Reviewer #2

Review of “Reduced non-Gaussianity by 30-second rapid update in convective-scale numerical weather prediction ” by J. Ruiz et al..

General comments:

This paper has investigated how the DA frequencies affect non-Gaussianity using a high resolution NWP model with LETKF method for data assimilation. DA experiments with different frequencies are conducted using real observations. They have some findings about the non-Gaussianity in data assimilation, which are quite new and interesting. They have used a high resolution DA system with very high DA frequencies to support their conclusions. And they have analyzed the results comprehensively. The manuscript is overall well-written. I am in support of publishing this manuscript after minor revision.

We would like to thank the reviewer for all the suggestions on how to improve and expand the discussion. Based on the reviewer’s comments we add important additional explanations and discussions.

Specific comments:

1. This work measures the non-Gaussianity (by KLD) of the analysis fields. They found that increasing the assimilation frequency up to 30 seconds and assimilating more observations can reduce KLD. This conclusion can be expected easily. As acknowledged, EnKF and LETKF are sub-optimal when the forecast error are non-Gaussian, and the non-Gaussianity of the forecast error grows during model integration. If the DA frequency is higher, the non-Gaussianity of the forecast will be smaller due to shorter integration period, therefore the EnKF will be more effective.
   However, they didn’t show the KLD of the prior error distribution. If they can compare the posterior KLD with prior KLD with different DA frequencies, they can better illustrate the “reduced non-Gaussianity by 30-second rapid update” in the title.

We agree with the reviewer and add a new figure (Fig. 7) to better illustrate this point. This figure provides a better insight on the effect of data assimilation on the non-Gaussianity of the error distribution and shows some interesting differences between the impact of the assimilation in the “raining” and “non-raining” grid points. We also include a discussion in the revised version of the paper.

To investigate the effect of the analysis update on non-Gaussianity we present the time series of the KLD of the analysis and first guess vertically and horizontally averaged over the “raining” and “non-raining” grid points (Fig. 7). At most times and variables over the “raining” and “non-raining” grid points KLD is reduced during the assimilation step. Experiments with longer windows experience more KLD growth during the forecast as expected, but also a larger reduction at the analysis step, which is not as effective as the more frequent updates in reducing the analysis KLD. As noted before, the specific humidity over the “non-raining” grid points behaves differently, in this case, KLD increases during the assimilation step for almost all times and experiments leading to larger KLD at shorter assimilation windows (Figs. 6b,f of the submitted manuscript). In this area mostly “non-raining” observations are assimilated to suppress spurious clouds. Interestingly in the “non-raining” grid points 5MIN-4D is the experiment providing the lowest KLD for all variables (Figs. 7b,d,f). This result suggests the potential benefits of treating “non-raining” observations differently.

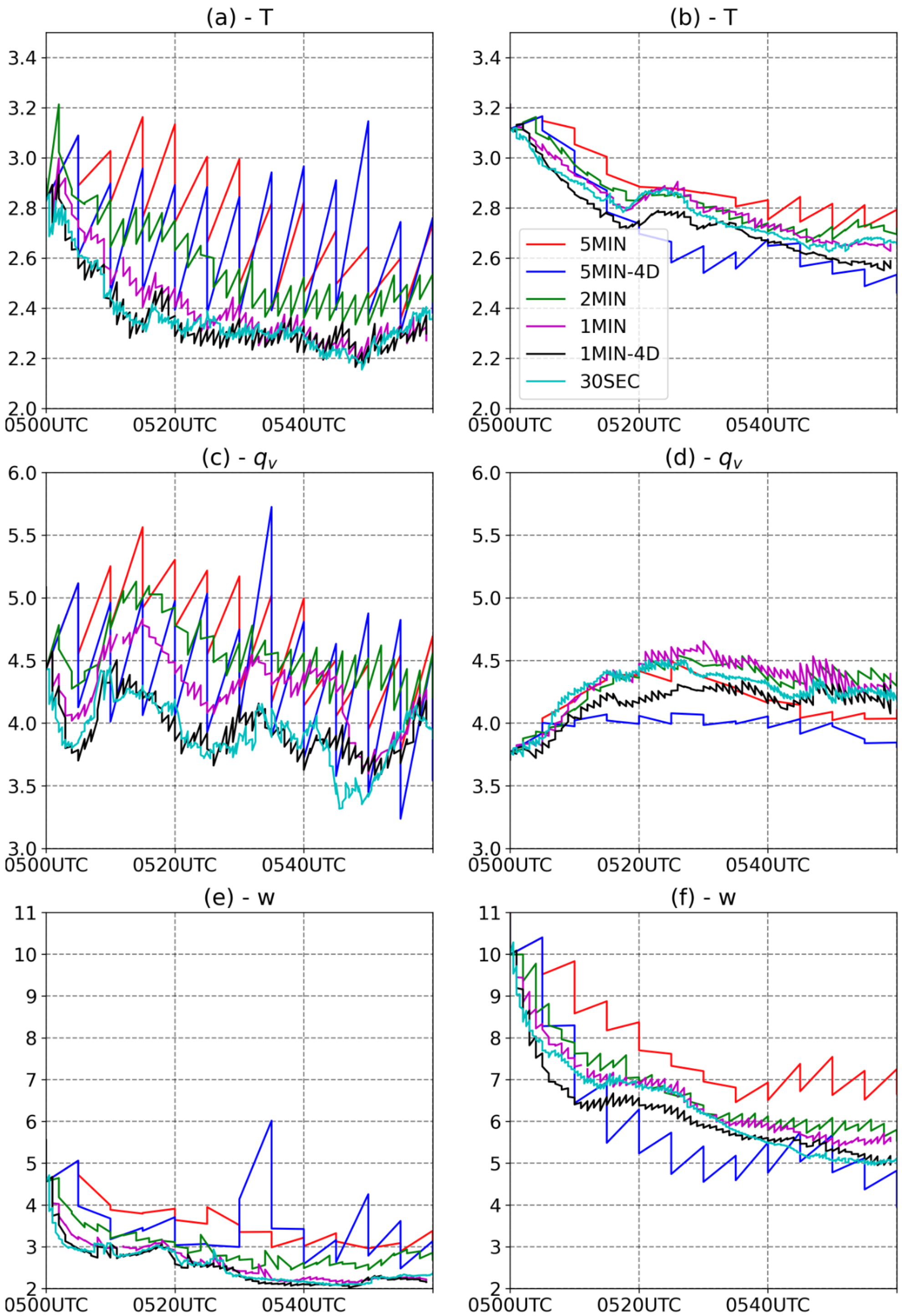

Figure 7: Sawtooth time-series of the KLD (10^{-2}) of the analysis and first guess horizontally and vertically averaged over the rainy (<0dBZ, a,c,e) and non-rainy (>30dBZ, b,d,f) grid points for temperature (a,b), specific humidity (c,d) and vertical velocity (e,f) and for the

5MIN (red), 5MIN-4D (blue), 2MIN (green), 1MIN (magenta), 1MIN-4D (black) and 30SEC (cyan) experiments.

2. Page 5, lines 110-125 and figure 2. Compared with the rest of this article, the readability of this paragraph is poor. They have shown too much information in figure 2, such that they need to use parentheses constantly to indicate the subplots and features (shades or contours) in figure 2. And there are also some problems with the order of expression in this paragraph, therefore the readers have to look at the subplots back and forth. I suggest splitting the paragraph from line 116 or 117.

We agree with this comment. To improve the readability of this section we split the original Figure 2 into 2 figures. The proposed Figure is included as part of the answer to the following comment. We also reorder the discussion to reduce the need to go back and forward from one figure to the next. We hope that these changes helped to improve the clarity of the discussion.

3. Figure 2e-h, they use shades to show KLD for W, while use blue contours for KLD for T and red contours for ensemble spread. This is very odd. In my opinion, use contours of different colors to show KLD for different variables seems more reasonable.

We agree with the reviewer’s comment, Figure 2 in the original version of the manuscript, contains too many lines of different colors in the same panel. To address this, we add a new row in Figures 2 and 3 to separate the KLD and ensemble spread for W and T. Now the KLD is shown in shaded for both variables and the ensemble spread is shown in contours. Following is the new version of Figure 2:

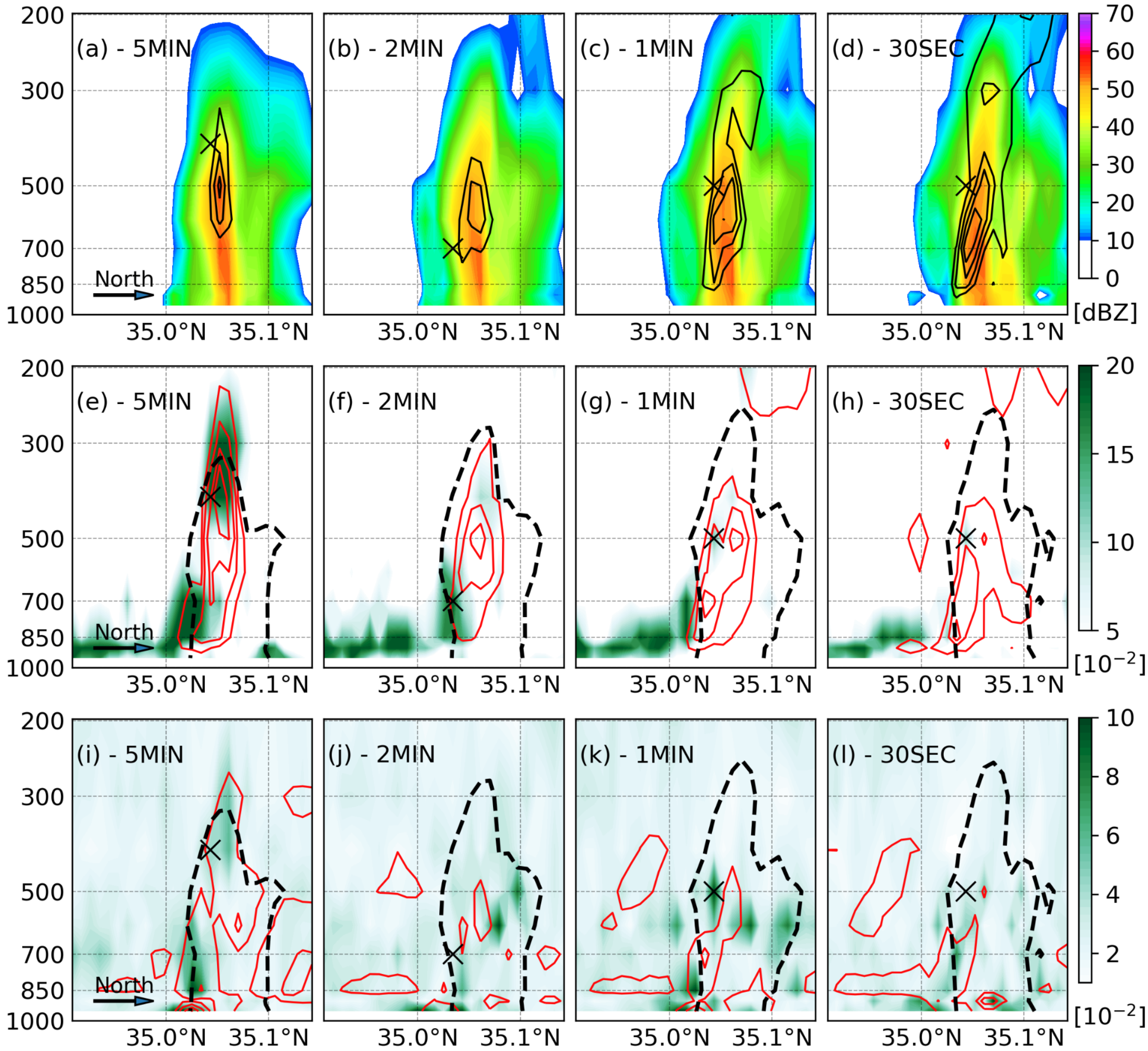

Figure 2: (a-h) South-North vertical cross-section along the black line indicated in Fig. 1b-d at 0530 UTC for (a-d) first-guess ensemble-mean reflectivity (Z, shades, dBZ) and vertical velocity (W, contours every 2.5 ms^{-1}), (e-h) vertical velocity KLD (shades, 10^{-2}) and ensemble spread (red contours at 1.0, 2.5, 5.0 and 10.0 ms^{-1}), and (i-l) temperature KLD (shades, 10^{-2}) and ensemble spread (red contours at 0.2, 0.5, 1.0 and 2.0 K). Blacked dashed contours indicate reflectivity over 30 dBZ. The black cross in panels (i-l) indicates the location of the maximum KLD within the grid points at which Z > 30dBZ.

4. Figure 2a-h, the location of the maximum KLD for vertical velocity is shown by blue circles. I think the circle is too large and its color is inappropriate. I cannot clearly see whether the ensemble spread maxima are slightly out of phase with respect to the KLD maxima. What about a black x or plus sign?

We agree with this comment. Following the reviewer's suggestion we replace the blue circle by a black cross (See new version of Figure 2 in the answer to the previous comment). Also by reducing the number of contours in the same panel, now the cross is more visible. We also added more detail on to what extent the distribution of the ensemble spread can be associated to that of the KLD in this particular case.

Kondo et al. 2019 found that in synoptic scales, the ensemble spread maxima are collocated with the KLD maxima. This is an important result meaning that the distribution of statistics like KLD that requires large ensemble sizes to be accurately estimated, can be approximated by statistics like the ensemble variance that can be robustly computed with smaller ensemble sizes. At convective scales for W, the ensemble spread maxima (Fig. 2e, red contours) are not necessarily collocated. For example, larger departures from the Gaussian are found above the ensemble spread maximum associated with the main updraft in the 5MIN experiment. For temperature also there is no clear relation in the distribution of the ensemble spread and the KLD, although KLD maxima seem to occur within areas of relatively large ensemble spread. As the assimilation frequency increases it is more difficult to find a relationship between KLD and ensemble spread either for W or T (Fig. 2 second and third rows).

5. Line 114 and line 117. The authors have shown that “KLD is reduced more from 5MIN to 2MIN than from 1MIN to 30SEC” and “The ensemble spread for W is reduced significantly from 5MIN to 2MIN”. I think this is also associated with the nonlinearity of this model. Could it possible that the non-Gaussianity of prior distribution grows fastest during the freerun between 2min to 5min?

We would like to thank the reviewer for raising this interesting point. We agree with this hypothesis and we add a discussion starting in the revised version of the manuscript.

There are two possible ways in which more frequent DA can result in error distributions closer to the Gaussian. First, more frequent DA contributes to a quasi-linear evolution of the forecast error due to forecast lengths which are shorter than the predictability limit for the resolved scales. This also helps keeping the amplitude of the perturbation small which can additionally contribute to quasi-linear perturbation dynamics. Second, our results show that the analysis step effectively contributes to reducing non-Gaussianity for different variables, although this may not be the case for “non-raining” reflectivity observations that produce an increase in KLD for the specific humidity. Non-gaussianity reduction during DA with longer windows is larger. However, it is not enough to compensate for the effect of more rapid and non-linear error growth during the forecast step in the lower update frequency experiments.

From the point of view of KLD reduction, the largest impact is found between 5MIN and 2MIN updates. This suggests that non-linear error growth becomes more important after the first 2 minutes of integration at these scales. This hypothesis is partially supported by the reduction in RMSE and ensemble spread, which is also observed between these experiments. To the best of our knowledge, there is no study addressing error dynamics at these short time scales that can confirm this hypothesis thus this particular aspect requires further investigation. A 2-minute update frequency seems to provide a good compromise between the computational cost and non-Gaussianity of the error distributions. However, from the point of view of the analysis accuracy more frequent DA provides a better fit to the observed quantities. The specific role of reduced non-Gaussianity on this is not clear and should be further investigated. Gaussian error distributions may contribute to more accurate analysis updates, but in the current experimental setting other factors like the increase in the number of assimilated observations may also lead to the reduction in the RMSE for observed quantities.

6. Since increasing the analysis update frequency from 5 minutes to 2 minutes has most significant impact upon non-Gaussianity. So can we say it is a optimal strategy considering the trade-off between cost and efficiency?

We agree that this would be a good compromise in terms of computational cost and non-Gaussianity. However, other aspects have to be taken into account like for example the impact of update frequency on the imbalance in the initial conditions (also mentioned by reviewer #1) which can negatively affect the quality of the forecast. In this work we investigate the impact on non-Gaussianity which can contribute to improving the quality of the initial conditions with more frequent updates, but in the context of a data assimilation cycle other aspects have to be taken into account. In the new version of the manuscript we include this analysis but also a caution notice regarding the effect of assimilation frequency upon the balance in the initial conditions.