and $\mathbf{N} = \mathbf{N}^{1/2} \mathbf{N}^{1/2} = \text{diag}(\text{normalization factors})$.

- Compute the *local* diffusion tensor from ([7])

$$\boldsymbol{\kappa}(\mathbf{x}) = \frac{1}{2M - d - 2} \mathbf{H}^{-1}(\mathbf{x}) \quad (3)$$

where $\mathbf{H}(\mathbf{x})$, the correlation Hessian tensor, can be estimated from ([4])

$$\mathbf{H}_{\text{sam}}(\mathbf{x}) = \sum_{p=1}^{N_e} \nabla \hat{\epsilon}'_p(\mathbf{x}) (\nabla \hat{\epsilon}'_p(\mathbf{x}))^T \quad (4)$$

Method 2: Localization using Diffusion

- A common way to localize covariances in the EnKF is to compute the Schur (element-by-element) product \circ of the sample correlation matrix (1) with a prescribed localized correlation matrix \mathbf{C}_{loc} :

$$\mathbf{B}_2 = \mathbf{D}^{1/2} [\mathbf{C}_{\text{sam}} \circ \mathbf{C}_{\text{loc}}] \mathbf{D}^{1/2} \quad (5)$$

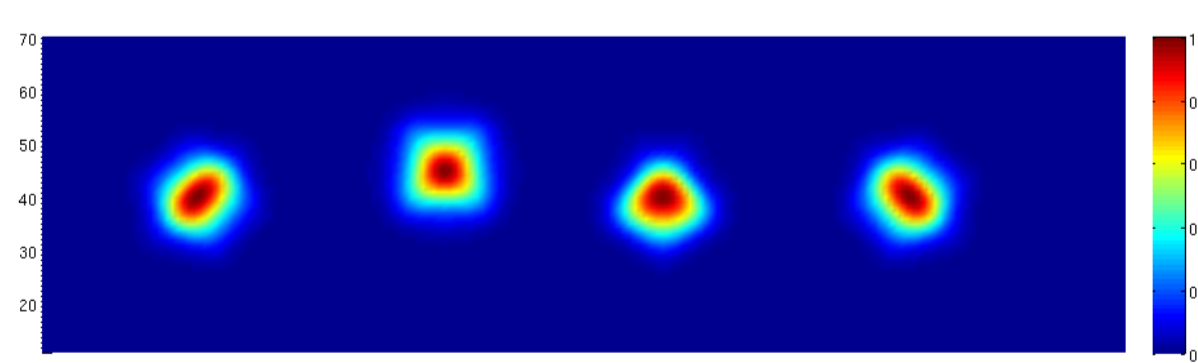
- A more convenient form of Eq. (5) for CG is ([2])

$$\mathbf{B}_2 = \mathbf{D}^{1/2} \left[\sum_{p=1}^{N_e} \mathbf{D}_{\hat{\epsilon}'_p} \mathbf{C}_{\text{loc}} \mathbf{D}_{\hat{\epsilon}'_p} \right] \mathbf{D}^{1/2} \quad (6)$$

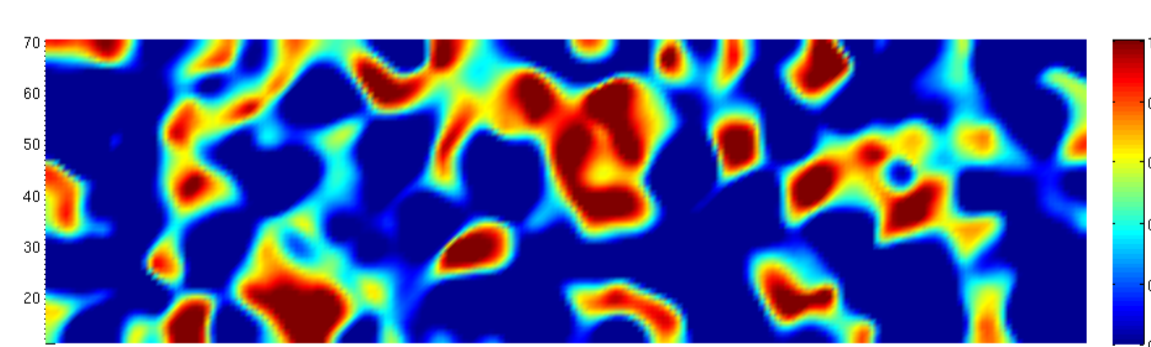
where $\mathbf{D}_{\hat{\epsilon}'_p} = \text{diag}(\hat{\epsilon}'_p)$.

- The diffusion operator \mathbf{C}_{dif} can be used to define \mathbf{C}_{loc} in Eq. (6).
- The localization function can be made *adaptive* by setting the diffusion tensor in $\mathbf{C}_{\text{loc}} = \mathbf{C}_{\text{dif}}$ to $\alpha \boldsymbol{\kappa}_{\text{sam}}$ where $\boldsymbol{\kappa}_{\text{sam}}$ is estimated from Eqs (3)-(4) and $\alpha > 1$.

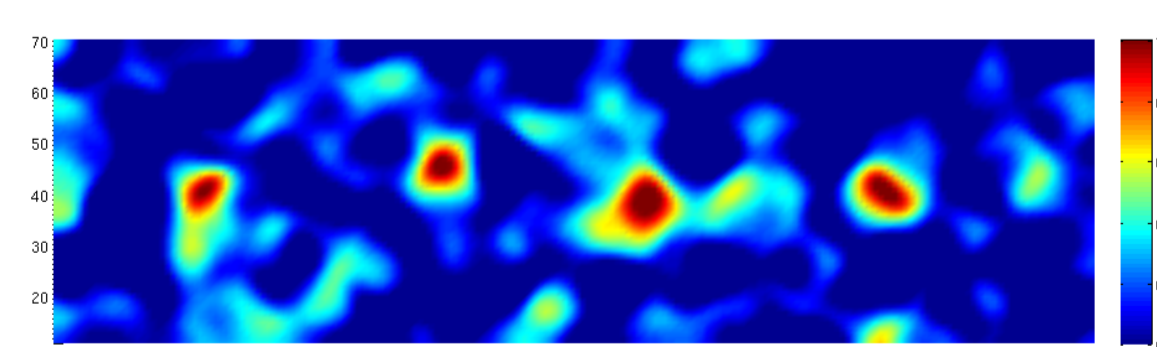
Idealized Example involving Anisotropic and Inhomogeneous Correlations



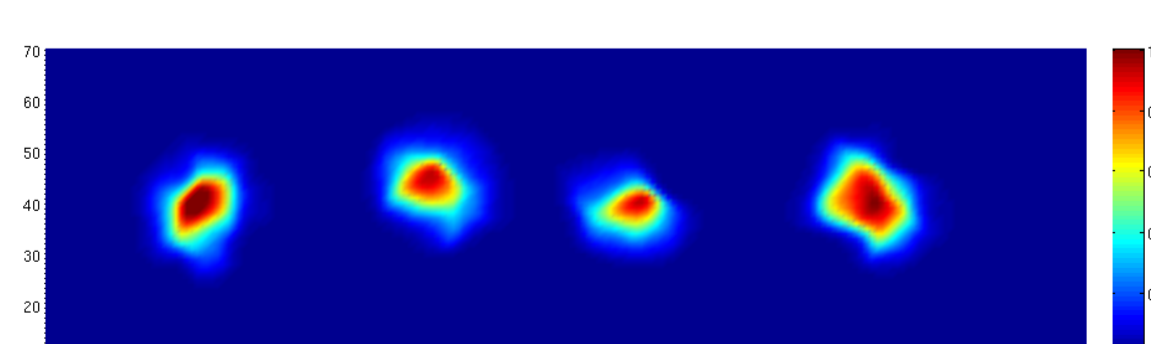
True correlations at selected points



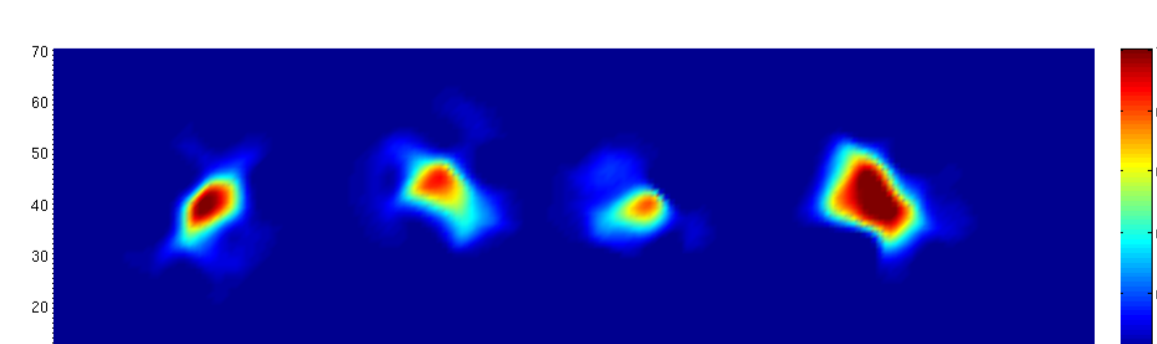
Raw correlations with $N_e = 10$



Raw correlations with $N_e = 100$



Estimated correlations using Method 1 with $N_e = 10$



Estimated correlations using Method 2 with $N_e = 10$ and $\alpha = 2$.

Remarks

- Method 1 requires the estimation of $O(N)$ diffusion tensor elements for each of the analysis variables and one application of \mathbf{C}_{dif} per CG iteration.
- Method 2 can be implemented with simpler (e.g., non-adaptive) diffusion operators, has greater flexibility for specifying multivariate covariances, but requires N_e applications of \mathbf{C}_{dif} per CG iteration.
- Spatial filtering of the variances and tensor elements can help reduce the effects of sampling error ([1]).
- Hybrid formulations that combine \mathbf{B}_1 and \mathbf{B}_2 are being considered for the NEMOVAR ocean data assimilation system ([5]).

References

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- [3] Guttorp, P. and T. Gneiting, 2006: *Biometrika*, **93**, 989–995.
- [4] Michel, Y., 2012: *Q. J. R. Meteorol. Soc.*, DOI: 10.1002/qj.2007.
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