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Discussions

Interactive comment on "Identifying robust bias adjustment methods for extreme precipitation in a pseudo-reality setting" *by* Torben Schmith et al.

Torben Schmith et al.

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Author reply to:

Short comment #1 on "Identifying robust bias adjustment methods for extreme precipitation in a pseudo-reality setting" by Torben Schmith et al.

We will start by thanking our collegues in science for this short comment. We will comment (marked with »> . . . «<) on each of their items below.

Comment on 'Identifying robust bias adjustment methods for extreme precipitation in a pseudo-reality setting' T. Kelder, R. L. Wilby, T. Marjoribanks, L. Slater

Torben Schmith and co-authors address a complex, but important topic. Climate model

corrections typically assume stationary biases between simulated and observed extreme precipitation but, in practice, such biases may well be nonstationary (i.e. distributions may shift significantly in the future). Robust evaluation of bias correction methods is hampered by the inability to analyse future model biases, since there are obviously no observations of the future. To address this issue, the authors use model simulations as a pseudo-reality of the present and future climate to evaluate the robustness of various bias correction methods within these 'virtual' worlds. The authors processed a large amount of data from the EURO-CORDEX ensemble and we commend them for this interesting research and their purposeful discussion of findings. The paper concludes by recommending a preferred bias correction method for climate projection. We offer a few suggestions and raise some issues for further elaboration by the authors.

1. Given that the analysis is based on an ensemble of climate model experiments, the logic should be explained for treating model-to-model biases in extreme precipitation as equivalent to model-to-observation biases. The paper acknowledges the limited ability of _10km resolution model simulations at representing convective processes. Hence, more explanation is needed for an unfamiliar reader on why model experiments can be used to draw conclusions about the best bias correction methods on hourly timescales, if one cannot trust the model simulations to realistically represent convective processes.

»>Our approach of treating model-to-model biases as equivalent to model-to-observations is named 'indistinguishable interpretation', as opposed to the 'truth plus error interpretation' (Sanderson and Knutti 2012). Our motivation of adopting the former is indirect. For variables, such as the large-scale surface temperature, which are used as measure in the tuning process of models, the truth plus error is the canonical choice. Precipitation is not directly linked to the tuning process and has smaller scale, and as such the indistinguishable interpretation can be argued for (Christiansen 2020).

Acknowledging that the models represent convection imperfect, we are actually better off evaluating the bias correction methods between models than between model and observation. We are here addressing the statistical nature of the corrections, not the physical processes which bias correction methods are not suitable for anyway. We do not promote, naively applying these methods to hourly data from these models. However, the presented methods can in the future be applied to convection permitting model simulations that better represent the convective process, and results from our current manuscript would apply equally to that case. We do not presently have a large ensemble available of such models to perform our study on. We will explain this view in a revised manuscript.«<

2. Related to #1, a few cautionary remarks could be made about some of the GCMs used to drive the CORDEX experiments (see: Liepert and Lo, 2013). The realism of the downscaled extreme precipitation depends on the realism of the boundary forcing. Use of an 'ensemble of opportunity' is not unusual, but some studies narrow the choice of candidate models (and hence uncertainty) based on physical realism tests (e.g. McSweeney et al., 2015; Rowell, 2019).

»>We only partly agree with this. The large-scale atmospheric state is certainly determined by the boundary forcing; though, the RCM is able to modulate it. Distribution of precipitation intensities are to a large extent determined by the RCM (see e.g. (Christensen and Kjellström 2020)). This is particularly true for the high-extreme end of the spectrum.

We are aware of the use of selection procedures put forward in the cited papers. There is, however, no simple quality index that can be generally applied. Any discrimination of GCMs depends depend on area, season, and the meteorological field and property being investigated (Gleckler et al. 2008); e.g. their Fig. 9). Furthermore, these tests and selection procedures are based on subjective criteria and come with major caveats that impact the uncertainty range largely (Madsen et al. 2017). We therefore choose, in accordance with most other similar studies, to use 'ensemble of opportunity' for the present study.«<

3. In the inter-model cross-validation setup, every model/pseudo-reality combination is used. This setup can be useful for assessing relationships between present and future bias correction factors (e.g. Fig. 9), but does not mimic climate projections, where the ensemble mean, and range are typically used. In the present setup, a future projection is treated as a deterministic prediction, rather than a probabilistic projection. Perhaps use of the climate 'pseudo-observed' run might be favoured over future predictions simply because there is less variability in the present climate? How sensitive are the results to taking the mean of all ensemble members minus the 'pseudo-reality' member (e.g. Fig. 3 in Räty et al. 2014)? This has the added benefit of involving much fewer permutations (and hence calculations).

»>Actually a good idea, which we have implemented in our analysis suite (see attached plots). We think we can find the space for two extra plots and some associated text in the revised version. «<

4. The range of the projection matters. For example, Fig. 4 shows that there are future scenarios that exceed the present climate range. Hence, the worst-case 10-year precipitation event from the 'pseudo-obs' range would not include plausible future 10-year events. Therefore, more qualification is needed in the Abstract and Conclusions to guard against this possibility and the potentially misleading assertion that "the superior approach is to simply deduce future return levels from observations". Overall, the headline findings of the research could be presented in more nuanced ways, especially within the Abstract.

»>We are afraid that we do not understand the central statement of this point ("Hence, the worst-case . . .). Therefore, we are not able to comment on it.«<

5. The Abstract and Introduction assert that "Severe precipitation events are usually projected using Regional Climate Model (RCM) scenario simulations." We gently remind the authors that statistical downscaling is also widely used for projecting severe precipitation events and suggest that more inclusive wording be used.

»>We agree that this suggestion is appropriate. It could easily be met by referring to work by Wilby, Mauraun, and others.«<

References

Liepert, B.G. and F. Lo, 2013: CMIP5 update of 'Inter-model variability and biases of the global water cycle in CMIP3 coupled climate models'. Environ. Res. Lett., 8(2), p.029401, https://iopscience.iop.org/article/10.1088/1748-9326/8/2/029401/meta.

McSweeney, C.F., Jones, R.G., Lee, R.W. and Rowell, D.P., 2015: Selecting CMIP5 GCMs for downscaling over multiple regions. Clim. Dyn., 44(11), 3237-3260, https://doi.org/10.1007/s00382-014-2418-8.

Räty, O., J. Räisänen, and J. S. Ylhäisi, 2014: Evaluation of delta change and bias correction methods for future daily precipitation: intermodel cross-validation using ENSEMBLES simulations. Clim. Dyn., 42, 2287–2303, https://doi.org/10.1007/s00382-014-2130-8.

Rowell, D.P., 2019: An observational constraint on CMIP5 projections of the East African Long Rains and Southern Indian Ocean warming. Geophys. Res. Lett., 46(11), 6050-6058, https://doi.org/10.1029/2019GL082847.

»>Our added references:

Christensen, O. B., and E. Kjellström, 2020: Partitioning uncertainty components of mean climate and climate change in a large ensemble of European regional climate model projections. Clim. Dyn., 54, 4293–4308, https://doi.org/10.1007/s00382-020-05229-y.

Christiansen, B., 2020: Understanding the Distribution of Multimodel Ensembles. J. Clim., 33, 9447–9465, https://doi.org/10.1175/JCLI-D-20-0186.1.

Gleckler, P. J., K. E. Taylor, and C. Doutriaux, 2008: Performance metrics for climate models. J. Geophys. Res., 113, D06104, https://doi.org/10.1029/2007JD008972.

Madsen, M. S., P. L. Langen, F. Boberg, and J. H. Christensen, 2017: Inflated Uncertainty in MultimodelâĂŘBased Regional Climate Projections. Geophys. Res. Lett., 44, 11,606-11,613, https://doi.org/10.1002/2017GL075627.

Sanderson, B. M., and R. Knutti, 2012: On the interpretation of constrained climate model ensembles. Geophys. Res. Lett., 39, n/a-n/a, https://doi.org/10.1029/2012GL052665. «<

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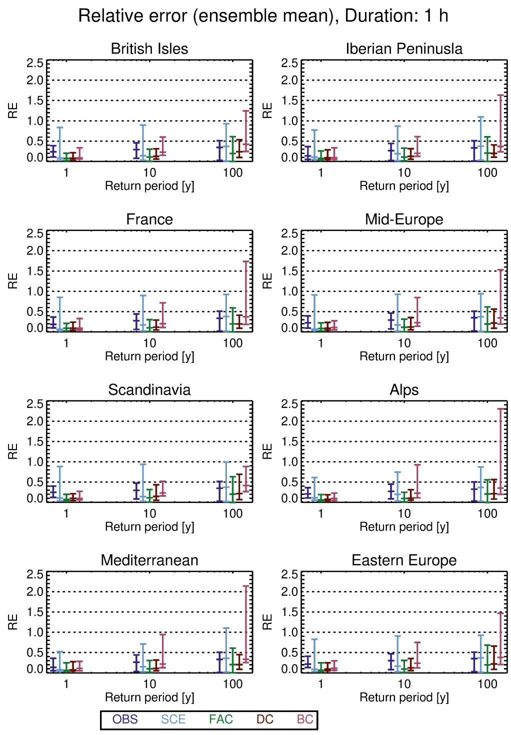
Relative error (ensemble mean), Duration: 1 h
British Isles
Iberian Peninusla
France
Mid-Europe
Scandinavia
Alps
Mediterranean
Eastern Europe
RE
2.5
2.0
1.5
1.0
0.5
0.0
1
10
100
Return period [y]
OBS SCE FAC DC BC

Fig. 1.

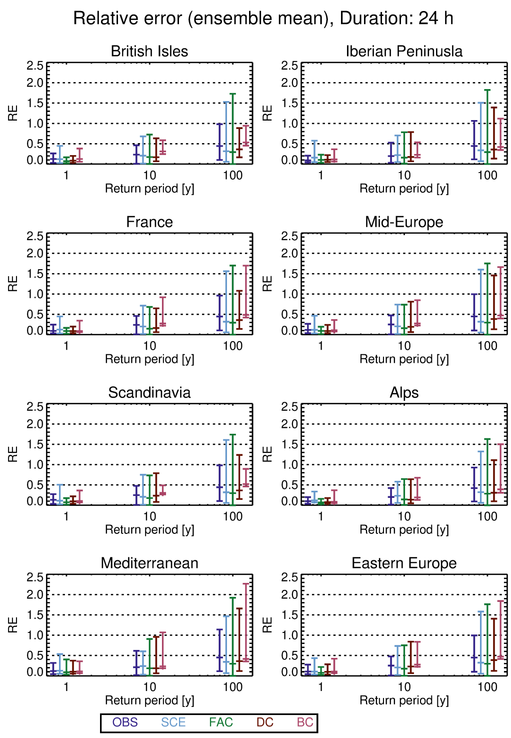
Relative error (ensemble mean), Duration: 24 h
British Isles
Iberian Peninusla
France
Mid-Europe
Scandinavia
Alps
Mediterranean
Eastern Europe
RE
2.5
2.0
1.5
1.0
0.5
0.0
1
10
100
Return period [y]
OBS SCE FAC DC BC

Fig. 2.