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Nonlinear Processes in Geophysics
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Interactive comment on "Quasi static ensemble variational data assimilation" *by* Anthony Fillion et al.

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We are grateful to the Reviewer for his suggestions.

1. **In section 3 (Quasi Static algorithms) it is worth to mention and to put into context the 'Sequential Quasi Static Variational Assimilation' (section 4.2 of (Pires et al. 1996)) as a variation of the QS scheme**

   Indeed. Thank you for pointing this out. We now refer to this *sequential* QSVA scheme in the revised manuscript. Note that this can be seen as an ancestor of the MDA IEnKS. However, as shown in Bocquet and Sakov (2014), a sequential QSVA cannot be transposed directly into an EnVar scheme without further modification because of the multiple assimilation of the same observations, hence the

   MDA IEnKS.

2. **In the discussion of upper triangles of Figs. 8 (L95) and 9 (L63), showing the average smoothing and filtering errors, the authors should discuss how far it is useful to increase the DAW length. In Pires et al (1996), it is presented the concept of useful assimilation window -ln(0.01/(2 Lambda-max), beyond which the DA is not useful anymore where Lambda-max is the Largest Lyapunov value. Giving the steps delta-t and lambda-max, the authors may provide the largest useful DAW length Lmax.**

   The idea of useful data assimilation length is a very nice concept introduced by Pires et al. (1996). For both low-order models, one obtains $L^{L95}_{max} = \frac{-\ln(0.01)}{2\lambda^{L95}\Delta t^{L95}} = \frac{-\ln(0.01)}{2\times 1.7\times 0.05} \simeq 27$ and $L^{L63}_{max} = \frac{-\ln(0.01)}{2\lambda^{L63}\Delta t^{L63}} = \frac{-\ln(0.01)}{2\times 0.91\times 0.02} \simeq 127$. This concept is now recalled (twice) in the revised manuscript with a reference to Pires et al. (1996).

   Note, however, that it has some limitations. First, it applies to the filtering error (at present time), not to the smoothing error – at least not directly. Second, this result does not easily translates to an advanced cycled scheme such as the IEnKS$_{QS}$, where a lot of observations have already been assimilated and their information condensed in the background. Thus, the performance gain with the DAW length comes from the precision of this Gaussian background approximation – a precision that the linearized theory is not able to evaluate. We have shown in Bocquet and Sakov (2013, 2014) and in the present manuscript, that one can go very far in the past – well beyond $27\Delta t$ in the L95 case – and still improve the smoothing RMSE. Third, this useful length does not account for nonlinearities, the appearance of local minima, and correlatively potential saturation. As a result there is a somehow arbitrary constant in its definition (0.01 here). In Pires et al. (1996), it is related to the targeted error.

   The length that we estimate in Sec. 2.4 can be seen to some degree as an improvement on Pires et al. (1996)' endeavor of a useful length by estimating the constant resorting to saturation and the occurence of local minima in the cost function.

3. **In the discussion and conclusions, the authors should add a small paragraph on the limitations of extending the DAW length in DA with nonperfect models (refer to Swanson et al 1998).**

   Thank you for the suggestion. Extending the DAW length is less relevant for significantly noisy models. Swanson et al. (1998) showed that the perfect model results are expected to extend to the imperfect model case provided that the growth rate of the model error is similar to that of the leading Lyapunov vectors of the system. This is discussed in the revised manuscript at the end of the conclusion and a reference to Swanson et al. (1998) has been added.

References

Bocquet, M., Sakov, P., 2013. Joint state and parameter estimation with an iterative ensemble Kalman smoother. Nonlin. Processes Geophys. 20, 803–818. doi:10.5194/npg-20-803-2013.

Bocquet, M., Sakov, P., 2014. An iterative ensemble kalman smoother. Q. J. R. Meteorol. Soc. 140, 1521–1535. doi:10.1002/qj.2236.

Pires, C., Vautard, R., Talagrand, O., 1996. On extending the limits of variational assimilation in nonlinear chaotic systems. Tellus A 48, 96–121. doi:10.3402/tellusa.v48i1.11634.

Swanson, K., Vautard, R., Pires, C., 1998. Four-dimensional variational assimilation and predictability in a quasi-geostrophic model. Tellus A 50, 369–390. doi:10.1034/j.1600-0870.1998.t01-4-00001.x.

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