Authors’ comment

We thank the reviewers for their thorough and helpful comments on the manuscript. In replying to the reviewers, we have collated the response into six section as follows:

1. Sharpening of the research question
2. Better description of NARCliM models and data in section 2 of the manuscript
3. Addressing the credibility of underlying climate models
4. Assessing the effect of bias correction on change factors in the future (i.e. whether to select bias correction methods that preserve trends)
5. Inflation and maintaining spatial correlation for runoff modelling
6. Consistency between rainfall and other atmospheric variables

More generally, for the revised version of the manuscript, we plan an updated literature review (encompassing the references and discussion points below) for the introduction, an updated discussion section (again using the response below), a critical review of the figures including reduction in the total number, and an updated evaluation of the bias correction method in line with referee #2’s comment. Finally, we thank the reviewers for their minor comments and will incorporate these in the revised version.

1 Sharpening of the research question

As discussed in the existing introduction to the manuscript, there is a growing need for hydrological projections due to climate change to provide scientifically based water planning frameworks. End users of hydroclimate projections need more spatially detailed information as well as information on water metrics for low- and high-flow events, as well as interdecadal metrics (Potter et al., 2018). Dynamical downscaling of future climate information (such as provided by the NARCliM project) has potential to provide this type of information, however there remain challenges associated with this data. In this paper, we examine the suitability of NARCliM projections for providing hydroclimate projections for south-eastern Australia. Specifically, we look at the extent of biases in rainfall, which necessitate daily bias correction, and the effect of quantile-quantile mapping bias correction on rainfall sequencing metrics that are important for runoff generation. Subsequent research in a related paper (Charles et al., submitted) focuses attention on the effect of these biases on runoff.

2 Better description of NARCliM models and data in section 2

NARCliM (https://climatechange.environment.nsw.gov.au/Climate-projections-for-NSW/About-NARCliM; Evans et al., 2014) is a regional climate change project to deliver high resolution dynamically downscaled climate change projections. As noted previously, GCMs run at a spatial resolution that is unable to provide meaningful information for decision makers at catchment and basin scale. Dynamical downscaling uses regional climate models (RCMs) forced by atmospheric variables output from GCMs to resolve subgrid processes. Out of the 23 CMIP3 GCMs available at the time the NARCliM project started, four were eventually chosen for downscaling: MIROC3.2 (medres), ECHAM5, CCCM3.1 and CSIRO-Mk3.0. Initially, GCMs that did not adequately represent climate dynamics of the region were eliminated. Based on a meta-analysis, GCMs were then ranked, and independence of model error, as well as future changes, was assessed to represent the range of model ensemble (Evans and Ji, 2012a). A similar procedure was applied to select the configurations of the RCM (WRF) used to downscale each host GCM (Evans and Ji, 2012b). The three selected RCM configurations are denoted R1, R2 and R3, further information is provided elsewhere (Evans et al., 2012; Ekström, 2016; Gilmore et al., 2016). Current work (NARCliM1.5) is continuing to develop the modelling framework at a higher spatial resolution (5km × 5km), using CMIP5 models and improved RCM configuration (Downes et al., 2019).

Daily accumulated precipitation is produced at approximately 10km × 10km grids, which was bilinearly interpolated to a regular grid using Climate Data Operators (CDO; https://code.mpimet.mpg.de/projects/cdo). NARCliM also provides bias corrected data (Evans and Argüeso, 2014), through a parametric gamma distribution quantile-quantile mapping procedure, which is similar in many respects to the non-parametric procedure we apply to the raw NARCliM data in this paper. We discuss the credibility of the NARCliM ensemble in greater detail below.

3 Addressing the credibility of underlying climate models

We acknowledge that the performance of GCMs in accurately simulating the climate dynamics of the region under consideration is extremely important. In the context of the study area of the manuscript, South-Eastern Australia, GCM selection and screening has been an on-going research strand both for the CMIP3 climate model ensemble, which is used for the current NARCliM dataset (Smith and Chandler, 2010; Kirono and Kent, 2011; Kent et al., 2013; CSIRO, 2012; Evans and Ji, 2012a; McMahon et al., 2015), as well as the CMIP5 ensemble (see CSIRO and Bureau of Meteorology, 2015; Hope et al., 2016). Likewise, the RCM component of NARCliM, WRF, has been tested extensively (Evans and McCabe, 2010; Evans et al., 2012; Evans and Ji, 2012b; Andrys et al., 2016; Ekström, 2016; Olson et al., 2016; Ji et al., 2016; Gilmore et al., 2016).

The use of models that produce plausible climate dynamics is of course desirable, however in practice it is not necessarily always possible. Apart from the fact that the 'best' models identified by the above references differ according to the criteria used, using a dynamical downscaling ensemble for hydrological applications is an opportunistic endeavour, relying largely on existing data products, which have been prepared with many applications in mind, not just hydrological applications. As such, it is not necessarily practical to choose the GCMs and RCMs that best represent climate dynamics important for hydrological applications. Nevertheless, screening of less suitable models is always possible; although many studies have also contended that accuracy in representing historical conditions is no guarantee that future changes are correctly modelled (e.g. Knutti et al., 2010; Racherla et al, 2012).

Overall, there is reasonable confidence in NARCliM projections generally, for both rainfall and temperatures (Evans et al., 2012; Olson et al., 2016; Ji et al., 2016), particularly at daily scale for rainfall (Gilmore et al., 2016), although NARCliM has a quantitative cold and wet bias generally (Ji et al., 2016). In analysing the RCM component (WRF) of NARCliM, Evans and McCabe (2010) conclude that the El Niño-Southern Oscillation, the chief climate process modulating interannual variability of rainfall (Power et al., 1999), was well modelled over south-eastern Australia. Evans and McCabe (2010) also concluded that the severity and duration of recent prolonged droughts over south-eastern Australia were also captured, although the spatial pattern was not characterised exactly. The sub-tropical ridge, which determines the seasonal positioning of storm tracks over southern Australia, was less well represented by WRF (Andrys et al., 2016). For hydrological applications, a specific combination of land and atmospheric circulation schemes (R2) is recommended for hydrological applications (Olson et al., 2016). Although we consider the entire modelling ensemble in this paper, in a related paper (Charles et al., submitted) we use only that specific RCM physics scheme for modelling runoff. Based on the results cited above, we have confidence in the modelling setup of NARCliM to represent atmospheric circulation for southern Australia reasonably well, although we acknowledge that bias correction of NARCliM for end-user applications should consider model skill in atmospheric circulation.

4 Assessing the effect of bias correction on change factors in the future (i.e. whether to select bias correction methods that preserve trends)

Section 3.4 of the manuscript shows that bias correction can affect change signals (future relative to historical) of different hydroclimatic metrics (see also Hagemann et al., 2011; Gutjahr and Heinemann, 2013; Dosio, 2016). Under the assumption that bias is time invariant, Gobiet et al. (2015) argue that bias correction improves the accuracy of climate change signals. Cannon et al. (2015), however, argue that trend-preserving methods should be used (see also Li et al., 2010; Wang and Chen, 2014). Maraun (2016) and Maraun et al. (2017) summarise the debate surrounding the use of trend-preservation methods and conclude that the decision should be informed by the credibility or otherwise of the GCMs in representing the processes driving the changes. This further highlights the need for informed selection and screening of GCMs at the start of the modelling process. This has certainly occurred for the NARCliM projections as discussed above. However, we argue that there is value in reporting both pre- and post-bias correction future changes in light of the difficulties involved in model selection and assessment, particularly in the case of pre-existing and computationally expensive projections such as dynamically downscaled ensemble such as NARCliM.

5 Inflation and maintaining spatial correlation for runoff modelling

Inflation refers to a phenomenon in bias correction (Maruan, 2013) or statistical downscaling (von Storch, 1999) where an unmeasured predictand variable is estimated using the predicted values from a statistical model. Since models contain error, the variance of a timeseries of predicted values is expected to be less than the variance of the true time series of the variable. In the present context of bias correcting rainfall from RCMs, Maraun (2013) demonstrates that bias correction reduces subgrid spatial heterogeneity compared to actual precipitation, and that this is particularly problematic when GCM or RCM resolution is much greater than that of observations. In this case, the spatial correlation between gauges is increased. As a result, large rainfall amounts become overestimated and low amounts underestimated. Preserving the correct spatial correlation between gauges or gridpoints is an important issue, and the issue of unintended spatial effects of (temporal) bias correction is compounded by applying bias correction independently to each gridcell, as we have done here – although this tends to reduce subgrid spatial correlation (see Bardossy and Pegram, 2012; Hnilica et al., 2017). Maraun (2013) recommends aggregating catchment rainfall prior to bias correction to reduce the issue of inflation, and Charles et al. (2019, submitted) examine this in more detail in relation to catchment runoff production. Variance inflation due to differing grid cell sizes (Maraun, 2013) is less an issue for the current study, as NARCliM grid cell size is comparable to that of the gridded rainfall observations. Furthermore, the next generation of dynamically downscaled climate projections (Downes et al., 2019) is to be provided at 0.05°×0.05° resolution, identical with the gridded rainfall products used in Australia. However, the issue of using a bias correction methodology that corrects daily amounts (and more generally temporal structure) while preserving spatial structure across catchments and basins remains a challenge and is a direction for further research.

6 Consistency between rainfall and other atmospheric variables

In this study, rainfall alone is bias corrected; temperature or a different measure of atmospheric demand is not considered here. For runoff applications, a suitable representation of potential evapotranspiration is needed. Methods exist for correcting rainfall and temperature simultaneously (e.g. Hoffmann and Rath, 2012; Piani and Haerter, 2012; Mehrotra et al., 2018). However, potential evapotranspiration has a second-order effect on runoff compared to rainfall (Chiew, 2006; Potter et al., 2011), and bias correction was shown to not significantly affect the inherited relationships between rainfall and temperature (Wilcke et al., 2013). Certainly, the host GCM and RCM should correctly represent relationships between atmospheric variables in the study region, further highlighting the need for climate model assessment in construction of the model ensemble.

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