ORIGINAL ARTICLE

The influence of bias correction of global climate models prior to dynamical downscaling on projections of changes in climate: a case study over the CORDEX-Australasia domain

Karuru Wamahiu[1] · Jatin Kala[1] · Jason P. Evans[2,3]

Abstract

We investigate the influence of bias correction of Global Climate Models (GCMs) prior to dynamical downscaling using regional climate models (RCMs), on the change in climate projected. We use 4 GCMs which are bias corrected against ERA-Interim re-analysis as a surrogate truth, and carry out bias corrected and non-bias corrected simulations over the CORDEX Australasia domain using the Weather Research and Forecasting model. Our results show that when considering the effect of bias correction on current and future climate separately, bias correction has a large influence on precipitation and temperature, especially for models which are known to have large biases. However, when considering the change in climate, i.e the Δchange (future minus current), we found that while differences between bias-corrected and non-corrected RCM simulations can be substantial (e.g. more than 1 °C for temperatures) these differences are generally smaller than the models' inter-annual variability. Overall, averaged across all variables, bias corrected boundary conditions produce an overall reduction in the range, standard deviation and mean absolute deviation of the change in climate projected by the 4 models tested, over 61.5%, 62% and 58% of land area, with a larger reduction for precipitation as compared to temperature indices. In addition, we show that changes in the Δchange for DJF tasmax are broadly linked to precipitation changes and consequently soil moisture and surface sensible heat flux and changes in the Δchange for JJA tasmin are linked to downward longwave heat flux. This study shows that bias correction of GCMs against re-analysis prior to dynamical downscaling can increase our confidence in projected future changes produced by downscaled ensembles.

Keywords Bias correction · Regional climate modeling · Weather research and forecasting model · Dynamical downscaling · CORDEX

✉ Karuru Wamahiu
k.wamahiu@murdoch.edu.au

Jatin Kala
j.kala@murodch.edu.au

Jason P. Evans
jason.evans@unsw.edu.au

[1] Environmental and Conservation Sciences, Harry Butler Institute, Centre for Terrestrial Ecosystem Science and Sustainability, Murdoch University, Murdoch 6150, WA, Australia

[2] Australian Research Council Centre of Excellence for Climate Extremes, University of New South Wales, Sydney, Australia

[3] Climate Change Research Centre, University of New South Wales, Sydney, Australia

1 Introduction

Regional climate models (RCMs) are regularly used to produce high resolution regional climate simulations of past climate and projections of future climate over limited areas (e.g., Winterfeldt and Weisse 2009; Argüeso et al. 2012; Gao et al. 2012; Ma et al. 2015; Andrys et al. 2016). RCMs dynamically downscale global climate models (GCMs) and reanalysis to higher resolutions (often by an order of magnitude). They add value by better resolving the effects of factors such as topography and land-use on mesoscale weather systems, and are able to better simulate short-duration and extreme weather events (Rummukainen 2016). However, GCMs suffer from systematic biases, which degrade the downscaled simulations when GCMs are used as input to RCMs via lateral boundary conditions (LBCs, e.g., 6-hourly winds, potential temperature, sea surface temperatures, etc),

(Warner et al. 1997; Kim et al. 2000; Rojas and Seth 2003; Caldwell et al. 2009). Furthermore, even as GCMs performance continues to improve, systematic biases still persist (e.g., Grose et al. 2020) and as such there remains a need to reduce biases in the LBCs prior to downscaling (e.g., Done et al. 2013; Bruyére et al. 2013).

A number of statistical bias correction methods have been used to reduce biases in LBCs from GCMs used as input to RCMs. A popular approach is the pseudo-global-warming (PGW) correction, which involves reconstructing LBCs by adding projected changes in future climate from a GCM ensemble to reanalysis products (e.g., Schär et al. 1996; Wu et al. 2005; Hara et al. 2008; Kawase et al. 2009). However, PGW eliminates diurnal and synoptic effects and assumes no change in inter-annual variability at the boundaries. An approach which retains inter-annual variability and diurnal and synoptic effects in the LBCs involves removing climatological mean biases from the LBC using reanalysis as the surrogate truth (e.g., Holland et al. 2010). Xu and Yang (2012) extended this mean shift approach to correct both the mean and variances in the Community Atmosphere Model (CAM, Neale et al. 2010), using the National Oceanic and Atmospheric Administrations Centres for Environmental Prediction (NCEP)/National Center for Atmospheric Research (NCAR) Reanalysis (NNRP, Skamarock et al. 2008) as a surrogate truth, and found that the downscaled simulations better represented surface air temperatures and precipitation. Bruyére et al. (2013), used the method by Holland et al. (2010), to bias correct zonal and meridional winds, geopotential height, temperature, relative humidity, land and sea surface temperature and mean sea level pressure from the Community Climate System Model version 3 (Collins et al. 2006, CCSM3,) using NNRP reanalysis as a surrogate truth prior to downscaling. They found that when compared against observations (using IBTracs, Knapp et al. 2010), the bias corrected GCMs improved tropical cyclone representation in their regional climate model simulations. An alternative approach is to correct LBC using quantile mapping, which has been found to improve simulations of surface temperature and precipitation over Europe (Colette et al. 2012). White and Toumi (2013) compared the mean shift method and the quantile mapping approach and found that the former was a more reliable and accurate method for correcting LBCs prior to downscaling.

While it is well established that downscaled simulations are sensitive to biases from LBCs, few studies have investigated the value of dynamically downscaling bias corrected versus non-bias corrected GCMs over the Coordinated Regional Downscaling Experiment framework Australasian region (CORDEX Australasia). Rocheta et al. (2017) evaluated the impact that downscaling bias corrected Commonwealth Scientific and Industrial Research Organization (CSIRO) MK3.5 GCM (Gordon et al. 2010) had on low

frequency rainfall variability, using the mean shift method (Holland et al. 2010), a more complex variance correction (Xu and Yang 2012) and low frequency variability bias correction (Johnson and Sharma 2012). Overall they found that the mean shift method produced the largest improvements in low frequency rainfall, and similar to White and Toumi (2013), the more complicated techniques led to incrementally more skillful simulations.

Using this mean shift method Wamahiu et al. (2020) bias corrected and dynamically downscaled outputs from 4 GCMs over the CORDEX Australia domain under current/historical climate. They evaluated the performance of the non-bias corrected and bias corrected simulations against observations and found that, overall, large precipitation and temperature biases were removed. However, in some instances, small biases were either introduced where there were none or there was a slight deterioration in biases in some regions over the domain. Nevertheless, due to its potential to reduce large systematic biases, Wamahiu et al. (2020) found that there was value in using this mean shift method to correct biases in the GCMs prior to downscaling over the CORDEX-Australasia domain.

The above studies demonstrate that using bias corrected GCM boundary conditions produce RCM simulations with lower biases. To the best of our knowledge, no studies have evaluated the impact of using bias corrected GCM boundary conditions in RCM simulations in relation to the projected change in climate—i.e., what is the difference in the change in climate (future minus current climate) between bias corrected and non-corrected simulations? Furthermore, we investigate whether bias-correction of the lateral boundary conditions reduces the uncertainty in the projected changes in climate. We answer these questions by building on our previous study (Wamahiu et al. 2020), in order to examine the impact on future changes projected.

2 Methods

2.1 Model configuration

Following our previous study (Wamahiu et al. 2020), historical and future regional climate simulations, using 4 CMIP3 GCMs as boundary conditions, were carried out between 1970–1999 and 2030–2059 from a single initialization with a 3 model month spin up. Historical (and similarly future climate simulations) consisted of 4 control simulations, using non-bias corrected GCMs and 4 simulations that were bias corrected using ERA-Interim re-analysis (Dee et al. 2011) as the surrogate truth. Following our previous studies (Andrys et al. 2016; Wamahiu et al. 2020) the 4 GCMs were: Max Planck Institute ECHAM5 model (ECHAM) (Roeckner et al. 2003), Center for Climate System Research Model

for Interdisciplinary Research on Climate 3.2 (MIROC) (Hasumi and Emori 2004), National Center for Atmospheric Research Community Climate System Model version 3 (CCSM) (Collins et al. 2006) and the Commonwealth Scientific and Industrial Research Organization (CSIRO) MK3.5 (Gordon et al. 2010), and we used the A2 scenario for future climate.

All WRF simulations utilized a single 50 km horizontal resolution domain covering the CORDEX Australasia region as shown in Fig. 1, with 30 vertical levels spaced more closely within the boundary layer; and further apart in the upper atmosphere. The WRF parameterization options used were identical to Andrys et al. (2015, 2016), which were based on a previous sensitivity study by Kala et al. (2015). This includes the single-moment 6-class microphysics scheme (Hong and Lim 2006), RRTM long-wave radiation model (Mlawer et al. 1997), Dudhia short-wave radiation (Dudhia 1989), Yonsei University planetary boundary layer scheme (Hong and Lim 2006), the MM5 surface layer scheme (Grell et al. 2000), convective parameterization from Kain Fritsch (Kain 2004) and Noah land surface model (Chen and Dudhia 2001). Similar to Andrys et al. (2015), simulations were carried out over the period 1970–1999 and spectral nudging was used to avoid model drift to ensure the retention of the large scale features in the GCM, a common practice for regional climate simulations (e.g., Argüeso 2011). In particular an x and y wavenumber of 5 and 4 were chosen and all variables (U and V winds, geopotential height and potential temperature) above the planetary boundary layer for wavelengths exceeding 1000 km were nudged.

2.2 Bias correction

Following Holland et al. (2010), temperature, geopotential height, meridional and zonal winds, and relative humidity lateral boundary conditions, as well as sea level pressure and sea surface temperature (SST) lower boundary conditions from ERA-Interim were used to correct the GCMs. The mean climatological components are defined over a 20 year base period (1980–1999) for both ERA-Interim and the GCMs.

To correct the GCMs, 6 hourly GCM and ERA-Interim reanalysis data was first broken down into a mean climatological component plus a perturbation term:
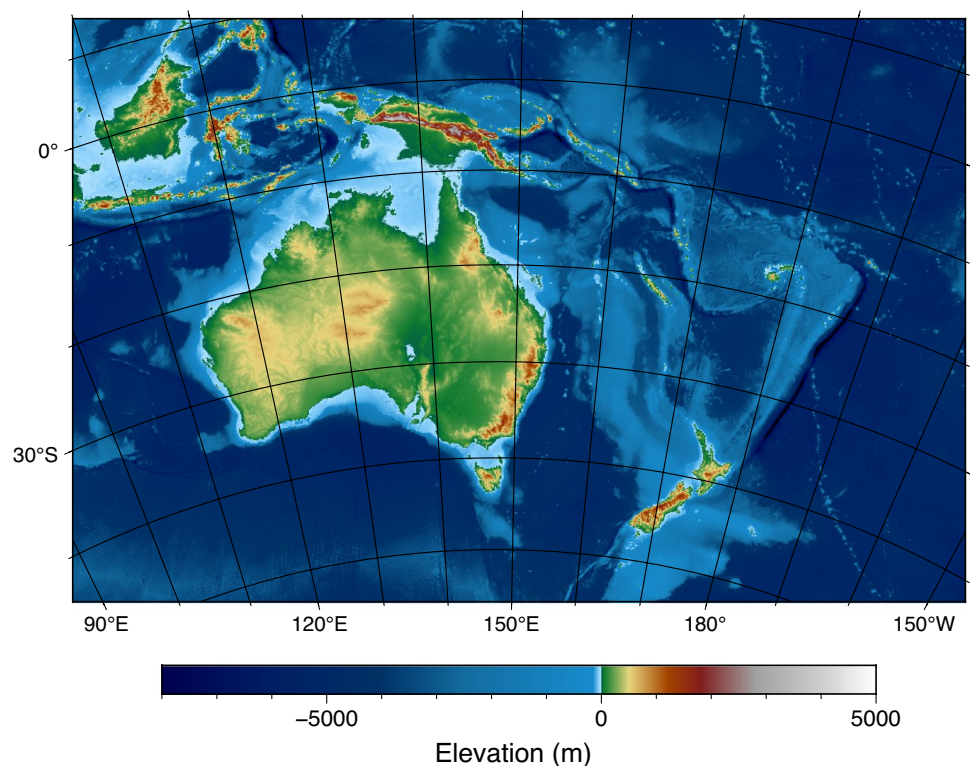
$$GCM = \overline{GCM} + GCM' \tag{1}$$

$$ERA = \overline{ERA} + ERA' \tag{2}$$

For any considered period of interest, i.e,. 1970–1999 for current climate and 2030–2059 for future climate, the bias corrected LBCs for the period, denoted as GCM_c^* are computed as:

$$GCM_c^* = \overline{ERA}_b + GCM' \tag{3}$$

Fig. 1 Topographical map showing the extent of the CORDEX Australasia domain

where $\overline{\text{ERA}}_b$ is mean over the base-period, and GCM' is computed over the considered period of interest.

2.3 Analysis methods

To examine the effect of bias correction on the change in climate, we evaluate the Δchange (future - historical), in the bias corrected (BC) and non-bias corrected (NC) simulations, between future (2030–2059) and historical (1970–1999) climate. We focused our analysis on a few select variables: summer maximum temperature (DJF tasmax), winter minimum temperatures (JJA tasmin), yearly total precipitation (PRCPTOT), as well as the following extreme indices recommended by the Expert Team on Sector-Specific Climate indices: annual maximum value of daily maximum temperature (TXX), annual minimum value of daily minimum temperature (TNN), and rainfall > 95th percentile (R95P) in a given period. When assessing these changes we calculate the statistical significance for each grid cell using the non-parametric Mann–Whitney U-test ($\alpha = 0.05$), with stippling used to indicate areas with statistical significance. We then evaluate the differences in the Δchange between BC and NC simulations for each variable.

To understand whether the changes are important we examine them relative to inter-annual variability. We calculated the normalised difference between BC and NC simulations using the historical inter-annual standard deviation from NC as follows:

$$\frac{\mu_{\text{BC}} - \mu_{\text{NC}}}{\sigma_{NC}} \tag{4}$$

Equation 4 allows us to quantify the extent to which the changes introduced by the bias correction are larger/smaller than inter-annual standard deviation, i.e., internal model variability. For these plots, stippling is used to highlight grid cells with values > 1 or < -1, which indicate that differences between the BC and NC means are larger than the inter-annual standard deviation. This analysis is carried out for all variables for each GCMs/RCM under historical climate, future climate, as well as the Δchange (future - historical).

Next, we examined whether bias correction of GCMs to a common re-analysis reduces the range and variability in the Δchange between the downscaled simulations. To answer these questions we first examined the differences in the maximum range:

$$\text{range}(BC) - \text{range}(NC)$$

where range(X) is defined as the difference between the maximum and minimum values in (X). We then examined the standard deviation (σ) and the difference in mean absolute deviation (MAD)

$$\sigma(BC) - \sigma(NC)$$

$$\text{MAD}(BC) - \text{MAD}(NC)$$

where MAD is defined as median of the absolute deviations from the data's median $\tilde{X}$

$$\text{MAD} = \text{median}(|\, X_i - \tilde{X} \,|)$$

For example, suppose the Δchange in DJF tasmax at a particular grid point from the 4 GCM/RCM NC and BC simulations is, respectively, [2.0, 2.5, 1.5, 4.0] and [1.5, 1.8, 1.4, 2.0]. Then the difference between BC and NC in their range, σ and MAD is then -1.9 ($0.6 - 2.5 = -1.9$), -0.8 ($0.28 - 1.28 = -0.8$) and -0.3 ($0.2 - 0.5 = -0.3$). This tells us that at this grid point for DJF tasmax, bias correction has reduced the range and variability in the Δchange, and hence, reduced uncertainty with higher convergence of results between the 4 simulations. These calculations are carried out for each variable separately, and to produce an overall summary for temperature and precipitation indices, we then normalized the differences by the observed inter-annual standard deviation, using gridded observations from the Australian Water Availability Project (AWAP) (Jones et al. 2009) dataset, which provides daily gridded observations of maximum and minimum temperature and precipitation at a 5 by 5 km resolution.
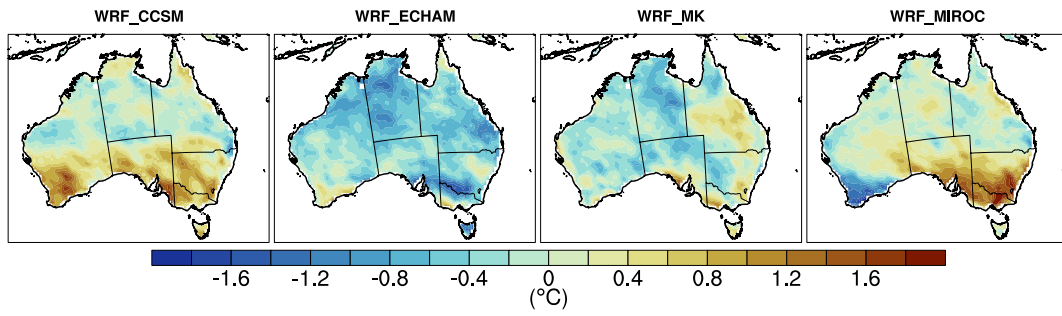
3 Results

Figure 2a–d show the differences in the Δchange (2030–2059 minus 1970–1999) between BC and NC (BC minus NC) for DJF tasmax, TXX, JJA tasmin and TNN respectively. These plots show spatially varying differences between BC and NC simulations which can be quite large, with differences for DJF tasmax (Fig 2a) and TXX (Fig. 2b) of up to ±1.6 °C. For DJF tasmax in WRF_CCSM, the BC simulations have a larger Δchange than NC by up to +1.2 °C over the southeast of Australia. For WRF_ECHAM and WRF_MK, BC simulations tend to simulate a smaller Δchange than NC, especially in the north, and for WRF_MIROC, BC simulations have a larger Δchange for most of the east of approximately +1.2 °C but smaller Δchange over the southwest of up to −1.0 °C. For TXX in WRF_MIROC, BC simulations simulates a smaller Δchange than NC by up to −1.4 °C over the southwest and a larger change by up to +1.6 °C over the southeast of Australia. In WRF_CCSM, the Δchange in TXX is similarly larger over both the southeast and the southwest, and for WRF_ECHAM and WRF_MK, the BC simulations generally simulate a smaller Δchange. Similarly, JJA tasmin (Fig. 2c) and TNN (Fig. 2d) show spatially varying differences which can be quite large. WRF_ECHAM and WRF_MIROC BC simulations showed consistently larger
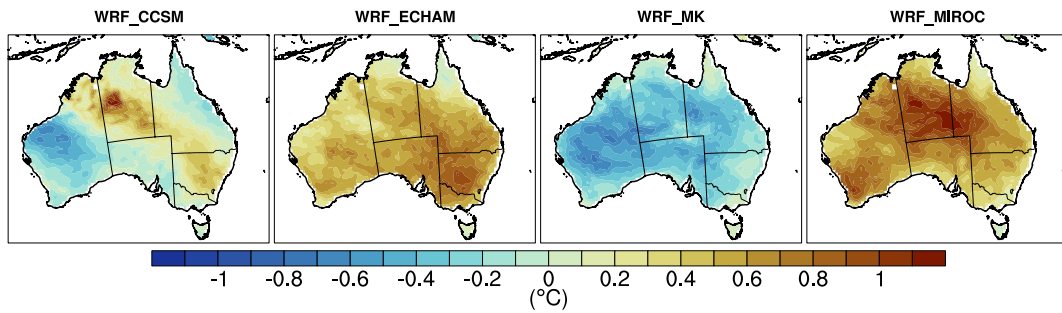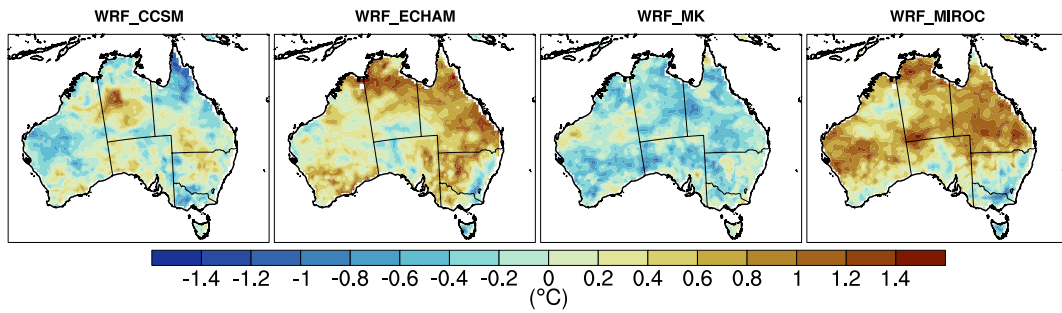
(a) DJF tasmax
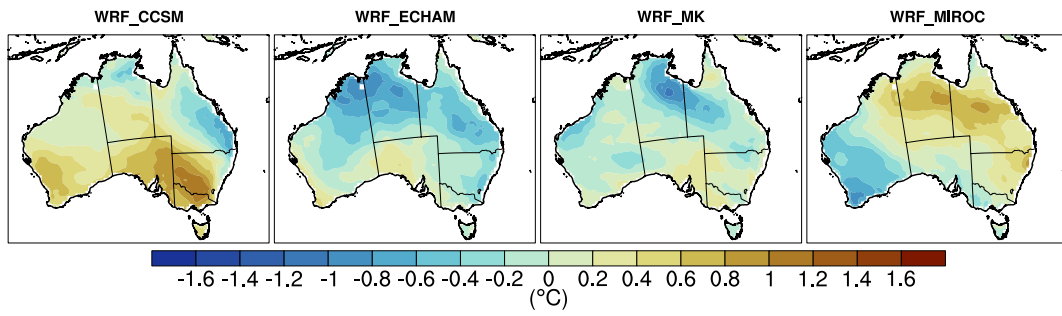
(b) TXX

(c) JJA tasmin

(d) TNN

Fig. 2 Differences in the Δchange between BC and NC for DJF tasmax, TXX, JJA tasmin, TNN

Δchange in JJA tasmin over most of the continent by up to +1.0 °C, whereas WRF_MK showed the opposite result, and WRF_CCSM showed regions of both larger and smaller changes. Overall, the TNN results reflected the JJA tasmin results. When considering the Δchange in BC and NC separately for DJF tasmax, JJA tasmin, TXX and TNN (Figs. S1–S4), results show very consistent warming signals, that were statistically significant across the entire, if not most of the continent. However, what Fig. 2a–d clearly highlight, is that the magnitude of the Δchange can be large.

To better contextualize the differences in the Δchange between BC and NC simulations, we next examined the normalized differences, which compares differences in the Δchange between BC and NC relative to the model inter-annual variability. This is shown in Fig. 3a–d with stippling indicating regions where normalized changes are < −1 or > 1 and hence showing where the effect of bias correction is larger than the models inter-annual variability. The plots show that normalized differences generally lie between −1 and 1 for all 4 variable over most of the continent, but there are some exceptions. Regions in these plots where the differences are larger than the models inter-annual variability (i.e. less than −1 and greater than 1) tend to correspond to areas where the differences in the Δchange between BC and NC are ±1 °C (Fig. 2a–d), but the converse is not always true. For DJF tasmax, except for relatively small parts of southeast Australia in WRF_CCSM and southwest Australia in WRF_MIROC, differences are less than model inter-annual variability. Similar for TXX, there are only small parts in southwest Australia in WRF_CCSM and WRF_MIROC where changes are greater than model inter-annual variability. However, for JJA tasmin, there are much larger areas that show differences greater than model inter-annual variability, in WRF_ECHAM over southeast Australia and WRF_MIROC over southwest Australia and part of eastern Australia. Results for TNN were quite similar to TXX with only relatively small regions where the changes where greater than +1. Overall, except for JJA tasmin for two of the 4 models, the difference in the Δchange is not distinguishable from the model's inter-annual variability. This provides confidence in the Δchange irrespective of whether bias correction is used or not.

When considering the historical and future periods separately (S5–S8), the normalized difference plots show that difference in the Δchange between BC and NC can be larger than the models inter-annual variability (i.e. less than −1 or greater than 1) over large parts, if not most of the continent, unlike differences in the Δchange (Fig. 3a–d). In particular, for DJF tasmax (Fig. S5) and TXX (Fig. S6) these differences are larger in WRF_MIROC and WRF_MK over the continent, and, in WRF_ECHAM over large parts of the continent, except for the future period in TXX where they are smaller. For JJA tasmin (Fig. S7) differences tend to be

larger than the models inter-annual variability over more of the continent under the future climate than under historical climate, with normalized differences in WRF_ECHAM and WRF_MIROC greater than +1 over a majority of the continent under future climate. Results for TNN are similar to JJA tasmin, with being differences are larger than the models inter-annual variability over more of the continent under future climate than historical climate, but only in WRF_ECHAM are the normalized differences greater than +1 over a majority of the continent. These plots highlight that bias correction can have a large influence on historical and future climate when they are considered individually (rather than the Δchange). These findings are consistent with our previous work (Wamahiu et al. 2020) which showed that for large systematic maximum temperature biases found in WRF_ECHAM, WRF_MIROC and WRF_MK, bias correction had a large influence, and for smaller systematic biases found in WRF_CCSM, bias correction had less of an influence. Overall, Fig. S5–S8 show that while the differences in the Δchange between BC and NC can be quite large (Fig. 2a–d), these differences are generally smaller than the models inter-annual variability (Fig. 3a–d).

We next examine differences in the Δchange between BC and NC in PRCPTOT and R95P (Fig. 4a–b). For PRCPTOT, in WRF_CCSM, WRF_ECHAM and WRF_MK, the BC simulations have a larger Δchange than the NC simulations over the a majority of the continent, with differences of up to +400 mm over northern Australia in WRF_ECHAM and WRF_MK. In WRF_MIROC, the plots show that BC simulations has a larger Δchange over western Australia with differences of up to +100 mm, but smaller Δchange over northern Australia with differences of up to −300 mm. Results for R95P are similar to PRCPTOT in WRF_CCSM, WRF_MK and WRF_MIROC. Result for R95P are generally similar to PRCPTOT. When the future and historical periods are considered separately (Fig. S9 and S10), the plots show that the direction and magnitude of the changes are not consistent and that these changes are generally not statistically significant, except for small parts of the continent. In spite of this, what Fig. 4a, b highlight, is that the magnitude of the Δchange can be large, particularly over northern Australia.

Figure 5a, b show the normalized differences in the Δchange between BC and NC, and illustrate that differences are smaller than the models inter-annual variability (i.e. lie between −1 and 1) across the continent except for small regions in WRF_MIROC and WRF_ECHAM where the differences are larger. When the future and historical periods are considered separately (Fig. S11 and S12), the plots show for PRCPTOT that the effect of bias correction is generally smaller than the inter-annual variability across most of the continent in all models except for WRF_MIROC, where it is larger across most of the continent and, hence, indicating that, for this model, bias correction had a large influence.

(a) DJF tasmax

(b) TXX

(c) JJA tasmin

(d) TNN
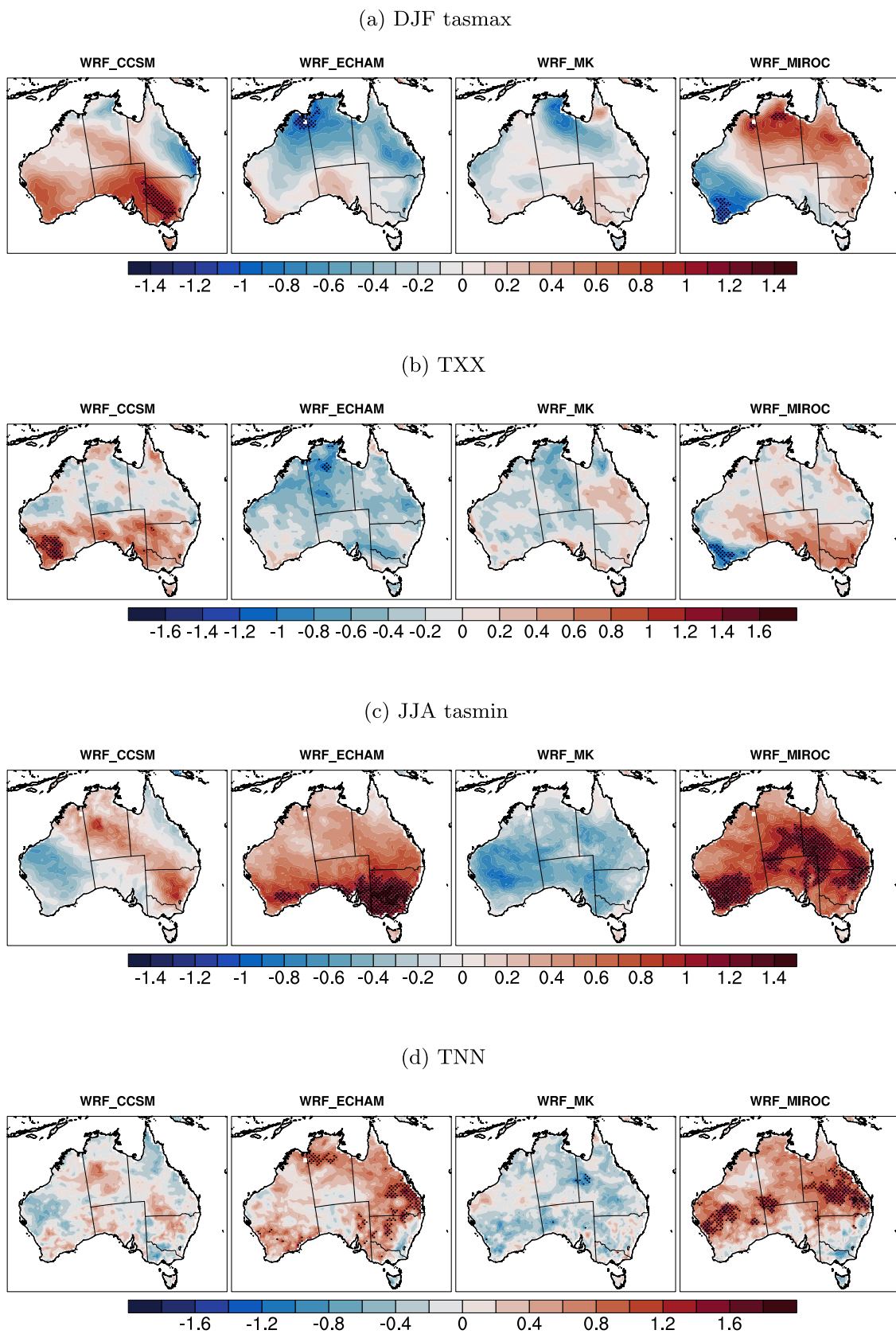
Fig. 3 Differences in the Δchange normalized against the inter-annual standard deviation from the historical NC simulations (σ_{NC}) for DJF tasmax, TXX, JJA tasmin, TNN. Stippling shows regions where normalized difference < -1 or > 1

(a) PRCPTOT

(b) R95P
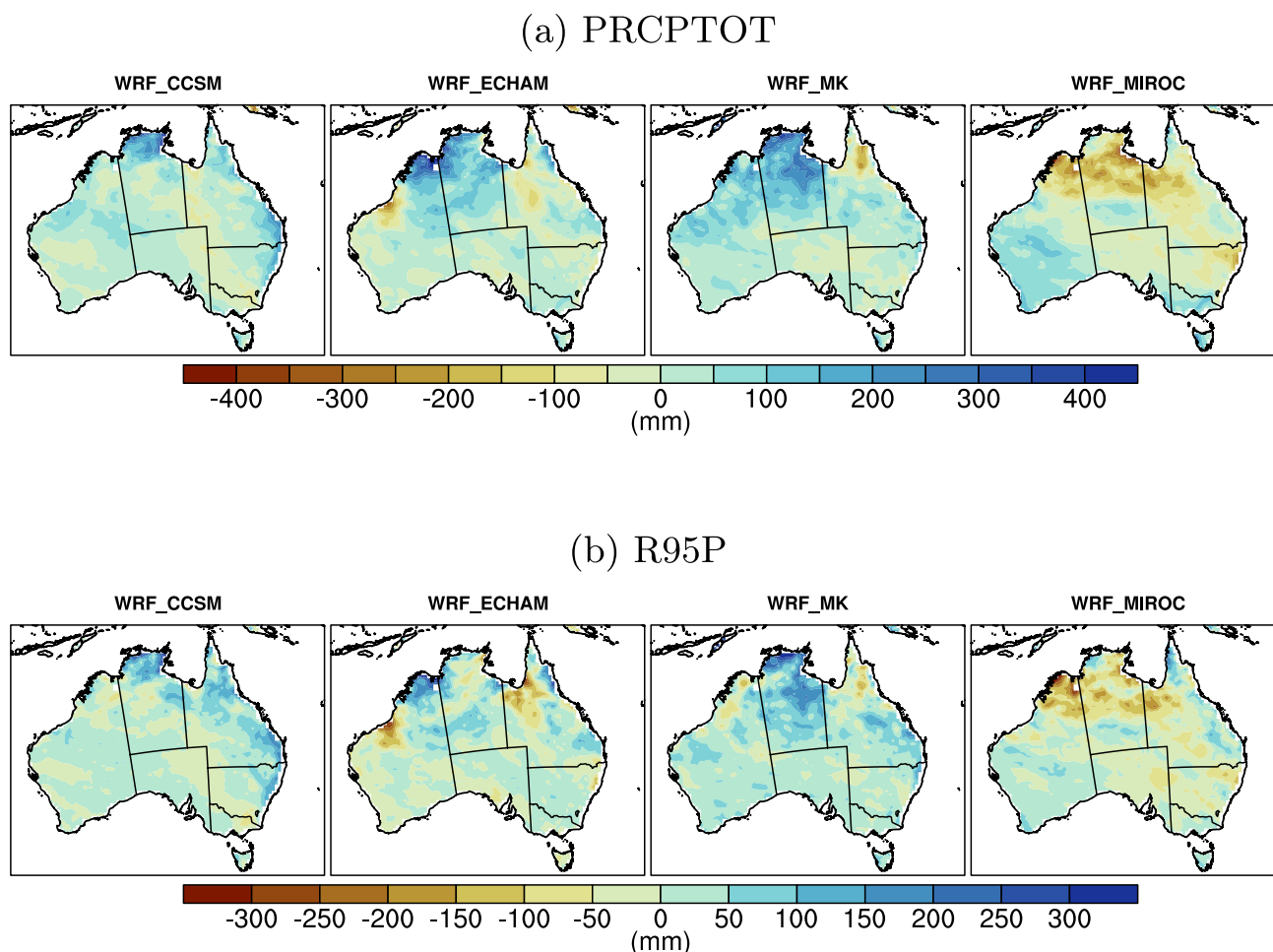
Fig. 4 Differences in the Δchange between BC and NC for the future period for PRCPTOT, R95P

These findings are broadly consistent with our previous work (Wamahiu et al. 2020), which demonstrated that for large seasonal precipitation biases in WRF_MIROC, bias correction had a large influence in reducing model biases when compared against observations. For R95P (Fig. S12), the plots show that the effect of bias correction is smaller than the inter-annual variability over most of the (if not the entire) continent, except under future climate in WRF_MIROC over large parts of northwestern and northern Australia. Similar to the temperature indices, while the differences in the Δ change between BC and NC can be quite large (Fig. 4), these changes are generally smaller than the models inter-annual variability (Fig. 5).

Having examined the change in temperature and precipitation indices we next examine if bias correction of GCMs to a common re-analysis reduces the range and variability in the Δchange. Figure 6 and Figures S13 and S14 in the supplementary material show the mean normalized difference in the range, standard deviation (σ) and median absolute deviation (MAD) in Δchange, for the temperature indices,

precipitation indices and when all the variables are combined (i.e. for both temperature and precipitation indices). When all the variables are combined the plots show that percentage of land area where a reduction in the range, σ and MAD is observed is 61.53%, 62.24% and 58.85% respectively. These were largely driven by a large reduction in the precipitation indices relative to the temperature indices. For the precipitation indices the plots show that percentage of land area where a reduction in the range, σ and MAD is observed is 74.3%, 75.07% and 69.53% compared to 37%, 38.07% and 43.08% for the temperature indices. These results show that bias correction can have a large influence on the ensemble range and variability; particularly for precipitation changes. This is consistent with previous studies that have demonstrated that bias correction has a large influence on systematic precipitation biases for regional climate simulations over Australia (Rocheta et al. 2017; Wamahiu et al. 2020).

Finally, we examine possible mechanisms that are driving differences in the Δchange, particularly with regards

(a) PRCPTOT

(b) R95P
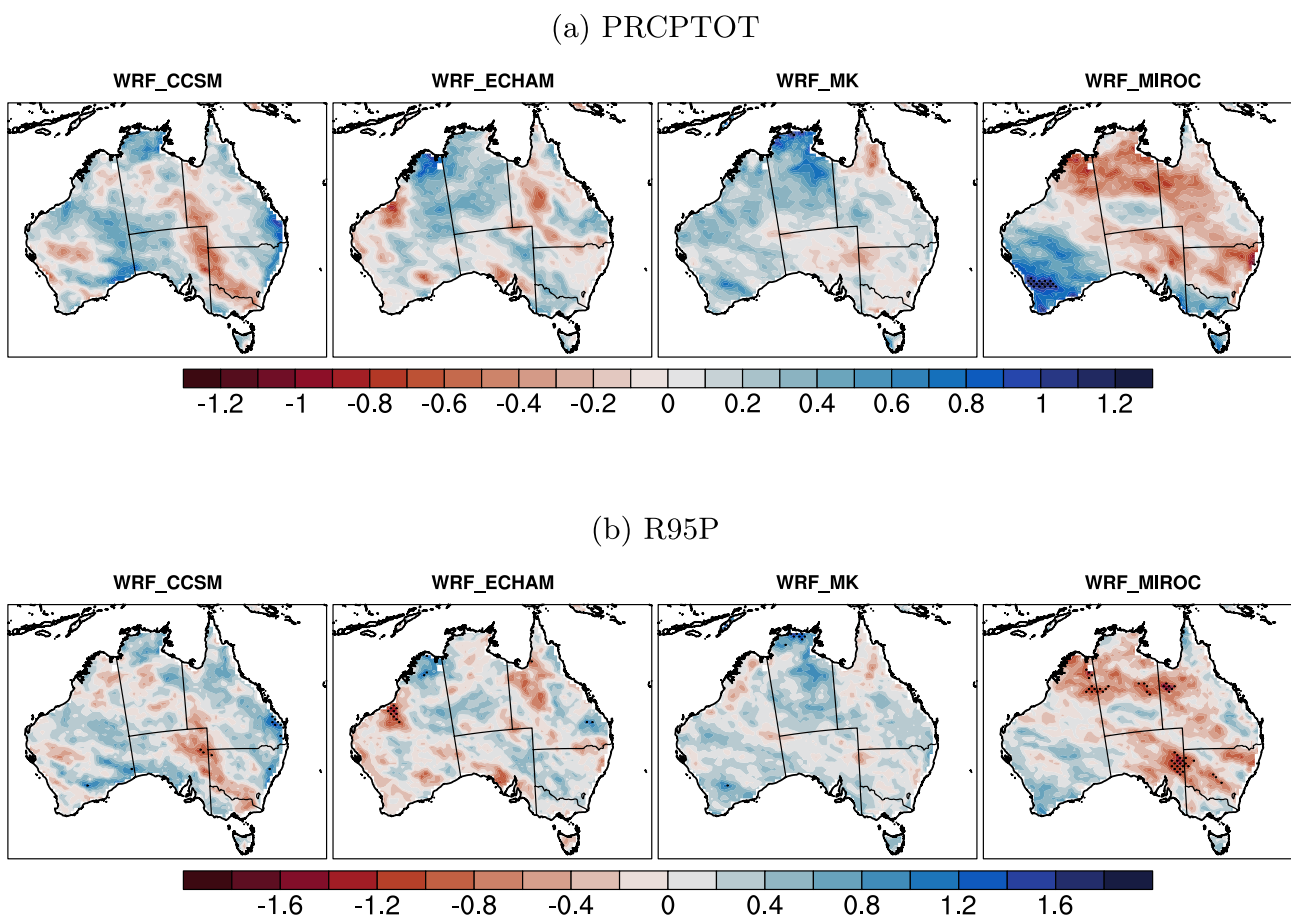
Fig. 5 Differences in the Δchange normalized against the inter-annual standard deviation from the historical NC simulations (σ_{NC}) for PRCP-TOT and R95P. Stippling shows regions where normalized difference < −1 or > 1
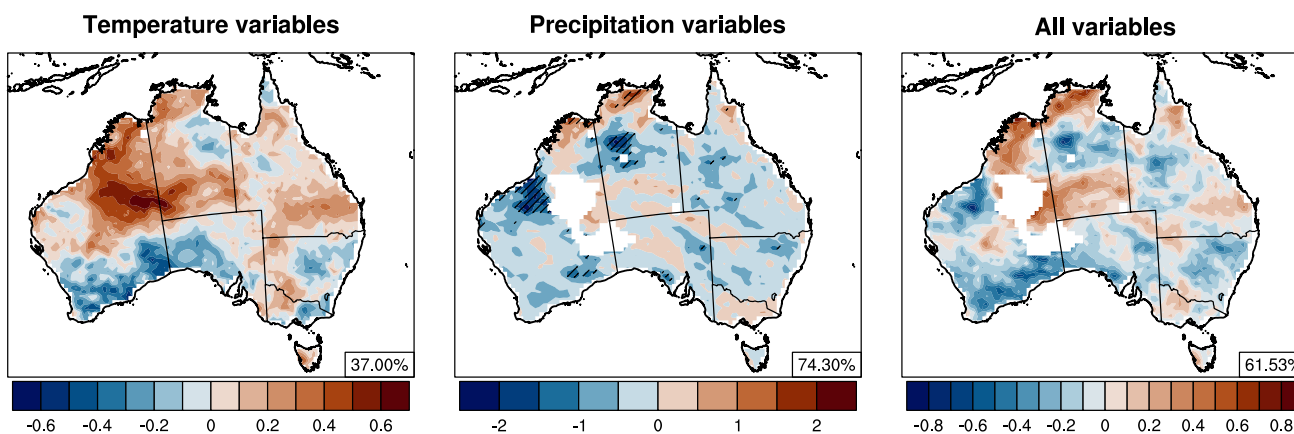

Fig. 6 Mean normalized differences (BC − NC) of the range in the Δ change from the 4 models for the temperature indices, precipitation indices and combined precipitation and temperature indices. Percentages at the bottom right indicate the percentage of land area where there is a reduction in the range. Stippling shows where the mean normalized differences are larger than +1 or smaller than −1. Areas which are white indicate regions where observed precipitation data is missing

to the changes in DJF tasmax and JJA tasmin (Fig. 2). Given that previous studies over the CORDEX Australasia domain have highlighted that changes in precipitation have a large influence on changes in maximum temperature in this region (Di Virgilio et al. 2019), we examined the changes in DJF total precipitation, soil moisture (SMOIS), and surface sensible (HFX) and latent heat (LH) fluxes. This is illustrated in Fig. 7a–d showing the differences in the Δ change (2030–2059 minus 1970–1999) between BC and NC (BC minus NC) in WRF_CCSM for DJF for WRF_CCSM. Results show similar spatial patterns, which tend to correspond to the differences in the Δchange in DJF tasmax in WRF_CCSM (Fig. 2a). Over the southeast of Australia, BC simulations show a smaller Δchange in total precipitation, which corresponds to lower SMOIS and a corresponding decrease in LH and increase in HFX, which can explain the spatial patterns observed in differences in the Δchange

between the BC and NC simulations in WRF_CCSM DJF tasmax (Fig. 2a). Results for the other 3 models are shown in Fig. S15, S17 and S19, and similar mechanisms can explain most of the changes in DJF tasmax, however, for some models, e.g., WRF_MK, there are clearly other processes that we have not identified that are also driving changes in DJF tasmax.

Projected minimum temperature increases can be associated with an increase in nighttime cloud cover, as clouds are effective at reflection and emission of terrestrial longwave radiation to the surface. This is illustrated in Fig. 8a–c showing the differences in the Δchange between BC and NC (BC minus NC) in WRF_CCSM for low level (LL, 300 m) and mid level (ML, 600 m) cloud fraction (CLDFRAC) and downward longwave flux at the surface (GLW) during JJA for WRF_CCSM. The plots show a prominent northwest-southeast pattern that corresponds to the changes in the Δ
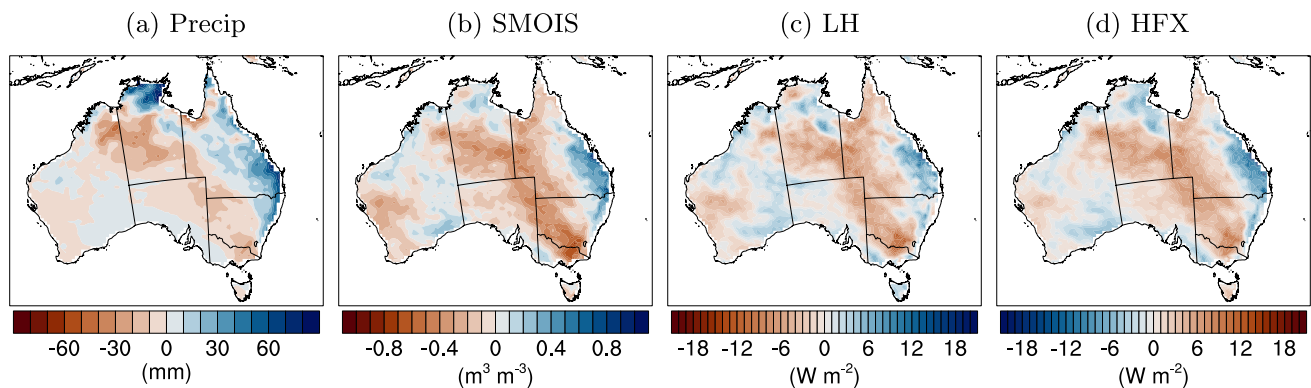
Fig. 7 Differences in the Δchange for WRF_CCSM between BC and NC showing DJF **a** precipitation, **b** soil moisture at the surface, **c** latent heat flux at the surface and **d** upward heat flux at the surface
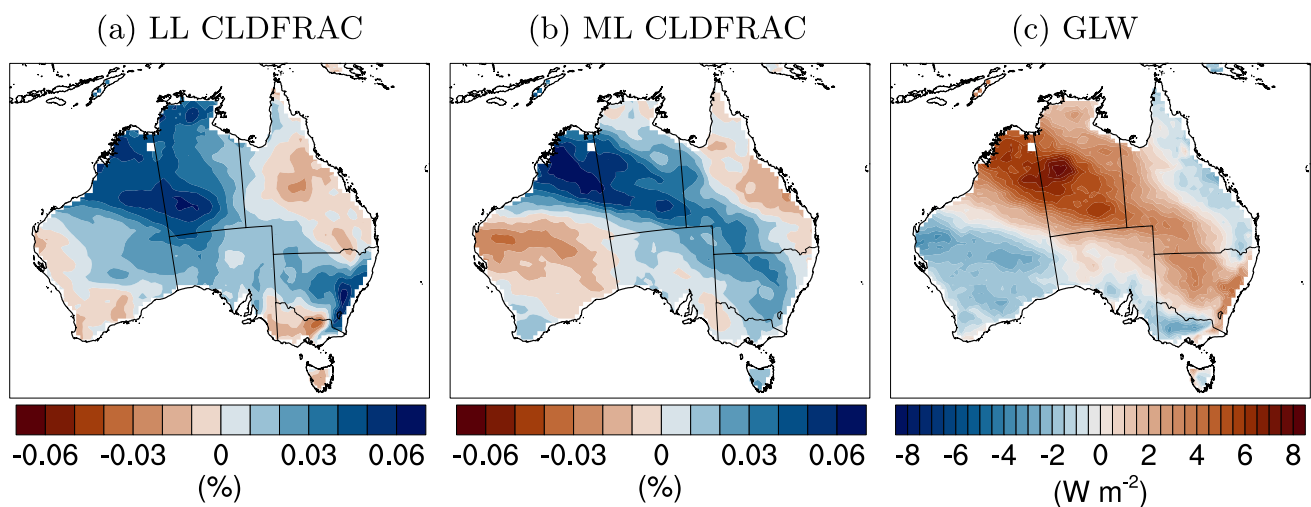
Fig. 8 Differences in the Δchange for WRF_CCSM showing JJA **a** low level cloud fraction (300 m), **b** mid level cloud fraction (600 m), **c** downward longwave heat flux at the surface

change for WRF_CCSM JJA tasmin (Fig. 2c). The BC simulation has a larger Δchange across this northwest-southeast band in both LL and ML CLDFRAC, and this correspond the and BC simulations having a larger Δchange in GLW. These changes help explain the large Δchange in JJA tasmin over this region. Results for the other 3 models are shown in Fig. S16, S18, and S20 show that changes in JJA JJA tasmin largely correspond to changes in GLW, however, the changes in LL and ML CLDFRAC do not always explain the changes in GLW. This is particularly evident for WRF_MK, and this requires further investigation.

While we have explored possible mechanisms that drive the maximum and minimum temperature changes, we have not explored how bias correction influences factors that drive the changes in precipitation (for TMAX changes) and cloud fraction (for TMIN changes). These could be due to a number of complex interactions that would require substantial further analysis that is beyond the scope of this paper.

4 Discussion and conclusion

While a number of studies have demonstrated the added value of bias correcting GCMs against re-analysis prior to dynamical downscaling over the CORDEX Australasia domain (eg. Rocheta et al. 2017; Wamahiu et al. 2020) and other regions (eg. Bruyére et al. 2013; Xu and Yang 2012), to the best of our knowledge, no study has evaluated the effect of using bias corrected LBCs on the change in climate (i.e. the Δchange) projected by regional climate model simulations. In this study, we build upon our previous work (Wamahiu et al. 2020), where we evaluated the value of using the mean shift method to bias correct 4 GCMs (CCSM3, ECHAM5, MIROC32 and MK35) for use in RCM simulations over the CORDEX Australasia domain under historical climate, and showed that bias correction reduced large systematic precipitation and temperature biases. In this study, we use future climate simulations to investigate the effect of bias correction on the Δchange (future minus historical), the effect of bias correction relative to models' inter-annual variability, and whether bias correction of a GCM ensemble using a common re-analysis reduces the uncertainty (i.e. the range and variability) in the mean change in climate in the RCM simulations.

We found that while DJF tasmax, JJA tasmin, TXX and TNN (Fig. S1–S4) showed broadly consistent projected temperature increases, differences in the Δchange between BC and NC (Fig. 2) projections exceeded ±1 °C in some regions. However, these differences were generally smaller than the models' inter-annual variability, and hence not distinguishable from year-to-year variations. When considering historical and future periods separately, the effect of bias correction was quite large and greater than model

inter-annual variability, especially for models which we found to have large systematic biases in our previous study (Wamahiu et al. 2020). However, since the bias correction is applied to both current and future climate, differences in the Δchange remain small relative to model inter-annual variability.

Differences between BC and NC PRCPTOT changes show that BC simulations are wetter than in NC simulations, especially over the tropics for 3 out of the 4 GCMs used, however, these differences were not considered statistically significant. Similar to our results for temperature, the effect of bias correction on the Δchange in PRCPTOT was smaller than the models' inter-annual variability. For historical and future periods alone, the effect of bias correction was also smaller than the inter-annual variability in all models except for WRF_MIROC. This is consistent with our previous work (Wamahiu et al. 2020) which showed that WRF_MIROC had a large reduction in precipitation bias under historical climate when bias correction was used.

Overall, when averaged across all variables, bias correction resulted in a reduction in the range and variability of the projected change in climate from the 4 models, with a larger reduction for precipitation as compared to temperature indices. That is, the future change projected by the ensemble tends to converge if the LBCs are bias-corrected. This occurs despite the difference in the Δchange between BC and NC for any individual model and variable being small compared to inter-annual variability. This convergence in the future change improves our confidence in the projections, especially for precipitation. Finally, the fact that overall differences in the Δchange were generally smaller than model inter-annual variability provides confidence in studies that do not use bias correction prior to downscaling to within this range of uncertainty.

We acknowledge that while downscaling 4 GCMs is reasonable size for dynamic dowsaling, this is still a small sample size. In addition, we use of CMIP3 GCMs rather than the more up-to-date CMIP5 and CMIP6 GCMs, and this was due to our previous work (Wamahiu et al. 2020) being based on CMIP3. However, our results are relevant irrespective of the family of GCM used, and our results provide useful guidance on the use of bias correction for future studies that used CMIP5 and CMIP6 GCMs. We also note that studies comparing changes in temperature and precipitation over Australia between CMIP3 and CMIP5 GCMs report broadly similar magnitudes of change (Li et al. 2015), and this gives us confidence that our results are useful in informing future projected changes in climate over Australia. Our future work will focus on CMIP5 and CMIP6 GCMs.

Data availability Data will be made available upon request to the corresponding author.

Declarations

Conflict of interest The authors have no conflicts of interest to declare that are relevant to the content of this article.

References

Andrys J, Lyons TJ, Kala J (2015) Multidecadal evaluation of WRF downscaling capabilities over Western Australia in simulating rainfall and temperature extremes. J Appl Meteorol Climatol 54:370–394. https://doi.org/10.1175/JAMC-D-14-0212.1

Andrys J, Lyons TJ, Kala J (2016) Evaluation of a WRF ensemble using GCM boundary conditions to quantify mean and extreme climate for the southwest of Western Australia (1970–1999). Int J Climatol 36:4406–4424. https://doi.org/10.1002/joc.4641

Argüeso D (2011) High-resolution projections of climate change over the Iberian Peninsula using a mesoscale model. PhD thesis, Department of Applied Physics

Argüeso D, Hidalgo-Muñoz JM, Gámiz-Fortis SR et al (2012) Evaluation of WRF parameterizations for climate studies over southern Spain using a multistep regionalization. J Clim 24:5633–5651. https://doi.org/10.1175/jcli-d-11-00073.1

Bruyére C, Done J, Holland G et al (2013) Bias corrections of global models for regional climate simulations of high-impact weather. Clim Dyn 43:1–10. https://doi.org/10.1007/s00382-013-2011-6

Caldwell P, Chin HNS, Bader DC et al (2009) Evaluation of a WRF dynamical downscaling simulation over California. Clim Change 95:499–521. https://doi.org/10.1007/s10584-009-9583-5

Chen F, Dudhia J (2001) Coupling an advanced land surface-hydrology model with the Penn State-NCAR MM5 modeling system. Part I: model implementation and sensitivity. Mon Weather Rev 129:569–585. https://doi.org/10.1175/1520-0493(2001)129<0569:caalsh>2.0.co;2

Colette A, Vautard R, Vrac M (2012) Regional climate downscaling with prior statistical correction of the global climate forcing. Geophys Res Lett. https://doi.org/10.1029/2012gl052258

Collins WD, Rasch PJ, Boville BA et al (2006) The formulation and atmospheric simulation of the community atmosphere model version 3 (CAM3). J Clim 19:2144–2161

Dee DP, Uppala SM, Simmons AJ et al (2011) The ERA-interim reanalysis: configuration and performance of the data assimilation system. Q J R Meteorol Soc 137:553–597. https://doi.org/10.1002/qj.828

Di Virgilio G, Evans JP, Alejandro DL et al (2019) Evaluation of ERA-Interim-driven CORDEX regional climate model simulations over Australia. Clim Dyn 53:2985–3005

Done JM, Holland GJ, Bruyère CL et al (2013) Modeling high-impact weather and climate: lessons from a tropical cyclone perspective. Clim Change 129:381–395. https://doi.org/10.1007/s10584-013-0954-6

Dudhia J (1989) Numerical study of convection observed during the winter monsoon experiment using a mesoscale two-dimensional model. J Atmos Sci 46:3077–3107. https://doi.org/10.1175/1520-0469(1989)046<C3077:NSOCOD>E2.0.CO;2

Gao X, Shi Y, Zhang D et al (2012) Uncertainties in monsoon precipitation projections over China: results from two high-resolution RCM simulations. Climate Res 52:213–226. https://doi.org/10.3354/cr01084

Gordon HB, O'Farrell S, Collier M et al (2010) The CSIRO Mk3. 5 climate model. CSIRO and Bureau of Meteorology. http://www.cawcr.gov.au/technical-reports/CTR_021.pdf

Grell GA, Emeis S, Stockwell WR et al (2000) Application of a multiscale, coupled MM5/chemistry model to the complex terrain of the VOTALP valley campaign. Atmos Environ 34:1435–1453. https://doi.org/10.1016/S1352-2310(99)00402-1

Grose MR, Narsey S, Delage FP et al (2020) Insights from CMIP6 for Australia's future climate. Earth's Fut. https://doi.org/10.1029/2019ef001469

Hara M, Yoshikane T, Kawase H et al (2008) Estimation of the impact of global warming on snow depth in Japan by the pseudo-global-warming method. Hydrol Res Lett 2:61–64. https://doi.org/10.3178/hrl.2.61

Hasumi H, Emori S (2004) K-1 coupled model (MIROC) description. K-1 Technical Report 1. Center for Climate System Research, University of Tokyo, Tokyo

Holland G, Done J, Bruyère C et al (2010) Model investigations of the effects of climate variability and change on future gulf of Mexico tropical cyclone activity. Offshore Technol Conf. https://doi.org/10.4043/20690-MS

Hong SY, Lim JOJ (2006) The WRF single-moment 6-class microphysics scheme (WSM6). J Korean Meteorol Soc 42:129–151. https://doi.org/10.12691/marine-3-1-2

Johnson F, Sharma A (2012) A nesting model for bias correction of variability at multiple time scales in general circulation model precipitation simulations. Water Resour Res. https://doi.org/10.1029/2011wr010464

Jones DA, Wang W, Fawcett R (2009) High-quality spatial climate data-sets for Australia. Aust Meteorol Oceanogr Soc J 58:233–248

Kain JS (2004) The Kain-Fritsch convective parameterization: an update. J Appl Meteorol 43:170–181. https://doi.org/10.1175/1520-0450(2004)043<0170:TKCPAU>2.0.CO;2

Kala J, Andrys J, Lyons TJ et al (2015) Sensitivity of WRF to driving data and physics options on a seasonal time-scale for the southwest of Western Australia. Clim Dyn 44:633–659. https://doi.org/10.1007/s00382-014-2160-2

Kawase H, Yoshikane T, Hara M et al (2009) Intermodel variability of future changes in the Baiu rainband estimated by the pseudo global warming downscaling method. J Geophys Res. https://doi.org/10.1029/2009jd011803

Kim J, Miller NL, Farrara JD et al (2000) A seasonal precipitation and stream flow hindcast and prediction study in the western United States during the 1997/98 Winter season using a dynamic downscaling system. J Hydrometeorol 1:311–329. https://doi.org/10.1175/1525-7541(2000)001<0311:aspasf>2.0.co;2

Knapp KR, Kruk MC, Levinson DH et al (2010) The international best track archive for climate stewardship (IBTrACS). Bull Am Meteorol Soc 91(3):363–376. https://doi.org/10.1175/2009bams2755.1

Li Y, Erwin T, Bedin T et al (2015) Climate change in Australia. Projections for Australia's NRM regions. Technical report. https://doi.org/10.4225/08/58518c08c4ce8

Ma J, Wang H, Fan K (2015) Dynamic downscaling of summer precipitation prediction over China in 1998 using WRF and CCSM4. Adv Atmos Sci 32(5):577–584. https://doi.org/10.1007/s00376-014-4143-y

Mlawer EJ, Taubman SJ, Brown PD et al (1997) Radiative transfer for inhomogeneous atmospheres: RRTM, a validated correlated-k model for the longwave. J Geophys Res 102(16):663. https://doi.org/10.1029/97jd00237

Neale RB, Chen CC, Gettelman A et al (2010) Description of the NCAR Community Atmosphere Model (CAM 5.0). NCAR Tech Note NCAR/TN-486+ STR 1:1–12. http://www.cesm.ucar.edu/models/cesm2/atmosphere/docs/description/cam5_desc.pdf

Rocheta E, Evans JP, Sharma A (2017) Can bias correction of regional climate model lateral boundary conditions improve low-frequency rainfall variability? J Clim 30:9785–9806. https://doi.org/10.1175/jcli-d-16-0654.1

Roeckner E, Bäuml G, Bonaventura L et al (2003) The atmospheric general circulation model ECHAM 5. Model description. Technical report, Max Planck Institute for Meteorology, PART I

Rojas M, Seth A (2003) Simulation and sensitivity in a nested modeling system for South America. Part II: GCM boundary forcing. J Climate 16:2454–2471. https://doi.org/10.1175/1520-0442(2003)016<2454:sasian>2.0.co;2

Rummukainen M (2016) Added value in regional climate modeling. Wiley Interdiscip Rev Clim Change 7(1):145–159. https://doi.org/10.1002/wcc.378

Schär C, Frei C, Lüthi D et al (1996) Surrogate climate-change scenarios for regional climate models. Geophys Res Lett 23:669–672. https://doi.org/10.1029/96GL00265

Skamarock WC, Klemp JB, Dudhia J et al (2008) A description of the advanced research WRF version 3. Ncar technical note, NCAR. https://doi.org/10.5065/D68S4MVH

Wamahiu K, Kala J, Andrys J (2020) Influence of bias correcting global climate models for regional climate simulations over the CORDEX-Australasia domain using wrf. Theor Appl Climatol 142(3–4):1493–1513. https://doi.org/10.1007/s00704-020-03254-9

Warner TT, Peterson RA, Treadon RE (1997) A tutorial on lateral boundary conditions as a basic and potentially serious limitation to regional numerical weather prediction. Bull Am Meteorol Soc 78:2599–2617. https://doi.org/10.1175/1520-0477(1997)078<2599:atolbc>2.0.co;2

White RH, Toumi R (2013) The limitations of bias correcting regional climate model inputs. Geophys Res Lett 40(12):2907–2912. https://doi.org/10.1002/grl.50612

Winterfeldt J, Weisse R (2009) Assessment of value added for surface marine wind speed obtained from two regional climate models. Mon Weather Rev 137(9):2955–2965. https://doi.org/10.1175/2009mwr2704.1

Wu W, Lynch AH, Rivers A (2005) Estimating the uncertainty in a regional climate model related to initial and lateral boundary conditions. J Climate 18:917–933. https://doi.org/10.1175/jcli-3293.1

Xu Z, Yang ZL (2012) An improved dynamical downscaling method with GCM bias corrections and its validation with 30 years of climate simulations. J Climate 25:6271–6286. https://doi.org/10.1175/jcli-d-12-00005.1