We thank both Glen Peters and one anonymous reviewer for their comments and suggestions. We have attempted to address each comment in turn, with point-by-point responses in the separate response documents. In addition to our responses to the specific comments made by the reviewers, we have also updated the manuscript in a number of other places. These changes aim to ensure the text and model is fully up-to-date with the current state of the literature, and make several improvements to the transparency and robustness of the analysis within the manuscript. These additional changes are set out directly below.

We now use emission data solely from RCMIP throughout, for reasons of consistency and transparency.

We use CMIP6 data from https://cmip6.science.unimelb.edu.au/ where possible throughout, processed as set out in Nicholls et al., 2021. This includes the CMIP6 tunings.

Updates to the default parameterisation:

We have updated the ozone parameterisation in line with the recent studies from Thornhill et al., 2021, and Skeie et al., 2020. This parameterisation means we no longer distinguish between tropospheric & stratospheric ozone.

The default aerosol parameters are now set to be equal to the central values of the CONSTRAINED ensemble.

The default climate response is set to be equal to the central response of the CONSTRAINED ensemble.

We now include (where data is available) verification runs for the CMIP6 climate response emulation, using the abrupt-2xCO2 and abrupt-0p5xCO2 experiments as verification experiments for the tunings (which are computed using the abrupt-4xCO2 and 1pctCO2 experiments). However, these data are not available for all models we emulate, so we cannot verify the tuned parameters for each model.

We have updated the constraint methodology used to determine CONSTRAINED parameter sets from the FULL ensemble. Before, we used a simple pass/fail criterion based on the global warming index calculation (GWI, Haustein et al., 2017). While this was very straightforward, it did not make full use of the GWI, which provides an estimate of the distribution of current level and rate of warming; and additionally it sampled from regions of exceptionally low likelihood in level/rate space. In our updated constraint, we set the probability of selecting an individual ensemble member equal to the likelihood of the present-day level & rate of warming as determined by the GWI. This is a significantly stricter criterion (only ~8 % of the FULL ensemble is retained).

Within this new constraint methodology, in addition to the sensitivity to prior assumptions on climate response, we also test the sensitivity to the observational dataset used to compute the GWI (particularly relevant with the arrival of HadCRUT5). This demonstrates how future projections can be impacted by the choice of observational dataset used in such a constraining procedure. We believe that this additional test of sensitivity is particularly useful given the several recent papers that use observed warming to constrain future projections.

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