Comparison of various climate change projections of eastern Australian rainfall

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The Australian eastern seaboard is a distinct climate entity from the interior of the continent, with different climatic influences on each side of the Great Dividing Range. Therefore, it is plausible that downscaling of global climate models could reveal meaningful regional detail, or 'added value', in the climate change signal of mean rainfall change in eastern Australia under future scenarios. However, because downscaling is typically done using a limited set of global climate models and downscaling methods, the results from a downscaling study may not represent the range of uncertainty in plausible projected change for a region suggested by the ensemble of host global climate models. A complete and unbiased representation of the plausible changes in the climate is essential in producing climate projections useful for future planning. As part of this aim it is important to quantify any differences in the change signal between global climate models and downscaling, and understand the cause of these differences in terms of plausible added regional detail in the climate change signal, the impact of sub-sampling global climate models and the effect of the downscaling models themselves. Here we examine rainfall projections in eastern Australia under a high emissions scenario by late in the century from ensembles of global climate models, two dynamical downscaling models and one statistical downscaling model. We find no cases where all three downscaling methods show the same clear regional spatial detail in the change signal that is distinct from the host models. However, some downscaled projections suggest that the eastern seaboard could see little change in spring rainfall, in contrast to the substantial rainfall decrease inland. The change signal in the downscaled outputs is broadly similar at the large scale in the various model outputs, with a few notable exceptions. For example, the model median from dynamical downscaling projects a rainfall increase over the entirety of eastern Australia in autumn that is greater than the global models. Also, there are some instances where a downscaling method produces changes outside the range of host models over eastern Australia as a whole, thus expanding the projected range of uncertainty. Results are particularly uncertain for summer, where no two downscaling studies clearly agree. There are also some confounding factors from the model configuration used in downscaling, where the particular zones used for statistical models and the model components used in dynamical models have an influence on results and produce additional uncertainty.

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Introduction

Global climate models (GCMs) are our primary tool for examining the climate response to future scenarios of greenhouse gas emissions. A large ensemble of GCMs run for a variety of emission scenarios, such as the archives of the Coupled Model Inter-comparison Project phase 3 (CMIP3; Meehl et al. 2007), or phase 5 (CMIP5; Taylor et al. 2012), is a useful tool for making climate projections for future planning. However, impacts studies often desire locally-relevant information about climate and climate change, at a resolution finer than GCMs. GCMs do not resolve some important regional details in the current climate of many regions, and may potentially not resolve robust regional features in the climate change signal of those regions (e.g. Schmidli et al. 2007; Evans and Alsamawi 2011; Grose et al. 2013). Downscaling using a dynamical regional climate model (RCM) or statistical downscaling model may be useful for filling this gap since it offers the prospect of regional-scale detail in the projected climate change signal with a physically plausible basis, or 'added value' (Ekström et al. 2015). Physical plausibility refers to the consistency between a projected change and the combination of known drivers of change. At the regional scale this is a matter of expert judgment, but may be strengthened if changes coincide with surface factors introduced through downscaling (e.g. topography) that would be expected to affect rainfall change. We define added value in this context as consistent regional detail in the climate change signal produced by downscaling.

There are several issues to contend with when using downscaling. Robust and physically plausible regional detail in the climate change signal from downscaling is not guaranteed, and may be hard to gauge. Also, because downscaling can have a high demand for computational resources or requires specific data inputs not available from each GCM, it is often done on a subset of GCMs rather than the whole ensemble. If not carefully chosen, this subset may not be representative of the full range of plausible climate change represented in the ensemble. Importantly, different downscaling methods give different results, both in terms of the regional detail that is revealed but also in larger scale climate changes. For dynamical downscaling, different model structures, model physics and parameterisation schemes all contribute to producing different results (Foley 2010). Similarly, statistical downscaling draws on different techniques that could yield uncertainty in output (Wilby and Wigley 1997). Thus, results from one downscaling method may produce a restricted range of projected change at the large scale that may not provide a representative sampling of the full range of plausible changes indicated by the GCM ensemble. Therefore, to use a set of downscaling outputs as comprehensive climate projections for a region, it is useful to assess both regional detail revealed by downscaling and also its representativeness of the full range of plausible projected change produced by the GCM ensemble. The range of change projected by an ensemble of GCMs may not represent the full range of uncertainty in the climate response to a given emissions scenario. However, unless there is a viable constraint on the ensemble range then the GCM spread represents some minimum range of uncertainty that should be represented in any projections.

An ensemble of RCMs or other downscaling together with an ensemble of GCMs can be used to account for the range of results from different methods, such as the ENSEMBLES (Van der Linden et al. 2009), NARCCAP (Mearns et al. 2012) and CORDEX (Giorgi et al. 2009) projects. However, ensembles of RCMs are not yet available in every country, and none are available yet in Australia. There are various individual downscaling experiments available, however, and comparing results from these various studies may reveal useful insights into both the regional climate change signal and also model behaviours. Where multiple downscaling studies point to a consistent regional signal that was absent from GCMs and where this difference has a connection to higher spatial resolution or better depiction of surface forcings (e.g. topography) or synoptic-scale phenomena (e.g. thunderstorms, extratropical cyclones and fronts), there is a more compelling case for 'added value' than if there is disagreement between methods.

Different studies have found different relative contribution of uncertainty from GCMs and RCMs. For example, in the PRUDENCE project the boundary forcing from host GCMs made a larger difference than the RCM used (Déqué et al. 2007), including in projections of rainfall extremes (Fowler and Ekström 2009). This contrasts with the NARCCAP project, where the RCMs tended to produce stronger climate changes for rainfall than the host GCMs and CMIP3 as a whole, including larger rainfall increases in northern USA in winter and greater rainfall decreases in central USA in summer (Mearns et al. 2012). Statistical downscaling matched the NARCCAP RCM projections somewhat but did not produce some of the fine-scale features over complex terrain (Gutmann et al. 2012).

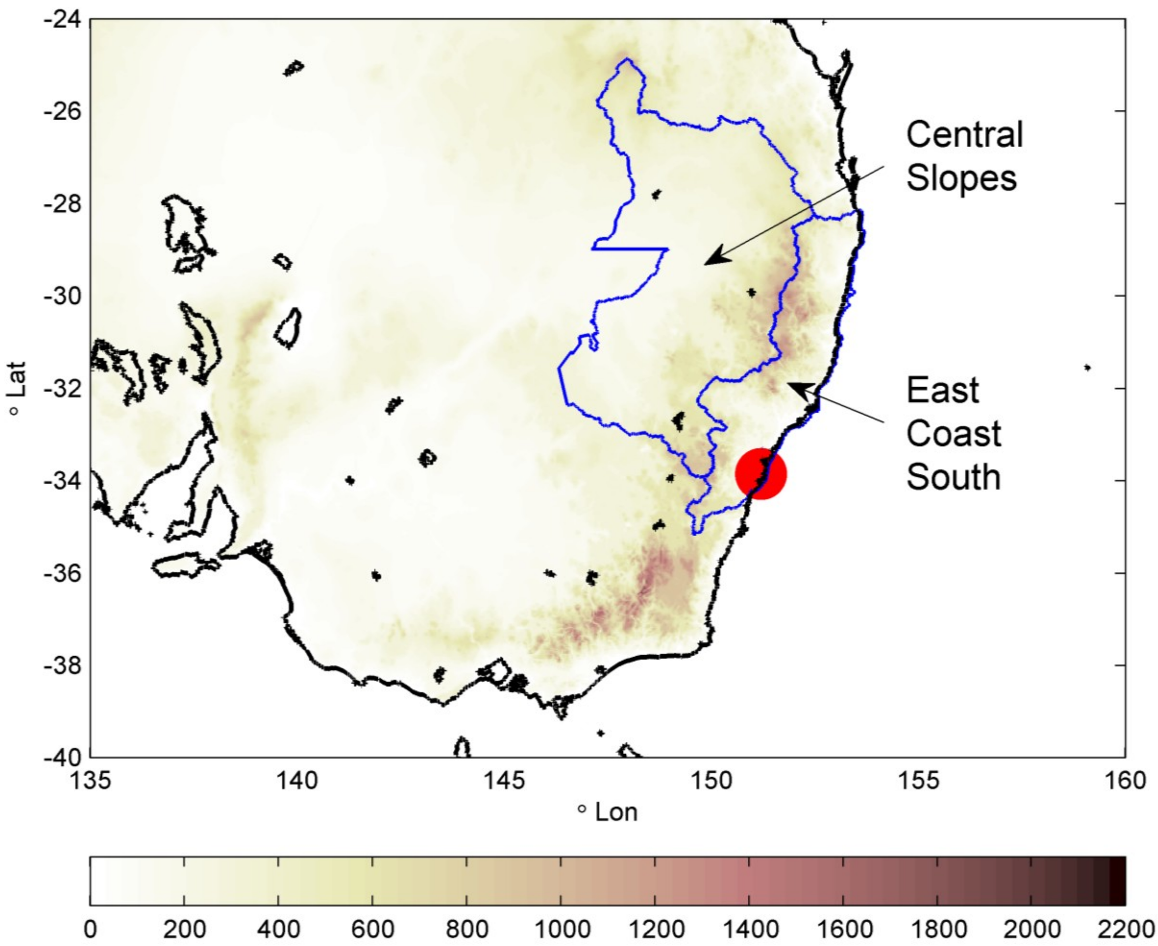
Users of an individual downscaling study would benefit from understanding not only whether and where downscaling may have produced added value in the climate change signal, but also the context of ranges of change in the set of host GCMs, other ensembles of GCMs and the output from other downscaling techniques. The choice of host models to downscale and the choice of downscaling model will both affect the ranges of change in the results for any one study. These choices are important context for the use of the downscaling results into impacts research. The Climate Projections for Australia's Natural Resource Management Regions (NRM) project (CSIRO and Bureau of Meteorology 2015) provided projection information and datasets for all of Australia based on CMIP5 and two downscaling methods using CMIP5 as input. The New South Wales (NSW) and Australian Capital Territory (ACT) Regional Climate Modelling (NARCliM) project delivered climate projection information and datasets for eastern Australia based on CMIP3 and downscaling using CMIP3 as input (Evans et al. 2014). Here we examine the regional climate projections for eastern Australia from all of these sources.

We consider issues of both added value in the climate change signal and representativeness of ranges of change. We use an approach similar to the Representative Climate Futures framework of Whetton et al. (2012), where projections can be categorised and compared in multiple categories and on multiple dimensions (such as 'wetter' or 'drier' and 'hotter' and 'much hotter' for temperature and rainfall dimensions).

Projections of rainfall change in eastern Australia have a higher level of uncertainty than for some other regions such as southwest Western Australia where there is high confidence in reducing rainfall (CSIRO and Bureau of Meteorology 2007; CSIRO and Bureau of Meteorology 2015). However, projections for eastern Australia are of great interest, particularly for the eastern seaboard as it contains many population centres including Australia's largest city, Sydney. The eastern Australian region is a candidate for 'added value' from downscaling because GCMs are likely to poorly resolve some key regional features and their effect on regional rainfall. These features include the significant influence from the topography of the Great Dividing Range and the effect of the coastlines to the east of this range.

We examine mean rainfall change over much of sub-tropical eastern Australia, focussing on two specific regions used in the NRM projections (CSIRO and Bureau of Meteorology 2015). These regions are the East Coast South (ECS) sub-cluster that covers much of New South Wales (NSW) east of the Great Dividing Range, and Central Slopes (CS) that covers a large region of inland NSW and Queensland (Figure 1). The boundary between these two regions marks the ridge line of the Great Dividing Range, which we use as the boundary of the eastern seaboard.

Figure 1 Map of eastern Australia showing surface height (m), black lines show coast lines, blue lines show borders of cluster regions examined here, red point marks the location of Sydney.



The eastern seaboard is a distinct climatic entity from the inland region. Rainfall on the east coast is greater than over inland parts of southeast Australia and is less influenced by the subtropical ridge (Timbal 2010). Also, eastern seaboard rainfall is less influenced by tropical sea surface temperature variability such as the El Niño Southern Oscillation (ENSO) and the Indian Ocean Dipole (IOD) than inland, and in fact the effect of the IOD opposes ENSO during the cool season (Pepler et al. 2014). Neither region shows significant trends in mean annual rainfall over the last century (CSIRO and Bureau of Meteorology 2015). Recent trends in seasonal rainfall in the two regions are similar in some broad terms, such as a decline in autumn, but show many differences including the magnitude of changes in all seasons and a different trend in spring, reflecting the differing climatic influences (Timbal 2010).

Rainfall in the CS and ECS regions is often associated with one of a number of different phenomena including fronts (Catto and Pfahl 2013), subtropical cyclones (Hopkins and Holland 1997) and thunderstorms (Kuleshov et al. 2006). Projected changes to rainfall associated with these synoptic systems are either currently unavailable or have a high degree of uncertainty associated with them in the east Australia region (see Dowdy et al., 2015). However, the intensity of the severe weather events (including heavy rainfall) associated with these systems is likely to be better represented by certain downscaling methods than by the relatively coarse spatial and temporal scales of current GCMs (e.g. Kendon et al. 2012). Consequently, downscaling can potentially add significant value to projections of heavy rainfall, and therefore potentially improve projections of mean rainfall since heavy rainfall events can make a significant contribution to total rainfall amounts. Model disagreement in the projection of heavy rainfalls was the largest cause of difference in regional mean rainfall projections from downscaling in the mountainous western seaboard of California (Pierce et al. 2013) and there could be a similar situation in eastern Australia.

The frequency of fronts and the proportion of rainfall associated with fronts can be simulated well by GCMs (while noting that the intensity of the rainfall is underestimated in many regions), with GCM projections indicating a decrease in the number of fronts and frontal rain during the cooler months particularly in southern Australia (Catto et al. 2013). Pepler et al. (2013) showed that rainfall in the Australian eastern seaboard associated with subtropical cyclones and their intense form, East Coast Lows (ECLs), is highest during the cooler months of the year and nearer to the coast than further inland. Although there is considerable uncertainty associated with future changes in the magnitude of rainfall associated with ECLs (Dowdy et al. 2013), projections indicate fewer ECLs towards the end of this century based on both a form of statistical downscaling (Dowdy et al. 2014) and dynamical downscaling (Ji et al. 2015). Thunderstorms are more common nearer the coast than further inland and occur about four times more frequently during the warmer months of the year than the cooler (Kuleshov et al. 2006; Dowdy and Kuleshov 2014). The most likely change to the occurrence of thunderstorms in Australia with a warmer climate is currently not clear. Some studies project a possible increase in global thunderstorm activity, while other studies do not indicate a significant change, relating to considerable uncertainties associated with the current understanding of physical processes relating to thunderstorm occurrence (Williams 2005).

Dynamical downscaling generally has finer resolution than GCMs, however, the simulation of cyclones and ECLs is not only affected by resolution but also by the choice of model components such as planetary boundary layer, cumulus, microphysics and radiation schemes (Ji et al. 2011; Ji et al. 2014). In fact, an analysis of ECL events suggested that differences in rainfall simulations were larger for the stronger ECL events than weaker systems (Evans et al. 2012; Ji et al. 2014). Also, statistical downscaling may also provide insights through a transfer between the synoptic scale and rainfall at the local scale, but again the model configuration (e.g. predictors used, spatial domain considered) is likely to have an important influence.

Methods and data

Here we compared the projected change in mean rainfall in eastern Australia from the CMIP5 and CMIP3 GCM archives and from three quite disparate downscaling techniques used in the NRM and NARCliM projects. These three methods are not part of a coordinated program, but are a collection of opportunity containing methods used in two studies (NRM and NARCliM).

CMIP5 and CMIP3

For an overview of the rainfall response under different emissions scenarios by late in the 21st Century, we examined the projected change in mean rainfall in Run 1 from 39 CMIP5 models between 1986-2005 and 2080-2099 for all four Representative Concentration Pathways (RCPs, Moss et al. 2010): RCP2.6, RCP4.5, RCP6 and RCP8.5. These 39 models are those that were available at the time of writing; there will be more than 50 models in CMIP5 when complete.

For further comparisons we focussed only on results for the highest emission scenario (RCP8.5) by late in the 21st Century, as this represents the strongest forcing among the RCPs and is likely to show the strongest climate change signal in the projections. For CMIP5-based results we used RCP8.5 projections between 1986-2005 and 2080-2099, and for CMIP3-based work we examined changes under the A2 scenario from the Special Report on Emission Scenarios (SRES, Nakicenovic et al. 2000) between 1990-2009 and 2060-2079 (periods used in the NARCliM project). The A2 scenario is similar to RCP8.5 in that it represents relatively high emissions where atmospheric greenhouse gas concentrations continue to rise throughout the 21st Century. However, the A2 scenario produces slightly lower concentrations at the end of the century than RCP8.5, and the two scenarios have different treatment of other emissions such as aerosol. We examined changes in the 19 CMIP3 GCMs with available data (Table 1), examining primarily Run 1 but using Run 4 of CCCMA-CGCM3.1 (T47) to match the downscaling.

Statistical downscaling

We examined outputs from the statistical technique used in the NRM project; the Bureau of Meteorology statistical downscaling model (BOM-SDM) of Timbal and McAvaney (2001). This is an analogue-based statistical model that models local-scale rainfall data using a transfer function from larger-scale predictors such as mean sea level pressure (MSLP) patterns, humidity and upper level winds. BOM-SDM outputs were produced using inputs from Run 1 of 22 CMIP5 models as hosts (Table 1); the maximum number of models that were available and saved sufficient daily outputs to run the model. The model outputs were calibrated to and produced at the 0.05° (~5 km) grid of the Australian Water Availability Project (AWAP) climate dataset (Jones et al. 2009). The BOM-SDM uses the large-scale and synoptic-scale features from the host model to select the best analogue in the collection of observed climate. This produces regional-scale features of mean climate and in the change signal that are different from the host GCM.

Table 1 CMIP5 and CMIP3 models used in this study, and used for downscaling

	CMIP5 Name	*BOM-SDM*	*CCAM*		*CMIP3 Name*	*NARCliM*
1	ACCESS1.0	X	X	1	BCCR-BCM2.0	
2	ACCESS1.3	X		2	CCCMA-CGCM3.1(T47)	X
3	BCC-CSM1.1			3	CCSM3	
4	BCC-CSM1.1(m)	X		4	CNRM-CM3	
5	BNU-ESM	X		5	CSIRO-Mk3.0	X
6	CanESM2	X		6	CSIRO-Mk3.5	
7	CCSM4	X	X	7	ECHAM5/MPI-OM	X
8	CESM1(BGC)			8	ECHO-G	
9	CESM1(CAM5)			9	GFDL-CM2.0	
10	CMCC-CESM			10	GFDL-CM2.1	
11	CMCC-CM			11	GISS	
12	CMCC-CMS	X		12	INGV-ECHAM4	
13	CNRM-CM5	X	X	13	INM-CM3.0	
14	CSIRO-Mk3.6.0	X		14	IPSL-CM4	
15	EC-EARTH			15	MIRCO3.2(medres)	X
16	FGOALS-g2			16	MRI-CGCM2.3.2	
17	FIO-ESM			17	NCAR-PCM	
18	GFDL-CM3		X	18	UKMO-HadCM3	
19	GFDL-ESM2G	X		19	UKMO-HadGEM1	
20	GFDL-ESM2M	X				
21	GISS-E2-H					
22	GISS-E2-H-CC					
23	GISS-E2-R					
24	GISS−E2−R−CC					
25	HadGEM2-AO					
26	HadGEM2-CC	X				
27	HadGEM2-ES					
28	INM-CM4					
29	IPSL-CM5A-LR	X				
30	IPSL-CM5A-MR	X				
31	IPSL-CM5B-LR	X				
32	MIROC5	X				
33	MIROC−ESM	X				
34	MIROC−ESM−CHEM	X				
35	MPI-ESM-LR	X	X			
36	MPI−ESM−MR	X				
37	MRI-CGCM3	X				
38	NorESM1-M	X	X			
39	NorESM1-ME					

CCAM dynamical downscaling

We examined outputs from the dynamical model used in the NRM project, the Cubic Conformal Atmospheric Model (CCAM) of McGregor and Dix (2008). CCAM is a global atmospheric model with a grid that can be stretched to downscale for a particular region. The configuration of CCAM used for this study employs a globally uniform 0.5° (~60 km) grid and takes from the host model only sea ice concentrations and sea surface temperatures (SSTs) that were bias and variance corrected towards monthly observed SSTs based on the optimal interpolated SST dataset version 2 (OI.v2, Reynolds et al. 2007). First, the monthly SST anomalies were multiplied with a correction factor of the ratio of observed and modelled SST variance, then the climatological bias was subtracted. CCAM outputs were produced using Run 1 from six CMIP5 GCMs as hosts (Table 1), chosen primarily on their performance in the current climate but also to encompass a reasonable spread in projected SST changes in the West Pacific and therefore in projected rainfall change over Australia and southeast Asia. CCAM may produce quite a different mean climate and climate change signal than the host models as it generates its own atmosphere and employs bias correction of SST inputs. In addition, the bias correction of CCAM inputs means that the simulation of the current climate is more similar in each CCAM run than in different GCMs.

Five host models were common to both CCAM and BOM-SDM outputs (ACCESS-1.0, CCSM4, CNRM-CM5, MPI-ESM-LR and NorESM1-M), so the spatial patterns of change from these two groups of five simulations were compared to the host GCMs and to each other.

NARCliM dynamical downscaling

We also examined outputs from the NARCliM project produced using version 3.3 of the Weather Research and Forecasting (WRF) model, described in Skamarock et al. (2008). NARCliM outputs were produced using a two-stage downscaling process to arrive at ~10 km resolution over eastern Australia. WRF is a Limited Area Model (LAM) that can use a large array of components and configurations. The NARCliM outputs were produced using 3 configurations of WRF chosen because they perform well compared to observations and produced different (independent) model errors. The choice of configurations preserved key ensemble characteristics of mean and spread (Evans et al. 2013). The downscaling used four CMIP3 GCMs chosen to represent a robust range of change for NSW from CMIP3 under A2 where data are available (Evans et al. 2013). GCMs used are Run 4 of CCCMA-CGCM3.1 (T47) and Run 1 of MIROC3.2(medres) that simulate an increase in mean annual rainfall over NSW, and Run 1 of ECHAM5/MPI-OM and Run 1 of CSIRO-Mk3.0 that project a decrease. Full details of the NARCliM modelling methods are outlined in Evans et al. (2014).

Comparing and combining projection distributions

The results from CMIP3-based outputs were not directly comparable to CMIP5-based work, as they were created for different model inputs, emission scenarios and time periods. However, the results were compared in a qualitative sense under the general context of results being used in applications as a guide to plausible climate change by late in the 21st Century. The results were also compared by scaling results by the magnitude of global warming using a simple linear scaling to warming, to place the projections on the same scale so they can be compared.

To show the total range of uncertainty in rainfall change if we take each simulation as a legitimate projection, we produced a combined projection distribution using a similar approach to that of Method 1 in Ekstrom et al. (2007). This means a projection of regional change for a particular period is generated by the combination of two probability distribution functions, one of global annual average temperature increase, and one of regional change in precipitation per degree of global temperature increase (see also Jones 2000b; Jones 2000a). The method assumes that the regional change in precipitation is zero for a zero change in global average temperature, and that the regional change scales linearly with global average temperature (e.g., Mitchell 2003). For both distributions, a uniform shape is assumed, representing the view that within the specified range, all results are equally plausible. For CS and ECS results, we combine the regional response of all presented downscaling results scaled by the warming of their respective host model (°C^{-1}), with that of the global warming by the CMIP5 ensemble under RCP8.5 for 2090 (°C). The 10th and 90th percentiles are shown for consistency with previous bar charts. Within each distribution, 100,000 samples are drawn randomly (assuming a uniform distribution), and then combined into a single distribution presented in Figure 7. The approach assumes all downscaled projections are equally legitimate and can be weighted equally.

We considered only the projected changes in each set of outputs relative to their own baseline climate, and do not evaluate the performance of models in the current climate. The climate change signal present in downscaling is not independent of the host model, its biases and its change signal, so the evaluation framework of downscaling is different than for GCMs. Therefore, metrics of regional skill in simulating the current climate for downscaling don't necessarily have a direct relationship to the confidence in their projected change signal. In addition, some downscaling models are designed to have lower regional biases (e.g. BOM-SDM is calibrated to AWAP, CCAM employs bias correction of SST input). This study is not aiming to reject or weight outputs based on their simulation of the current climate, but rather it aims to compare the results of each study as a set of plausible projections.

Outputs were used on their native grids at their native resolutions. We focussed primarily on the ranges of change averaged over the CS cluster and the ECS sub-cluster (Figure 1), as this represents areas of interest to both projects (both NRM and NARCliM), and are at a scale where added value may be produced. Area-averages were made using area-weighted masks unique to each model. The significance of differences between CS and ECS were estimated at the 95% confidence level using a Wilcoxon signed rank test of the two populations. This non-parametric test was used instead of a Student's *t*-test as we don't expect distributions to be normal. Ranges of change are presented by the 10th, 50th (median) and 90th percentile of the range in each model group. The 10th and 90th percentiles are considered as a plausible 'dry case' and 'wet case' when considering the range of projections in a framework similar to Representative Climate Futures (Whetton et al. 2012). We also look at the spatial pattern of change in each study, primarily to examine any artefacts behind the area-averages but also to examine any features in the change signal at scales smaller than the clusters.

Results

Here we describe the changes given by the CMIP3 and CMIP5 ensembles for the region of eastern Australia, then compare this to the changes projected in each downscaling study in turn. We describe the changes in two respects: first the range of change compared to the GCM ensemble (titled 'context') and then the appearance of regional-scale details in the change signal (titled 'regional detail').

Changes in CMIP5 and CMIP3

Projections using up to 39 models from the CMIP5 archive show a wide spread of rainfall change for both the CS cluster and the ECS sub-cluster over the century in each season (Figure 2). Model agreement is not high in each season and in each RCP (bars are spread across the zero line), and projected changes in many models (~60% of models in some seasons) are within the range expected from natural variability without greenhouse forcing (grey bars). The response under each RCP is generally in the same direction, but with greater change for the higher greenhouse forcing. An important exception is for DJF in both regions, where the median projection for RCP2.6 is opposite in sign to other RCPs (noting that the median projection is close to zero for RCP2.6 and RCP4.5 in both regions).

For the highest scenario by the period late in the century, both CMIP3 and CMIP5 projections are similar (Table 2; Figure 3). When results are scaled by global warming to make them comparable, the results show even greater similarity (Figure 4). GCM results are not statistically different between CS and ECS in almost all cases (Table 2). The only exception is spring rainfall changes in CMIP5, which are more negative in CS than in ECS with a mean difference of 5%.

Summary statements on mean rainfall change in CMIP5 and CMIP3 (Table 3) represent the type of high-level messages that may be used by impact research. The main message is of uncertainty in projected change for summer and autumn, but more agreement on decrease in winter and spring in both sets of GCMs. Note this simple system of defining major change (>10%) is different from the comparison to the spread in different ensemble members presented in Figure 2 and used in NRM reports (CSIRO and Bureau of Meteorology 2015). This simpler system is used because there are not multiple members for each model using each method and there are relatively few simulations for some methods.

Figure 2 Projected change in seasonal precipitation for 2080-99 with respect to 1986-2005 from up to 39 CMIP5 models for (left) Central Slopes and (right) East Coast South clusters of NRM regions. The thick bars show the 10th to 90th percentile range of the CMIP5 results and the dark line indicates the median. The scenarios from left to right are: Natural variability only, calculated from the modelled range given different initial conditions (grey), RCP2.6 (green, 28 models), RCP4.5 (yellow, 38 models), RCP6 (blue, 20 models), RCP8.5 (red, 39 models). Seasons are austral summer (DJF), autumn (MAM), winter (JJA) and spring (SON).

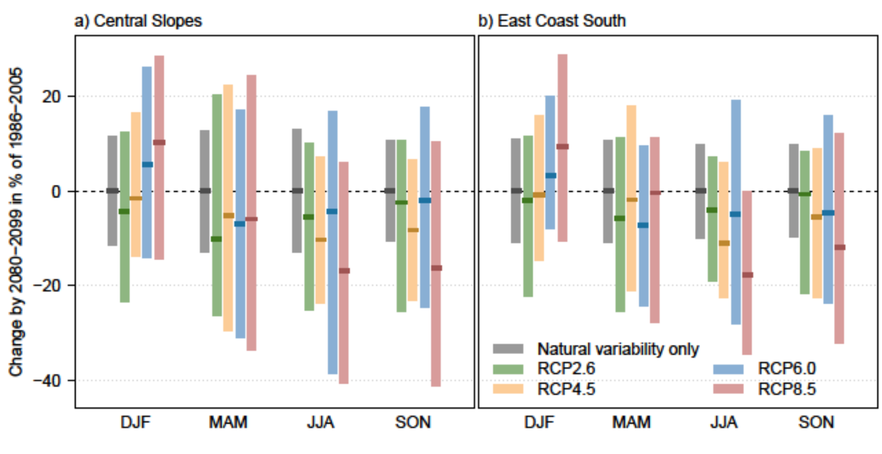


Table 2 Proportional rainfall change (%) for NRM cluster regions for each calendar season from CMIP5, CCAM, and BOM-SDM (1986-2005 to 2080-2099, RCP8.5), as well as CMIP3 and NARCliM (1990-2009 to 2060-2079, A2). The first two columns show the median, 10th percentile and 90th percentile of each model range (bold where the downscaling differs from the host models used for downscaling, at the 95% confidence level using a Wilcoxon signed rank test) and the third column shows the mean of the differences between the two regions in each model group (underlined where difference is significant at the 95% confidence level using a Wilcoxon signed rank test).

	Central Slopes (%)	*East Coast South (%)*	*Mean of CS-ECS (%)*
	CMIP5 (39 simulations)		
DJF	+10 (-14 to +29)	+11 (-12 to +27)	-2
MAM	-4 (-35 to +27)	-2 (-28 to +20)	-2
JJA	-17 (-39 to +15)	-17 (-31 to +1)	1
SON	-14 (-40 to +11)	-8 (-30 to +14)	-5
	BOM-SDM (22 simulations)		
DJF	**-1 (-18 to +25)**	**-11 (-35 to 0)**	13
MAM	-14 (-35 to +18)	-10 (-27 to +7)	-2
JJA	-22 (-38 to -6)	**-29 (-40 to +8)**	2
SON	-22 (-34 to -1)	**2 (-24 to +30)**	-22
	CCAM (6 simulations)		
DJF	**+20 (+10 to +35)**	**+26 (+10 to +35)**	-4
MAM	**+3 (-9 to +31)**	**+13 (-8 to +36)**	-6
JJA	-1 (-17 to +13)	-4 (-13 to +10)	2
SON	-11 (-23 to +27)	-9 (-28 to +27)	0
	CMIP3 (19 simulations)		
DJF	+8 (-6 to +23)	+6 (-6 to +25)	0
MAM	-3 (-19 to +22)	-1 (-18 to +21)	-2
JJA	-13 (-38 to +10)	-7 (-32 to +11)	-3
SON	-12 (-32 to +10)	-6 (-31 to +8)	-3
	WRF-NARCliM (12 simulations)		
DJF	+10 (-8 to +28)	+11 (-7 to +21)	2
MAM	**+14 (-1 to +43)**	+12 (-4 to +35)	4
JJA	+4 (-28 to +40)	-8 (-23 to +25)	7
SON	-9 (-18 to +17)	**0 (-15 to +32)**	-8

Bureau SDM and host models

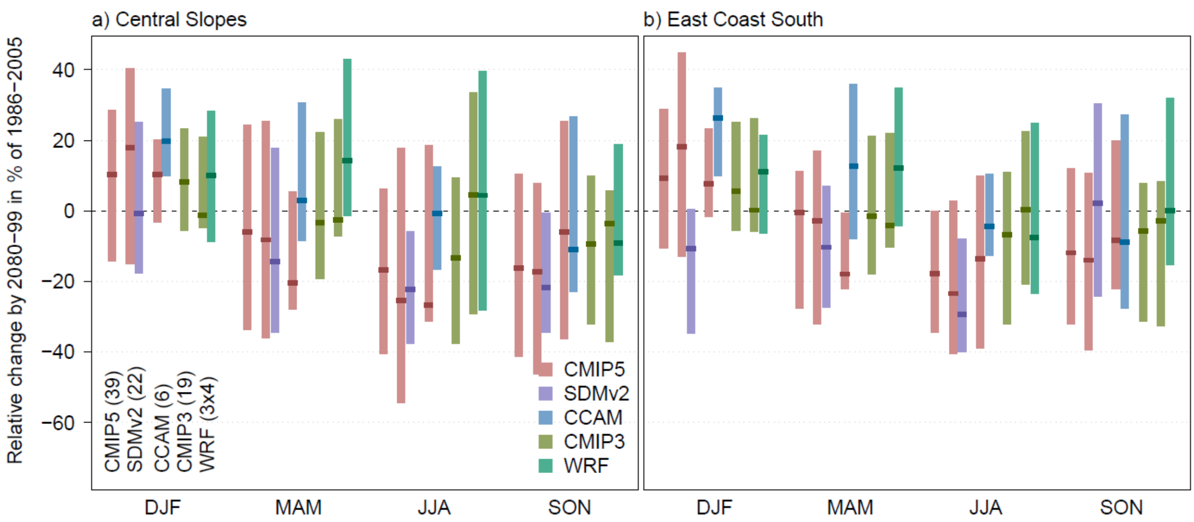
Context

Using 22 GCMs provides a good sampling of the range of projected change in CMIP5. Area averages of these 22 models show a fairly consistent range of change compared to the entire archive (Figure 3). Therefore, differences in the ranges of projected change in the entire set of BOM-SDM results from CMIP5 are primarily the effect of the downscaling rather than sub-sampling.

The projections in BOM-SDM tend more towards rainfall decrease across both CS and ECS than the host models in DJF and MAM and this gives a very different median projection and summary statements for both regions (Table 2 and 3). However, the 10th percentile (a plausible 'dry case' for impact studies) is only lower than host models in DJF in ECS.

The tendency for decrease in rainfall at the large scale is discernible in the spatial pattern of change in five models compared to their hosts, with broader regions of projected decrease in much of eastern Australia in every season, with higher model agreement (Figure 5).

Figure 3 Projected change in mean rainfall (%) from CMIP5 and various modelling studies season averaged over NRM cluster regions Central Slopes (left panel) and East Coast South (right panel). CMIP5-based results are for RCP8.5 1986-2005 to 2080-2099 and CMIP3-based results are for SRES A2, 1990-2009 to 2060-2079. Bars in each panel show from left to right: a single bar showing results from 39 CMIP5 models (red); two bars showing BOM-SDM results: 22 CMIP5 models input to BOM-SDM (red) and BOM-SDM results (purple); two bars showing CCAM results: six GCMs input to CCAM (red) and CCAM results (blue); a single bar showing results from 19 CMIP3 models (olive); and two bars showing NARCliM results: 4 CMIP3 models used as input into NARCliM (olive) and NARCliM results (green). Bars show the 90th and 10th percentile of the model range and dark lines mark the 50th percentile (median).



Regional detail

There is a statistically significant difference in the area-average projected rainfall changes in CS compared to ECS in DJF, JJA and SON in the BOM-SDM outputs (Table 2). In particular, the BOM-SDM results in ECS show a greater decrease in DJF and a much reduced decrease in SON than inland.

However, interpreting the regional detail of projections from BOM-SDM results and its distinction between CS and ECS is confounded by the hard boundary in the middle of ECS. This boundary is an artefact of the downscaling method, where a different set of predictors was used in the north and the south within ECS. The BOM-SDM was developed prior to the NRM boundary definitions and uses ten distinct climate entities roughly following the rotated Empirical Orthogonal Functions for rainfall suggested by Drosdowsky (1993). In the comparison of the spatial pattern of change in five simulations (Figure 5), the changes in ECS in DJF and SON are a mixture of a smaller zone in the north and a larger zone in the south with an opposite sign of change.

The spatial comparison of five simulations also features some fine-scale regional features in the BOM-SDM projections (Figure 5a). In DJF there are some areas of rainfall increase on the slopes of the Great Dividing Range in the south of ECS, contrasting with the rainfall decrease in surrounding areas. In JJA and SON some coastal areas show a greater rainfall decrease than surrounding areas.

CSIRO CCAM and host models

Context

The CCAM results use only six host GCMs, so represent a smaller sub-sample than the BOM-SDM results. However there are many cases where the range of change in the six models is similar to the ensemble of 39 models, or only slightly reduced (Figure 3). A notable exception is the sampling of mainly the drier end of projections in MAM in both CS and ECS.

CCAM produces a different projection to the host models at the large scale of eastern Australia in most seasons. The range of change in CCAM is more positive than hosts in DJF, MAM and JJA (Figure 3), and the difference from the six hosts is significant in DJF and MAM in both clusters (Table 2). This leads to a difference in the direction of projected change in MAM, with the host GCMs projecting little change or drying in CS and ECS but most CCAM simulations projecting a rainfall increase (Figure 3, Table 2), and this fundamentally changes the summary statement (Table 3). Also, CCAM projects little change in JJA in contrast to the distinct rainfall decrease from GCMs. The spatial extent of these differences is visible in the five models compared to their hosts (Figure 5).

The 90th percentile projection (which may be a suitable ‘wet case’ for impact studies) is more positive in CCAM than CMIP5 in DJF, MAM and SON in both clusters.

Regional detail

These CCAM simulations have ~ 50 km resolution, meaning any possible regional detail is not as finely resolved as in BOM-SDM or NARCliM. However, the CCAM results include some cases of regional distinction between CS and ECS. In MAM, the CCAM projections are significantly more positive in ECS than in CS (Table 2). The projection in CS is not different compared to ECS in any other season. However, the mean of the five models compared in Figure 5 shows some enhancement of the rainfall increase for regions near the coast compared to inland and offshore in DJF and SON. In SON there is a region of rainfall increase near the east coast compared to the decrease in the surrounding regions including CS, a feature not present in the host models. However, the changes are not consistent and widespread enough over ECS to mean that the area-average median projection is positive (Figure 3), or to create a significant difference between the two clusters in this season (Table 2). The enhanced rainfall increase near the east coast in DJF in CCAM is the opposite of the enhanced rainfall decrease in BOM-SDM.

NARCliM and host models

Context

Projected rainfall change is more positive in NARCliM than CMIP5, CMIP3 and the four host models in MAM (Figure 3). When results are scaled per degree of global warming, the NARCliM projections in MAM and JJA in CS show the largest increase of all studies, both in the median and 90th percentile (Figure 4). Some differences are partly explained by sub-sampling, such as JJA in CS where the four models used produce a rainfall increase in contrast to the full ensemble of 19 (Figure 3). However, the NARCliM results are significantly different from the four host models in CS in MAM (Table 2). Interestingly, some changes in NARCliM are comparable to CMIP3 despite the influence of uneven sub sampling, such as in DJF in CS. The tendency for more positive rainfall change, with higher model agreement is similar to the results from the other dynamical model CCAM, and can be seen in maps of change (Figure 6).

A notable difference between NARCliM and both CMIP3 and CMIP5 is in the 90th percentile of rainfall projections. The 90th percentile is markedly higher in NARCliM than GCMs in MAM and JJA. Some individual NARCliM simulations show extraordinary rainfall changes of >60% increase in many regions in DJF and MAM. Also of note is that changes are typically more different between runs of different GCMs than between different WRF configurations.

Regional detail

There are some distinct patterns of mean rainfall change in the Eastern Seaboard compared to offshore and inland in NARCliM, and these vary by season (Table 2, Figure 3, 6). The rainfall projection is significantly drier for CS than for ECS in SON (Table 2). In DJF and MAM most NARCliM simulations project a greater rainfall increase in CS than ECS that contradicts the CCAM results, but in JJA they project a greater decrease in JJA in ECS than in CS confirming the CCAM results (Table 2). However, because of the range of results in these seasons, the two results are not significantly different in DJF, MAM or JJA (Table 2). Some of these patterns are discernible in maps of change, particularly the difference in sign on the eastern seaboard compared to inland present in JJA and SON (Figure 6).

The 90th percentile of projections (a plausible ‘wet case’ for impact studies) is higher in CS than in ECS in DJF, MAM and JJA but is higher in ECS than in CS in SON in the NARCliM results (Figure 5).

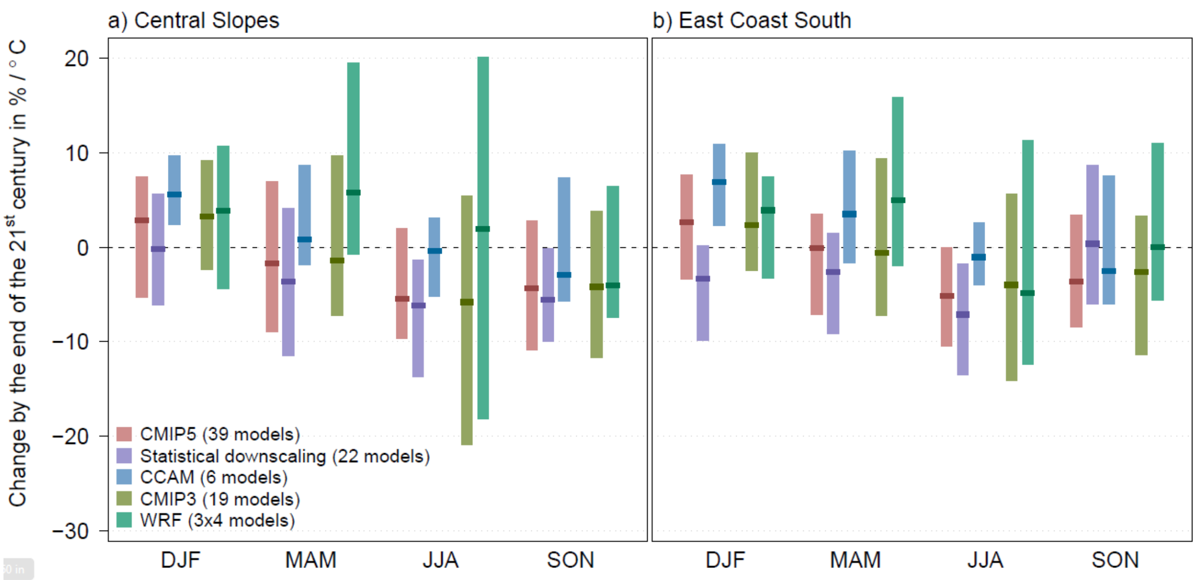
Combined distribution

The combined distribution (Figure 7) gives a broader range of change than just CMIP5 for each season, including a wetter ‘wet case’ in every case and a drier ‘dry case’ in some cases (particularly winter). The dry case is similar in some instances, such as spring in ECS. There is a more positive median projection in the combined distribution compared to CMIP5 in a few cases, particularly in ECS in spring but also in CS in spring and ECS in winter. These differences reflect the potential added value brought by downscaling described above, particularly for spring in ECS.

Table 3 Median direction of change and summary statements on projections for Central Slopes (CS) and East Coast South (ECS) for late in the 21st Century for each season under a high emissions scenario (A2 or RCP8.5) from various model ensembles. Sign of the median projection is given as positive (+) or negative (-) or as Little Change (L/C, where the median is <5%). Summary statements are given by the agreement on substantial increase >10%, decrease <10%, or little change (-10 to 10%) in each model (where the main category is the largest proportion, and exceptions of >10% model proportion are listed).

Season	*Ensemble*	*Cluster*	*Median*	*Summary statement*
DJF	CMIP5	CS	+	Increase, but L/C also possible
		ECS	+	Increase, but L/C also possible
	CMIP3	CS	+	L/C, but Increase also possible
		ECS	+	L/C, but Increase also possible
	BOM-SDM	CS	L/C	Increase or Decrease possible
		ECS	-	Decrease, but L/C possible
	CCAM	CS	+	Increase
		ECS	+	Increase
	NARCliM	CS	+	Increase
		ECS	+	Increase
MAM	CMIP5	CS	L/C	L/C, but Increase or Decrease also possible
		ECS	L/C	L/C, but Increase or Decrease also possible
	CMIP3	CS	L/C	L/C, but Increase also possible
		ECS	L/C	L/C, but Increase also possible
	BOM-SDM	CS	-	Decrease, but L/C also possible
		ECS	-	Decrease, but L/C also possible
	CCAM	CS	L/C	L/C, but Increase also possible
		ECS	+	Increase
	NARCliM	CS	+	Increase
		ECS	+	Increase, but L/C also possible
JJA	CMIP5	CS	-	Decrease
		ECS	-	Decrease
	CMIP3	CS	-	Decrease
		ECS	-	Decrease
	BOM-SDM	CS	-	Decrease
		ECS	-	Decrease
	CCAM	CS	L/C	L/C, but Increase or Decrease also possible
		ECS	L/C	L/C, but Decrease also possible
	NARCliM	CS	L/C	Increase or Decrease both possible
		ECS	-	Increase or Decrease both possible
SON	CMIP5	CS	-	Decrease
		ECS	-	Decrease, but L/C also possible
	CMIP3	CS	-	Decrease, but L/C also possible
		ECS	-	L/C, but decrease also possible
	BOM-SDM	CS	-	Decrease
		ECS	L/C	Increase or Decrease both possible
	CCAM	CS	-	Decrease, but L/C also possible
		ECS	-	Decrease, but L/C also possible
	NARCliM	CS	-	Decrease
		ECS	L/C	L/C, but Increase also possible

Figure 4 Projected change in mean rainfall per degree of global warming (%/°C) for various modelling studies by calendar season averaged over NRM cluster regions Central Slopes (left) and East Coast South (right). CMIP5-based results are for RCP8.5 1986-2005 to 2080-2099 and CMIP3-based results are for SRES A2, 1990-2009 to 2060-2079. Bars in each plot show projections from left to right: 39 CMIP5 models (red), BOM-SDM results (purple), CCAM results (blue), CMIP3 results (olive), and NARCliM results (green). Thick bars show the 90th and 10th percentile of the model range and dark lines mark the 50th percentile.



Discussion

The results from different climate model downscaling studies of eastern Australia show some noteworthy changes that differ from the host models used, and these differences arise for a variety of reasons. There are no examples of a consistent message from all three downscaling studies that contradict the broad findings of CMIP5, but there are some cases where two of the three studies indicate a difference in rainfall projections between Central Slopes and East Coast South. There are also cases where downscaling provides a different range of change over the entire eastern Australian region than CMIP5 (seen in consistent results for CS and ECS in bar plots and Table 2, and in maps of change in Figure 5 and 6). There are several cases where downscaling project changes for clusters that are outside the CMIP5 range.

Projections of mean rainfall change over the century from CMIP3 and CMIP5 are broadly similar for both the East Coast South and Central Slopes clusters. One of the most notable projections in terms of potential impacts is a decrease in winter rainfall for both clusters, with the possibility of a substantial decrease. Both GCM ensembles indicate that increases or decreases are possible in summer and autumn, with the possibility of little change. The GCMs also project that a rainfall decrease in spring is more likely than not, but with some distinction between a decrease in CS and a smaller decrease in ECS. Model agreement is not high on the projected direction of change for rainfall in most seasons, especially in ECS. This is broadly consistent with previous studies, indicating that the degree of confidence in projections of future rainfall in the Eastern Seaboard region is generally not as high as in many other regions of Australia (CSIRO and Bureau of Meteorology 2007). This is due in part to the considerable influence of small-scale topography on rainfall in this region and how it is handled in different models (Evans and McCabe 2013). It is likely that the different handling of various synoptic systems by different models also contributes to differences in results.

These issues highlight the importance of considering a range of modelling methods including downscaling in this region. Downscaling may be useful in this region however these results show that interpreting downscaled projections is not straightforward.

Downscaling can only be run for a subset of GCMs due to computational or data limitations. Therefore, the influence of sub-setting on the final projections is important to consider when interpreting the results of a downscaling study as an overall climate projection. Here we find that the subsets used in these downscaling studies are broadly consistent with the overall GCM ensemble, with some exceptions. The six GCMs chosen for CCAM downscaling are weighted towards rainfall decreases in autumn in NSW. CMIP3 sampling by the NARCliM study is broadly representative for these two clusters, except for a difference in the median projection for summer and winter in the four models compared to the whole of CMIP3.

Figure 5 Projected change in mean rainfall (%) between 1986-2005 and 2080-2099 from Run 1 from five CMIP5 GCMs (ACCESS-1.0, CCSM4, CNRM-CM5, MPI-ESM-LR, NorESM1-M), five SDM runs using these GCMs as input and 5 CCAM simulations using these GCMs as input for four calendar seasons. Stippling shows where at least four out of the five simulations agree on the direction of change.

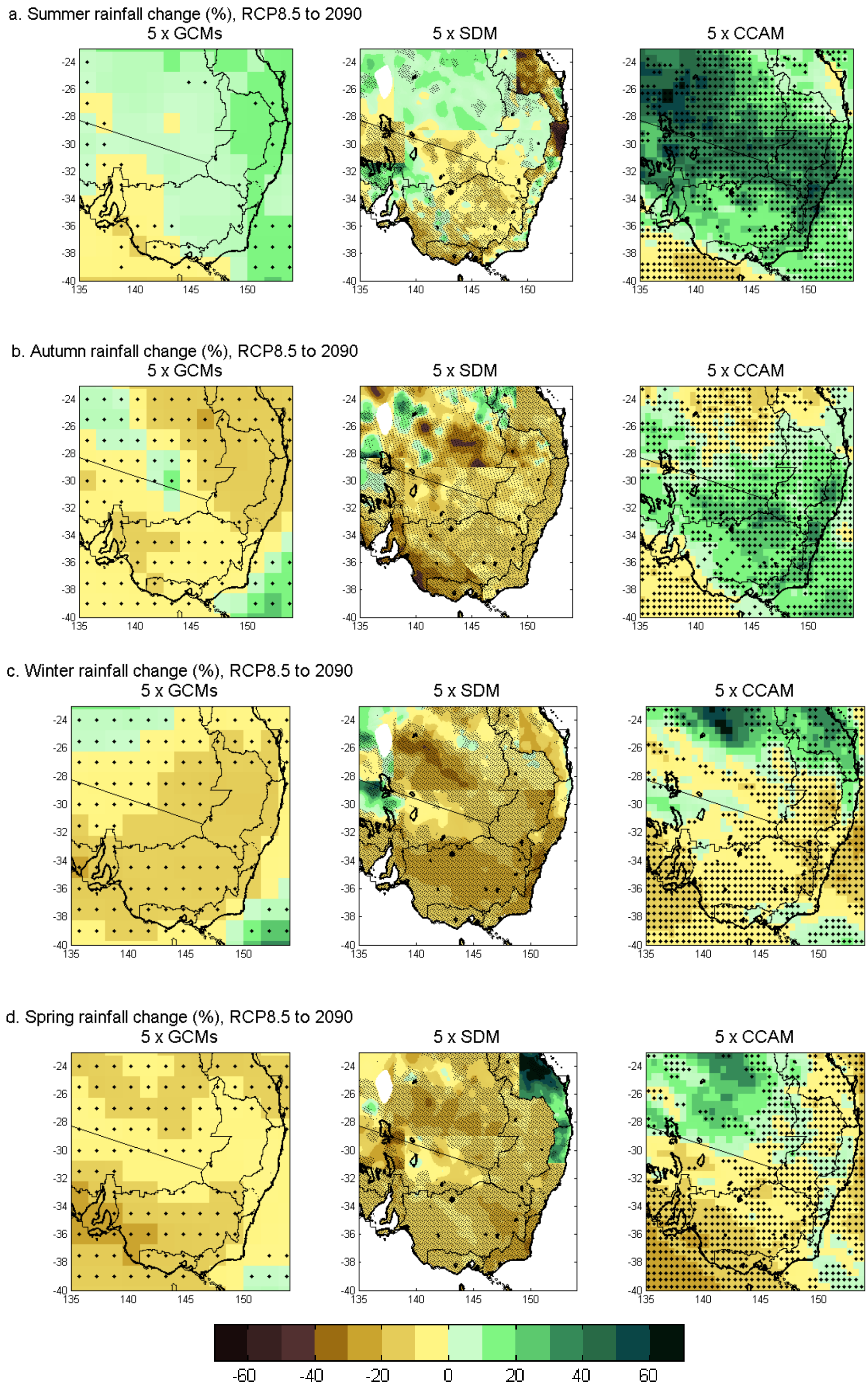


Figure 6 Projected changes in mean rainfall (%) between 1990-2009 and 2060-2079 for the A2 scenario in calendar seasons. The left column shows the mean of four CMIP3 GCMs (CGCM3.1-T47, CSIRO-Mk3.0, ECHAM5-MPI/OM and MIROC3.2(medres)) regridded to the grid of CSIRO-Mk3.0, stippling shows where all four models agree on the sign of change. Right column shows mean of 12 WRF simulations form NARCliM, stippling shows where at least ten out of the twelve simulations agree on the direction of change.

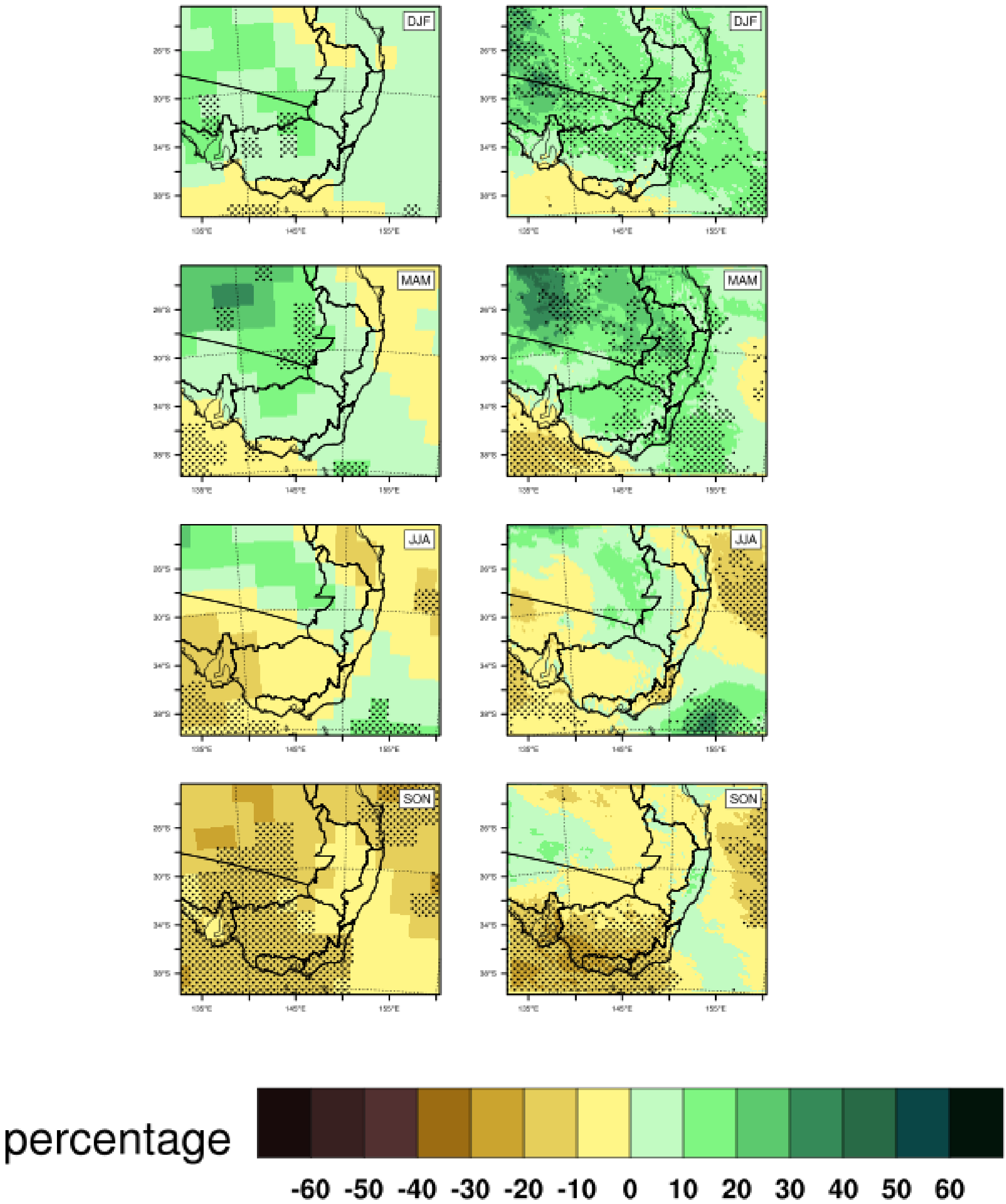
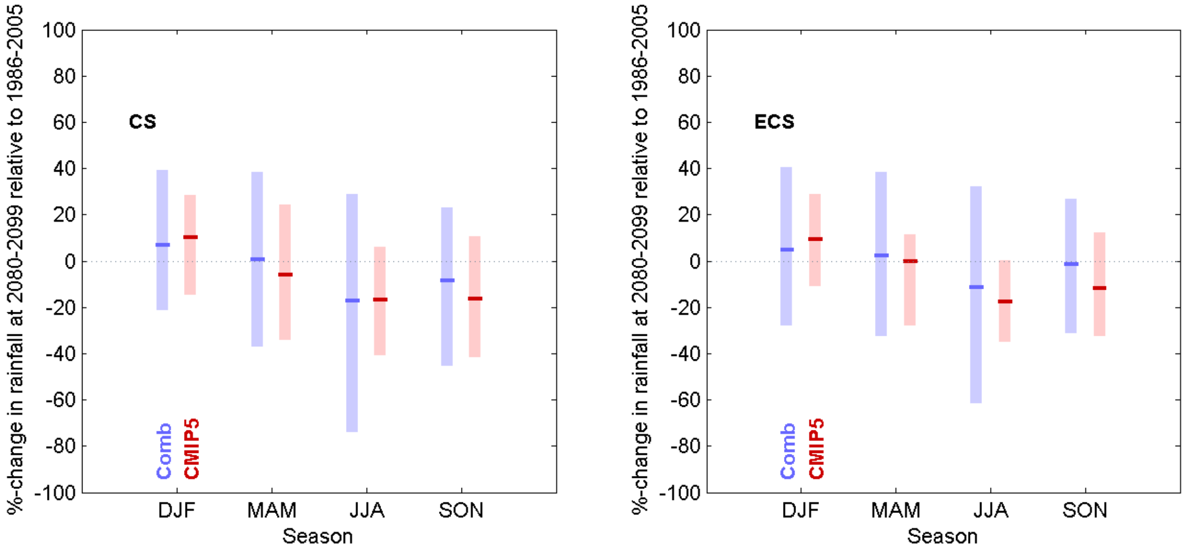


Figure 7 Combined distributions of all models for rainfall projections in two eastern Australian clusters under RCP8.5 for 2090. The bars give the range of the resulting product sample from combining 100,000 randomly drawn samples from two uniform probability density distributions. The first distribution is bounded by the 10th and 90th percentile of the downscaled response (proportional change (%) in CCAM, NARCliM and BOM-SDM scaled by the global annual average warming of their respective host model) and the second by the 10th and 90th percentile of CMIP5 (proportional change (%) for RCP8.5 for 2090 for the global warming as simulated).



The downscaling studies examined here produced some different projections compared to CMIP5 at the large scale of eastern Australia. The BOM-SDM statistical downscaling produced a generally drier projection than the GCMs for summer in both clusters, whereas CCAM and NARCliM produced significantly wetter projections than their host models in most seasons. The scale of Central Slopes and East Coast South combined is broader than that at which the extra resolution of the effect of topography or coastlines may be expected to have a direct effect. Therefore, it is unlikely that the extra resolution of topography alone accounts for the difference in projected change between GCMs and the dynamical downscaling. Propagating changes from the small scale to the larger scale, known as ‘upscaling’ is an important consideration in regional modelling and may explain some of the difference between downscaling and host GCMs (Leung et al. 2006). An example may be orographic effects that influence the broader circulation over the region, which may be present over the Great Dividing Range. Also, results from CCAM downscaling could differ from the host models because of the bias correction of SSTs. However, there may also be cases where the model components and behaviour affect the results. This shows that the downscaling method has an effect on the broader scale projection, and influences the overall range of change that is not necessarily ‘added value’ at the regional scale that downscaling is used to examine. This context-setting of the broader scale change is important when examining the regional-scale changes that are of strong interest from downscaling studies.

The downscaling studies suggest some distinction in the regional climate change signal in mean rainfall between the eastern seaboard and inland is plausible in some seasons. However, the signal is not consistent across every study. CMIP5 shows a distinction between the two areas in spring, and the downscaling generally makes this distinction more marked (Table 2, Figure 3, 5, 6). Both dynamical methods suggest that spring rainfall could show little change or increase in some regions of the eastern seaboard, in contrast to the rainfall decrease inland and offshore. The statistical downscaling also shows this distinction, but the result here is confounded by artefacts in the model output due to the different zones used. But taking the results from BOM-SDM on face value, treating them as a legitimate weighted average of two distinct climate zones, then the results broadly agree with the NARCliM dynamical downscaling. There is also a larger 90th percentile change projection in ECS in spring in each downscaling study, which may be considered as a ‘wet case’ for impact studies, in an approach such as the Representative Climate Futures approach of Whetton et al. (2012).

A distinction between the eastern seaboard and inland is less clear in summer and autumn than in spring. Both CCAM and NARCliM dynamical downscaling studies project an enhanced rainfall increase across the whole region compared to the host models used, but CCAM also produced a significantly enhanced signal in the eastern seaboard in autumn (Table 2, Figure 5). The artefact in the SDM is almost as prominent in summer as it was in spring, making interpretation difficult for these outputs in this season.

ECLs and thunderstorms are generally more prevalent and bring more rainfall in ECS than in CS. Therefore, changes to the average incidence of these systems would be expected to affect the rainfall projection in each cluster differently. For example, an increase in rainfall associated with ECLs or thunderstorms and a decrease in rainfall associated with fronts is a plausible cause for enhanced rainfall increase in parts of the eastern seaboard as compared to further inland in spring in the downscaling (Table 2). These changes to synoptic systems are not inconsistent with current understanding of physical processes, and may be related to a better representation of the systems or the rainfall they bring in downscaling. Notably, NARCliM projects the frequency of ECLs to slightly increase in summer and decrease in winter (Ji et al. 2015).

There are differences in the large-scale rainfall change and regional detail in the dynamical downscaling compared to statistical downscaling examined here, and there is no clear reason to accept one over another. The uncertainty in projections of future changes in heavy rainfall associated with relatively small-scale phenomena such as thunderstorms, ECLs and intense frontal systems may explain some of the differences in the various studies. So the projections from dynamical downscaling of rainfall increase over all of eastern Australia in summer and autumn rainfall beyond that from GCMs are very plausible, and may be driven by an increase in rainfall associated with thunderstorms and ECLs. Changes to heavy rainfall contributed strongly to differences in projection for the west coast of the United States (Pierce et al. 2013), a location with many similarities to the Australian eastern seaboard. The results presented here suggest that further investigation of changes to the rainfall distribution and synoptic climatology in GCMs compared to downscaling is worthwhile, particularly for spring but also for summer and autumn. Also see review of physical plausibility of changes in Dowdy et al. (2015).

Differences between methods create differences in the summary statements from each set of results (Table 3). Even when scaled by the amount of global warming to account for differences in emissions scenarios and time periods (Figure 4), the main messages are still quite different in important respects. Summary statements such as these can be a very prominent output of a regional climate change study and are likely to be used by planners and applied researchers to explore climate change impacts and adaptation options, either as qualitative information or as quantitative datasets that represent that understanding. The differences in Table 3 make it clear that different approaches give different take-home messages in each case. The combined distribution (Figure 7) reflects the potential added value brought by downscaling in expanding the range of potential rainfall projections, particularly for spring in ECS.

This comparison shows that downscaling generally does not narrow uncertainties in climate projections, but broadens them. The combined distribution gives a more complete picture of what the projections from several legitimate sources of projection information show as a plausible projected change. It also highlights that using one set of downscaling outputs in isolation may not give the broad enough picture of plausible future change. The spatial scale of the CS and ECS clusters is still fairly broad, and differences for highly regional projections would be much larger and downscaling is likely to provide some much higher or lower extremes for highly regional projections.

The NARCliM project uses the WRF downscaling described here and complements this with CMIP3 projections. The NRM national climate projections project (CSIRO and Bureau of Meteorology 2015), considers the CMIP5 ensemble as the primary source of quantitative projections, but complements these results with insights in temperature and rainfall projections from CCAM and BOM-SDM downscaling and from NARCliM in the East Coast cluster. The comparison presented here suggests that downscaling has potential benefits in the region but to gauge the full range of uncertainty in rainfall change it is necessary to place any set of model runs in context of other available simulations. A legitimate alternative approach to consider a wider range of uncertainty would be to use the combined distribution of all available projections (Figure 7).

Conclusions

The comparison of the mean rainfall change in downscaling compared to GCMs has suggested some plausible cases of new regional detail revealed by downscaling. A difference between the spring rainfall projection in East Coast South compared to Central Slopes is present in CMIP5 (but not in CMIP3) and downscaling generally suggests this difference could be more marked than CMIP5 suggests. Downscaling suggests that there could be little change or a moderate rainfall decrease in East Coast South compared to the substantial decrease inland in spring, with rainfall increase in some regions of the eastern seaboard. Downscaling also produces a plausible wetter 'wet case' projection for East Coast South in spring than GCMs produced. Finer resolution in the downscaling may produce a different projection of change in heavy rainfall (e.g. associated with thunderstorms, ECLs or fronts) and this may contribute to these differences.

Dynamical downscaling studies generally suggest a wetter median change and wetter 'wet case' over the whole eastern Australia region compared to GCMs, particularly in summer and autumn. The interaction between different model components and configurations combined with the move to finer spatial resolution through the process of downscaling may contribute to this difference. Downscaling does not necessarily produce a more plausible projection in this regard, and the cause of the difference to hosts is worthy of further investigation.

The comparison has also highlighted the uncertainties introduced by the downscaling process, and cases where the projections do not encompass the plausible range of change projected by GCMs. The effect of using a sub-set of GCMs as input and the influence from particular downscaling methods present non-negligible sources of uncertainty in the projections. The use of sub-regions for BOM-SDM statistical downscaling and systematic shift in the projection range in dynamical downscaling presented a particular challenge to interpreting results. Placing the data used by a particular impacts study in the context of other available projections, or using a combined distribution of projected change are useful measures to partly deal with the issue.

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