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ORIGINAL PAPER

Bias-corrected regional climate projections of extreme rainfall in south-east Australia

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Abstract This study presents future changes in extreme precipitation as projected within the New South Wales and Australian Capital Territory Regional Climate Modelling (NARCliM) project's regional climate ensemble for south-east Australia. Model performance, independence and projected future changes were considered when designing the ensemble. We applied a quantile mapping bias correction to the climate model outputs based on theoretical distribution functions, and the implications of this for the projected precipitation extremes is investigated. Precipitation extremes are quantified using several indices from the Expert Team on Climate Change Detection and Indices set of indices. The bias correction was successful in removing most of the magnitude bias in extreme precipitation but does not correct biases in the length of maximum wet and dry spells. The bias correction also had a relatively small effect on the projected future changes. Across a range of metrics, robust increases in the magnitude of precipitation extreme indices are found. While these increases are often in-line with a continuation of the trends present over the last century, they are not found to be statistically significant within the ensemble as a whole. The length of the maximum consecutive wet spell is projected to remain at present-day levels, while the length of the maximum dry spell is projected to increase into the future. The combination of longer dry spells and increases in extreme precipitation magnitude indicate an important change in the character of the precipitation time series. This could have considerable hydrological implications since changes in the sequencing of events can be just as important as changes in event magnitude for hydrological impacts.

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1 Introduction

Precipitation extremes can have serious impacts on human and natural systems. Studies have shown that the majority of the globe has been experiencing an increasing trend in the intensity of the maximum annual 1-day precipitation (Westra et al. 2012), indicating an increase in this natural hazard. These trends are projected to increase in the future over much of the globe (Sillmann et al. 2013; Toreti et al. 2013). Characterising these changes at scales suitable for management decisions (10 km or less) is required to enable reasonable strategies to enhance resilience to these future changes.

Extreme precipitation can occur over relatively small spatial scales due to the influence of local features such as topography and dynamics such as the development of convective cells. This high spatial variability means that the resolution of a climate model can influence the fidelity with which precipitation extremes are represented. Studies have shown that modelling at resolutions of 10–50 km improves the representation of precipitation extremes over those present in usual Global Climate Model (GCM) simulations at resolutions of 150 km or greater (Kopparla et al. 2013). These studies have been performed over most continents, e.g. Europe (Torma et al. 2015), Australia (Di Luca et al. 2016a; Andrys et al.

2015; Evans and McCabe 2013), Asia (Lee and Hong 2014) and Africa (Dosio et al. 2014). Studies have also found that the simulation of precipitation extremes can be further improved by increasing resolution toward 10 km (Chan et al. 2013; Di Luca et al. 2016a; Prein et al. 2015a; Tripathi and Dominguez 2013) or by using convection permitting scales (<4 km) (Chan et al. 2014; Prein et al. 2015b; Westra et al. 2014). The evidence suggests that high-resolution regional climate models are likely to provide a better, more reliable projection of precipitation extremes.

A number of studies have evaluated simulations of precipitation for south-east Australia based on CMIP3 (Colman et al. 2011; Perkins et al. 2007; Suppiah et al. 2007) and CMIP5 GCMs (Bhend and Whetton 2015; Moise et al. 2015). Hope et al. (2015) found that CMIP5 GCMs generally agree on a drying trend across southern Australia though they failed to capture some synoptic types that are major contributors to extreme rainfall (e.g. cutoff lows). Over south-east Australia, this drying has been connected to a projected strengthening and poleward movement of the sub-tropical ridge (Grose et al. 2015a), though uncertainty exists as these characteristics are poorly simulated over the recent past. A number of projections of eastern Australian precipitation were compared by Grose et al. (2015b). They broadly find projections for decreases in winter and increases in summer though there is often a large spread between the various methods examined. Precipitation change over the Eastern Seaboard has been examined by Dowdy et al. (2015) who found a projected winter (JJA) decrease. This seasonal change has been supported by studies examining changes in the maritime low systems near the eastern seaboard (Dowdy et al. 2013b; Ji et al. 2015; Pepler et al. 2016).

Fewer studies have explicitly examined precipitation extremes in this region. Over Tasmania, White et al. (2013) used an ensemble of regional climate projections (0.1° resolution) and showed that both the annual maximum 1-day precipitation (Rx1day) and the length of the annual maximum consecutive dry day sequence (CDD) were projected to increase in the future. Using CMIP5 GCMs Sillmann et al. (2013) also found CDD and very wet days to be increasing over much of Australia. This suggests a more variable climate with longer dry spells and heavier rainfall in between. Evans and McCabe (2013) examined a single high-resolution climate projection over south-east Australia and similarly found that increases in extreme precipitation could be co-located with decreases in mean precipitation, though these changes need not be consistent with the driving GCM.

Bias correction techniques are commonly applied in hydrological studies of future conditions given a global warming scenario (Argüeso et al. 2013; Chen et al. 2013; Quintana Seguí et al. 2010; Teng et al. 2015; Teutschbein and Seibert 2012). It is important to know how these bias corrections are impacting the precipitation extremes which are subsequently applied to hydrological systems. Previous studies have investigated this in the context of droughts (Johnson and Sharma 2015) finding that applying bias correction can substantially change the projected drought characteristics which are strongly related to persistence in the precipitation time series. While many bias correction techniques have also been shown to produce similar changes to mean values, they can produce a range of changes to the high precipitation extremes (e.g. Teutschbein and Seibert 2012).

This study uses an ensemble of high-resolution (10 km) Regional Climate Model (RCM) projections to examine the future of precipitation extremes in south-east Australia. The ensemble performance, including projected changes in mean precipitation, was examined by Olson et al. (2016). They show that while the RCM ensemble is able to improve the representation of mean precipitation compared to the driving GCMs, a general overestimation remained. They also found that future changes in mean precipitation were mostly non-significant compared to inter-annual variability, with summer and autumn having increases, while winter and spring had little change or even decreases. This study builds on the mean precipitation analysis through an examination of precipitation extremes. The RCM ensemble is first evaluated against observations of extreme precipitation indices. This evaluation is repeated on the ensemble after bias correction. Then, the future projections of these indices are examined across the 12-member ensemble to determine whether the projected changes are significant compared to current inter-annual variability, whether they are consistent across the full ensemble, and how they are affected by bias correction.

2 Method

2.1 Observations

Here, we present observed precipitation indices calculated from the AWAP data produced by the Bureau of Meteorology (Jones et al. 2009). AWAP is a daily dataset at 5 km by 5 km spatial resolution. The dataset is generated by interpolating surface station measurements of precipitation. AWAP data starts in 1900 for precipitation and extends to the present. During most of the period of NARCliM historical runs (1990–2009), AWAP gridded dataset includes information from ~6000 to 7000 rainfall stations. This dataset was examined for its efficacy in reproducing extreme rainfall characteristics by King et al. (2013). They determined that this gridded dataset can be used to investigate extreme rainfall trends and variability, though they noted a tendency to underestimate the extreme heavy rainfall events compared to station data. Before analysis, we interpolate the AWAP observations onto the NARCliM domain 2 (10 km) grid using a simple inverse distance weighting method.

2.2 Regional climate model ensemble

The NARCliM project was designed to create regional scale climate projections for use in climate change impacts and adaptation studies and, ultimately, to inform climate change policy (Evans et al. 2014). Details on NARCliM can be found on the website http://www.ccrc.unsw.edu.au/NARCliM/. Data produced in NARCliM underpins the AdaptNSW website http://www.climatechange.environment.nsw.gov.au/Climate-projections-for-NSW/About-NARCliM/.

NARCliM is a unique project because its design used a bottom-up approach, heavily involving end users input. This was intended to facilitate usability of model outputs by the end users (e.g. adaptation community). A remarkable benefit of early end-user involvement is the improved understanding by the end users of the climate modelling process and its limitations. The project includes a 12-member RCM ensemble. This has been created by choosing four global climate models (GCMs) and downscaling each of these with three different RCMs (three versions of the Weather Research and Forecasting (WRF) modelling system V3.3 (Skamarock et al. 2008) that used different parameterizations of sub-grid atmospheric physics). All RCM simulations were performed at 10 km resolution over NSW/ACT. The NARCliM domain is shown in Fig. 1.

The three RCMs are used to downscale four GCMs in three 20-year time slices (1990–2009, 'present day'; 2020–2039, 'near future'; 2060–2079, 'far future'). For future projections, the SRES A2 emission scenario is used. This scenario assumes an overall relatively high growth rate of atmospheric greenhouse gas emissions. A careful choice of both RCMs and GCMs is required for this small ensemble to adequately sample the model uncertainty. This choice was made by considering model performance (to ensure no consistently poor performing models were chosen (Evans et al. 2012; Ji et al. 2014)), model independence (to ensure we retain as much information in the small ensemble as possible (Bishop and Abramowitz 2013; Evans et al. 2013)) and the span of projected future changes in temperature and precipitation in the region (to include all plausible future changes). The GCMs chosen are from the Coupled Model Intercomparison Project phase 3 (CMIP3) archive and are MIROC3.2, ECHAM5, CCCMA3.1 and CSIRO-MK3.0. The chosen RCMs and the parametrizations used therein are given in Table 1. These are versions of the WRF model for different parametrizations of planetary boundary layer, surface layer, cumulus physics and radiation. The final ensemble therefore contains 12 members where each of four GCMs drives each of three RCMs.

The RCM simulated precipitation contains biases. This study uses the bias-corrected RCM output (i.e. RCM output corrected for biases between the models and observations). This correction uses a quantile matching technique as described in Piani et al. (2010) that allows correction of the full distribution of daily precipitation. First, Gamma distributions are fitted to the observed and modelled daily precipitation time series. Then, corrections are applied so that the fitted distributions of daily RCM output match the fitted distributions of daily observations. As opposed to empirical techniques, the use of fitted distributions allows corrections to be applied to all future values even if they are outside the present-day range. The AWAP observations for period 1990–2009 are used to calculate corrections. These corrections are assumed to be independent of future climate change and the same corrections are also applied to the precipitation values in the future projections. Note that as this method relies on fitting a theoretical distribution, errors in this fitting can result in bias remaining after the correction is applied.

2.3 ETCCDI indices

In order to establish a baseline set of indices that characterise moderate extremes of temperature and precipitation, the

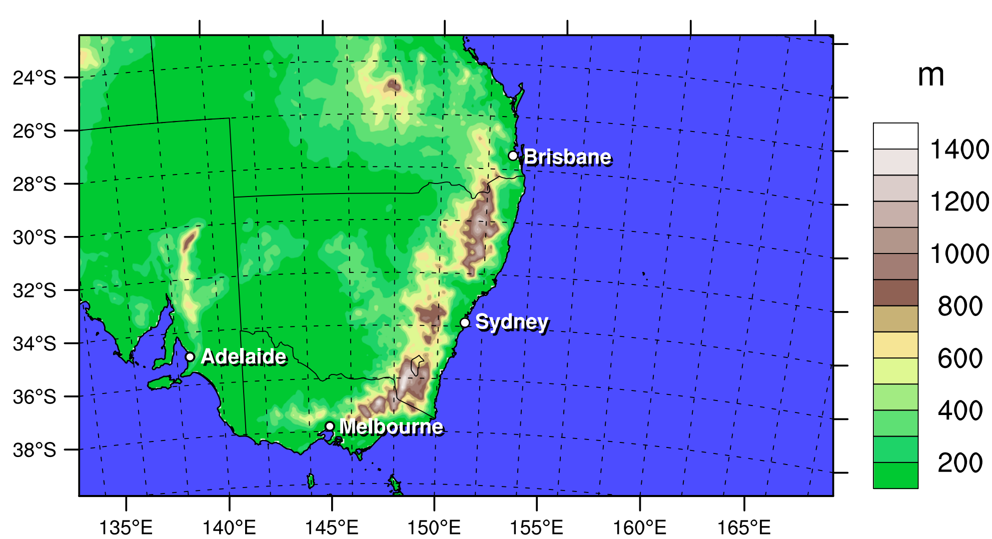

Fig. 1 NARCliM 10 km resolution domain

Table 1 Physics parameterisations used in WRF based RCMs

NARCliM ensemble member	Planetary boundary layer physics/surface layer physics	Cumulus physics	Shortwave/longwave radiation physics	Micro-physics
R1	MYJ / Eta similarity	KF	Dudhia / RRTM	WDM 5 class
R2	MYJ / Eta similarity	BMJ	Dudhia / RRTM	WDM 5 class
R3	YSU / MM5 similarity	KF	CAM / CAM	WDM 5 class

CCl/CLIVAR/JCOMM Expert Team on Climate Change Detection and Indices (ETCCDI) (http://etccdi.pacificclimate.org) has compiled a set of 27 indices, 11 of which pertain to precipitation. While the full set of indices was calculated, only the subset shown in Table 2 is presented here.

The official definitions are used for all indices, except R95p which relies on percentiles calculated on a base period. The official base period is 1961–1990; here, we use 1990–2009 as our base period. Note that Rx1day is defined on a monthly basis, while all the other indices are defined on an annual basis.

The three indices chosen to represent extreme precipitation include a threshold exceedance measure in R20mm, a wet-day percentile measure in R95p and an all-day percentile measure in Rx1day (equivalent to the all-day percentile of ~99.7 % for the annual values and ~98.9 % for the seasonal values.). The consecutive wet and dry day measures do not reflect extreme precipitation per se; instead, they are indicators of precipitation timing and sequencing. These characteristics are very important when assessing the impact of changes in precipitation time series on many different natural and human systems.

2.4 Statistical significance

For each GCM-RCM simulation, the present-day bias and the future changes are tested for significance using a non-parametric Mann-Whitney U test ($\alpha = 0.05$) to see if the two samples come from the same population. This procedure tests whether the bias or change is large compared to the inter-annual variability in the time series, given the number of samples. In the observations, trends are estimated using a linear trend model employed in the Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment Report (IPCC 2013). Trend slopes in such a model are the same as those in a standard Ordinary Least Squares regression model but allow for first-order autocorrelation in the residuals. Statistical significance is tested at the 5 % level using a non-parametric Mann-Kendall test.

We present our ensemble results on significance following Tebaldi et al. (2011). The multi-model biases and changes are separated into three categories. In 'insignificant' areas, less than half of the models show a significant bias or change. Here, multi-model mean bias or change is shown in colour. In 'significant agreeing' areas (stippled), at least half of the models have significant biases or changes and at least 80 % of the significant models agree on the direction. Finally, in 'significant disagreeing' areas (shown in white over land), at least half of the models have significant biases or changes but less than 80 % of significant models agree on the direction. The terms 'insignificant', 'significant agreeing', and 'significant disagreeing' are used throughout the document to refer to the three categories above.

3 Results

First, the NARCliM ensemble is compared to the observed climatology for the present day (1990–2009). This establishes a baseline for model performance to consider while examining future changes. Next, observed trends over the past century are presented. These provide context when assessing the projected future changes.

Table 2 Precipitation-related ETCCDI indices used in this study

Indicator ID	Name	Calculation	Units
Rx1day	Monthly maximum 1-day precipitation	Let RR_{ij} be the daily precipitation amount on day i in period j. The maximum 1-day value for period j is: $Rx1day_j = max(RR_{ij})$	mm
R20mm	Number of very heavy precipitation days	Let RR_{ij} be the daily precipitation amount on day i in period j. Count the number of days where: $RR_{ij} \geq 20$ mm	days
R95p	Contribution from very wet days	Let RR_{wj} be the daily precipitation amount on a wet day ($RR \geq 1$ mm) in period j and let $RR_{wn}95$ be the 95th percentile on wet days in the 1990–2009 period. If W represents the number of wet days in the period then: $R95p_j = \sum_{w=1}^{W} RR_{wj} where RR_{wj} > RR_{wn}95$	mm
CDD	Consecutive dry days	Maximum number of consecutive days with $RR < 1\ mm$	days
CWD	Consecutive wet days	Maximum number of consecutive days with $RR \geq 1\ mm$	days

3.1 Present-day climatology

The observed present-day (1990–2009) precipitation extreme indices are shown in Figs. 2 and 3. For the Rx1day, the east coast has a clear maximum on an annual basis, with values generally decreasing toward the west and south. On the north-east coast, the highest values occur in summer and autumn, while on the south-east coast they are more evenly distributed throughout the year. Similar distributions are found for R20mm and R95p (Fig. 3a, b) though the Snowy Mountains region in the south-east has values as large or larger than those found along the east coast. The CDD (Fig. 3c) has a minimum in the south-east with just over 10 days per year. CDD increases toward the arid zone in the north-west where the

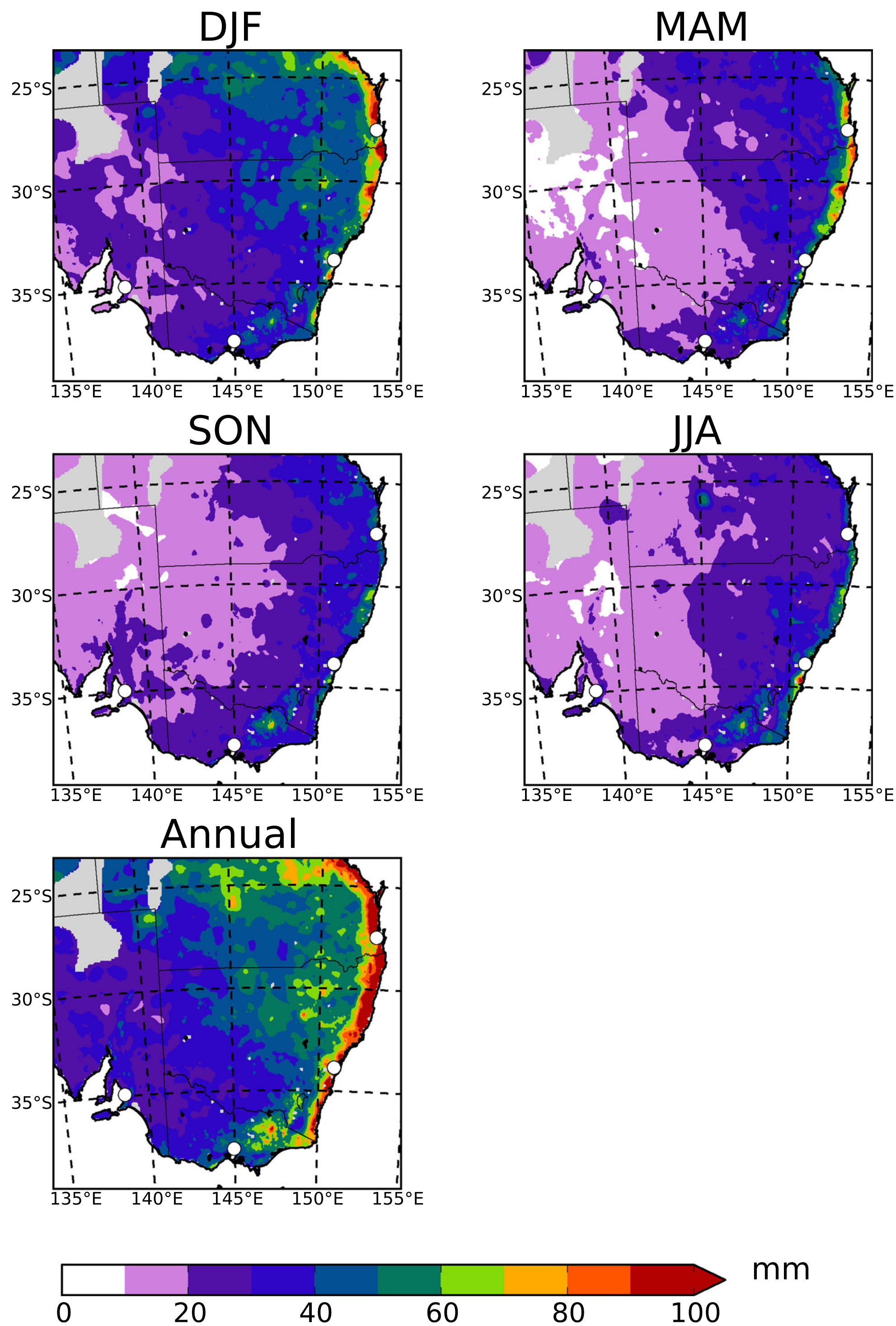

Fig. 2 Present-day (1990–2009) seasonal and annual AWAP maximum 1-day precipitation (Rx1day). *White circles* (*left to right*): Adelaide, Melbourne, Sydney, Brisbane

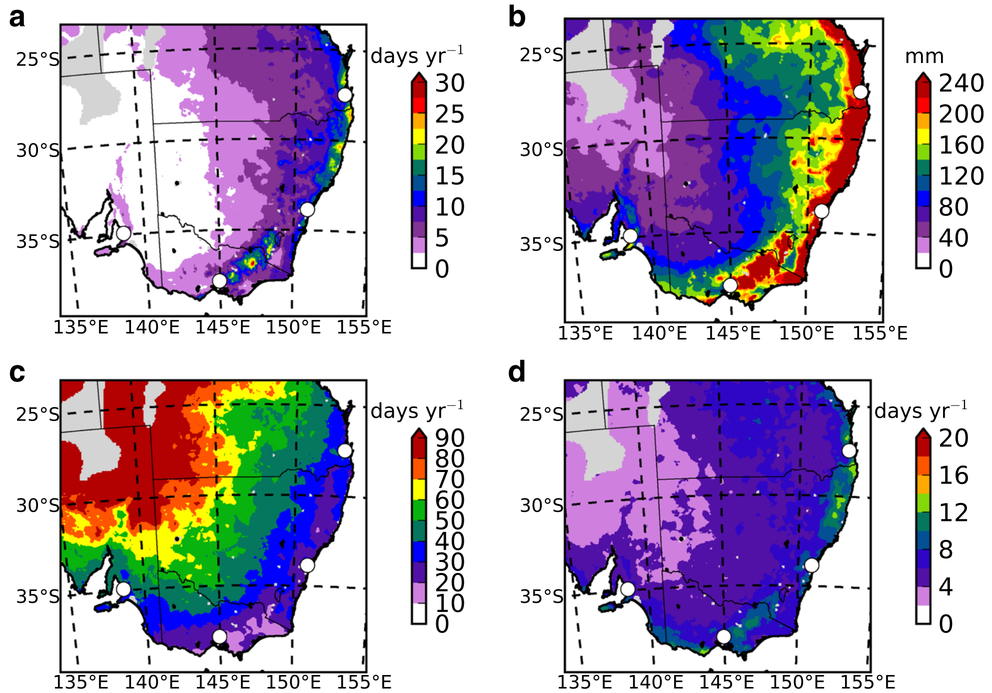

Fig. 3 Present-day (1990–2009) average AWAP annual. **a** Number of very heavy precipitation days (R20mm), **b** contribution from very wet days (R95p), **c** maximum consecutive dry days (CDD) and **d** maximum consecutive wet days (CWD). *White circles* (*left to* right): Adelaide, Melbourne, Sydney, Brisbane

maximum dry spell can last over 3 months. CWD (Fig. 3d) has a pattern almost inverse to CDD with arid zone (north-west) wet spells lasting less than 4 days, and wet spells on the north-east coast and Snowy Mountains lasting around 2 weeks.

3.2 Present-day biases

In this section, ensemble biases as compared to observations are presented. In the bias plots, the 'insignificant' areas are where the bias in most models is relatively small, which is the most desired outcome. In 'significant agreeing' areas (stippled), the ensemble bias tends in one direction, which is the least desired outcome. Note that no 'significant disagreeing' areas are present. Grey indicates missing data in the observational dataset. In this case, if any year has missing data, that location is simply masked as missing. These regions occur in the north-west of the domain where station density is very low and hence the observations are least reliable.

The raw model ensemble contains a general overestimate of the mean precipitation (Olson et al. 2016), and this translates to a general overestimate of the extreme precipitation indices (Supplementary Figs. 1 and 2). Here, we examine the biases remaining in the extreme precipitation after application of a theoretical quantile mapping bias correction. It should be noted that since the extremes are a very small part of the total daily precipitation time series, the fitting of the theoretical distribution is not influenced by these points very much; hence, a perfect match to the extremes is not guaranteed.

For Rx1day (Fig. 4), R20mm (Fig. 5a) and R95p (Fig. 5b), few significant agreeing biases are present. Some seasonal influence can be seen in the Rx1day biases with a small area of significant agreeing overestimates in Autumn and significant agreeing underestimates in winter. This provides confidence in using this ensemble to examine these extreme rainfall indices. CWD (Fig. 5d), however, shows the ensemble to contain significant agreeing underestimation biases over much of the domain, while the east and south coastal areas have significant agreeing overestimation biases. In this coastal region, CDD (Fig. 5c) has a significant agreeing underestimation indicating an overall wetter regime with small magnitude rain days more common in the model ensemble than the observations. This concurs with previous work that also found WRF to underestimate CDD (Barrera-Escoda et al. 2014). Inland, however, like CWD, CDD also has significant agreeing underestimation biases. In this region, the model ensemble fails to capture the persistence in the hydrologic cycle (wet days and dry days) and produces more day-to-day variability than is present in the observations. This contrasts with Andrys et al. 2016 who found that CDD was overestimated by their WRF models in inland south-west Western Australia and perhaps indicates a strong location dependence to this bias.

3.3 Observed trends

Examining observed trends in extreme precipitation over the last century reveals a general increase in the magnitude of these extremes, though in many cases these increases are not significant. Most of the significant increasing trends in

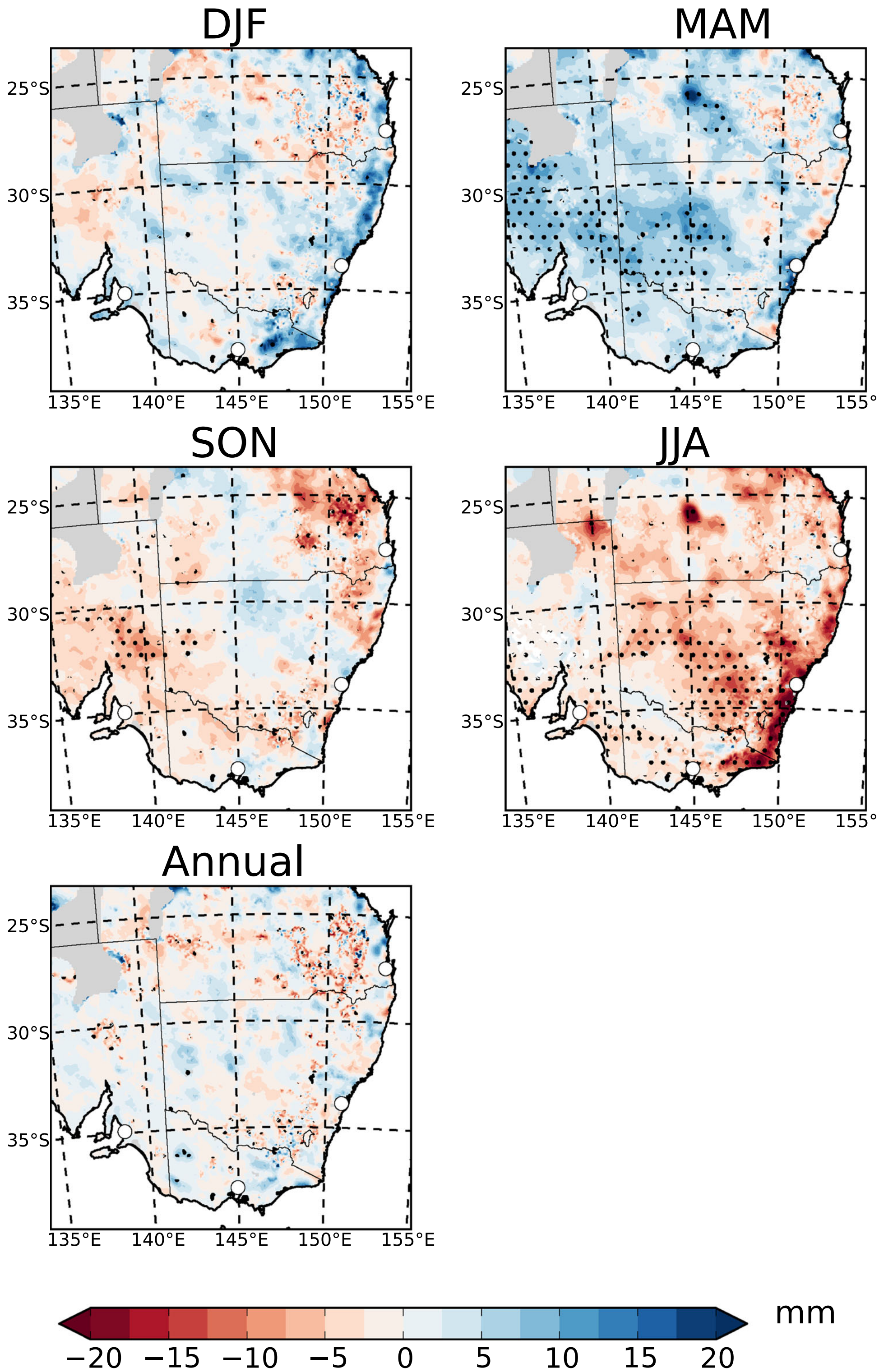

Fig. 4 Present-day (1990–2009) multi-model average bias (model output minus AWAP observations) for seasonal and annual maximum 1-day precipitation (Rx1day). Stippling indicates that the bias is 'significant agreeing' at the 5 % level. *White circles* (*left to right*): Adelaide, Melbourne, Sydney, Brisbane

Rx1day (Fig. 6) occur in summer, and the fewest significant trends occur in spring. The trends in R20mm (Fig. 7a) and R95p (Fig. 7b) are quite similar to the annual Rx1day trends with increases almost everywhere and significant increases in a swath through the centre of the region. Over much of the region, there is a significant trend toward shorter consecutive dry day periods (Fig. 7c), while the trends in CWD are mixed though only the decreasing trends in the south are significant. This southern area is unique in having significant decreasing trends in both CDD and CWD, suggesting a decrease in the hydrologic persistence in this region.

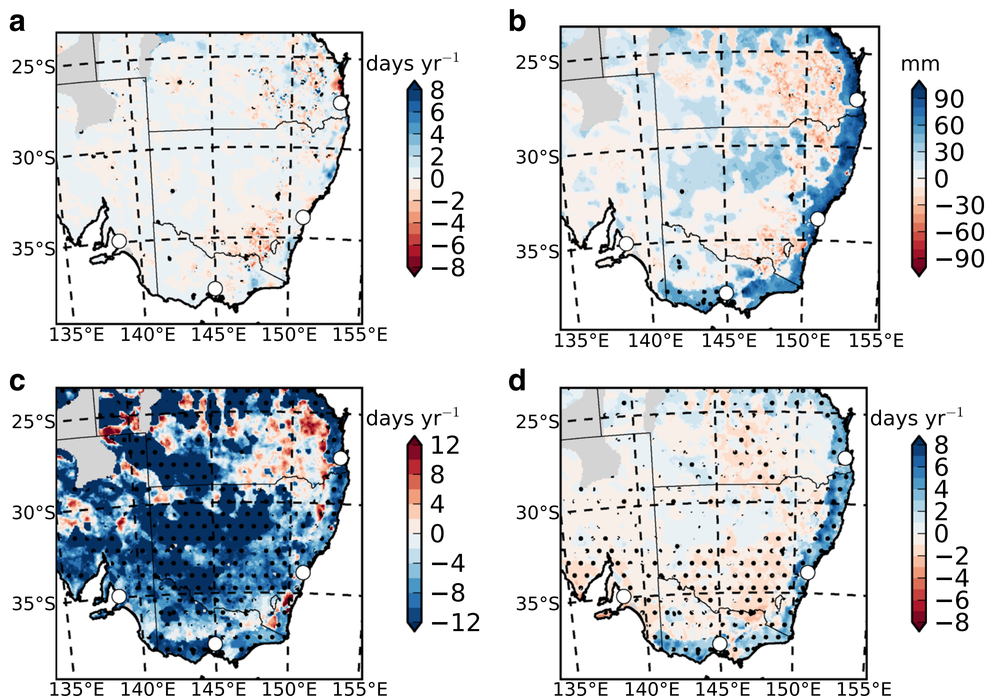

Fig. 5 Present-day (1990–2009) multi-model average annual bias (model output minus AWAP observations) for: **a** Number of very heavy precipitation days (R20mm), **b** contribution from very wet days (R95p), **c** maximum consecutive dry days (CDD) and **d** maximum consecutive wet days (CWD). Stippling indicates that the bias is 'significant agreeing' at the 5 % level. *White circles* (*left to right*): Adelaide, Melbourne, Sydney, Brisbane

3.4 Future changes

Changes into the future are presented as the present-day mean (1990–2009) subtracted from the future mean (2060–2079). In the future change figures, areas with insignificant changes (shown in colour) occur where less than half of the models show a significant change compare to inter-annual variability. Here, projected changes tend to be relatively small. In 'significant agreeing' areas (stippled), at least half of the models show a significant change and at least 80 % of the significant models agree on the direction of change. This indicates a robust projected change in a particular direction. Finally, in 'significant disagreeing' areas (shown in white), at least half of the models show a significant change and less than 80 % of significant models agree on the direction of the change. This is the least desired outcome from a policy perspective as any future change remains highly uncertain.

Future increases in Rx1day (Fig. 8) are projected over most of the region in summer, autumn and on an annual basis. Little change is projected in winter and spring. These projected future changes are however not significant. The future change in R20mm and R95p (Fig. 9a, b) similarly shows increases everywhere, though few places have increases that are significant agreeing. It is worth noting that a number of individual ensemble members do produce significant increases into the future (supplementary Fig. 5), so from a risk analysis perspective, the largest plausible changes are indeed significant. CDD displays insignificant increases almost everywhere (Fig. 9c), while CWD shows little change (Fig. 9d) except perhaps for some insignificant decreases over the southern coast region.

4 Discussion

The changes in extreme precipitation discussed here take place within the context of overall changes in the mean precipitation field. These changes, as present in the NARCliM ensemble, were examined by Olson et al. (2016). They found that future changes in mean precipitation were mostly non-significant with summer and autumn having increases, while winter and spring had little change or even decreases. The seasonal difference in future precipitation is reflected in CMIP5 projections for southern Australia (Hope et al. 2015) and in both CMIP5 and downscaled (statistical and dynamic) projections for eastern Australia (Grose et al. 2015b).

The bias-corrected NARCliM ensemble is able to simulate the various extreme precipitation indices with little bias providing a reliable platform from which to examine future changes in extremes. This, however, is not true for the hydrologic persistence measures, CDD and CWD, which display large areas of significant agreeing underestimation bias. For CDD, this represents a decrease in the significant agreeing underestimation biases compared to the raw model ensemble (Supplementary Fig. 2). For CWD, the raw ensemble displays significant agreeing areas of high biases across the northern part of the domain. The bias correction applied has altered these biases considerably, producing significant agreeing underestimation biases in the interior and overestimation biases along the eastern (and southern) seaboard. The dry spells (CDD) are underestimated by around 15–30 %, while the wet spells (CWD) are more variable but are underestimated by similar proportions in many locations. Like all bias correction techniques, it is the magnitude of precipitation each day

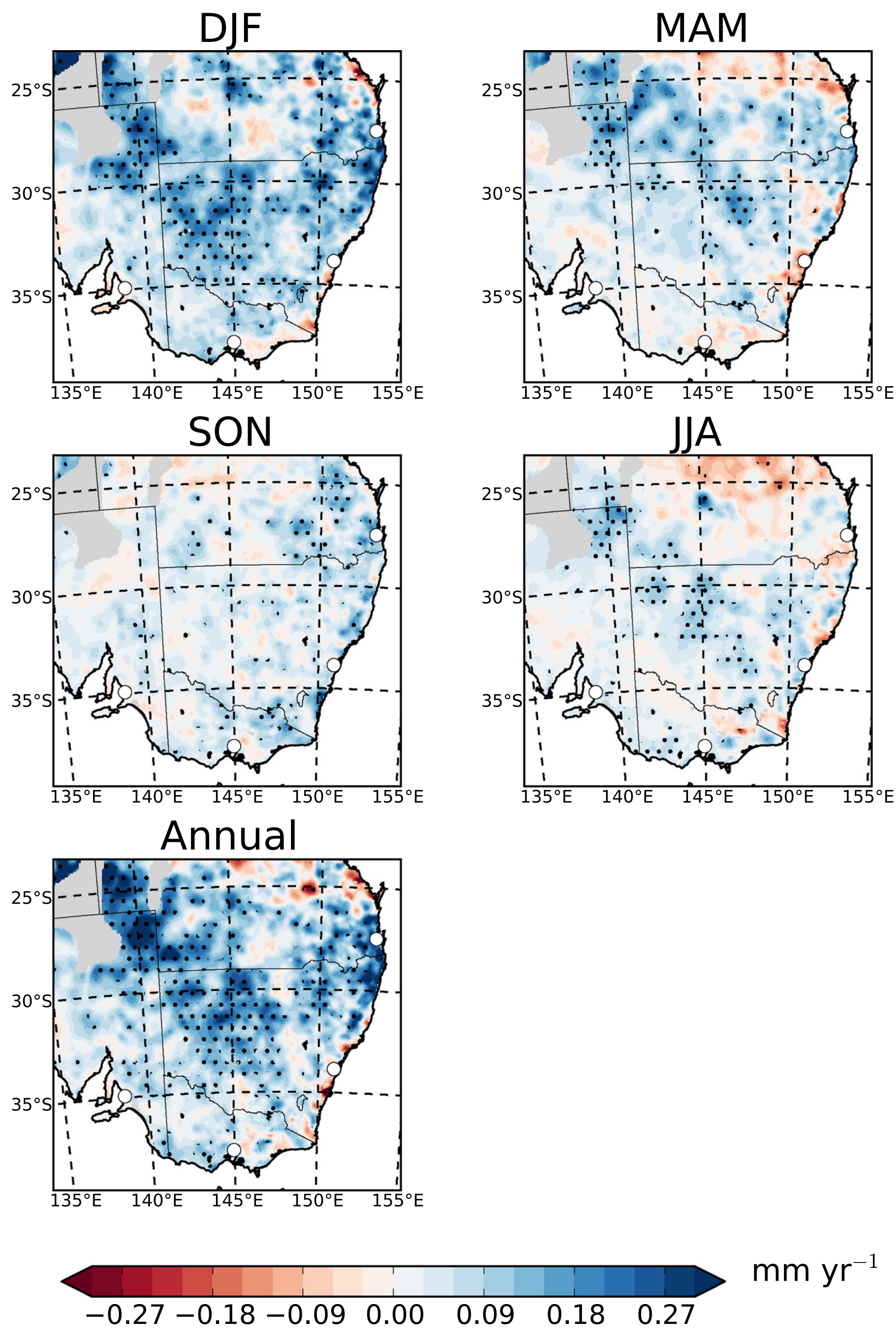

Fig. 6 AWAP trends from 1911 to 2014 in seasonal and annual maximum 1-day precipitation (Rx1day). Stippling indicates that the trend is significant at the 5 % level. *White circles* (*left to right*): Adelaide, Melbourne, Sydney, Brisbane

that is altered not the temporal sequencing of wet and dry days. The differences caused by bias correction are due to days being shifted across the 1 mm/day threshold to be classed as dry days when they were previously classed as wet days. The actual corrections required to cross this threshold can be very small but can lead to fairly large changes in CDD and CWD. We also note that the tendency for the ensemble to underestimate the persistence in wet and dry spells is at least partly due to the lack of persistence in the GCM boundary conditions (Rocheta et al. 2014) and needs to be kept in mind when examining projected future changes.

The observations over the last century often show significant increasing trends in extreme precipitation over most of the region. As a general rule, these trends are projected to continue into the future. In fact, for the annual Rx1day, the future change projected for the centre of the domain is very

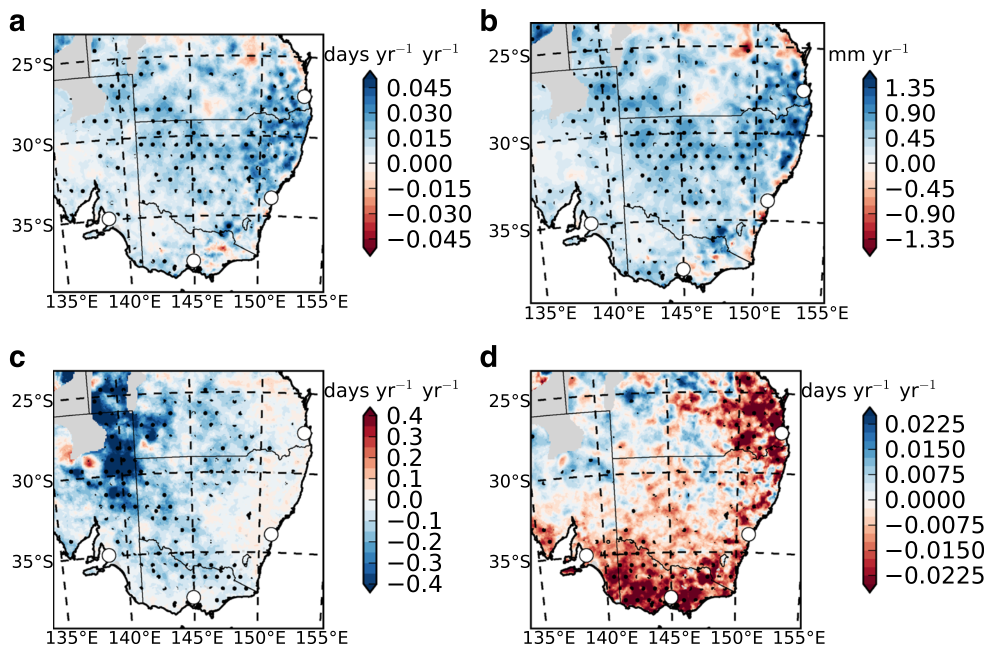

Fig. 7 AWAP trends from 1911 to 2014 in annual. **a** Number of very heavy precipitation days (R20mm), **b** contribution from very wet days (R95p), **c** maximum consecutive dry days (CDD) and **d** maximum consecutive wet days (CWD). Stippling indicates that the trend is significant at the 5 % level. *White circles* (*left to right*): Adelaide, Melbourne, Sydney, Brisbane

similar to what would be expected by a continuation of the observed trend. This is also true for R20mm and R95p, suggesting that while most projected future changes are not significant agreeing, the overall projection of increases in precipitation extremes is robust to the definition of extreme used. These future changes are also relatively unaffected by the bias correction with very similar patterns of (slightly larger) changes present in the raw ensemble (supplementary Figs. 3 and 4). Rx1day also shows distinct seasonality in future increases with summer and autumn, which often produce the largest extremes today, projected to have the largest increases in these extremes in the future.

Current observed climatology shows that the largest precipitation extremes occur along the east coast. A significant proportion of these extremes is produced by maritime storm systems known as East Coast Lows (ECLs). ECLs can be identified using a variety of methods ranging from large-scale vorticity-based methods (Dowdy et al. 2013a; Ji et al. 2015) to local mean sea level pressure gradient methods (Di Luca et al. 2015; Pepler et al. 2014). The NARCliM ensemble has been shown to provide a good representation of the climatology of ECLs (Di Luca et al. 2016b). By applying a range of these methods to the NARCliM ensemble, Pepler et al. (2016) showed that a robust decrease in winter ECLs is projected, while little change, or a small increase, is expected in summer. This is consistent with Fig. 8 where a decrease in Rx1day on the Eastern Seaboard is projected in winter. On an annual basis, Rx1day increases in this region in agreement with the findings of Dowdy et al. (2015) due to increases in summer and autumn.

These results can be compared to those projected directly by the CMIP5 ensemble for late in the twenty-first century (Sillmann et al. 2013). For R95p, the CMIP5 results generally show an increase that is not significant in agreement with the high-resolution results presented here. It is worth noting, however, that CMIP5 ensemble produces a more mixed result with some areas, showing a significant increase and others decreases that are not significant, while the NARCliM ensemble results are more consistent across the region. Sillmann et al. (2013) also report R10mm as showing a consistent, though not significant, decrease across the region. Though not directly comparable, this is in contrast to the R20mm results reported here and their own R95p result.

In terms of hydrologic persistence measures, the projected future change in CWD is also broadly similar to a continuation of the observed trend over the last century. CDD, however, projects a reversal of the observed trend from a decrease to an increase. That is, if the observed trend was to continue to 2070 in the centre of the domain, where a CDD of 65 days is currently observed, then a decrease of around 14 days would be expected. Instead, the ensemble projects an increase of around 6 days. Examining the observed trend over the last 30 years (since 1984) shows that large parts of the region are already showing an increasing trend in CDD over recent decades. The future projections suggest that this change to an increasing CDD will spread throughout the region over coming decades. The CMIP5 ensemble also projects an increase in CDD for this region.

Over most of the domain, a combination of increasing length of maximum dry spell (CDD) and increasing magnitude of extreme precipitation exists. Thus, while much of the region shows relatively little change in the annual precipitation (Olson et al. 2016), the nature of the precipitation is changing toward heavier downpours interspersed with longer

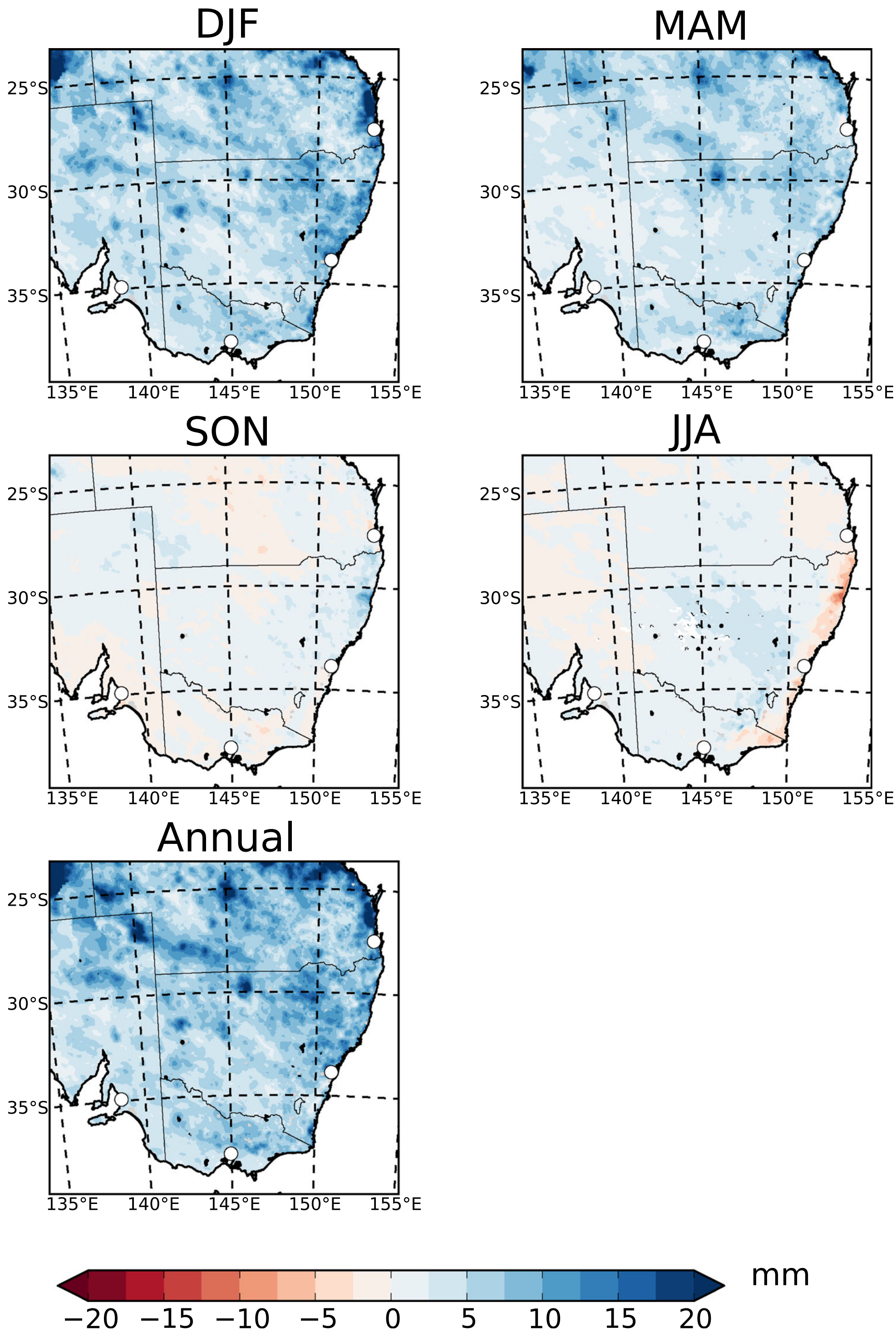

Fig. 8 Multi-model mean changes between the present day (1990–2009) and far future (2060–2079) in seasonal and annual maximum 1-day precipitation (Rx1day). Stippling indicates that the changes are 'significant agreeing' at the 5 % level. *White circles* (*left to right*): Adelaide, Melbourne, Sydney, Brisbane

dry spells, as well as being seasonally redistributed. This combination of an increase in the length of dry spells (CDD) and in the intensity of extreme precipitation (R95p) has also been found in locations such as the Mediterranean basin (Argüeso et al. 2012; Barrera-Escoda et al. 2014) and Tasmania (White et al. 2013).

Recently, Schär et al. (2016) pointed out the use of all-day percentiles (such as Rx1day) or wet-day percentiles (such as R95p) can produce very different results when examining future changes. In this work, we find remarkable consistency in the future projections revealed by these measures. Schär et al. (2016) show that wet-day percentiles are sensitive to changes in the wet-day frequency. Here, we find that wet-day frequency has only minor changes into the future (supplementary Fig. 6). Despite the bias correction producing substantial changes in wet-day frequency in some locations in the present,

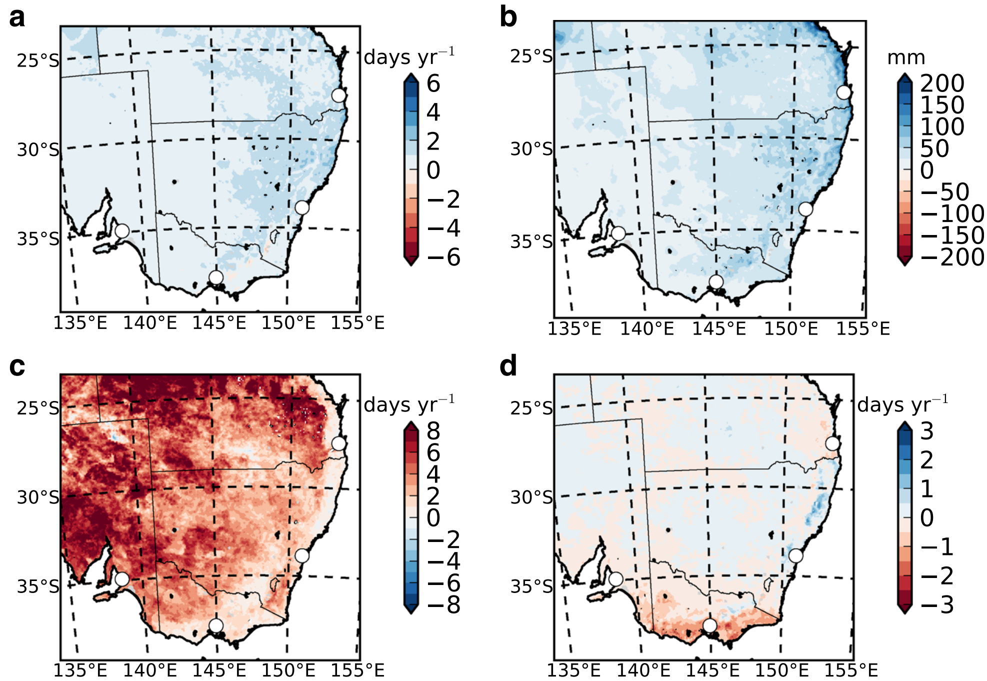

Fig. 9 Multi-model mean changes between the present day (1990–2009) and far future (2060–2079) in annual. **a** Number of very heavy precipitation days (R20mm), **b** contribution from very wet days (R95p), **c** maximum consecutive dry days (CDD) and **d** maximum consecutive wet days (CWD). Stippling indicates that the changes are 'significant agreeing' at the 5 % level. *White circles* (*left to right*): Adelaide, Melbourne, Sydney, Brisbane

the future changes are little affected. As a result, the various extreme precipitation indices produce a consistence change into the future.

5 Conclusions

This study presents future changes in extreme precipitation as projected within the NARCliM regional climate ensemble for south-east Australia. The ensemble is built by driving three RCMs with boundary conditions derived from four GCMs to create a 12 member ensemble. Both the RCMs and the GCMs were carefully chosen to maximise the information content of the ensemble (by considering model independence) as well as spanning the plausible future climate changes present in the full CMIP3 ensemble. It is shown that applying a theoretical distribution function-based quantile mapping bias correction technique is successful in removing most of the magnitude bias in extreme precipitation but does not correct biases in the length of maximum wet and dry spells. The bias correction also had a relatively small effect on the projected future changes. Due to the removal of present-day bias and the robustness of the future changes, the bias-corrected data is recommended for use in climate change impacts and adaptation studies that may have sensitivities to particular precipitation thresholds.

Across a range of metrics, robust increases in the magnitude of precipitation extreme indices are found. While these increases are often in-line with trends present over the last century, they are not found to be significant within the ensemble as a whole. It is worth noting that several ensemble members have large areas with statistically significant increases so that, from a risk analysis perspective, a highest plausible scenario would include significant increases.

The length of the maximum consecutive wet spell is projected to remain unchanged, while the length of the maximum dry spell is projected to increase into the future. While not all members of the ensemble agree that this increase is significant, the combination of longer dry spells and increases in extreme precipitation magnitude indicate an important change in the character of the precipitation time series. This could have significant hydrological implications since changes in the sequencing of events can be just as important as changes in event magnitude for hydrological impacts. These changes in the nature of the precipitation regime will present water resource managers with challenges not encountered in the historical record and emphasises the need to include more than just annual mean future changes in their planning processes.

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