Atmos. Meas. Tech. Discuss.,
doi:10.5194/amt-2019-61-AC2, 2019

Atmospheric Measurement Techniques Discussions

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AMTD

Interactive comment

Interactive comment on "The application of mean averaging kernels to mean trace gas distributions" *by* Thomas von Clarmann and Norbert Glatthor

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Received and published: 27 May 2019

The authors thank both reviewer for the helpful suggestions which will add clarity to the paper.

Comment: *This manuscript discusses an important and often ignored issue involving the application of averaging kernels to mean profiles. A solution to the problem is presented where the covariance between the averaging kernel and the atmospheric state is calculated. Examples are shown applying the method to MIPAS, and recommendations are given to data producers of monthly zonal mean data.*
The manuscript is well written and suitable for publication in AMT after a few comments are taken into account.

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Discussion paper

Reply: We thank the reviewer for this positive evaluation.

Comment: *General Comments*
The discussion and conclusion (including the recommendations) of the paper focuses on the ideal case where the data producer actually calculates (and stores) an averaging kernel for each individual profile. It is somewhat common to only produce representative averaging kernels and perhaps use them as a metric for retrieval performance in a validation/retrieval paper or data quality document. Would a possible recommendation of this work be that a few of these covariance terms should be calculated and included as an assessment of the data quality?

Reply: These covariance terms refer to mean averaging kernels. We have no idea to which degree they are applicable to representative individual averaging kernels. Since the covariance terms depend on the ensemble over which it is averaged, and since it may not be known in advance what kind of averages the data user wants, it will not be easily possible to produce useful covariance profiles in advance. Instead one might consider to calculate the averaging kernels for each retrieval (which is not so much additional effort) and to calculate zonal mean profiles and averaging kernels immediately as the last step of each individual retrieval. In this case one would have the mean averaging kernels and the covariances without storing each averaging kernel. They can be deleted immediately after their consideration for the mean values.

Comment: *Related to the above point, I have to wonder, is the covariance profile useful beyond a correction when applying the mean averaging kernel? My (perhaps wrong) interpretation is that when the covariance profile is 0, the mean of the retrieved profile is a smoothed version of the true mean atmospheric state. I suppose what I* *am asking is that if the covariance profile is not 0, is it wrong to interpret the retrieved mean as a smoothed version of the true atmospheric mean? If so, I would like to see a discussion of this included in the manuscript.*

Reply: We are not aware of any other interpretation beyond the one offered. The interpretation that zero covariance means that the mean of the retrieved profiles is a smoothed version of the true mean atmospheric state is not true, at least not in a general sense. Assume a case with infinite noise, i.e., no measurement information. The retrieval will then be identical to the a priori. Assume further that a constant (e.g. climatological) a priori has been chosen. The the result will not vary at all. Thus also the covariance will be zero although the mean result is fully determine by the a priori, in shape and values.

Comment: *Minor Comments*
p.1 l.9: ". . . on a given altitude grid . . . "
Here and throughout this section it is written that altitude is the vertical coordinate, however all of the arguments should equally apply to any vertical coordinate.

Reply: With "altitude" we mean any vertical coordinate, not only geometrical altitude. We will change the wording to make this clear.

Comment: *p.2 l.18: "For a constrained retrieval of the type" The way this is presented the reader may assume that what follows only applies to retrievals applying a (possibly iterative) form of eq. 1, when the concepts here are more general.*

Reply: We agree, but this type or retrieval is the only one for which averaging kernels are reported at all. But you are right, in principle our arguments hold for any other type of retrievals if averaging kernels are made available. These can be evaluated, e.g., by perturbation studies. We will try to reword the text to make this clear.

Comment: *p.2 l.29: eq. 4: Somewhere here I would like to see a brief mention that* $x_original$ *needs to be converted to the same grid and representation (vmr/number density and altitude/pressure) as the retrieval.*

Reply: agreed.

Comment: *p.3 l.5: "Calculation of zonal averages over L profiles . . . " Why restrict to zonal?*

Reply: This is meant as an example. We will add 'e.g.'.

Comment: *p.3 l.12: "For a retrieval with* x_a *= 0 . . . " This is a nitpick and I don't necessarily think it should be changed, but the same would be true with* $_x$*a=constant and a Tiknonov regularized retrieval. I guess the general condition would be if* x_a *is in the null space of R.*

Reply: ok, indeed for an altitude-constant prior and an A with unity measurement response in all altitudes, we have $< A >< x_a >=< x_a >$, which cancels with the first $< x_a >$ term. And a covariance involving a time-constant x_a will also be zero. We will think about a wording which makes a more general statement without being too complicated.

Comment: *p.3 l.22: "For a retrieval where an individual prior xa is used for each profile*

. . . " I suppose this assumes that the prior used is a good representation of the true atmospheric state/variability.

Reply: Yes, this is indeed a precondition for Eq 10. We will mention this.

Comment: *p.3 l.15: "cov(A; x) and be approximated by $cov(A; \hat{x})$" I have a hard time intuitively understanding the implications of this approximation. I think that there are two things going on here, the first is the switch from the true state to the smoothed state, which I don't expect to have a large effect. But since the intention is to use this to compare two measurements, are we also assuming that both instruments have approximately equal sampling within whatever bin is being averaged?*

Reply: Although there exists literature on comparison between instruments where the averaging kernels of both instruments are considered (Rodgers and Connor, 2003), the approaches most often taken are to do a direct comparison (without using averaging kernels) as long as the vertical resolutions are similar and the measurement response is large, and to apply the averaging kernel of the coarser resolved retrieval to the result of the better resolved retrieval, if the contrast in resolution justifies this (Connor et al. 1995). In none of these cases we have to deal with averaging kernels of both instruments, thus no such assumption is necessary. The same holds for model-measurement comparisons. Here the averaging kernel of the measurement is typically applied to the model output. Also in this case no such assumption is necessary.

Comment: *p.4 l.8: "For retrievals performed in the log-space, all this becomes slightly more complicated . . . " It is fine to ignore the issues with log retrievals, since, as stated, averaging may have its own issues, but I have to wonder is this not a more* *general representation issue? Presumably if our goal was to compare a high resolution and a low resolution retrieval that both operated in log space, it would be possible using this framework if the averaging was done in log space.*

Reply: Averaging in the log-space typically does not solve related problems; particularly it will not remove biases introduced by the retrieval in the log space (see, Funke and von Clarmann, 2012).

Comment: *p.4 l.10: eq. 12 Perhaps related to above, but this equation is hard to interpret when the x's do not represent the same thing (some are in linear space some are logarithmic). Or maybe all the x's are intended to be in linear space and the logarithm being applied to xoriginal is missing?*

Reply: The latter is the case; it should read $Ax_{original}$. Thanks for spotting!

Comment: *p.7 l.12: "The covariance effects can exceed 10% and thus need to be considered when mean profiles are used for quantitative analysis and mean averaging kernels are applied." This statement had me wondering about the implications of this effect beyond comparisons of two measurements. Say a data user is using zonally averaged MIPAS HCN data, but not actually applying any mean averaging kernel. Would having knowledge of the magnitude of this covariance term guide them in their analysis, similar to the way having a measure of vertical resolution from the averaging kernel would?*

Reply: We do not have any idea how to use the covariance term for other purposes than that described in the paper.

Comment: *Technical Comments*
p.4 l.18: eq. 13 Equation has extra equal signs.

Reply: Thanks for spotting; they will be removed.

Comment: *p.7 l.3: "consistes" consistes ! consists*

Reply: Typo will be corrected

Comment: *p.7 l.17: "we recommed" recommed ! recommend*

Reply: *Typo will be corrected. Thanks for spotting.*

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