Geoscientific
Model Development
Discussions

Interactive comment on "Comparison of the ensemble Kalman filter and 4D-Var assimilation methods using a stratospheric tracer transport model" *by* S. Skachko et al.

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We appreciate very much the Anonymous Referee 2's comments. We have answered all questions. Each answer starts with "ANSWER:". We have kept the original Referee's comments in Bold.

Major comments: 1. The following argument: "Since the biases are markedly similar, they have most probably the same causes: these can be deficiencies in the model and in the observation dataset, but not in the assimilation algorithm nor in the error calibration." can be specious because similar biases is not sufficient to prove that the assimilation and error calibration are correct. I suggest

removing the last part after "but".

ANSWER: We are agree with the referee and have removed this part.

2. Please explain the experimental setup [preferably between 3 and 3.1] for the two strategies. Is EnKF restarted?

ANSWER: No, it uses flow-dependent background covariance from the beginning of the integration and is never restarted.

Is 4D-Var started from the previous forecast?

ANSWER: Yes, it is restarted using 24 h forecast of the previous 4D-Var analysis. But, the 4D-Var background error statistics is not cycled from one 24h assimilation window to the next.

Also please provide more details about the model and observations; how sparse are the observations? Some details are provided in Sec. 2.1

ANSWER: Sect.2.1 contains the information about the numerics, the temporal and spatial resolution, advection scheme used for the model used in the study. In this experiment, it is run as a pure tracer transport model, and no further details are needed. Sect.3.1 describes the spacing and the number of EOS Aura-MLS ozone profiles. It is a dense and complete global coverage in a 24 h period which is not shown here.

3. Consider analyzing the the 4D-Var and EnKF solutions against each other. OmF is an indicator of how far are they from the observations, but if the two are indeed close than that would be an interesting conclusion.

ANSWER: Fig. 7 of the article shows this comparison at a given time and for monthly means. We showed that individual analyses of EnKF and 4D-Var may have differences. However, the monthly mean show any important difference.

4. Similar conclusions as expressed in argument 1. above may be obtained if the assimilation is constrained by data. Details in point 2. may clarify this

item; however, leaving out observations may truly elucidate this point. Moreover, leaving out observations may also be used in a cross-validation experiment and will enhance any conclusions from 2.

ANSWER: The aim of the paper is to compare both assimilation systems on the same level of performance and assimilating the identical observations. So, we did not think remove observations from our experiments.

5. The calibration of the observation error covariance in EnKF and 4D-Var can have Bayesian interpretation. In this case, r is a stationary random variable with it's own uninformative prior or a hyperparameter. This variable is calibrated first, and its maximum likelihood value is used. This means that the error model for the observations is assumed to be additive and the actual errors to be unknown and part of the inverse problem and it should be stated as such.

ANSWER: By multiplying the observation error covariance by r, we continue to assume that the observation error is uncorrelated and additive to the state.

6. EnKF and 4D-Var use different statistical assumptions. The most problematic in this comparison is the model error, and therefore are directly comparable unless there is no model error. This does not invalidate the conlusions of this study; however, the conclusions can be overstated. In particular, the use of the same r in both strategies may be inadequate.

ANSWER: We modified the following part of the introduction: 'In the 4D-Var scheme, the evolution of forecast error within the assimilation window is computed by the model (whether it is accurate and appropriate or not) and is used generally as a strong constraint. By contrast the EnKF relaxes this assumption into a weak constraint by adding a model error covariance to the analysis error covariance which becomes dynamically-propagated. Hence, the model error covariance is of great importance for the filter performance.' Besides, we have the first paragraphe on the page 362 regarding the mentionned problem.

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7. The posterior covariance of EnKF - readily available - is not used to assess its correct forecast. This is just a suggestion, but I realize the challenge in processing such datasets.

ANSWER: The OmF statistics is computed as a zonal and temporal mean, whereas the forecast error covariance matrix is instantenious. This is why, we decided to use the χ^2 diagnostic allowing to compare the error covariances at the observation points.

9. The covariance tuning for EnKF may become unstable based on the results presented herein. How would it be affected if the assimilation would have been started on September 1st where there is a distinctive growth in the chi factor?

ANSWER: The error covariance calibration was performed using the whole experiment period. And the obtained values of the adjustable parameters infer a stable χ^2 values.

Graphics comments: Suggest using Julian date (or day of year) in on the x axis in Fig. 2, 5, 6.

ANSWER: Our choice of using month rather than the number of days from the beginning of the year seems to be more useful to identify geophysical events like the beginning of the ozone hole, for example.

Typographical errors: P 352, L 23: missing "to be"

ANSWER: Done

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