

Interactive comment on “A method to encapsulate model structural uncertainty in ensemble projections of future climate” by Jared Lewis et al.

Anonymous Referee #2

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Jared and colleagues present a method to compute distributions of local weather variables, and provide an example of how it can be applied to the case of New Zealand. For each geographic location, the method generates combinations of local climatology, long-term forced changes, and stochastic weather. By combining long-term temperature projections consistent with a large set of AOGCMs and carbon-cycle models, the paper claims to encapsulate model structural uncertainty in ensemble projections of future climate, and climate change.

The method proposed by the paper is interesting. However, the paper neglects references to earlier literature that have proposed related approaches. Furthermore, the method as it is currently described shows some serious shortcomings, particularly in the assessment and inclusion of structural uncertainty in the Probability Density Functions (PDFs) suggested. Two issues stand out:

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1) Rather than encapsulating structural model uncertainty in a sensible and robust way, the current method basically multiplies and preserves model sampling bias. Just like the proposed method explores stochastic weather variations with an EOF analysis to understand dominant modes of variability, the same should be carried out for the 19 AOGCMs and carbon-cycle models. The implicit assumption that each AOGCM realization is statistically or structurally independent is not supported. This would benefit strongly from appreciating the findings from Masson & Knutti (2011) or Knutti et al (2013) to determine the structural independence of AOGCMs, and apply the methods of model weighting as described in Knutti et al (2017) in order to address structural model uncertainty in a meaningful way.

2) The proposed method hinges on the assumption that fields of variable X are independent of the structural model uncertainty in AOGCMs. This assumption is not supported by any evidence. Not all patterns have to be equally probable to occur with a certain T_{global} response to a specific forcing path. What is required here is evidence based on a re-analysis of AOGCM data which shows that local patterns (or patterns of boundary conditions for the RCM) are either equally probably across high and low-response AOGCMs, or differ across these responses pointing towards the limitations of the proposed method.

The claims about the applicability and usefulness of the method would be unsupported if both these points are not addressed in a significantly revised manuscript.

Smaller editorial comments:

P4L28: T_{global} is formatted incorrectly

P5L2: Please edit this sentence for spelling and grammar. The authors need to provide evidence to make the claim that the methodology is valid for any chosen GHG emissions scenario.

P6Fig2: Color descriptions do not match the figure.

C2

References:

Masson, D., and R. Knutti (2011), Climate model genealogy, *Geophys. Res. Lett.*, 38, L08703, doi:10.1029/2011GL046864.

Knutti, R., D. Masson, and A. Gettelman (2013), Climate model genealogy: Generation CMIP5 and how we got there, *Geophys. Res. Lett.*, 40, 1194–1199, doi:10.1002/grl.50256.

Knutti, R., J. Sedláček, B. M. Sanderson, R. Lorenz, E. M. Fischer, and V. Eyring (2017), A climate model projection weighting scheme accounting for performance and interdependence, *Geophys. Res. Lett.*, 44, 1909–1918, doi:10.1002/2016GL072012.

Interactive comment on *Geosci. Model Dev. Discuss.*, doi:10.5194/gmd-2017-36, 2017.