Response to Reviewer #2

Dear Reviewer,

We would like to thank the reviewer's instrumental suggestions, which have greatly improved our manuscript. We have conducted new experiments to fully explore the performance of the new method. Our manuscript is significantly revised to include the results of new experiments and to address your comments and suggestions. Please see our point-by-point responses to your comments as follows.

Major comments:

1. It would be beneficial to conduct more experiments and include their results and analysis of the results in the manuscript to demonstrate how the use of this method affects data assimilation. In particular, I would recommend exploring how varying localization, observation density and observation errors affect the results, since all of those parameters influence the "effective observation dimension" (the degrees of freedom that are required for assimilating observations (Kirchgessner et al, 2014)).

Thank you very much for this comment. We have conducted more experiments to investigate how the performance of this method is sensitive to different assimilation configurations, including observation density, observation errors, assimilation intervals and ensemble size.

2. The results presented in Figure 6 suggest a bigger benefit from using N+1=7 ensemble members in DA vs using N ensemble members + 1 pseudomember. While I agree that using pseudomember vs ensemble member saves on running an ensemble forecast, the savings are only N/(N+1) for the ensemble forecast runs. It would be interesting to see if there are benefits of using more than one or two ensemble pseudomembers so the savings on not running extra ensemble forecasts may be more justifiable.

Thank you very much for this important comment. We have conducted a new series of experiments using 20 ensemble members to investigate how much computation can be saved by this method, and whether the benefit will be saturated with more pseudo-members. As shown in the new Table 3, the benefit of adding pseudomembers based on IESVs increases as the number of pseudomember increases. When the standard LETKF (CNTL_M20) has large analysis RMSE, using more than 10 IESVs can reduce the analysis RMSE by more than 45% and the IESV1 (M20_Orth_IESV1) provides the dominant effect. The improvement rate with 15 IESVs saturates for the following 30-step forecast. Such a performance (M20_Orth_IESV1-15) is better than the 25-member standard LETKF in general and even better than the 30-member standard LETKF for the group of mildly large analysis errors. The forecast computation is only 66% of the 30-member LETKF.

We have included the following figure (new Figure 6) and relevant discussion at lines 154-159 in the revised manuscript.

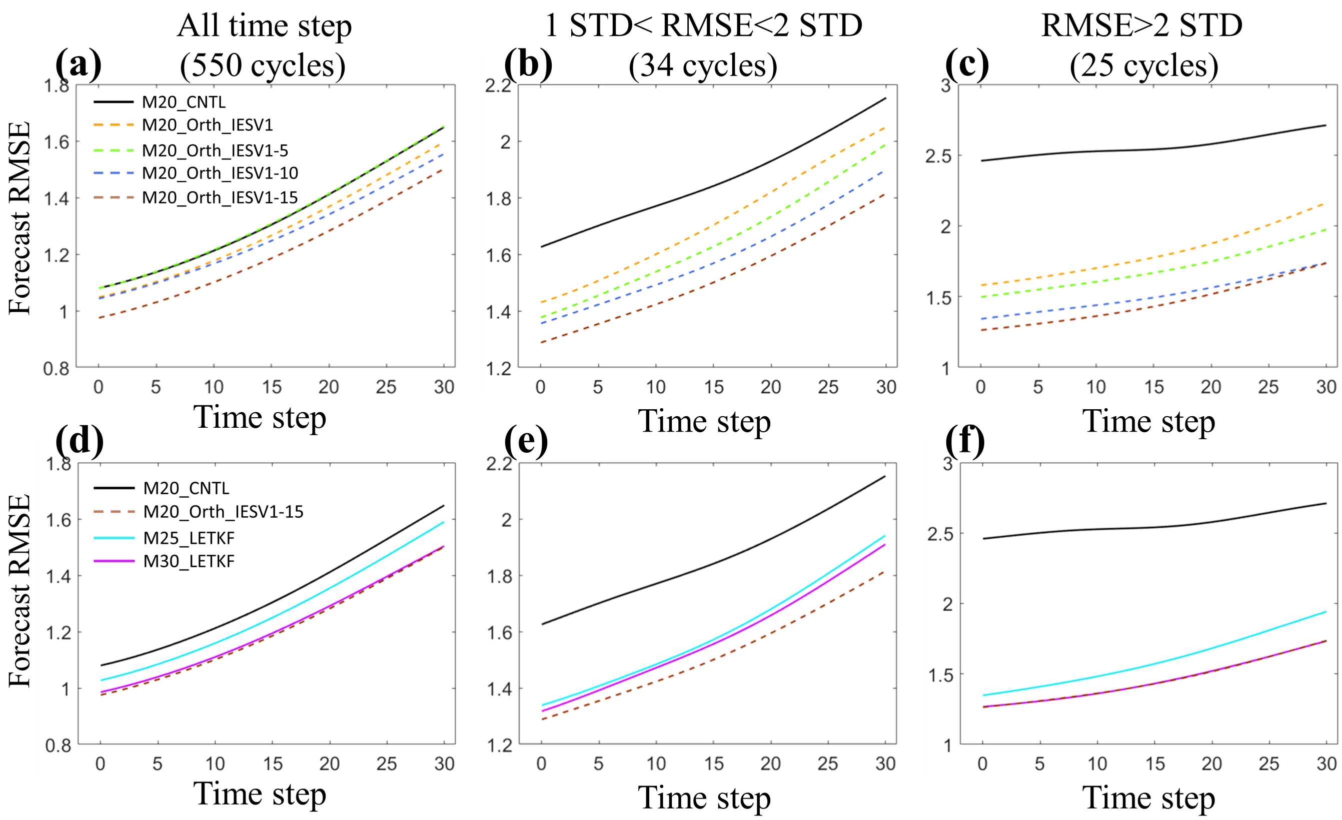

Figure: The mean RMSE of the forecast error during the 30-step integration. CNTL_M20, M25-mem_LETKF and M30_LETKF use the standard LETKF with 20, 25 and 30 members, respectively. M20_Orth_IESV1, M20_Orth_IESV1-5, M20_Orth_IESV1-10 and M20_Orth_IESV1-15 use 20 members and orthogonal components of IESVs as the pseudomembers.

3. Experiments in section 3.2 include analysis (in Figure 5) of results when IESV1 and EMV are used with and without orthogonalization. Please include description of what the difference between those are.

Figure 5 in the previous manuscript is removed. We now compare the results with Table 2. When IESV1 and EMV used with orthogonalization means that we took the component of IESV (or EMV) orthogonal to the ensemble space. We have clarified the differences between those experiments at lines 73-74.

4. Please describe what “average RSV” means for the experiments in section 3.2 (Figure 5). From Figure 5 it appears that results with “average RSV” are similar to results with orthogonal IESV1. It may be good to include the statistical significance of the differences between the experiments and also discuss this particular result.

Due to the limitation of the manuscript length, we removed the results of RSV in the revised manuscript. To show the significance of the new method, we have repeated the standard experiment 10 times (each time with a different random seed). The results of RMSE are summarized in Table 2 in a form of mean and STD.

With the 10 randomly initialized standard experiments, adding IESV1 or EMV as the pseudovector is always effective in improving the CNTL analysis. When the CTRL has large analysis errors, both IESV1 and EMV can even reach a mean improvement rate larger than 46%. On average, the Orth_EMV show a larger mean improvement than the EMV.

Please see our discussions at line 134-141.

Specific/inline comments:

1. Figure 5: the gray line is very hard to see, I suggest changing the color.

We apologized for the unclear line. Figure 5 is now removed from the revised manuscript.

2. Figure 3c: it is very hard to see the distinction between different experiments, it may be good to include statistics of the error differences.

Following the reviewer’s suggestion, the statistics of the error are included in Table 3 with improvement rates. We also replot Figure 3c to better illustrate the different experiments.