

Studies about DAs

Lorenz-96 (Lorenz et al., 1998)

$$dX_{j} / dt = (X_{j+1} - X_{j-2})X_{j-1} - X_{j} + F$$
 For j=1,...,J, $X_{j} = X_{j+1}$

Advection term

Dissipation term

Forcing term

1. EKF:

$$0.01 \le \delta \le 0.30$$

$$P^f \leftarrow P^f (1+\delta)^2$$

2. 3DVAR:

$$0.20 \le b \le 1.00$$

$$B_{ij} = \begin{cases} b & when(i = j) \\ 0 & when(i \neq j) \end{cases}$$

3. EnSRF & LETKF:

$$0.01 \le \delta \le 0.10$$

$$E^f \leftarrow E^f (1 + \delta)$$

$$1.0 \le \sigma \le 10.0$$

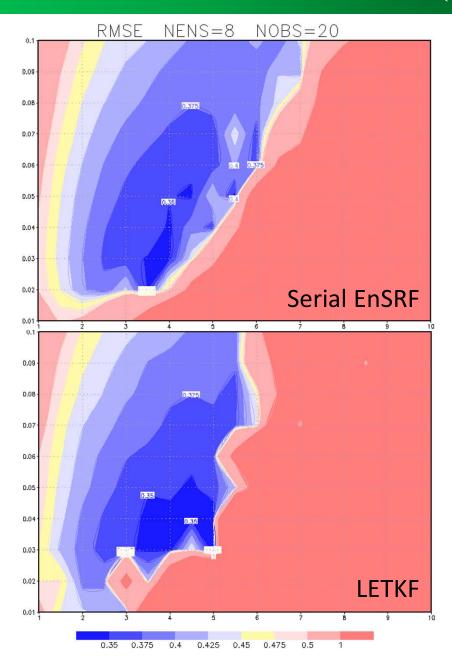
$$r = \frac{d}{\sqrt{10/3}\sigma}$$

5. PF:

$$0.2 \le \gamma \le 0.5$$

$$x_t^{a(l)} \leftarrow x_t^{a(l)} + \gamma \cdot N(0,1)$$

EnSRF vs LETKF (ave. 10 simulations)



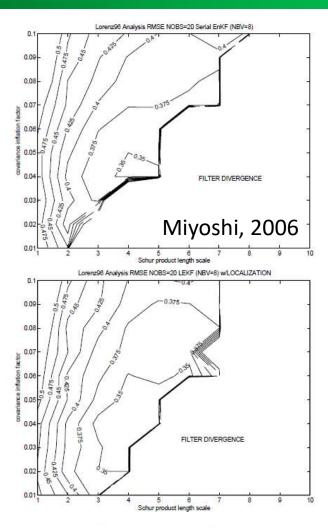
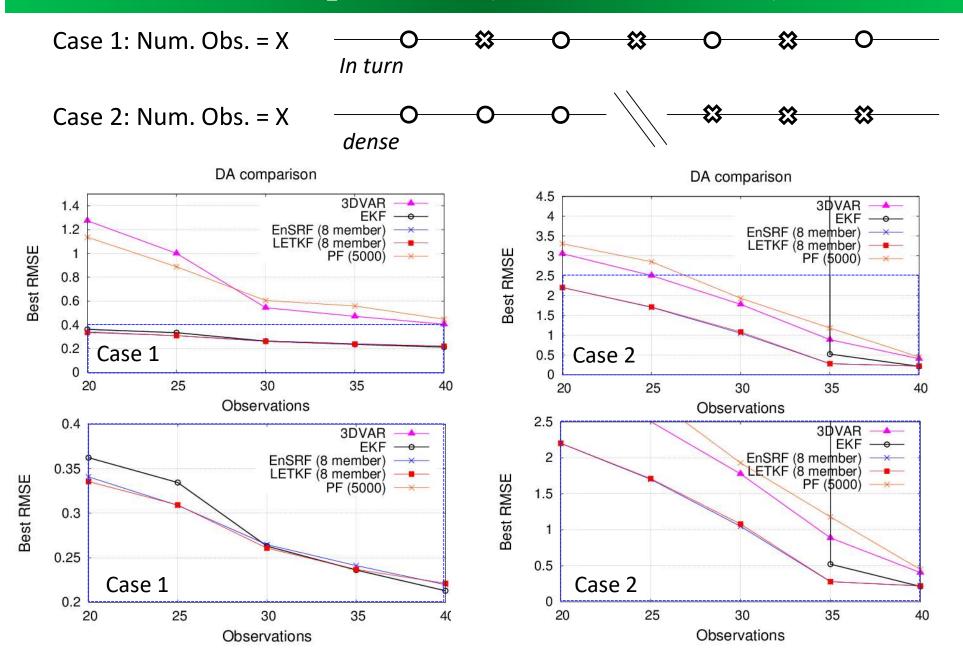


図 6.5.1 40 格子点のうち 20 点を観測し、アンサンブルメンバー数を 8 としたときの Lorenz モデルでの EnKF の解析 RMSE。縦軸は共分散膨張パラメータ、横軸は局所化パラメータを示す。上が Serial EnSRF(最小値は 0.34)、下が LEKF(最小値は 0.33)を表す。"FILTER DIVERGENCE"と書かれている領域は、誤差が発散しフィルタがうまく働かない領域を表す。

DA comparisons (without 4DVAR)



(1)
$$x_t^{f(l)} = M x_{t-1}^{a(l)}$$

(2)
$$p(x_t \mid y_{1:t}) \approx \sum_{l=1}^{N} w_t^{(l)} \delta(x_t - x_{t|t-1}^{(l)})$$
$$w_t^{(l)} = R(y_t \mid x_{t|t-1}^{(l)}) / \sum_{l} R(y_t \mid x_{t|t-1}^{(l)})$$

Dont resampling (Tachikawa et al., 2011)

$$R(y_{t} \mid x_{t|t-1}^{(l)}) \propto \exp\left[-\frac{1}{2}(Hx_{t}^{f(l)} - y_{t})^{T} R^{-1}(Hx_{t}^{f(l)} - y_{t})\right]$$

Observation covariance is approximated as Gaussian Function.

(3)
$$x^a = \sum_{l=1}^N w_t^{(l)} x_{t|t-1}^{(l)}$$

(4) Resampling and perturbation
$$x_t^{a(l)} \leftarrow x_t^{a(l)} + \gamma \cdot N(0,1)$$

error variance or likelihood estimation

KF, EnKF

Minimizing error variance estimation

$$P^{a} = \left\langle \delta x^{a} \cdot \delta x^{aT} \right\rangle$$
$$\frac{\partial}{\partial K} \left(trace(P^{a}) \right) = 0$$

$$P_t^f = MP_{t-1}^a M^T$$

P^f is time dependent.

3DVAR, PF

Maximizing likelihood estimation

$$p(x | y) = \frac{p(y | x)p(x)}{p(y)}$$

Bayes' theory

$$p(x) \propto \exp\left[-\frac{1}{2}(x-x^f)^T B^{-1}(x-x^f)\right]$$
3DVAR

$$p(x_t \mid y_{1:t}) \approx \frac{1}{N} \sum_{l=1}^{N} \frac{\delta(x_t - x_{t|t-1}^{(l)})}{PF}$$

p(x) is time independent.

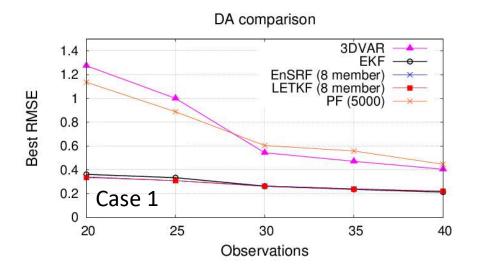
error variance or likelihood estimation

KF, EnKF

Minimizing error variance estimation

$$P_t^f = MP_{t-1}^a M^T$$

Pf is time dependent.



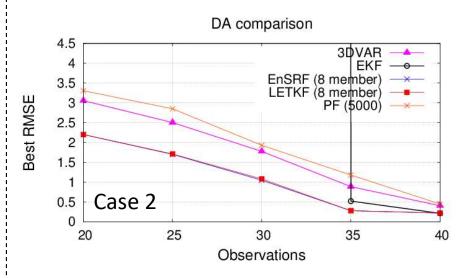
3DVAR, PF

Maximizing likelihood estimation

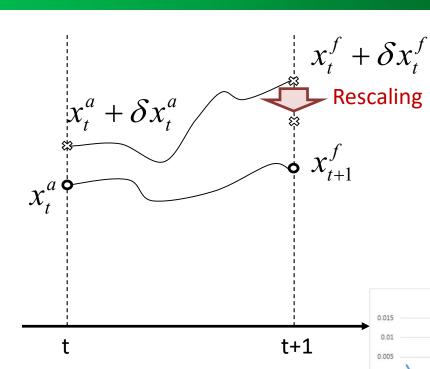
$$p(x) \propto \exp\left[-\frac{1}{2}(x-x^f)^T B^{-1}(x-x^f)\right]$$

$$p(x_t \mid y_{1:t}) \approx \frac{1}{N} \sum_{l=1}^{N} \frac{\delta(x_t - x_{t|t-1}^{(l)})}{PF}$$

p(x) is time independent.



Breeding vectors with EKF cycle



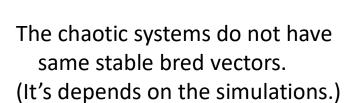
$$\delta x^a = \alpha \cdot \delta x^f$$

$$\alpha = \alpha_{init} / \left| \delta x^f \right|$$

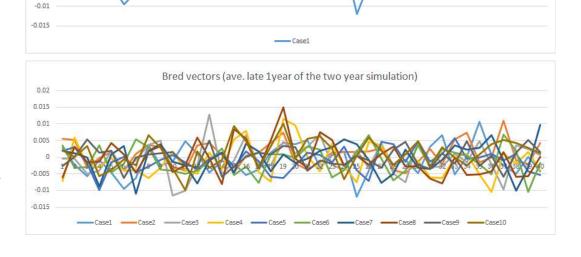
For each grids, rescaling is performed when

$$\left|\delta x^f\right| > \alpha_{init}$$

Bred vectors (ave. late 1 year of the two year simulation)



However, the chaotic system seems to have a stable bred vector.



Ongoing work

- Development of 4DVAR
 - On the way to coding the quasi Newton's method

$$J = \frac{1}{2} \left(x_0^a - x_0^f \right)^T B^{-1} \left(x_0^a - x_0^f \right) + \frac{1}{2} \left[H \begin{pmatrix} x_0^a \\ \vdots \\ x_N^a \end{pmatrix} - y^o \right]^T R^{-1} \left[H \begin{pmatrix} x_0^a \\ \vdots \\ x_N^a \end{pmatrix} - y^o \right]$$

$$g = B^{-1}(x_0^a - x_0^f) + \sum_{t=0}^{T} M_0^T \cdots M_{t-1}^T R_t^{-1} \left[H_t(M^t(x_0^a)) - y_t^o \right]$$

Are these <u>B</u> and <u>joint models</u> are time independent or not? (Of course, it is better to change depends on time.)