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The NARCliM project: model agreement and significance of climate projections

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ABSTRACT: NARCliM (New South Wales and Australian Capital Territory Regional Climate Modelling project) is a climate downscaling project for Australia and the surrounding regions. Present and future climate simulations are performed using a 1-way nested dynamical downscaling approach and span 2 domains. We focus on the inner 10 km domain that extends across south-east Australia. Three regional climate models (RCMs) based on the Weather Research and Forecasting System (WRF) version 3.3 dynamically downscale 4 global climate model (GCM) simulations to finer resolutions. This project complements and improves on already available GCM projections for the region. Our simulations cover 3 epochs: present (1990–2009), near future (2020–2039), and far future (2060–2079). Here, we focus on the mean surface air temperature and precipitation. The RCMs are better able to capture spatial patterns of temperature and precipitation and improve the temperature root mean square error (RMSE) compared to the GCMs, at least for the inner domain. The RCMs tend to be biased cold compared to observations and are wetter than the GCMs during warm seasons. The downscaled RCM projections exhibit a weaker warming over land compared to the GCMs. The RCMs project no significant precipitation changes in the far future over most areas. However, Victoria is expected to see significant springtime drying of 15 mm mo^{-1}, which is considerably higher than previous GCM results. This drying is associated with a larger strengthening of the subtropical ridge than modelled previously by the GCMs. In addition, the RCMs project significant precipitation changes in contradicting directions for some inland areas during winter.

KEY WORDS: Regional climate modelling · NARCliM · Dynamical downscaling · Southeast Australia

1. INTRODUCTION

As anthropogenic climate change intensifies (Kirtman et al. 2013), there is an increasing need for robust local-scale projections of key climate variables to inform decision-making. Global climate models (GCMs) can provide global projections at a relatively coarse resolution, on the order of hundreds of kilometres. However, it is increasingly recognised that such projections are not suitable for local-scale impacts and adaptation studies due to the differences in scales between the projections and the input needed for such studies. Moreover, on the regional scale, these models often poorly simulate standard variables such as precipitation, especially in areas with considerable topography (Suppiah et al. 2007, Flato et al. 2013, Torma et al. 2015). This weakness is of particular relevance for south-east Australia, which features the Great Dividing Range separating a relatively narrow coastline from the drier interior. For example, Fig. 1 exposes a severe failure of some GCMs to capture the cooler temperatures over the

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Snowy Mountains and the warmer area further inland.

To bridge the gap between the GCM and the impacts scale, downscaling methods need to be applied to the GCMs. Such methods include statistical downscaling and dynamical downscaling, or a blend of the two. Statistical downscaling uses statistical relationships between larger-scale climate fields and local-scale observations to make climate projections (Maraun et al. 2010, Evans et al. 2012b). Dynamical downscaling uses regional climate models (RCMs). RCM take GCM climate projections as input and solve the equations governing the atmosphere on the regional scale to produce higher-resolution regional projections (Giorgi & Bates 1989, Christensen et al. 2007, Giorgi et al. 2009, Evans et al. 2012b, Mearns et al. 2013, Di Luca et al. 2014, Torma et al. 2015, Rummukainen 2016).

Dynamically downscaled projections are more computationally intensive to produce compared to GCM projections. While the RCMs can not correct for large-scale circulation problems of the GCMs they are driven with (Hall 2014), they add detail and often improve the representation of spatial climate patterns, especially in regions with considerable topographic features and coastlines (van der Linden & Mitchell 2009, Prömmel et al. 2010, Feser et al. 2011, Evans & McCabe 2013). The advantage of using RCMs has been investigated and demonstrated by many studies examining the added value of regional models (e.g. recently Di Luca et al. 2013, 2015, Torma et al. 2015, Rummukainen 2016).

With the proliferation of regional climate models and the increase in computing power, several multi-model regional climate modelling projects have been conducted. These projects include PRUDENCE (Christensen et al. 2007), ENSEMBLES (van der Linden & Mitchell 2009), NARCCAP (Mearns et al. 2013), CLARIS-LPB (Solman et al. 2013), and CORDEX (Giorgi et al. 2009). However, to date, no extensive dynamical downscaling project has been undertaken for south-east Australia.

NARCliM is a new regional climate modelling project that aims to cover this gap (Evans et al. 2013a, 2014). NARCliM is a collaboration with state governments to produce a climate projection ensemble that can be used across government departments to include future climate change in planning processes in a systematic and consistent way. NARCliM improves on other projects in the rigour of model selection: the GCMs and the RCMs were chosen using evaluation of model skill (directly or through meta-data analysis), and based on independence. In addition, the GCMs were selected so that they cover the future temperature–precipitation change space found in the World Climate Research Programme (WCRP) Coupled Model Intercomparison Project phase 3 (CMIP3) multi-model dataset (Meehl et al. 2007). NARCliM employs a full matrix of 4 GCMs and 3 RCM versions, resulting in a total of 12 GCM–RCM combinations. The RCMs are integrated using a double nesting approach with an outer CORDEX domain (50 km resolution) covering Australia and the surrounding area and a fine inner domain (10 km resolution; Fig. 2) over south-east Australia. Climate projections are analysed for the periods 2020–2039 (near future), 2060–2079 (far future), and 1990–2009 (present day). Here, we focus on the results for seasonal mean surface air temperature and precipitation for the present and the far future.

The use of several thoroughly selected GCMs and RCMs allows us to systematically sample future RCM

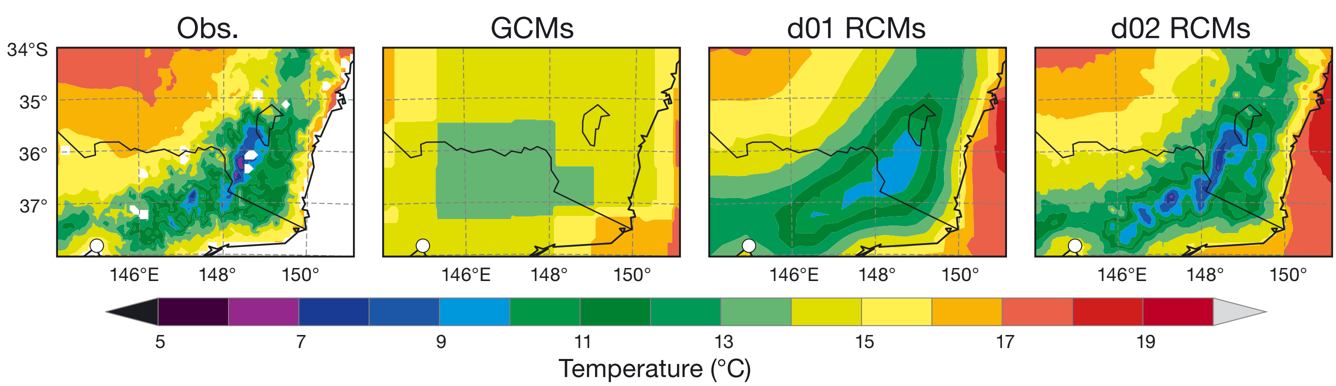

Fig. 1. MAM temperature climatology for the Snowy Mountains and other parts of south-east Australia for (left to right) observations from Australian Water Availability Project (AWAP); mean of 4 GCMs MIROC3.2, ECHAM5, CCCMA3.1, and CSIRO-Mk3.0; mean of domain 01 output of 12 NARCliM Regional Climate Models driven by the aforementioned GCMs; and the same for domain 02 output. Australian state boundaries are also shown. The white circle denotes Melbourne. See Section 3 for details on observations and model set-up

and GCM model uncertainty at an unprecedented resolution over south-east Australia. The main aim of this study is to summarise the NARCliM projected future climate change, identify the significance and model agreement of these changes, and place them within the context of existing GCM projections. We address 5 inter-related questions:

(1) What is the significance and model agreement of present-day model biases?

(2) What is the magnitude of projected far-future local and state-averaged changes?

(3) Where are the projected changes statistically significant?

(4) Do models agree on the direction of change?

(5) How do the RCM projections compare between domains and to GCM projections?

2. BRIEF SUMMARY OF CLIMATE OF SOUTH-EAST AUSTRALIA

South-east Australia (Fig. 2) contains a narrow coastline, separated from the inland lowlands by the Great Dividing Range. The climate of the region varies drastically, from desert in the north-west to temperate warm summer (DJF) along the southern coast (Peel et al. 2007). The temperature typically increases inland and to the north, with the austral winter (JJA) minimum over the Australian Alps being <5°C (see Fig. 3). Precipitation (see Fig. 4) strongly varies spatially and seasonally. In all seasons, the east coast is wetter than the inner western regions. In summer, the precipitation is lowest over South Australia and highest over coasts of Queensland and northern New South Wales (NSW), with values exceeding 220 mm mo^{-1}. This region is where south-easterly trade winds bring in moisture from the Tasman Sea, which can then experience lift during the interaction with local topographic features. Here, rainfall can also result from easterly troughs (Risbey et al. 2009).

In austral winter, the action shifts to the south-east of the domain, with greatest precipitation over the Australian Alps. During this season, the south of the region is prone to mid-latitude low systems and cold fronts. Other synoptic features over the area include cut-off lows (usually associated with blocking highs over the Tasman Sea) and East Coast Lows (ECLs). ECLs are powerful low-pressure systems occurring off the east coast of Australia. They can cause extreme rainfall and flooding over the region (Speer et al. 2009) and have been projected to vary in frequency under future climate change (Ji et al. 2015, Pepler et al. 2016).

The rainfall in the region is also influenced by remote drivers, of which El Niño–Southern Oscillation (ENSO) deserves special mention. El Niño is associated with drier conditions in south-east Australia, particularly in winter (JJA) and spring (SON; Risbey et al. 2009). However, van Oldenborgh (2005) reports, using CMIP3 models, that only minor future changes in ENSO sea level pressure variability are expected. This pattern limits ENSO as a key factor responsible for potential future climate change in the region, and we do not discuss ENSO further in detail here. Other remote precipitation drivers in the area include the Indian Ocean Dipole, Madden-Julian Oscillation, and Southern Annular Mode (Risbey et al. 2009).

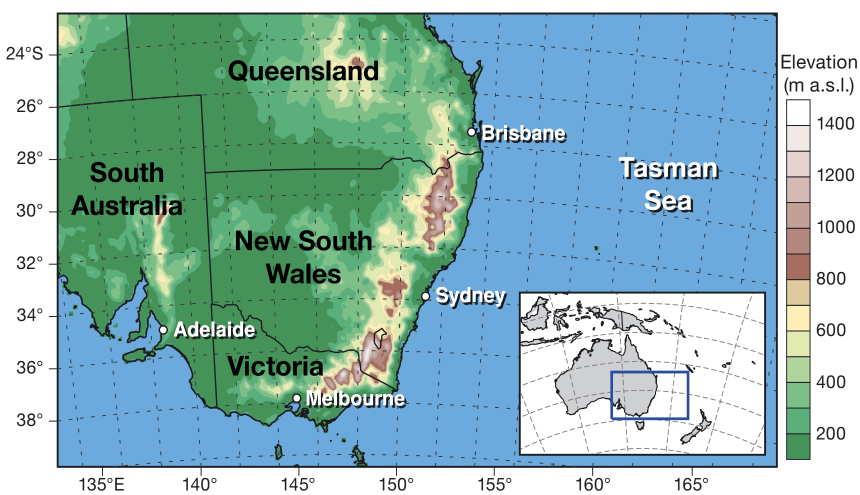

Fig. 2. Topographic map of the NARCliM inner domain. The inset shows the inner domain position within the outer domain

Precipitation drivers in south-east Australia are not limited to the atmospheric disturbances and variability modes. For example, Murphy & Timbal (2008) also discuss the importance of extra-tropical sea surface temperatures and local soil moisture.

The region has been recently affected by a prolonged and unprecedented drought, termed the Millennium Drought. The drought affected Victoria, southern parts of NSW, and parts of the Queensland coast (e.g. van Dijk et al. 2013). Here, we hope to shed more light on whether permanent future drying in south-east Australia in response to climate change is expected.

3. MATERIALS AND METHODS

3.1. Experimental set-up

The NARCliM experimental set-up was described in detail by Evans et al. (2014), and only a summary is provided here. There are 2 experimental domains. The outer domain (domain 01) is at 50 km resolution and covers the CORDEX-AustralAsia region. The inner domain (domain 02) is at 10 km resolution and spans south-eastern Australia (Fig. 2).

The GCMs and the RCMs were selected based on literature review, their skill in representing climate over the region of interest (Evans et al. 2012a, Ji et al. 2014), model independence (based on correlation of model errors for minimum and maximum temperature and for precipitation; Bishop & Abramowitz 2013, Evans et al. 2013b), and on the availability of the GCM outputs required as inputs to the RCMs. Additionally, the GCMs were chosen so that they covered the future temperature–precipitation change space of the full CMIP3 multi-model dataset in a manner similar to that in Whetton et al. (2012). From the CMIP3 GCMs, 4 models were selected: MIROC3.2-medres, ECHAM5, CCCMA3.1, and CSIRO-Mk3.0. The 3 RCMs to downscale the GCMs are all based on Weather Forecasting and Research (WRF) modelling system version 3.3 (Skamarock et al. 2008), which was modified to include time-varying climate forcings. These RCMs (which we call R1, R2, and R3) differ in planetary boundary layer physics, surface physics, cumulus physics, and radiation parameterisations (Table 1). Each of the RCMs was forced with each of the GCMs, resulting in 12 GCM–RCM combinations.

Whenever model subsets are chosen from a larger ensemble, there is a question of sampling bias (e.g. that the chosen models are a biased representation of a larger ensemble) and reduced inter-model variance. Through our explicit use of model independence in the selection process, we are able to maximise the information content of the chosen small ensemble. While it is not guaranteed that sampling bias is entirely removed, Evans et al. (2013b) show that this methodology provides a better outcome in this respect than the use of performance measures alone when selecting the models, as has been done in previous regional climate projection studies. It is an open question how the variance in climate diagnostics between these WRF versions compares with what would be obtained using 3 'totally independent' RCMs (e.g. 3 RCMs developed independently by different modelling groups). That is, although we had explicitly considered the independence issue in the selection of the RCMs, we expect some common behaviours across the WRF versions to arise, resulting in reduced ensemble variance. Nonetheless, multi-physics ensemble spreads can be similar in magnitude to multi-model spreads (Jerez et al. 2013), depending on the variable. This pattern suggests a paramount role of physical parameterisations in inter-model differences and justifies our use of a single WRF modelling system.

All 12 simulations were run for 3 time periods: present (1990–2009), near future (2020–2039), and far future (2060–2079). Future runs use the SRES A2 emissions scenario (Nakicenovic & Swart 2000). Here, we focus on the evaluation of present model biases and changes between the present and the far future in temperature and precipitation. Results for the near future are referenced briefly; more information about these runs is included in Sections 2 and 3 of the Supplement at www.int-res.com/articles/suppl/c069p209_supp.pdf.

3.2. Data extraction and significance testing

For each GCM–RCM combination, we calculate seasonal and annual mean biases for present-day near-surface air temperature and precipitation, as well as near-future and far-future changes. All future changes are defined as future minus present-day model outputs. The GCM output is interpolated to the RCM grid using nearest-neighbour interpolation prior to the analysis. Here, we use raw RCM output, to simplify the comparison with GCMs, which were not bias-corrected. We do not make any elevation corrections. For each model, domain, variable and

Table 1. WRF versions used in the NARCliM ensemble. Reproduced from Evans et al. (2014) with permission

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

grid point, we calculate the significance of present-day seasonal- and annual-mean biases compared to observations (discussed in Section 3.3) and of changes from the present to the far future using a t-test ($\alpha = 0.05$) for the difference of means assuming equal variance. This procedure tests whether the bias or change is large, factoring in the inter-annual variability in the time series. This test assumes (1) stationarity, (2) temporal independence, and (3) normality of the data. While yearly precipitation is often normally distributed, on a monthly scale it is often non-normal and can sometimes be described by a log-normal distribution (Tilahun 2006). Hence, we repeat our RCM t-tests with the model output transformed using a natural logarithm after replacing the data for months with no precipitation with 0.01 mm for computational purposes. We do not find large differences from the case of the non-transformed data, suggesting that the RCM results are not very sensitive to the distributional assumptions about precipitation. We repeat a subset of our RCM t-tests relaxing the equal variance assumption, and the results appear virtually identical to the equal variance t-tests.

3.3. Observations

The dataset used to evaluate the RCM and GCM temperature and precipitation output is provided by Australian Bureau of Meteorology's Australian Water Availability Project (AWAP; Jones et al. 2009). This dataset contains daily and monthly spatial climate analyses on a 0.05° × 0.05° grid (approximately 5 km × 5 km) which are prepared from station observations. These data are more dense in the coastal areas compared to the interior, with considerably more rainfall stations compared to temperature stations. The typical cross-validation errors over this region for years 2001 to 2007 are between 0.5 and 1.0°C for monthly maximum and minimum temperatures and between 10 and 25 mm mo^{-1} for monthly rainfall (Jones et al. 2009). We interpolate AWAP data to the RCM grids using a simple inverse distance weighting method prior to the analysis. We calculate monthly mean temperature as a simple average of the mean daily maximum and minimum temperatures from the AWAP dataset. Throughout the paper, we use the AWAP observations on the RCM grids. For the GCM bias plots, we additionally average these data over each GCM's grid boxes for better visualisation (we still use the un-averaged data to calculate the root mean square error [RMSE] and pattern correlation). Mean AWAP temperature and precipitation for years 1990 to 2009 are shown in Figs. 3 & 4, respectively (the observations are only available over land).

4. RESULTS

4.1. Present-day models compared to observations

4.1.1. Stippling convention

We present our results on significance following Tebaldi et al. (2011). The multi-model biases are separated into 3 categories. In insignificant areas, less than half of the models show a significant bias. Here,

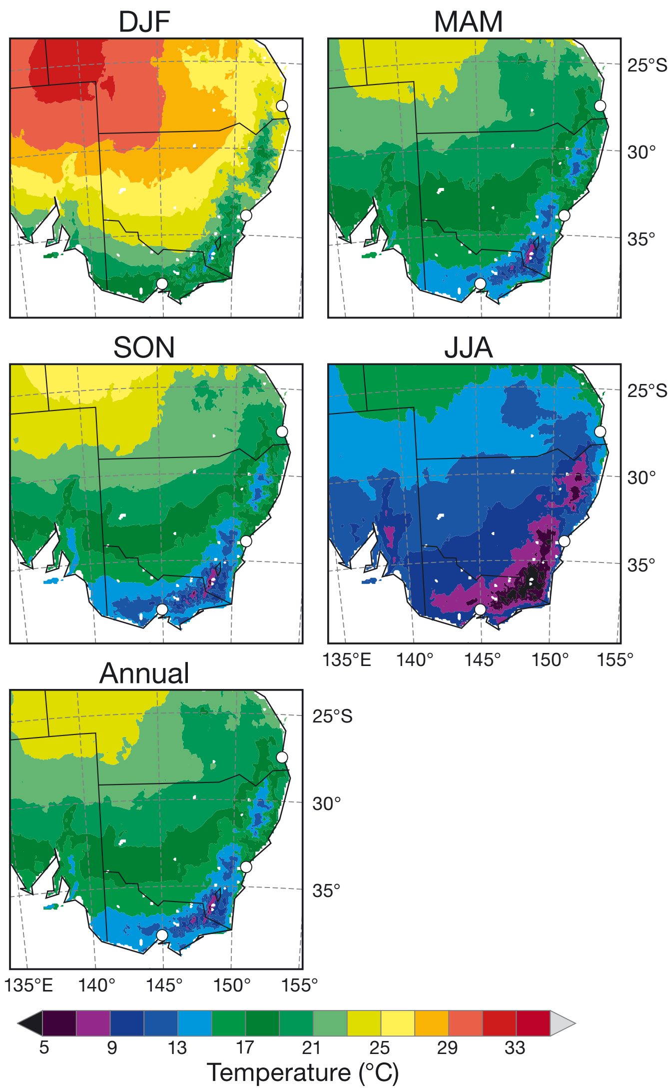

Fig. 3. Seasonal and annual mean near-surface air temperature observations from the AWAP project interpolated to the inner domain. Here and in the rest of the figures, white circles (top to bottom) represent Brisbane, Sydney, and Melbourne

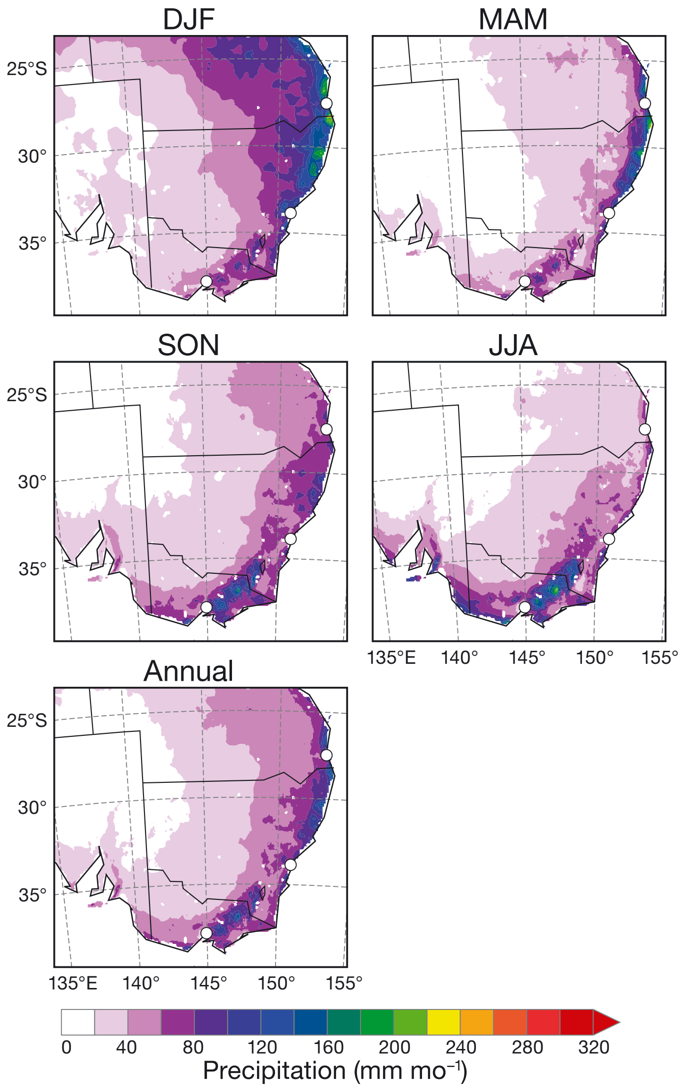

Fig. 4. Seasonal and annual mean precipitation observations from the AWAP project interpolated to the inner domain (mm mo^{-1})

multi-model mean bias is shown in colour; this is where the bias in most models is relatively small, which is the most desired outcome. In significant agreeing areas (stippled), at least half of the models are significantly biased, and at least 80% of the significant models agree on the bias direction. In these areas, the ensemble bias tends in one direction, which is the least desired outcome. Finally, in significant disagreeing areas (shown in white over land), at least half of the models are significantly biased, and <80% of significant models agree on the direction. The terms 'insignificant', 'significant agreeing', and 'significant disagreeing' are used throughout Section 4.1 to refer to the 3 categories above. Note that ocean areas are coloured white in the bias plots due to the absence of AWAP observations there.

4.1.2. Temperature

Inner-domain RCMs show an improvement over GCMs in terms of pattern correlation with observations and RMSE for all seasons (Table 2). The most marked improvement occurs in winter (JJA), when the GCM performance is the worst. On average, the RCMs have consistently negative biases over many parts of the region (Fig. 5). These biases are significant in at least half of the models. The biases appear to be greatest in the outer domain output. Here, over the significantly biased regions, the most negative model mean biases occur over the south-eastern mountains in austral winter (JJA) and spring (SON) and over eastern Queensland throughout the year, reaching as high as 3°C. However, the inner-domain RCMs show a marked improvement in winter (JJA) bias over the outer-domain results. Some of the RCM cold biases may be at least partly caused by the unified Noah land surface model used in all simulations. This model has been previously shown to have cold biases over snow-covered regions in winter and to simulate overly high summertime soil moisture and evaporation (García-Díez et al. 2015).

In many south-eastern coastal areas, the GCMs tend to show a significant warm bias, whereas this bias is largely absent in the RCMs. This difference is possibly due to better representation of coastal topography in the RCMs.

4.1.3. Precipitation

The inner-domain RCMs are better able to capture the spatial pattern of precipitation, compared to GCMs, as evidenced by model-mean pattern correlation (Table 3). However, the performance of RCMs is

Table 2. Ensemble mean diagnostics for 12 RCMs on the inner domain and 4 driving GCMs for seasonal and annual mean near-surface atmospheric temperature for years 1990 to 2009. **Bold** values indicate RCM improvement over a corresponding driving GCM. The diagnostics were calculated as averages of the diagnostics for each individual model, with AWAP observations as a reference

	Model-mean RMSE (°C)		Model-mean pattern correlation	
	RCMs	GCMs	RCMs	GCMs
DJF	**1.59**	1.82	**0.982**	0.926
MAM	**1.50**	2.01	**0.977**	0.884
JJA	**1.51**	2.50	**0.971**	0.769
SON	**1.47**	1.77	**0.987**	0.930
Annual	**1.43**	1.81	**0.985**	0.906

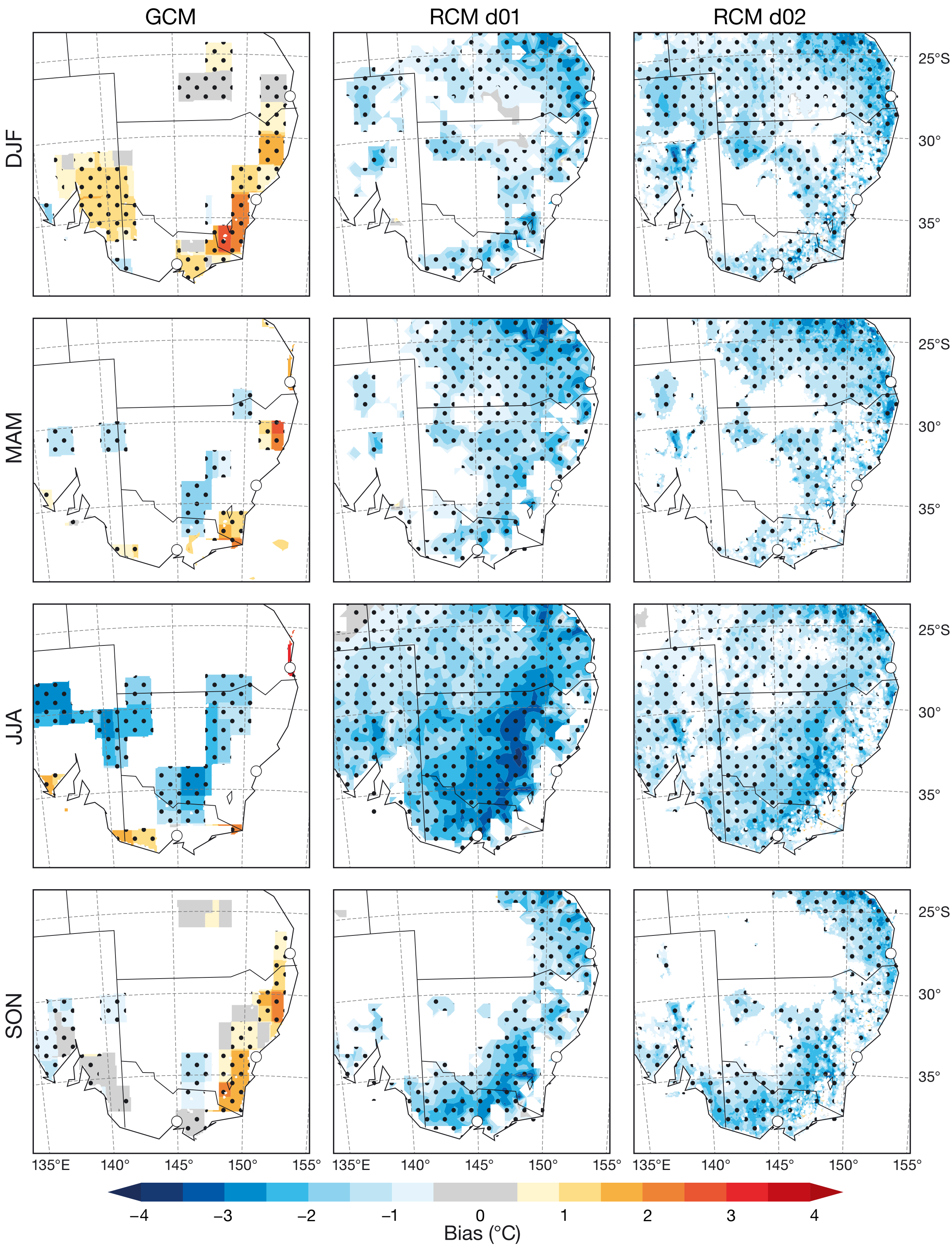

Fig. 5. Multi-model seasonal mean near-surface atmospheric temperature bias (°C) with respect to AWAP observations for the GCMs, the RCMs on domain 01, and the RCMs on domain 02. Stippled (significant agreeing) areas indicate that half or more models show statistically significant bias, with 80% of more significant models biased in the same direction. White (significant disagreeing) areas over land indicate that half or more models show statistically significant bias, with less than 80% of significant models biased in the same direction

Table 3. Ensemble mean diagnostics for 12 RCMs on the inner domain and 4 driving GCMs for seasonal and annual mean precipitation for years 1990 to 2009. **Bold** values indicate RCM improvement over a corresponding driving GCM. The diagnostics were calculated as averages of the diagnostics for each individual model, with AWAP observations as a reference

	Model-mean RMSE (mm mo^{-1})		Model-mean pattern correlation	
	RCMs	GCMs	RCMs	GCMs
DJF	53.8	26.3	**0.873**	0.868
MAM	30.9	20.4	**0.834**	0.776
JJA	20.6	19.9	**0.812**	0.704
SON	21.3	20.4	**0.890**	0.817
Annual	28.5	18.2	**0.853**	0.835

worse in terms of RMSE. The RCM precipitation is typically too wet; however, there are significant disagreeing areas as well, especially during spring (SON; Fig. 6). The output from both domains is remarkably similar, with the inner domain showing minor improvements in terms of the wet bias in winter (JJA). However, inner-domain results still have large local biases in the Snowy Mountains in the SE of the domain. Many aspects of the RCM behaviour are inherited from the driving GCMs, although the GCMs are typically drier than the RCMs, especially along the coast (Fig. 6). The RCM biases are most ubiquitous during summer (DJF) and autumn (MAM). In contrast, in winter (JJA) for the inner domain and spring (SON) for both domains, most models are not significantly different from the observations in many areas, and inner-domain RMSE is lowest compared to other seasons (Fig. 6, Table 3). Of particular concern is a very large (~100 mm mo^{-1}) bias over eastern Queensland and northern New South Wales (NSW) coast during summer present in both domains. This bias contrasts with the coastal dry bias in the driving GCMs. On both domains, RCMs R1 and R3 forced with MIROC3.2 and CSIRO-Mk3.0 model the wettest climate in this region (not shown). Further research is required to elucidate the cause of the wet biases. Wet biases in WRF under several parameterisations have been previously found over Europe by García-Díez et al. (2015), and a variety of possible explanations were suggested, including the absence of radiative effects of unresolved cumulus clouds. Future analysis could involve testing models' ability to simulate each of the phenomena affecting precipitation that were previously outlined in Section 2 (e.g. easterly troughs, ECLs, cut-off lows), verifying model representation of vertical fluxes of moisture and heat that influence convection as well as investigating the observations for potential under-catch issues, which have previously been found to be quite large in mountainous regions and especially in winter (Bormann et al. 2014, Torma et al. 2015).

4.2. Changes from present

Here, we present local and state-averaged temperature and precipitation changes between present climate conditions (1990–2009) and the far future (2060–2079). The near-future changes are provided in Sections 2 and 3 of the Supplement at www.int-res.com/articles/suppl/c069p209_supp.pdf. Here, we focus on the multi-model mean changes; annual mean model-by-model projections can be found in Section 4 of the Supplement.

4.2.1. Stippling convention

The stippling convention for future changes is similar to the one for the biases (Section 4.1). In insignificant areas (shown in colour), less than half of the models show a significant change. 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 pattern 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 because any future change remains highly uncertain.

4.2.2. Temperature

Maps of GCM and RCM ensemble mean far-future warming are shown in Fig. 7, while inner-domain state-averaged changes for states of NSW and Victoria are presented in Table 4. The RCMs project significant warming everywhere across the region, for both domains. This warming, at least over the land areas, is markedly higher compared to the present-day observed internal variability (Section 1 of the Supplement and Fig. S1). On an annual-mean basis, each of the 12 models project, on the inner domain, a significant temperature change throughout the

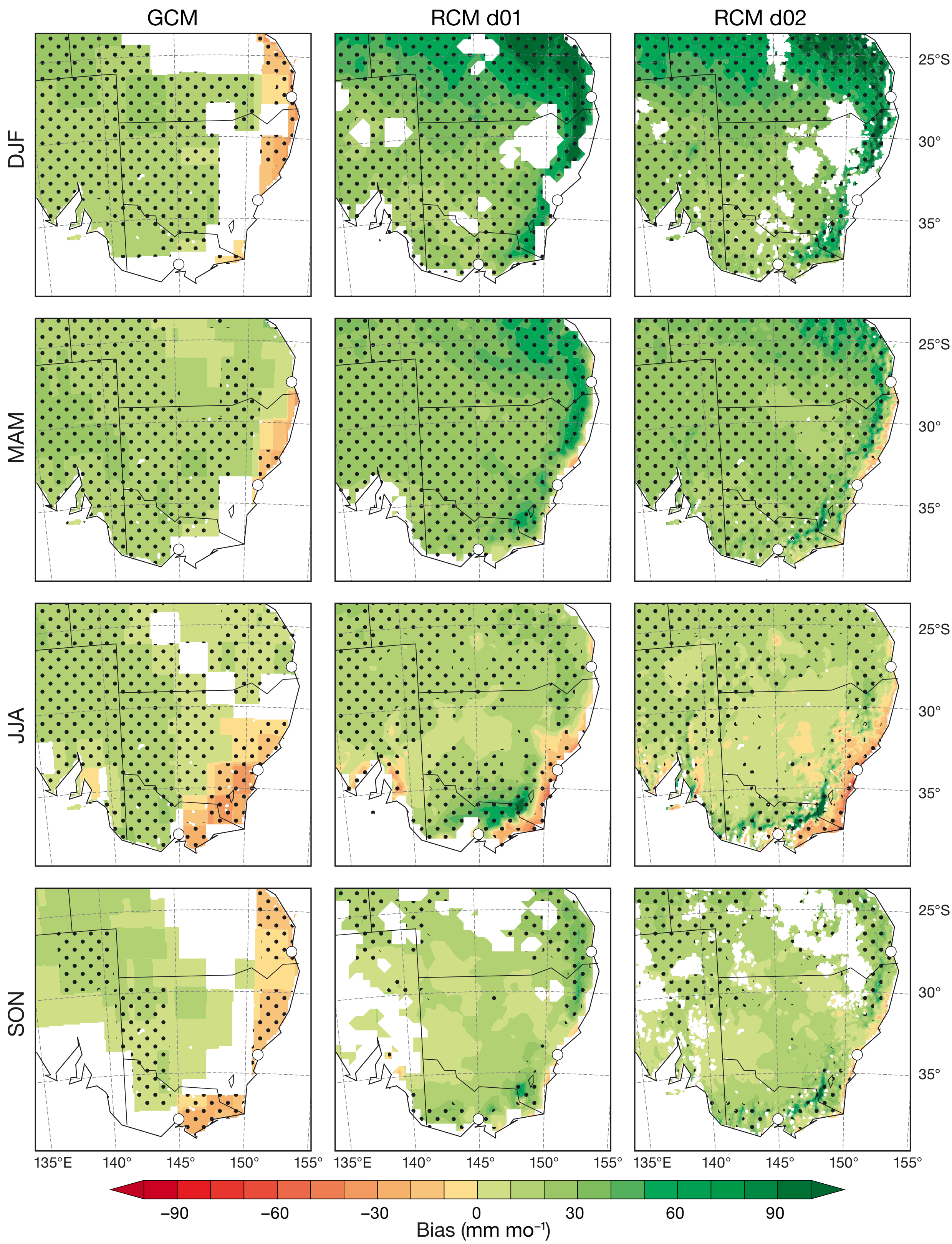

Fig. 6. Multi-model seasonal mean precipitation bias (mm mo^{-1}) with respect to AWAP observations for the GCMs, the RCMs on domain 01, and the RCMs on domain 02. Stippling and white colouring convention as in Fig. 5

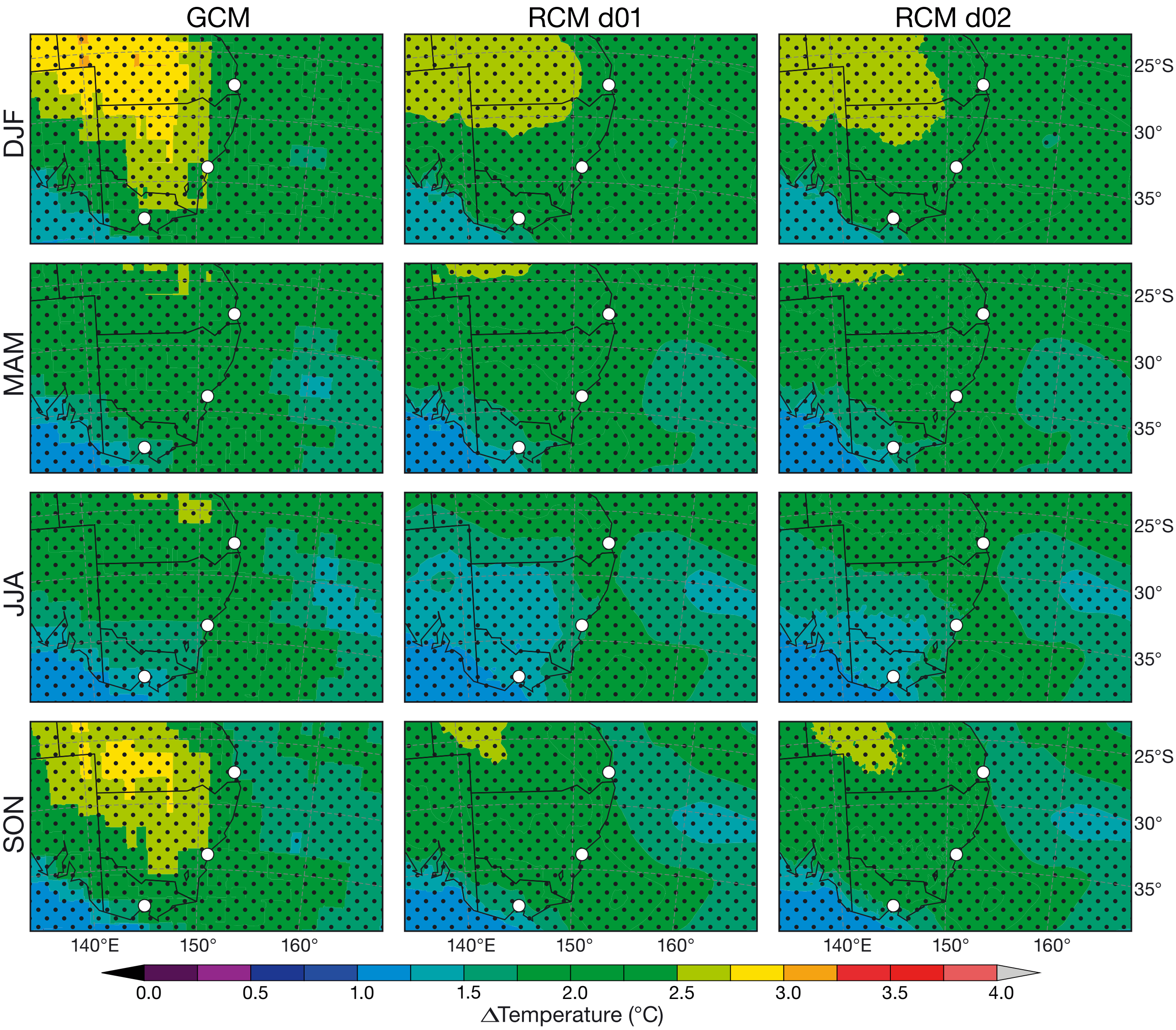

Fig. 7. Ensemble mean seasonal mean near-surface atmospheric temperature change (°C) from present day (1990–2009) to far future (2060–2079) for the GCMs, the RCMs on domain 01, and the RCMs on domain 02. Stippled (significant agreeing) areas indicate that half or more models show a statistically significant change, with 80% of more significant models changing in the same direction. White (significant disagreeing) areas indicate that half or more models show a statistically significant change, with less than 80% of significant models changing in the same direction

domain. This is broadly consistent with GCM results (Collins et al. 2013, Kirtman et al. 2013). The highest warming (exceeding 2.5°C) is expected over land areas and in summer (DJF). Specifically, as inner domain output indicates, NSW is projected to warm by 2.4°C and Victoria by 2.1°C (Table 4). Higher warming over land is consistent with previous work (Collins et al. 2013, Suppiah et al. 2007). This feature is a well established phenomenon, and in the GCMs, it has been associated with a limited supply of soil moisture, a reduction of the lower atmosphere relative humidity, and a decrease in cloudiness over land in a warmer climate (Fasullo 2010). While in our work, summertime (DJF) warming is greatest, for Suppiah et al. (2007), the greatest warming for a future period centred on 2070 occurred during spring (SON). In contrast to our study, Suppiah et al. (2007) used a simple scaling methodology that utilised a linear relationship between a local-scale seasonal-mean climate change in 15 GCMs and a global mean

Table 4. RCMs ensemble mean state-averaged near-surface atmospheric temperature changes between present (1990–2009) and far future (2060–2079) (°C) for the inner domain, compared to multi-model changes from driving GCMs. **Bold** values indicate significant agreeing changes

	RCM output		GCM output	
	NSW	Victoria	NSW	Victoria
DJF	**2.4**	**2.1**	**2.6**	**2.2**
MAM	**2.0**	**1.7**	**2.1**	**1.7**
JJA	**1.7**	**1.4**	**1.9**	**1.5**
SON	**2.2**	**1.8**	**2.5**	**2.0**
Annual	**2.1**	**1.7**	**2.3**	**1.9**

change. Here, the least warming is projected in austral winter (JJA) over the southern part of the domain (1.4°C over Victoria on the inner domain). The winter warming is even smaller on the outer domain.

The RCM warming over south-east Australia is generally less than that simulated by the GCMs (Fig. 7, Table 4). Like the RCMs, the GCM warming is 'significant agreeing' everywhere over the region. Both the RCMs and the GCMs feature a 'warm spot' off south-east Australia in the Tasman Sea. This spot has been previously associated with changes in the southern extension of the East Australian Current (Oliver & Holbrook 2014).

The warming simulated in the 2 domains is generally similar in summer (DJF) and autumn (MAM). However, inner domain results feature a somewhat warmer response over land in winter (JJA) and spring (SON).

4.2.3. Precipitation

Far-future local changes in RCM precipitation (mm mo^{-1}) are shown in Fig. 8, while state-averaged changes from the inner domain are presented in Table 5. On the local scale, in most areas, the precipitation changes tend to be insignificant. Indeed, these changes typically fall within the observed interannual variability (Section 1 and Fig. S2 in the Supplement). However, because the *t*-test is prone to Type II error (false negatives), the absence of significance is merely suggestive of no change, noting that there may not be enough information in the data to establish significance. Over land, there are 2 areas with significant changes: a drying over the state of Victoria in spring (SON) and disagreeing model responses over parts of NSW and Queensland in winter (JJA). In winter over the inner domain, CCCMA3.1-driven runs become wetter over most of the land area, while CSIRO-Mk3.0-driven runs become drier, and the ECHAM5-driven runs project insignificant change over almost all land areas (Fig. 9). The MIROC3.2-driven models project significant wetting over north-central NSW but insignificant change elsewhere over land.

The changes are largely similar over both domains, suggesting that the 50 km outer-domain resolution might be appropriate for making projections over most regions. However, inner-domain results add local detail over south-eastern mountains and project less Tasman Sea summer drying.

The RCM Victorian drying deserves special attention. In spring (SON), it is considerably greater than the corresponding GCM drying. Victoria sits on the southern flank of a subtropical ridge that sets up in autumn and breaks down in spring (Fig. 10). Over Victoria (and the rest of south-east Australia), this ridge is associated with drier conditions (Grose et al. 2015). The RCMs show a substantial future strengthening of this ridge in the spring (Fig. 11), which very likely contributes to the drying. The GCMs exhibit much weaker future changes in this season. Grose et al. (2015) show that GCMs under-represent the observed strengthening of the cold season subtropical ridge (in fact, the modelled trends are generally not significant, while the observed trend is) as well as the observed negative correlation between the ridge intensity and precipitation. During any period with a mean condition dominated by such a high-pressure ridge, precipitation is associated with perturbations away from this mean condition. These perturbations are generally caused by relatively small-scale, short-duration disturbances that allows the longer-term mean condition to remain. Because RCMs can resolve small-scale synoptic features, such as fronts and cyclones (Ji et al. 2015, Rummukainen 2016), and because jet stream latitude and blocking are better simulated by higher-resolution climate models (Guemas & Codron 2011, Arakelian & Codron 2012, Anstey et al. 2013), it seems likely that the NARCliM RCMs might attain a more realistic representation of the small-scale disturbances and, as a consequence, of the sub-tropical ridge. This suggests that a larger future Victorian drying than is present in previous results is likely.

In winter (JJA) and spring (SON), there is a significant drying spot in the northern Tasman Sea at approximately (160° E, 30° S). Additionally, there is a significant wetting spot in winter to the south-west of the drying spot, in the Tasman Abyssal Plain. The models show contradicting responses in the areas between the 2 features, due to an uncertainty about

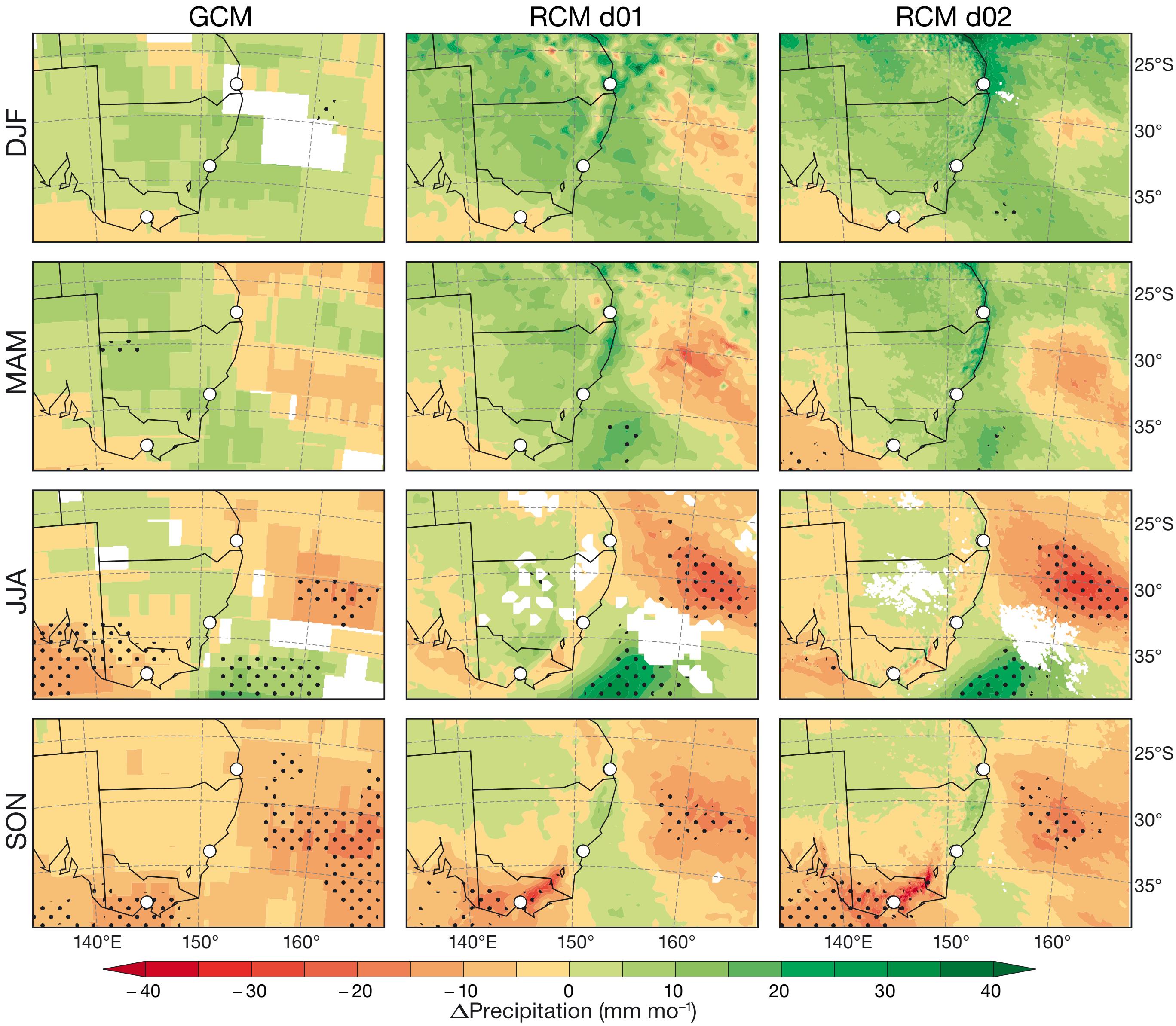

Fig. 8. Ensemble mean seasonal mean precipitation change (mm mo^{-1}) from present day (1990–2009) to far future (2060–2079) for the GCMs, the RCMs on domain 01, and the RCMs on domain 02. Stippling convention as in Fig. 7

Table 5. RCM ensemble mean mean state-averaged precipitation changes between present (1990–2009) and far future (2060–2079) (mm mo^{-1}) for the inner domain, compared to multi-model changes from driving GCMs. **Bold** values indicate significant agreeing changes

	RCM output		GCM output	
	NSW	Victoria	NSW	Victoria
DJF	9.7	2.1	5.4	0.74
MAM	6.5	2.9	4.9	1.0
JJA	0.46	–1.8	–0.068	**–4.2**
SON	–1.5	**–15**	–3.5	**–8.9**
Annual	3.8	–2.9	1.7	–2.8

the precise location of these features (Fig. 8). Note that this uncertainty in the location of the drying and wetting features is fundamentally different from the uncertainty in winter (JJA) over land, where some of the models show significant drying, whereas other models show significant wetting.

While many of the RCM features appear to be inherited from the driving GCMs, there are also some considerable differences (Fig. 8). First, the largest significant Victorian drying area in the RCMs occurs in spring (SON), whereas it is largest in winter (JJA) in the GCMs. The magnitude of springtime drying is

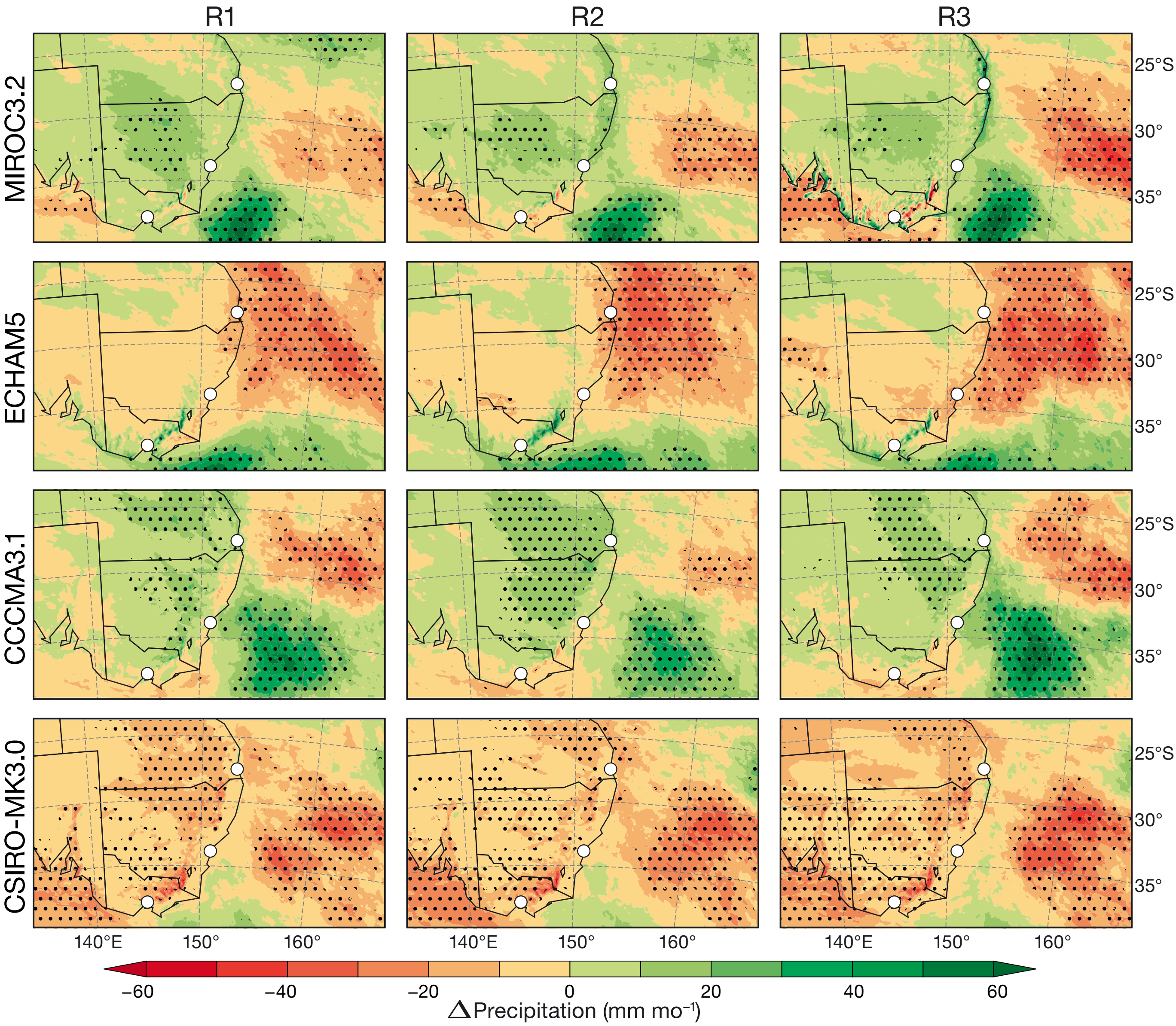

Fig. 9. JJA precipitation change from present day (1990–2009) to far future (2060–2079) from each of the RCMs (mm mo^{-1}) on domain 02. Stippling indicates statistically significant changes

also now much greater in the RCMs (Fig. 8, Table 5). Second, there are differences in small-scale features over the Snowy Mountains and Eastern Seaboard. For example, the RCMs extend substantial significant Victorian drying well into the Snowy Mountains. In addition, in contrast to the GCMs, the RCMs project a winter (JJA) drying across the entire NSW coast as well as spring (SON) wetting along considerable portions of coast — features that are different from the GCMs. Finally, the RCMs project the largest Tasman Sea drying in winter (JJA), unlike the GCMs which project this drying in spring (SON).

During summer (DJF) and autumn (SON), the projected widespread land wetting broadly agrees with results reported by Suppiah et al. (2007). On the other hand, Suppiah et al. (2007) reports widespread decreases across south-east Australia in winter (JJA) and spring (SON), while our results exhibit wetting in many inland areas. However, since the wetting is not significant, it might be simply due to internal climate variability.

The significance of state-averaged RCM changes on the inner domain mirrors the local-scale results (Fig. 8, Table 5). On the state scale, the only signifi-

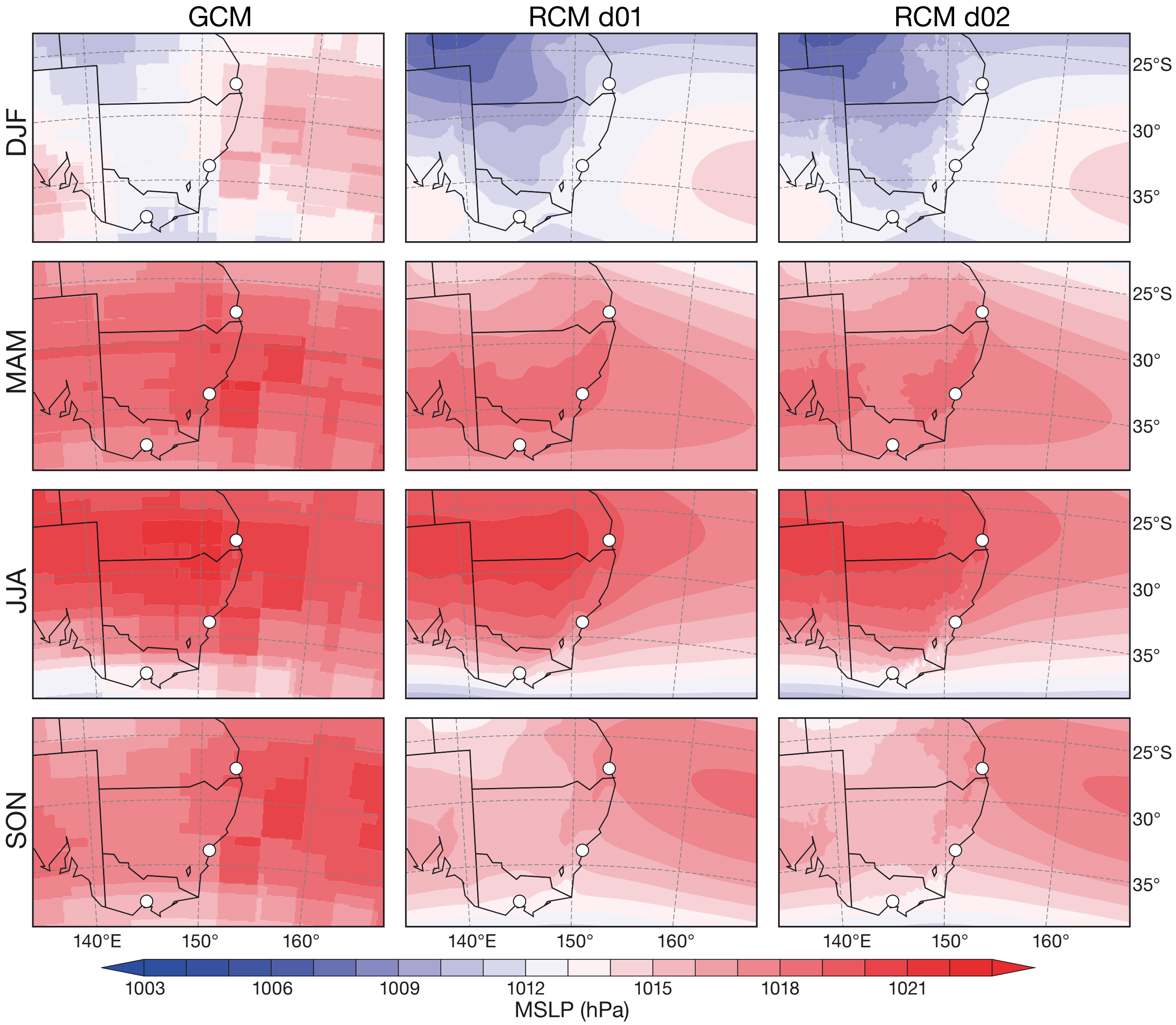

Fig. 10. Ensemble mean present-day (1990–2009) seasonally averaged mean sea level pressure (MSLP, hPa) for the GCMs, the RCMs on domain 01, and the RCMs on domain 02

cant RCM change is Victorian drying in spring (−15 mm mo^{-1} averaged over the state; Table 5). This value is considerably greater than that given by the driving GCMs.

5. DISCUSSION

Our work is subject to several limitations and caveats which should be taken into account when interpreting the results. First, the significance results of the RCMs and GCMs represent different scales because each GCM data point represents an average over a larger area than the RCMs. The internal variability of climate decreases with the increasing scale (Kirtman et al. 2013). Because the *t*-test statistic is inversely proportional to inter-annual standard deviation, we expect the same change to become more significant when averaged on larger scales ('increasing scale effect'). However, we find (see Section 5 of the Supplement at www.int-res.com/articles/suppl/c069p209_supp.pdf) that averaging inner-domain RCM output over driving GCM cells does not consistently affect the significant agreeing area because of

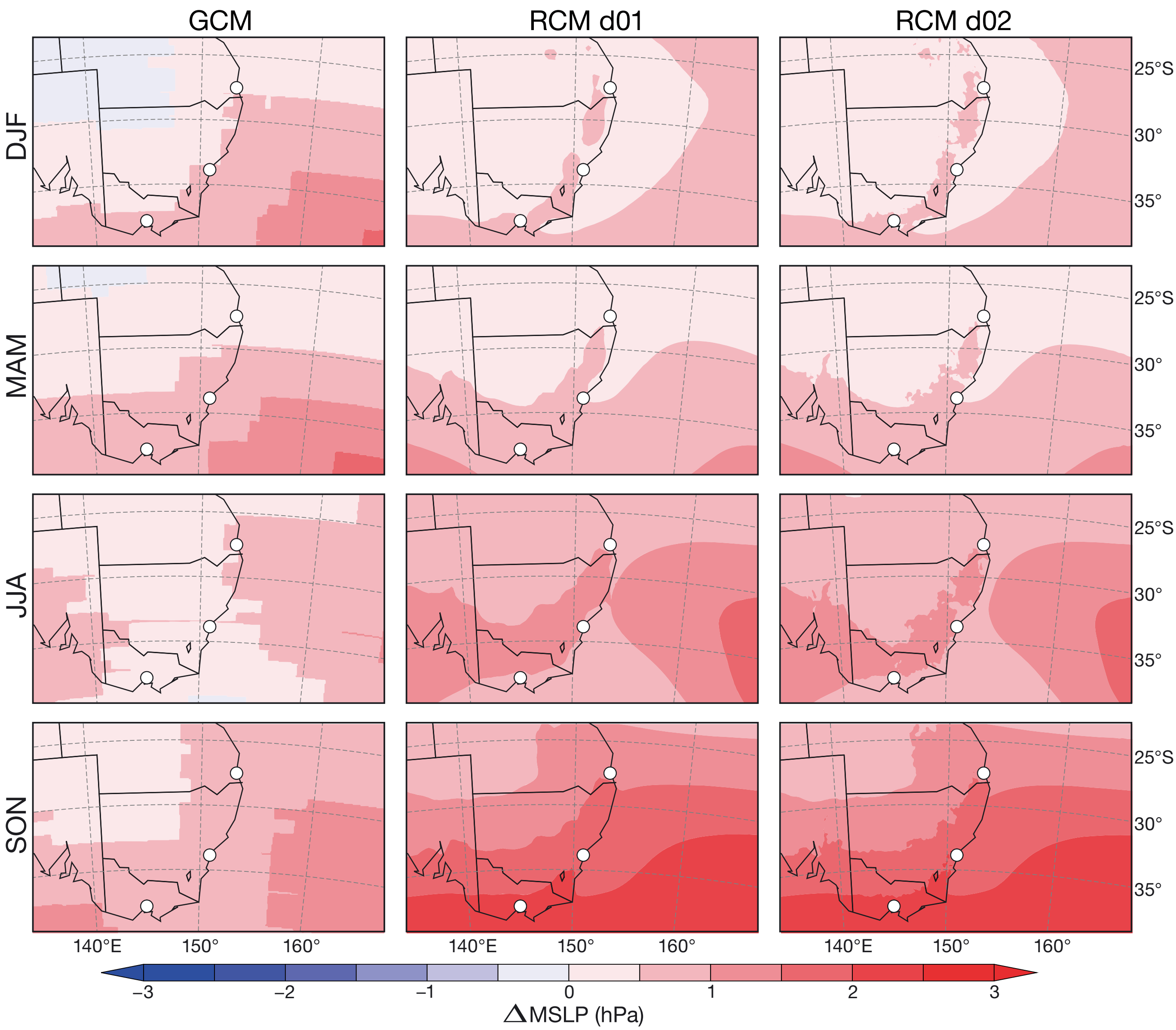

Fig. 11. RCM ensemble mean seasonal mean sea level pressure change (MSLP, hPa) from present day (1990–2009) to far future (2060–2079) [hPa] for the GCMs, the RCMs on domain 01, and the RCMs on domain 02

the counteracting effects of GCM grid scale and location mismatches.

Second, we use a simple *t*-test to establish significance. However, as discussed previously, our results for precipitation do not appear to depend strongly on the distributional assumption. Furthermore, the *t*-test and similar approaches are by far the most common test used in climate science to estimate significance of modelled changes (Tebaldi et al. 2011, Kirtman et al. 2013, Decremer et al. 2014), and research suggests that the *t*-test performs better than more advanced techniques for modelled area-averaged seasonal mean temperature and precipitation changes, except for in cases with strong autocorrelation $\rho > 0.6$ (Decremer et al. 2014), a condition that appears to be uncommon for these variables on seasonal time scales (Madden 1977, Decremer et al. 2014).

Third, due to computational constraints, we use a single emissions scenario: SRES A2. For the far future, this scenario has a slightly lower radiative forcing compared to the newer high-emissions RCP8.5 scenario (Moss et al. 2010). The projections will be different for different emissions scenarios.

Fourth, the driving CMIP3 models have some problems in simulating El Niño–Southern Oscillation (ENSO), a factor influencing precipitation in this region in austral winter and spring. However, model representation of ENSO was explicitly considered during the GCM selection process (van Oldenborgh et al. 2005, Evans et al. 2014). Moreover, the premise of using statistical tests in this study is to attempt to find areas of significant change due to shifts of atmospheric state as opposed to the stationary internal climate variability (e.g. ENSO). Finally, CMIP3 models generally project either no or a weak response of ENSO sea level pressure variability to climate change (van Oldenborgh et al. 2005), suggesting that permanent future ENSO changes will likely be minor.

Fifth, we do not make any elevation corrections to model output prior to the analysis. Correcting for elevation can improve GCM model performance relative to the RCMs. However, Di Luca et al. (2016) analyse the added value of the NARCliM RCM ensemble across a range of seasons, regions, resolutions, parameterisations, global driving datasets, measures, and variables and find that RCMs tend to add value to the driving data, even across the flat terrain where topography corrections are important. Moreover, the improvement generally holds even after performing topography correction.

Finally, the RCMs exhibit significant biases compared to the observations for temperature and precipitation. The RCM biases are not surprising because, due to computational constraints, the models were not selected based on their performance on the climatological scale. Rather, their skill was evaluated for selected 2 wk periods around several storm events. However, many of the precipitation biases are inherited from the driving GCMs, and the RCMs, at least on the inner domain, have better pattern correlations with observations and smaller errors in modelling temperature compared to the GCMs (Tables 2 & 3). Hence, while not perfect, the selected models represent our best attempt at reasonably simulating the climate of the south-east Australia while accounting for model uncertainty. An approach has been designed to correct the projections for the biases (Evans & Argüeso 2014). However, we do not present bias-corrected model output here to simplify the comparison with the GCMs, which were not bias-corrected. Moreover, far-future results using bias-corrected data show little impact on the significantly changing areas.

The main focus of the paper is on the significance of future RCM projections, model agreement, the differences between the RCMs and the driving GCMs, and the link between the far-future strengthening of the subtropical ridge and the Victorian drying. Of considerable scientific interest are also the driving mechanisms underlying future precipitation changes (e.g. fronts, ENSO, Indian Ocean Dipole, etc.). These questions will be more fully addressed in future work.

6. CONCLUSIONS

Here, we present seasonal average temperature and precipitation projections from the NARCliM project, a large regional climate modelling project for south-east Australia. The project is unique in the number of regional climate models that are used as well as in the rigour of how these models were selected. Twelve regional climate model (RCM) integrations are performed at ~50 and ~10 km resolution for the years 2060 to 2079 and are compared to simulations over years 1990 to 2009. This comparison allows us to address the question of model agreement and significance of future projections of key climate variables.

While RCMs show cold biases in many regions, their skill at modelling spatial patterns of temperature and precipitation, at least on the inner domain, is better than that for the driving global climate models (GCMs), especially for winter (JJA). The inner domain results exhibit smaller winter temperature biases over many regions compared to the outer domain. The inner-domain RCMs also improve on the driving GCMs' temperature biases, as evidenced by RMSE. However, they exhibit higher RMSE for precipitation, exhibiting wet biases in many areas.

Significant warming is projected everywhere in the region, with highest warming in summer (DJF) over land. According to the inner-domain results, the state of NSW is projected to warm by 2.4°C in summer and Victoria to warm by 2.1°C. Each of the 12 models exhibits significant warming on an annual scale throughout the region.

RCM precipitation changes tend to be insignificant over most areas and appear to be within present-day climate variability. On land, there are 2 notable exceptions. First, inner-domain results show that Victoria is projected to get drier by 15 mm mo^{-1} in spring (SON), a statistically significant value that is considerably higher than previous results from lower-resolution GCMs. This greater drying appears to be associated with, arguably, a better representation of the subtropical ridge in the RCMs which shows a substantial far-future spring strengthening, a feature that is not prominent in the GCMs. Second, models disagree on the direction of significant precipitation change over parts of NSW and Queensland during winter (JJA).

The use of 2 modelling domains allows us to address the resolution sensitivity of the projections. The inner 10 km domain adds extra detail to the coarser 50 km outer-domain output, but the changes are largely similar to the outer domain for most regions, suggesting that the use of high-resolution 10 km modelling is only warranted in limited cases (e.g. winter temperature, south-eastern mountains).

For the first time, a summary of a comprehensive dataset of high-resolution temperature and precipitation projections is provided for south-east Australia, with many other NARCliM variables being analysed in parallel studies. The projections differ from previously available GCM results in terms of the magnitude of some changes (e.g. generally less warming over land), some specific features (e.g. the dominant time of significant drying in the south shifts from winter to spring), and the level of fine-scale detail (e.g. substantial springtime drying over the Snowy Mountains, a feature that is too small to be represented by the driving GCMs). Ongoing and future work allows for examinations of these and many other variables over states, state planning regions, river basins, etc. for input into local impact-assessment studies as well as hydrologic models. Future research will also focus on more thorough elucidation of physical processes responsible for the changes in precipitation, as well as on obtaining probability distribution functions of future projections, with a special focus on significant areas of change (e.g. Victorian drying in spring).

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