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Interactive comment on "Improving $PM_{2.5}$ forecast over China by the joint adjustment of initial conditions and source emissions with an ensemble Kalman" *by* Zhen Peng et al.

Anonymous Referee #1

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The author extends the EnSRF algorithm to adjust the chemical initial conditions (ICs) and the pollutant emissions to obtain better forecasting of surface PM2.5 over China. They compare analyzed and forecasted PM2.5 concentration fields with the control simulation that has no data assimilation, and find that optimized initial condition and emissions achieves much better forecasting for the 48-h forecasts. Their results suggest that the joint adjustment (not only ICs but also emissions) contributes the substantial improvement in the longer (34–48 hours) forecasts. Their investigation is interesting and valuable. The manuscript is well written and structured. I recommend publication after addressing the following concerns.

General comments:

1:The authors suggest that the joint adjustment (initial conditions and emissions) provides substantial improvements in from 34- to 48-h forecasts. Do you perform an assimilation and forecasting experiment in which only ICs are adjusted. Comparing between results from the joint adjustment and the IC only adjustment will reinforce your suggestion.

2:Both analyzed and forecasting results are validated by only observations that used in the assimilation. You should include the independent data, which is not used in the observational constraint, in the validation.

Specific comments:

3: Line 40, There are more recent research papers of ensemble-based assimilations with observations derived from in-situ measurements and geostationary satellite.

Dai, T., et al. (2014) Improvement of aerosol optical properties modeling over Eastern Asia with MODIS AOD assim- ilation in a global non-hydrostatic icosahedral aerosol transport model, Environ. Pollut., 195, 319–329.

Ying, X.M., et al. (2016) Estimation of aerosol properties over the Chinese desert region with MODIS AOD assimilation in a global model, Adv. Clim. Change Res., 7, 90–98.

Yumimoto, K., et al. (2016), Aerosol data assimilation using data from Himawari-8, a next-generation geostationary meteorological satellite, Geophys. Res. Lett., 43, 5886–5894.

4: Line 90, Does the observation operator (H) include function (conversion) for the emission scaling factor (lambda) or, in other words, does the lambda directly affect the model results in the observation state (Hx) through the observation operator? If no, how does the observations adjust the emission scaling factors in the assimilation process?

5: Line 139, The ensemble concentration ratio (Kappa) is defined by concentrations of the ensemble forecasting. Can you confirm that the ensemble concentration ratio is random and the ensemble mean of Kappa becomes 1?

6: Line 152 or Equation (10), The denominator in the right hand should be 1/M+1?

7: Line 183, As shown in Equation (12), dust and sea salt aerosols can contribute PM2.5 concentrations. Do you include emissions of dust and sea salt in the assimilation process?

8: Line 190, A period may drop in the end of state.

9: Figure 1, Could you check figure 1 again? Some characters and numbers of equation are different from those in the manuscript.

10: Line 202, Does this means that you need to perform the 50-member ensemble forecast twice in your assimilation system?

11: Line 254, How often did this exclusion occur? Figure 3a and 8a imply that quite a few large departures occurs in the JJJ region during 9–10 October.

12: Line 281, How do you decide the ensemble member of 50?

13: Line 349, Could you add mean distribution of PM2.5 concentration from the control and assimilation simulations in Figure 4? These will make the reader to understand a priori distribution and the adjustment of PM2.5 concentrations easily. Plotting mean observed PM2.5 concentrations on these map will be even better.

14: Line 349, We can find adjustments over the SE Asia and India where you have no PM2.5 observation.

15: Figure 5, Overlaying of a priori emissions (it will be flat lines) in Figure 5 may emphasize that the assimilation can generate the temporal variations in the emissions.

16: Line 375, Is the burning of crop residues limited in the JJJ region? Li et al. shows that the northern part of YRD also has large emissions from the burning.

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17: Line 382, Do you confirm that temporal and horizontal distributions of a posteriori gaseous emissions are reasonable? Could you show temporal distribution of temporal variation of gaseous emissions (like Figure 5 and Figure 6)?

18: Figure 6, We can find there are adjustments of lambda over the ocean where we have no PM2.5 emission (Figure 7a). Do you define the lambda over the ocean?

19: Line 395, "less constraint on the sources of the secondary aerosol precursors" means that the adjustments of emissions of the secondary aerosol precursors have little effect on PM2.5 forecasting?

20: Line 467, The exclusion due to large discrepancy between first guess and observed concentrations may be partly responsible for the sparse observational constraint in the JJJ region during the heavy PM2.5 event.

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