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The CORDEX-Australasia ensemble: evaluation and future projections

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Abstract

A new regional climate projection ensemble has been created for the Australasia region as part of the World Climate Research Programs Coordinated Regional Downscaling Experiment (CORDEX). The CORDEX-Australasia ensemble is the largest regional climate projection ensemble ever created for the region. It is a 20-member ensemble made by 6 regional climate models downscaling 11 global climate models. Overall the ensemble produces a good representation of recent climate. Consistent biases within the ensemble include an underestimation of the diurnal temperature range and an underestimation of precipitation across much of southern Australia. Under a high emissions scenario projected temperature changes by the end of the 21st century reach ~5K in the interior of Australia with smaller increases found toward the coast. Projected precipitation changes are towards drying, particularly in the most populated areas of the southwest and southeast of the continent. The projected precipitation change is very seasonal with summer projected to see little change leaning toward an increase. These results provide a foundation enabling future studies of regional climate changes, climate change impacts, and adaptation options for Australia.

1. Introduction

Future changes in global climate are locked in for the next couple of decades. These changes will impact both human and natural systems in different ways depending on the location. Enabling pathways for adaptation is critical for the resilience of these systems to future climate changes. Providing future climate change information at the regional and local scales relevant for adaptation decisions is required to both understand the likely impacts on various systems and the possible adaptation pathways.

The Coordinated Regional Downscaling Experiment (CORDEX) was implemented, as an element of the World Climate Research Program, to coordinate international downscaling efforts, improve our understanding and modelling of regional climate, and provide regional scale climate projections that can be used in climate change impact and adaptation studies (Giorgi & Gutowski 2015). The CORDEX phase 1 experiment involves a model evaluation stream and a climate projection stream, each performed over a series of regional domains covering all continental land masses at a resolution of 0.44°. In the model evaluation stream the ERA-Interim reanalysis is downscaled and the results are evaluated against observational datasets. The climate projection stream involves downscaling Global Climate Model (GCM) simulations, performed as part of the Coupled Model Intercomparison Project phase 5 (CMIP5).

The model evaluation stream is designed to allow quantification of regional model errors with the assumption that the ERA-Interim reanalysis provides “perfect” boundary conditions. Analysis of this stream provides insight into the strengths and limitations of the regional climate models (RCMs) used. It also provides a “best case” for RCM performance that can be expected from the historical simulations in the climate projection stream. Many CORDEX domains have performed studies of simulations in the model evaluation stream. For example, Kotlarski et al. (2014) examined simulations from the EURO-CORDEX domain evaluation stream. They found that the RCMs were able to capture the basic features of European climate though common model biases included a warm and dry summer over southern Europe, and wet and cold biases over most of Europe in the other seasons. Also for this domain and stream, Knist et al. (2017) examined the land-atmosphere coupling and found that the RCMs were able to capture the strong coupling in southern Europe and the weak coupling in northern Europe but struggled to accurately represent the central European transition zone. The spread in the land-atmosphere coupling was primarily attributed to the land-surface models. Kim et al. (2014) evaluated simulations from the CORDEX-Africa evaluation stream. While they find that the basic climatological features are simulated reasonably, they also find model biases that vary by region, variable and metric, precluding a simple conclusion about model performance. Solman et al. (2013) examined ERA-Interim driven RCM simulations over the CORDEX-South America domain finding the overall climate to be simulated adequately, with larger biases in the tropics compared to the extra-tropics. Some systematic biases are present, particularly over the La Plata Basin region. Prein et al. (2019) examine whether ERA-Interim driven simulations over the North America CORDEX domain can simulate observed large-scale weather types. They highlight the role of the GCM in capturing observed weather types, while the RCMs improve the variability within weather types. For CORDEX-Australasia, Di Virgilio et al. (2019) evaluated ERA-Interim driven simulations finding each RCM to have a unique set of biases and the ensemble mean to have lower biases in general. Overall the ensemble tended to underestimate maximum temperature over most of Australia, particularly in the east where it also tended to overestimate precipitation. Hirsch et al. (2019) evaluated the same RCMs for their ability to simulate the climatological attributes of Australian heatwaves. Overall the ensemble underestimating the frequency of heatwave days, with half the models also underestimating the heatwave intensity. Many other studies have examined model evaluation stream simulations for these and other CORDEX domains (e.g. Jacob et al. 2012; Gbobaniyi et al. 2013; Martynov et al. 2013; Whan and Zwiers 2015; Fantini et al. 2016; Jury et al. 2018). While highlighting the biases of individual RCMs is useful for users and developers of that RCM, it is the systematic shared biases shown in these studies that need to be considered when interpreting results from a CORDEX domain ensemble.

The climate projection stream includes GCM driven historical and future simulations. Many CORDEX domains have had their historical simulations evaluated against observations and their future climate change quantified. For example, future projections for CORDEX-Africa have been examined in terms of changes in the temperature and extreme heat (Dosio 2016), and precipitation (Dosio et al. 2019). They report substantial increases in temperature (much higher than the global average) and related heat extremes. They also identify regions with statistically significant changes in precipitation and find these correspond quite well with changes projected by the driving GCMs. However, regions such as the Ethiopian highlands have precipitation changes that diverge from the driving GCMs and this is attributed to the representation of topography. The climate projection stream simulations for the EURO-CORDEX domain have been examined in several studies (Jacob et al. 2014, Rajczak & Schär 2017, Frei et al. 2018). They found that: the projected climate changes are generally similar to those found in earlier regional climate model projection ensembles; heavy and extreme precipitation intensify across most of Europe even in some locations that have a decline in mean precipitation; and a robust signal of decreasing snowfall over the Alps. Many other studies report the future climate changes projected for individual models in various CORDEX domains (e.g. (Teichmann et al. 2013)Teichmann et al., 2013). However many domains, including CORDEX-Australasia, are yet to perform a study of the future changes projected by the full RCM ensemble.

In a second phase the CORDEX-CORE experiments have been completed with the aim of creating an initial homogeneous downscaled ensemble with a resolution of 0.22°, to cover most of populated land area of the world, to allow transversal research across multiple domains on a similar phenomena, to assess the consistency of the climate change signal and possible added value (Jabob et al, to be submitted; Coppola et al, to be submitted). Initially the CORE experiment uses a core set of RCM models (RegCM and REMO) to downscale a core set of GCMs with medium, low and high climate sensitivity. Also the CORE experiment includes an evaluation and a projections stream for two scenarios the RCP2.6 and RCP8.5.

Previously regional climate projections have been produced for various regions, often States, within Australia. Perhaps the earliest example was produced through the “Climate Futures for Tasmania” project which downscaled six CMIP3 GCMs using the Conformal Cubic Atmospheric Model (CCAM) to ~14km resolution over Tasmania (Corney et al. 2013, White et al. 2013). The New South Wales/Australian Capital Territory Regional Climate Modelling (NARCliM) project downscaled four CMIP3 GCMs using three RCMs built within the Weather Research and Forecasting (WRF) modelling framework to ~10km resolution over southeast Australia excluding Tasmania (Evans et al. 2014, Cortés-Hernández et al. 2015, Ji et al. 2016, Olson et al. 2016). Over southwest Western Australia Andrys et al. (2016, 2017) downscaled four CMIP3 GCMs using a single configuration of WRF to a resolution of ~5km. Other dynamically downscaled regional projections have also been produced for Queensland and Victoria using CCAM. While each of these downscaling exercises provided valuable climate change information, they were performed independently of each other and contain a number of limitations: They each downscale a small set of GCMs with a single (or small set) of RCMs; they do not cover all of Australia; and they do not use a consistent experiment design. CORDEX-Australasia offers the opportunity to overcome each of these limitations.

Here we present the first analysis of the climate projection stream simulations for the CORDEX-Australasia domain. This includes an analysis of the GCM driven historical simulations compared to observations which provide a quantitative measure of the performance of each GCM-RCM pair and of the ensemble as a whole. Then the future climate projections under a high emission scenario are examined and end of century changes in both means and extremes of precipitation and temperature are presented and discussed. This study provides the basic information about climate changes projected by the CORDEX-Australasia ensemble that will be needed in future climate change impacts and adaptation studies for the region.

2. Data and Methods

2.1. RCM data

Six RCMs (two within WRF (Powers et al. 2017); CCLM (Rockel et al. 2008); REMO2015 (Remedio et al. 2019); RegCM4.7 (Giorgi et al. 2012) and one variable resolution global model (CCAM, (McGregor & Dix 2008, Katzfey et al. 2016)) have been used to downscale eleven CMIP5 GCMs over the CORDEX-AustralAsia region (Table 1). Configuration details of the downscaling models can be found in supplementary Table S1 and the corresponding GCMs in Table S2. Time periods simulated varied slightly between models. The common periods analysed here are 1976 to 2005 for the historical simulation, and 2070 to 2099 for the future Representative Concentration Pathways (RCP) 8.5 simulations. All model data are interpolated to a common 0.5° grid for comparison.

GCM selection was made by the individual modelling groups, though generally the GCMs were required to provide a reasonable historical simulation and span a range of climate sensitivities. This can be seen in Smith and Chandler (2010) and Evans et al. (2014) where the chosen GCMs are amongst the adequately performing GCMs over Australia, and span the range of future temperature change (climate sensitivity, see Table S2). The GCM selection for the CCAM simulations was based on the GCMs ability to realistically capture current climate and climate features such as El Niño-Southern Oscillation (ENSO) as well as on the range of change signals of the SSTs in the Pacific (Katzfey et al. 2016).

Table 1: GCM-RCM pairs that provided downscaled simulations for both the historical and future (RCP8.5) scenarios for the CORDEX-AustralAsia domain.

RCM **GCM**	WRFJ	WRFK	CCLM	REMO2015	RegCM4.7	CCAM
ACCESS1.0						
ACCESS1.3						
CanESM2						
EC-EARTH						

MPI-ESM-LR						
MPI-ESM-MR						
NORESM1-M						
HadGEM-ES						
CNRM-CM5						
NCAR-CCSM4						
GFDL-CM3						

2.2. Observation data

To evaluate the historical simulations gridded datasets of temperature (daily minimum and maximum) and precipitation, first developed through the Australian Water Availability Project (AWAP; Jones et al. 2009) are used. This daily dataset has a 0.05° grid resolution and is produced through interpolation of station observations across Australia. A higher density of stations exist in the more heavily populated coastal regions compared to inland regions. Areas where the station density is so low that it produces gaps in the observational grid have been masked out of the analysis. These observational grids are interpolated to the common 0.5° model grid using the conservative area-weighted re-gridding scheme of the Iris version 2.1 library (Met Office) for the Python version 3.6 programming language.

2.3. Methods and metrics

The bias, root mean square error (RMSE) and spatial correlation are calculated for the annual and monthly climatology of the precipitation and temperature (daily minimum and maximum). The statistical significance of biases and future changes, compared to inter-annual variability in each simulation, is tested using a Student’s t-test assuming equal variance for temperature (α=0.05). Due to the non-normality of precipitation the Mann-Whitney U test was used to test for significance of biases and future changes of precipitation (α=0.05). For visualization of the ensemble biases and changes, each pixel was placed in one of three classes following Tebaldi et al. (2011). Pixels where fewer than half of the models indicate a significant bias (or change) are shown in colour. Pixels where at least half of models indicate a significant bias (or change), and at least 75% of those with a significant change agree on the direction of change, are shown stippled. Pixels where at least half of models indicate a significant bias (or change) and less than 75% of these agree on the direction of change, are shown in white.

3. Results

3.1. Evaluation of historical simulations

Before examining projected future changes we assess the ensemble ability to simulate the historical climate (1976 to 2005). Here we focus on the ensemble biases presented such that the best outcome is shown in colours. In these areas the colours show the mean bias and a lack of stippling indicates that most individual models are close to the observations (do not have significant biases). Areas that are stippled are areas where most models have significant biases in the same direction, and are referred to as “significant agreeing”. This is a less desirable outcome as it indicates that the ensemble as a whole is consistently distant from observations, in the same direction (over or underestimation). Hence the observations tend to be near one end of the model range. Finally, areas shown in white indicate that most models have large (significant) biases and they are split either side of the observations, referred to as “significant disagreeing”. Hence the observations lie within the model range but few models are close to the observations.

Figure 1 shows the observed mean annual, summer (DJF) and winter (JJA) daily maximum temperature and related ensemble biases. Individual bias estimates for the ensemble members for annual and seasonal periods are provided in supplementary figures S1-S4. In general the ensemble significantly underestimates the daily maximum temperature, especially over eastern Australia. In winter this extends across southern Australia. Much of western Australia has significant disagreeing biases indicating that the observations fall within the ensemble spread. The RMSE calculated on the monthly climatology of the maximum temperatures shows that while the errors vary substantially by model, the ensemble has overall higher RMSE in parts of northern and eastern Australia (supplementary figure S5). Mean statistics are summarised in Table S3 for the regional models and Table S4 for the driving GCMs. The Figure 2 shows the biases of individual models for DJF and demonstrates the different biases in eastern and western Australia. Eastern Australia has 17 models with significant underestimation and only 2 with significant positive biases. In contrast, western Australia has 8 models with significant underestimation and 5 models with significant overestimation which results in the “significant disagreeing” classification.

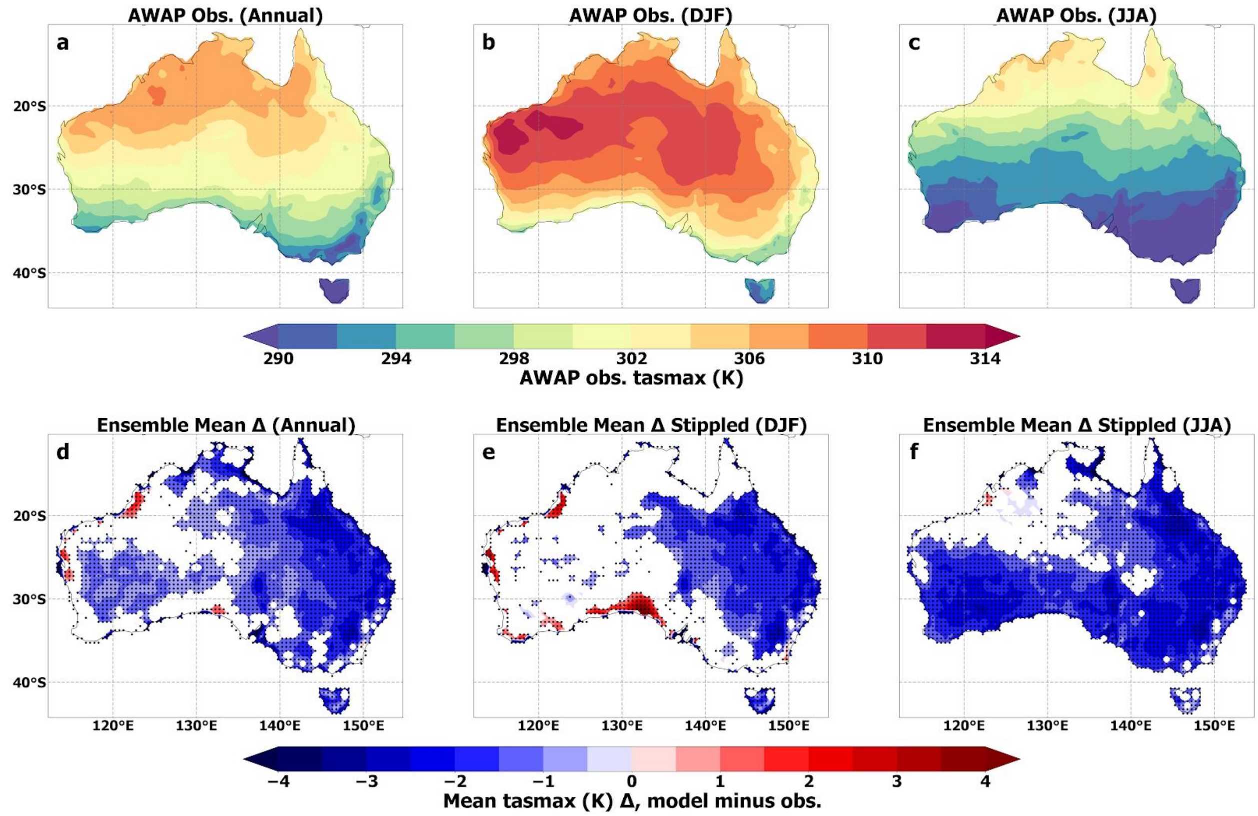

Figure 1: Annual and seasonal mean near-surface maximum temperature bias for the ensemble with respect to observations. **c,f,i** Significance stippling (α = 0.05) for the ensemble mean biases follows Tebaldi et al. (2011). Statistically insignificant areas are shown in colour, denoting that less than half of the models are significantly biased. In significant agreeing areas (stippled), at least half of RCMs are significantly biased, and at least 75% of the significant RCMs agree on the direction of the bias. Significant disagreeing areas are shown in white, and are where at least half of the models are significantly biased and less than 75% significant models agree on the bias direction.

In Figure 2, we can also see that DJF maximum temperature biases depend on the RCM at least as much, if not more than, the GCM (Figure 3). However, the GCMs have large areas of significant biases compared to the RCMs. This dominance of the RCM in producing the spatial pattern of biases is true for both daily maximum and minimum temperature across all seasons (see supplementary figures S1-4, S10-14). Comparing Figure 2 and Figure 3 shows that much of the cold bias in the downscaled ensemble is inherited from the driving GCMs. ACCESS 1.0 and CanESM2 are the only GCMs to have warm biases over most of Australia. EC-EARTH, NorESM1-M, CCSM4 and GFDL-CM3 all have cold biases in daily maximum temperature that exceed 5K over some parts of Australia. Generally the RCM has reduced these extreme cold biases when these GCMs have been downscaled. Figure 2 shows that, regardless of the driving GCM, REMO2015 has a warm bias, while CCLM and RegCM4.7 have cold biases. The WRF simulations also have considerable cold biases across southeastern Australia and warm biases along northwest Australia. The spatial pattern in the WRF biases are comparable despite different atmospheric configurations. CCAM also produces similar biases regardless of the driving GCM. In this ensemble CCAM, which is a global variable resolution model, is unique in using only bias and variance corrected sea surface temperatures (SSTs) (Hoffmann et al. 2016) and sea ice concentrations (SIC) from the driving GCM (no atmospheric information), hence the difference between GCM driving data seen by CCAM is very small compared to that seen by the other RCMs.

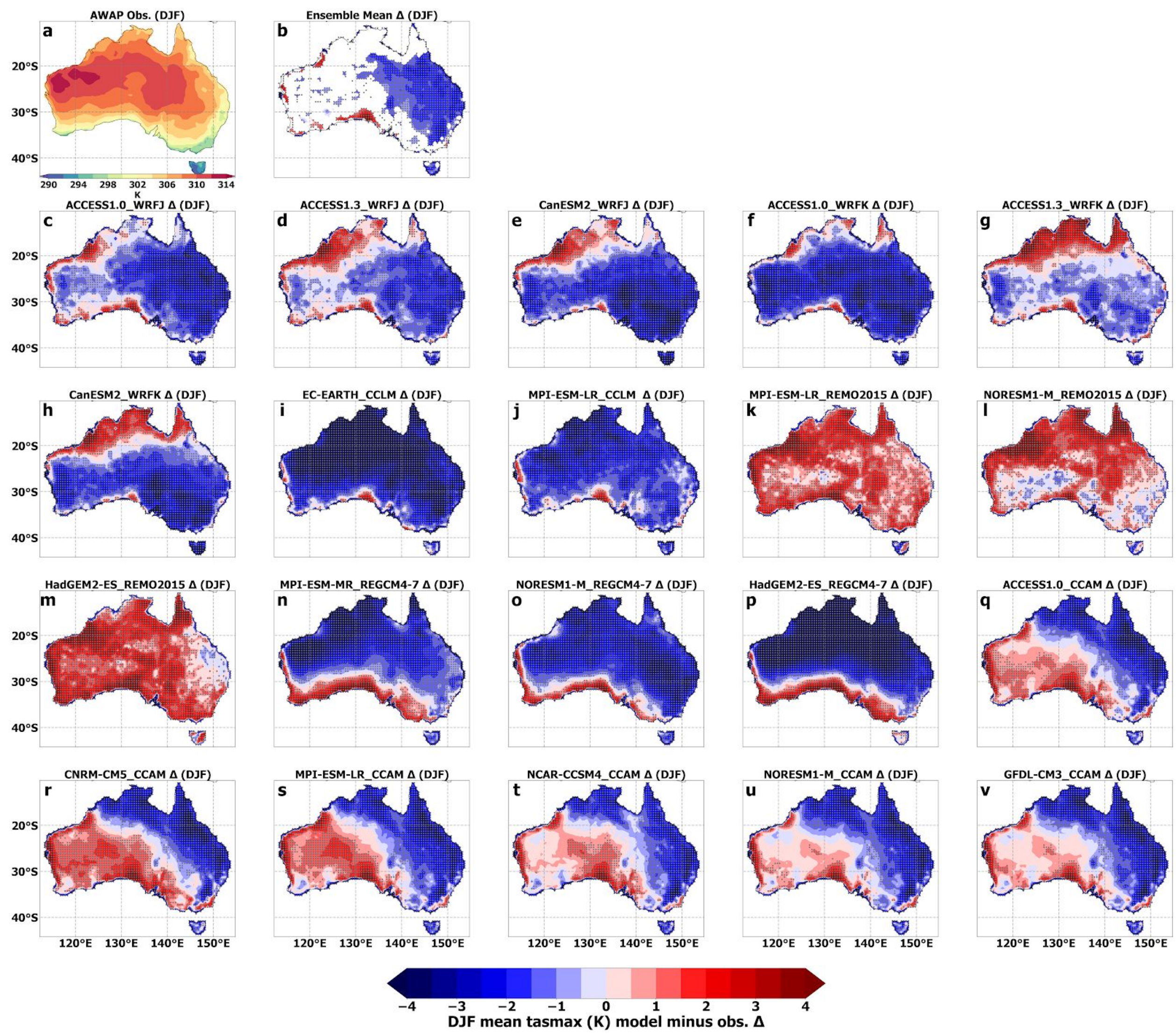

Figure 2: Summer (DJF) maximum temperature biases of individual ensemble members with respect to observations with stippling indicating a significant difference (α=0.05) using the Student's t-test.

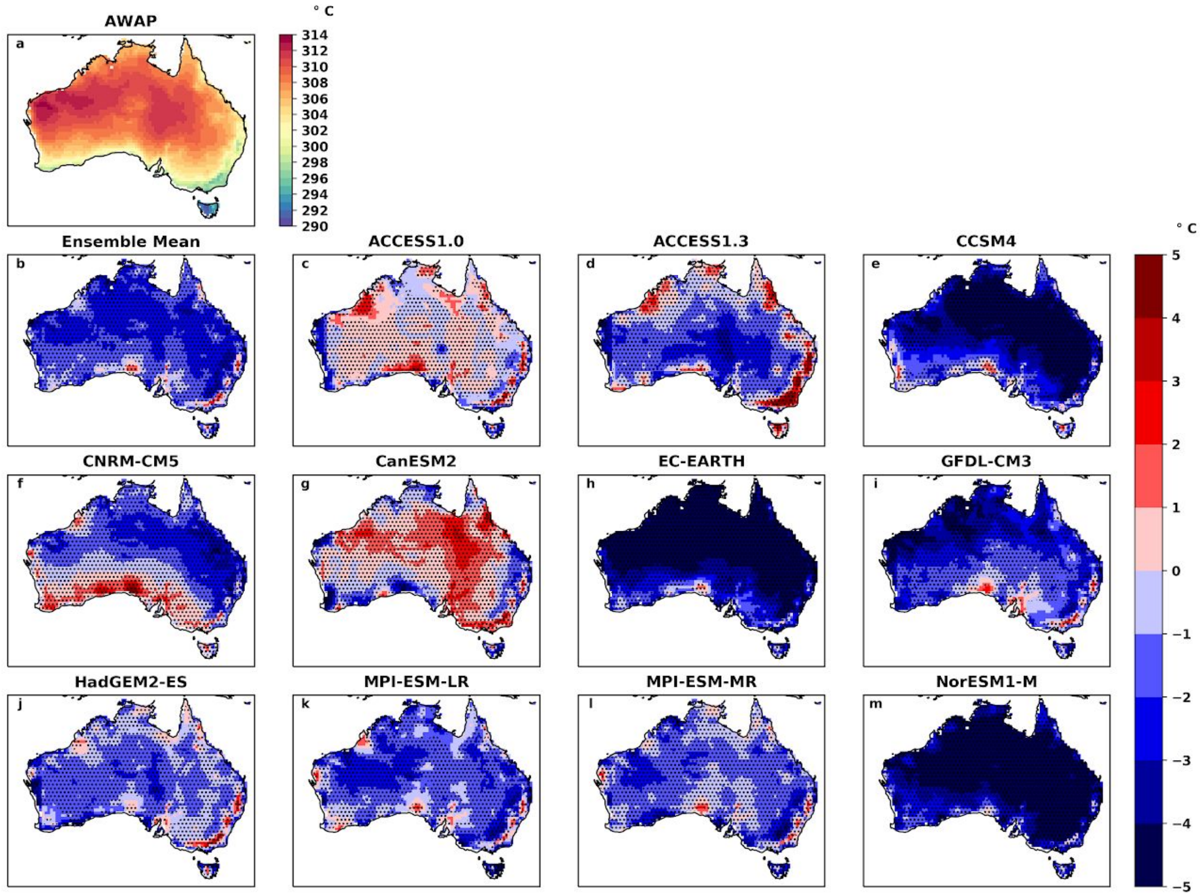

Figure 3: Summer (DJF) maximum temperature biases of individual driving GCMs with respect to observations with stippling indicating a significant difference (α=0.05) using the Student's t-test.

Figure 4 shows the ensemble biases for daily minimum temperature. In general the ensemble has a mixture of significant agreeing model overestimations, particularly in winter (JJA), and significant disagreeing areas. Areas of northern Australia show significant disagreeing biases in DJF (and annually), while southwestern Australia consistently has significant disagreeing biases. In this case it is only the WRF models that are dominated by underestimation biases (Figure S10-14).

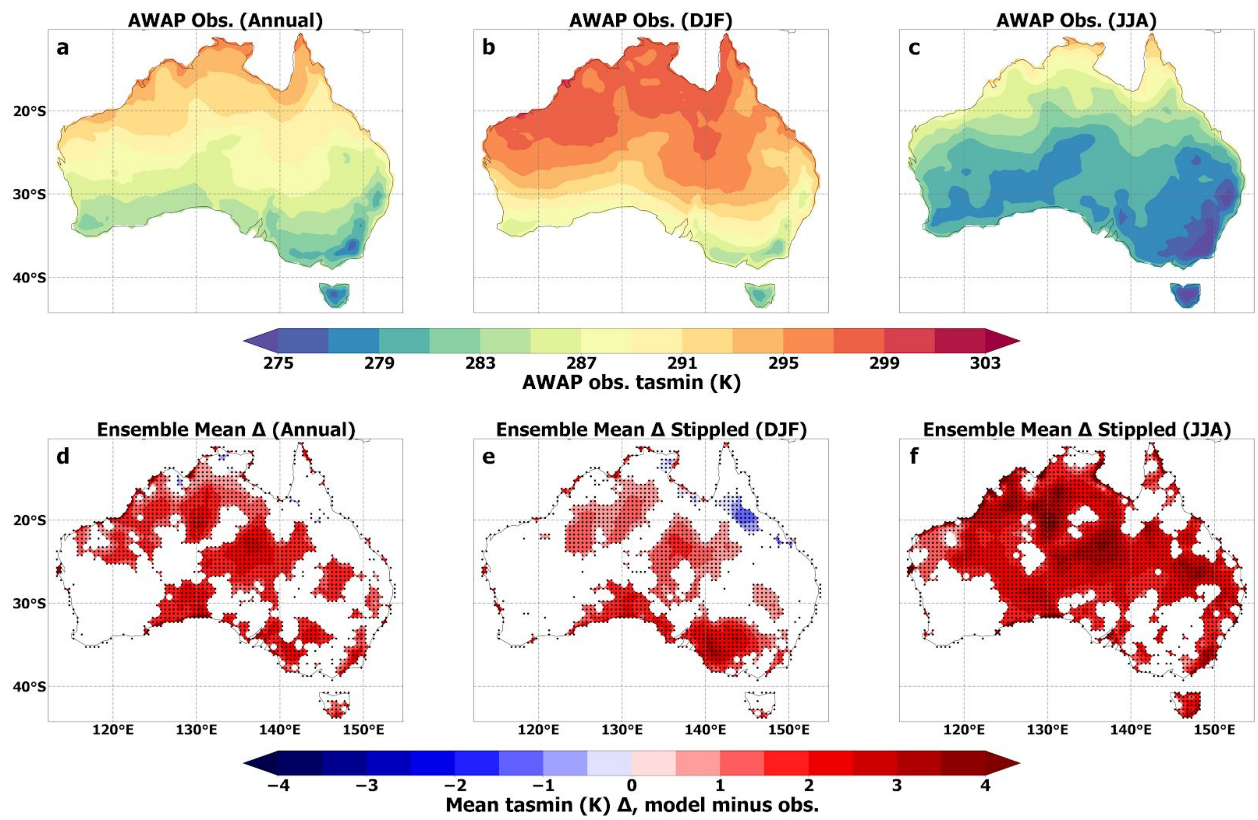

Figure 4: Annual and seasonal mean minimum temperature bias for the ensemble with respect to observations. Significance stippling as per Figure 1.

Figure 5 shows that ensemble mean precipitation biases are generally insignificant across Australia. There are significant agreeing overestimation biases in different parts of southern Australia dependant on the season. Southern Australia receives most rain in winter (JJA) when consistent overestimation biases are produced by RegCM4.7 and CCAM (Figure S24). Northern Australian precipitation is dominated by summer (DJF) monsoonal rain which varies between the RCMs and results show a large region with significant disagreeing biases along the coast. However during DJF some northern regions demonstrate significant agreeing underestimation biases. The ensemble RMSEs are generally high in coastal regions that have relatively high observed precipitation (Figure S26).

Precipitation biases show more variability than temperature biases for a given RCM such that the driving GCM also plays an important part in the pattern of biases produced. The exception to this is CCAM, similar to the temperature biases, the precipitation biases produced by CCAM are always similar regardless of the driving GCM (supplementary figures S21-25). Again, this is due to the forcing of CCAM by bias and variance corrected SSTs.

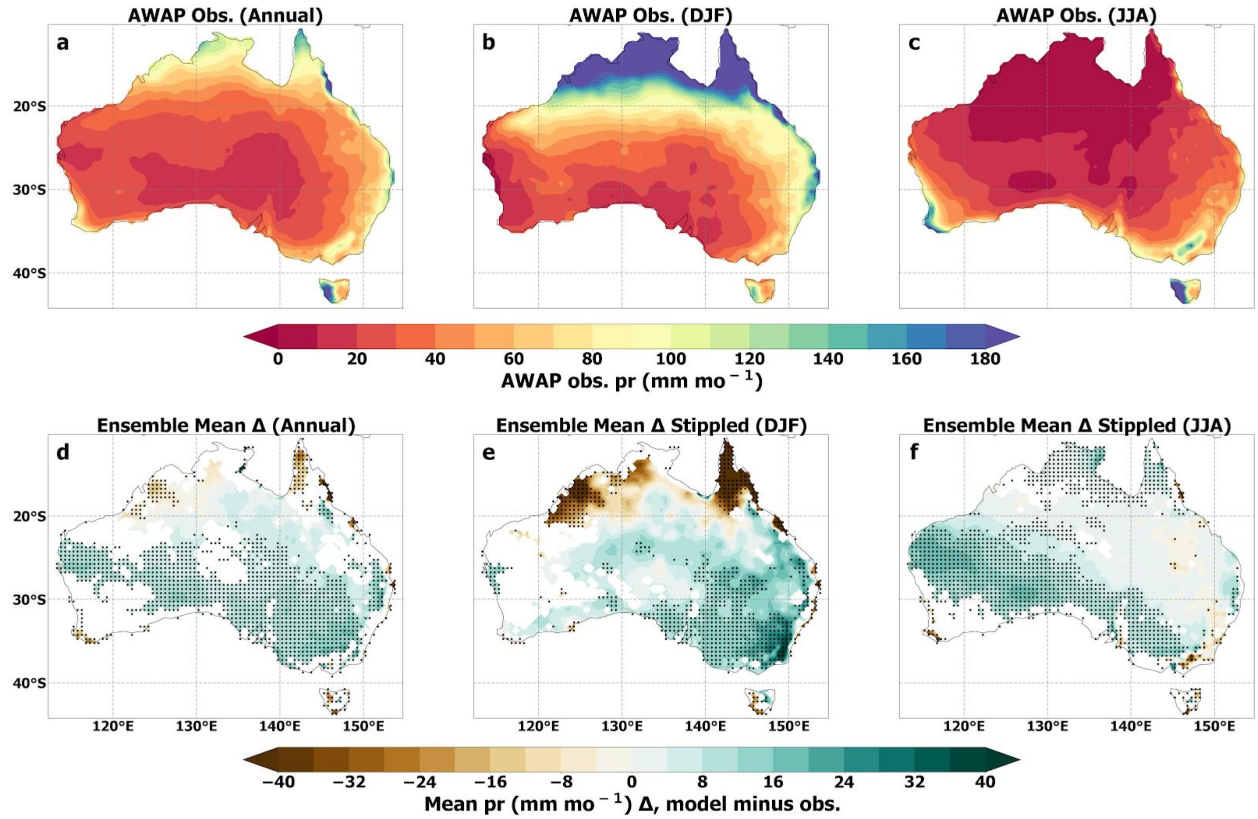

Figure 5: Annual and seasonal mean precipitation bias for the ensemble with respect to observations. Significance stippling as per Figure 1.

Figure 6 shows ensemble biases associated with climate extremes. Most of Australia has significant disagreeing biases for the 99th percentile daily maximum temperature, significant agreeing overestimation of 1st percentile daily minimum temperature, and significant agreeing underestimation of the 99th percentile daily precipitation. For the 99th percentile maximum temperature biases the RCMs are split with WRF and RegCM4.7 simulations being dominated by underestimation while REMO2015 and CCAM are dominated by overestimations.

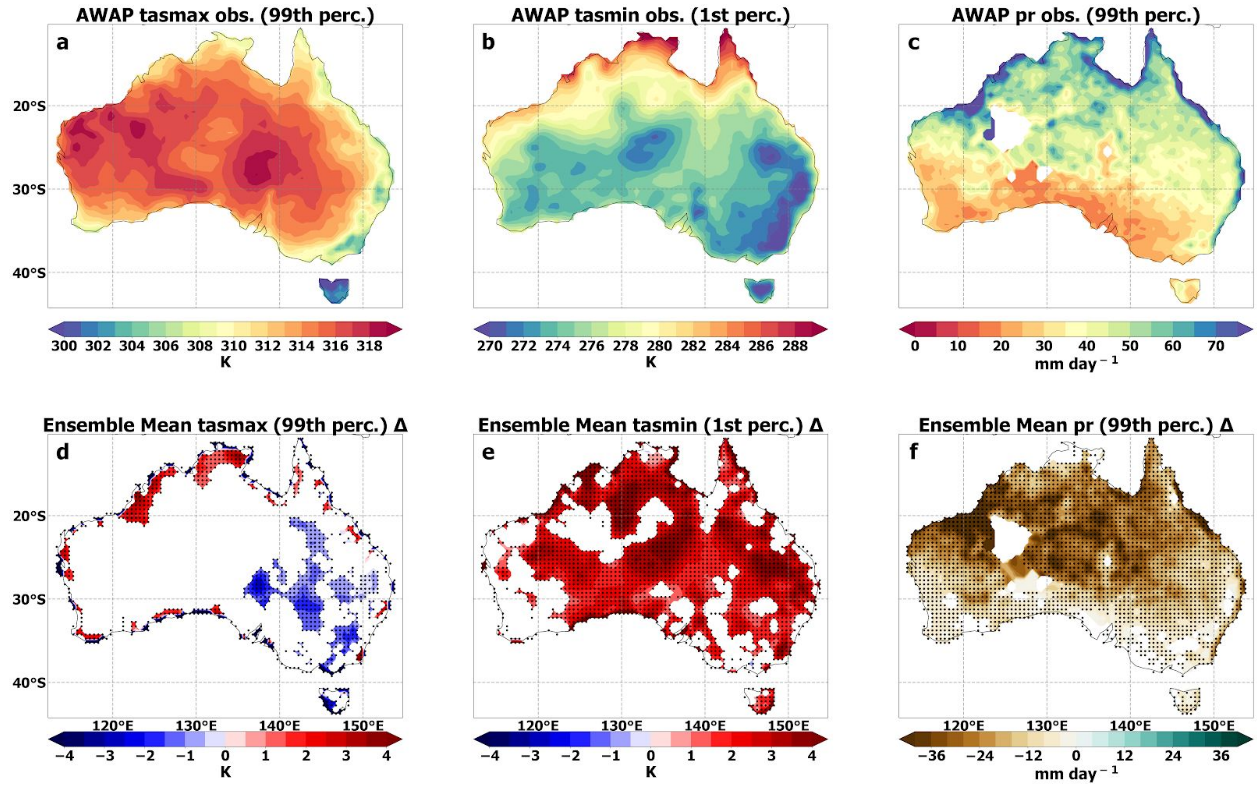

Figure 6: Annual ensemble mean biases for extremes of variables with respect to observations. Significance stippling as per Figure 1.

3.2. Projections of future change

Ensemble projected mean changes in daily maximum (minimum) temperature are shown in Figure 7 (Figure 8). Changes are shown as far future (2070-2099) minus present day (1976-2005). The largest temperature increases are projected to be around 5K. Generally, inland regions warm faster than coastal regions. The tropical north warms faster during its dry season (JJA) then during its wet season (DJF). In all cases the increases in temperature are significant agreeing with all RCMs projecting significant temperature increases.

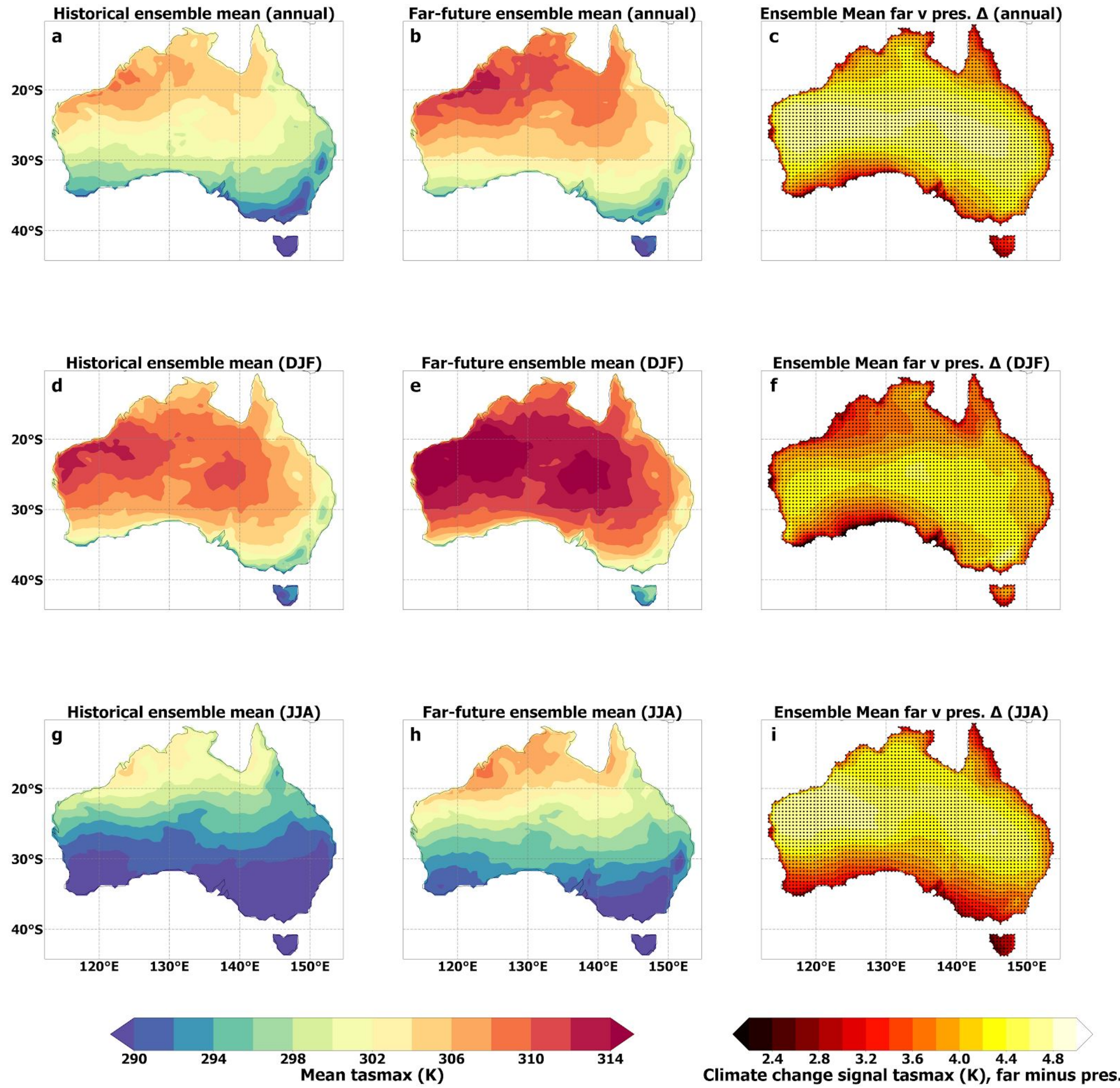

Figure 7: Historical (1976-2005) and far-future (2070-2099) ensemble mean (**a-b**) annual; (**d-e**) summer; and (**g-h**) winter mean maximum temperatures; **c,f,i** ensemble mean climate change signal (far-future minus historical) for mean maximum temperatures. Statistically insignificant changes are shown in colour, denoting that less than half of the models simulate significant changes. In significant agreeing areas (stippled), at least half of RCMs have significant changes, and at least 75% of the significant RCMs agree on the direction of the change. Significant disagreeing areas are shown in white, and are where at least half of the models have significant changes and less than 75% of significant models agree on the change direction.

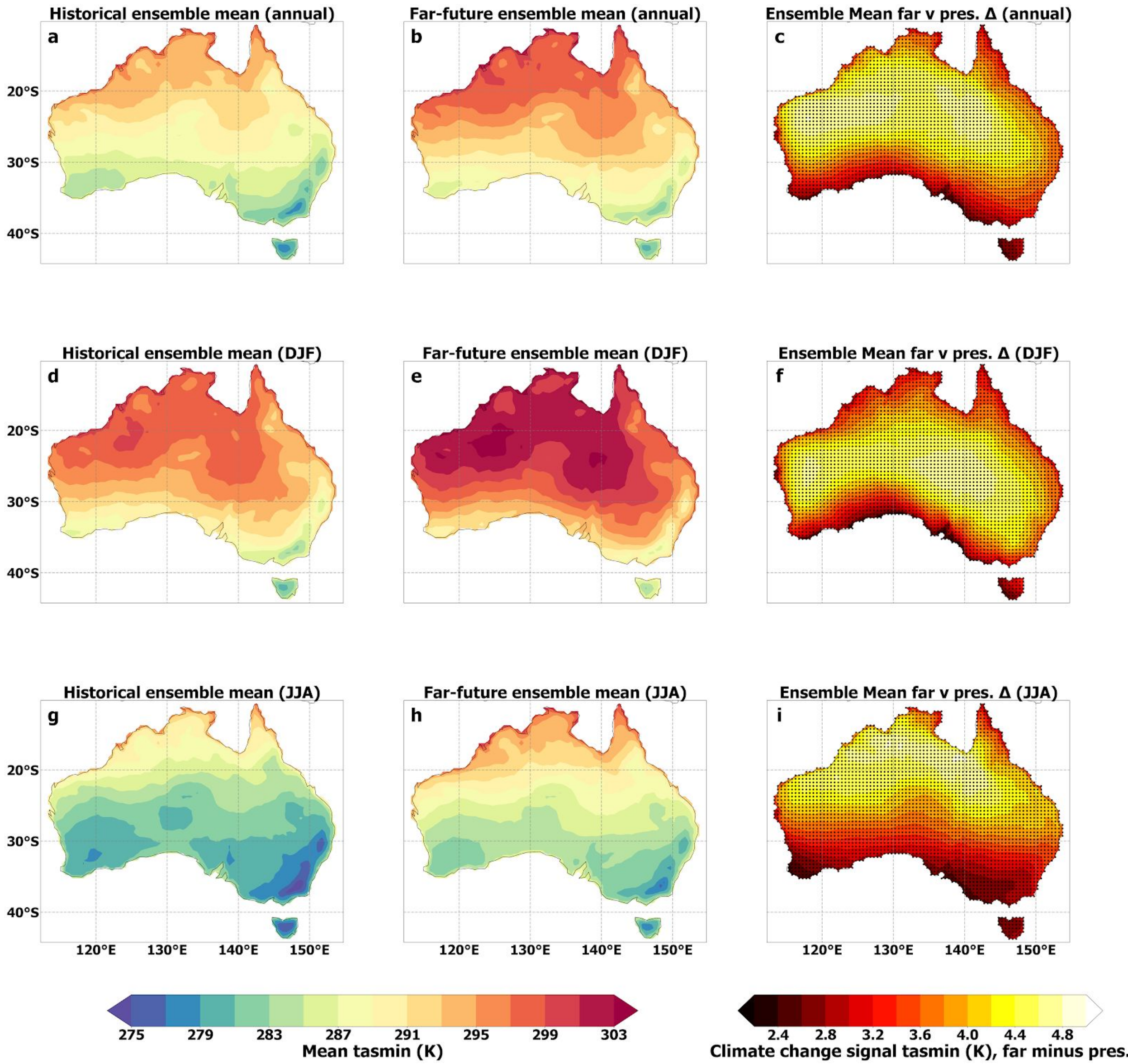

Figure 8: Historical (1976-2005) and far-future (2070-2099) ensemble mean (**a-b**) annual; (**d-e**) summer; and (**g-h**) winter mean minimum temperature; **c,f,i** ensemble mean climate change signal (far-future minus historical) for mean minimum temperature. Significance stippling as per Figure 7.

While the projected annual average precipitation changes are dominated by drying across Australia (with some notable areas of RCM disagreement), these changes are strongly season dependent (Figure 9). In winter (JJA), the change is dominated by drying though it is not significant for most of the continent. Areas of significant agreeing drying are the southwest, and parts of southern and eastern Australia. In summer (DJF), most of the continent is projected to have an increase in precipitation that is not significant compared to inter-annual variability. While the far north and western Tasmania are both projected to decrease. Western Tasmania is the only area that is projected to experience significant agreeing changes in both seasons: a decrease in summer and an increase in winter. Figure 10 presents the JJA changes for each individual ensemble member demonstrating the substantial variation between members.

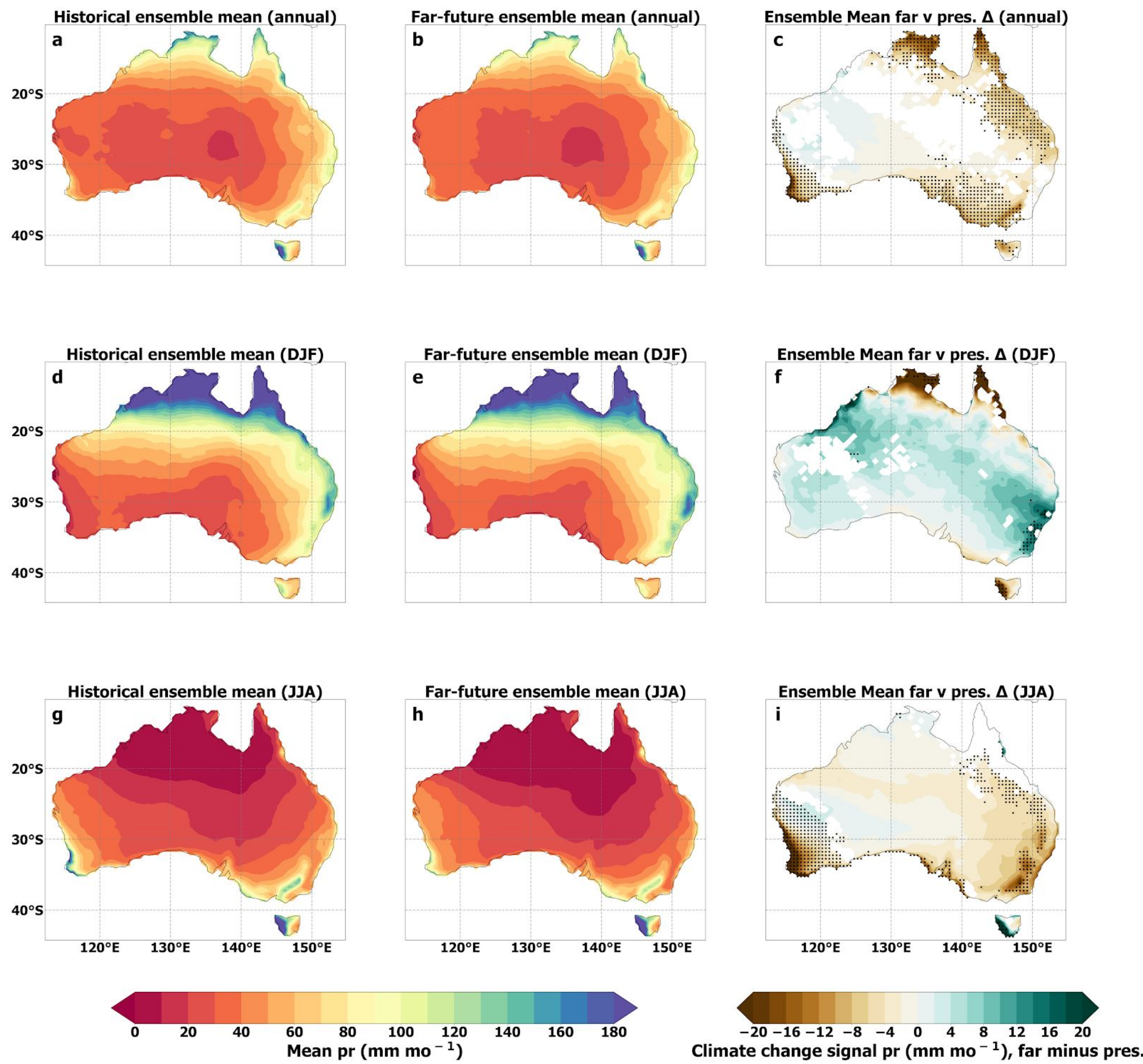

Figure 9: Historical (1976-2005) and far-future (2070-2099) ensemble mean (**a-b**) annual; (**d-e**) summer; and (**g-h**) winter mean precipitation; **c,f,i** ensemble mean climate change signal (far-future minus historical) for mean precipitation. Significance stippling as per Figure 6.

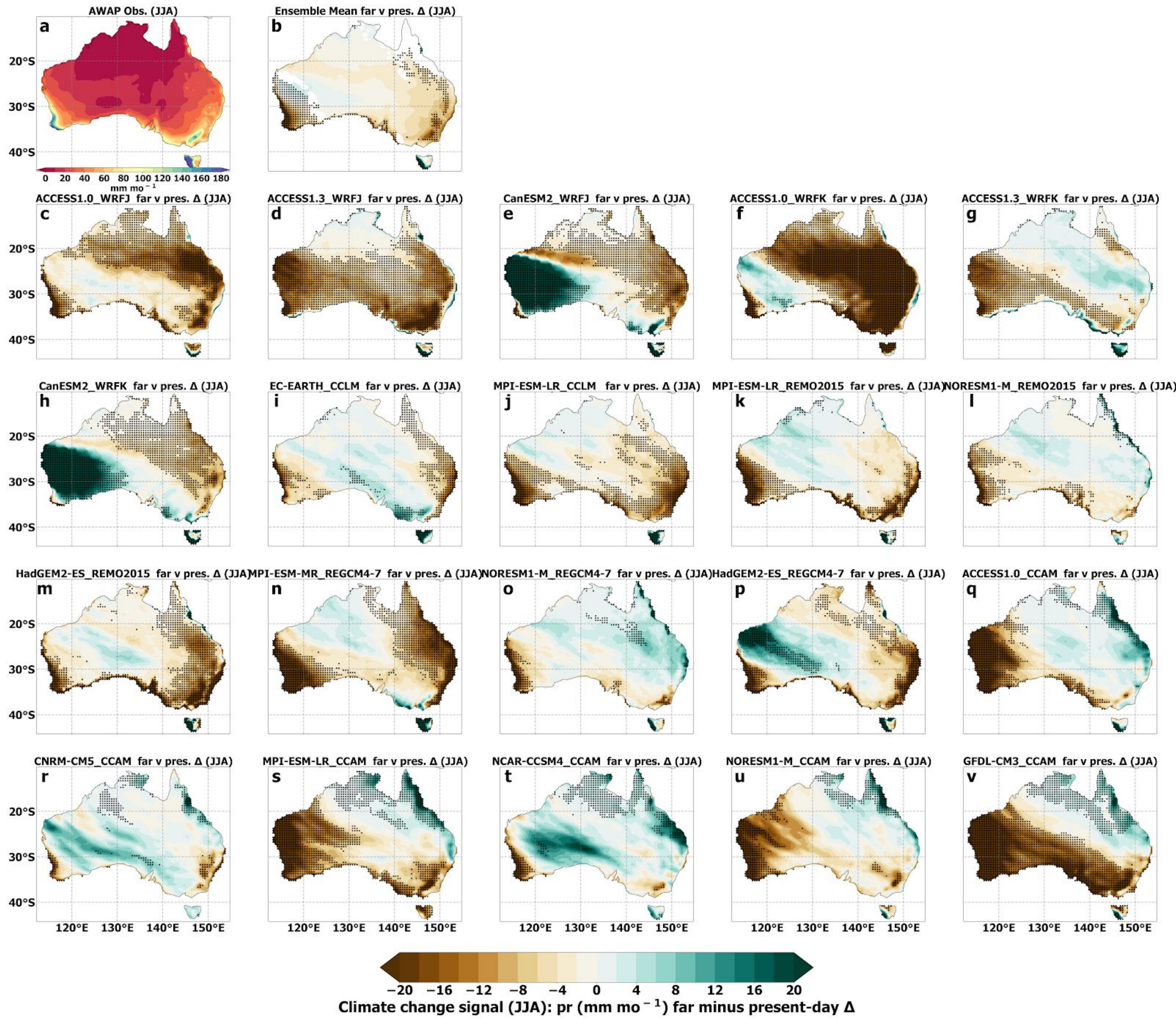

Figure 10: Winter (JJA) precipitation change between Historical (1976-2005) and far-future (2070-2099) of individual ensemble members with stippling indicating a significant change (α=0.05) using the Mann-Whitney U test.

Temperature extremes increase a similar amount to the mean changes. In Figure 11, we can see that there are significant agreeing increases in the 99th percentile maximum temperatures similar to the annual increase in maximum temperatures. The change in 1st percentile minimum temperatures is significant agreeing everywhere and resembles the mean changes in the winter (JJA) minimum temperature. Changes in the 99th percentile precipitation differs more from the annual mean change than the temperature variables did. For precipitation, most of the continent shows non-significant decreases, areas in the southwest and northeast have significant agreeing decreases in both the mean annual precipitation and the 99th percentile precipitation.

In contrast, areas in the southeast show significant agreeing declines in mean annual precipitation but non-significant increases in the 99th percentile precipitation.

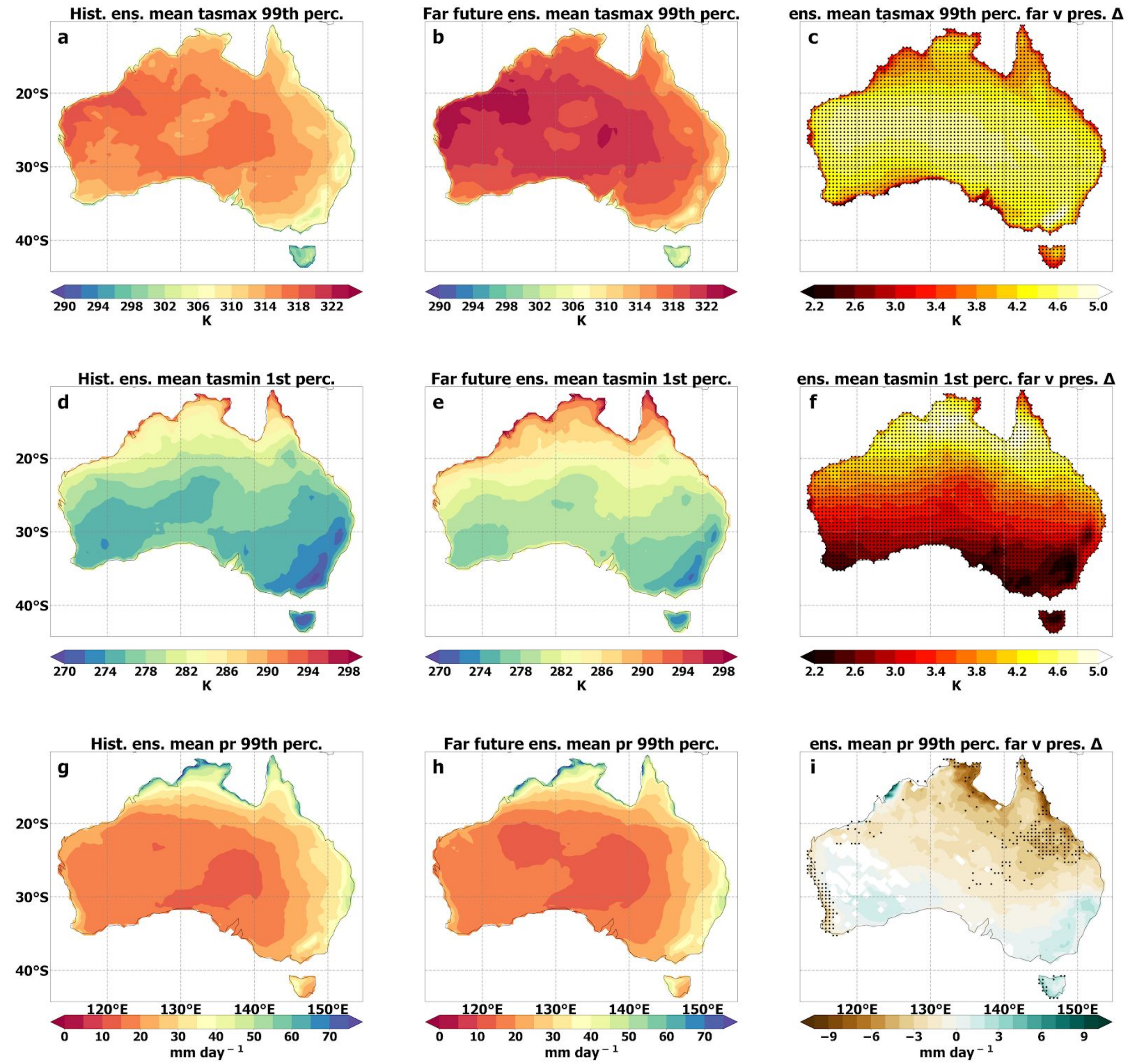

Figure 11: adg, beh historical (1976-2005) and far-future (2070-2099) mean ensemble annual variable extremes; **c,f,i** ensemble mean climate change signal (far-future minus historical) for variables extremes. Significance stippling as per Figure 6.

4. Discussion

4.1. Evaluation

Overall, the ensemble tends to underestimate the maximum temperatures and overestimate the minimum temperatures (Figures 1 and 4). This leads to a diurnal temperature range that is too narrow compared to observations. While most model evaluations have focused on mean temperature, the few that have examined maximum and minimum daily temperature separately have found a reduced diurnal range (Kim et al. 2014, Dosio 2016). In particular, Di Virgilio et al. (2019) examined the diurnal range simulated by CORDEX-Australasia ERA-Interim driven simulations and found that underestimation of the diurnal range was a common feature of all models tested. Similar to the results presented here, Di Virgilio et al. (2019) found that maximum temperature was frequently underestimated, while minimum temperature biases were more variable. Examining the CMIP5 GCM ensemble reveals only small underestimation biases (Moise et al. 2015), while the GCM subset used here generally underestimates maximum temperature (Figure 3) and overestimates minimum temperature. This suggests that some of this reduced diurnal range, particularly the underestimated maximum temperatures, is inherited from the driving GCMs. The reduced diurnal range has also been associated with an overestimation of cloud fraction in RegCM (Nogherotto et al. 2016). Another contributing cause of the RCM underestimation of maximum temperature is the overestimation of precipitation in some models. This relationship was previously identified in CORDEX-Australasia RCMs by Di Virgilio et al. (2019), and has also been found in observations (Hope & Watterson 2018). Previous downscaling studies over southeastern (Olson et al. 2016) and southwestern Australia (Andrys et al. 2016) both show underestimation biases for maximum temperature similar to those found here from a much larger ensemble.

The ensemble tends to underestimate the precipitation in tropical northern Australia, indicating that most RCMs underestimate the strength of the Australian monsoon. The ensemble tends to overestimate precipitation in southern Australia, possibly indicating that too much precipitation is produced by synoptic systems interacting with the extra-tropical storm track by these models over Australia (Grose et al. 2019a). There are some similarities between model biases when driven by ERA-Interim (Di Virgilio et al. 2019) and those shown here when driven by various GCMs. However, these similarities are weaker than the temperature related biases and indicate that both the GCM and RCM are contributing to the precipitation biases. Previous downscaling over southeastern Australia (Olson et al. 2016) also found a general overestimation of precipitation similar to these results. Over southwestern Australia we find that biases are significant disagreeing, while previous downscaling (Andrys et al. 2016) found an underestimation near the coast with an overestimation further inland during winter when most rain falls in this region.

4.2. Projections

Here, we examine projected changes under RCP8.5 between the historical (1976-2005) and far-future period (2070-2099). Temperature increases vary from around 3K near the coast, up to 5K in some inland areas. Over southeastern Australia downscaling using 4 GCMs and 3 RCMs (Olson et al. 2016) and over southwestern Australia downscaling using 3 GCMs and a single RCM (Andrys et al. 2017) estimated slightly smaller temperature increases (accounting for differences in time periods examined) than the larger ensemble examined here. In both cases the SRES A2 emission scenario was used compared to the RCP8.5 scenario used here which accounts for these differences.

The precipitation changes projected for southern Australia agree qualitatively with those projected by the CMIP5 GCM ensemble (Hope et al. 2015), with significant annual declines by late in the century. These declines occur dominantly in the cool season. This cool season decline was also robust across previous statistical and dynamical downscaling studies (Hope et al. 2015, Grose et al. 2015b, Olson et al. 2016, Andrys et al. 2017), and has been associated with an increase in the intensity and a poleward shift of the subtropical ridge (Grose et al. 2015a, Hope et al. 2015), and an associated poleward shift of the extratropical storm track (Grose et al. 2016). Since many of the RCMs we studied have overestimation biases for precipitation related to storm track interactions, the poleward shift of the storm track results in projected precipitation declines that are larger than they would otherwise be. These precipitation declines are most evident in the southwest and southeast, and are reflected in enhanced maximum and minimum temperature increases in these areas. This temperature effect is a land-atmosphere feedback that has been found in observation (Hope & Watterson 2018) and model based studies (Hirsch et al. 2014), including for heatwave events (Hirsch et al. 2019). Western Tasmania is projected to have significant agreeing declines in summer precipitation but significant agreeing increases in winter precipitation. Again, this qualitatively agrees with the assessment in Hope et al. (2015) based on CMIP5 model projections. Additionally, the small alpine region in the southeast shows enhanced wetting in summer and drying in winter in agreement with earlier regional climate projections (Grose et al. 2019b).

This CORDEX-Australasia ensemble projects significant agreeing declines for parts of northern Australia precipitation, most of which occurs in summer (Figure 9). This differs from the projections in the CMIP5 ensemble which has a wide range with a mean change near zero (Moise et al.). Brown et al. (2016) examined the CMIP5 projections and found that models that projected a drier northern Australia tended to have higher SST biases in the region. They attributed lower confidence to these projections and favoured a wetter projection for northern Australia, opposite to the projections here. The CCAM projections use bias and variance corrected SSTs, largely eliminating this problem. These simulations project a mixture of areas getting wetter and areas getting drier across northern Australia (Figure S24). When averaged over northern Australia this produces a projection of little change, in agreement with the CMIP5 model projections, but suggests that discrimination of areas within northern Australia is important to gain more confidence in these projections.

Figure 10 shows the winter precipitation change for each individual ensemble member. While substantial variation between ensemble members is evident, most show the majority of Australia to have precipitation changes that are small (not significant). The southwest is one area where most models project significant changes. The ensemble mean map (Figure 10b) shows a large part of the southwest to have significant agreeing changes that are strongly drying in the furthest southwest but become weakly wetting toward the northeast of the area. For the furthest southwest drying we can see that at least 11 models (and up to all models) indicate significant drying, with even the wettest models in this region projecting drying for the southwest corner. However, in the northwest part of this southwest significant agreeing area (Figure 10b) we have 6-8 models with significant drying (Figure 10d,g,j,k,n,q,s,v) and 2 models with significant wetting (Figure 10e,h). The level of wetting by these 2 models is high, and combined with the non-significant wetting simulated by many other models, this results in an ensemble mean change of weak wetting despite the clear majority of significant changes being toward drying.

Both the extreme hot temperatures (99th percentile daily maximum temperatures) and the extreme cold temperatures (1st percentile daily minimum temperatures) have significant agreeing increases similar to those projected for mean temperature. Sillmann et al. (2013) examined projections of climate extremes in the CMIP5 ensemble. They found that the annual minimum of the daily minimum temperatures are projected to change in the 3-5K range, similar to the projections of the 1st percentile minimum temperatures shown here. They found that the maximum of the daily maximum temperature would increase by 4-7K, which is more than the 99th percentile maximum temperatures shown. Sillmann et al. (2013) also examine the 95th percentile of precipitation and shows qualitative agreement with the 99th percentile results shown here in that most of Australia has changes that are not significant. They do however show significant increases across northern Australia and in the southeast which are not found here.

5. Conclusions

The CORDEX-Australasia regional projection ensemble is currently a 20-member ensemble made by 6 regional models downscaling 11 global climate models at a horizontal resolution of 25 to 50 km. Overall the ensemble produces a good representation of recent climate. Biases present in the ensemble include widespread under-estimation of daily maximum temperature and (less widespread) over-estimation of daily minimum temperature resulting in a general under-estimation of the diurnal temperature range. The ensemble generally overestimates precipitation across the southern half of Australia. Despite these biases the

CORDEX-Australasia ensemble produces a better representation of Australian climate than the driving GCMs across most variables and metrics. In terms of extremes, the ensemble range generally includes the observed 99th percentile of daily maximum temperature though most models have significant biases. The ensemble generally overestimates the 1st percentile of the daily minimum temperatures. The ensemble underestimates the 99th percentile of precipitation despite overestimating the mean precipitation over much of the country.

In general, the regional models have a substantial, or even dominant, influence on the temperature biases, while the precipitation biases are affected by both the GCM boundary conditions and the RCM. CCAM is an exception to this as, unlike the other regional models, it uses only bias and variance corrected SSTs from the driving GCMs which results in CCAM simulation biases being similar to each other regardless of the driving GCM. It is worth noting that this similarity in bias does not carry-over to the future projections that can vary substantially for different driving GCMs.

The projected changes broadly agree with changes projected by earlier climate model ensembles. By the end of the century, temperatures are projected to increase by as much as 5K in the interior of Australia, with smaller increases towards the coast, particularly in southern Australia where temperature increases may be less than 3K. The ensemble projects precipitation changes to be dominated by drying, particularly in the north, northeast, southwest and southeast. This drying occurs predominantly in the cool season with summer projected to have little change, leaning towards wetting. Future changes in the 99th percentile of daily maximum temperature are similar to the mean change in the interior but with a much reduced coastal influence compared to the mean change. Projected changes in the 1st percentile minimum temperature have a strong latitudinal dependence somewhat similar to the mean winter (JJA) change. Future changes in the 99th percentile precipitation are mixed. Significant declines are projected for the south-western coast and parts of the northeast, meanwhile significant increases are projected for coastal Tasmania.

This study provides a platform for more detailed studies of the model biases and future changes shown here. We hope that this paper, including the supplementary material, will provide a valuable resource for studies into these projected climate changes, their impacts on human and natural systems and potential climate change adaptation options for the region.

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