

Answers to Referee Lori Bruhwiler comments: *Review of Calibration of a multi-physics ensemble for greenhouse gas atmospheric transport model uncertainty estimations*

We thank the referee for the helpful comments that will improve the manuscript. In the text below, we have tried our best to respond to all the general and specific comments provided by the reviewer.

Comments to Author:

This is a very interesting study that seems to make some progress on an important issue for atmospheric inversions - how can we estimate atmospheric transport uncertainties? Most of us just use educated guesses, so it's really nice to be shown a potential way to do better even if it appears to be a lot of work and computational expense. I think the paper should be useful to the community of "flux inversers". One slightly disappointing thing is that CO₂ BC errors cannot be distinguished from transport errors making me look forward to trying this with a global model.

I have mainly minor comments, and there are a few things I didn't follow and would like to better understand.

REF-C1: Abstract, L19 - I think "observations" should be added to the beginning of this sentence.

Author-C1: Done.

P1, L19: "Observed meteorological variables critical to inverse flux estimates, PBL wind speed, PBL wind direction and PBL height, are used to calibrate our ensemble over the region."

REF-C2: P2, L1- On what basis do these studies rule out spatial scale as a factor in inversion differences? Some of these studies use results from models with different spatial resolutions.

Author-C2: The spatial scale is indeed an important factor to be considered for discrepancies among inversions. The text was modified as follows:

P2, L1: "Large uncertainty and variability often exist among inverse flux estimates (e.g., Gurney et al., 2002; Sarmiento et al., 2010; Peylin et al., 2013; Schuh et al., 2013). These posterior flux uncertainties arise from varying spatial resolution, limited atmospheric data density ..."

REF-C3: P2, L30 - The measurement people would object to the use of "ppmv" rather than "ppm" here because CO₂ deviates from being an ideal gas. ppmv also appears elsewhere.

Author-C3: We corrected the unit:

P2, L30: "Approximately 3 ppm uncertainty in CO₂ mole fractions have been attributed to PBLH errors over Europe during the summer time (Gerbig et al., 2008; Kretschmer et al., 2012)."

P8, L8: "Transport model errors in atmospheric inversions are described in the observation error covariance matrix, hence in CO₂ mole fractions (ppm²)."

REF-C4: P5, L25 and throughout - The v in the for the virtual potential temperature gradient should be subscript to avoid confusion with a product.

Author-C4: We corrected the v of virtual potential temperature:

P5, L25: "The PBLH was estimated using the virtual potential temperature gradient ($\nabla\theta_v$). The method identifies the PBLH as the first point above the atmospheric surface layer where (1) $\nabla\theta_v$ is greater than or equal to 0.2 K/km, and (2) the difference between the surface and the threshold level virtual potential temperature is greater than or equal to 3 K ($\theta_{vs} - \theta_v \geq 3K$)."

REF-C5: P5, L26 - How robust is this definition for the PBLH? Is there a reference discussing this?

Author-C5: We use Seibert et al. (1999) and Seidel et al. (2010) to define the PBLH used in this study. However, evaluation of multiple vertical profiles from both simulations and radiosonde were used to explore the best technique and definition to define the PBLH height. The two definitions that we explored the most was the Bulk Richardson Number and the virtual potential temperature gradient. The Richardson number was showing a consistent underestimation of the PBLH. We identified the virtual potential temperature gradient as the most reliable algorithm to estimate PBLH. This evaluation relies on visual inspection of vertical potential temperature profiles, which may vary depending on expert judgement. However, for a lack of a better definition, we decided to use the virtual potential temperature gradient as the main definition of PBLH for both the model and the observation.

Reference:

- Seibert, P., Beyrich, F., Gryning, S.-E., Joffre, S., Rasmussen, A., and Tercier, P.: Review and intercomparison of operational methods for the determination of the mixing height, *Atmos. Environ.*, 34, 1001–1027, 1999.
- Seidel D., A, C. O., and Li, K.: Estimating climatological planetary boundary layer heights from radiosonde observations: Comparison of methods and uncertainty analysis, *J. Geophys. Res.*, 115, D16113, doi:10.1029/2009JD013680, 2010.

REF-C6: P6, L11- There’s an extra “s” after rank.

Author-C6: Done

P6, L11: *“The criteria used for our down-selection process include rank histograms, rank histogram scores and ensemble bias.”*

REF-C7: P6, L20-25 - Would it be better to describe an under-dispersive ensemble as a distribution that is sharply peaked and shows less variability than observed? This would match up with the description of over-dispersive as having too much variability. Just a minor point though, I had to read the sentence a couple of times, but then understood it.

Author-C7: We agree with the reviewer that a sharply peaked distribution may explain the lack of variability in the ensemble. However, an ensemble that is underdispersive may not only be affected by the lack of variability, but can also be affected by biases. We refer to Hamill (2001) who carefully explored the meaning of underdispersive ensembles. Rank histograms correspond to the evaluation of the ensemble for each observation, hence impacted by the spread but also the skill of the ensemble. We edited this part of the manuscript to avoid confusion:

P6, L20-25: *A rank histogram that deviates from the flat shape implies a biased, overdispersive or underdispersive ensemble. A “U-shaped” rank-histogram indicates that the ensemble is underdispersive, normally in this type of ensembles the observations tend to fall outside of the envelope of the ensemble, this kind of histogram are associated with a lack of variability or an ensemble affected by biases (Hamill, 2001). A “central-dome” (or “A-shaped”) histogram indicates that the ensemble is overdispersive ...”*

REF-C8: P6, Eqn 1 - Is N the number of ensemble members and is this the same as “the number of models”? Also, it could be noted that the expectation is obs. evenly distributed over bins.

Author-C8: : Yes, “the number of models” is the number of ensemble members. We changed this to the number of members, in case this may cause confusion. See part of the edit to the sentence below.

P6, L29-30: “and should ideally be close to 1 (Talagrand et al., 1999; Candille and Talagrand, 2005). In Eq.(1), N is the number of members (i.e., models)...”

REF-C9: P7, L1 - Where does our statistical expectation of how well the ensemble matches the observed variability come from? Suppose that $r_j = \bar{r}$ in equation 1, then it seems that the model is getting the observed variability right, but what helps us to decide that this is overconfidence and not an extremely successful model?

Author-C9: We agree with the reviewer that rank histograms alone cannot solve that problem. Our expectation is based on $r_j = \bar{r}$, following equation 1. One way to evaluate if the ensemble is overconfident or extremely good is by combining the rank histograms to other statistical analyses. An overconfident ensemble shows an uncertainty (model-data mismatch) larger than the spread. Therefore, a statistical analysis that will give us more information about the spread and the uncertainty is the spread-skill relationship plot (see Figure 7). Figure 7 from the paper shows the spread-skill relationship of the three variables (i.e., wind speed, wind direction and PBLH) for the large ensemble. If we look at the PBLH spread-skill relationship (Figure 7c), the spread of the ensemble is smaller than the skill (uncertainty), this behavior also shows up when we calibrate our ensemble to a rank histogram that is 1 or below 1. Therefore, we were able to improve the rank histogram score of all the variables, especially PBLH getting close to 1 or lower, but the spread-skill relationship indicates that the spread is comparable to the skill of our ensemble. We note here that on a daily basis, the two quantities do not correlate which indicates a lack of resolution at fine time scales.

REF-C10: P7, L4 - Does “samples” in this sentence refer to ensemble members or observations? If covariances are underestimated, would this mean that there is nonindependent data and over-representation in a certain bin?

Author-C10: In this case the sample is the simulated variable at the different stations or grid points. Error correlations could lead to an over-representation of certain bins. Based on a more recent study currently under review in ACPD (<https://www.atmos-chem-phys-discuss.net/acp-2018-1113/>) and Figure 15 in the discussion section, our tower observations should remain independent thanks to the long distances between tower locations (>150km). But we fully agree that correlated observations would bias the histograms if the distance between the observations locations were smaller.

REF-C11: P7, L9- I think “mismatches” should not be plural here.

Author-C11: We change it to mismatch:

P7, L9: “The bias, or the mean of the model-data mismatch, was used to assist the selection of the calibrated sub-ensemble.”

REF-C12: P7, L17-19 - Check the grammar here, “These” appears twice.

Author-C12: Done

P7, L17-19: “These statistical analyses will be used to describe the performance of each member (standard deviations and correlations), ensemble spread (root mean square deviation) and error structures in space (error covariance), which will allow us to evaluate all the important aspects of an ensemble.”

REF-C13: P8, L26 - The “flatness score” is the rank histogram score? Should stick with same terminology if possible.

Author-C13: We fix the terminology, to keep everything consistent.

P8, L26: “In this study, SA and GA techniques will randomly search for the different combinations of members and compute the rank histogram score.”

REF-C14: P8, L27 - Is this N the same as the N that was used previously (e.g. the number of ensemble members)? I think this must be a different N that is something less than the previous one.

Author-C14: Yes, this N is the same that was used previously, which represents the number of ensemble members. Throughout the paper N always represents the number of members or models used in each ensemble, regardless of the size.

REF-C15: P8, L28 - It seems like a new symbol is being used for the rank histogram score here (it is delta in eqn 1). Is this because it’s going to be optimized by the SA/GA procedures and so a cost function will be defined?

Author-C15: We changed J to delta to keep everything consistent.

Section 2.5

For the first test, we will use these algorithms to choose the combination of members that optimize the score of the reduced ensemble $\delta(S)$ (i.e., rank histogram score) for each variable. With this evaluation, we determine if each optimization technique yields similar calibrated ensembles, and if the calibrated ensembles are similar among the different meteorological variables. In the second test, we calibrate the ensemble for all three variables simultaneously, where we use the sum of the score squared: $[\delta(S)]^2$:

$$[\delta(S)]^2 = [\delta_{wspd}(S)]^2 + [\delta_{wdir}(S)]^2 + [\delta_{pblh}(S)]^2, \quad (3)$$

to control acceptance of the sub-ensembles. In Eq. (3), $\delta_{wspd}(S)$, $\delta_{wdir}(S)$ and $\delta_{pblh}(S)$ are the scores of the sub-ensemble for PBL wind speed, PBL wind direction and PBLH respectively.

Section 2.5.1

To minimize the score δ , only two transitions to the neighbours are possible. First transition, if the score of the neighbour sub-ensembles $\delta(S')$ is lower than the current sub-ensemble $\delta(S)$, then S' becomes the current sub-ensemble and a new neighbour sub-ensemble is generated.

Second transition, if the score of the neighbour sub-ensemble $\delta(S')$ is greater than the current sub-ensemble $\delta(S)$, moving to the neighbour S' only occurs through an acceptance probability.

This acceptance probability is equal to $\exp(-\frac{\delta(S')-\delta(S)}{T})$ and it only allows the movement to the

neighbor S' if $u < \exp(-\frac{\delta(S')-\delta(S)}{T})$. For the acceptance probability, u is a random number uniformly drawn from $[0,1]$ and T is called temperature and it decreases after each iteration following a prescribed schedule. The acceptance probability is high at the beginning and the probability of switching to neighbour less at the end of the algorithm. The possibility to select a

less optimal state S' , i.e., with higher $\delta(S')$ is meant to escape local minima where the algorithm could remain trapped.

REF-C16: P9, L9-21 - I have a few questions about this description. First, isn't the deviation of delta from 1 what is being optimized here? I don't see how this is explicit in the notation. The other question I have is about the size of the sub-ensemble. Can the procedure test sub-ensemble sizes all of the way to N-1 and all of the way down to some minimum number, maybe 2?

Author-C16: Yes, the deviation of delta from 1 is what is being optimized. To keep everything consistent we changed J by delta (δ) as in equation 1 and following **REF-C15**. This change in symbol was applied to section 2.5 and 2.5.1.

Technically, it would be ideal to have the solutions for all ensemble sizes and evaluate which one is the minimum. Instead, we used an approach described in Garaud and Mallet (2011) to define the minimum size of the ensemble. To double-check their approach, we decided to test the method with three different ensemble sizes. We briefly explained how we select the size of the ensembles in section 2.5 and define the number of ensemble members in section 3.2. The paragraphs below from two different sections explain how we select the sub-ensembles size and establish that the calibration will be performed for three different sub-ensembles (ensemble size). We decided to add some lines to the document, where we specify that we can try all the potential solution, but for this study we decided to use a technique to decide that number of members:

Section 2.5, P8, L17-19: In this study, we want to test the ability to reduce the ensemble from 45-members to an ensemble with smaller number of members that is still capable of representing the transport uncertainties and does not include members with redundant information. *The number of ideal ensemble members could have been decided by performing the calibration for all the different size of ensemble smaller than 45-member. However, we decided to use an objective approach to select total number of members of the sub-ensemble. Therefore, we use the Garaud and Mallet (2011) technique to define the size of the calibrated sub-ensemble that each optimization technique will generate, the size of the sub-ensemble was determined by dividing the total number of observations by the maximum frequency in the large ensemble (45-members) rank histogram.* We are going to generate sub-ensembles...”

REF-C17: P9, L30-31 - Is mutation a separate step here? Or is considered part of “crossover”?

Author-C17: In our genetic algorithm process, we only go through the selection and the crossover. We do not include a mutation process to the algorithm. Please find the edit version of these sentence below, to make the process clear.

P9, L30-31: *“Then this population will go through two out of the three steps of the genetic algorithm, (1) selection and (2) crossover.”*

REF-C18: P10, L103 - I have the same question that I had for the SA, are the sizes of sub-ensembles allowed to vary?

Author-C18: Yes, the size of the sub-ensembles can vary for Genetic Algorithm (see **Author-C16**).

REF-C19: P12, Section 3.2 - Does this answer my question about exploring the sizes of the sub-ensembles? One uses the largest frequency from the rank histogram and since this happens to be the first box, then than one gets used? Why are 5-member ensembles used?

Author-C19: Yes, this section as explained on **Author-C16** answers your question about the exploration different sub-ensemble sizes. To define this number, we used Garaud and Mallet (2011) technique as explained section 2.5, where the total number of observations is divided by maximum frequency of the full ensemble (45-members) histogram in our case the first bin of the histogram (r_0). Because we were not clear in the article about the rank histogram that was going to be used to define this number of members, we decided to add this to the following sentences:

P8, L17-19, Section 2.5: *“Therefore, we use the Garaud and Mallet (2011) technique to define the size of the calibrated sub-ensemble that each optimization technique will generate. The size of the sub-ensemble was determined by dividing the total number of observations by the maximum frequency in the large ensemble (45-members) rank histogram.”*

P12, L19-20, Section 3.2: *“To compute the size of the sub-ensemble we use the maximum frequency of the rank histogram using the large ensemble (Figure 6). In this case the maximum frequency is the left bar (r_0) of every rank histogram.”*

The maximum number of members that we could use based on Garaud and Mallet (2011) technique was 10 to 8 members based in the variable as explained in section 3.2. However, we decided to explore a smaller ensemble to see how this will change our results and also how this will end up contributing to future analysis such as the errors covariance.

REF-C20: P16, L7-9 - I’m struggling with the implication of this statement. It means that even though the sub-ensemble has the right spread it doesn’t mean the simulation will encompass the true values? What about bias? If the model is biased one could get this situation, right?

Author-C20: The text was clarified. We are trying to explain here that the rank histogram score indicates that our calibrated ensembles have a good spread, but the spread-skill is telling us that our ensemble will not systematically encompass the true values for any given observation. Yes, our results show some biases in our model and therefore the ensemble. This bias can be associated to the model itself, the forcing data or the specific parameterization. We have minimized the bias, but future studies should perform model correction by using data assimilation or by improving the physics. We have modified the text to clarify our point.

Section 4.3, P16, L7-9: *“The calibrated ensembles show the rank histogram score closer to one (Table 4), that is, flatter rank histograms (Figure 9) compared to the 45-member ensemble (Table 2 and Figure 6). The sub-ensembles do have a greater variance than the large ensemble (i.e., improved reliability) (Figure 14). However, the spread-skill relationship (i.e., resolution) of the calibrated ensembles do not show any major improvement compared to the 45-member ensemble, implying that the spread of the ensemble does not represent the day-to-day transport errors well. **While the rank histogram suggests that the different calibrated ensembles have enough spread, the spread-skill relationship indicates that our ensemble does not systematically encompass the observations. The disagreement between the rank histogram and the spread-skill relationship can be associated with the metric used for the calibration (i.e., rank histogram) and the biases included in the calibrated ensemble. Using the score of the rank histogram alone may***

not be sufficient to measure the reliability of the ensemble (Hamill, 2001), therefore, future down-selection studies should incorporate the resolution as part of the calibration process (skill score optimization). The biases in the model are a complex problem because there are many sources systematic errors within an atmospheric model (e.g., physical parameterizations, and meteorological forcing). Future studies should consider data assimilation or improvement of the physics parameterizations to reduce or remove these systematic errors. To improve the representation of daily model errors, additional metrics should be introduced and the initial ensemble should offer a sufficient spread, possibly with additional physic parameterizations, additional random perturbations, or modifications of the error distribution of the ensemble (Roulston and Smith, 2003)."

REF-C21: P16, Section 4.4 - I'm not sure I follow this argument. I see from Fig 15 that the spatial correlations of CO2 get closer to 1 or -1, but I'm not sure why this happens with fewer ensemble members. It's stated that this is because of sample size (i.e. number of realizations?) but why should this result in a more intense correlation pattern? I would like to understand this.

Author-C21: This is an important and subtle point raised by the reviewer. We re-phrased the section 4.4 to clarify our conclusions. The concept of sampling noise can be compared to few random draws out of a complex distribution. It tends to generate spurious correlations (requiring a regularization similar to those used in the ensemble Kalman filters) depending on the shape of the true distribution. As a consequence, the error correlations increase or decrease randomly both near the observation location and at long distances. The variance of spurious correlations is in the order of $1/N$ with N the number of members (Bartlett, 1935, JRSS) and depends on the true distribution. In our case, considering the complexity of error distribution in space and time, we cannot predict the minimum size to avoid sampling noise but we clearly observe increased/decreased error correlations with 5 members.

"Figure 15 shows the spatial correlation of 300 m DDA CO₂ errors with respect to the Round Lake site on DOY 180. Error correlations increase significantly as our ensemble size decreases. With fewer members, spurious correlations increase, resulting in high correlations at long distances. Assuming we sample only a few times the distribution of errors, our ensemble is very likely to be affected by spurious correlations with a variance on the order of $1/N$."