Response to editor's comments on "*Monte Carlo Drift Correction – Quantifying the Drift Uncertainty of Global Climate Models*"

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Dear Dr Gromov,

Thank you for reading our revised manuscript and for your decision. Below, we provide a response to your insightful comments (quoted in *green italics*).

Thank you for submitting the revised version of the manuscript. I sincerely apologise for an exceptionally long review process caused mainly by a great difficulty of finding the reviewers for your study (I have never had more than two dozen declines while editing for GMD) and overcommitment of the latter which added up to the delay.

I am generally satisfied with the review process and your replies to the reviewers' comments. Should only the latter have been addressed, I would be happy to continue with the publication "as is". However, I notice considerable changes in the methodology (i.e., the "agnostic MCDC") introduced which would normally trigger me to send the manuscript out for another round of reviews, which I would like to spare us from by offering myself for a round of discussion (luckily we are allowed to do that in GMD).

Thank you for overseeing the review process and for assessing our replies to the reviewers' comments. Thank you also for your comments on our revised methodology.

The reason here is that I see the same criticism as was earlier brought by both reviewers regarding the "mixed" use of estimates of short-term drift samples. In the agnostic MCDC – by combining linear, quadratic and cubic fits in one MC statistic – you may spuriously increase the final uncertainty estimate, as obviously one or two of the fit models are inferior. Why not testing each of the three models separately and selecting the one that yields the best fit (for a given ESM)? Combining the three also has little physical sense – would not you expect the underlying process to be a mere linear, quadratic or cubic function of time (through whatever, perhaps unidentified, reason in the model build)?

*I believe the point of combining the three fit models in one statistic has to be justified in the revised manuscript. Alternatively, using the best-fitting model will not require such justification. At last, why only the quadratic and cubic fits are considered as an alternative to the linear one? As the underlying functional relation for drift temporal evolution is not known, you could use a general "exponential" form (e.g., c+a*t^p, with c, a and p being the fitting parameters) which will reduce the estimates to the two general cases: classic linear (p=1) and non-linear (p<>1, c representing whatever accumulating hidden unbalanced component of the system prior to the branch time). In my view, this would be the most sensible way to study whatever non-linear option for the estimate, whilst keeping the "traditional" (or read expected from the first-principle $\Delta H - \Delta E - \Delta Z$ relation) option for comparison as well.*

We developed our agnostic-method MCDC approach in response to the reviewers' comments, following further consideration of the published literature. In our original submission, we accounted for possible non-linearity in the drift by randomly sampling segments of the control time series.

When criticising this approach, the reviewers helpfully pointed out that the branch-time metadata are likely reliable, enabling non-linear models of drift to be applied to the entire control time series.

We could test many different non-linear models, including the exponential form you suggest. As you further suggest, we could then compare the statistical models and select the best-performing model(s). This could be described as a "best-fit" approach. We agree that this best-fit approach would be a sensible way to correct drift. Accordingly, we have now expanded our brief discussion of the "best-fit" approach in Sect. 5.2 (fourth paragraph): "A possible further step would be to fit and compare alternative statistical models of drift *a posteriori*, using measures such as the Bayesian information criterion. We could then select the best statistical model(s) for a specific time series. When applying this "best-fit" approach, we could also consider additional statistical models of drift, including signal processing filters (e.g. Palmer et al., 2011). This best-fit approach would be a sensible way to correct drift. Application of the best-fit approach should lead to a reduction in drift uncertainty."

However, this best-fit approach does not correspond to the way climate scientists generally correct drift in global climate model simulations. In Sect. 3.1, we now write, "Among recent studies focusing on the earth's energy budget or sea-level change, a few consider the possibility that results may be sensitive to alternative linear, quadratic, and/or cubic models of drift (e.g. Sen Gupta et al., 2013; Hobbs et al., 2016; Jackson and Jevrejeva, 2016; Lyu et al., 2021; Hermans et al., 2021; Irving et al., 2021). However, most studies use only a single statistical model of drift: either linear (Jevrejeva et al., 2016; Palmer et al., 2018; Cuesta-Valero et al., 2021; Hamlington et al., 2021; Lambert et al., 2021), quadratic (e.g. Gleckler et al., 2016; Lyu et al., 2020; Harrison et al., 2021; Jevrejeva et al., 2021), or cubic (e.g. Irving et al., 2019). We observe that researchers generally select a statistical model *a priori*, before analysing any data. They do not generally compare the *a posteriori* performance of alternative statistical models."

Our agnostic-method corresponds to this common practice. In Sect. 3.2 (penultimate paragraph), we now write, "In addition to sampling the uncertainty associated with the parameters of a given statistical model, agnostic-method MCDC also samples the uncertainty associated with the choice between alternative statistical models: we assume that linear, quadratic, and cubic models of drift are equally valid. This corresponds to the common practice of selecting one of these alternative statistical models *a priori* (Sect. 3.1)."

Your comment has helped us to clarify the reasoning behind agnostic-method MCDC. Thank you.

In addition to this one general comments, I have outlined a few specific ones below.

L115 Consider revising the sentence (wordiness)

We have now shortened this sentence: "To derive a single best estimate of drift, we should use the entire control time series" (Sect. 3.1, first paragraph).

LL200-201 Looking at Fig.3, I note that the agnostic-method drift uncertainty is approximately twice as large as the ensemble median" for more than one model

We have now revised this sentence: "The ensemble maximum drift uncertainty is 0.17 YJ, approximately twice as large as the ensemble median (Table 1; Fig. 3h)" (Sect. 4.2, fourth paragraph).

L405 Are there no uncertainty estimates available for η at all?

By changing the time period to 1971–2018 (instead of 2010–2018), we can now reference two alternative estimates: "For the period 1971–2018, η is estimated to be approximately 0.89–0.91 (von Schuckmann et al., 2020; Forster et al., 2021)" (Appendix A). Neither of these published estimates includes a standard error.

For consistency, we have also changed the time period used for the estimate of E': "E' is estimated to be 0.47 ± 0.1 W m^{-2} for the period 1971–2018 and is increasing (von Schuckmann et al., 2020)" (Appendix A).

L438 I understand that XX will be replaced by a given no. in the future?

Yes, we have now replaced XX with a number: "This work comprises EOS contribution number 547" (Acknowledgements).

Fig.2, left and centre columns: What is the essence of presenting the fit at times prior to the branch time? I am not sure that this anyhow quantifies anything sensibly

The entire control time series – including times prior to the branch time – is used when fitting the statistical model of drift. Therefore, we choose to show the entire control time series in Fig. 2, which illustrates the application of MCDC.

Fig.2, caption: Please use "plotted alongside the uncorrected control time series" only once, in the sentence preceding explication of panels (a), (b) and (c)

We have now revised these sentences in the Fig. 2 caption: "The first row (a–c) shows integrated-bias-method MCDC results: (a) drift samples derived using the integrated-bias method, (b) integrated-bias-method drift-corrected control time series, and (c) integrated-bias-method drift-corrected historical time series, plotted alongside the uncorrected time series."

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